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Ride-Pooling Efficiency in Large, Medium-Sized and Small Towns - Simulation Assessment in the Munich Metropolitan Region

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Abstract

This study introduces an autonomous ride-pooling service to six communities with varying population sizes and trip densities in the Munich Metropolitan Region. We analyze a) a laissez-faire scenario without additional policies, defining the modal shift through an incremental mode choice model and b) a draconian scenario in which each within-city car trip is replaced by ride-pooling. Results indicate a logarithmic increase in system efficiency with increasing trip densities. While the results confirm the potential of ride-pooling systems to reduce private car fleets drastically, a reduction of traveled km is identified for scenarios with more than 1,000 requests per km^2 per day.

Keywords: On-demand mobility; Ride-sharing; New mobility; Population density; Pooling efficiency; Shared autonomous vehicles

1. Introduction

In the course of digitization on-demand transport services have emerged world-wide. They offer a personalized and convenient transportation service bookable via smartphone app, and promise to reduce required resources to satisfy mobility needs compared to a system in which everybody drives alone in a private car.
There are multiple studies assessing the impacts of on-demand services. While private cars are usually only used for a few daily trips of one person, hailed vehicles can serve multiple travel parties, and thus, the number of required vehicles is reduced [17, 9]. Unpooled on-demand services generally lead to an increase of vehicle kilometers travelled (VKT) due to additional trips to pick up customers and to reallocate vehicles to areas with high expected demand [7].

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When trips are pooled, meaning that trips with a similar route are undertaken in the same vehicle, the potential to reduce fleet sizes and VKT increases [17]. In this paper, we investigate the potential of pooled on-demand mobility in six different cities with population sizes ranging from 16 thousand to 1.5 million inhabitants and quantify the impact of request density on service efficiency. The work is based on a previous simulation assessment introducing ride-pooling (RP) in Munich [22].
A market analysis by Foljanty [6] showed that there were more than 200 active ride-pooling projects as of September 2020, most of which were launched after 2015. While the largest ride-pooling service by Via [20] employed a fleet of more than 6,000 vehicles in New York City in 2019 [19], most of the mentioned services operate with small fleet sizes below 50 vehicles. The majority of the services are designed either as a feeder service for the first/last mile to transit or in scenarios with low-demand densities to replace inefficient bus routes.
Reck and Axhausen [18] investigated multiple first/last mile feeder on-demand services and point out that for many of the services ridership is below the previous expectations of the respective promoters. They conceptually explain the low usage by the additional transfer and wait times and by the additional costs that often exceed values of travel time savings of potential users. Given these challenges, there is a risk that trips cannot be efficiently bundled due to a low density of demand, resulting in an increase in VKT.
The impact of varying demand densities on fleet sizes and pooling rates has been analyzed in a recent study by Kaddoura and Schlenther [10]. They used population samples ranging from 5 % to 100 % in two German regions and find disproportionately small pooling rates at low population samples and demand densities. In this study, we consider 100 % population samples throughout all scenarios in order to represent realistic pooling efficiencies.
While there are multiple studies quantifying the impact of ride-pooling, we did not find any papers analyzing the effects of ride-pooling for different town sizes and urban environments systematically. We introduce an autonomous ride-pooling system with equal service parameters in six different towns in Bavaria, Germany, employ a mode choice model to define mode shifts and simulate a ride-pooling fleet large enough to serve all customers. Thereby, we provide relevant statistics to predict the efficiency of ride-pooling services in varying urban contexts.

2. Methodology and Simulation Setup

The methodology is in line with [22] to ensure comparability of the five newly developed scenarios here and the mentioned simulation assessment for Munich.
The open-source agent- and trip-based demand model MITO (Microscopic Transportation Orchestrator) [13] was used to obtain travel demand for each agent of the synthetic population of the Munich metropolitan area. The synthetic population includes persons, households, jobs and dwellings and was prepared with an iterative proportional updating method [14]. The multi-agent transport simulation MATSim [8] was used to assign all agents' car and ride-pooling trips on the network, which was derived from OpenStreetMap (OSM) [16].
For the simulation of ride-pooling we made use of the *drt* extension introduced by Bischoff et al. [5]. We implemented a door-to-door service with a maximum wait time of 10 min and a maximum detour of 10 min + 50 % of the travel time for the trip without detouring. The stop duration is set to 30 s. We enabled the default rebalancing described in [4]. All service parameters are in line with the door-to-door scenarios in [22].
The study area with the six considered service areas is shown in Figure 1. Each cell of the study area is pigmented according to the number of trips departing in the respective cell. The service area in Munich is derived from [22], while all other service areas were selected to cover the most densely populated areas (in relation to the community's total population) in and around each city border. They display a range of population sizes and densities and represent each of the four Bavarian city typologies [2].
The characteristics of each service area are shown in Table 1. The population numbers were obtained from [3] and account for the entire city that can slightly deviate from the population size in the respective service areas. The car ownership rate is based on the synthetic population of each service area. Car ownership was not included in official census data and is not controlled as such. However, a car ownership model was estimated based on socio-demographic attributes, such as income, home area type, distance to transit and driver licenses [15].
We simulated two scenarios for each service area: A *laissez-faire* scenario in which autonomous ride-pooling is implemented and available to all agents for within-service-area trips and a *draconian* scenario in which all car trips within the service area are replaced by ride-pooling trips. The mode choice results in the laissez-faire scenario were

