Automated Mobility on Demand: A comprehensive simulation study of cost, behaviour and system impact for Zurich

Sebastian Hörl[a,*], Felix Becker[a], Kay W. Axhausen[a]

[a] *Institute for Transport Planning and Systems, ETH Zurich*

Abstract

Automated Mobility on Demand (AMoD) is a concept that has recently generated much discussion. In cases where large-scale adoption of an automated taxi service is anticipated, the service's impacts may become relevant to key transport system metrics, and thus to transport planners and policy-makers as well. In light of this increasingly important trend, this paper presents an agent-based transport simulation with AMoD. In contrast to earlier studies, all scenario data (including demand patterns, cost assumptions and customer behaviour) is obtained for one specific area, the city of Zurich, Switzerland. The simulation study fuses information from a detailed bottom-up cost analysis of mobility services in Switzerland, a specifically tailored survey about automated mobility services conducted in the canton of Zurich and a detailed agent-based transport simulation for the city, based on MATSim. Methodologically, a comprehensive approach is presented that iteratively runs these components to derive states in which service cost, waiting times and demand are in equilibrium for a cost-covering AMoD operator with predefined fleet size. For Zurich, several cases are examined, with 4,000 AMoD vehicles leading to the maximum demand of around 110,000 requests per day that can be attracted by the system, based on stated user preferences. Within these parameters, customers are willing to accept average waiting times of around 2.5 minutes at a price of 0.75 CHF/km. Further cost-covering cases with lower demand are presented, where either smaller fleet sizes lead to higher waiting times, or larger fleet sizes lead to higher costs. Caused by modal shifts, our simulations show an increase of driven distance in the system of up to 100%, but a reduction in the number of active vehicles. Contrary to previous research, more than one feasible system state is provided. Instead, a selection of service regimes with different trade-offs between comfort and accessibility is presented, to build a basis for future policy analysis and decisions.

Keywords: automated, vehicles, AMoD, MATSim, Zurich, transport, simulation, dynamic, demand, discrete choice

1. Introduction

Automated vehicles have been widely discussed in society and research recently. While technology is developing quickly, questions related to planning and policy-making become ever more important.

Automated vehicles' expected positive effects include increased travel comfort; people can perform activities other than driving. More mobility is expected to emerge for various user groups such as the elderly and children because a missing driving license or reduced alertness will no longer be obstacles. Accident rates are also predicted to drop as vehicles have shorter reaction times than human drivers and are not prone to fatigue. A large share of automated vehicles may free up space in the urban environment, because vehicles can park far away or in hidden, compact facilities. Efficient sharing strategies, within or among households, could reduce the total number of vehicles required.

Therefore, many see automated mobility as the next step for the ride-hailing industry. In an *Automated Mobility on Demand* (AMoD) service, customers would call an automated taxi and be picked up at a predefined point. They would then be driven to their destination, potentially sharing the ride with others on the way, and dropped off. Such a system has the potential to decrease the number of vehicles in the city, further enabling city planners to re-allocate urban space (Cugurullo et al., 2020).

However, automated mobility also comes with problems. Besides ethical considerations about their behavior in conflict situations, legal liability issues and challenges in cyber-security, problems with re-

*Corresponding author

Email addresses: sebastian.hoerl@ivt.baug.ethz.ch (Sebastian Hörl), felix.becker@ivt.baug.ethz.ch (Felix Becker), axhausen@ivt.baug.ethz.ch (Kay W. Axhausen)

bound effects and induced demand remain. If travelling becomes so comfortable and easy that more trips take place than before, would automated vehicles create even more congestion on the roads that before (Meyer et al., 2017)? Would they attract demand from aggregated public transport and degrade its service level? Additionally, automated vehicles, especially when operated as a fleet service, come with empty rides, as is the case for today's taxis, but potentially on a much larger scale. While studies predict up to two-thirds less cars on the roads (Spieser et al., 2014) with a large Automated Mobility on Demand system, what are the societal and environmental gains (Taiebat et al., 2018; Williams et al., 2020; Wadud et al., 2016) if such a fleet covers more distance than all private cars today?

Such questions are inherently connected to the attractiveness of an AMoD service. As has been shown, price and waiting times (service level) are major drivers of the decision to opt for, or against, an (automated) on-demand service (Becker and Axhausen, 2017). Likewise, waiting times are strongly connected to the demand level, i.e. how many customers use the system, driving up waiting times. Furthermore, service cost strongly depends on how much distance the fleet vehicles drive with a paying customer and how empty they are. This ratio, in turn, affects operators' incomes and, consequently, prices requested from customers. Hence, the problem of understanding utilization and impact of an AMoD service (at a given fleet size) emerges from a complex interplay of customer preferences and fleet management.

In this paper, we report on a comprehensive treatment of these interactions, presenting a simulation of individual decision-making customers, who interact with a fleet of automated vehicles. In our approach, we show how demand drives prices and waiting times of an AMoD- system and how, in turn, customers dynamically react to those variables assuming a fully self-financing service. Finally, we report on system states in which prices, waiting times and travel demand are in equilibrium. While conceptually similar simulation studies exist (see below), we present a consistent set-up based on user preferences and vehicle costs specifically obtained for one city, thus rendering a consistent picture of a potential future automated mobility system for Zurich or other cities.

The paper is structured as follows. Section 2 gives an overview of existing studies and how methodology has evolved. In Section 3, we present the building blocks of our proposed dynamic demand simulation. Key results of future Zurich mobility scenarios are provided in Section 4, followed by a discussion of our method and planning implications. Section 6 concludes the paper.

2. Background

While extensive comparative literature reviews on system-wide simulation studies of automated mobility are available (see, e.g., Gurumurthy et al. (2019a); Pernestål and Kristoffersson (2019); Jing et al. (2020); Narayanan et al. (2020)), the following overview will focus on the demand and supply interplay in available studies.

Fagnant and Kockelman (2014) present one of the first simulation studies with system impact in mind. They impose a static, artificially generated demand on a grid network to study an AMoD system's impact on waiting times and empty miles. A similar approach is followed by Zhang et al. (2015). Chen et al. (2016); Fagnant and Kockelman (2018) extend the framework with infrastructure placement for charging facilities and ride-sharing. The demand is made more realistic by generating individual trips, based on *origin-destination* (OD) flows for Austin. While previous studies use a custom-made simulator, Liu et al. (2017); Loeb et al. (2018) present a MATSim-based simulation for Austin in a trip-based, static setting, where fleet outcomes do not feed back into demand. Methodology is based on (Boesch et al., 2016), who applies it in one of the first studies in the Swiss context.

Just as the studies mentioned before, others exist based on a static (one-shot) demand, such as (Martinez and Viegas, 2017) for Lisbon, (Javanshour et al., 2019) for Melbourne, (Lokhandwala and Cai, 2018) based on New York taxi data, (Poulhès and Berrada, 2020) for a campus application in France and (Balac et al., 2020) for an automated on-demand public transport system in Zurich. What those static-demand simulations have in common is that fleet outcomes, such as waiting times or price, do not influence demand. Rather, it is imposed statically; the studies report on fleet sizes required to achieve certain acceptable waiting times (see Figure 1a).

Additional behavioral realism is added by simulations allowing travellers to make dynamic decisions. As one of the first papers with active decision makers, Chen and Kockelman (2016) use a multinomial logit model with mode-independent VOTs and price sensitivities to test different pricing schemes. Furthermore, customers react to waiting times by first assuming a 2.5 minute waiting time for the trip, which increased in every time step, eventually making the customer switch to either his or her car, or public transport. A similar logic is applied in a campus simulation for Delft (Scheltes and de Almeida Correia, 2017) and in

a simulation for Ann Arbor, Michigan (Lu et al., 2018), where waiting times are communicated per trip at the time of request. Dandl et al. (2019) extends the concept by simulating detailed customer-operator interactions of request, quote, dispatching and potential drop-out.

While the simulations above assume bookings on short notice (similar to the use of ride-sharing services today), a range of studies looks at the wider scope when AMoD would be available as a transport mode for regular trips. Here, the focus is shifted to customers' longer-term planning which requires making them aware of the service level offered. Levin et al. (2017) points out that a simulations with iterative structure help increase the level of realism; waiting times, travel times and congestion can go into equilibrium with demand. Such closed-loop simulation studies usually apply a demand model, followed by a simulation of the transport system and a subsequent feedback of information to the demand model. Studies that follow this pattern are presented by Wen et al. (2018), Liu et al. (2019) and Gurumurthy et al. (2020), all of which make use of predefined pricing schemes.

Those studies were still based on individual trips, rather than interconnected and constrained daily activity patterns. Simulations that take full-day activity chains into account are performed with the SimMobility framework for Singapore (Azevedo et al., 2016; Le et al., 2019). Their model goes one step further: not only mode decisions are dynamic, but also generation of daily activity patterns based on increases or decreases of accessibility in the transport system (Oh et al., 2020a,b; Nahmias-Biran et al., 2020).

MATSim (Horni et al., 2016) is frequently used as another option to simulate automated vehicles. While a detailed description of the model will be given below, previous efforts of simulating AMoD services are presented here. Initially, Bischoff and Maciejewski (2016) propose a static demand simulation, based on taxi data for Berlin (and later Barcelona, Maciejewski et al. (2016b)) without dynamic decision-making. Later, the authors extend the simulation with detailed demand patterns, using individual daily activity patterns and socio-demographic attributes of Berlin residents (Ziemke et al., 2019) to study the effect of automated vehicles' capacity improvements (Maciejewski and Bischoff, 2018). Yet, demand is still static, based on trips of their synthetic traveller population. Hörl (2017) applies the framework first in a dynamic context for an artificial test scenario of Sioux Falls, which is later extended for ride-pooling services (Wang et al., 2018). In these simulations, service characteristics, such as waiting times, directly influence the decision-making of the agents. Simoni et al. (2019) and Gurumurthy et al. (2019b) present simulations for Austin that follow the same idea. Kamel et al. (2019) apply the MATSim components in a first study on potential demand in Paris, and later, in the French city of Rouen (Vosooghi et al., 2019a,b). Related simulations have been performed for Budapest (Hamadneh and Esztergar-Kiss, 2019; Ortega et al., 2020) and Greenwich (Segui-Gasco et al., 2019) in combination with an external fleet control component.

These studies were based on the MATSim-specific *co-evolutionary algorithm* for decision-making, making them suitable only for scenario-based analysis where preferences for a future AMoD transport mode must be defined relative to the existing modes of transport. To date, no consistent way of translating the result of survey results (including underlying sensitivities) into MATSim scoring parameters has been proposed. Hörl et al. (2019b), therefore, explore a method to directly integrate survey-based discrete choice models in MATSim (while dropping evident advantages of MATSim's standard scoring-based approach, see discussion). A first application of this extension was presented by Hörl et al. (2019a), where a fleet of automated taxis is simulated in Paris. The paper is also the first in MATSim where customer decisions depend on both waiting time and price, which both change iteratively based on fleet utilization.

Figure 1 shows the simulation dynamics evolution: first, (green), a static demand was assumed with resulting travel times having no influence on the demand. However, a low level of service should lead to low demand, so it was tackled by the next generation of simulations (orange). To the the authors' knowledge, all studies so far except the last one mentioned assume static prices based on taxi data, or propose fixed price structures in their scenario analysis. In the present study, based on a detailed cost analysis for Switzerland, we close the loop from the operator-side by imposing an (at least) cost-covering price on the customers. Hence, our goal is to arrive at a demand curve (blue) with a distinguishable *maximum demand* fleet size.

Based on these considerations, we can summarize the the present paper's contribution as follows:

- While most studies assume fixed prices, we adapt prices dynamically to offer a cost-covering AMoD service based on a realistic cost model for Switzerland.

- We furthermore adapt customer-decisions dynamically, based on a survey in the canton of Zurich, specifically designed to capture residents' attitudes towards AMoD, while most studies assume

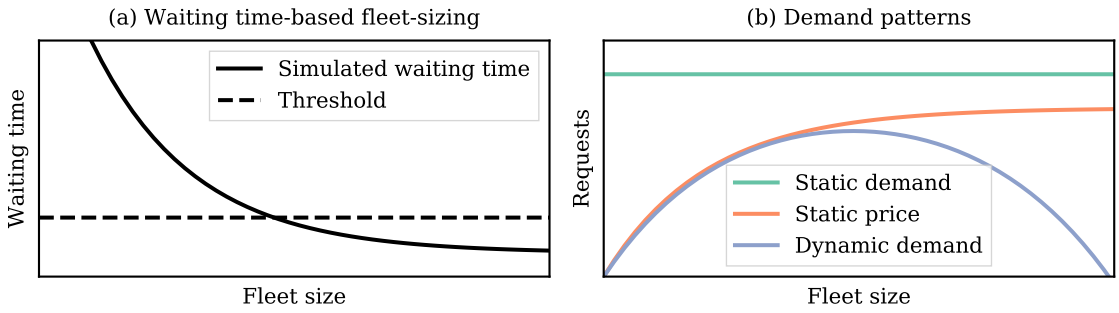

Figure 1: Typical configuration of a fleet sizing study: fleet size is varied with resulting waiting times and the optimal fleet size is chosen were a minimum level of service threshold is reached (a). However, many studies have assumed static demand (b), where a demand curve with waiting time-sensitive customers would be increasing, while an additional price-sensitivity would drive the demand down again for large fleet sizes.

preferences relative to existing modes.

