Shifts in perspective

Operational aspects in (non-) autonomous ride-pooling simulations

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

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Abstract

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

1 Introduction

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

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

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

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

[1] `https://www.uber.com/de/de/ride/uberpool/`
[2] `https://www.grab.com/sg/transport/share/`
[3] `https://www.clevershuttle.de/`
[4] `https://www.moia.io/`

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

2 Related ride-pooling studies

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

2.1 Demand and supply characteristics

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

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

		Demand			
		Toy demand	Static synthetic demand	Synthetic demand based on mode choice model	Historical ride-pooling/taxi requests
Supply	Static fleet	Fagnant and Kockelman (2014)* Zhang et al. (2015) Farhan and Chen (2018)	Merlin (2017) Fagnant and Kockelman (2018) Engelhardt et al. (2019) Loeb and Kockelman (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)

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

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

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

2.2 Electric vehicles

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

Vosooghi et al. (2020) assessed the impact of different charging policies and battery capacities on an autonomous ride-pooling fleet in MATSim (Horni et al., 2016). Vehicles are constantly operating and only sent to a charging facility once the state of charge (SoC) is below 20 %. The authors found a substantially lower performance of electric fleets with less passenger kilometers transported and more empty vehicle kilometers travelled compared to non-electric fleets. System performance improvements may be achieved through rapid chargers and a battery swapping policy.

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

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

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

2.3 Contribution

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

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

Our contribution to existing ride-pooling studies is threefold:

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

3 Methodology

3.1 Simulation framework

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

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

3.2 DRT extension

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

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

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

3.3 Driver shift and break implementation

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

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

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

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

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

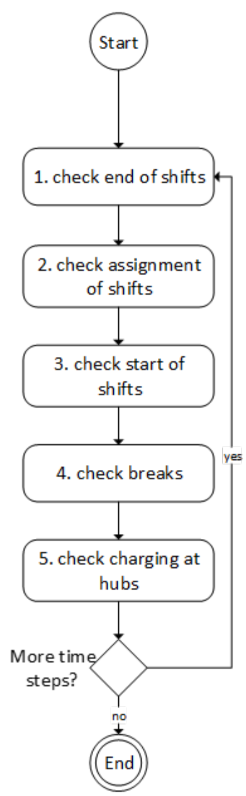

Figure 1: Basic steps of the central shift dispatcher.

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

1. **Check end of shifts**
   One hour (configurable) before the end of a shift, a changeover task including a relocation to the nearest operational hub with enough capacity is scheduled. The remaining trips are still served and additional requests may be accepted if the planned shift end is not exceeded.

2. **Check assignment of shifts**
   Planned shifts are assigned to suitable vehicles 30 minutes (configurable) ahead of their start time. Preferably, an already active vehicle that is about to end its shift and has a minimum state of charge (SoC) is assigned. Shifts can only be assigned to vehicles within their service time (i.e. their operation time in the autonomous use case). If no suitable vehicle is found, the shift remains in the queue and is checked again in the next time step.

3. **Check start of shifts**
   The queue of assigned shifts is checked for shifts starting in the given time step. The shift start may be delayed by previously delayed shift ends and only starts once the assigned vehicle is idle.

4. **Check breaks**
   All active shifts are checked whether a break corridor begins. If this is the case, the nearest operational facility with enough capacity is identified. The break is scheduled for the end of the current vehicle's schedule. New requests along the route may be served as long as the whole duration of the break inside the break corridor is ensured. If required and charger capacity permits, the vehicle may be charged during the break. Passengers may be scheduled to be picked up after the end of the break.

5. **Check charging at hubs**
   The dispatcher checks for all idle vehicles without shifts assigned and parked at hubs whether they require re-charging. If a vehicle is not planned to serve a shift until the estimated end of charging, a charging task is set up. This step is omitted if conventional cars with internal combustion engines (ICE) are simulated.

