AUTONOMOUS RIDE-POOLING IN HAMBURG - RESULTS FROM AN INTEGRATED TRAVEL DEMAND AND FLEET SIMULATION MODEL

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ABSTRACT
More and more mobility services are appearing on the market that provide customers with a good alternative to private cars through demand-responsive offerings. Since the impact of these services is not always positive, hopes are currently pinned on ride-pooling. Currently, the effects of these bundled trips on the transportation system is limited due to e.g., to small fleets. As drivers account for a large proportion of operating costs, an automated fleet holds great potential for cost reduction and hence a large-scale roll-out. In this study, the traffic effects of an automated ride-pooling service are investigated using the city of Hamburg, Germany as an example. For this purpose, an agent-based travel demand model (mobiTopp) is coupled with a fleet simulation to model the demand and supply sides in detail, respectively. Simulations show that a reduction of fares and a larger service area as well as a larger fleet help to decrease the total vehicle kilometers traveled of private vehicles and mobility services combined. The ride-pooling demand increases by factor 12 while fleet performance indicators improve: The empty mileage decreases from 28.7% to 15.9% and the vehicle occupancy increases from 1.3 to 1.7. A larger service area leads to longer trips on average. However, a base fare guarantees that the number of trips for both active modes and public transportation is hardly affected.

Keywords: ride-pooling, mobility-on-demand, autonomous mobility

INTRODUCTION

The popularity and utilization of mobility-on-demand services have surged in the last decade. A goal of these systems is that the population becomes less dependent on private vehicles. Therefore, these services have a similar goal as public transport and want to be viewed as complements, which can offer comfort and service levels comparable to the private vehicle. However, today's implementations of mobility-on-demand systems still have several shortcomings. The growth of carsharing seems to have stopped (*1*) and at its current scale, it has minor impacts on the whole transportation system. Ride-hailing systems actually seem to increase the level of congestion on the streets (*2*), especially due to a large share of deadheading of approximately 40 %. The combination of ride-hailing and ride-pooling with users having the option to choose between both also seems to have overall negative impacts (*3*). For this reason, pure ride-pooling services have emerged, where all users implicitly agree to share a ride by using this service. However, even the largest ride-pooling fleet in Europe, namely MOIA, with its fleet of a few hundred vehicles operating in Hamburg, Germany, has currently minor impacts on the transportation system. The cost structure with drivers prohibits offering the service at a cheaper price point, which will be necessary to attract more demand and upscale the ride-pooling system. Recently, it was announced that the service will be operated with autonomous vehicles starting 2025 (*4*).

The goal of this study is to estimate impacts of such ride-pooling system at a much cheaper price point. This study benefits from having real-world data of the current ride-pooling service, which serves as a starting point for further scenarios. Nevertheless, the effect of a cheaper fare can only be investigated with the help of models for supply, demand and their interaction. In order to estimate future demand, it is necessary to reproduce the operational details of a ride-pooling service as major trip characteristics such as waiting or in-vehicle time strongly depend on the state of the fleet and routing strategies.

LITERATURE REVIEW

The operational aspects of vehicle fleets have been studied in so-called vehicle routing problems and research intensified with the introduction of mobility services utilizing mobile-internet (*5*). This type of studies typically assume exogenous demand to compare different solution strategies. Among other strategies, recent studies include heuristic insertions of new requests (*6*), global optimization of currently known vehicle-request assignments (*7, 8*) and repositioning of vehicles to prepare for expected future demand (*9, 10*). Studies showed that ride-pooling could decrease congestion in general (*11*), but that door-to-door service might still increase traffic in minor roads (*12*). To avoid this, methods for travelers to meet at designated pick-up and drop-off locations were developed (*13, 14*).

In general, the traveler perspective is modeled with demand models. Macroscopic four-step models help to estimate the number of trips between given origin-destination pairs. However, agent-based demand models are beneficial in the ride-pooling context as the trips of individuals are combined into one itinerary, which cannot be depicted properly in aggregated models. Agent- and activity-based models use a much higher resolution to better cope with the heterogeneity in the population (*15*). To this end, the travel behavior – including important aspects such as destination choice and mode choice – of an area's population is modeled by the attributes of the agents. Discrete choice models require both characteristics (specific for e.g. a destination or trip with a certain mode) and coefficients representing the agents' attitude towards these characteristics.