- We simulate full-day activity patterns based on a detailed synthetic population for Switzerland, which restricts the attractiveness of the service for certain complex mobility patterns, but also captures influences of attributes like car ownership.

As far as the authors know, we are therefore presenting the first study in which (as of today) realistic use-case-specific preferences are combined with a detailed case-specific cost structure and a detailed synthetic population, leading to a consistent estimate of potential AMoD demand. While previous studies assume pre-defined pricing schemes, we analyze, based on our case-specific cost model, a cost-covering operator.

3. Methodology

We propose a dynamic demand simulation with three major components, visualized in Figure 2. The transport system, including an AMoD service, is simulated in the *mobility simulation*. As described in detail below, we use a mesoscopic simulator, able to track decisions and movements of a large number of travellers, represented as agents. They interact with each other and with the vehicle agents of an automated vehicle service, which is simulated in detail. From the full day simulations, we can measure a number of metrics, like distance driven with a customer, or the vehicle fleet's empty distance. Those metrics are fed into the *cost calculator* component, based on data for Zurich, that can estimate the minimum price that an operator would need to ask from customers to sustain a cost-covering service. This price, along with other choice attributes that can be measured from simulation, is fed into a *discrete choice model* where individual travellers - with their individual mobility patterns - decide which mode of transport to use for each trip.

By running this loop of models iteratively, we can analyze the complex interplay between supply and demand in an AMoD system: Initially, a price and fleet size is fixed for the service, which motivates a certain number of travellers to use it. As more travellers use the service, waiting times become higher. Thus, attractiveness decreases, along with the likelihood of choosing this mode of transport. Eventually, the system stabilizes in an equilibrium where prices, waiting times, and demand are in a consistent state. These values are then analyzed for different fleet sizes. Secondary metrics can be measured, like the ratio of empty distance, changes in mode shares, total distance driven in the system, etc. It is thus possible to quantify an AMoD operator's systemic impact on a city, in this case Zurich.

The three components, (a) *cost calculator*, (b) *discrete choice model*, and (c) *mobility simulation* will be described in detail in the following sections.

3.1. Cost structure model

The cost model used in this study was developed specifically for the Canton of Zurich in Switzerland (Bösch et al., 2018). It is a bottom-up study of cost components leading to final per passenger-kilometer (pkm) and vehicle-kilometer (vkm) costs of various forms of mobility, from private vehicle ownership to taxis, trains and buses. Full costs are thus derived from investment costs, cleaning costs, maintenance costs, vehicle management costs, cost of capital, profit margin and others.

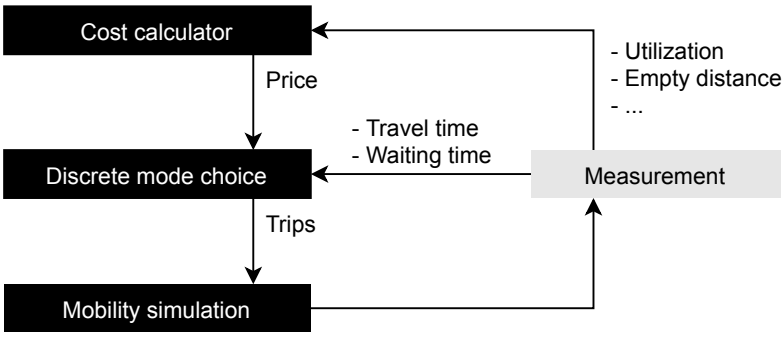

Figure 2: The three components of the model are shown: cost calculator, discrete choice model and agent-based transport simulation. Arrows indicate information flow between the three components, which are executed iteratively.

While the cost study considers urban and non-urban environments, only urban results are relevant to this study. The study finds that urban buses could see a cost reduction from around 0.53 CHF/pkm to 0.24 CHF/pkm if they were to be automated. In contrast, costs for private vehicle ownership would stay about the same in Switzerland as today, at around 0.50 CHF/pkm. The largest decrease, though, would be for taxi services. The cost study predicts that taxi service costs in Switzerland would drop from around 2.73 CHF/pkm to only 0.41 CHF/pkm, which would make them highly competitive with private cars. It is, therefore, reasonable to assume that private operators will offer these services[1].

It should be noted that costs in Bösch et al. (2018) are based on best-guess predictions of fleet utilization and empty distances, which strongly affect the service costs. In the present study, we, therefore, feed the cost model with measured values from the agent-based transport simulation. Prices then reflect actual simulated fleet usage rather than being fixed, which would distort the results. Costs in (Bösch et al., 2018) are assigned to three reference quantities: per kilometer, per trip (cleaning) and per vehicle. Total fleet cost can be described by:

$$C_{\text{Fleet}} = c_{\text{perDistance}} \cdot x_{\text{fleetDistance}} + c_{\text{perTrip}} \cdot x_{\text{numberOfTrips}} + c_{\text{perVehicle}} \cdot x_{\text{fleetSize}} \tag{1}$$

From Bösch et al. (2018) we derive the following values:

- $c_{\text{perDistance}} = 0.098$ CHF/vkm
- $c_{\text{perTrip}} = 0.375$ CHF
- $c_{\text{perVehicle}} = 33.30$ CHF/day

In our simulations, we consider a service where prices asked from customers are adapted so that the service cost is covered. However, we may define - a priori - a base fare b to be paid per trip. The price per kilometer is then calculated as:

$$p_{\text{AMoD}} = \max\left\{0 \quad , \quad \frac{C_{\text{Fleet}} - b \cdot x_{\text{numberOfTrips}}}{x_{\text{customerDistance}}}\right\} \quad \text{in} \quad [\text{CHF/pkm}] \tag{2}$$

Hence, for a zero base fare, service price entirely depends on fleet characteristics of total driven vehicle distance, customer distance, number of trips and fleet size. The larger the base fare becomes, the more costs are recovered from base fare revenues. Eventually, the base fare may be so high that the distance fare is zero and the operator makes excess profits. However, in most cases we consider below, the cost model operates in the non-profit zone.

3.2. Discrete choice-based demand estimator

To gain insights on how people would use an AMOD service in Zurich, a survey was performed in the canton with 343 respondents. This survey was conducted in two phases; in the first, respondents provided socio-demographic information and two regular trips - below and above 50km, respectively, along with the mode of transport they would normally choose. In a second phase, mode choice experiments were

[1] For costs in other cities worldwide see Becker et al. (2020)

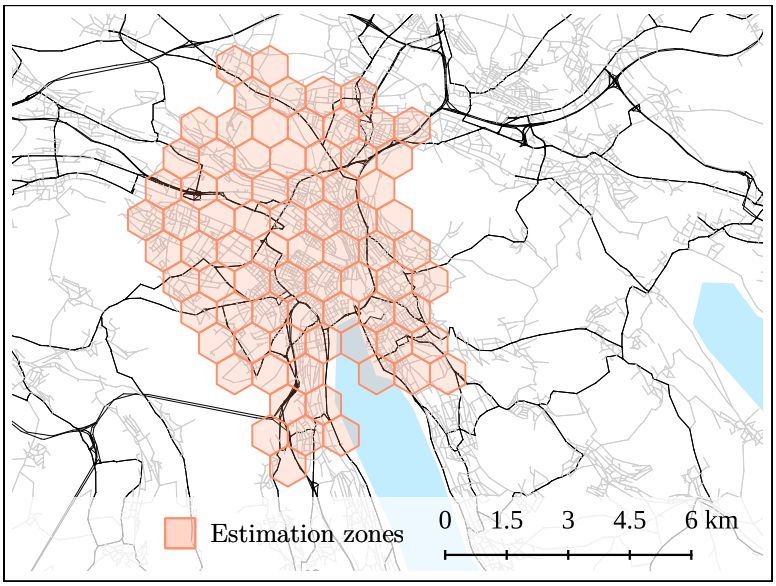

Figure 3: Zurich, Switzerland with the AMoD operating area for the present study colored in orange. The hexagons represent zones for the waiting time estimation process.

presented that included conventional and automated modes. Conventional motorized modes included public transport and private car; active modes included walk and bike. For automated modes, private automated cars, individual and pooled automated taxis, and automated feeders to train stations were considered.

For all alternatives, including the AMoD (individual automated taxi), different price and waiting time levels were presented to respondents to understand their preferences in such a service. A multinomial logit model compatible with the chosen simulation architecture is estimated in this study. For a detailed survey description and a more comprehensive model formulation, readers are referred to Hörl et al. (2019c).

Here, automated modes other than individual automated taxis are excluded from the estimation.

The data is weighted according to socio-demographic and trip attributes of the Zurich region. Reference values are derived from the national household travel survey (BFS and ARE, 2018); trips starting or ending inside the study area are selected. For re-weighting, we choose Iterative Proportional Fitting with household-level attributes *number of cars* and *income*, person-level attributes *age* and *type of public transport subscription*, trip-level attributes *mode* and *Euclidean distance*.

The model is defined by utilities for the modes *car*, *public transport*, *bicycle*, *walking* and *AMoD*.

The utility for *car* is defined by the equation

$$\begin{aligned} u_{car} = & \beta_{\text{ASC,car}} \\ & + \beta_{\text{inVehicleTime,car}} \cdot \xi_{\text{TD}} \cdot x_{\text{inVehicleTime,car}} \\ & + \beta_{\text{work,car}} \cdot x_{\text{work}} + \beta_{\text{city,car}} \cdot x_{\text{city}} \\ & + \beta_{\text{cost}} \cdot \xi_{\text{CD}} \cdot \xi_{\text{CI}} \cdot x_{\text{cost,car}} \end{aligned} \tag{3}$$

with β describing the main model parameters to estimate and x the trip-level attributes. The ξ describe elasticities as defined below. The attribute x_{work} defines whether the trip originates or ends at a *work* activity; attribute x_{city} describes whether the trip starts or ends inside the city area of Zurich (Figure 3).

For public transport, the following equation has been defined:

$$
\begin{aligned}
u_{pt} = & \beta_{\text{ASC,pt}} \\
& + \beta_{\text{inVehicleTime,train}} \cdot \xi_{\text{TD}} \cdot x_{\text{inVehicleTime,train}} \\
& + \beta_{\text{inVehicleTime,other}} \cdot \xi_{\text{TD}} \cdot x_{\text{inVehicleTime,other}} \\
& + \beta_{\text{inVehicleTime,feeder}} \cdot x_{\text{inVehicleTime,feeder}} \\
& + \beta_{\text{transferTime,pt}} \cdot x_{\text{transferTime,pt}} \\
& + \beta_{\text{accessEgressTime,pt}} \cdot x_{\text{accessEgressTime,pt}} \\
& + \beta_{\text{headway,pt}} \cdot x_{\text{headway,pt}} \\
& + \sum_{G} \beta_{\text{ptQuality,G}} \cdot x_{\text{ptQuality,G}} \\
& + \beta_{\text{cost}} \cdot \xi_{\text{CD}} \cdot \xi_{\text{CI}} \cdot x_{\text{cost,pt}}
\end{aligned} \tag{4}
$$

Travel time for public transport is defined such that different public transport modes are taken into account. Attribute $x_{\text{inVehicleTime,train}}$ determines how much time the traveler spends in a train. If the connection *additionally* contains stages of other modes, such as buses or trams, travel time in these vehicles is considered as $x_{\text{inVehicleTime,feeder}}$, while $x_{\text{inVehicleTime,other}}$ is zero. *Only* if there is no train stage on the chosen route, travel time in buses, trams or ferries is considered as $x_{\text{inVehicleTime,other}}$ while $x_{\text{inVehicleTime,feeder}}$ is set to zero.

The attribute $x_{\text{ptQuality}}$ relates to a methodology defined by the Federal Office of Land Use in Switzerland that quantifies accessibility to public transport in any place in Switzerland, based on proximity to public transport stops and stations and frequency of the respective lines (ARE, 2011). It is defined on five levels $G \in \{\text{A}, \text{B}, \text{C}, \text{D}, \text{None}\}$, with A the highest.

Utilities for cycling and walking are defined as

$$
\begin{aligned}
u_{bicycle} = & \beta_{\text{ASC,bicycle}} \\
& + \beta_{\text{travelTime,bicycle}} \cdot \xi_{TD} \cdot x_{\text{travelTime,bicycle}} \\
& + \beta_{\text{highAge,bicycle}} \cdot [a_{\text{age}} \geq 60]
\end{aligned} \tag{5}
$$

and

$$
\begin{aligned}
u_{walk} = & \beta_{ASC,walk} \\
& + \beta_{travelTime,walk} \cdot \xi_{TD} \cdot x_{\text{travelTime,walk}}
\end{aligned} \tag{6}
$$

Variables a refer to agent-level attributes, and, for the case of the *bicycle* mode, specifically to the age of each agent. Agent's age is not included in the *walk* alternative, since its parameter does not have a significant influence.

