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1 Shifts in perspective: Operational aspects in (non-) autonomous  
2 ride-pooling simulations

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11 **Declaration of Interests:** Felix Zwick is currently a PhD candidate at ETH Zurich and  
12 scientifically studies the impacts of ride-pooling. However, it is also acknowledged that he is employed  
13 at the ride-pooling provider MOIA.

14

## Abstract

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In this article, we simulate and evaluate the operational challenges of non-autonomous ride-pooling systems through driver shifts and breaks and compare their capacity and efficiency to automated on-demand services. We introduce shift and break schedules and a new hub return logic to perform the respective tasks at different types of vehicle hubs. This way, currently operating on-demand services are modelled more realistically and the efficiency gains of such services through autonomous vehicles are quantified.

The results suggest that operational challenges substantially limit the ride-pooling capacity in terms of served rides with a given number of vehicles. While results largely depend on the chosen shift plan, the presented operational factors should be considered for the assessment of current operational real-world services. The contribution of this study is threefold - from a technical perspective, it is shown that the explicit simulation of operational constraints of current services is crucial to assess ride-pooling services. From a policy perspective, the study shows the potential of future autonomous services in direct comparison with non-autonomous services. Lastly, the paper adds to the literature a realistic ride-pooling simulation use case based on observed real-world demand and shift data.

**Keywords:** ride-sharing, pooled on-demand mobility, MATSim, electric vehicles, operations research

## 33 1 Introduction

34 Over the past years, research interest has evolved around new mobility options such as ride-hailing  
35 and -pooling. Several app-based dynamic ride-pooling services such as UberPool<sup>1</sup>, GrabShare<sup>2</sup>,  
36 Clevershuttle<sup>3</sup> or MOIA<sup>4</sup> have been introduced and promise to reduce traffic volumes and resources  
37 consumed in urban areas, as several car trips can be bundled and replaced by a single pooled trip.  
38 Although several simulation studies have shown the great potential of pooled mobility services to  
39 reduce vehicle fleets and vehicle kilometers traveled (VKT) in urban environments, ride-pooling ser-  
40 vices are not yet widely available. One reason for this are the high operating costs of large-scale  
41 ride-pooling services, especially for non-autonomous fleets where labor costs lead to high service  
42 costs (Bösch et al., 2018). This makes operators and transit planners all the more hopeful that  
43 autonomous vehicles can reduce costs and increase ridership and service coverage. Under these con-  
44 ditions, large-scale ride-pooling systems have a large potential to provide a reliable and convenient  
45 mobility service that is more sustainable than the current urban transport system.

46  
47 While even experts during the initial euphoria predicted a very early introduction of autonomous  
48 vehicles around the year 2020 (in which the New York Times published an article titled "This Was  
49 Supposed to Be the Year Driverless Cars Went Mainstream", (Metz and Griffith, 2020)), current  
50 (public) voices on the introduction of autonomous vehicles seem more conservative, as can be seen  
51 in various statements (Gessner, 2020; Valdes-Dapena, 2021; Hagon, 2019; Bubbers, 2019; Blouin,  
52 2021). In a study on future implementations of fully autonomous services, Kannan and Lasky  
53 (2020) concluded that "fully autonomous vehicles are several decades away". The authors base this  
54 on shortcomings of current artificial intelligence (AI) technologies and difficulties in designing and  
55 testing fully autonomous vehicles. Leonard et al. (2020) claim that widespread autonomous driving  
56 will take at least a decade. Similarly, Litman (2017) predicts that fully autonomous vehicles will  
57 only be introduced in the 2030s or 2040s with limited performance and at high prices. Shladover  
58 (2016) even goes as far as saying that level 5 autonomous driving might even need until around 2075  
59 to become fully available. The ride-hailing provider Uber recently shifted focus from autonomous  
60 taxis to easier-to-implement autonomous trucks because of financial and legal challenges (Metz and  
61 Conger, 2020). MOIA's latest timeline doesn't call for autonomous vehicles to be introduced until  
62 2025 (MOIA, 2021). Then, the first level 4 autonomous vehicles are to be deployed on test sections.  
63 This will still require drivers who can intervene in an emergency.

64  
65 As such, current ride-hailing and -pooling companies are likely to continue their service with non-  
66 autonomous vehicles and drivers for at least a few more years. This includes operational challenges  
67 such as driver shifts and breaks that have to be taken into account for a more realistic modeling  
68 perspective of current services. In this study, we present an extension to an existing ride-pooling  
69 extension in the simulation framework MATSim (Horni et al., 2016) to reflect the impact of human  
70 driver shifts and resulting operational trips toward break or hub facilities. In addition, we have  
71 adapted the existing MATSim extension for electric vehicles (EVs) to include charging procedures  
72 during the operational breaks.

73  
74 Using the new extension, we assess the impact of operational challenges faced by on-demand  
75 mobility services in a world of non-autonomous vehicles and compare them to a fully autonomous

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<sup>1</sup><https://www.uber.com/de/de/ride/uberpool/>

<sup>2</sup><https://www.grab.com/sg/transport/share/>

<sup>3</sup><https://www.clevershuttle.de/>

<sup>4</sup><https://www.moia.io/>

76 system. This way, on-demand mobility operators, public authorities and transport researchers are  
 77 able to reassess the introduction of large-scale ride-pooling services, which in the past have been  
 78 evaluated mainly with simplified assumptions regarding operational complexity.

## 79 2 Related ride-pooling studies

80 In order to assess operational challenges, fleet and user behavior or implications on the transport  
 81 system of a new on-demand mobility system, a common approach is to simulate the proposed ser-  
 82 vice within a transport model. The minimum requirement for such simulations is a street network,  
 83 demand and supply and an assignment logic that matches requests and vehicles. In recent years,  
 84 numerous such simulation studies have been conducted in the field of on-demand mobility, often  
 85 also described as Autonomous Mobility on-Demand (AMoD) or Shared Autonomous Vehicle (SAV)  
 86 systems. A broad overview of these simulation studies has been provided by Pernestål and Kristof-  
 87 fersson (2019) and Jing et al. (2020), who reviewed 26 and 44 simulation studies of (autonomous)  
 88 on-demand services, respectively. While many of these studies deal with unpooled systems, we focus  
 89 on ride-pooling systems here.

### 90 2.1 Demand and supply characteristics

91 Table 1 provides an overview of a few selected ride-pooling simulation studies assessing different  
 92 demand and supply characteristics. We classify the studies into four demand categories with *toy*  
 93 *demand* being the least and *historical on-demand requests* being the most realistic representation  
 94 of real-world ride-pooling systems. The supply categories *Static fleet* and *Pseudo shifts* show if  
 95 temporal limitations of vehicles were taken into account.

Table 1: Demand and supply characteristics in existing ride-pooling studies.

		<b>Demand</b>			
		Toy demand	Static synthetic de- mand	Synthetic demand based on mode choice model	Historical pooling/taxi requests
<b>Supply</b>	Static fleet	Fagnant and Kockel- man (2014)* Zhang et al. (2015) Farhan and Chen (2018)	Merlin (2017) Fagnant and Kock- elman (2018) Engelhardt et al. (2019) Loeb and Kockel- man (2019) Vosooghi et al. (2020) Ruch et al. (2020) Zwick et al. (2021a)	Hörl (2017) Martinez and Viegas (2017) Vosooghi et al. (2019a) Gurumurthy et al. (2020) Wilkes et al. (2021) Kaddoura and Schlenther (2021) Zwick et al. (2021a)	Alonso-Mora et al. (2017) Ruch et al. (2020) Zwick and Axhausen (2020a)
	Pseudo-shifts				Martinez et al. (2015) Bischoff et al. (2017) Lokhandwala and Cai (2018) Zwick and Axhausen (2020b)

96 In the majority of the existing ride-pooling simulation studies, a static vehicle fleet is employed,  
97 meaning that the number of employed vehicles is constant throughout the simulation. Vehicles are  
98 assumed to operate autonomously and are constantly available to transport passengers or to re-  
99 balance to areas with high expected demand. In some of the listed studies the impact of varying  
100 fleet sizes is investigated in different scenarios but during one simulation run the fleet size is static.  
101 Some simulation studies evaluated the on-demand systems using example scenarios with artificially  
102 generated demand (Fagnant and Kockelman, 2014; Zhang et al., 2015; Farhan and Chen, 2018) in  
103 toy scenarios. In recent years, more and more studies were conducted in real-world scenarios taking  
104 demand from synthetic populations in transport models. Demand was defined either by a certain  
105 proportion of previous trips being made with ride-pooling or by a mode-choice model. We found  
106 by far most studies in these two categories, which seems to be plausible given the availability of  
107 data. Still, the spatio-temporal distribution of demand can differ from real-world on-demand mo-  
108 bility services and it therefor provides additional realism if historical taxi or ride-pooling requests  
109 are used as an input for the simulation. Alonso-Mora et al. (2017) and Ruch et al. (2020) used  
110 open taxi data from New York City and San Francisco, whereas Zwick and Axhausen (2020a) used  
111 demand data from the ride-pooling operator MOIA in Hamburg that also serves as a data source here.

112  
113 Less studies taking into account shift times of drivers were found. Bischoff et al. (2017) used  
114 historical taxi demand and supply from Berlin, and Zwick and Axhausen (2020b) used historical  
115 demand and shift plans of MOIA in Hamburg to assign a service time to each simulated vehicle with  
116 begin and end times according to the data. While the temporal distribution of vehicles approximate  
117 the real-world systems, there are no operational duties for shift breaks or hub returns at an end of a  
118 shift taken into account. The same accounts for a study of Martinez et al. (2015) who extracted taxi  
119 demand from a mobility survey and employed shared taxis with drivers weighing up the benefits of  
120 cruising or heading to a taxi rank to find new customers. Driver shifts were modeled in that a cab  
121 becomes inactive as soon as the shift ends and returns either to the cab company or, in the case of an  
122 independent cab, to a randomly chosen network node. The model did not include an actual dynamic  
123 traffic assignment and assumed fixed travel times. Lokhandwala and Cai (2018) modeled taxi shifts  
124 in New York City based on aggregated vehicle availability data. They compared the system with  
125 driver shifts with an autonomous service where all vehicles are active during the entire simulation  
126 time. They find a lower coverage of low-demand areas in the shift service due to the restricted fleet  
127 size since vehicles tend to stay in areas with high demand. However, operational challenges that  
128 come with driver shifts such as hub returns for breaks and shift changes were not modeled.

