Transportation Research Part A 165 (2022) 300–320

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

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

Felix Zwick [a,b,*], Nico Kuehnel [b,c], Sebastian Hörl [d]

[a] Institute for Transport Planning and Systems, ETH Zurich, Zurich, Switzerland
[b] MOIA GmbH, Hamburg, Germany
[c] Department of Civil, Geo and Environmental Engineering, Technical University of Munich, Arcisstr. 21, 80333 Munich, Germany
[d] Institut de Recherche Technologique SystemX, Palaiseau, France

ARTICLE INFO

Keywords:
Ride-sharing
Ride-splitting
Pooled on-demand mobility
MATSim
Electric vehicles
Operations research

ABSTRACT

On-demand ride-pooling systems have gained increasing attention in science and practice in recent years. Simulation studies have shown an enormous potential to reduce fleet sizes and vehicle kilometers traveled if private car trips are replaced with ride-pooling services. However, existing simulation studies assume operation with autonomous vehicles, with no restrictions on operational tasks required when the vehicles are operated by manual drivers.

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 autonomous on-demand services. Based on the existing ride-pooling service MOIA in Hamburg, Germany, we introduce shift and break schedules and implement a new hub return logic to perform the respective tasks at different types of vehicle hubs. This way, currently operating on-demand services are modeled 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 operational challenges of a ride-pooling service with non-autonomous vehicles and the potential of future autonomous services. Lastly, the paper adds to the literature a practical ride-pooling simulation use case based on observed real-world demand and shift data.

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 as UberPool,[1] GrabShare,[2] Clevershuttle[3] or MOIA[4] have been introduced and promise to

* Corresponding author at: Institute for Transport Planning and Systems, ETH Zurich, Zurich, Switzerland.
E-mail address: felix.zwick@ivt.baug.eth.ch (F. Zwick).

[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/

https://doi.org/10.1016/j.tra.2022.09.001
Received 21 May 2021; Received in revised form 8 April 2022; Accepted 9 September 2022
Available online 5 October 2022
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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, which are largely defined by labor costs (Bösch et al., 2018). This makes operators and transit planners all the more hopeful that autonomous vehicles (AVs) 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 AVs 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 fully designing and testing AVs. Leonard et al. (2020) claim that widespread autonomous driving will take at least a decade. Similarly, Litman (2017) predicts that AVs 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. In a more recent article Shladover (2022) acknowledges that after a 'hype-cycle', recent statements have become more realistic. It is expected that market entry will now be gradual and that it may take decades for widespread adoption in U.S. cities. 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 does not call for AVs to be introduced until 2025 (MOIA, 2021).

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 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.

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. Nevertheless, the spatio-temporal distribution of demand may differ from real on-demand mobility services, so using historical taxi or ride-pooling requests as input to the simulation provides additional realism. For instance, Alonso-Mora et al. (2017), Ruch et al. (2020), and Ruch et al. (2021) used open taxi data from New York City, Chicago, and San Francisco. Zwick and Axhausen (2020a) used demand data from the ride-pooling operator MOIA in Hamburg, which also serves as a data source here.

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. (2021b)	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. (2021b)	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)

Fewer 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 reported 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. Additionally, we found two simulation studies with unpooled fleets where pseudo shifts are applied: Wittmann et al. (2020) present a study dealing with taxi fleet optimizations. Here, the authors dynamically adjust fleet sizes based on observed numbers of active taxis. Similarly, Jäger et al. (2017) simulate taxis that sample a desired shift duration at their respective operation start time. Long durations are possible to represent two-shift operations. However, breaks, changeover times and hub returns are ignored in both studies.

Overall, we did not find any studies simulating the operational challenges of hub returns for breaks and shift changes for on-demand mobility services. A general lack in the existing infrastructure is that analyses mostly focus on single-day evaluations, while operational differences over a longer time span (such as a full week) are neglected.

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 were constantly operating and only sent to a charging facility once the state of charge (SoC) was below 20%. The authors found a substantially lower performance of electric fleets with less passenger kilometers transported and more empty vehicle kilometers traveled 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. Cost implications of (non-)autonomous vehicles

The cost of on-demand services is critical for their utilization and must be competitive with existing mobility offerings to attract customers. The expected emergence of autonomous vehicles will change the current cost structures of human-driven mobility services drastically and multiple studies agree on the increased societal, ecologic and economic benefit through centrally organized, connected, and shared AV systems (Burns et al., 2013; Fagnant and Kockelman, 2015; Lempert et al., 2021).

Bösch et al. (2018) provided a comprehensive breakdown of the cost structures for conventional and future on-demand services (taxi in their case) in Switzerland, distinguishing ten different cost types. They found that salaries are the main driver of current taxi operations, accounting for 88% of the total cost of 1.61 CHF per passenger kilometer (PKM). For an autonomous taxi service, salaries are no longer considered, and the main cost drivers are cleaning, overhead and vehicle operations, and depreciation, resulting in a cost of 0.29 CHF per PKM. The cost is lower than for autonomous private cars (0.5 CHF/PKM) and only slightly higher than for autonomous buses (0.24 CHF/PKM), making fleets of pooled on-demand services a very competitive alternative mode of transport.

Negro et al. (2021) analyzed the cost structures of on-demand ride-hailing services in the context of automation and electrification in Munich, Germany. Like Bösch et al. (2018), they found a substantial cost drop with autonomous vehicles due to saved driver costs. They consider so-called teleoperators to support autonomous vehicles remotely at 1% of their operating time. Costs per vehicle kilometer (VKM) are expected to drop from more than 1 € to less than 0.5 €. With pooling, the costs per PKM could even be reduced.

The reduced costs of future autonomous on-demand services are expected to trigger their competitiveness and enable large-scale operations. Hörl et al. (2021) used a mode-choice model developed for Zurich, Switzerland, to estimate and simulate the interdependences of price, customer behavior and operations for an automated unpooled taxi system. They found a maximum demand of 150,000 daily requests, representing a distance-based mode share of almost 20%, served by 4,000 vehicles with cost-covering operations at a fare of 0.75 CHF/km.

Kagerbauer et al. (2021) estimated a mode-choice model with users of the ride-pooling service MOIA in Hamburg, Germany, and simulated multiple scenarios with conventional and fully autonomous ride-pooling vehicles. They found a demand increase from current 0.1% trip-based mode share to almost 3% mode share when the current MOIA fares are halved and additional policies are introduced.

While the costs play a decisive role for the competitiveness of future ride-pooling services, they are only marginally addressed in this study for the following reasons:

- We use historical ride-pooling requests to illustrate a realistic non-autonomous service. Thus, mode choice effects across scenarios are difficult to model as real-world requests are not available for a comparable autonomous service.
- We focus on the comparison of operational policies with and without AVs and aim to isolate those effects. A varying demand pattern would hinder a structured comparison.
- Operational costs are subject of constant change and depend on a variety of factors (wages, operational scheme, vehicle costs, energy costs, etc.) that require detailed analyses, which would go beyond the scope of this study.

2.4. Contribution

In summary, we find that existing simulation studies usually consider AVs 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 learned 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 AVs 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 AVs 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 operational 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 present a realistic ride-pooling simulation for an entire week based on real-world demand and shift data of the ride-pooling operator MOIA. We assess how the operation of the service can be improved by adding operational facilities.

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 trip-based demand, which is not represented by full activity schedules but by individual historic trip requests of the real-world ride-pooling service MOIA. 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 based on an insertion heuristic. 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 time 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 considering the defined service constraints, the request is rejected. The detailed functionality of the algorithm is described in Bischoff et al. (2017).

The pre-defined service constraints are shown in Table 2. Previous studies (Bischoff et al., 2017; Zwick and Axhausen, 2020b) have shown their high impact on the DRT system performance and the necessity to select the parameters wisely. The maximum wait time is set to 10 minutes to ensure a good balance between an efficient and a user-friendly service. Zwick and Axhausen (2020b) have shown for a similar historic MOIA scenario in Hamburg that a further increase of the maximum wait time leads to higher average wait times but does not increase the system efficiency substantially.