Elasticities of Euclidean distance on travel time ξ_{TD} and on cost ξ_{CD} are defined as

$$
\xi_{TD} = \left(\frac{x_{\text{euclideanDistance}}}{\theta_{\text{referenceDistance}}} \right)^{\lambda_{\text{TD}}} \qquad \text{and} \qquad \xi_{CD} = \left(\frac{x_{\text{euclideanDistance}}}{\theta_{\text{referenceDistance}}} \right)^{\lambda_{\text{CD}}} \tag{7}
$$

with λ describing additional model parameters that must be estimated. Reference distance is set as 39 km, the observed average.

Elasticity of household income on cost ξ_{CI} is defined as

$$
\xi_{CI} = \left(\frac{a_{\text{householdIncome}}}{\theta_{\text{referenceIncome}}} \right)^{\lambda_{\text{CI}}} \tag{8}
$$

Reference household income amounts to 12,260 CHF, the observed average.

Costs for the *car* mode are defined as 0.27 CHF/km, based on driven distance along the planned route. Costs for public transport are based on additional agent-level attributes, such as subscription ownership for the GA, which is a commonly used, annually billed subscription giving access to the entire Swiss public transport system.

While the model presented so far refers to modes available in the baseline case, an additional *AMoD* utility can be defined based on the survey:

$$
\begin{aligned}
u_{AMoD} = & \beta_{\text{ASC,AMoD}} \\
& + \beta_{\text{inVehicleTime,AMoD}} \cdot \xi_{\text{TD}} \cdot x_{\text{inVehicleTime,AMoD}} \\
& + \beta_{\text{accessEgressTime,AMoD}} \cdot x_{\text{accessEgressTime,AMoD}} \\
& + \beta_{\text{waitingTime,AMoD}} \cdot x_{\text{waitingTime,AMoD}} \\
& + \beta_{\text{work,AMoD}} \cdot x_{\text{work}} \\
& + \beta_{\text{highAge,AMoD}} \cdot [a_{\text{age}} \geq 60] \\
& + \beta_{\text{cost}} \cdot \xi_{\text{CD}} \cdot \xi_{\text{CI}} \cdot x_{\text{cost,AMoD}}
\end{aligned} \tag{9}
$$

Estimated model parameters are documented in Table 1. The model was estimated with the R-package Apollo (Hess and Palma, 2019b,a).

Table 1: Mode choice model

	Parameter	Estimate	Rob. std. err.	Rob. t-ratio(0)
Private car	$\beta_{\text{ASC,car}}$	0.224	0.698	0.320
	$\beta_{\text{inVehicleTime,car}}$	-0.019	0.010	-1.880
	$\beta_{\text{work,car}}$	-1.161	0.515	-2.250
	$\beta_{\text{city,car}}$	-0.459	0.621	-0.740
Public transport	$\beta_{\text{ASC,pt}}$	0.000	-	-
	$\beta_{\text{inVehicleTime,feeder}}$	-0.045	0.029	-1.550
	$\beta_{\text{inVehicleTime,other}}$	-0.012	0.024	-0.510
	$\beta_{\text{inVehicleTime,train}}$	-0.007	0.006	-1.220
	$\beta_{\text{transferTime,pt}}$	-0.012	0.020	-0.610
	$\beta_{\text{accessEgressTime,pt}}$	-0.014	0.023	-0.620
	$\beta_{\text{headway,pt}}$	-0.030	0.018	-1.670
	$\beta_{\text{ptQuality,B}}$	-1.744	0.578	-3.020
	$\beta_{\text{ptQuality,C}}$	-1.641	0.609	-2.700
	$\beta_{\text{ptQuality,D}}$	-0.965	0.680	-1.420
	$\beta_{\text{ptQuality,None}}$	-1.089	0.911	-1.190
Bicycle	$\beta_{\text{ASC,bicycle}}$	0.152	0.769	0.200
	$\beta_{\text{travelTime,bicycle}}$	-0.126	0.071	-1.780
	$\beta_{\text{highAge,bicycle}}$	-2.659	0.974	-2.730
Walking	$\beta_{\text{ASC,walk}}$	0.590	0.879	0.670
	$\beta_{\text{travelTime,walk}}$	-0.046	0.086	-0.530
AMoD	$\beta_{\text{ASC,AMoD}}$	-0.061	0.747	-0.080
	$\beta_{\text{inVehicleTime,AMoD}}$	-0.015	0.010	-1.530
	$\beta_{\text{waitingTime,AMoD}}$	-0.093	0.100	-0.930
	$\beta_{\text{work,AMoD}}$	-1.938	0.610	-3.180
Others	β_{cost}	-0.089	0.021	-4.270
	μ_{SP}	0.942	0.155	6.060
	λ_{CI}	-0.817	0.352	-2.320
	λ_{CD}	-0.221	0.078	-2.840
	λ_{TD}	0.115	0.403	0.290
	$\theta_{\text{referenceDistance}}$	39.000	-	-
	$\theta_{\text{referenceIncome}}$	12.260	-	-
	LL(0)		-5904.720	
	LL(final)		-2252.310	
	Adj.Rho-square		0.610	
	#Individuals		343	
	#Parameters		28	
	#Observations		5159	

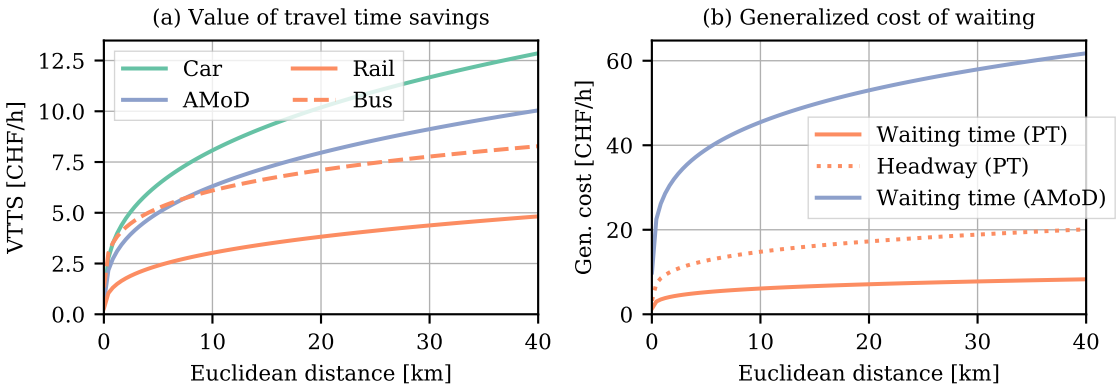

Figure 4: Choice modeling results by crow-fly distance: (a) VTTS defined as the valuation of in-vehicle travel time divided by the cost coefficient, and (b) VWTS defined as the valuation of transfer waiting time divided by the cost coefficient. Note that waiting time for public transport refers *only* to waiting time between two transit stages, while valuation of headway divided by the cost coefficients refers more closely to the schedule day that is associated with an AMoD trip.

For the scope of this research, it is interesting to compare the value of travel time savings (VTTS), defined as

$$VTTS = \frac{\partial u_m}{\partial x_{\text{travelTime,m}}} / \frac{\partial u_m}{\partial x_{\text{cost,m}}} \tag{10}$$

of various modes to each other. For the reference income, respondents are willing to pay less to reduce the travel time in an AMoD service compared to their private cars (Figure 4). This indicates that they expect it to be more comfortable. In fact, the VTTS are comparable to the bus, but considerably higher than for trains. Since the travel times of an AMoD service are very competitive, this shows that there is a substantial market potential, also from a behavioral perspective.

However, Figure 4 also shows the VWTS (value of transfer waiting time savings) defined as

$$VWTS = \frac{\partial u_m}{\partial x_{\text{waitingTime,m}}} / \frac{\partial u_m}{\partial x_{\text{cost,m}}} \tag{11}$$

and a analogously derived value for the valuation of the transit connection's headway. Note that waiting time for public transit in the model refers to waiting time between two transit stages, hence the valuation of the headway translates more closely to the schedule delay experienced before entering an AMoD vehicle. In any case, both valuation of transit waiting time and headway are substantially lower than valuation of waiting time for the AMoD service. This finding indicates - unsurprisingly - that a major objective for any AMOD operator should be to minimize customer waiting times.

3.3. Baseline simulation

For the simulation, the agent- and activity-based transport simulation framework MATSim (Horni et al., 2016) is used. MATSim is an agent-based transport simulation framework, in which travelers in the real world are represented by artificial agents. Those agents have socio-demographic attributes such as age and gender, as well as a daily mobility plan. These plans consist of activities, containing information about location of those activities, their start times, durations and types. Further, those activities are connected by trips described by a specific mode of transport and a route through the transport system.

The simulation considers a 24 hour day. The day is simulated second by second, in which agents are either in an activity (being at one specific location) or in transport (for instance, on the road network or in a public transport vehicle). Movements of vehicles (like private cars, busses, or trains) are simulated along a directed graph network representing roads and tracks of the infrastructure. Such infrastructure has capacities (for instance, limited space on roads) such that interactions between agents lead to congestion or crowding. Congestion is simulated through a queue-based traffic simulation.

The basis of an agent-based MATSim simulation is a synthetic population of the case study area. For Switzerland, a range of rich data sources is available that make setting up such a population possible with detailed socio-demographic and behavioral attributes. In the following, the process will be described in brief. A more detailed description of the Swiss data sets and how they have been processed can be found in (Hörl, 2020). Furthermore, (Hörl and Balac, 2020) describes the methodology in detail for the case

of Paris and Île-de-France. There, unlike Switzerland, all necessary data sets are publicly and openly available to replicate the process.

Initially, the synthetic Swiss population is based on the STATPOP data set, which is an comprehensive census of Switzerland, including attributes like age and gender of all residents, but - most notably - also location by coordinate of each household. Persons and households from this data set are used directly as a basis of the Swiss synthetic population. Afterward, work or educational locations for each synthetic person are added. For that, the Structural Survey is used, which, unlike the registration-based census data, is a detailed household survey conducted for around 3% of the Swiss population each year. From this data set, an origin-destination matrix between home and work/education municipalities in Switzerland can be derived, then used to proportionately sample destination zones for each agent, based on their home zone. In the third step, the national Mobility and Transport Microcensus is employed: a classical household travel survey providing full day activity patterns for around 60,000 respondents. We use a statistical matching procedure to sample and attach activity chains to the synthetic persons, based on socio-demographic attributes. This way, activity patterns correlating with certain age groups or gender are assigned according to the population. These activity chains contain activity types, durations and connecting modes of transport as reported in the survey data. As departure and arrival times are rounded as strongly as in any survey, they are blurred using a fixed random offset of +/- 30 minutes on all departure and arrival times in an agent's daily plan. Finally, specific work and education locations are sampled, based on the destination zones of the agents, from STATENT, the national enterprise census, which lists all facilities in Switzerland by coordinate. Further, secondary activities in the agents' plans (such as shopping or leisure), are assigned to discrete facilities using a specifically-designed algorithm for secondary location assignment (Hörl and Axhausen, 2020). To complete the simulation data, an exhaustive digital public transit schedule for Switzerland is integrated into the simulation and the road network is extracted from OpenStreetMap, including all roads from motorways to residential roads. In total, this process yields a synthetic representation of Switzerland that reproduces the daily mobility needs of the population and available infrastructure.

This data serves as an input to a MATSim simulation. Here, it is used in combination with a new Discrete Mode Choice package presented by Hörl et al. (2019b). Such a simulation runs multiple iterations between mobility simulation and the choice process. First, initial synthetic population plans are simulated in the capacitated network. As the synthetic population contains predefined transport modes from the household travel survey, some roads are unrealistically empty or congested. Travel times on the links are tracked and then, a small percentage of agents performs new mode choices for all trips in their daily plan based on the model described above, but also based on measured travel times. Hence, car trips with heavy congestion are avoided. In the next iteration, different agents use their car at different times during the day, leading to new travel times, which are, in turn, fed back to the next round of decision making. This way, we simulate a large-scale mode choice experiment with a synthetic population. Note that MATSim, in principle, is also able to consider departure time choices or even location choice through its *co-evolutionary algorithm*, which is a different process of decision-making *not* used here; our goal was to directly integrate a discrete choice model into MATSim. Unlike the standard approach, it inherently contains consistent information about the trade-offs people make between choice dimensions when faced with the automated mobility option. The standard co-evolutionary algorithm would only allow us to perform sensitivity analyses on the relatively unspecific attractivity level of the new transport mode.

For this study, an area of 30km around the city center of Zurich is cut out from the Switzerland model and population. Through-traffic, as well as agents who enter or exit the area at some point during the day, are included. In total, this gives around 2.2 million agents performing 7.2 million activities and a network of around 150,000 links.

The simulation was run with the choice model described above for calibration, without the AMoD mode included. In our simulation set-up, the trip-based model is served with the respective trip attributes, but choices are made on the level of home-based tours. For that, all possible combinations of modes along a tour are constructed. Then, for each chain of modes, the trips' cumulative utility is calculated. Based on these cumulative utilities, one chain is chosen according to the logit formula. In combination with tour-level constraints (e.g., a car or a bike can not be left behind, but must be brought back home), this approach has been shown to provide realistic mode shares (Hörl et al., 2019b,a). However, due to specific survey characteristics, such as generally long distances asked from the respondents, adjustments needed to be added to the model, especially to achieve a good fit with reference mode shares for small distances.