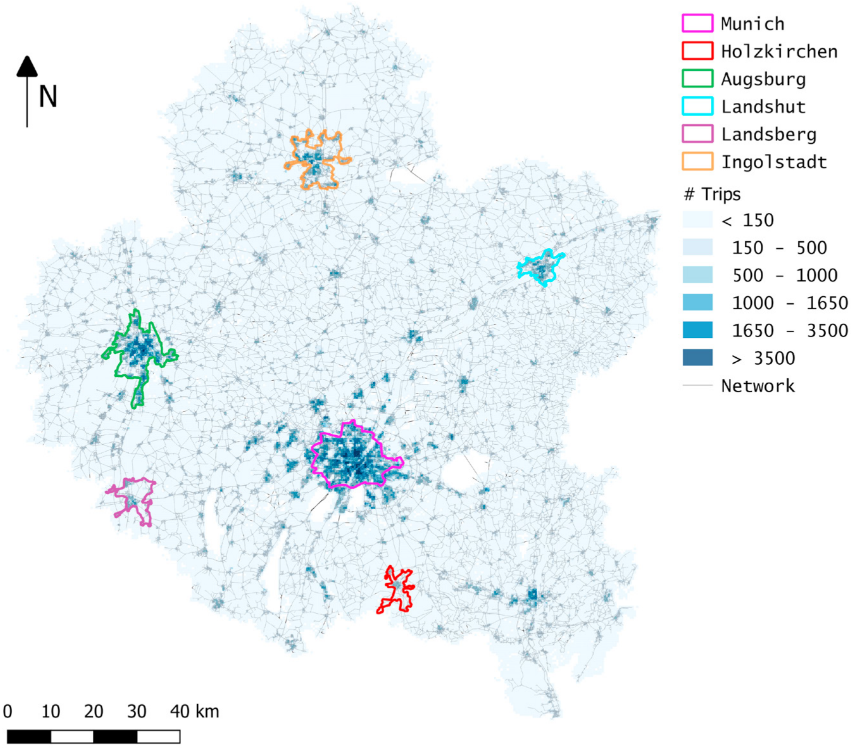

Fig. 1. Study area overview including six service areas.

Table 1. Service area characteristics.

Area	Population	Mean car ownership per household	Service area size [km^2]	Laissez-faire scenario: RP share [%]	Laissez-faire scenario: RP trips	Laissez-faire scenario: RP trip density [trips/km^2]	Draconian scenario: RP trips	Draconian scenario: RP trip density [trips/km^2]
Munich	1,471,104	0.775	195.7	16	503,037	2,570	1,912,783	9,774
Augsburg	295,216	0.795	127.4	15	132,802	1,042	521,783	4,096
Ingolstadt	137,408	0.901	98.8	14	35,408	358	246,957	2,500
Landshut	72,560	0.998	40.6	12	16,382	403	128,623	3,168
Landsberg	29,165	1.228	50.2	11	4,209	84	61,443	1,224
Holzkirchen	16,750	1.237	34.1	7	653	19	30,536	895

determined with an incremental logit model approach described by Koppelman [11]. The choice parameters for ride-pooling are based on the *car passenger* mode in MITO's default mode choice model, with updated generalized costs that take into account waiting and detour time as well as costs of the service. The modal shifts towards ride-pooling increase with the population size. Reasons can be the lower car ownership in large towns and longer trip distances.

In the draconian scenario, we first employed a full-scale base case simulation of MITO's car travel demand in MATSim and let it iterate until equilibrium was reached. Thereby, we identified trips that enter, leave or are completely inside each use case's respective service area. In the next step, we cropped all trips outside of the service area and replaced the remaining car trips by ride-pooling, such that agents will arrive or leave the service area at the same time and location as they would have in the car simulation. As this scenario mimics a policy in which the usage of private cars inside the service area is completely forbidden, trips that cross the service area are not considered as they are expected to route around the service area in reality.