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

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

3.4 Charging behaviour

For the shift and break optimization, we consider a service with electric vehicles. Each vehicle has a gross battery capacity of 77 kWh. The hubs are equipped with conventional slow chargers with a charging power of 7 kW, whereas the in-field break facilities are equipped with fast chargers with a charging power of 100 kW. The numbers are based on a real ride-pooling service (see below), but differ slightly.
It is recommended to keep the vehicles' SoC between 20 % and 80 % to decrease the batteries'

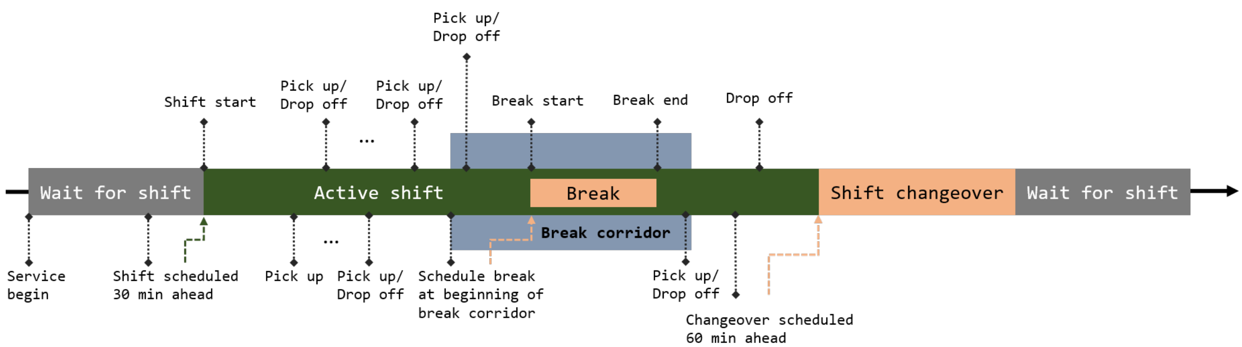

Figure 2: Illustrative implementation of driver shifts for a single DRT vehicle.