Several studies, mostly as stated preference and sometimes as revealed preference, have evaluated these characteristics, also with respect to ride-hailing and sometimes ride-pooling (*16, 17*). Alonso-González et al. (*18*) found that respondents had a higher willingness to pay for pooled on-demand services compared to conventional public transport. Further, they found reliability to be more important than travel time for waiting and in-vehicle stage. Morsche et al. (*19*) investigated demand-responsive transport (DRT) preferences in the Netherlands. They concluded that more flexible demand-responsive transport systems are more attractive for the respondents and that current travel behavior is a good predictor for future mode choice. Further, there are different investigations on users in pilot projects (*20, 21*). Due to the different framework conditions (e.g., smaller service areas, smaller fleets, lower prices), it is, however, questionable how well the results correspond to urban transportation systems and large-scale applications that are conceivable in the future. For example, König and Grippenkoven (*22*) found that respondents, who have experienced ride-pooling, value service attributes differently than people without former experience. Hence, it can be assumed that surveying real users provides more realistic results when modeling future behavior. Therefore, within the MOIA accompanying research, Kostorz et al. (*23*) surveyed a large-scale user basis of a well-established ride-pooling service for the first time to deepen knowledge on users and usage patterns. The information obtained in this investigation serves as a data source for the model in this study.

The effects that autonomous vehicles will cause are still uncertain and range from "no substantial effects on travel behavior" (*24–26*) to "disruption in car ownership and usage" (*27*). There is greater agreement that automation holds potential for a simplified shared use of vehicles. However, most studies so far focus either on privately-owned autonomous vehicles or autonomous carsharing (e.g., (*28–32*)). Pooled autonomous services are rather rarely investigated. Stoiber et al. (*33*) found that pooled shared cars are more attractive as they are more efficient than regular cars. Lavieri and Bhat (*34*) confirm the willingness to use shared autonomous vehicles with strangers on commuting trips, as long as waiting, pick-up and drop-off times are reasonable. Thomas states that many customers of driverless mass transit are not aware of the fact that the systems run without an operator (*35*). Further, he claims that customers believe in the proof of concept before implementing such systems. Hence, this study – as many others – does not consider uncertain effects on the attitude towards autonomous vehicles. Furthermore, it is possible that automated driving becomes the new normal and the absence of a driver does not affect the decision-making of travelers.

Autonomous vehicles provide a new cost structure to mobility systems (*36, 37*). Thereby, much lower fares can be offered to users, which in turn can attract more demand (*38–40*). Liu et al. (*38*) investigated the impact of an autonomous hailing system in Austin, Texas. They found a sharp increase in demand for fares between 0.75 $ and 0.5 $ per mile, for which the modal share reached up to 43.3%, and made a sensitivity analysis for the required fleet sizes. Oke et al. (*39*) studied the effects of automated mobility-on-demand systems for auto-dependent cities (based on a Boston, Massachusetts model), for which the mode share of private vehicle is above 75%. They reduced the fares for both ride-hailing and ride-pooling by 50% and assumed that the share between ride-hailing and ride-pooling remains similar to today. In their study, the modal share for autonomous mobility-on-demand (AMOD) was twice to three times as high as in the current scenario with manually driven vehicles. Due to the extensive use of hailing, they observed increased levels of congestion, especially if AMOD was introduced as a replacement of mass transit, which previously had a modal share of approximately 11% in so-called auto innovative cities. Wilkes et al. (*40*) introduced a new framework, in which the mode-choice of an agent-based model is based on real-time fleet control and information, thereby reaching balance between supply and demand in single simulations. They studied the fleet behavior and price-sensitivity towards a ride-pooling service in a small German town with approximately 20,000 inhabitants.