129  
130 Overall, we did not find any studies simulating the operational challenges of hub returns for  
131 breaks and shift changes for on-demand mobility services.

## 132 **2.2 Electric vehicles**

133 Another operational challenge of mobility systems arises when electric vehicles (EVs) are used in-  
134 stead of internal combustion engine vehicles due to their shorter range and longer charging times  
135 compared to refueling. Electric vehicles were taken into account in multiple ride-pooling simulation  
136 studies.

137  
138 Vosooghi et al. (2020) assessed the impact of different charging policies and battery capacities on  
139 an autonomous ride-pooling fleet in MATSim (Horni et al., 2016). Vehicles are constantly operating  
140 and only sent to a charging facility once the state of charge (SoC) is below 20 %. The authors  
141 found a substantially lower performance of electric fleets with less passenger kilometers transported

142 and more empty vehicle kilometers travelled compared to non-electric fleets. System performance  
143 improvements may be achieved through rapid chargers and a battery swapping policy.

144

145 Loeb and Kockelman (2019) come to a similar conclusion. They evaluated the costs of different  
146 pooled and shared autonomous electric vehicle (SAEV) fleets and state that "starting an SAEV  
147 fleet from the ground up is not financially advantageous over a traditionally-fueled SAV fleet". Main  
148 reasons for this conclusion are the higher costs of EVs, replacement batteries and charging stations  
149 and additional empty VKT in operation. Profits are found to be highest with fast-chargers and  
150 long-range fleets. Similar to Vosooghi et al. (2020), vehicles are only sent to charge if their SoC is  
151 below 5 % and they have no other operational duties.

152

153 Farhan and Chen (2018) compared a long-range and a short-range pooled SAEV fleet to an  
154 unpooled fleet and found substantial efficiency gains through pooling with a reduced fleet size of  
155 roughly 50 % and 30 % less required charging stations. Long-range EVs lead to less required charging  
156 stations and lower waiting times.

157

158 An operational optimization potential of unpooled SAEVs was studied by Iacobucci et al. (2019).  
159 They optimized the charge scheduling by considering historic electricity price data in Tokyo and  
160 also evaluated the vehicle-to-grid potential. By using two model-predictive control optimization  
161 algorithms in parallel, one optimizing the transport service and one optimizing charging, charging  
162 cost reductions of 10 % are found while service quality reduction is small.

## 163 2.3 Contribution

164 In summary, we find that existing simulation studies usually consider autonomous vehicles and do  
165 not explicitly account for operational constraints in non-autonomous ride-pooling services. Chal-  
166 lenges of EVs have been studied more frequently.

167

168 In order to translate the learnings of the numerous simulation studies to today's non-autonomous  
169 ride-pooling systems, we aim to consider the most relevant operational constraints that were learnt  
170 from the real-world ride-pooling operator MOIA. For this purpose, we are able to use historical shift  
171 and demand data of the service in Hamburg. This way we can investigate how well simulations  
172 with autonomous vehicles or *pseudo shifts* (i.e. vehicles may be active for limited time windows but  
173 without driver breaks and shift changeovers at hubs) can be used to describe current driver-based  
174 services by comparing against an explicit simulation of driver shifts and breaks. In addition, by  
175 direct comparison, this study quantifies the impact that future autonomous vehicles may have on  
176 quality and efficiency of ride-pooling services.

177

178 Our contribution to existing ride-pooling studies is threefold:

- 179 • We add the technical functionality to consider operational duties such as shift breaks and shift  
180 changes with charging processes to an existing ride-pooling simulation environment.
- 181 • We evaluate the potential of future autonomous services in direct comparison with non-  
182 autonomous services that are currently in operation. This way, we also assess the comparability  
183 of most existing ride-pooling studies and currently operating services.
- 184 • We complement the literature of realistic ride-pooling simulation with a simulation scenario  
185 based on real-world demand and shift data of the ride-pooling operator MOIA.

## 186 3 Methodology

### 187 3.1 Simulation framework

188 The simulation is carried out by the Multi-Agent Transport Simulation MATSim (Horni et al.,  
189 2016), which has been frequently used to study the impact of dynamic transport services (Guru-  
190 murthy et al., 2019; Vosooghi et al., 2019b; Kaddoura et al., 2020; Yan et al., 2020; Hörl et al., 2021).  
191 It is an agent-based transport simulation framework that utilizes an iterative, co-evolutionary learn-  
192 ing approach in which each agent tries to maximize their daily score for a given plan of activities.  
193 Agents obtain positive scores for performing scheduled activities (such as working) and negative  
194 scores for traveling or arriving late at an activity. After every iteration, agents evaluate their last  
195 executed plan with a resulting score. While some agents modify their plan by, e.g., choosing a new  
196 route or another mode of transport, the remaining agents choose from existing plans based on their  
197 scores. MATSim eventually leads to a stochastic user equilibrium in which no agent can unilaterally  
198 increase their perceived score by adapting their plan. MATSim is an open-source Java program.

199  
200 In our setup we use MATSim as a pure dynamic traffic-assignment model with a fixed demand.  
201 In addition, the demand is not represented by full activity schedules but by individual ride-pooling  
202 *trips* as observed by historic real-world MOIA ride requests. As we are only concerned with the  
203 ride-pooling service in this study, we ignore other modes such as private cars, public transport or  
204 walking and any user adaptation between iterations.

### 205 3.2 DRT extension

206 There are several MATSim extensions to simulate on-demand mobility systems (Maciejewski, 2016)  
207 out of which the DRT (demand responsive transit) extension developed by Bischoff et al. (2017)  
208 has been predominantly used in recent simulation studies. The extension handles incoming requests  
209 and assigns them to available vehicles in the system. When a trip request with pick-up and drop-off  
210 coordinates is submitted, the algorithm searches for all vehicles that can serve the request under  
211 consideration of a maximum wait time and maximum detour for the waiting customer and all  
212 customers traveling in the vehicle. The algorithm then inserts the new request into the route of the  
213 vehicle where the least travel delay is imposed on all on-board and planned requests along the route.  
214 Once selected, the assignment of a customer to a vehicle is binding. If no vehicle is found that can  
215 serve an incoming request, the request is rejected.

216 The pre-defined constraints highly impact the DRT system performance (Bischoff et al., 2017;  
217 Zwick and Axhausen, 2020b). In order to ensure a good balance between service quality and sys-  
218 tem performance, we set the maximum wait time to 10 minutes and allow a maximum detour of  
219 10 minutes + 50 % of the direct ride duration. The stop duration for a pick-up or drop-off is set to  
220 30 seconds.

221 The DRT extension comes with a rebalancing algorithm developed by Bischoff and Maciejewski  
222 (2020) to ensure that idle vehicles are sent to areas with high expected demand, which has shown  
223 to improve the system capacity in terms of acceptance rate (Zwick and Axhausen, 2020a).

### 224 3.3 Driver shift and break implementation

225 We build upon the existing (electric) DRT extension of MATSim and further extend it with a  
226 representation of driver shifts and breaks. Therefore, the simulation assumes the following input as  
227 exogenous input:



228 • A description of driver shifts with their start and end times as well as optionally planned  
229 breaks.

230 • A description of hubs and possible in-field break facilities. In-field break facilities can be, for  
231 instance, existing parking lots at grocery stores or gas stations with optional charging plugs.

232 While shift starts and ends are fixed, breaks are defined more flexibly inside a given corridor  
233 (earliest start time - latest end time) with a fixed duration. In our default setup, the typical break  
234 duration is set to 30 minutes. To Each operational facility the type *hub* or *in-field* can be assigned.  
235 In addition, each facility has a capacity for parked vehicles and, optionally, a number of chargers for  
236 electric vehicles.

237  
238 The basic functionality is provided by a central shift dispatcher that assigns shifts to suitable  
239 vehicle agents in MATSim. Vehicles can only serve ride-pooling requests as long as they have an  
240 active shift. Shift start and end times are accounted for in the scheduling of requests and may  
241 lead to the rejection of requests that would lead a driver to exceed the shift end time. Similarly,  
242 no requests can be served during driver breaks. Breaks have to be scheduled within their defined  
243 corridor. Passengers may be picked up/dropped off at the beginning/end of breaks. When a shift  
244 ends, a changeover period of 15 minutes has to be scheduled for the vehicle, in which no new shift  
245 can be started. During breaks and changeover times, electric vehicles may be charged if chargers  
246 are available. Idle vehicles located at hubs with no shift assigned may also be charged.

247

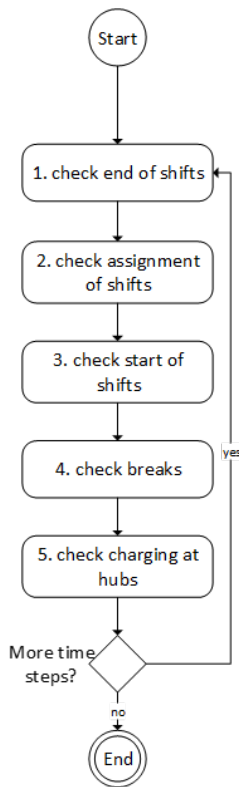


Figure 1: Basic steps of the central shift dispatcher.