A similar issue arises for the maximum allowed detour time. Long detours are inconvenient for customers, but they increase the pooling potential and thus the efficiency of the system. The maximum allowed detour time, t_{detour}, is defined by

$$t_{\text{detour}} = \min(t_{\text{constant}} + \alpha \cdot t_{\text{direct}}, t_{\max}), \quad \text{with } 0 <= t_{\text{constant}} <= t_{\max} \text{ and } \alpha >= 0 \tag{1}$$

where t_{constant} denotes the constant detour time, α denotes the relative detour factor, t_{direct} denotes the direct travel time without any detours and $t_{\max}$ denotes the maximum allowed absolute detour time. The stop duration for each pick-up or drop-off of a customer is assumed to be 30 seconds. A potential additional duration for groups is not considered.

The pooling algorithm includes a repositioning strategy developed by Bischoff and Maciejewski (2020) to ensure that idle vehicles are sent to areas with high expected demand. Every 10 minutes, the demand (based on previous iterations) and supply (idle and soon-idle vehicles) in each zone of a 500 m × 500 m grid is calculated and vehicles are dispatched from zones with a surplus of vehicles to zones with a lack of vehicles to serve all requests. This has shown to substantially improve the system capacity in terms of acceptance rate (Zwick and Axhausen, 2020a).

All relevant input parameters of the pooling algorithm are summarized in Table 2.

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. Each driver shift is linked to a hub where it start and ends.

Table 2
Summary of DRT input parameters.

Input variable	Symbol	Value
Max. wait time		10 min
Absolute detour time	t_{constant}	5 min
Relative detour factor	α	0.5
Maximum absolute detour	$t_{\max}$	15 min
Stop duration		30 s
Repositioning interval		10 min
Repositioning grid size		500 m × 500 m

Table 3
Shift extension parameters.

Parameter	Value
Changeover duration	900 s
Break duration	1800 s
Start-of-shift look-ahead	1800 s
End-of-shift look-ahead	3600 s

- A description of hubs and possible in-field break facilities with equipment for charging and driver breaks. 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. The typical break duration is set to the in Germany legally required break duration of 30 min. Each operational facility is of the type *hub* or *in-field*. 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 min 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.

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

1. **Check end of shifts**
   One hour ('End-of-shift look-ahead', configurable) before the end of a shift, a changeover task including a relocation to the designated hub is created. 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 min ('Start-of-shift look-ahead', 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**
   For all active shifts, it is checked whether a break corridor has started. In that case, an operational facility 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. The vehicle may be charged during the break if it is required and charger capacity permits it.
5. **Check charging at hubs**
   For all idle vehicles that do not have a shift assigned and are parked at hubs, the dispatcher checks 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.

Table 3 summarizes the parameters of the shift logic.

For the planning of shift breaks, the identification of the facility tries to minimize empty mileage. Consider $S(t,v) = \{s_{1,t,v}, s_{2,t,v}, \dots, s_{n,t,v}\}$ as the scheduled sequence of stops for a vehicle v of the fleet of vehicles $V = \{v_1, v_2, \dots, v_n\}$ at time t. At the beginning of the break corridor t_{bs}, the vehicle chooses among the set of operational facilities (hub or in-field) $F = \{f_1, f_2, \dots, f_n\}$.

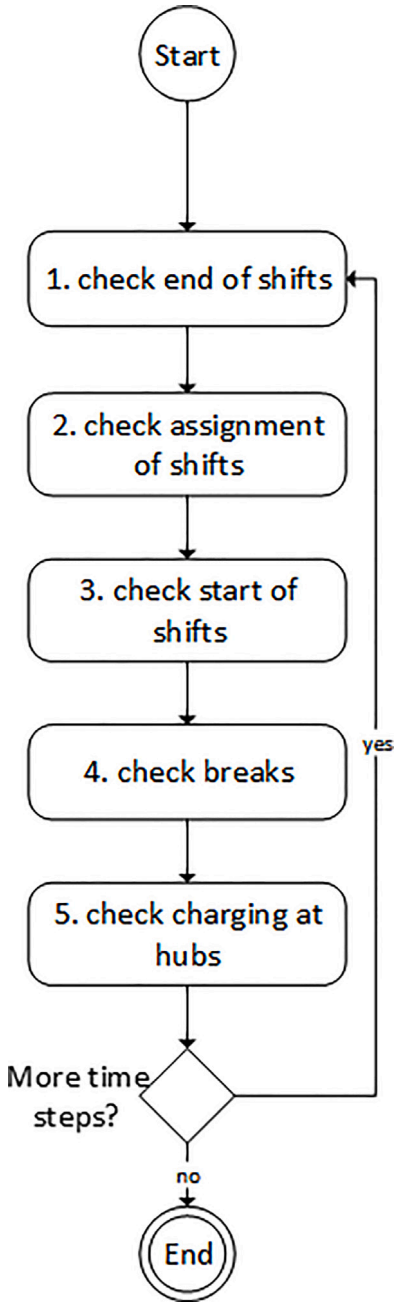

Fig. 1. Basic steps of the central shift dispatcher.

Thereby, the expected travel time $t_{\text{travel}}(s, f)$ from a stop s to the facility f should be minimized. The travel time equals the current routed path travel time. As stated above, only facilities with sufficient capacity $c_f(t)$ at time t may be selected:

$$f_{\text{selected}}(v, t_{\text{bs}}) = \arg\min_{f \in F} \; t_{\text{travel}}(s_{n,t_{\text{bs}},v}, f) \tag{2}$$

$$\text{s.t. } c_f(t_{bs}) > 0 \tag{3}$$

The capacity $c_f(t)$ is reduced as soon as a vehicle plans to perform an operational task at the facility. It is released as soon as vehicles start shifts or end breaks at the facility. While the scheduled break location is fixed, the arrival time is not. Instead, vehicles may accept new passengers along the route. However, the break stop is assigned a detour constraint defined in Eq. (1), with $t_{\text{direct}} = t_{\text{travel}}(s_{n,t_{\text{bs}},v}, f_{\text{selected}}(v, t_{\text{bs}}))$ and $t_{\max} = t_{\text{remaining}} - t_{\text{travel}}(s_{n,t_{\text{bs}},v}, f_{\text{selected}}(v, t_{\text{bs}}))$. Here, $t_{\text{remaining}}$ is the remaining buffer

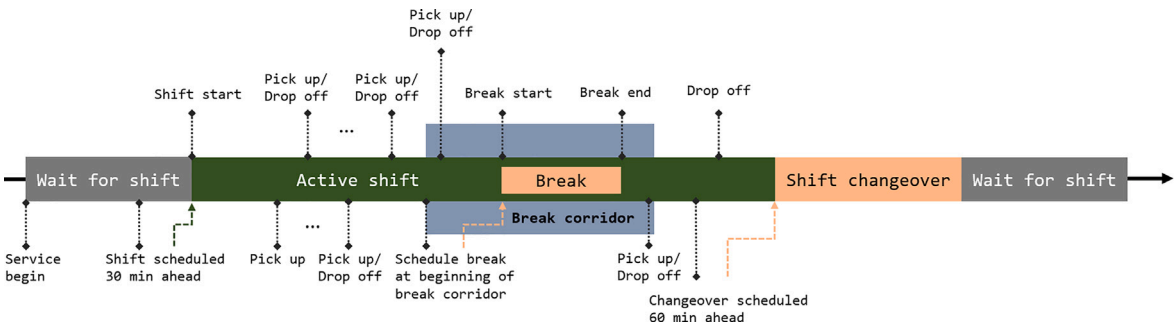

Fig. 2. Illustrative implementation of driver shifts for a single DRT vehicle.

Table 4
Electric fleet parameters.

Parameter	Value
Request assignment battery threshold	15%
Shifts: Shift assignment battery threshold	60%
Shifts: Charge at hub threshold	80%
Shifts: Charge during break threshold	80%
Autonomous: relocate to charge battery threshold	15%

time until the break has to start the latest, such that it still fits into the break corridor: $t_{\text{remaining}} = t_{\text{be}} - t_{\text{bd}} - t_{\text{bs}}$, where t_{be} is the end time of the break corridor and t_{bd} is the break duration.

Given this basic functionality, an illustrative timeline for a vehicle is depicted in Fig. 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. Electric fleet behavior

For the scenarios in this study, we also consider services with electric vehicles. It is recommended to avoid very high and very low SoC's to decrease the batteries' degradation and ensure efficient charging (Kostopoulos et al., 2020). This is why the SoCs in this study represent the net-capacity to which vehicles are charged at maximum, below which operation becomes harmful to the battery, and for which the charging curve is almost linear. The hubs are equipped with slow and fast chargers with a charging power of 7 kW and 100 kW, respectively. The in-field break facilities are always equipped with fast chargers only. The numbers are based on the ride-pooling service MOIA (see Section 4.1).