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

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

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

4 Data preparation and scenario setup

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

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

[5] www.openstreetmap.org
[6] www.tomtom.com

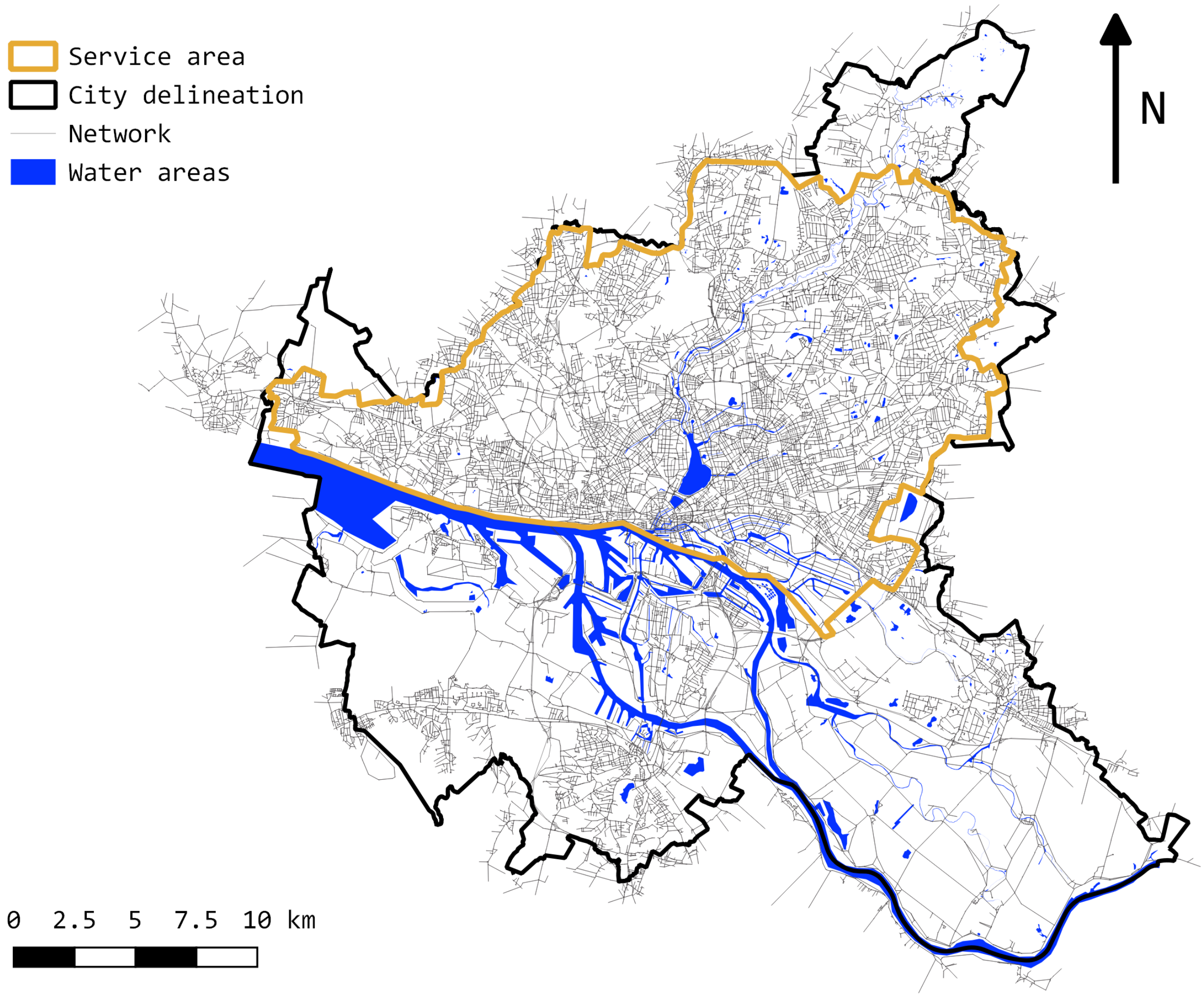

Figure 3: Study and service area of the Hamburg scenario, including road network and water areas.

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

4.1 Demand and supply data

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

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

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

4.2 Scenarios

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

4.2.1 Autonomous vs. shift service

In order to evaluate the impact of operational duties with non-autonomous ride-pooling services compared to autonomous ride-pooling services, we apply three different service designs as shown in 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**
Initial vehicle location	Vehicle hub	Vehicle hub	Vehicle hub
Final vehicle location	Anywhere in-field	Anywhere in-field	Vehicle hub
Vehicle service times	No limitation	According to shift service times	According to shift service times
Rebalancing	Yes	Yes	Yes
Service breaks in hubs	No	No	Yes

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

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

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

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

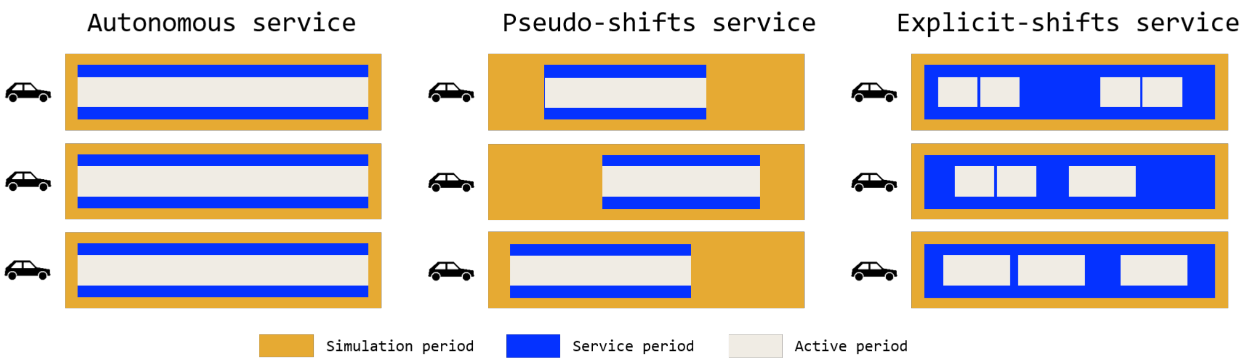

Figure 4: Qualitative representation of the three service set-ups. Vehicles are only able to serve requests when active.