248 The shift dispatcher applies the following basic procedure in each time step (see Figure 1):

- 249 **1. Check end of shifts**  
250 One hour (configurable) before the end of a shift, a changeover task including a relocation to  
251 the nearest operational hub with enough capacity is scheduled. The remaining trips are still  
252 served and additional requests may be accepted if the planned shift end is not exceeded.
- 253 **2. Check assignment of shifts**  
254 Planned shifts are assigned to suitable vehicles 30 minutes (configurable) ahead of their start  
255 time. Preferably, an already active vehicle that is about to end its shift and has a minimum  
256 state of charge (SoC) is assigned. Shifts can only be assigned to vehicles within their service  
257 time (i.e. their operation time in the autonomous use case). If no suitable vehicle is found,  
258 the shift remains in the queue and is checked again in the next time step.
- 259 **3. Check start of shifts**  
260 The queue of assigned shifts is checked for shifts starting in the given time step. The shift  
261 start may be delayed by previously delayed shift ends and only starts once the assigned vehicle  
262 is idle.
- 263 **4. Check breaks**  
264 All active shifts are checked whether a break corridor begins. If this is the case, the nearest  
265 operational facility with enough capacity is identified. The break is scheduled for the end of  
266 the current vehicle's schedule. New requests along the route may be served as long as the whole  
267 duration of the break inside the break corridor is ensured. If required and charger capacity  
268 permits, the vehicle may be charged during the break. Passengers may be scheduled to be  
269 picked up after the end of the break.
- 270 **5. Check charging at hubs**  
271 The dispatcher checks for all idle vehicles without shifts assigned and parked at hubs whether  
272 they require re-charging. If a vehicle is not planned to serve a shift until the estimated end  
273 of charging, a charging task is set up. This step is omitted if conventional cars with internal  
274 combustion engines (ICE) are simulated.

275 Given this basic functionality, an illustrative timeline for a vehicle is depicted in Figure 2. For  
276 the scheduling of requests, additional hard constraints have been added to the DRT scheduler:

- 277 • Passengers cannot be picked up/dropped off after a shift changeover task.
- 278 • Passengers cannot be picked up/dropped off if the request would violate the break corridor of  
279 a planned upcoming break task.
- 280 • Passengers cannot be picked up/dropped off if the request would delay the end of a shift (i.e.  
281 drivers should not work overtime).

### 282 **3.4 Charging behaviour**

283 For the shift and break optimization, we consider a service with electric vehicles. Each vehicle has  
284 a gross battery capacity of 77 kWh. The hubs are equipped with conventional slow chargers with  
285 a charging power of 7 kW, whereas the in-field break facilities are equipped with fast chargers with  
286 a charging power of 100 kW. The numbers are based on a real ride-pooling service (see below), but  
287 differ slightly.

288 It is recommended to keep the vehicles' SoC between 20 % and 80 % to decrease the batteries'

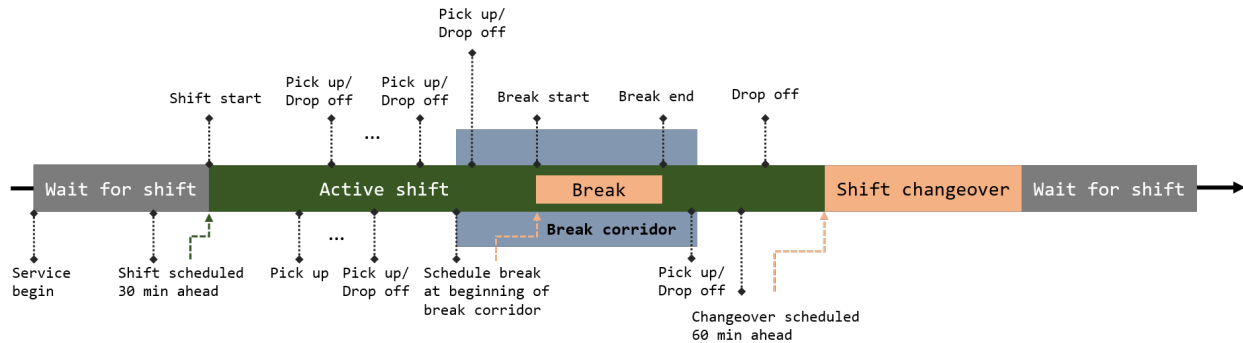


Figure 2: Illustrative implementation of driver shifts for a single DRT vehicle.

289 degradation and ensure efficient charging (Kostopoulos et al., 2020), leading to the following charging  
 290 policies:

- 291
- Vehicles are only charged if their SoC is below 80 %.
  - 292 • Vehicles are charged to up to 90 % SoC. We outreach the optimal charging limit of 80 % to  
 293 avoid capacity shortages during high demand hours. Since the vehicle is already plugged in,  
 294 charging it up to 90 % is no additional operational effort.
  - 295 • Vehicles can only be picked for a shift if their SoC is above 60 % to ensure that the power  
 296 lasts for the shift.
  - 297 • Vehicles stop accepting requests if their SoC is below 15 % to avoid running out of power in  
 298 the field.

299 The electric vehicles consume energy while driving and when staying idle during a shift with  
 300 values taken from Ohde et al. (2016). Vehicles that are idle and do not have an active shift do  
 301 not consume energy. Since we only simulate one day, we assume a starting distribution of battery  
 302 charging states that we obtain from the end of a previous simulation day to represent more realistic  
 303 states of charge at the beginning of the day.

## 304 4 Data preparation and scenario setup

305 We demonstrate the application of shifts using the stop network, demand and shift data from  
 306 Europe’s largest ride-pooling provider MOIA in Hamburg, Germany. MOIA operates since its launch  
 307 in 2019 with up to 500 vehicles in a 300 km<sup>2</sup> service area covering large parts of the city shown in  
 308 Figure 3. Although the input data reflects the real-world service, it should be noted that the ride-  
 309 pooling simulation, the used algorithms and the results only remotely resemble MOIA’s real-world  
 310 operation.

311  
 312 The street network is based on OpenStreetMap<sup>5</sup> data and MOIA’s more than 10,000 virtual  
 313 pick-up and drop-off stops are matched on it. We only simulate the ride-pooling service and thus  
 314 observe no congestion through car traffic in the system. In order to obtain realistic travel times  
 315 throughout the day, we use GPS-based speed data of all weekdays in November 2019 from Tom-  
 316 Tom<sup>6</sup> and match it to our MATSim network with the help of a map-matching algorithm described

<sup>5</sup>[www.openstreetmap.org](http://www.openstreetmap.org)

<sup>6</sup>[www.tomtom.com](http://www.tomtom.com)

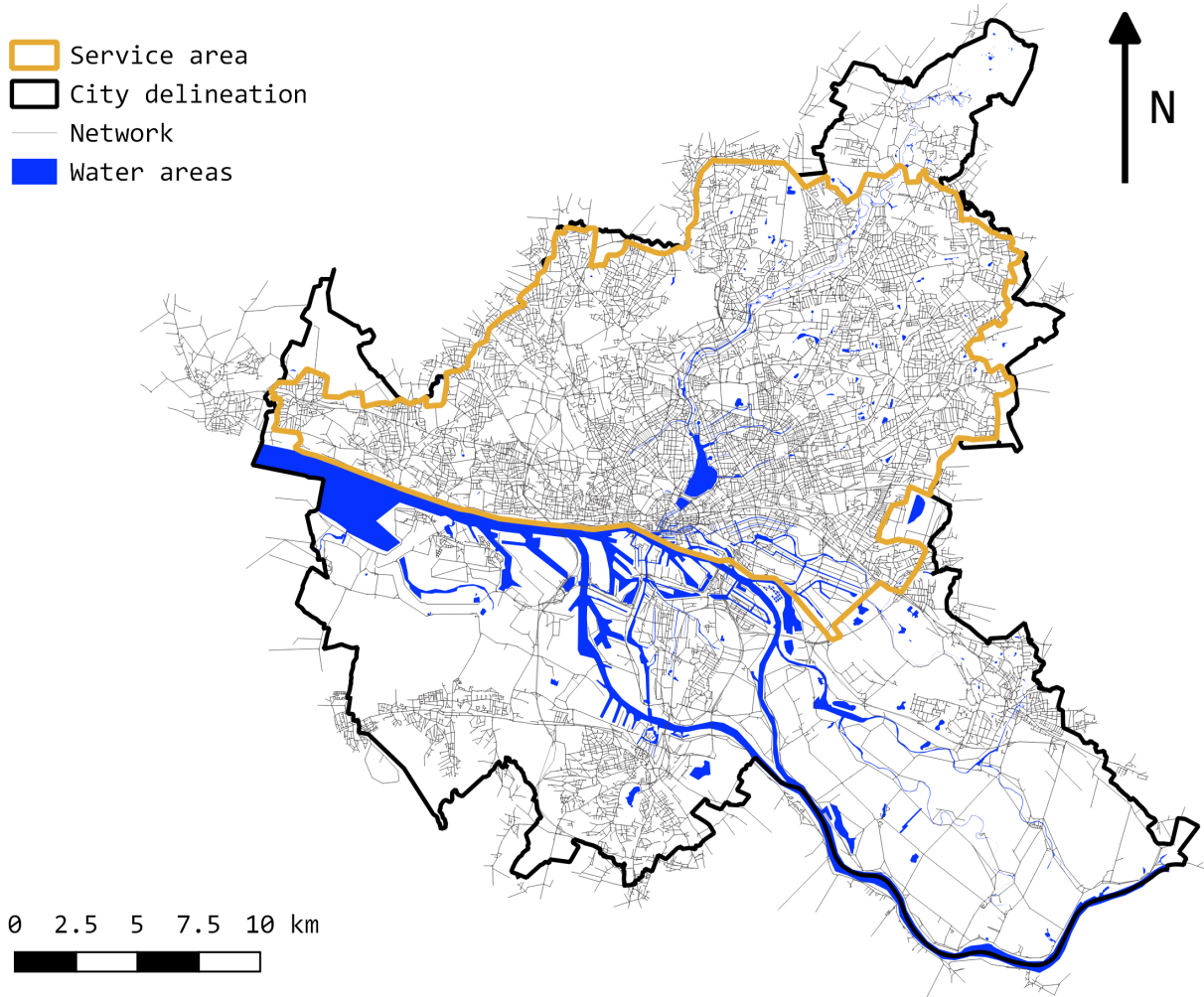


Figure 3: Study and service area of the Hamburg scenario, including road network and water areas.

317 by Yang and Gidófalvi (2018). Based on these matches, the network links' attributes are updated  
 318 throughout the simulation to reflect current travel times based on a 60 minutes resolution. Thereby,  
 319 each link's freespeed has been set to the average travel time of the respective GPS data in each given  
 320 time bin.