The behavior of electric fleet has been implemented as follows. For request insertion, only vehicles above 15% SoC are considered, to avoid vehicles running out of battery. While, in theory, it could be allowed to let the battery reach an SoC of 0% (as the SoC represents the net-capacity) the threshold is set to a higher value as the vehicles will still need to return to a hub or facility for charging. In addition, air condition and engine power are throttled at low SoC's which should be avoided. In the scenarios that use the newly developed explicit representation of driver shifts, three additional parameters were introduced. The shift assignment battery threshold is the required SoC for vehicles to be eligible to be assigned a driver shift. This is set to 60% to ensure vehicles have enough capacity to serve a whole shift. The charge at hub threshold is set to 80% and represents the SoC at which electric vehicles will (continue to) charge when being idle at the hub. Similarly, the charge during break threshold, below which vehicles will try to charge during a break, is also set to 80%. These thresholds have been set rather high to avoid overcrowding at chargers and reduce charging actions overall. In the autonomous electric scenarios, vehicles will move to a hub and charge once the SoC falls below 15%, which should be enough to ensure that the vehicle can make it back to the hub. The parameters related to the electric fleet behavior are summarized in Table 4.

The default MATSim e-DRT extension for AVs comes with the assumption that idle vehicles *always* return to their depot as soon as they do not have any passenger action scheduled. This is to ensure that vehicles visit the hub regularly to charge. However, this assumption introduces a lot of unnecessary empty mileage caused by large amount of hub returns.

As AVs in the simulation so far do not have other operational tasks that can be combined with charging, we implemented a simpler alternative logic in which vehicles only relocate to charge once their SoC is below a certain threshold (see Table 4). In the case an electric AV requires to charge, a selection logic similar to the one defined in Eq. (2) is employed. However, in this case the vehicle will not only look at travel times but additionally take into account the required time for charging and waiting at a charger

Table 5
Description of base case hubs including number of plugs per charger type.

Name	Vehicle capacity	Slow chargers	Fast chargers
Horn	65	52	4
Wandsbek	100	90	12
Stellingen	100	83	7

of type $c_{f,l} \in C = \{c_{f_1,\text{slow}}, c_{f_1,\text{fast}}, c_{f_2,\text{slow}}, c_{f_2,\text{fast}}, \dots, c_{f_n,\text{slow}}, c_{f_n,\text{fast}}\}$ of charger types $l \in \{\text{'slow'}, \text{'fast'}\}$ located at one of the facilities $f \in F$. Therefore, the expected total operational task time

$$t_{\text{total}}(v, c_{f,l}, t) = t_{\text{travel}}(s_{n,t,v}, c_{f,l}) + t_{\text{wait}}(c_{f,l}) + t_{\text{charge}}(v, c_{f,l}) \tag{4}$$

for vehicle v at facility f using a charger type $c_{f,l}$ at time t includes the travel time from last stop s_n to charger-type-at-facility $c_{f,l}$, expected waiting time t_{wait} and expected remaining time to charge t_{charge}. Consider $V_{f,l}$ as the set of vehicles v currently plugged or queued at facility f for a charger of type l and $n_{f,l}$ as the number of charging plugs of type l at facility f (see Table 5). Then t_{wait} is approximated by

$$t_{\text{wait}}(c_{f,l}, t) = \frac{\sum_{v \in V_{f,l}} t_{\text{charge}}(v, c_{f,l})}{n_{f,l}} \tag{5}$$

Note that this approximation does not include newly assigned vehicles that are still on the way to the facility. The approximation of t_{charge} depends on the charger type and the current SoC of a vehicle. For simplification in our simulations, we assumed linear charging curves which were observed for the net-battery capacity range. Consequently, the charger type and facility combination $c_{selected}$ is selected by minimizing the total operational task time:

$$c_{\text{selected}}(v, t) = \underset{c_{f,l} \in C}{\arg\min}\ t_{\text{total}}(v, c_{f,l}, t) \tag{6}$$

In addition, the constraint of Eq. (3), which ensures sufficient capacity at the facility, applies. Autonomous vehicles relocating to charge are not allowed to serve passengers along the way. It is assumed that all further operational tasks such as cleaning, etc. are performed during the charging processes.

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 198 km^2 service area covering large parts of the city shown in Fig. 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 TomTom[6] and match it to our MATSim network with the help of a map-matching algorithm described 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 min 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 one week between 17/01/2022 and 23/01/2022 have been collected. 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 min after the first request. In total, the dataset contains 59,784 requests with an average trip length of 6.8 km.

The MOIA shift plan of the same week is used to define the shift supply. The shift plan is designed to fit the expected demand. However, the actual operational shift plan of MOIA deviates due to short-term changes in the planning. The shifts are assigned to 280 available 6-seater vehicles. The fleet size is defined by the maximum number of shifts that are active at the same time (254) plus 10% to ensure vehicle availability even if some vehicles are unavailable due to operational tasks such as shift changes. The pseudo-shift and autonomous service are operated with 254 vehicles as these vehicles are always in service and have no additional operational tasks besides charging. In this way, we ensure the maximum comparability across scenarios as all services have a maximum number of 254 vehicles in service.

Lastly, three hubs with chargers have been defined based on MOIA's real-world hub locations (see Fig. 5). A description of hub capacities and chargers is presented in Table 5.

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

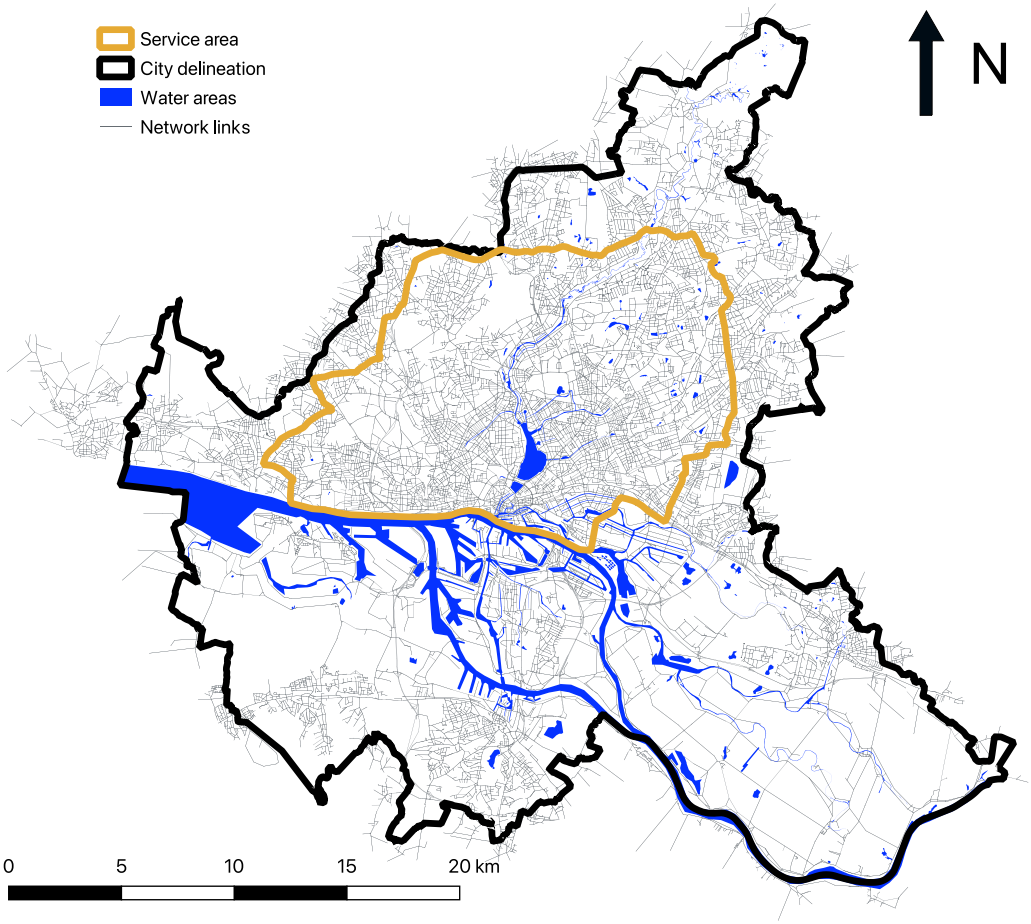

Fig. 3. Study and service area of the Hamburg scenario, including road network and water areas.