4.2.2 Conventional vs. electric fleets

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

4.2.3 Shift and break optimization

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

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

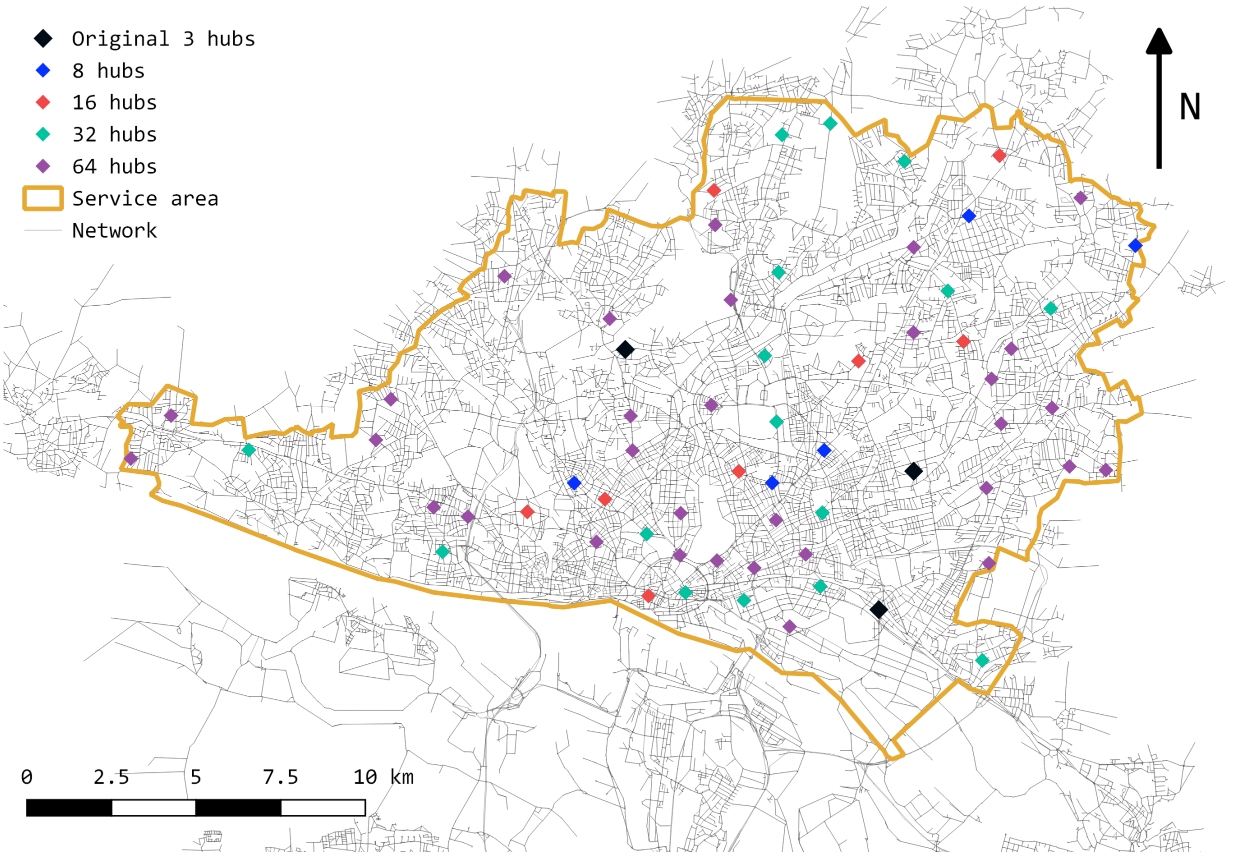

Figure 5: Original MOIA hubs and locations of additional, fictional hubs resulting from the random sample. Each increase in hubs includes all locations of hubs of the scenarios with fewer hubs.