321

#### 322 4.1 Demand and supply data

323 We draw upon recorded ride-pooling requests from MOIA to generate the demand. Requests from  
 324 four typical weekend days have been collected between 19/09/2020 and 10/10/2020. We randomly  
 325 sample one fourth of each day's requests to avoid outlying extreme demand scenarios of a single  
 326 day. All requests are combined and assumed to occur on the same simulated day. In order to avoid  
 327 clustered requests from the same person, which would then be easily poolable in the simulation,  
 328 we excluded all requests from a person within a time range of 30 minutes after the first request.  
 329 Additionally, the departure time of each request is randomized by 10 minutes. In total, the dataset  
 330 contains 24,032 requests with an average trip length of 7.3 km.

331

332 Similarly, we sample historic real-world MOIA shifts from these same days and obtain 476 shifts  
 333 in total from 4:45 am to 6:30 am the next day. The time range was chosen by a) making sure to  
 334 cover the time period from 5:00 am to 5:00 am the next day of all requests and b) to include all  
 335 shifts that *start* on the given simulation day.

336

337 Lastly, three hubs with chargers have been defined based on MOIA’s real-world hub locations  
 338 (see Figure 5).

339

## 340 4.2 Scenarios

341 We compare multiple service set-ups to evaluate the impact of the operational challenges that come  
 342 with non-autonomous ride-pooling systems. After comparing two autonomous services with the  
 343 shift service, we have a closer look on the impacts of charging and additional hubs or in-field break  
 344 locations.

### 345 4.2.1 Autonomous vs. shift service

346 In order to evaluate the impact of operational duties with non-autonomous ride-pooling services  
 347 compared to autonomous ride-pooling services, we apply three different service designs as shown in  
 348 Table 2.

In the *autonomous service*, the entire vehicle fleet is available to pick up and drop off passengers

Table 2: Autonomous vs. shift services

	Autonomous service	Pseudo-shifts service	Explicit-shifts service
<b>Initial vehicle location</b>	Vehicle hub	Vehicle hub	Vehicle hub
<b>Final vehicle location</b>	Anywhere in-field	Anywhere in-field	Vehicle hub
<b>Vehicle service times</b>	No limitation	According to shift service times	According to shift service times
<b>Rebalancing</b>	Yes	Yes	Yes
<b>Service breaks in hubs</b>	No	No	Yes

349

350 and to be rebalanced throughout the simulated day. All vehicles start their day at one of the hub  
 351 locations but do not need to return to an operational facility. This kind of service has been predom-  
 352 inantly investigated in existing ride-pooling simulation studies as shown in Section 2.

353

354 In the *pseudo shifts* scenario, one autonomous vehicle is generated for each driver shift of the  
 355 input shifts. These vehicles will have a limited service time that equals the planned shift start/end  
 356 times. As such, it mimics a service with driver shifts but without driver breaks and shift changeover  
 357 times including respective hub returns.

358

359 In the *shift service* we consider the shift restrictions, a mandatory break of 30 minutes in one of  
 360 the hubs or in-field break locations and the mandatory return to one of the hubs by the end of each  
 361 shift. This service mimics existing non-autonomous ride-pooling systems including their operational

362 constraints.

363

364 Figure 4 summarizes the technical setup of the vehicle fleets in the three simulation scenarios.

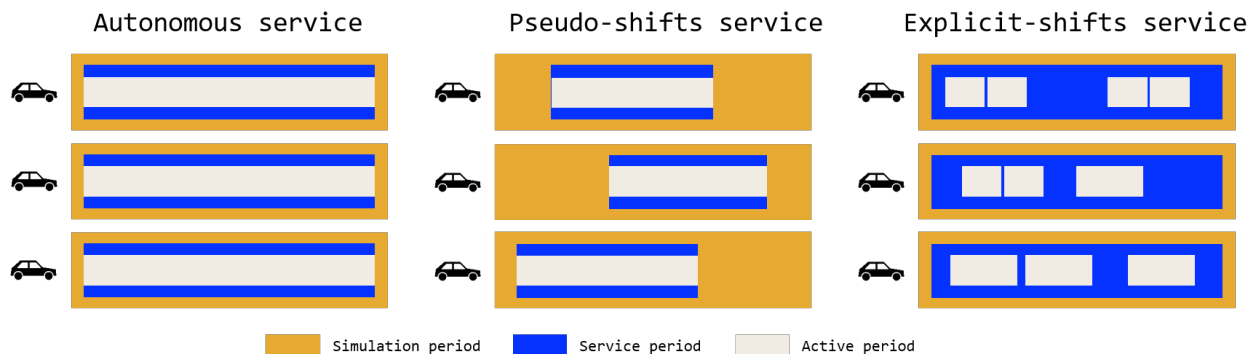


Figure 4: Qualitative representation of the three service set-ups. Vehicles are only able to serve requests when active.

#### 365 4.2.2 Conventional vs. electric fleets

366 After identifying the impacts of explicitly simulating shifts of the ride-pooling service, we add addi-  
367 tional operational constraints by employing an electric fleet with the assumptions given in Section 3.4.  
368 We do this after the analysis of the impact of explicit shifts to extract the individual contributions  
369 of these operational constraints. In addition, the existing electric version of the autonomous service  
370 in MATSim does not include an efficient charging strategy, as it requires all vehicles to always return  
371 to their depot for charging once they're idle, thereby introducing a lot of possibly unnecessary empty  
372 mileage. A comparison with the implemented charging strategy for the shift service is therefore not  
373 feasible.

#### 374 4.2.3 Shift and break optimization

375 Lastly, we investigate on the potential to optimize the electric explicit shift service with additional  
376 infrastructural facilities. We therefore add more hubs where drivers can do their break, start and  
377 end their shifts and vehicles can be charged. We incrementally add more hubs to the existing 3 hubs  
378 to obtain scenarios with 8, 16, 32 and 64 hubs, all equipped with 7 kW slow chargers. While the  
379 location of the initial three hubs is kept fixed, the location of additional hubs is selected randomly  
380 among all links in the network within the service area. At the same time, we ensure that each hub is  
381 at least 1 km away from every other hub. All additional hubs are equipped with chargers and have  
382 a capacity of 100 vehicles. The resulting distribution of hubs can be seen in Figure 5.

383

384 Additionally, we add a new type of facility, *in-field break facilities*, where drivers can have their  
385 break and the vehicles can be charged. Still, shifts need to be started and finished at one of the  
386 three hubs. The in-field locations are meant to be designated areas for parking vehicles during a  
387 break and could represent, e.g., gas stations which have a contract with the service provider that  
388 permits temporary parking of a small number of vehicles. Here, the in-field break facilities will have  
389 the same locations as the hubs in the respective hub-increase scenarios. They are equipped with 2  
390 fast chargers with a power of 100 kW. The configuration of the services is shown in Table 3.

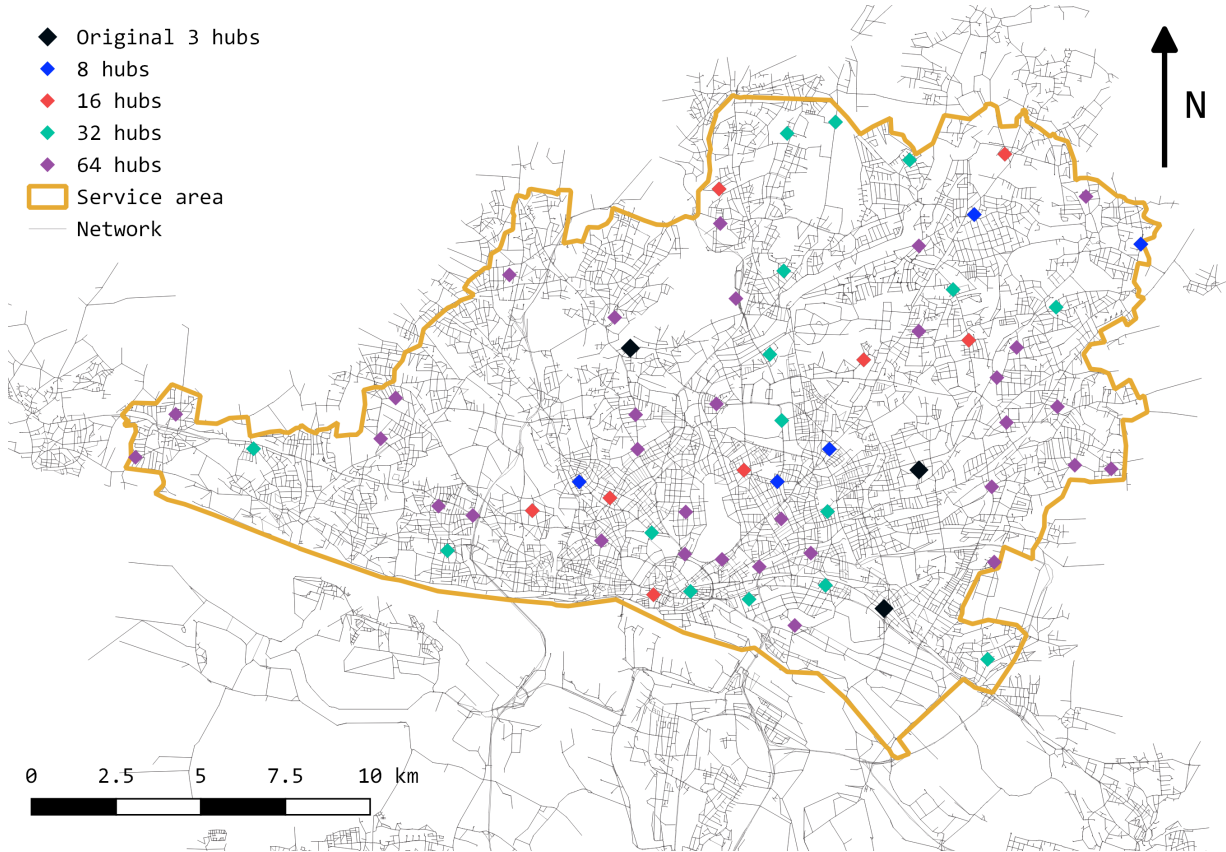


Figure 5: Original MOIA hubs and locations of additional, fictional hubs resulting from the random sample. Each increase in hubs includes all locations of hubs of the scenarios with fewer hubs.

Table 3: Shift service optimization through additional infrastructural facilities.