To correct for an increased attractiveness of the *walk* mode, its utility function is adjusted as follows:

$$u'_{\text{walk}} = u_{\text{walk}} - \exp\left(\log(101) \cdot \frac{x_{\text{travelTime,walk}}}{\theta_{\text{walkThreshold}}}\right) + 1 \tag{12}$$

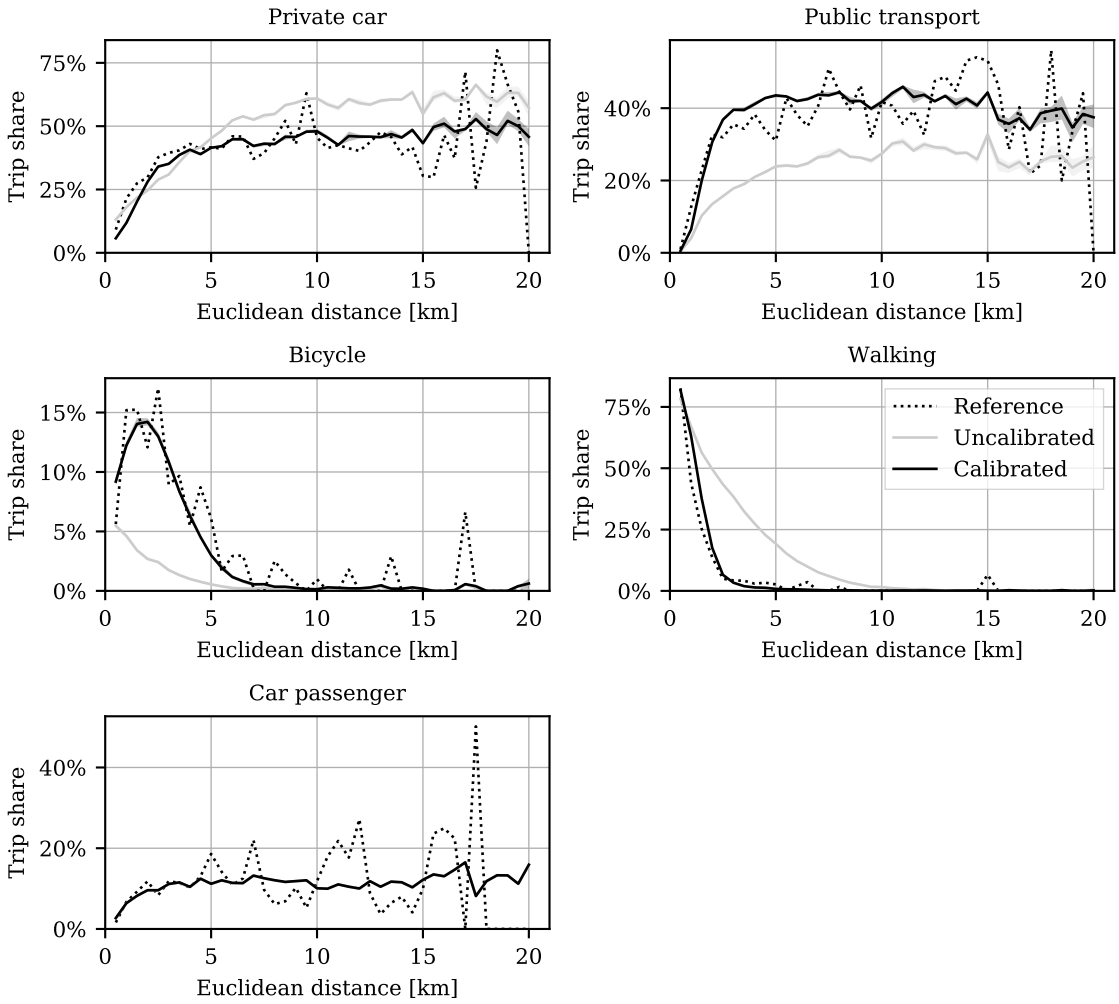

Figure 5: Calibration of the baseline model: The figures show how mode shares by distance class of the simulation fit well to reference values from the national household travel survey, filtered for the study area. Note that for certain combinations of modes (especially bike) and distance classes, reference data becomes rather sparse on the 500m resolution used in this analysis. We furthermore compare against the uncalibrated outcomes obtained when running the simulation with the survey-based choice model without additional adjustments.

For small walk distances, the additional penalty term is close to zero, while for a walking time equal to the threshold calibration parameter $\theta_{\text{walkThreshold}} = 120\text{min}$, there is a large offset of -100.

Furthermore, the value of $\beta_{\text{ASC,car}}$ needed to be adjusted to achieve a good model fit. The value was changed from 0.223 to $\beta'_{\text{ASC,car}} = -0.8$. This offset equals a perceived cost of around 11CHF and can be explained by a couple of factors, which would be interesting to include in future surveys and models. Among them are the additional cost of parking for car trips, a general perception of sunk costs (not included in the per-distance cost), time spent for parking search and the access/egress time.

Figure 5 shows mode shares in the baseline model compared to reference data from the household travel survey. Note that both simulation data and reference data are filtered for trips that take place entirely within the study area. It can be seen that the reference data is rather sparse e.g. for bike, and other modes for longer trips), but that the simulated mode shares closely follow the curve shapes. The plots also show how the adjustments described above have improved the model fit. Making sure that the mode choice behavior is consistent with reality was our primary calibration objective, because changes towards an AMoD system can only be meaningful in comparison to a a solid baseline case. It should be noted that the "car passenger" mode was not considered explicitly in the survey, but needs to be included in the simulation to align with a consistent relation between agents' car ownership attribute and the modal split for private cars. Therefore, trips with this mode are kept fixed as generated from the population synthesis step, based on the household survey data.

The second calibration objective was to achieve travel times that fit reality well. This can be seen

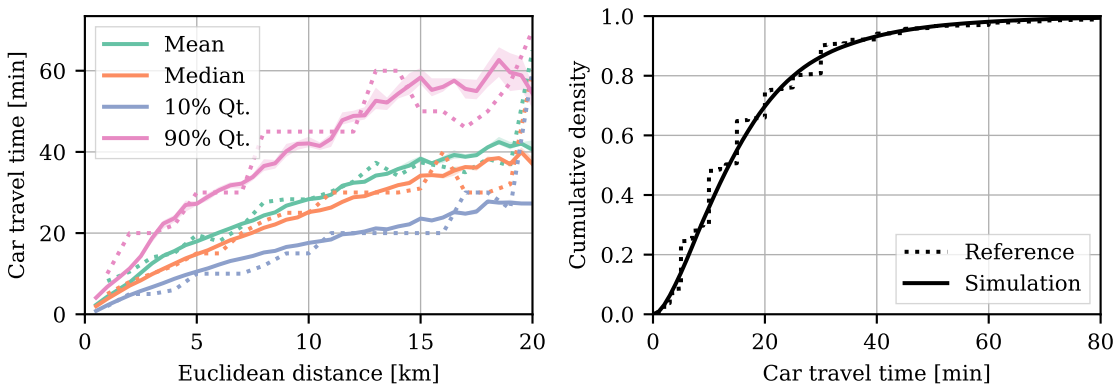

Figure 6: Calibration of the baseline model: We compare travel time distributions for Euclidean distance classes (in 500m intervals) and overall distribution of travel times with reference data obtained from the national household travel survey. We show door-to-door travel times.

in Figure 6, where the mean, median and 10% and 90% quantiles of car trip durations are shown in distance classes of 500 meters, both for the uncalibrated and calibrated simulation and for the household travel survey. Note that these are average travel times calculated by the difference between the time of departure and arrival.

3.4. AMoD simulation

A couple of extensions exist in the MATSim ecosystem to simulate dynamic transport services such as AMoD. Their common denominator is the DVRP extension of MATSim (Maciejewski et al., 2017). Unlike standard traveller agents, which follow predefined daily plans in every iterative run of the mobility simulation, DVRP allows us to control agents dynamically, second by second. A streamlined implementation of this process is provided by Hörl (2017). Using this component, a dynamic fleet operator can dispatch vehicles to customers, which are picked up on arrival, transported to their destination and then dropped off. The virtual operator receives requests from traveller agents (without any pre-planning) and reacts to them by deciding which idle vehicle to send to which customer.

Using this framework, simulations have already been performed in the Zurich context in a set-up very similar to the one described here. In (Hörl et al., 2019d), the authors compare different fleet operating policies in terms of how well they are able to serve the total (static) motorized mobility demand of Zurich. For the current study, the Load-Balancing Heuristic Policy first introduced by (Bischoff and Maciejewski, 2016) is chosen because Hörl et al. (2019d) show that it provides a good trade-off between produced empty distance and waiting time, but, most importantly, can be executed very quickly. In brief, the control policy first determines whether it should operate in "over-supply" mode (if there are more idle vehicles than open requests) or in "under-supply" mode (the other way round) at the beginning of each decision period of ten seconds in simulated time. In over-supply mode, the algorithm loops through all requests and assigns the closest vehicle, which allows for an even service across the region with potentially long empty rides. However, in under-supply mode, the algorithms loops through all idle vehicles and assigns the closest waiting request, effectively reducing demand surges. In our model configuration, all issued requests must be served, although long waiting times may occur.

To integrate the AMoD simulation into our dynamic demand experiment, two additional components had to be added: functionality for predicting waiting times and functionality to calculate fleet cost and resulting prices, both to be fed into the choice model for the AMoD alternative.

Waiting times are estimated based on hexagonal zones of 500m (outer) radius as shown in Figure 3 and in 15 minute intervals. We denote estimated waiting times as $\hat{w}_{t,s,i}$ with t referencing time bins and s referencing zones in iteration i. Initially, we define a starting value $\hat{w}_{t,s,0}$ of 10 minutes. During every mobility simulation, we can track when agents in each time bin and zone depart and when they enter a fleet vehicle, resulting in measured waiting times $w_{t,s,i}$. These measured waiting times are then used to define the estimate for the next choice-making phase:

$$\hat{w}_{t,s,i+1} = \begin{cases} \xi_w w_{t,s,i} + (1-\xi_w)\hat{w}_{t,s,i} & \text{if} \quad w_{t,s,i} \leq \hat{w}_{t,s,i} \\ (1-\xi_w) w_{t,s,i} + \xi_w \hat{w}_{t,s,i} & \text{else} \end{cases} \tag{13}$$

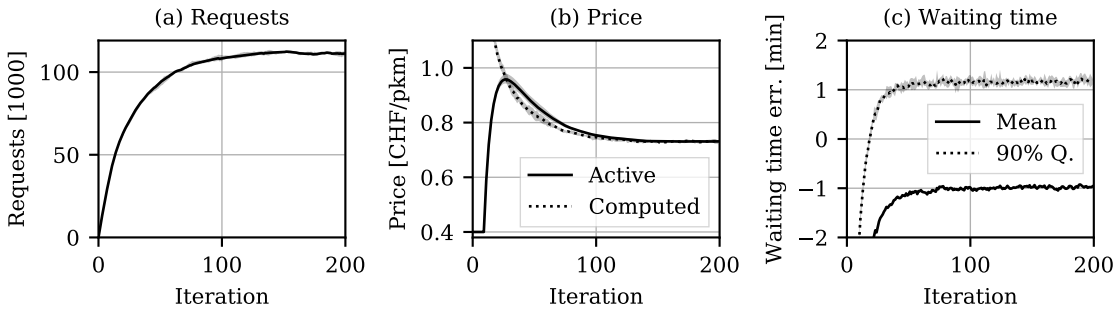

Figure 7: Convergence of the model for a fleet size of 4,000 vehicles: (a) Number of requests over multiple iterations, (b) Progression of instantaneously calculated price by the calculator vs. progression of the interpolated value used in simulation, (c) Progression of waiting time prediction error based on all observed AMoD trips. The error is calculated as the difference between observed travel time and predicted travel time used in the choice model.

Hence, we interpolate between the new measurement per zone and time bin and the historical estimate. If no waiting time was observed for a combination of time bin and zone in iteration i, we assume the value from the previous iteration ($w_{t,s,i} = w_{t,s,i-1}$). For the simulations presented below, a value of $\xi_w = \frac{1}{10}$ was chosen in preliminary experiments to provide a good speed of convergence, but sufficiently stable estimates.

A similar approach was chosen to define the price $\hat{p}_i$ used in the choice process for iteration i. Again, given the agent-based fleet simulation, it is possible to measure the number of AMoD trips, fleet distance and customer distance in detail. Fleet size is known a priori as we fix it for every simulation. Those values are fed into the cost model defined in Equation 2, leading to a price p_i which *would have been* the cost-covering price in the preceding daily simulation. This value is then interpolated with the previously used estimate to dampen its trajectory:

$$\hat{p}_{i+1} = \xi_p p_i + (1 - \xi_p)\hat{p}_i \tag{14}$$

The simulations presented below are started without any demand for the AMoD option. Therefore, we start with a fixed price of 0.4 CHF for the first *ten* iterations. Only after that period, interpolation starts with $\xi_p = \frac{1}{10}$. This way, prices are either over- or underestimated after ten iterations, but we avoid having prices skyrocket in the first few iterations due to large fleet sizes, but very little demand. Over the following iterations, the price then converges to a realistic level in line with the cost model.