3. Service Results

The ride-pooling service was evaluated for each scenario with a focus on system efficiency. Table 2 shows the service performance indicators for each scenario. The required fleet size is defined by the maximum number of vehicles in service, i.e. transporting passengers or driving towards a pick-up or relocating, at the same time over the course of a day. We do not account for additional vehicles that are required due to charging or maintenance breaks to ensure comparability across the scenarios. However, the input fleet sizes are slightly larger. The service level is similar across all scenarios with an average wait time between 4:29 minutes and 5:38 minutes, with the exception of the laissez-faire scenario in the small city of Holzkirchen with an average wait time of 2:50 minutes. The mean detour ranges between 37 % and 51 % with the highest detour rates in small service areas with short trip distances. The rejection rate is below 0.2 % for all scenarios.

Table 2. Simulation results for each scenario.

	Area	Required fleet size	Mean direct trip distance [km]	Mean detour [%]	Mean wait time [min]	PKB/ vehicle	η_{RP}	Mean occupancy
Laissez-faire scenario								
	Munich	5,672	6.6	42	5:34	589	1.72	2.39
	Augsburg	1,430	5.8	41	5:38	541	1.48	2.02
	Ingolstadt	346	4.9	42	5:13	497	1.33	1.81
	Landshut	137	3.6	51	4:59	430	1.21	1.73
	Landsberg	39	2.6	51	4:28	285	1.02	1.48
	Holzkirchen	8	2.1	37	2:50	171	0.88	1.07
Draconian scenario								
	Munich	16,699	6.9	40	5:30	786	1.89	2.55
	Augsburg	4,671	7.0	39	5:14	781	1.77	2.36
	Ingolstadt	1,882	6.0	37	5:11	795	1.70	2.27
	Landshut	834	4.4	48	5:00	681	1.60	2.27
	Landsberg	453	4.9	37	4:49	665	1.47	2.00
	Holzkirchen	194	4.3	42	4:29	680	1.39	1.94

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

To define the system efficiency, we measured the passenger kilometers booked (PKB) in each scenario through the product of ride-pooling trips and the mean *direct* trip distance. The PKB value reflects the number of kilometers that would have been driven if all agents had travelled alone in a private vehicle. Per vehicle, up to 600 PKB are covered in the laissez-faire scenarios and up to 800 km are covered in the draconian scenario. Considering average trip distances far below 10 km, this result shows the enormous potential to reduce the required vehicle fleet size and is an important indicator for ride-pooling operators to estimate fleet sizes for a given expected demand.
A performance indicator for ride-pooling systems is the system efficiency, η_{RP}, defined as the ratio of the passenger kilometers booked (PKB), d_{PKB}, to the vehicle kilometers travelled (VKT), d_{VKT}, proposed by Liebchen et al. [12]. This indicator takes into account the following three factors:

- *mean detouring* (less detouring leads to higher efficiency), represented by the ratio of PKB, d_{PKB}, to the passenger kilometers travelled including detours (PKT), d_{PKT},
- *mean occupancy* (higher occupancy leads to higher efficiency), represented by the ratio of PKT, d_{PKT}, to the overall amount of vehicle kilometers driven occupied (VKO), d_{VKO} and
- *occupied km* (more occupied km, i.e. less empty km, lead to higher efficiency), represented by the ratio of VKO to vehicle kilometers travelled (VKT), d_{VKT}:

$$\eta_{\mathrm{RP}} = \frac{1}{\text{mean detouring}} \cdot \text{mean occupancy} \cdot \text{occupied km share} = \frac{d_{\mathrm{PKB}}}{d_{\mathrm{PKT}}} \cdot \frac{d_{\mathrm{PKT}}}{d_{\mathrm{VKO}}} \cdot \frac{d_{\mathrm{VKO}}}{d_{\mathrm{VKT}}} = \frac{d_{\mathrm{PKB}}}{d_{\mathrm{VKT}}}. \tag{1}$$