	Base case	Hub increase	In-field break facility increase
Number of hubs	3	8 – 64	3
Number of in-field break facilities	0	0	4 – 64

## 391 5 Results

392 Ride-pooling systems have manifold implications on an existing transport system that need to be  
 393 considered for a comprehensive evaluation. Since we only simulate ride-pooling in this study, we do  
 394 not directly measure inter-dependencies with other transport mode and modal shifts. However, we  
 395 measure the average service quality of the system through the average waiting time and the average  
 396 detour customers experience. Those are two important indicators quantifying the convenience of the  
 397 system, which is necessary for a broad user acceptance.

398

399 In addition, we quantify and evaluate the efficiency of the ride-pooling system using several  
 400 performance indicators and compare the impact of different operational designs as well as the ride-  
 401 pooling system to other modes of transportation. The traffic impact may be measured through the  
 402 VKT, empty km and the share of empty km. However, these indicators do not take into account how  
 403 many customers are transported and how well the system pools multiple travel parties. Through the

404 average occupancy, the number of passengers traveling on each vehicle kilometre is also measured.  
405 This indicator generally shows an efficient system but does not take into account the negative effect  
406 of long detours, which lead to a higher occupancy. Therefore, Liebchen et al. (2020) proposed a  
407 performance indicator for ride-pooling systems that takes into account the factors mean detouring,  
408 mean occupancy and ratio of occupied km, which we introduced as  $\eta_{RP}$  in a former study (Zwick  
409 et al., 2021b). Using a mathematical simplification,  $\eta_{RP}$  can be calculated through the division of  
410 passenger kilometers booked (PKB) by VKT. The result is also comparable to other modes like car  
411 or taxi.

412 Two other relevant variables are the number of rides and the PKB per vehicle, which are crucial for  
413 the ride-pooling operator. While the number of rides indicates how large the service is in total, the  
414 PKB per vehicle indicates how many vehicles are necessary to transport a certain amount of trips  
415 depending on the average trip length. With a non-autonomous service, the operating vehicle hours  
416 are also crucial and evaluated here, since drivers need to be employed to maneuver the vehicles.

## 417 5.1 Autonomous vs. shift services

418 Table 4 shows the simulation results obtained by the three different scenarios defined in Section 4.2.1.  
419 Obviously and as expected, a service running with fully autonomous vehicles is able to serve con-  
420 siderably more ride requests when compared to services with constrained vehicle availability due to  
421 driver shifts and breaks. As such, the rejection rate increases from 1 % for the autonomous service  
422 to 13 % and 20 % for the pseudo-shift and explicit-shift simulations, respectively. We can therefore  
423 observe that, in terms of served/rejected rides, the pseudo-shift simulation is closer to the explicit  
424 simulation of shifts, even though a significant difference persists which would lead to a more opti-  
425 mistic evaluation of the service.

426  
427 The average wait time is substantially lower with a static fleet, which can be explained by a  
428 better distribution of empty vehicles throughout the entire service area. The pseudo-shift service  
429 shows similar patterns in terms of detours and waiting times as the explicit-shift service.

430  
431 In addition to the overall number of rides/requests, the efficiency  $\eta_{RP}$  may be overestimated if  
432 shifts are not explicitly modeled. This can be explained by the fact that the explicit consideration  
433 of shifts includes hub returns for vehicles that need to schedule a break or a driver changeover. This  
434 leads to more empty kilometers and detours, and consequently to a reduced average occupancy. Dur-  
435 ing these relocations, the vehicles are also less likely to serve requests that would violate the time or  
436 detour constraints. In addition, the actual breaks will make the vehicles unavailable for passenger  
437 requests. Lastly, during both, relocation and breaks, the vehicles cannot be used for strategic fleet  
438 rebalancing to serve anticipated demand, rendering this strategy less effective. These factors impact  
439 the service efficiency  $\eta_{RP}$ . In fact, it can be seen that the pseudo-shift simulation, which disregards  
440 hub returns and breaks, results in a more optimistic efficiency value of 1.61 when compared to the  
441 efficiency of 1.44 in explicit-shift simulation. The autonomous service results in the same efficiency  
442 as the pseudo-shift service. This means that, while considerably less rides can be served in the  
443 pseudo-shift scenario, these are served with a similar efficiency when compared to the autonomous  
444 service.

445  
446 Regarding vehicle hours, which is the time vehicles are actively performing a task, e.g. serving  
447 customers or rebalancing, the autonomous service results in the highest value with 3,763 hours. This  
448 is because the whole fleet can be active for the whole day and more rides are served. The pseudo-shift  
449 approach has the lowest value of 3,249 hours while the explicit shifts simulation, despite serving the



450 least amount of rides, results somewhere in between with a value of 3,584 hours. This can be ex-  
 451 plained by the additional empty relocations of vehicles returning to a hub for breaks and changeover  
 452 activities. The same pattern can be seen in the total vehicle kilometers travelled (VKT).

453

454 Another important indicator is the empty kilometer share, which indicates how much of the  
 455 vehicle kilometers are driven without (paying) customers. Again, the explicit-shift simulation leads  
 456 to the worst results, with the highest share of 24.2 % because of hub returns. Since vehicles in the  
 457 pseudo-shift scenario do not need to return to their hubs for breaks or at the end of their shift,  
 458 the pseudo-shift scenario leads to a similar empty-kilometer share as the autonomous service, with  
 459 values between 17.3 % and 18 %.

460

Table 4: Simulation results for the autonomous, pseudo-shifts and explicit-shift services.

	Autonomous service	Pseudo-shifts service	Explicit-shifts service
Rides	23,839	20,831	19,162
Rejections	193	3,201	4,870
Avg. detour [%]	30.2	26.8	25.9
Avg. wait time [min]	6:11	8:06	8:30
Fleet size	300	476	300
Vehicle hours [h]	3,763	3,249	3,584
VKT [x1000 km]	108.6	95.2	97.3
Empty km	19.5	16.5	23.6
Empty km share [%]	18.0	17.3	24.2
Avg. occupancy	2.10	2.04	1.81
PKB / vehicle	584	510	467
$\eta_{RP}$	1.61	1.61	1.44

PKB: Passenger kilometers booked excluding detours;  $\eta_{RP} = \text{PKB}/\text{VKT}$

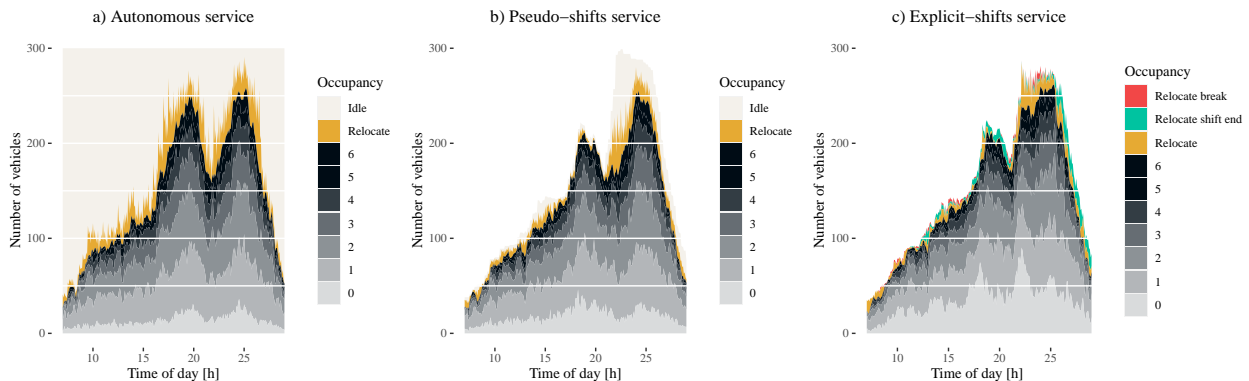


Figure 6: Vehicle occupancy over the course of a simulated day for two autonomous services with (a) a static fleet and (b) pseudo shifts and (c) for a service with explicit shifts.

461

462 Figure 6 shows the vehicle occupancy throughout the simulated day. The highest occupancy  
 463 is observed with the autonomous service, which is not surprising given that all vehicles operate  
 464 throughout the day. Substantially more relocation drives are executed compared to the shift ser-  
 465 vices, which leads to a well-distributed fleet in the service area a lower average wait time compared  
 466 to the shift services. With the pseudo-shift service we observe a similar occupancy but a lower  
 first evening peak, for which more shifts would be required to serve the entire demand. During

467 the second evening peak, many vehicles are either idle or relocating, which indicates a slight over-  
 468 supply of shifts. In the explicit-shift service we observe a similar occupancy as with pseudo-shifts.  
 469 However, vehicles cannot transport passengers throughout their service times but relocations take  
 470 place to bring drivers to one of the three vehicle hubs for breaks or shift ends. In Section 5.3 we  
 471 analyze the potential to reduce these hub drives by providing more break and hub facilities in the city.

472  
 473 An overview of the sampled shifts including breaks in the explicit-shift scenario can be seen in  
 474 Figure 7. It becomes obvious that most shifts are active in the late evening/night hours, with a  
 475 peak of almost 300 simultaneously active shifts. However, it is also clear that with the given shift  
 476 plan, the high demand of the first peak shortly before 8:00 pm (see autonomous service in Figure 6)  
 477 cannot be fully served.