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

5 Results

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

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

average occupancy, the number of passengers traveling on each vehicle kilometre is also measured. This indicator generally shows an efficient system but does not take into account the negative effect of long detours, which lead to a higher occupancy. Therefore, Liebchen et al. (2020) proposed a performance indicator for ride-pooling systems that takes into account the factors mean detouring, mean occupancy and ratio of occupied km, which we introduced as η_{RP} in a former study (Zwick et al., 2021b). Using a mathematical simplification, η_{RP} can be calculated through the division of passenger kilometers booked (PKB) by VKT. The result is also comparable to other modes like car or taxi.
Two other relevant variables are the number of rides and the PKB per vehicle, which are crucial for the ride-pooling operator. While the number of rides indicates how large the service is in total, the PKB per vehicle indicates how many vehicles are necessary to transport a certain amount of trips depending on the average trip length. With a non-autonomous service, the operating vehicle hours are also crucial and evaluated here, since drivers need to be employed to maneuver the vehicles.

5.1 Autonomous vs. shift services

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

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

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

Regarding vehicle hours, which is the time vehicles are actively performing a task, e.g. serving customers or rebalancing, the autonomous service results in the highest value with 3,763 hours. This is because the whole fleet can be active for the whole day and more rides are served. The pseudo-shift approach has the lowest value of 3,249 hours while the explicit shifts simulation, despite serving the least amount of rides, results somewhere in between with a value of 3,584 hours. This can be explained by the additional empty relocations of vehicles returning to a hub for breaks and changeover activities. The same pattern can be seen in the total vehicle kilometers travelled (VKT).

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

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
η_{RP}	1.61	1.61	1.44

PKB: Passenger kilometers booked excluding detours; η_{RP} = PKB/VKT

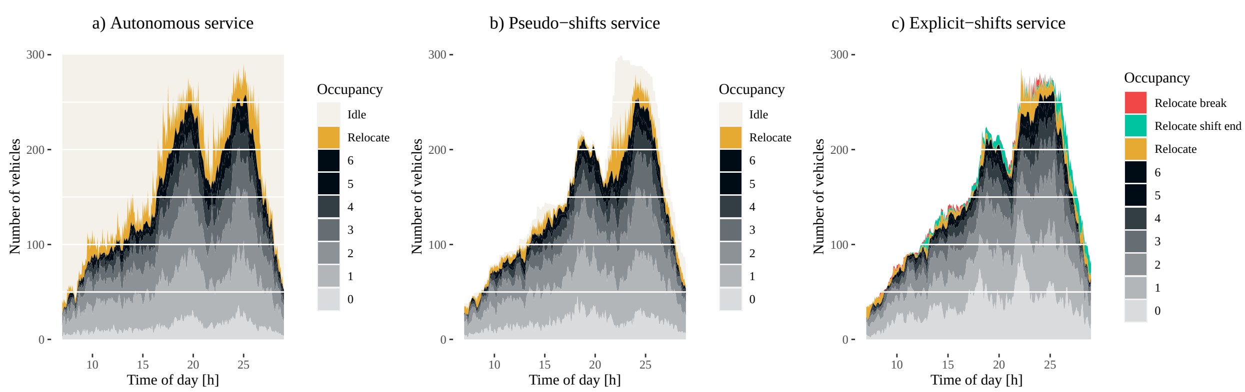

Figure 6: Vehicle occupancy over the course of a simulated day for two autonomous services with (a) a static fleet and (b) pseudo shifts and (c) for a service with explicit shifts.

Figure 6 shows the vehicle occupancy throughout the simulated day. The highest occupancy is observed with the autonomous service, which is not surprising given that all vehicles operate throughout the day. Substantially more relocation drives are executed compared to the shift services, which leads to a well-distributed fleet in the service area a lower average wait time compared 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 the second evening peak, many vehicles are either idle or relocating, which indicates a slight over-supply of shifts. In the explicit-shift service we observe a similar occupancy as with pseudo-shifts. However, vehicles cannot transport passengers throughout their service times but relocations take place to bring drivers to one of the three vehicle hubs for breaks or shift ends. In Section 5.3 we analyze the potential to reduce these hub drives by providing more break and hub facilities in the city.