Table 6
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

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 6.

In the *autonomous service*, the entire fleet of 254 6-seater vehicles is available to pick up and drop off passengers 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

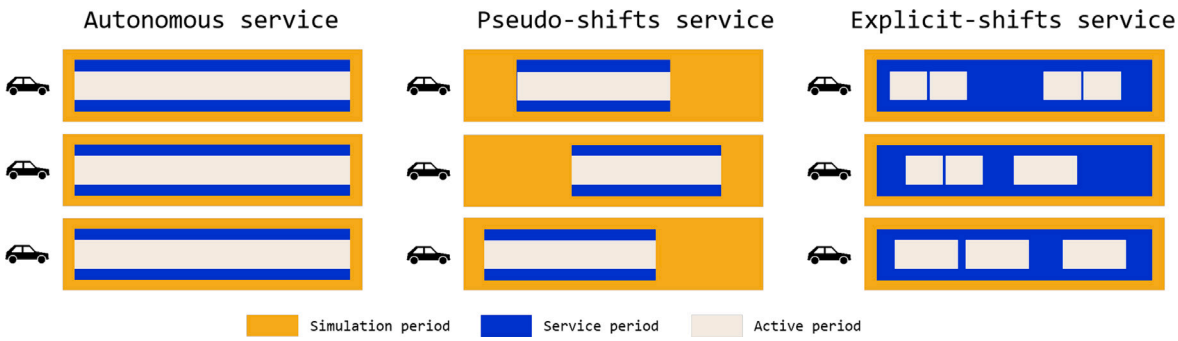

Fig. 4. Qualitative representation of the three service set-ups. Vehicles are only able to serve requests when active.

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 AV 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 *explicit-shifts service* we consider the shift restrictions, a mandatory break of 30 min 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.

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

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.

We implement the charging restrictions for the autonomous and the explicit-shift scenario. While the AVs are only charged when the battery is low, vehicles in the shift scenario are charged during breaks and in between shifts. Thus, the effects are expected to be different with each service. Based on MOIA's special purpose vehicles, the net-battery capacity is set to 77 kWh. Energy consumption is assumed to be 0.25 kWh/km on average for an assumed ambient temperature of 20 °C. See the Appendix for a sensitivity analysis of different battery capacities and consumption levels in the autonomous and the explicit-shift service. Changes in consumption levels could be attributed to technological advancements or changes in ambient temperature.

4.2.3. Shift and break optimization

Lastly, we investigate the potential to optimize the electric explicit-shifts service with additional infrastructural facilities. We therefore add a new type of facility, *in-field break facilities*, where drivers can do their break and 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.

We incrementally add more in-field break facilities to the existing 3 hubs to obtain scenarios with 2, 4, 8, 16, 32 and 64 facilities, all equipped with two 100 kW fast chargers. While the location of the initial three hubs is kept fixed, the location of the additional break facilities is selected randomly among all links in the network within the service area. We ensure that each facility is at least 1 km away from every other hub or in-field break facility to distribute them equally across the service area. The final distribution of hubs and the additional in-field break facilities are shown in Fig. 5.

5. Results

The system performance of the ride-pooling system is evaluated in multiple directions. Besides the number of rides and rejections, we measure the average service quality of the system through the average detour and the average wait time customers experience. Those are two important indicators quantifying the convenience of the system, which is necessary for a broad user acceptance.

The fleet size, vehicle operating hours and vehicle revenue hours show how many vehicles are assumed in the service and for how long they operate and generate revenue. During revenue hours, the vehicle performs a revenue generating performance (e.g. driving a customer), whereas operating hours also include all operational tasks like repositioning the vehicle or driver breaks. 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 kilometer is 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

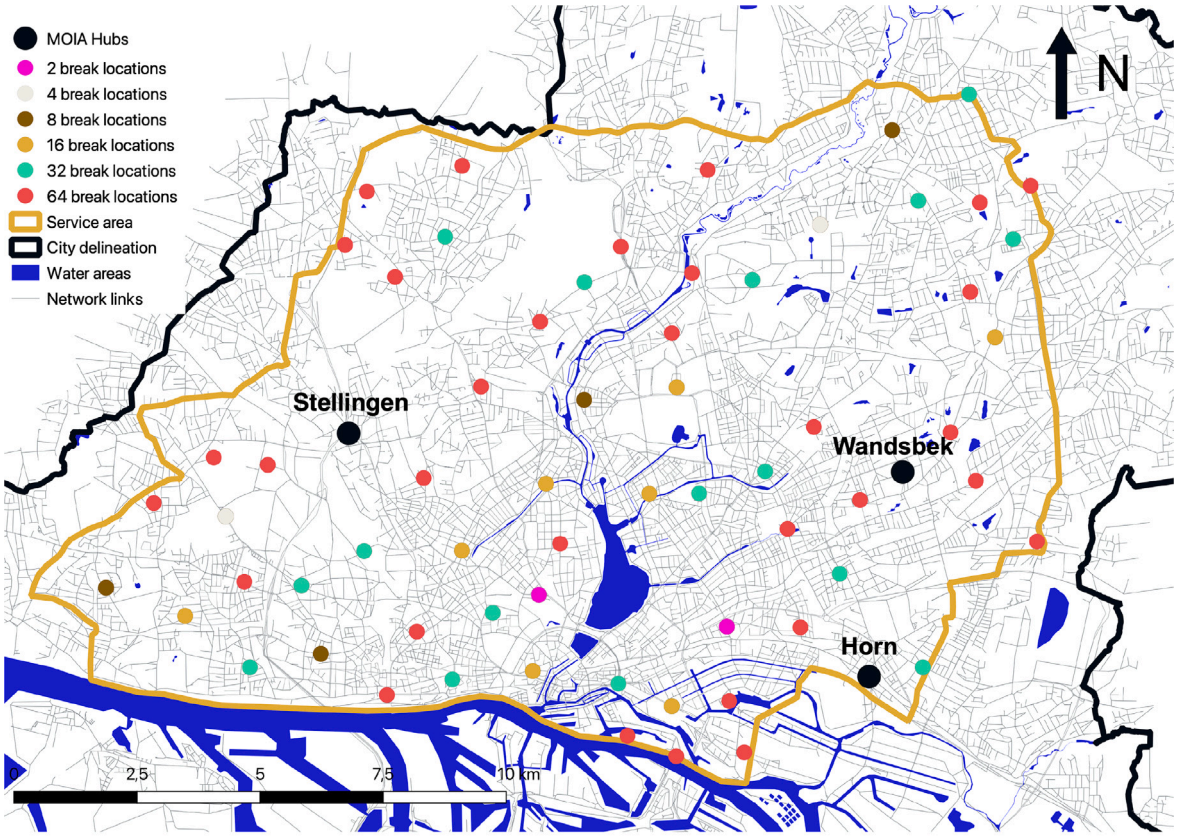

Fig. 5. Original MOIA hubs and locations of additional, fictional break facilities resulting from the random sample. Each facility increase includes all facilities of the scenarios with fewer facilities.

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., 2021a). 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.

The variable PKB per vehicle shows how many passenger kilometers are transported by each vehicle throughout the week. It can be directly compared to existing modes like car or taxi and is an indicator for how many (parked) vehicles can be replaced by the on-demand system.

5.1. Autonomous vs. shift services

Table 7 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 19% 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 detour is larger in the autonomous service with more served rides, which may be caused by more pooling options due to the higher trip density. The average wait time is substantially lower with a static autonomous fleet, which can be explained by a better distribution and availability 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.

The fleet size is smallest in the autonomous service with 254 vehicles. The explicit-shifts service requires a buffer of 10% more vehicles to be able to operate with the same number of vehicles in peak times. In the pseudo-shift service, each vehicles represents a shift and thus substantially more vehicles (1793) are employed in the simulation.

The vehicle operating hours represent the time vehicles are available to serve a request or actively performing an operational task, e.g. serving customers, repositioning, or returning to a hub. In contrast, the vehicle revenue hours represent the time vehicles

Table 7
Simulation results for the autonomous, pseudo-shifts and explicit-shift services.