We extended the framework of Wilkes et al. (*40*) by intermodal trips, a rebalancing module for idle vehicles and some heuristics to apply their methodology to a large-scale case study in Hamburg, Germany, with millions of people. In contrast to the before-mentioned studies, the status quo contains a high share of public transport users and focuses on a pure ride-pooling system to mitigate the negative impacts of ride-hailing. Moreover, we included data from a large-scale survey with more than 10,000 participants into the mode-choice model (*23*). As the majority of respondents had already experienced the ride-pooling service in Hamburg, they knew the research object very well and could easily relate to their everyday behavior when answering questions concerning mode choice (including ride-pooling use). Moreover, fleet data from the ride-pooling provider could be used to calibrate the model.

MODEL OVERVIEW

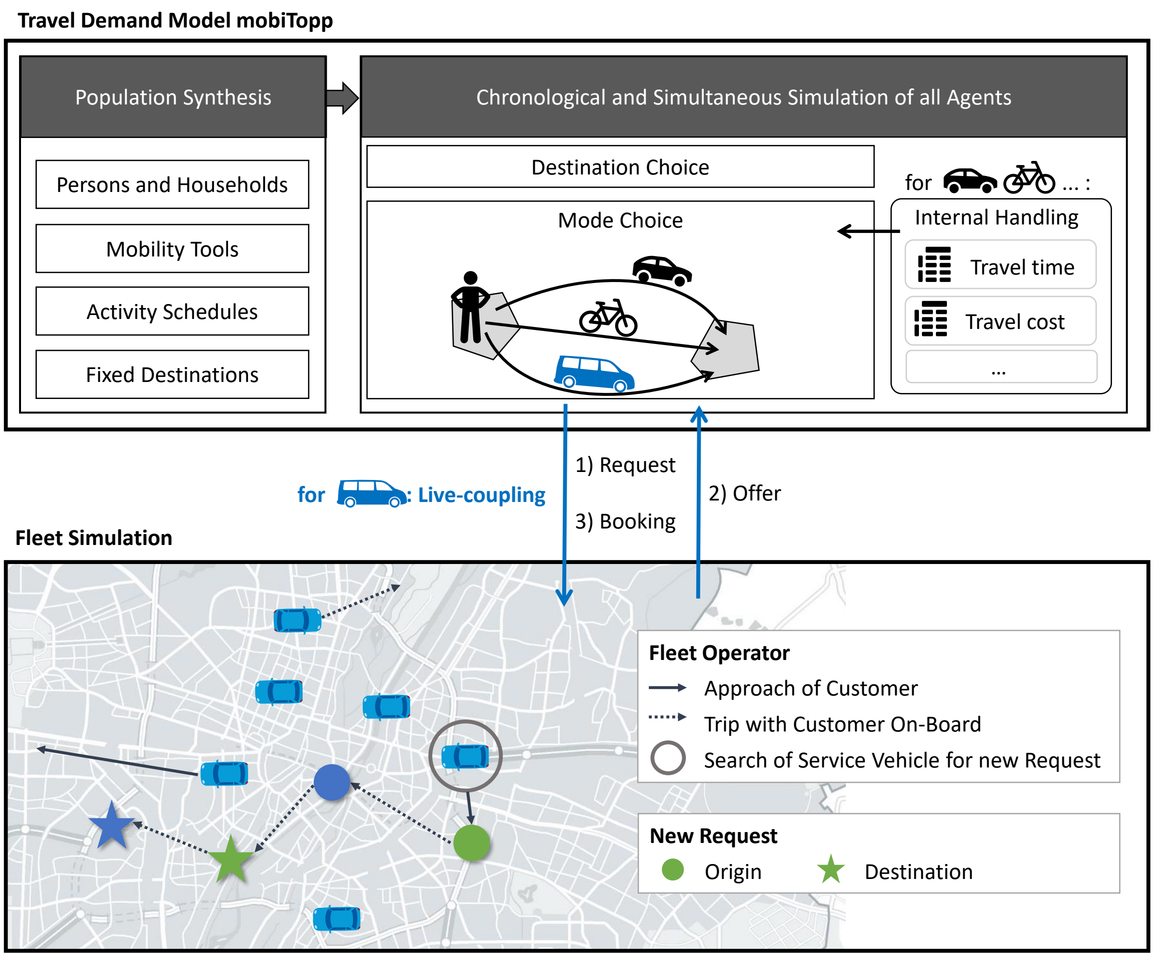

FIGURE 1: Overview of the entire simulation framework

mobiTopp

mobiTopp (*41, 42*) is an agent-based travel demand modeling framework. Agents, as defined by Bonabeau (*43*), represent the whole population of a designated planning area. Hence, it allows to model and to analyze travel behavior on an individual level. Travel demand emerges due to the agents' need to change locations to be able to perform activities according to their activity schedules.