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

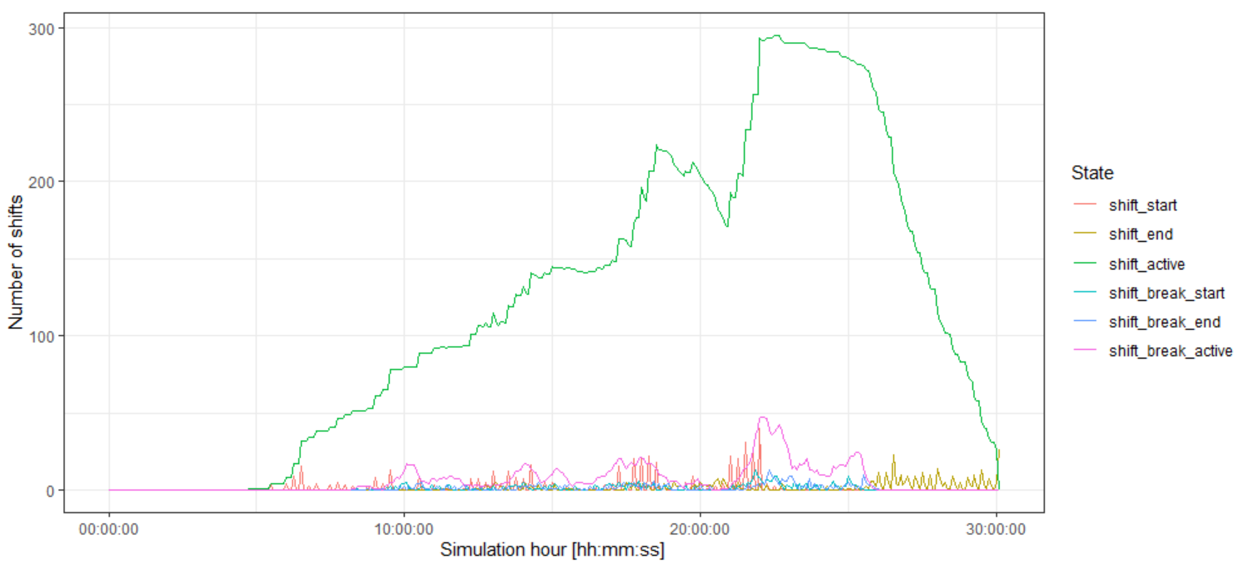

Figure 7: Shift histogram showing the number of shifts and breaks starting/ending/being active in each 5-minute time bin.

5.2 Impact of charging restrictions

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

Figure 8 presents individual vehicles' state of charge as well as charger occupancy throughout the simulation. It can be seen that vehicles do not fall below roughly 30 % of battery capacity, which suggests that no vehicle runs out of battery nor has to decline any requests because of an empty battery once on shift. The charging breaks and shift changeovers clearly stick out as little *bumps* 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
η_{RP}	1.44	1.45