	Autonomous service	Pseudo-shifts service	Explicit-shifts service
Rides	59,136	52,244	48,555
Rejections	648	7540	11,229
Avg. detour [%]	15.2	11.7	10.1
Avg. wait time [min]	4:35	6:05	6:40
Fleet size	254	1793	280
Vehicle operating hours	42,672	14,312	14,714
Vehicle revenue hours	10,336	9784	9433
VKT [x1000 km]	311.5	303.9	322.0
Empty km [x1000 km]	52.5	67.8	96.1
Empty km share [%]	16.9	22.3	29.9
Avg. occupancy	1.48	1.32	1.16
PKB/vehicle	1580	201	1204
η_{RP}	1.29	1.18	1.05

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

are actively performing a revenue-generating task, e.g. serving customers or driving to a pick-up. Times in which vehicles are idle are not counted as revenue hours.

In the autonomous service, all vehicles are constantly performing a task or are available to serve requests throughout the week. The vehicle revenue hours are substantially lower (10,336) as most of the time, vehicles are idle. The discrepancy of operating and revenue hours is much lower in the shift services. The pseudo-shift approach has the lowest amount of operating hours (14,312) even though more revenue hours are observed (9784) and more rides are served than in the explicit-shifts simulation. This can be explained by the additional empty relocations of vehicles returning to a hub for breaks and changeover activities.

The vehicle kilometers traveled (VKT) are similar across all services, but the explicit-shifts service causes most mileage, even though fewer trips are served than with the two other services. To assess the impact on the transport system, one must also report 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 29.9%. The pseudo-shifts service has a substantially lower share of empty km (22.3%). The vehicles start at one of the hubs and need to drive to be distributed at the beginning of the shift, but do not require relocation at the end of the shift. The autonomous service has the lowest percentage of empty km because the large number of available vehicles means that there is a high probability that a vehicle will be near an incoming request, and empty pick-up drives are substantially shorter.

In addition to the overall number of rides/requests, the average vehicle occupancy and the performance indicator 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 both, the average occupancy and the service efficiency indicator η_{RP}. In fact, it can be seen that the simulation of an autonomous and a pseudo-shifts service, which disregard hub returns and breaks, result in a more optimistic efficiency value of 1.29 and 1.18, respectively. The explicit-shifts simulation lead to an efficiency of 1.05. A similar pattern is observed for the average occupancy.

We observe that far more than 1,000 person kilometers are transported per week by each ride-pooling vehicle, which is substantially more than a private car transports. This indicates a potential to reduce the number of vehicles in a city, if car trips are replaced by ride-pooling or other on-demand services. In the pseudo-shifts simulation, each vehicle only operates for one shift and thus only transports 201 booked passenger kilometers.

Fig. 6 shows the vehicle occupancy throughout the simulated week for all three services. Overall, the occupancy is highest on weekends. It can also be observed that MOIA's service is paused during night times on workdays. The autonomous service operates with the entire fleet throughout the week, which explains the large amount of idle vehicles that would be available to serve additional demand.

The pseudo-shift and the explicit-shift service have similar patterns. The low share of idle vehicles shows that the shift plan is suitable to meet the demand and that there is no oversupply of vehicles. In the explicit-shift service, break and shift end drives are observed that contribute to the empty km share. In Section 5.3 we analyze the potential to reduce the empty drives by providing more break facilities in the city.

An overview of the occupation of hubs and employed shifts including breaks in the explicit-shift scenario can be seen in Fig. 7. The pattern of employed shifts is similar to the demand observed in Fig. 6 and most of the shifts are employed during the peak demand times on weekends at night. We observe that there are a lot of vehicles at the hubs during most times of the week. However, almost all vehicles are required for the peak times. One of the hubs runs out of available vehicles during some of the peak times, which underlines the importance of having some spare vehicles as a buffer and an elaborated shift-vehicle assignment.

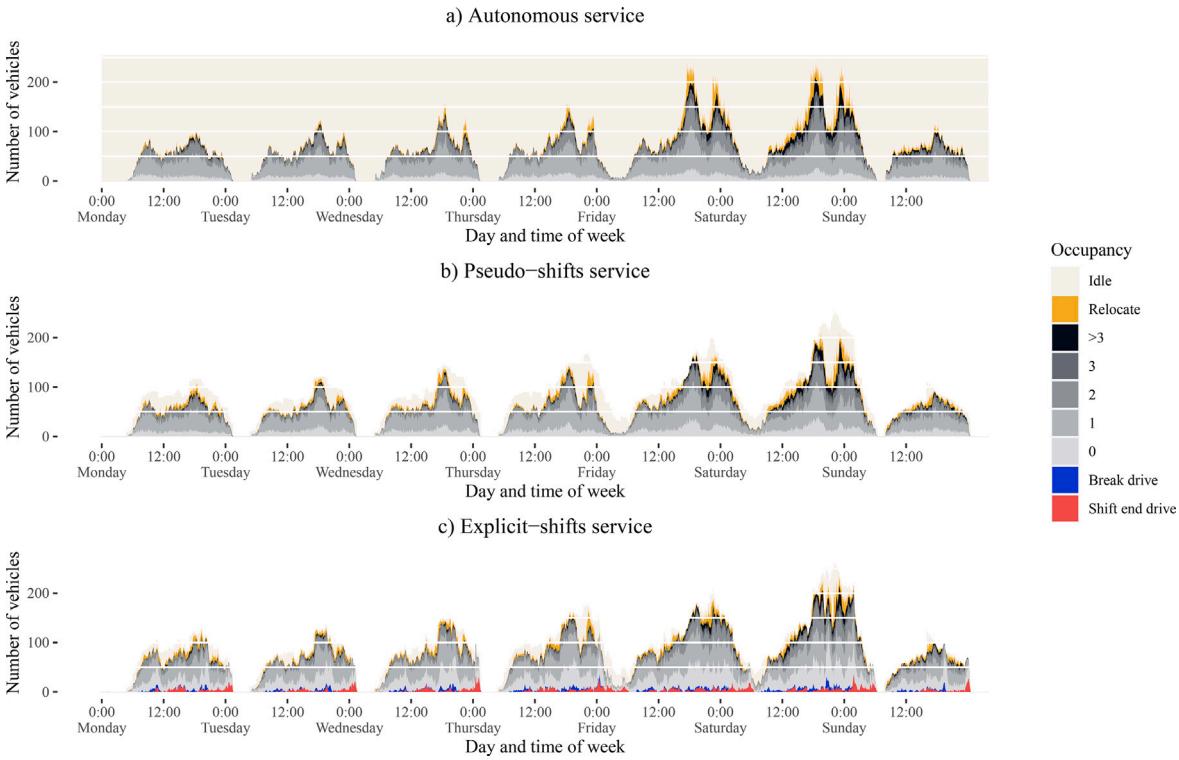

Fig. 6. Vehicle occupancy over the course of a simulated day for two autonomous services with (a) a static fleet and (b) pseudo shifts, and (c) for a service with explicit shifts.

5.2. Impact of charging restrictions

Next, the simulations with battery electric vehicles and the charging behavior defined in Section 3.4 are analyzed for the autonomous and the explicit-shifts service. The pseudo-shifts service is not considered since each vehicle operates for one shift only and charging or hub returns are not considered anyways.

The results in Table 8 show the performance comparison of both non-electric services and their respective electric service.

The electric autonomous service serves slightly less customers than the conventional service although the number of vehicle revenue hours increases. To recharge, the vehicles must travel to the hubs from time to time and then be distributed across the city again. A substantial increase of VKT and empty km are observed (21.1% compared to 16.9%), which is also explained by the empty rides towards hubs for charging. This also affects the average occupancy and the service efficiency negatively and the introduced efficiency indicator η_{RP} decreases from 1.29 to 1.2.

In the explicit-shifts service, we also observe a decrease of served rides when electric vehicles and charging are considered. Only 45,079 rides are served while 48,555 rides are served when charging is not considered. This is due to a lower availability of vehicles (reflected by less vehicle revenue hours) and suggests that the introduced buffer of vehicles of 10% is not sufficient to have a charged vehicle available at all times.

However, despite the lower availability the electric service is almost as efficient as the conventional service and the average occupancy and η_{RP} are only slightly lower.

Fig. 8 presents plugged vehicles per charger type and location over time. It can be observed that the fast chargers are only used for a short amount of time because vehicles are fully charged quickly or drivers return to the field after a 30-minute break. The slow chargers are mostly occupied in off-peak-times at night.