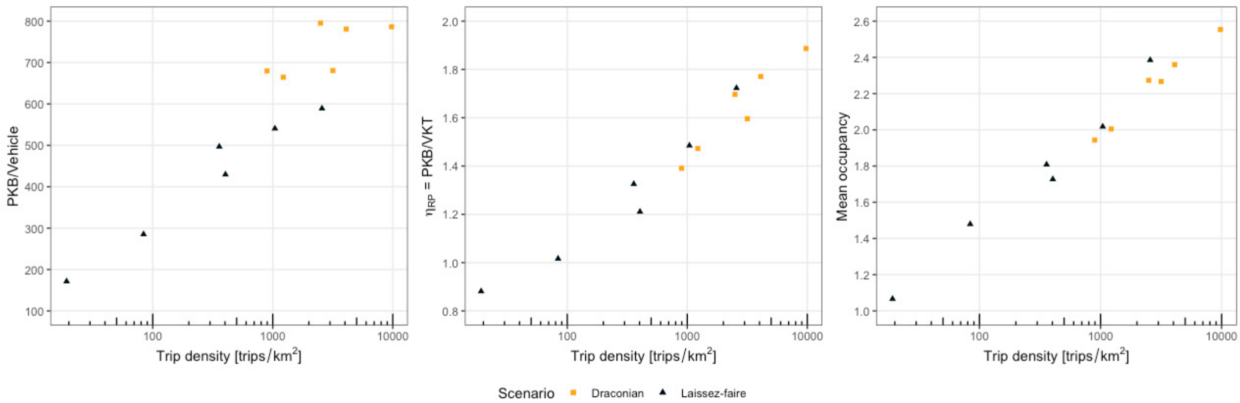

Fig. 2. Correlation of trip density and PKB per vehicle, PKB/VKT and average vehicle occupancy (note the $\log_{10}$-scale).

Liebchen et al. [12] give a value of 1.36 as the reference η_{RP} value for car travel, meaning that above this value the ride-pooling system causes fewer vehicle kilometers than if all passengers were driving by car (with a mean occupancy of 1.36). This value is calculated through the average occupancy of private cars in Germany but does not take into account other factors like parking search traffic or detours to avoid traffic. In the laissez-faire scenario, only the services in Munich and Augsburg exceed this value, whereas the draconian scenarios in all case study areas do.

The mean vehicle occupancy represents the average number of passengers in a ride-pooling vehicle for all driving vehicles over time, also taking into account empty km. Values vary from 1.07 to 2.55 and are higher in the draconian scenarios. It is noteworthy that group bookings, which would further increase efficiency, are not considered.

Figure 2 shows the three service-efficiency indicators plotted against trip density on a logarithmic scale. All indicators generally increase with increasing trip density. The PKB per vehicle increase logarithmically for the laissez-faire scenarios. In the draconian scenario, we observe stagnating values around 700 km for the smaller cities Landshut, Landsberg and Holzkirchen and around 800 km for the larger cities Munich, Augsburg and Ingolstadt, which might exhibit natural limits of the system. It also shows that PKB per vehicle do not only correlate with trip density but also with other factors, such as service area size, trip distances and total number of trips. Operational challenges like driver or charging breaks can decrease the efficiency of each vehicle and should be included in future research. The increases of η and mean occupancy with increasing trip density show a clear logarithmic pattern throughout all scenarios.

4. Conclusion

This study systematically analyses the system efficiency of ride-pooling systems in six urban areas with varying population sizes and densities. We show a clear logarithmic relationship between trip density and the system efficiency indicators η and *mean vehicle occupancy*. Liebchen et al. [12] stated that a positive impact on traffic compared to a system with everyone travelling by car is reached with a η value above 1.36. We observe that a daily trip density of at least 1000 trips/km^2 is necessary to reach this value. Current real-world ride-pooling implementations for first/last mile feeder services or in sparsely populated areas face much lower request densities, and thus a low utilization can be expected alongside the challenges mentioned by Reck and Axhausen [18]. Despite the low efficiency, a system facing such low demand may still add societal value if the attractiveness of public transportation is increased. Furthermore, we observe a great potential to satisfy the same travel demand with substantially fewer vehicles throughout all scenarios. In this study we only focus on one on-demand system with the same service parameters throughout all scenarios. Other ride-pooling policies like the one proposed by Alonso-Mora et al. [1] might lead to a more efficient pooling of passengers in different spatial environments. However, as shown by Zwick and Axhausen [21], the potential for an efficiency increase is rather low in scenarios with low rejection rates. A further potential could be the implementation of a non-on-demand system that pre-optimizes trips long before the trip departures. Future research may incorporate functionalities to collect pre-booked rides and assign the most efficient allocation in advance. Another limitation of this study is the consideration of an optimized autonomous service without any operational challenges, such as driver shifts and breaks, charging for electric vehicles, delayed passengers or construction sites. Future studies should define the impact of these challenges for electric non-autonomous ride-pooling services.

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