PKB: Passenger kilometers booked excluding detours; η_{RP} = PKB/VKT

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

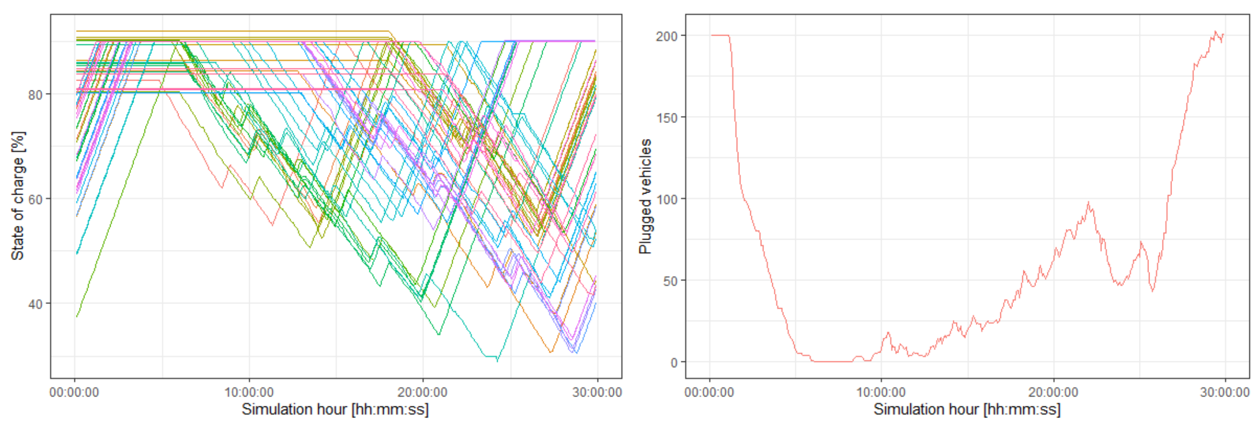

Figure 8: State of charge of individual ride-pooling vehicles (left) and charger occupation at hubs (right) across a simulation day.

5.3 Shift and break optimization

5.3.1 Hub facility increase

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

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

Table 6: Impact of hub increase.

	3 hubs	**8 hubs**	**16 hubs**	**32 hubs**	**64 hubs**
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
η_{RP}	1.45	1.48	1.48	1.49	1.50

PKB: Passenger kilometers booked excluding detours; η_{RP} = PKB/VKT

5.3.2 In-field break facility increase

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

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

On the one hand, the differing effects can be explained through the fast chargers in in-field break facilities, which lead to more vehicles being available for the service. On the other hand, hubs not only reduce (empty) travel distances to break facilities, but also to hubs at the end of a shift and thus reducing the share of empty VKT and increasing η_{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
η_{RP}	1.45	1.45	1.46	1.46	1.47	1.48

PKB: Passenger kilometers booked excluding detours; η_{RP} = PKB/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

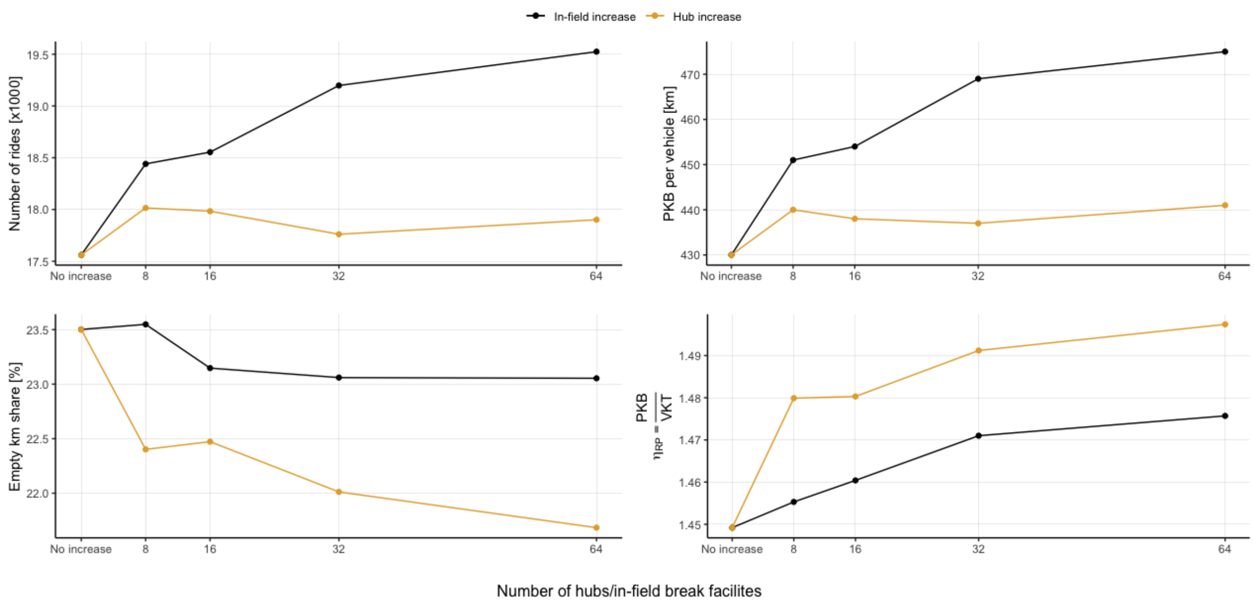

Figure 9: Service results with increased number of hubs (yellow) and in-field break locations (black).

the break.

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

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