A comprehensive sensitivity analysis of different battery and energy consumption configurations with the autonomous and explicit-shifts service can be found in the Appendix. It shows that the simulation results presented here are stable, but a certain minimum battery capacity and maximum energy consumption are required to provide service without major interruptions. It is expected that battery sizes will further increase in size and decrease in price in future thanks to technological developments (König et al., 2021).

5.3. Operational facility optimization

In a next step, we add in-field break facilities to reduce long relocation drives for charging and shift breaks. Each new facility is equipped with two 100 kW chargers. The spatial distribution of the facilities is shown in Fig. 5. The results of scenarios with an

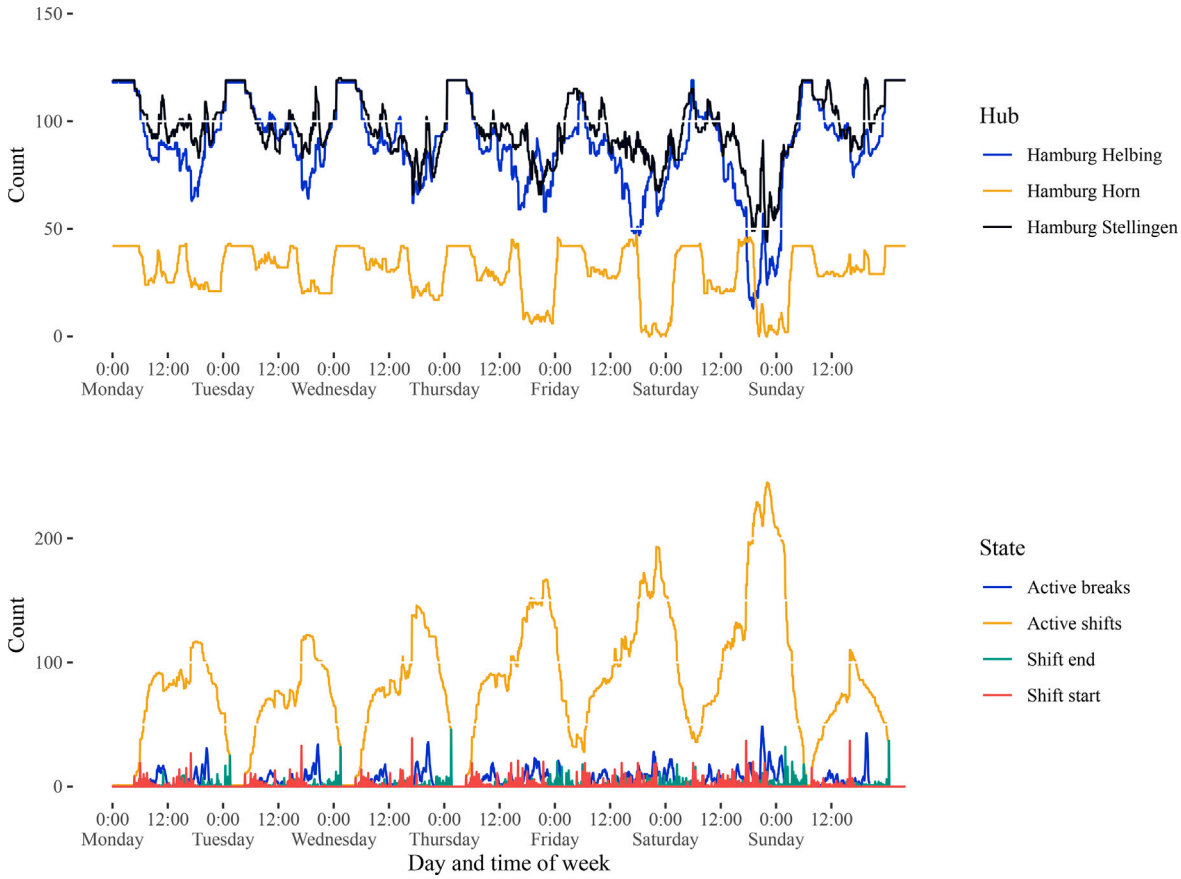

Fig. 7. Hub occupation over time (top) and histogram showing the number of shifts starting/ending and being active as well as being on break (bottom). Both plots represent the base case with explicit shifts.

Table 8
Simulation results for the conventional and the electric shift service.

	Autonomous – conventional	Autonomous – electric	Explicit shifts – conventional	Explicit shifts – electric
Rides	59,136	58,454	48,555	45,079
Rejections	648	1330	11,229	14,705
Avg. detour [%]	15.2	14.5	10.1	9.7
Avg. wait time [min]	4:35	4:49	6:40	6:55
Fleet size	254	254	280	280
Vehicle operation hours	42,672	42,672	14,714	13,805
Vehicle revenue hours	10,336	10,506	9433	9053
VKT [x1000 km]	311.5	330.4	322.0	304.9
Empty km [x1000 km]	52.5	69.8	96.1	89.8
Empty km share [%]	16.9	21.1	29.9	29.4
Avg. occupancy	1.48	1.38	1.16	1.14
PKB/vehicle	1580	1565	1204	1135
η_{RP}	1.29	1.20	1.05	1.04

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

increased number of in-field charging facilities are summarized for the autonomous services in Table 9 and for the explicit-shifts services in Table 10. Fig. 9 shows the evolution of four system performance indicators with an increasing number of in-field facilities with both service types.

In the autonomous service, it can be observed that the overall number of rides and rejections as well as detours and wait times do not change substantially and are only marginally improved. However, the total number of VKT and the (share of) empty kilometers decrease with an increasing number of in-field charging facilities, which can be explained by the fact that vehicles require shorter relocations to be charged as hubs are on average nearer to their current location. Consequently, the average occupancy and efficiency

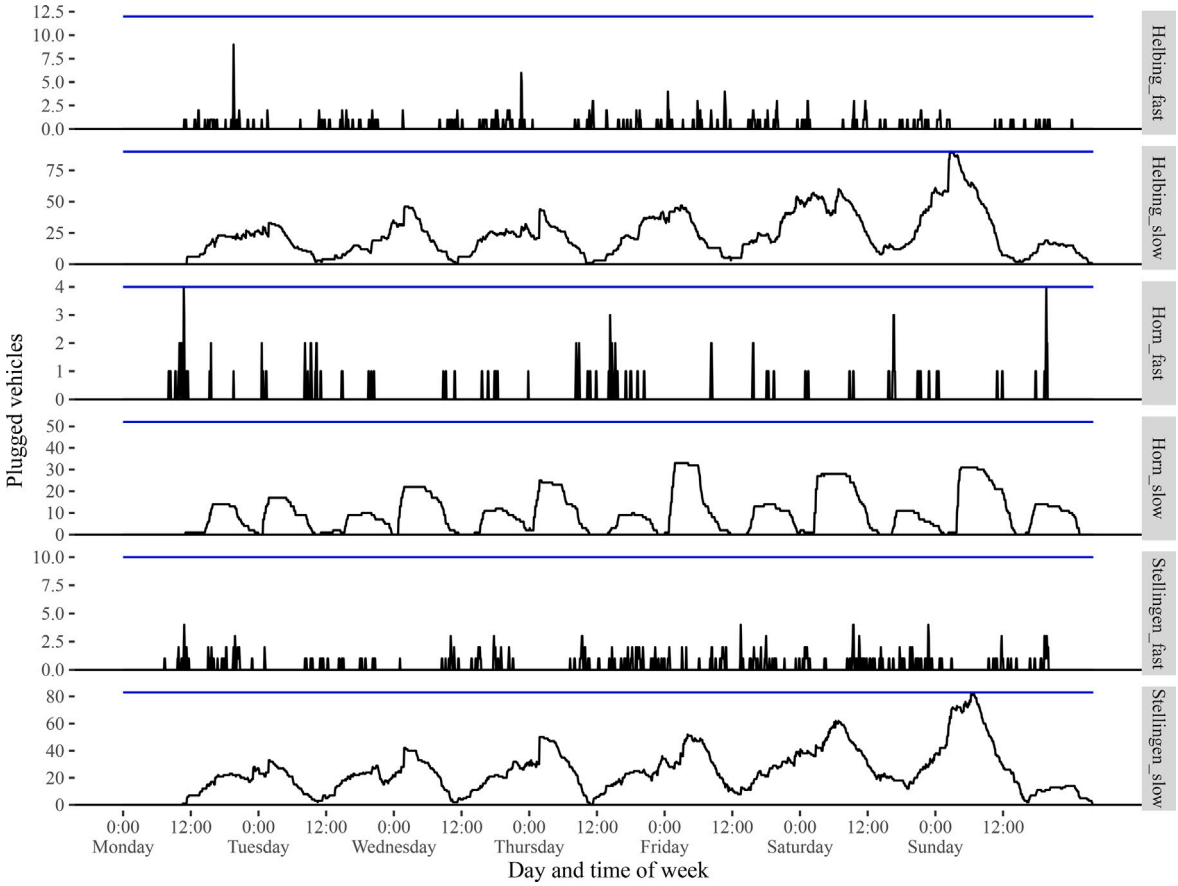

Fig. 8. Plugged vehicles per charger type and location over time. The blue lines depict the number of plugs per type and location. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 9
Impact of in-field charging facilities increase in the autonomous service.