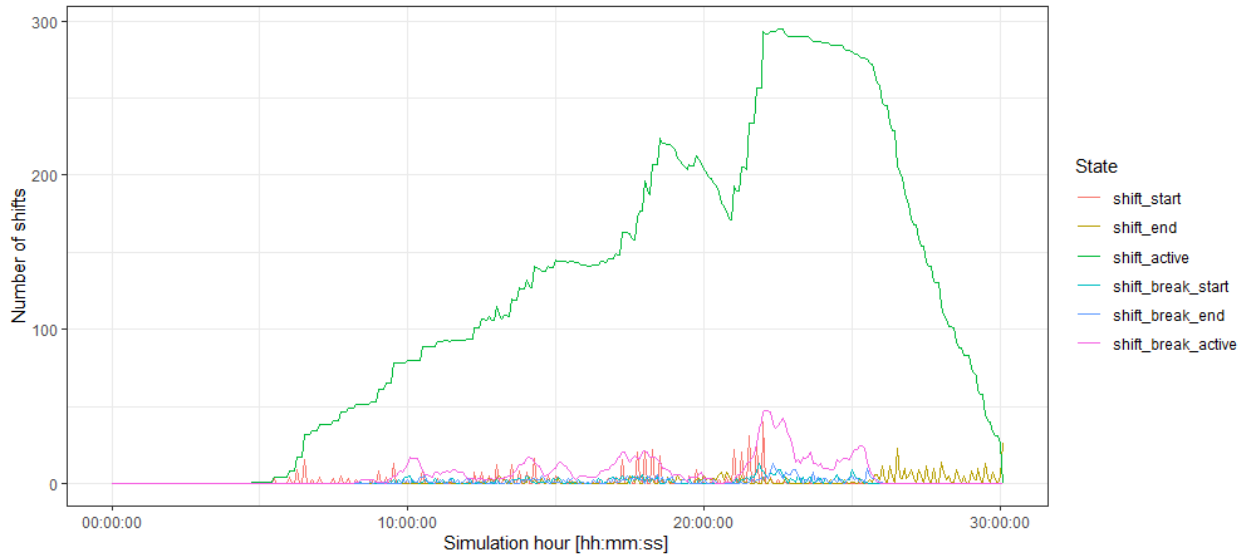


Figure 7: Shift histogram showing the number of shifts and breaks starting/ending/being active in each 5-minute time bin.

## 478 5.2 Impact of charging restrictions

479 Next, the simulations with battery electric vehicles and the charging behaviour defined in Section  
 480 3.4 are analyzed. Since the assumptions of Section 3.4 restrict shift assignment to undercharged  
 481 vehicles and require vehicles below a certain SoC to recharge at operational facilities, less vehicles  
 482 are available to operate at certain times of the day. The results shown in Table 5 show a decrease by  
 483 8 % of the number of vehicle hours when vehicles are electric and consequently 8 % less requests are  
 484 served and less passenger km are covered per vehicle and day. The service efficiency, however, is not  
 485 affected negatively and the average occupancy and the introduced efficiency indicator  $\eta_{RP}$  slightly  
 486 increase, while the empty km share decreases.

487  
 488 Figure 8 presents individual vehicles' state of charge as well as charger occupancy throughout  
 489 the simulation. It can be seen that vehicles do not fall below roughly 30 % of battery capacity, which  
 490 suggests that no vehicle runs out of battery nor has to decline any requests because of an empty  
 491 battery once on shift. The charging breaks and shift changeovers clearly stick out as little *bumps*  
 492 in the charging profiles. In terms of charger occupancy, it can be seen that occupancy increases

Table 5: Simulation results for the conventional and the electric shift service.

	Explicit shifts – conventional	Explicit shifts – electric
Rides	19,162	17,561
Rejections	4,870	6,471
Avg. detour [%]	25.9	25.3
Avg. wait time [min]	8:30	8:46
Fleet size	300	300
Vehicle hours [h]	3,584	3,307
VKT [x1000 km]	97.3	88.9
Empty km [x1000 km]	23.6	20.9
Empty km share [%]	24.2	23.5
Avg. occupancy	1.81	1.82
PKB / vehicle	467	430
$\eta_{RP}$	1.44	1.45

PKB: Passenger kilometers booked excluding detours;  $\eta_{RP} = \text{PKB}/\text{VKT}$

493 during times when many shifts end or pause. The occupancy is not perfectly periodic because of the  
 494 shortcoming of simulating a single day only, which excludes shifts that started late on the previous  
 495 day and start early on the next day. In addition, the simulated day is a Saturday, which sticks out  
 496 in terms of demand compared to the rest of the week.

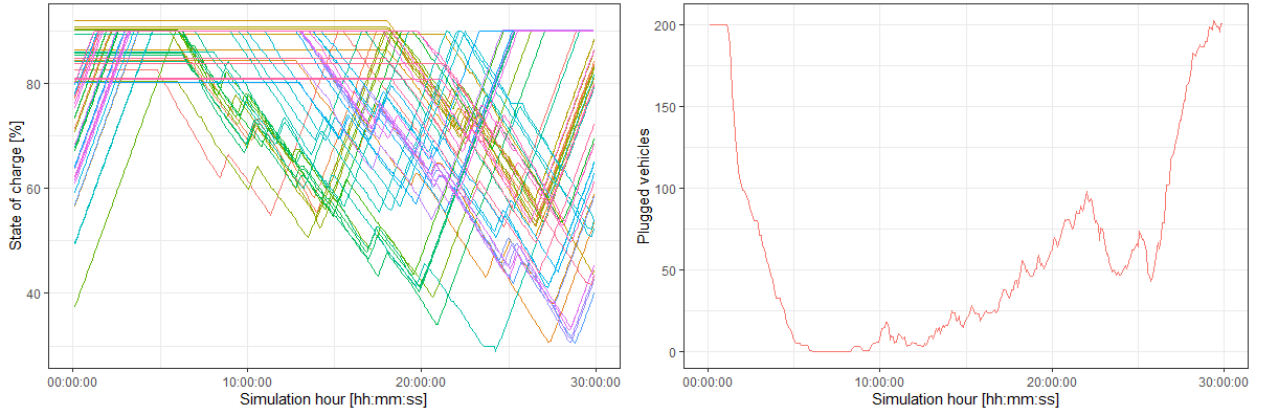


Figure 8: State of charge of individual ride-pooling vehicles (left) and charger occupation at hubs (right) across a simulation day.

### 497 5.3 Shift and break optimization

#### 498 5.3.1 Hub facility increase

499 In a next step, we increase the number of hubs in the service area to evaluate the potential to  
 500 increase service capacity and efficiency through operational facilities. The results of these scenarios  
 501 are summarized in Table 6. It can be seen that the overall number of rides and rejections as well  
 502 as detours and wait times do not change substantially. However, the total number of VKT and the  
 503 (share of) empty kilometers decrease with an increasing number of hubs, which can be explained  
 504 by the fact that vehicles require shorter relocations for breaks and shift changeovers as hubs are  
 505 on average nearer to their current location when scheduling operational stops. Consequently, the  
 506 average occupancy and efficiency  $\eta_{RP}$  of the system improves from 1.82 to 1.88 and from 1.45 to

507 1.50 respectively. The effects diminish with an increasing number of hubs as can be seen in Figure 9,  
 508 which indicates a kind of saturation effect. The overall impact of an increased number of hubs on  
 509 the ride-pooling service is, therefore, limited.

Table 6: Impact of hub increase.

	<b>3 hubs</b>	<b>8 hubs</b>	<b>16 hubs</b>	<b>32 hubs</b>	<b>64 hubs</b>
Rides	17,561	18,015	17,984	17,761	17,901
Rejections	6,471	6,017	6,048	6,271	6,131
Avg. detour [%]	25.3	25.5	25.4	25.3	25.6
Avg. wait time [min]	8:46	8:41	8:44	8:47	8:42
Vehicle hours	3,307	3,320	3,307	3,274	3,294
VKT [x1000 km]	88.9	89.3	88.8	87.9	88.4
Empty km	20.9	20.0	20.0	19.3	19.2
Empty km share [%]	23.5	22.4	22.5	22.0	21.7
Avg. occupancy	1.82	1.86	1.86	1.87	1.88
PKB / vehicle	430	440	438	437	441
$\eta_{RP}$	1.45	1.48	1.48	1.49	1.50

PKB: Passenger kilometers booked excluding detours;  $\eta_{RP} = \text{PKB}/\text{VKT}$

### 510 5.3.2 In-field break facility increase

511 Similarly to the increase of hubs, we increase the number of in-field break facilities in which vehicles  
 512 may stop for breaks and charging. Each facility is equipped with two 100 kW chargers to also  
 513 assess the impact of fast chargers. The results of these scenarios are summarized in table 7. The  
 514 empty kilometer share does reduce with increasing number of in-field locations, however the impact  
 515 is even lower than for the scenarios with an increased number of hubs. Up to eight in-field locations,  
 516 the impacts are virtually zero and even in the 64 in-field locations scenario, the empty kilometer  
 517 share merely reduces by 0.4 percentage points when compared to the base case. Different from  
 518 the previous scenario, the number of rides increases and the rejection rate drops to 18.8 % for the  
 519 64-in-field facilities scenario. This can be explained largely by the fact that the in-field chargers  
 520 are defined with fast chargers, which considerably reduce the impact caused by the implemented  
 521 charging restrictions. It should also be noted that the number of served rides is even higher than  
 522 the number of rides in the conventional vehicles scenario shown in table 5. This improvement is  
 523 largely driven by the number of in-field locations that reduce distances for hub returns. The given  
 524 changes in indicators lead to small increases in the efficiency  $\eta_{RP}$ . In summary, the proposed in-field  
 525 locations may improve the system in marginal amounts in terms of efficiency, while also increasing  
 526 the number of served rides.

527 Figure 9 shows the evolution of multiple system performance indicators with an increasing num-  
 528 ber of hubs (yellow) and in-field break facilities. With an increasing number of hubs we observe  
 529 that the number of rides and the PKB per vehicle stagnate, whereas the empty km share drops and  
 530 the efficiency indicator  $\eta_{RP}$  increases substantially. A different pattern is observed for an increasing  
 531 number of in-field break facilities. Here, the total number of rides and the PKB per vehicle increase,  
 532 meaning that the service capacity increases. In contrast, there is only a slight decrease of the empty  
 533 km share and a slight increase of  $\eta_{RP}$ .

534 On the one hand, the differing effects can be explained through the fast chargers in in-field break  
 535 facilities, which lead to more vehicles being available for the service. On the other hand, hubs not  
 536 only reduce (empty) travel distances to break facilities, but also to hubs at the end of a shift and  
 537 thus reducing the share of empty VKT and increasing  $\eta_{RP}$ .

Table 7: Impact of in-field break facilities increase.