Figure 7 shows an example of the whole modeling loop convergence behavior. On the left, the evolution of requests is shown. One can see how, over multiple iterations, the number of requests stabilizes. Furthermore, Figure 7b shows price progression: At first, the "active" price, i.e. interpolated value used in the choice model, is fixed to 0.4 CHF for few iterations; afterward, interpolation with the instantaneously computed price from the cost calculator starts. Again, the price stabilizes after about 175 iterations and active and computed prices become close to each other.

Last, Figure 7c shows stabilization of waiting time predictions over iterations. We calculate errors as $\delta^k = w^k - \hat{w}_{t,s,i}$ over all *observed* trips k by comparing observed waiting time with the one predicted for the corresponding time bin t and spatial zone s for the last available estimate. Distribution of waiting time errors is shown in Figure 7c. Errors stabilize at values smaller than one minute in 90% of the cases; an error of -1 minutes is observed in expectation. As this value is used in the choice model, waiting time *in expectation* is overestimated by one minute when mode choice decisions are made.

To enforce realistic behavior going beyond what the choice model is able to replicate, we introduce three constraints to the choice process for the AMoD service:

- **Service area**: Only trips that start and end (origin and destination coordinates) inside the operating area (Figure 3) are eligible for the AMoD service.
- **Minimum distance**: Trips shorter than 0.25 km (in Euclidean distance between origin and destination coordinates) cannot be performed with the AMoD mode.
- **Maximum waiting time**: Trips with a predicted waiting time of more than 15 minutes will not be offered AMoD as an alternative mode.

The first two constraints naturally define the service offer of the operator. In reality, it would be unlikely for such a service to dispatch vehicles for trips that only take a few seconds. The last constraint is more interesting, as it relates to the customer perspective. We assume that a customer who, at his or her usual time and place of departure, has an *expected* (i.e. common) waiting time of more than 15 minutes would refrain from using the service at all. Similarly, an operator may not even provide a trip beyond such a limit. Effectively, this constraint can therefore also be understood under the notion of trip rejection, commonly used in other models.

4. Simulation

We present a variety of simulation runs here, distinguishing between various a priori defined fleet sizes between 1,000 and 8,000 vehicles; we also differentiate base fare cases of zero cost, 1 CHF, and 2 CHF. We perform each simulation with five different random seeds, displaying the obtained value range, as well as the mean over the five obtained samples. All analyses are based on trips occurring entirely inside the operating area of the AMoD service, i.e. origin and destination are within this region. All simulations are carried out on a 10% sample of the population with an accordingly scaled fleet size, while the analyses show up-scaled simulation results.

4.1. Equilibrium states

First, it is worth having a look at the equilibrium states reached between supply and demand. Figure 8a shows the curve postulated in the paper's introduction. In our proposed model, small fleet sizes lead to low demand, while medium-sized fleets reach a level of maximum attraction, while even larger fleet sizes lose demand. For the chosen operating area in Zurich, we see that under the given behavioral and operational assumptions, a fleet of around 4,000 vehicles would attract most requests. Figure 8b shows that prices increase with larger fleet sizes because the operator needs to maintain fleet operation. Those prices push potential customers away from the system. On the other hand, Figure 8c shows how small fleet sizes lead to long waiting times, which, again, are less attractive to customers the higher they become.

At the maximum demand fleet size of 4,000 vehicles customers would be willing to accept average waiting times of around 2.5 minutes which are, in 90% of cases, shorter than 5 minutes. These waiting times are in equilibrium with a price of around 0.75 CHF/km when there is no base fare added to each trip. Figure 8b shows that distance fares adapt to the base fare imposed. Only with a base fare of 2 CHF, does the system enter a profit-generating state for the operator, where revenue from base fares exceeds the total fleet cost.

Figure 8d shows how average trip distances change with fleet size and base fare. With increasing fleet sizes, distances covered tend to become shorter, as longer travels are priced out of the service. Interestingly, the chosen cost-covering pricing scheme leads to high base fares attracting longer distances. Another interesting observation from Figure 8 is that distance fare and mean trip distance are sensitive to the base fare, while overall demand and accepted waiting times are nearly independent of it. This shows that adjusting the ratio of distance-based prices to trip-based fares may have an operational impact (depending on operating strategy, short trips may be easier or harder to handle than longer ones), but are barely effective in controlling generated demand.

4.2. Demand patterns

In the second analysis step, we are interested in a more detailed view of how customers experience and use the service. Figure 9 shows a temporal analysis of demand patterns. The upper left plot (a) shows the number of active requests by time of day, in comparison to currently waiting requests for various fleet sizes. At the maximum fleet size of 4,000 vehicles, one can see three peaks, one in the morning around 8am, one around noon and one in the afternoon around 6pm. For a fleet size of 2,000 vehicles, the morning peak is slightly reduced, while the afternoon peak is clearly capped.

The distances travelled with the AMoD service stay quite constant throughout the day, as shown in Figure 9b. Early in the morning, and in the afternoon, distances in the distribution tail become longer, indicating trips from and to less accessible areas further apart.

Waiting times (Figure 9c and 9d) depend on the time of day, with noticeable increases at times of high demand. As expected, waiting times are higher for small fleet sizes. For these cases, Figure 8 showed that prices are lower and, therefore, customers are willing to accept longer waiting times. At the maximum demand fleet size of 4,000 vehicles, waiting times on average do not exceed five minutes and, in most

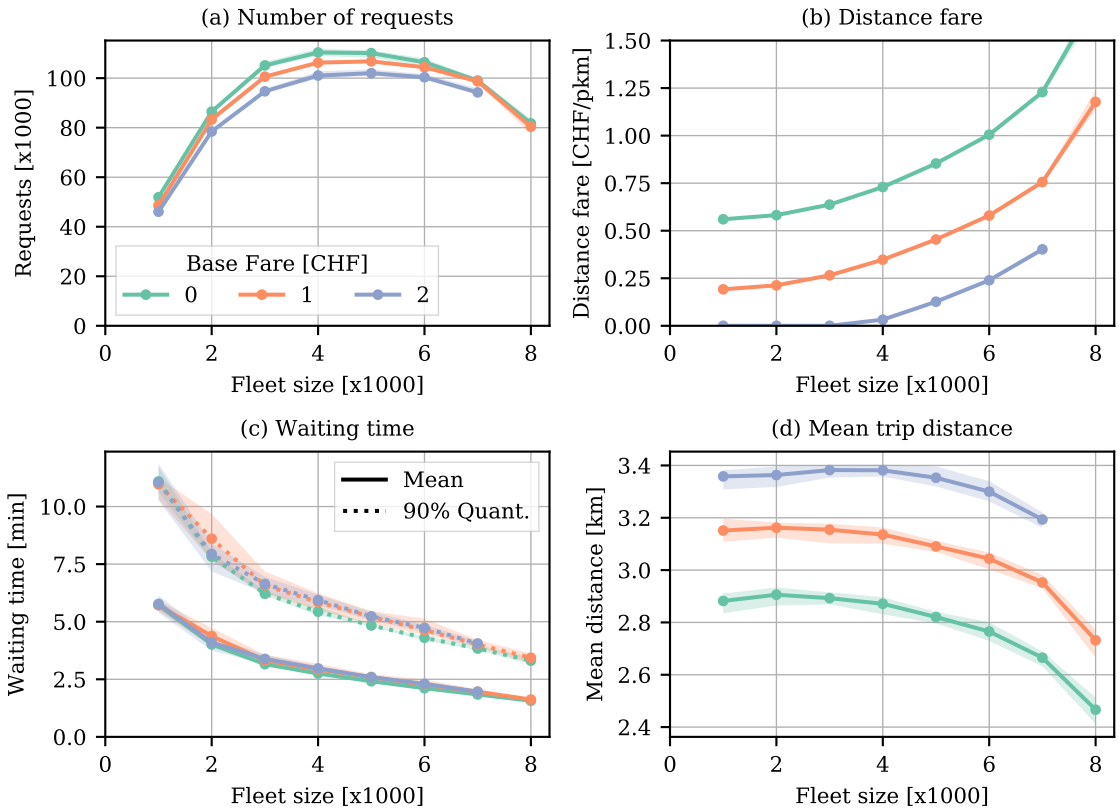

Figure 8: Service characteristics for various fleet sizes and base fares. Waiting times describe the mean and 90% quantile over the entire day. See further below for a temporal analysis.

cases, stay below ten minutes. For the small fleet size of 2,000 vehicles, waiting times can occasionally exceed this limit, but go not beyond 12 minutes.

Spatially, Figure 10 gives an insight into demand patterns, clearly showing areas of higher demand in Zurich city center, independent of the time of day. It is also interesting to see that departures and arrivals are nearly balanced at any time. Only in the evening do we observe an increased number of departures in the wealthier eastern part of Zurich, while arrivals still cluster in the city center.

4.3. Operational perspective

From an operational perspective, the most interesting metric is distance covered by the fleet. Figure 11 shows the absolute distance covered by fleet vehicles per day. In the case of 4,000 vehicles, we arrive at more than 400,000 km, which corresponds to about 65% of all distance covered on roads in the operating area counting AMoD and private cars, which is surprisingly high fraction.

Figure 12a shows that around 22% of fleet distance are driven by empty vehicles. Note that the strategy used in this research does not pro-actively redistribute vehicles in the network, but only reacts to direct customer requests. Hence, the empty distance exactly represents the distance covered to pick up customers.

Given the large distances covered by the entire fleet per day, it is interesting to ask how much each vehicle is used. Figure 12b shows the mean distance per day driven by the vehicles and the vehicle with the maximum covered distance. For the maximum demand case, each vehicle drives around 120 km per day, which indicates that refueling or recharging should generally not pose an operational hurdle. Even when looking at the maximum distance vehicle with around 200 km per day, we do not exceed the limits of modern battery-electric vehicles.

4.4. System impact

Finally, a central question must be asked; what system impact would a fleet of automated taxis in Zurich have? Figure 13 shows how mode shares change in the system after the AMoD fleet is put in place. For the zero base fare case and at 4,000 fleet vehicles, mode share of private cars drops from around 17%

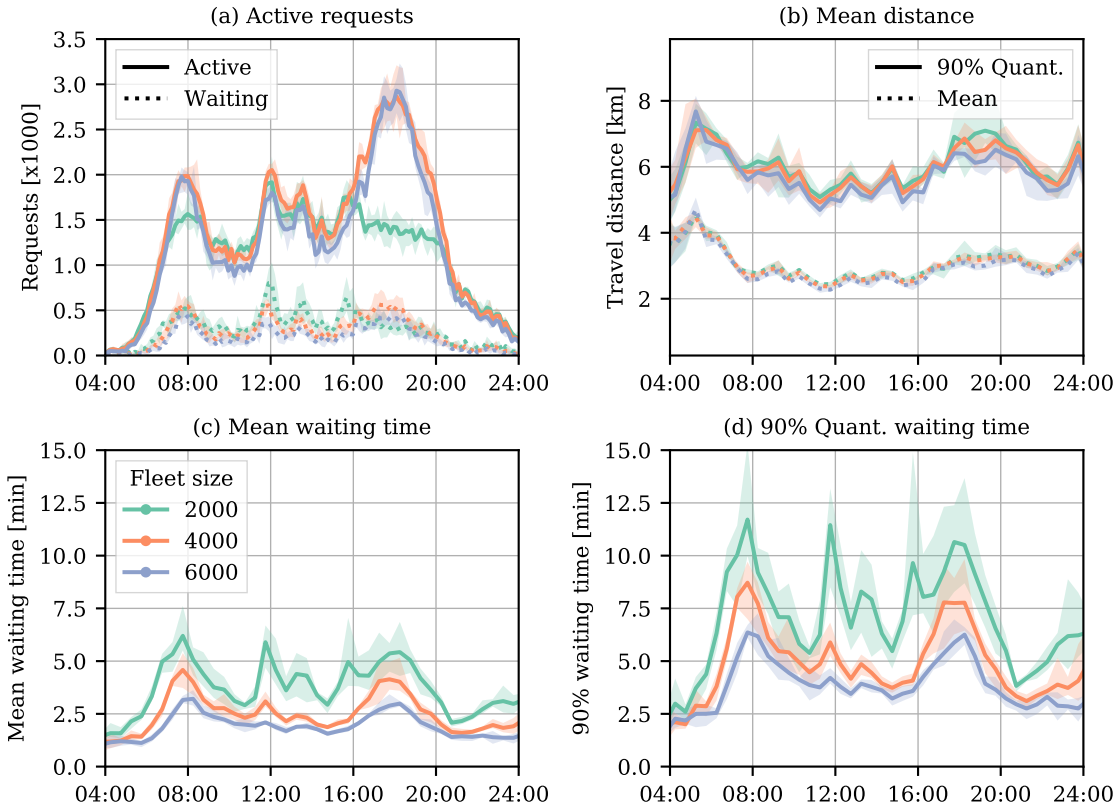

Figure 9: Temporal analysis of simulations without base fare for three different fleet sizes. (a) Active requests denote number of agents inside a vehicle in addition to agents waiting. Waiting requests are those not yet picked up by a fleet vehicle. (b) Distances are measured as Euclidean distance between origin and destination of each trip to account for variations due to routing and congestion. (c,d) Waiting times are measured in 30 minute intervals.