mobiTopp consists of two sub-modules. A synthetic population is generated in the long-term module based on data from population statistics and mobility surveys. All agents are modeled with different sociodemographic characteristics such as age and sex, and belong to a certain household. Furthermore, specific mobility-related attributes are assigned like car or public transport pass ownership or the membership for mobility services. Besides an activity schedule, every agent receives a fixed place of residence and if necessary a fixed destination for working or educational activities to ensure consistency during the simulation.

The short-term module consists of the simulation of all agents' travel behavior for the whole week. Two main decisions have to be made for every trip: destination and mode choice. Destination choice is skipped, if an activity is related to a predefined destination (e.g., work, home or education) whereas mode choice is conducted on every trip. For every decision, both the agent's characteristics and the model's current state, for instance the agent's current location, the distances to potential destinations for the next activity and the availability of different travel modes are considered. In the model specification presented in this paper, a multinomial logit (MNL) is used for destination and a cross-nested logit (CNL) for mode choice. However, mobiTopp's modular structure allows to replace the models for every assignment or decision step, depending on the available data.

mobiTopp allows modeling intermodal trips, i.e., trips that consist of multiple legs performed with different modes (*44*). In mobiTopp, this is performed by a differentiation between main modes and access and egress modes. In the study at hand intermodal legs are allowed for public transport. This is modeled with a two-step process: (i) The accessibility to public transport with different access and egress modes is included in the mode choice of the main mode. (ii) When public transport is chosen as main mode, the explicit modes for access to and departure from public transport stations are chosen subsequently. For further details of the intermodal extension, the reader is referred to (*45*). For the present study, the intermodal extension was enhanced to allow for live coupling with the fleet simulation.

Coupling of mobiTopp and Fleet Simulation

To give mobiTopp's agents access to a realistic ride-pooling service, the mobiTopp framework is coupled with a separate ride-pooling fleet simulation framework. mobiTopp is the simulation master communicating with the fleet simulation at several occasions as depicted in Figure 2. There are three main communication blocks:

(1) mobiTopp communicates initialization and termination at the start and end of the simulation, respectively.

(2) Most of the messages between mobiTopp and the fleet simulation are sent in the offer phase. mobiTopp agents with a ride-pooling membership request trips from the fleet simulation. We distinguish between monomodal and intermodal requests. In case of a monomodal request, origin, destination, earliest pick-up time and group size are communicated to the fleet simulation. The fleet simulation evaluates the current fleet state and replies, if possible, with an offer consisting of access

and egress time to the closest pick-up and drop-off location, respectively, the expected waiting and driving time and the corresponding fare. These attributes are used by mobiTopp to perform the mode choice and communicate to the fleet simulation whether the trip is booked or declined. An additional feature of the framework is that agents can request intermodal trips. In this case, not only a single option for the ride-pooling leg of the trip is communicated to the fleet simulation but a set of 10 possible transfer options to or from a public transport transfer location for first or last mile trips, respectively. For each of these transfer options, the travel time of the public transport leg is additionally communicated. The fleet simulation internally computes suitable offers for each of these transfer options and communicates the previously mentioned attributes of the ride-pooling leg for the option that minimizes the total travel time, i.e. the sum of public transport and ride-pooling legs. Again, mobiTopp uses these attributes to perform the agent's mode choice and sends the decision to the fleet simulation.

(3) At the end of a time step, after all agents performed their mode choice decision, mobiTopp synchronizes the simulation time and triggers fleet state updates and optimization processes. In this synchronization step, the fleet simulation reports back those agents that finished their ride-pooling trip at the end of the time step.