	3 Hubs +					
	0 in-field	4 in-field	8 in-field	16 in-field	32 in-field	64 in-field
Rides	17,561	17,826	18,441	18,554	19,198	19,525
Rejections	6,471	6,206	5,591	5,478	4,834	4,507
Avg. detour [%]	25.3	25.3	25.4	25.9	26.2	26.2
Avg. wait time [min]	8:46	8:44	8:38	8:33	8:27	8:24
Vehicle hours	3,307	3,348	3,434	3,451	3,542	3,566
VKT [x1000 km]	88.9	90.1	92.9	93.3	95.6	96.5
Empty km	20.9	21.2	21.9	21.6	22.0	22.3
Empty km share [%]	23.5	23.5	23.5	23.1	23.1	23.1
Avg. occupancy	1.81	1.82	1.83	1.84	1.86	1.86
PKB / vehicle	430	436	451	454	469	475
$\eta_{RP}$	1.45	1.45	1.46	1.46	1.47	1.48

PKB: Passenger kilometers booked excluding detours;  $\eta_{RP} = \text{PKB}/\text{VKT}$

## 6 Discussion and conclusion

The application of shifts in the existing ride-pooling extension of MATSim can help to study existing services more realistically and to account for operational challenges. At the same time, we show the potential of current services to operate an even more efficient and resource-saving service with autonomous vehicles. The example scenario with real-world requests and driver shifts applied here shows that operational challenges have major impacts on the number of served rides and efficiency. Due to multiple fictional parameters such as battery size, energy consumption, in-field break facilities or charging infrastructure, the simulation results are not directly comparable with MOIA’s real-world service.

It is evident that existing simulation studies of ride-pooling, while providing valuable insights, tend to underestimate the required number of vehicles and kilometers traveled to transport a given number of customers when applied to current operating services. The results reported here do not only show the importance of explicitly modeling operational challenges but also quantify the impact of future autonomous applications. It becomes apparent that service efficiency and the number of served rides increases considerably. Given the demand and supply of a real-world ride-pooling service, we observe that with autonomous vehicles 24 % more requests can be served and the share of empty km decreases from 24.2 % to 18 % compared to the current service set-up with shifts. In comparison, the conventional taxi fleet of Hamburg had a share of empty km of 53.4 % in 2016 (BWVI Hamburg, 2017), showing that the current ride-pooling system already adds value to the transport system. As operation costs of autonomous vehicles are expected to be lower than for current services, for which drivers have to be paid, it is clear that future autonomous fleets may yield a high economic potential for service providers.

We present updates to current existing ride-pooling simulations to improve realism of results. However, the shown approach still comes with limitations or unsolved questions. One issue is that shifts do not necessarily end where they started and the starting location of the shift is only decided at the time of vehicle assignment (i.e., 30 minutes before the start of shift), which may impose other operational challenges of driver (re-)allocation. Another limitation is that the decision of where to start a break is solely based on the distance to the nearest operational facility. However, in some cases it could be that it is worth driving to a more distant facility to anticipate higher demand after

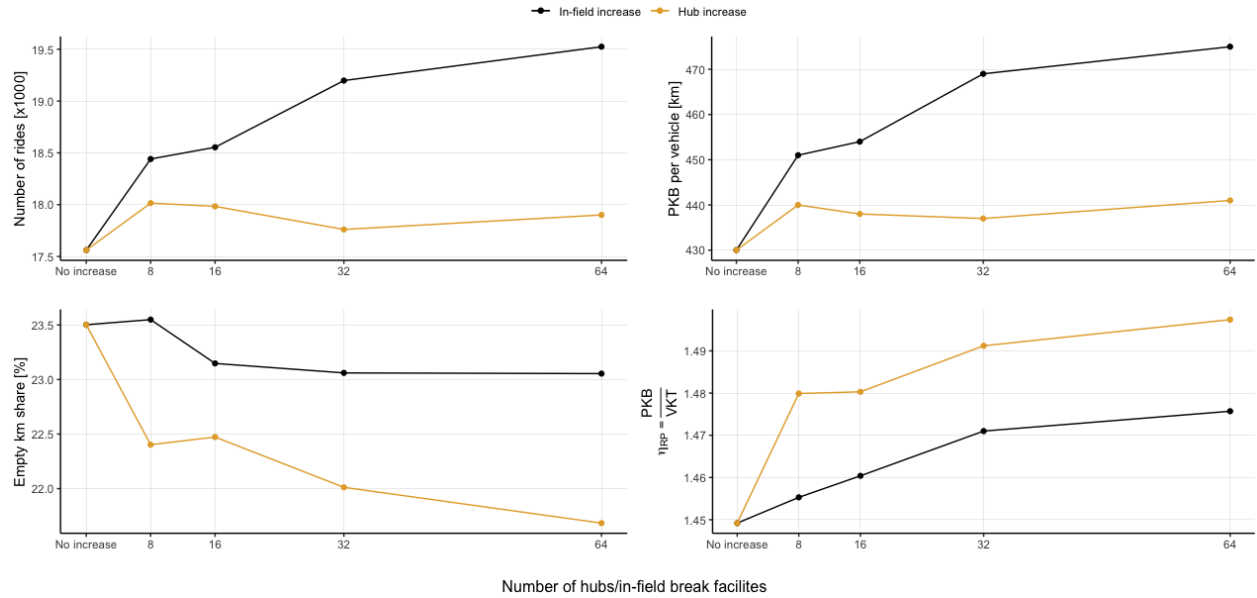


Figure 9: Service results with increased number of hubs (yellow) and in-field break locations (black).

569 the break.

570 Given the newly developed extension, a future use case could be the investigation of optimizing  
 571 shifts throughout iterations in MATSim. Similar to the co-evolutionary approach in MATSim, shifts  
 572 could be optimized using a genetic algorithm as has been shown by Li and Kwan (2003); Kwan et al.  
 573 (1999); Ramli et al. (2013); Kwan et al. (2001); Dias et al. (2002). An interesting feature would  
 574 be that shifts co-evolve with ride-pooling demand - i.e., shifts adapt to current demand, and user  
 575 adaptation of agents can in return lead to adaption of shifts.

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## References

- 579
- 580 Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., and Rus, D. (2017). On-demand high-  
581 capacity ride-sharing via dynamic trip-vehicle assignment. *Proceedings of the National Academy  
582 of Sciences of the United States of America*, 114(3):462–467.
- 583 Bischoff, J. and Maciejewski, M. (2020). Proactive empty vehicle rebalancing for Demand Responsive  
584 Transport services. *Procedia Computer Science*, 170:739–744.
- 585 Bischoff, J., Maciejewski, M., and Nagel, K. (2017). City-wide shared taxis: A simulation study in  
586 Berlin. *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*.
- 587 Blouin, L. (2021). Why your first driverless car is decades, not years, away. [https://umdearborn.  
588 edu/news/articles/why-your-first-driverless-car-decades-not-years-away](https://umdearborn.edu/news/articles/why-your-first-driverless-car-decades-not-years-away). Last ac-  
589 cessed: 2021-03-08.
- 590 Bösch, P. M., Becker, F., Becker, H., and Axhausen, K. W. (2018). Cost-based analysis of au-  
591 tonomous mobility services. *Transport Policy*, 64:76–91.
- 592 Bubbers, M. (2019). Why your dream of driving an autonomous  
593 car is still decades away. [https://www.thetelegram.com/wheels/  
594 why-your-dream-of-driving-an-autonomous-car-is-still-decades-away-390259/](https://www.thetelegram.com/wheels/why-your-dream-of-driving-an-autonomous-car-is-still-decades-away-390259/). Last  
595 accessed: 2021-03-08.
- 596 BWVI Hamburg (2017). Die wirtschaftliche Lage des Hamburger Taxengewerbes 2016. Technical  
597 report, Behörde für Wirtschaft, Verkehr und Innovation der Freien und Hansestadt Hamburg.
- 598 Dias, T. G., de Sousa, J. P., and Cunha, J. F. (2002). Genetic algorithms for the bus driver scheduling  
599 problem: a case study. *Journal of the Operational Research Society*, 53(3):324–335.
- 600 Engelhardt, R., Dandl, F., Bilali, A., and Bogenberger, K. (2019). Quantifying the Benefits of  
601 Autonomous On-Demand Ride-Pooling: A Simulation Study for Munich, Germany. In *2019  
602 IEEE Intelligent Transportation Systems Conference (ITSC)*, pages 2992–2997. IEEE.
- 603 Fagnant, D. J. and Kockelman, K. M. (2014). The travel and environmental implications of shared  
604 autonomous vehicles, using agent-based model scenarios. *Transportation Research Part C: Emerg-  
605 ing Technologies*, 40:1–13.
- 606 Fagnant, D. J. and Kockelman, K. M. (2018). Dynamic ride-sharing and fleet sizing for a system of  
607 shared autonomous vehicles in Austin, Texas. *Transportation*, 45(1):143–158.
- 608 Farhan, J. and Chen, T. D. (2018). Impact of ridesharing on operational efficiency of shared au-  
609 tonomous electric vehicle fleet. *Transportation Research Part C: Emerging Technologies*, 93:310–  
610 321.
- 611 Gessner, D. (2020). Experts say we’re decades from fully au-  
612 tonomous cars. Here’s why. [https://www.businessinsider.com/  
613 self-driving-cars-fully-autonomous-vehicles-future-prediction-timeline-2019-8](https://www.businessinsider.com/self-driving-cars-fully-autonomous-vehicles-future-prediction-timeline-2019-8).  
614 Last accessed: 2021-03-08.
- 615 Gurumurthy, K. M., de Souza, F., Enam, A., and Auld, J. (2020). Integrating Supply and De-  
616 mand Perspectives for a Large-Scale Simulation of Shared Autonomous Vehicles. *Transportation  
617 Research Record*, 2674(7):181–192.