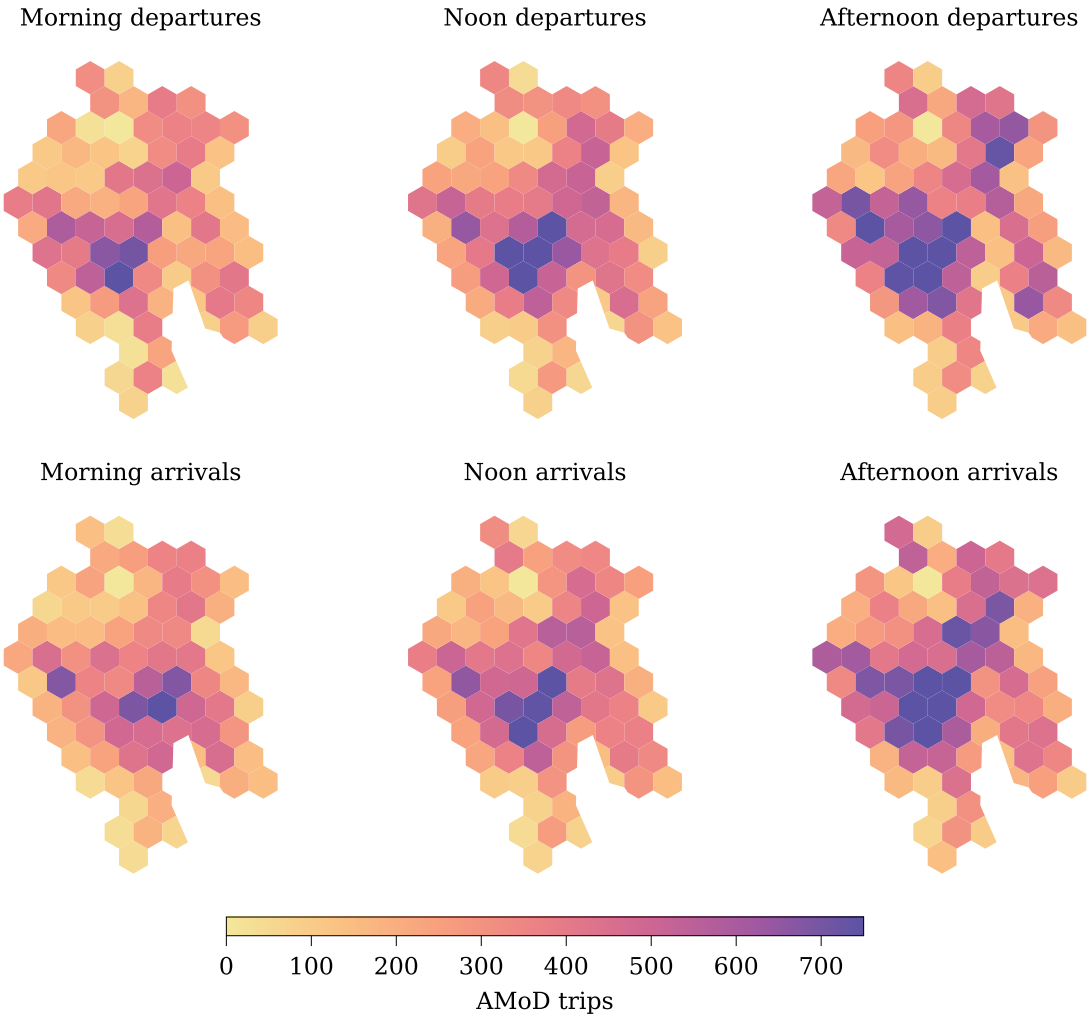

Figure 10: Spatial analysis of departures and arrivals with AMoD trips at different times of the day: morning (6am-10am), noon (11am-2pm), afternoon (16pm-20pm). Analysis is performed for a fleet size of 4,000 vehicles without base fare.

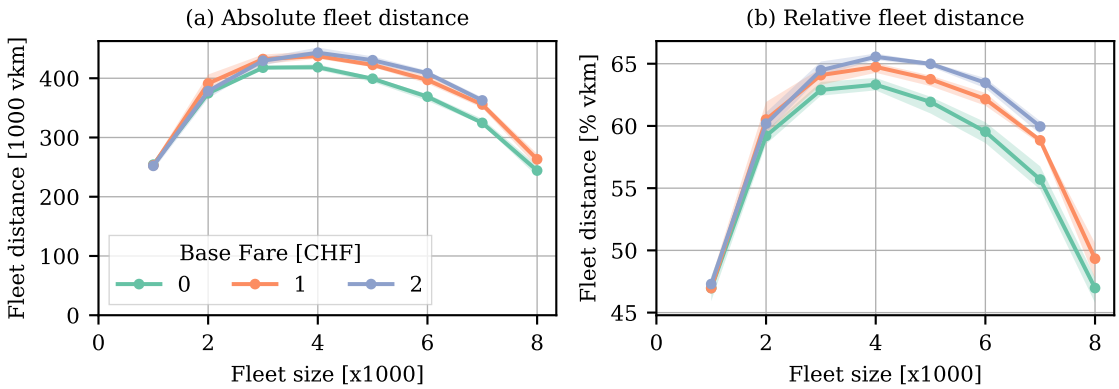

Figure 11: Analysis of distance produced by the AMoD fleet. In (b) share of AMoD fleet distance compared to total system road distances is shown.

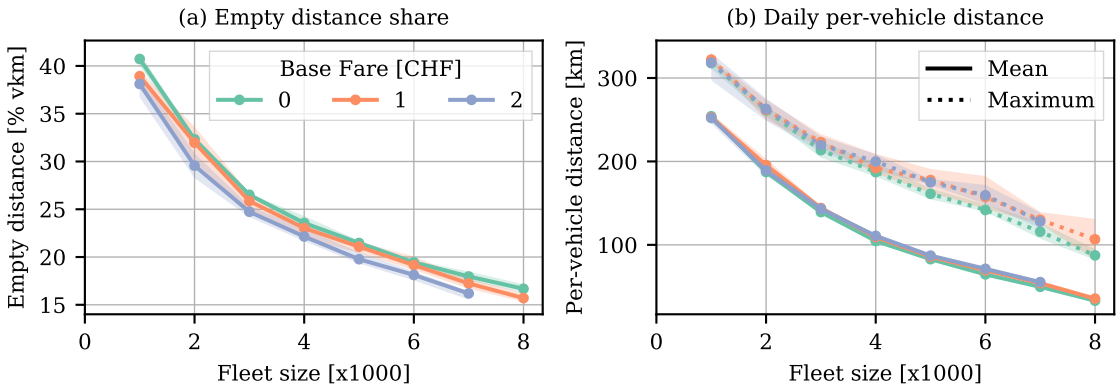

Figure 12: Distance-analysis from the operator perspective: On the left (a), share of empty distance based on total fleet distance is shown; on the right (b), mean and maximum distance per vehicle is shown.

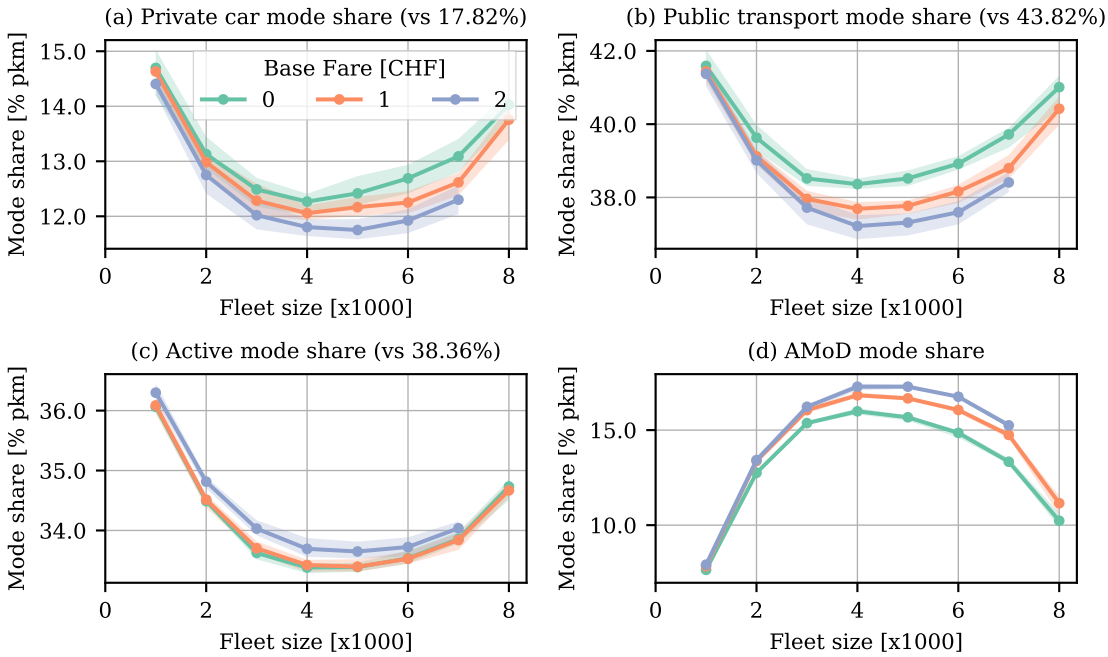

Figure 13: Mode shares for various fleet sizes and base fares.

to less than 12%. The situation is similar for shifts from public transport and active modes (walking and cycling). In total, the AMoD system reaches a mode share of more than 15%.

Interestingly, the choice of base fare has something of an effect on how mode shifts happen. For higher base fares, mode shares for private car and public transport drop more strongly than for lower base fares. On the other hand, mode share for active modes drops slightly less than for the zero base fare. Still, from an ecological point of view, shifts from public transport and active modes are not desirable.

In terms of cost for society, it is interesting to analyze how total distance driven on the roads changes. Figure 14a shows the respective numbers. For fleet sizes of 4,000 vehicles, we observe that the overall driven distance almost doubles what is measured in the baseline case. Note that this includes shifts from the private car to the AMoD fleet, but also shifts from public transport and active modes.

On the contrary, Figure 14b shows the number of vehicles still active in the system during an average day. Here, we count the number of AMoD fleet vehicles and private cars used at least once during the simulated day. In this metric, we see a clear reduction in vehicles of around 10% in the maximum demand case.

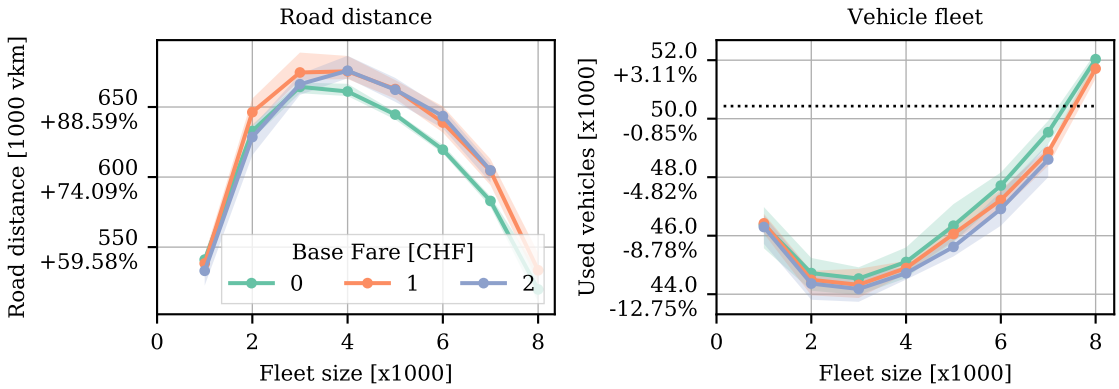

Figure 14: System-level analysis: (a) the total distance driven on roads in the city, and (b) the total number of "active vehicles", i.e. vehicles that are used at least once during one simulated day, including AMoD and private cars, but *not* public transit vehicles.

5. Discussion

The following sections will discuss the results we obtained. First, we draw conclusions on transport-related outcomes and put them into perspective for the context of Switzerland. After, we provide a technical discussion of the applied methodology.

5.1. Results and future analysis

The simulation results presented above are unique in that they combine a detailed simulation of an automated vehicle fleet, with context-dependent endogenous costs and user behavior for Zurich. It must be noted that all simulation cases presented are cost-covering equilibria, i.e. they all are economically feasible under the given assumptions. We thus transform the question of "how many vehicles are needed to serve a certain demand" into "what kind of AMoD service is desirable on the roads of Zurich"? The city and/or the citizens can then decide whether they want an expensive service providing very short waiting times, but one that is not universally economically accessible? Or do they want a lower-priced service with acceptable waiting times? Or does the city want a service producing limited empty distance? While, here, we provide first results, the framework can be extended to help design a future mobility system of Zurich while taking into account the requirements and wishes of various stakeholders.

For the present case, the simulation results indicate a strong increase in vehicle distance on public roads and must therefore be seen as a strong sign towards active and careful policy-making around the introduction and regulation of automated vehicle fleets. While other studies commonly predict smaller increases in additional mileage, we take into account mode shifts not only from private cars and public transport, but also active modes. In the urban environment, policy should especially target these use cases to avoid overcrowded city centers. Strategies to discourage taxi use for short distances such as additional pricing could be a viable option, but clearly more research on the attractiveness of automated taxi services on short distance rides is necessary.