	Number of in-field charging facilities						
	0	**2**	**4**	**8**	**16**	**32**	**64**
Rides	58,454	58,626	58,684	58,695	58,707	58,693	58,764
Rejections	1330	1158	1100	1089	1077	1091	1020
Avg. detour [%]	14.5	14.5	14.4	14.6	14.7	14.8	14.7
Avg. wait time [min]	4:49	4:42	4:46	4:44	4:40	4:41	4:40
Vehicle revenue hours	10,506	10,466	10,510	10,471	10,458	10,480	10,456
VKT [x1000 km]	330.4	325.3	326.3	322.4	319.3	318.8	317.1
Empty km	69.8	64.4	64.9	61.4	58.3	57.2	55.9
Empty km share [%]	21.1	19.8	19.9	19.0	18.3	17.9	17.6
Avg. occupancy	1.38	1.40	1.40	1.42	1.43	1.44	1.45
PKB/vehicle	1565	1569	1571	1571	1570	1571	1572
η_{RP}	1.20	1.23	1.22	1.24	1.25	1.25	1.26

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

η_{RP} of the system improves from 1.38 to 1.45 and from 1.20 to 1.26, respectively. These values are close to the values of the non-electric service (1.48 and 1.29). The effects diminish with an increasing number of hubs, as can be seen in Fig. 9, which indicates a saturation effect.

The results of scenarios with an increased number of in-field break and charging facilities for the explicit-shift service is summarized in Table 10.

We find that the number of trips with more in-field charging and break facilities is increasing. In this context, we observe that although the operating hours of the vehicles with more facilities decrease, the revenue hours of the vehicles increase and the vehicles are available longer for transporting customers.

Table 10
Impact of in-field charging and break facilities increase in the explicit-shift service.

	Number of in-field charging and break facilities						
	0	**2**	**4**	**8**	**16**	**32**	**64**
Rides	45,079	45,463	45,493	45,802	45,901	46,244	46,003
Rejections	14,705	14,321	14,291	13,982	13,883	13,540	13,781
Avg. detour [%]	9.7	9.6	9.8	9.8	9.6	9.8	9.9
Avg. wait time [min]	6:55	6:54	6:54	6:53	6:53	6:49	6:49
Vehicle operating hours	13,805	13,811	13,848	13,837	13,883	13,823	13,779
Vehicle revenue hours	9053	9094	9104	9145	9195	9183	9165
VKT [x1000 km]	304.9	304.1	304.6	305.2	303.5	302.3	300.3
Empty km	89.8	88.1	88.0	87.0	84.5	83.3	81.7
Empty km share [%]	29.4	29.0	28.9	28.5	27.9	27.5	27.2
Avg. occupancy	1.14	1.15	1.16	1.16	1.17	1.18	1.18
PKB/vehicle	1135	1143	1146	1153	1155	1162	1155
η_{RP}	1.04	1.05	1.05	1.06	1.07	1.08	1.08

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

This indicates a more efficient usage of the shift times with less operational (empty) rides. This is also reflected in the number of VKT and empty km, which are both substantially lower with more in-field facilities. The empty km share of 27.2% with 64 facilities is even lower than with the non-electric service because of the shorter rides to do breaks. For shift ends, drivers still have to drive to the hub where they started the shift. A higher flexibility of driver shift end locations and in-field driver changes could improve the results further and are part of further investigations.

The evolution of four system performance indicators for both services are shown in Fig. 9. The fitted curve based on a square root function and its 90% confidence interval shows a saturating effect for all four indicators with an increasing number of facilities.

Depending on the aim of the service, the costs for each operational facility, and the calculated gains through reduced VKT and higher efficiencies, operators and policy makers must evaluate how many operational facilities are suitable for the service. Due to the manifold cost structures of on-demand services outlined in Section 2.3 and many competing interests of users, operators and policy makers, we do not calculate an optimal number of break facilities here. If the costs of in-field charging facilities are low or the facilities are available anyways (e.g. public chargers), the amount of facilities should be as high as possible to reduce VKT and increase service efficiency.

In summary, we find that the proposed in-field facilities improve the overall system with electric vehicles in an autonomous and a non-autonomous service.

6. Discussion

We find that the application of shifts in the existing ride-pooling extension of MATSim supports the necessity to study existing on-demand services more realistically and to account for operational challenges. Existing simulation studies, as shown in Section 2.1, do not take into account these operational constraints. Only a few studies (Martinez et al., 2015; Bischoff et al., 2017; Lokhandwala and Cai, 2018; Zwick and Axhausen, 2020b) take into account pseudo shifts that limit vehicle availability but do not take into account certain operational tasks. Our study helps to understand the limitations of transferring their findings to existing non-autonomous on-demand ride-pooling services.

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. However, 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. This shows the high complexity when assessing on-demand ride-pooling systems.

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 electric ride-pooling service, we observe that with autonomous vehicles almost 30% more requests can be served and the share of empty km decreases from 29.4% to 21.1% 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 (Hamburg, 2017), showing that the current ride-pooling system already adds value to the transport system. Also, the number of PKB that each vehicle transports in a week is noteworthy. With over 1,000 PKB, each vehicle potentially replaces the mobility of several cars, which reduces parking space and vehicle production costs. As operation costs of AVs are expected to be lower than for current services, for which drivers need to be paid, it is clear that future autonomous fleets may yield a high economic potential for service providers.

The introduction of in-field break and charging facilities has shown to improve the ride-pooling in many ways. With more facilities less time and VKT is spent to reach a facility to perform an operational task. In this way, we quantified how many VKT and empty km are saved but also how many more customers can be served with the same number of vehicles and drivers. Also the efficiency, measured by the average occupancy and η_{RP} increases. An economic evaluation of the optimal number of facilities