- 618 Gurumurthy, K. M., Kockelman, K. M., and Simoni, M. D. (2019). Benefits and Costs of Ride-  
619 Sharing in Shared Automated Vehicles across Austin, Texas: Opportunities for Congestion Pric-  
620 ing. *Transportation Research Record: Journal of the Transportation Research Board*, 2673(6):548–  
621 556.
- 622 Hagon, T. (2019). Driverless cars decades away, says Audi tech guru. [https://www.whichcar.com.  
623 au/car-news/driverless-cars-are-decades-away-says-audi](https://www.whichcar.com.au/car-news/driverless-cars-are-decades-away-says-audi). Last accessed: 2021-03-08.
- 624 Hörl, S. (2017). Agent-based simulation of autonomous taxi services with dynamic demand responses.  
625 In *Procedia Computer Science*, volume 109, pages 899–904. Elsevier B.V.
- 626 Horni, A., Nagel, K., and Axhausen, K. W., editors (2016). *The Multi-Agent Transport Simulation  
627 MATSim*. Ubiquity Press, London.
- 628 Hörl, S., Becker, F., and Axhausen, K. W. (2021). Simulation of price, customer behaviour and  
629 system impact for a cost-covering automated taxi system in Zurich. *Transportation Research Part  
630 C: Emerging Technologies*, 123:102974.
- 631 Iacobucci, R., McLellan, B., and Tezuka, T. (2019). Optimization of shared autonomous electric  
632 vehicles operations with charge scheduling and vehicle-to-grid. *Transportation Research Part C:  
633 Emerging Technologies*, 100:34–52.
- 634 Jing, P., Hu, H., Zhan, F., Chen, Y., and Shi, Y. (2020). Agent-Based Simulation of Autonomous  
635 Vehicles: A Systematic Literature Review. *IEEE Access*, 8:79089–79103.
- 636 Kaddoura, I., Bischoff, J., and Nagel, K. (2020). Towards welfare optimal operation of innovative  
637 mobility concepts: External cost pricing in a world of shared autonomous vehicles. *Transportation  
638 Research Part A: Policy and Practice*, 136:48–63.
- 639 Kaddoura, I. and Schlenker, T. (2021). The impact of trip density on the fleet size and pooling  
640 rate of ride-hailing services: A simulation study. Technical report, Technische Universität Berlin.
- 641 Kannan, R. and Lasky, R. C. (2020). Autonomous vehicles still decades away: 2019. In *2020 Pan  
642 Pacific Microelectronics Symposium (Pan Pacific)*, pages 1–6.
- 643 Kostopoulos, E. D., Spyropoulos, G. C., and Kaldellis, J. K. (2020). Real-world study for the optimal  
644 charging of electric vehicles. *Energy Reports*, 6:418–426.
- 645 Kwan, A. S., Kwan, R. S., and Wren, A. (1999). Driver scheduling using genetic algorithms with  
646 embedded combinatorial traits. In *Computer-Aided Transit Scheduling*, pages 81–102. Springer.
- 647 Kwan, R. S. K., Kwan, A. S. K., and Wren, A. (2001). Evolutionary Driver Scheduling with Relief  
648 Chains. *Evolutionary Computation*, 9(4):445–460.
- 649 Leonard, J. J., Mindell, D. A., and Stayton, E. L. (2020). Autonomous Vehicles, Mobility, and  
650 Employment Policy: The Roads Ahead. Research Brief July 2020, [https://trid.trb.org/view/  
651 1727480](https://trid.trb.org/view/1727480).
- 652 Li, J. and Kwan, R. S. K. (2003). A fuzzy genetic algorithm for driver scheduling. *European Journal  
653 of Operational Research*, 147(2):334–344.
- 654 Liebchen, C., Lehnert, M., Mehler, C., and Schiefelbusch, M. (2020). Ridepooling-Effizienz messbar  
655 machen. *Der Nahverkehr*, 9:18–21.



- 656 Litman, T. (2017). Autonomous vehicle implementation predictions. Technical report, Victoria  
657 Transport Policy Institute Victoria, Canada.
- 658 Loeb, B. and Kockelman, K. M. (2019). Fleet performance and cost evaluation of a shared au-  
659 tonomous electric vehicle (SAEV) fleet: A case study for Austin, Texas. *Transportation Research*  
660 *Part A: Policy and Practice*, 121:374–385.
- 661 Lokhandwala, M. and Cai, H. (2018). Dynamic ride sharing using traditional taxis and shared  
662 autonomous taxis: A case study of NYC. *Transportation Research Part C: Emerging Technologies*,  
663 97:45–60.
- 664 Maciejewski, M. (2016). Dynamic Transport Services. In *The Multi-Agent Transport Simulation*  
665 *MATSim*, chapter 23, pages 145–152. Andreas Horni, Kai Nagel and Kay W. Axhausen.
- 666 Martinez, L. M., Correia, G. H. A., and Viegas, J. M. (2015). An agent-based simulation model  
667 to assess the impacts of introducing a shared-taxi system: an application to lisbon (portugal).  
668 *Journal of Advanced Transportation*, 49(3):475–495.
- 669 Martinez, L. M. and Viegas, J. M. (2017). Assessing the impacts of deploying a shared self-driving ur-  
670 ban mobility system: An agent-based model applied to the city of Lisbon, Portugal. *International*  
671 *Journal of Transportation Science and Technology*, 6(1):13–27.
- 672 Merlin, L. A. (2017). Comparing automated shared taxis and conventional bus transit for a small  
673 city. *Journal of Public Transportation*, 20(2):19–39.
- 674 Metz, C. and Conger, K. (2020). Uber, After Years of Trying, Is Handing Off  
675 Its Self-Driving Car Project. [https://www.nytimes.com/2020/12/07/technology/  
676 uber-self-driving-car-project.html](https://www.nytimes.com/2020/12/07/technology/uber-self-driving-car-project.html). Last accessed: 2021-03-08.
- 677 Metz, C. and Griffith, E. (2020). This Was Supposed to Be the Year Driver-  
678 less Cars Went Mainstream. [https://www.nytimes.com/2020/05/12/technology/  
679 self-driving-cars-coronavirus.html](https://www.nytimes.com/2020/05/12/technology/self-driving-cars-coronavirus.html). Last accessed: 2021-03-08.
- 680 MOIA (2021). Your MOIA, autonomous as of 2025. [https://www.moia.io/en/blog/  
681 moia-autonomous-as-of-2025](https://www.moia.io/en/blog/moia-autonomous-as-of-2025). Last accessed: 2021-05-14.
- 682 Ohde, B., Ślaski, G., and Maciejewski, M. (2016). Statistical analysis of real-world urban driving  
683 cycles for modelling energy consumption of electric vehicles.
- 684 Pernestål, A. and Kristoffersson, I. (2019). Effects of driverless vehicles : Comparing simulations to  
685 get a broader picture. *European Journal of Transport and Infrastructure Research*, 1(19):1–23.
- 686 Ramli, R., Ibrahim, H., and Shung, L. T. (2013). Innovative crossover and mutation in a genetic  
687 algorithm based approach to a campus bus driver scheduling problem with break consideration  
688 and embedded overtime. *Applied Mathematics & Information Sciences*, 7(5):1921.
- 689 Ruch, C., Lu, C., Sieber, L., and Frazzoli, E. (2020). Quantifying the Efficiency of Ride Sharing.  
690 *IEEE Transactions on Intelligent Transportation Systems*, pages 1–6.
- 691 Shladover, S. E. (2016). The truth about “self-driving” cars. *Scientific American*, 314(6):52–57.
- 692 Valdes-Dapena, P. (2021). The real self-driving revolution remains years away. [https://edition.  
693 cnn.com/2021/01/21/success/self-driving-car-technology-2021/index.html](https://edition.cnn.com/2021/01/21/success/self-driving-car-technology-2021/index.html). Last ac-  
694 cessed: 2021-03-08.

- 695 Vosooghi, R., Kamel, J., Puchinger, J., Leblond, V., and Jankovic, M. (2019a). Robo-Taxi service  
696 fleet sizing: assessing the impact of user trust and willingness-to-use. *Transportation*, 46(6):1997–  
697 2015.
- 698 Vosooghi, R., Puchinger, J., Bischoff, J., Jankovic, M., and Vouillon, A. (2020). Shared autonomous  
699 electric vehicle service performance: Assessing the impact of charging infrastructure. *Transporta-  
700 tion Research Part D: Transport and Environment*, 81.
- 701 Vosooghi, R., Puchinger, J., Jankovic, M., and Vouillon, A. (2019b). Shared autonomous vehicle  
702 simulation and service design. *Transportation Research Part C: Emerging Technologies*, 107:15–33.
- 703 Wilkes, G., Engelhardt, R., Briem, L., Dandl, F., Vortisch, P., Bogenberger, K., and Kagerbauer,  
704 M. (2021). Self-Regulating Demand and Supply Equilibrium in Joint Simulation of Travel De-  
705 mand and a Ride-Pooling Service. *Transportation Research Record: Journal of the Transportation  
706 Research Board*, page 036119812199714.
- 707 Yan, H., Kockelman, K. M., and Gurumurthy, K. M. (2020). Shared autonomous vehicle fleet  
708 performance: Impacts of trip densities and parking limitations. *Transportation Research Part D:  
709 Transport and Environment*, 89:102577.
- 710 Yang, C. and Gidófalvi, G. (2018). Fast map matching, an algorithm integrating hidden  
711 Markov model with precomputation. *International Journal of Geographical Information Science*,  
712 32(3):547–570.
- 713 Zhang, W., Guhathakurta, S., Fang, J., and Zhang, G. (2015). Exploring the impact of shared  
714 autonomous vehicles on urban parking demand: An agent-based simulation approach. *Sustainable  
715 Cities and Society*, 19:34–45.
- 716 Zwick, F. and Axhausen, K. W. (2020a). Analysis of ridepooling strategies with MATSim. In *20th  
717 Swiss Transport Research Conference*.
- 718 Zwick, F. and Axhausen, K. W. (2020b). Impact of Service Design on Urban Ridepooling Systems.  
719 In *2020 IEEE Intelligent Transportation Systems Conference (ITSC)*.
- 720 Zwick, F., Kuehnel, N., Moeckel, R., and Axhausen, K. W. (2021a). Agent-based simulation of  
721 city-wide autonomous ride-pooling and the impact on traffic noise. *Transportation Research Part  
722 D: Transport and Environment*, 90:102673.
- 723 Zwick, F., Kuehnel, N., Moeckel, R., and Axhausen, K. W. (2021b). Ride-pooling efficiency in  
724 large, medium-sized and small towns -simulation assessment in the munich metropolitan region.  
725 Technical report, Arbeitsberichte Verkehrs- und Raumplanung. Band1581. IVT, ETH Zurich.