Although not examined here, the framework could be used to go beyond assessing cost-covering systems towards subsidized or profit-maximizing scenarios. Pinpointed policy-measures like road pricing, or taxes on driven distance of an AMoD system can then be studied. The Federal Road Administration of Switzerland, for instance, estimates an infrastructure maintenance cost of around 0.06 CHF/vkm caused by road usage (BFS, 2019). Having an AMoD operator cover these costs could be an interesting additional experiment.

Futhermore, the agent-based simulation approach would make it possible to study the effects of an AMoD system on specific user groups, or even single users, their home locations, their work locations and their connected socio-demographic and socio-economic situations. Environmental and societal costs of the service could be assessed in more detail. Hot and cold emissions of the automated taxi service could be considered (see, e.g., Kaddoura et al. (2020)) to perform a full cost-benefit analysis. Further, connecting simulation insights with a life-cycle assessment of an AMoD system could yield interesting new results on the interplay between reduced overall vehicle fleet vs. increased driven distance. Additional topics of interest for the future would be operating area optimization, parking restrictions and strategies (Harper et al., 2018; Bischoff et al., 2019; Winter et al., 2020) and operational constraints like refueling or

recharging. In terms of service design, both dynamic pricing schemes and competition between multiple operators will be interesting use cases.

One actively debated topic missing in this study is the interplay of an AMoD system with public transport. While intermodal trips between AMoD and trains or busses are not considered in our simulation, substantial research exists for various use cases and degrees of interaction (Shen et al., 2018; Salazar et al., 2018; Pinto et al., 2020). For the present study, we argue that intermodality will not have a strong impact as public transport in the city area of Zurich is relatively dense. Taking an AMoD ride with several minutes of waiting time included would often exceed the time of walking to, and waiting for, a transit vehicle. However, the situation may change if remote areas are considered (Sieber et al., 2020). For Zurich, a natural and interesting use case would therefore be to study how an AMoD system might serve the commuter rail system connecting surrounding areas to the city center.

Our previous research (Hörl et al., 2019d) has shown (in a static demand case), that varying fleet dispatching and rebalancing operational policies can have strong effects on how the system is performing in terms of economy, ecology and equity. (Hörl et al., 2019d) indicates that substantially larger fleet sizes would be needed to provide waiting times of 5 minutes in a similarly defined operating area, but under the assumption that all private car and public transport trips in the area are to be served by the service. The demand obtained in the present study is only about half the imposed "maximum possible demand case" in (Hörl et al., 2019d), which must be regarded as a first (but clearly too optimistic) assumption in light of results presented above. However, (Hörl et al., 2019d) shows that that the chosen heuristic algorithm in this paper provides a good trade-off in service characteristics, but does not provide the best possible waiting times, which can be improved through rebalancing; it also does not provide the least possible empty distance, which can be achieved with more advanced customer-vehicle assignment algorithms.

While integrating more advanced algorithms (compared to the heuristic used here) would be technically feasible, the long additional run times for algorithms that must be solved thousands of times per simulated day have led to the decision to cover this topic in a future publication. Literature on specific operational policies is vast, ranging from heuristics (Maciejewski et al., 2016a) to optimization-based approaches (Hyland and Mahmassani, 2018) for single taxis to pooled operations (Alonso-Mora et al., 2017). Several studies compare such algorithms in simulation (Ruch et al., 2018, 2020; Hörl et al., 2019d) and extensive reviews are available (Hyland and Mahmassani, 2017; Mourad et al., 2019).

As shown by Dandl et al. (2019) or Hyland and Mahmassani (2020), uncertainty about how customers react to certain quotes and waiting time estimates immediately after sending a request can have a strong impact on service performance and poses new questions for fleet control. For the future, it would be interesting to think about how to include such dynamic interactions into the presented framework.

5.2. Method

Methodologically, this paper shows how the agent- and activity-based transport simulation framework MATSim can be run with a survey-based discrete choice model to derive agents' mode choice behavior. As described initially, many assumptions and concepts at the core of MATSim were discarded for this case. For instance, no scoring is taking place, where agents would introduce random changes to their daily activity chains, then test them in simulation and choose among in the past observed activity chains providing the best performance during simulation. Here, mode choices are imposed a priori, before simulating, but based on estimated choice dimensions from previous iterations. Through that, the choice process becomes more complex, but consistent with established discrete choice theory. A significant drawback here is that no other choices other than mode choice are considered. By default, MATSim also allows agents to update departure times and even their activities' locations. As these processes are inherently based on the scoring approach, they can not be easily recovered in the present set-up. Promising new approaches to further integrate discrete choice models and the MATSim scoring approach are currently being researched.

Currently, no explicit convergence criterion exists for the simulations presented in this work. As shown in Figure 7, we checked for various simulations that the key output metrics stabilize around clearly identifiable states. Based on this analysis, we chose to run every simulation for 200 iterations. In the future, it will be important to define clear convergence criteria, which can either be based on observed values of a single run or multiple, parallel chains with different random seeds together.

Temporal consistency of the activity chains was also only checked on a case-by-case basis in this research. As the choice model does not contain penalties for "being late" at the following activity in an agents' chain, there is no guarantee that agents adhere to hard constraints such as latest arrival times at the job. However, such restrictions are also not modelled in the baseline population, which makes it

hard to verify whether they are fulfilled. Looking at the distribution of departures by time of day (e.g. Figure 9), we conclude that realistic patterns are established.

Currently, all simulations are performed with a 10% sample of the population and a fleet that is 10% of the original size. All presented results are scaled up accordingly. It will be important to check whether there are systematic differences in demand and key metrics when performing simulations with a full 100% population. The 10% simulations with 200 iterations presented here take around 12h per simulation. In total, with all cases and ensemble runs, we arrive at around 120 simulations with a plain run time of about 60 days.

Finally, we want to comment on the replicability of the study. While the authors have presented methods and tools to produce a detailed agent-based transport scenario for Île-de-France and Paris based entirely on open data and open software (Hörl and Balac, 2020), this is not the case for Switzerland; the data sets involved are only provided for research, but without sufficient anonymization. For instance, we generate the underlying population directly from the Swiss census data set, which contains the location by coordinate for every household, including the socio-demographic structure of their members. In the future, it would be worth the effort to focus on generative algorithms that can replicate the Swiss population without conflicting with privacy concerns and to further engage with the responsible authorities to make that data easily and openly usable. The code used to run the simulations in the present paper is available as part of the *eqasim* framework[2], which aims to consolidate tools and data to run standardized, open, high-quality and out-of-the-box runnable MATSim simulations.

6. Conclusion

This paper introduces a first detailed case study for the integration of a survey-based discrete choice model into the agent- and activity-based transport simulation MATSim. Using this functionality, we present simulations in which costs, service level, and attracted demand are in equilibrium for a cost-covering automated taxi service. In those equilibria, costs, customer behavior and travel patterns are based on data directly derived for Zurich, Switzerland, and are therefore context-dependent.

Comparisons with previously performed static demand simulations (Hörl et al., 2019d), in which all trips by car and public transport needed to be served by the AMoD fleet, show that only about half the assumed demand there would actually be present with realistic user preferences. We thus show, for the example of Zurich, that such "maximum demand" assumptions tend to strongly over-estimate the attractiveness of an AMoD service. These results are in line with existing results for Paris (Hörl et al., 2019a).

For Zurich, we arrive at a "demand-maximizing" fleet of around 4,000 vehicles, which would attract around 110,000 trips per average week day. In this state, waiting times of around 2.5 minutes in the mean and 5 minutes in 90% of the cases are accepted by customers, at a price of 0.75 CHF/pkm if no additional base fare is imposed. From a systemic perspective, we see almost double the driven distance in the system than today, with a reduction in used vehicles of about 10%.

We therefore conclude that the introduction of automated taxis must be accompanied by confident and informed policy-making. Our simulations provide equilibrium states in which a cost-covering AMoD fleet can exist and provide first insights into policy-makers' options in deciding on the trade-offs between waiting time and cost, or vehicle distance and fleet reduction.

In future developments, the proposed methodology should be developed further to provide an integrated cost-benefit and welfare analysis of various configurations of Automated Mobility on Demand services.

7. Acknowledgements

This paper is based on research that was commissioned by the Association of Swiss Transport Engineers and Experts (SVI) and funded by the Federal Road Administration of Switzerland in the scope of the project SVI 2016/001: Induced demand by automated vehicles (Hörl et al., 2019c). We want to thank Karen Ettlin for editing the manuscript.

[2] `http://eqasim.org`

References

Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., Rus, D., 2017. On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. Proceedings of the National Academy of Sciences 114, 462–467.

ARE, 2011. ÖV-Güteklassen - Berechnungsmethodik ARE. Technical Report. Bundesamt für Raumentwicklung (ARE).

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 Supply of Autonomous Mobility On Demand. Transportation Research Record: Journal of the Transportation Research Board 2564, 21–30.

Balac, M., Hörl, S., Axhausen, K.W., 2020. Fleet Sizing for Pooled (Automated) Vehicle Fleets. Transportation Research Record: Journal of the Transportation Research Board .

Becker, F., Axhausen, K.W., 2017. Literature review on surveys investigating the acceptance of automated vehicles. Transportation 44, 1293–1306.

Becker, H., Becker, F., Abe, R., Bekhor, S., Belgiawan, P.F., Compostella, J., Frazzoli, E., Fulton, L.M., Guggisberg Bicudo, D., Murthy Gurumurthy, K., Hensher, D.A., Joubert, J.W., Kockelman, K.M., Kröger, L., Le Vine, S., Malik, J., Marczuk, K., Ashari Nasution, R., Rich, J., Papu Carrone, A., Shen, D., Shiftan, Y., Tirachini, A., Wong, Y.Z., Zhang, M., Bösch, P.M., Axhausen, K.W., 2020. Impact of vehicle automation and electric propulsion on production costs for mobility services worldwide. Transportation Research Part A: Policy and Practice 138, 105–126.

BFS, 2019. Kosten und Finanzierung des Verkehrs 2016. Technical Report. Swiss Federal Office of Statistics (BFS), Neuchâtel.

BFS, ARE, 2018. Mikrozensus Mobilität und Verkehr. Technical Report. Swiss Federal Office of Statistics (BFS) and Federal Office for Spatial Development (ARE), Neuchâtel.

Bischoff, J., Maciejewski, M., 2016. Simulation of City-wide Replacement of Private Cars with Autonomous Taxis in Berlin. Procedia Computer Science 83, 237–244.

Bischoff, J., Maciejewski, M., Schlenther, T., Nagel, K., 2019. Autonomous Vehicles and their Impact on Parking Search. IEEE Intelligent Transportation Systems Magazine 11, 19–27.

Boesch, P.M., Ciari, F., Axhausen, K.W., 2016. Autonomous Vehicle Fleet Sizes Required to Serve Different Levels of Demand. Transportation Research Record: Journal of the Transportation Research Board 2542, 111–119.

Bösch, P.M., Becker, F., Becker, H., Axhausen, K.W., 2018. Cost-based analysis of autonomous mobility services. Transport Policy 64, 76–91.

Chen, T.D., Kockelman, K.M., 2016. Management of a Shared Autonomous Electric Vehicle Fleet: Implications of Pricing Schemes. Transportation Research Record: Journal of the Transportation Research Board 2572, 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. Transportation Research Part A: Policy and Practice 94, 243–254.

Cugurullo, F., Acheampong, R.A., Gueriau, M., Dusparic, I., 2020. The transition to autonomous cars, the redesign of cities and the future of urban sustainability. Urban Geography , 1–27.

Dandl, F., Bogenberger, K., Mahmassani, H.S., 2019. Autonomous Mobility-on-Demand Real-Time Gaming Framework, in: 2019 6th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS), IEEE, Cracow, Poland.

Fagnant, D.J., Kockelman, K.M., 2014. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. Transportation Research Part C: Emerging Technologies 40, 1–13.

Fagnant, D.J., Kockelman, K.M., 2018. Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas. Transportation 45, 143–158.

Gurumurthy, K.M., Kockelman, K.M., Loeb, B.J., 2019a. Sharing vehicles and sharing rides in real-time: Opportunities for self-driving fleets, in: Advances in Transport Policy and Planning. Elsevier. volume 4, pp. 59–85.

Gurumurthy, K.M., Kockelman, K.M., Simoni, M.D., 2019b. Benefits and Costs of Ride-Sharing in Shared Automated Vehicles across Austin, Texas: Opportunities for Congestion Pricing. Transportation Research Record: Journal of the Transportation Research Board 2673, 548–556.

Gurumurthy, K.M., de Souza, F., Enam, A., Auld, J., 2020. Integrating Supply and Demand Perspectives for a Large-Scale Simulation of Shared Autonomous Vehicles. Transportation Research Record: Journal of the Transportation Research Board , 036119812092115.

Hamadneh, J., Esztergar-Kiss, D., 2019. Impacts of Shared Autonomous Vehicles on the Travelers' Mobility, in: 2019 6th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS), IEEE, Cracow, Poland.

Harper, C.D., Hendrickson, C.T., Samaras, C., 2018. Exploring the Economic, Environmental, and Travel Implications of Changes in Parking Choices due to Driverless Vehicles: An Agent-Based Simulation Approach. Journal of Urban Planning and Development 144.