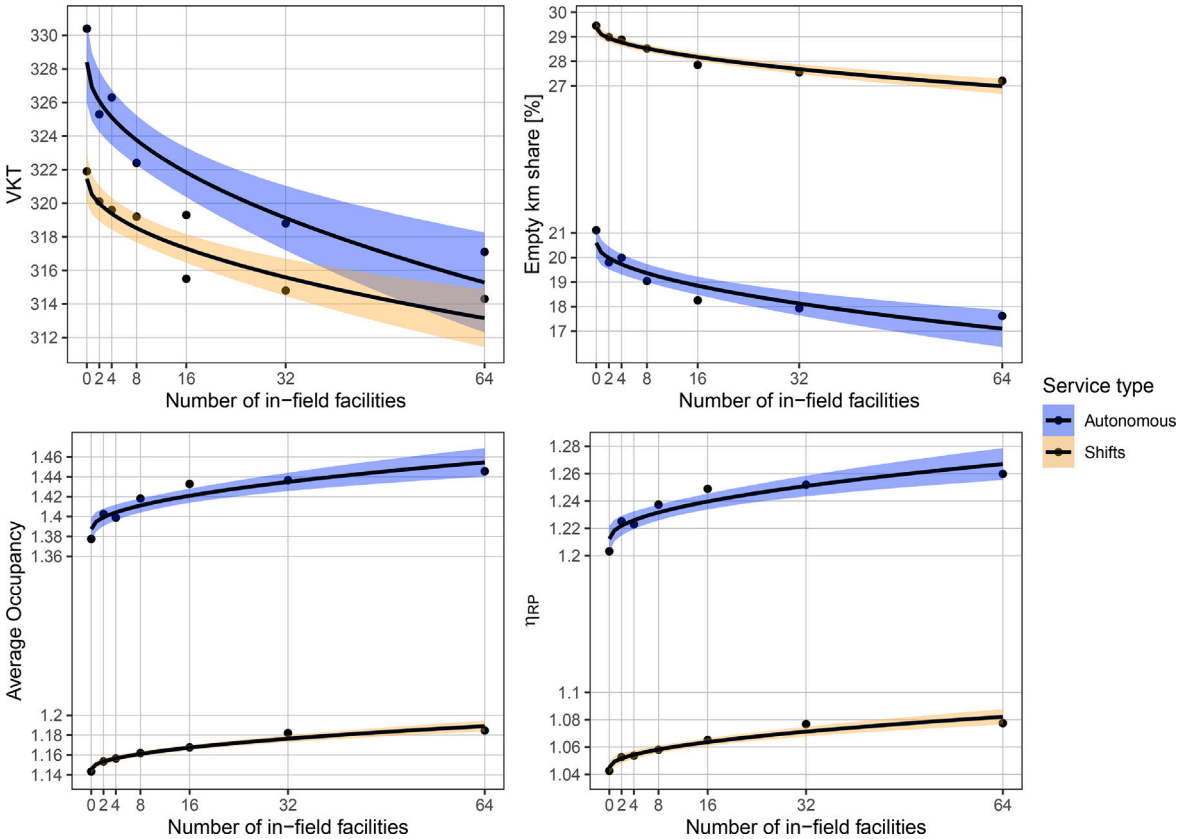

Fig. 9. Service results with increased number of in-field break locations in the autonomous and explicit-shifts service. The colored areas show the 90% confidence interval of the fitted curve based on a square root function. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

is not performed here, but simulation-based approaches such as presented by Vosooghi et al. (2020) could be applied in the future. The cost of each facility is to some extent arbitrary and the economic benefits of service efficiency and VKT saved are difficult to measure because multiple stakeholders (operator, customers, city) need to be considered.

The lack of economic evaluation of the service and subsequent differential user behavior is a strong limitation of our study. The introduction of autonomous vehicles is expected to reduce the overall costs of the service (see Section 2.3, which attracts additional customers. The additional customers are expected to increase the efficiency of the autonomous service even further and allow to scale the fleet size.

A common tool to take into account mode choice effects are discrete choice models (McFadden, 1974), which have been used in multiple previous studies (Kagerbauer et al., 2021; Hörl et al., 2021; Martinez and Viegas, 2017; Wilkes et al., 2021; Zwick et al., 2021b). The mode choice of individual agents depends on multiple parameters like travel time, wait time and costs and add a high complexity to the simulation scenarios, which is why we decided to exclude them from this study. In this way, we can isolate the impacts of simulating operational aspects in ride-pooling and do not mix them with other side effects. The mode choice effects need to be further investigated in future studies.

The simulation of AVs in this study considers charging as only operational task that takes place at hubs. However, it is expected that there will be additional tasks required such as cleaning, maintenance, damage check, sensor calibration among others. We do not consider these tasks here because we assume that most of the tasks can be done during charging and more time-consuming tasks occur less often than on a weekly base. Nevertheless, the additional operational tasks may be studied in future.

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 worth driving to a more distant facility to anticipate higher demand after the break. Dean et al. (2021) recently introduced and evaluated this joint optimization and found first promising results. The absence of this feature should, however, not limit the validity of our results.

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.

Table 11
Sensitivity analysis of battery capacity and discharging for the autonomous service.

Energy consumption [kWh/100 km]	50 kWh battery			77 kWh battery			100 kWh battery		
	15	25	35	15	25	35	15	25	35
Rides	58,512	57,947	57,329	58,882	58,454	58,013	58,888	58,721	58,249
Rejections	1272	1837	2455	902	1330	1771	896	1063	1535
Avg. detour [%]	14.3	13.9	13.3	14.7	14.5	14.0	14.9	14.6	14.4
Avg. wait time [min]	4:50	5:01	5:15	4:41	4:49	4:59	4:39	4:45	4:51
Vehicle revenue hours	10,534	10,609	10,676	10,445	11,506	11,575	10,400	10,447	10,492
VKT [x1000 km]	333.2	343.2	355.8	323.8	330.4	338.9	320.3	325.5	330.8
Empty km	72.0	81.3	93.3	63.5	69.8	77.2	60.5	65.3	70.3
Empty km share [%]	21.6	23.7	26.3	19.6	21.1	22.8	18.9	20.1	21.3
Avg. occupancy	1.37	1.31	1.25	1.42	1.38	1.33	1.44	1.41	1.37
PKB/vehicle	1567	1553	1540	1575	1565	1556	1575	1571	1561
η_{RP}	1.19	1.15	1.10	1.24	1.20	1.17	1.25	1.23	1.20

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

Table 12
Sensitivity analysis of battery capacity and discharging for the explicit-shift service.

Energy consumption [kWh/100 km]	50 kWh battery			77 kWh battery			100 kWh battery		
	15	25[a]	35[a]	15	25	35[a]	15	25	35
Rides	45,875	30,165	13,243	47,707	45,079	38,113	48,442	46,582	44,422
Rejections	13,909	29,619	46,541	12,077	14,705	21,671	11,342	13,202	15,362
Avg. detour [%]	9.7	8.1	6.8	9.9	9.7	9.0	10.1	9.8	9.6
Avg. wait time [min]	6:54	7:38	8:08	6:57	6:55	7:16	6:41	6:51	6:59
Vehicle operating hours	13,970	13,797	13,861	14,451	13,805	13,445	14,657	14,169	13,636
Vehicle revenue hours	9168	6775	3369	9388	9053	8064	9447	9240	8965
VKT [x1000 km]	309.0	231.1	135.2	318.4	304.9	270.6	321.4	312.1	300.9
Empty km	90.9	77.0	61.3	94.4	89.8	83.1	95.1	92.0	88.1
Empty km share [%]	29.4	33.3	45.3	29.6	29.4	30.7	29.6	29.5	29.3
Avg. occupancy	1.15	1.03	0.79	1.15	1.14	1.10	1.16	1.15	1.15
PKB/vehicle	1155	787	357	1193	1135	973	1207	1167	1124
η_{RP}	1.05	0.95	0.74	1.05	1.04	1.01	1.05	1.05	1.05

PKB: Passenger kilometers booked excluding detours; η_{RP} = PKB/VKT.
[a]Scenarios for which the assignment threshold and the minimum SoC had to be adjusted to ensure operations without vehicles running out of energy in the field.

7. Conclusion

We present updates to current existing ride-pooling simulations to improve realism of results. The technical functionality was added to the open-source simulation framework MATSim and allows the detailed simulation of existing ride-pooling services with any operational limitations. The code of our extension is available in MATSim's open-source repository[7].

With the updated functionality, we assess the operational aspects of current on-demand ride-pooling systems on the example of MOIA in Hamburg, operating a large-scale service with more than 200 vehicles in service. We show that the operational constraints through shifts with fixed start and end locations, breaks and charging tasks limit the efficiency of the ride-pooling fleet. Drivers are occupied performing the operational tasks and spend less of their working time for revenue generating tasks. Additionally, more VKT are caused since vehicles need to drive towards the operational facilities. We found that the introduction of additional decentralized operational facilities helps to reduce VKT and quantified the effect.

Our study contributes to the quickly evolving field of on-demand mobility in urban environments and supports future service introductions with or without autonomous vehicles. It is expected that it will take decades for autonomous vehicles to become widely accepted, so the operational aspects of a human-driven service will need to continue to be considered in the future.

The economic evaluation of the service needs to be followed up in future studies and is critical for user acceptance and a sustainable business model. We have presented several studies that consider the impact of mode choice, which must be taken into account for a comprehensive economic evaluation.

CRediT authorship contribution statement

Felix Zwick: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Visualization. **Nico Kuehnel:** Conceptualization, Methodology, Software, Validation, Formal analysis,

[7] https://github.com/matsim-org/matsim-libs/tree/master/contribs/drt/src/main/java/org/matsim/contrib/drt/extension

Investigation, Resources, Data curation, Writing – original draft, Visualization. **Sebastian Hörl:** Conceptualization, Writing – review & editing.

Acknowledgments

We thank Antonia Pawlowski for testing the new simulation features. We thank Giuliana Armellini for the preparation of MOIA input data. This work was funded by MOIA GmbH.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: It is acknowledged that Nico Kuehnel and Felix Zwick are employed at the ride-pooling provider MOIA.

Appendix

See Tables 11 and 12.

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