Hess, S., Palma, D., 2019a. Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application. Journal of Choice Modelling 32.

Hess, S., Palma, D., 2019b. Apollo version 0.1.0. User manual. Choice Modeling Centre, University of Leeds. Leeds.

Horni, A., Nagel, K., Axhausen, K.W. (Eds.), 2016. The Multi-Agent Transport Simulation MATSim. Ubiquity Press.

Hyland, M., Mahmassani, H.S., 2018. Dynamic autonomous vehicle fleet operations: Optimization-based strategies to assign AVs to immediate traveler demand requests. Transportation Research Part C: Emerging Technologies 92, 278–297.

Hyland, M., Mahmassani, H.S., 2020. Operational benefits and challenges of shared-ride automated mobility-on-demand services. Transportation Research Part A: Policy and Practice 134, 251–270.

Hyland, M.F., Mahmassani, H.S., 2017. Taxonomy of Shared Autonomous Vehicle Fleet Management Problems to Inform Future Transportation Mobility. Transportation Research Record: Journal of the Transportation Research Board 2653, 26–34.

Hörl, S., 2017. Agent-based simulation of autonomous taxi services with dynamic demand responses. Procedia Computer Science 109, 899–904.

Hörl, S., 2020. Dynamic Demand Simulation for Automated Mobility on Demand. Ph.D. thesis. ETH Zurich.

Hörl, S., Axhausen, K.W., 2020. Relaxation-discretization algorithm for spatially constrained secondary location assignment, in: 99th Annual Meeting of the Transportation Research Board, Washington, DC.

Hörl, S., Balac, M., 2020. Reproducible scenarios for agent-based transport simulation: A case study for Paris and Île-de-France. Arbeitsberichte Verkehrs- und Raumplanung 1499.

Hörl, S., Balac, M., Axhausen, K.W., 2019a. Dynamic demand estimation for an AMoD system in Paris, in: 2019 IEEE Intelligent Vehicles Symposium (IV), IEEE, Paris, France. pp. 260–266.

Hörl, S., Balać, M., Axhausen, K.W., 2019b. Pairing discrete mode choice models and agent-based transport simulation with MATSim, in: 98th Annual Meeting of the Transportation Research Board, Washington, DC.

Hörl, S., Becker, F., Dubernet, T., Axhausen, K.W., 2019c. Induzierter Verkehr durch autonome Fahrzeuge: Eine Abschätzung, Schlussbericht, SVI 2016/001. Schriftenreihe 1650, UVEK, Bern.

Hörl, S., Ruch, C., Becker, F., Frazzoli, E., Axhausen, K., 2019d. Fleet operational policies for automated mobility: A simulation assessment for Zurich. Transportation Research Part C: Emerging Technologies 102, 20–31.

Javanshour, F., Dia, H., Duncan, G., 2019. Exploring the performance of autonomous mobility on-demand systems under demand uncertainty. Transportmetrica A: Transport Science 15, 698–721.

Jing, P., Hu, H., Zhan, F., Chen, Y., Shi, Y., 2020. Agent-Based Simulation of Autonomous Vehicles: A Systematic Literature Review. IEEE Access 8, 79089–79103.

Kaddoura, I., Bischoff, J., Nagel, K., 2020. Towards welfare optimal operation of innovative mobility concepts: External cost pricing in a world of shared autonomous vehicles. Transportation Research Part A: Policy and Practice 136, 48–63.

Kamel, J., Vosooghi, R., Puchinger, J., Ksontini, F., Sirin, G., 2019. Exploring the Impact of User Preferences on Shared Autonomous Vehicle Modal Split: A Multi-Agent Simulation Approach. Transportation Research Procedia 37, 115–122.

Le, D.T., Zegras, P.C., Zhou, M., Fereirra, J., Nguyen-Phuoc, D.Q., Ben-Akiva, M., Oh, S., Seshadri, R., 2019. Simulating Multi-scaled Impacts of Automated Mobility-on-Demand Services, in: 2019 IEEE Intelligent Transportation Systems Conference (ITSC), IEEE, Auckland, New Zealand. pp. 1245–1250.

Levin, M.W., Kockelman, K.M., Boyles, S.D., Li, T., 2017. A general framework for modeling shared autonomous vehicles with dynamic network-loading and dynamic ride-sharing application. Computers, Environment and Urban Systems 64, 373–383.

Liu, J., Kockelman, K.M., Boesch, P.M., Ciari, F., 2017. Tracking a system of shared autonomous vehicles across the Austin, Texas network using agent-based simulation. Transportation 44, 1261–1278.

Liu, Y., Bansal, P., Daziano, R., Samaranayake, S., 2019. A framework to integrate mode choice in the design of mobility-on-demand systems. Transportation Research Part C: Emerging Technologies 105, 648–665.

Loeb, B., Kockelman, K.M., Liu, J., 2018. Shared autonomous electric vehicle (SAEV) operations across the Austin, Texas network with charging infrastructure decisions. Transportation Research Part C: Emerging Technologies 89, 222–233.

Lokhandwala, M., Cai, H., 2018. Dynamic ride sharing using traditional taxis and shared autonomous taxis: A case study of NYC. Transportation Research Part C: Emerging Technologies 97, 45–60.

Lu, M., Taiebat, M., Xu, M., Hsu, S.C., 2018. Multiagent Spatial Simulation of Autonomous Taxis for Urban Commute: Travel Economics and Environmental Impacts. Journal of Urban Planning and Development 144.

Maciejewski, M., Bischoff, J., 2018. Congestion effects of autonomous taxi fleets. Transport 33, 971–980.

Maciejewski, M., Bischoff, J., Hörl, S., Nagel, K., 2017. Towards a Testbed for Dynamic Vehicle Routing Algorithms, in: Bajo, J., Vale, Z., Hallenborg, K., Rocha, A.P., Mathieu, P., Pawlewski, P., Del Val, E., Novais, P., Lopes, F., Duque Méndez, N.D., Julián, V., Holmgren, J. (Eds.), Highlights of Practical Applications of Cyber-Physical Multi-Agent Systems. Springer International Publishing, Cham. volume 722, pp. 69–79.

Maciejewski, M., Bischoff, J., Nagel, K., 2016a. An Assignment-Based Approach to Efficient Real-Time City-Scale Taxi Dispatching. IEEE Intelligent Systems 31, 68–77.

Maciejewski, M., Salanova, J.M., Bischoff, J., Estrada, M., 2016b. Large-scale microscopic simulation of taxi services. Berlin and Barcelona case studies. Journal of Ambient Intelligence and Humanized Computing 7, 385–393.

Martinez, L.M., Viegas, J.M., 2017. Assessing the impacts of deploying a shared self-driving urban mobility system: An agent-based model applied to the city of Lisbon, Portugal. International Journal of Transportation Science and Technology 6, 13–27.

Meyer, J., Becker, H., Bösch, P.M., Axhausen, K.W., 2017. Autonomous vehicles: The next jump in accessibilities? Research in Transportation Economics 62, 80–91.

Mourad, A., Puchinger, J., Chu, C., 2019. A survey of models and algorithms for optimizing shared mobility. Transportation Research Part B: Methodological 123, 323–346.

Nahmias-Biran, B.h., Oke, J.B., Kumar, N., Lima Azevedo, C., Ben-Akiva, M., 2020. Evaluating the impacts of shared automated mobility on-demand services: an activity-based accessibility approach. Transportation .

Narayanan, S., Chaniotakis, E., Antoniou, C., 2020. Shared autonomous vehicle services: A comprehensive review. Transportation Research Part C: Emerging Technologies 111, 255–293.

Oh, S., Seshadri, R., Azevedo, C.L., Kumar, N., Basak, K., Ben-Akiva, M., 2020a. Assessing the impacts of automated mobility-on-demand through agent-based simulation: A study of Singapore. Transportation Research Part A: Policy and Practice 138, 367–388.

Oh, S., Seshadri, R., Le, D.T., Zegras, P.C., Ben-Akiva, M.E., 2020b. Evaluating Automated Demand Responsive Transit Using Microsimulation. IEEE Access 8, 82551–82561.

Ortega, J., Hamadneh, J., Esztergár-Kiss, D., Tóth, J., 2020. Simulation of the Daily Activity Plans of Travelers Using the Park-and-Ride System and Autonomous Vehicles: Work and Shopping Trip Purposes. Applied Sciences 10, 2912.

Pernestål, A., Kristoffersson, I., 2019. Effects of driverless vehicles. European Journal of Transport and Infrastructure Research 19.

Pinto, H.K., Hyland, M.F., Mahmassani, H.S., Verbas, I., 2020. Joint design of multimodal transit networks and shared autonomous mobility fleets. Transportation Research Part C: Emerging Technologies 113, 2–20.

Poulhès, A., Berrada, J., 2020. Single vehicle network versus dispatcher: user assignment in an agent-based model. Transportmetrica A: Transport Science 16, 270–292.

Ruch, C., Horl, S., Frazzoli, E., 2018. AMoDeus, a Simulation-Based Testbed for Autonomous Mobility-on-Demand Systems, in: 2018 21st International Conference on Intelligent Transportation Systems (ITSC), IEEE, Maui, HI. pp. 3639–3644.

Ruch, C., Lu, C., Sieber, L., Frazzoli, E., 2020. Quantifying the Efficiency of Ride Sharing. IEEE Transactions on Intelligent Transportation Systems .

Salazar, M., Rossi, F., Schiffer, M., Onder, C.H., Pavone, M., 2018. On the Interaction between Autonomous Mobility-on-Demand and Public Transportation Systems, in: 2018 21st International Conference on Intelligent Transportation Systems (ITSC), IEEE, Maui, HI. pp. 2262–2269.

Scheltes, A., de Almeida Correia, G.H., 2017. Exploring the use of automated vehicles as last mile connection of train trips through an agent-based simulation model: An application to Delft, Netherlands. International Journal of Transportation Science and Technology 6, 28–41.

Segui-Gasco, P., Ballis, H., Parisi, V., Kelsall, D.G., North, R.J., Busquets, D., 2019. Simulating a rich ride-share mobility service using agent-based models. Transportation 46, 2041–2062.

Shen, Y., Zhang, H., Zhao, J., 2018. Integrating shared autonomous vehicle in public transportation system: A supply-side simulation of the first-mile service in Singapore. Transportation Research Part A: Policy and Practice 113, 125–136.

Sieber, L., Ruch, C., Hörl, S., Axhausen, K., Frazzoli, E., 2020. Improved public transportation in rural areas with self-driving cars: A study on the operation of Swiss train lines. Transportation Research Part A: Policy and Practice 134, 35–51.

Simoni, M.D., Kockelman, K.M., Gurumurthy, K.M., Bischoff, J., 2019. Congestion pricing in a world of self-driving vehicles: An analysis of different strategies in alternative future scenarios. Transportation Research Part C: Emerging Technologies 98, 167–185.

Spieser, K., Treleaven, K., Zhang, R., Frazzoli, E., Morton, D., Pavone, M., 2014. Toward a Systematic Approach to the Design and Evaluation of Automated Mobility-on-Demand Systems: A Case Study in Singapore, in: Meyer, G., Beiker, S. (Eds.), Road Vehicle Automation. Springer International Publishing, Cham, pp. 229–245.

Taiebat, M., Brown, A.L., Safford, H.R., Qu, S., Xu, M., 2018. A Review on Energy, Environmental, and Sustainability Implications of Connected and Automated Vehicles. Environmental Science & Technology 52.

Vosooghi, R., Kamel, J., Puchinger, J., Leblond, V., Jankovic, M., 2019a. Robo-Taxi service fleet sizing: assessing the impact of user trust and willingness-to-use. Transportation 46, 1997–2015.

Vosooghi, R., Puchinger, J., Jankovic, M., Vouillon, A., 2019b. Shared autonomous vehicle simulation and service design. Transportation Research Part C: Emerging Technologies 107, 15–33.

Wadud, Z., MacKenzie, D., Leiby, P., 2016. Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. Transportation Research Part A: Policy and Practice 86, 1–18.

Wang, B., Ordonez Medina, S.A., Fourie, P., 2018. Simulation of Autonomous Transit On Demand for Fleet Size and Deployment Strategy Optimization. Procedia Computer Science 130, 797–802.

Wen, J., Chen, Y.X., Nassir, N., Zhao, J., 2018. Transit-oriented autonomous vehicle operation with integrated demand-supply interaction. Transportation Research Part C: Emerging Technologies 97, 216–234.

Williams, E., Das, V., Fisher, A., 2020. Assessing the Sustainability Implications of Autonomous Vehicles: Recommendations for Research Community Practice. Sustainability 12.

Winter, K., Cats, O., Martens, K., van Arem, B., 2020. Relocating shared automated vehicles under parking constraints: assessing the impact of different strategies for on-street parking. Transportation .

Zhang, W., Guhathakurta, S., Fang, J., Zhang, G., 2015. Exploring the impact of shared autonomous vehicles on urban parking demand: An agent-based simulation approach. Sustainable Cities and Society 19, 34–45.

Ziemke, D., Kaddoura, I., Nagel, K., 2019. The MATSim Open Berlin Scenario: A multimodal agent-based transport simulation scenario based on synthetic demand modeling and open data. Procedia Computer Science 151, 870–877.