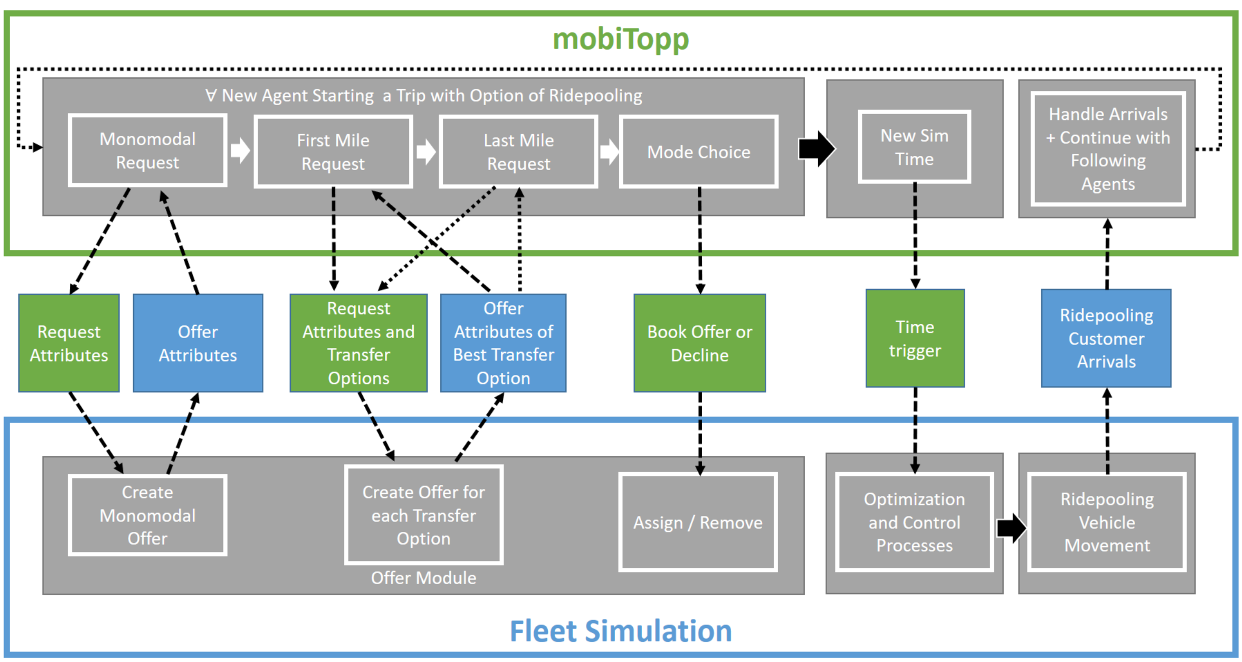

FIGURE 2: Flowchart of the main communication steps between mobiTopp and the fleet simulation

Fleet Simulation

The goal of the fleet simulation is to model the control of the ride-pooling fleet vehicles as well as the interaction of the operator with possible customers (agents) in high detail. Therefore, the fleet simulation is subdivided into four main modules: First, in the user-interaction module, the operator generates monomodal and intermodal offers as a response to agent requests which are triggered by mobiTopp. Additionally, the handling of accepted and declined offers are defined

here. Second, once all customer requests are processed and mobiTopp triggers a new time step, the re-optimisation module is called to recalculate vehicle-customer assignments based on a global optimization. Third, after time intervals of 12min vehicles are redistributed within the network according to expected future demand in the repositioning module. Fourth, a maintenance module is implemented, which manages the charging of fleet vehicles and activates or deactivates vehicles according to certain shift schedules. These modules are described on a high level in the following.
Fleet vehicles move on the street network according to assigned schedules. These schedules contain a sequence of tasks to pick up and drop off customers at specified locations in the network and their respective timings. Schedules are regarded as feasible, if for each customer the pick-up is scheduled before the dropp-off, the number of on-board passengers does not exceed vehicle capacities, pick-ups take place within an earliest and a latest pick-up time, and finally the in-vehicle time for each customer does not exceed a certain maximum detour time.
To create offers for mobiTopp's agents, an insertion heuristic is applied in the user-interaction module. In this heuristic requests are inserted into all currently assigned schedules of vehicles that can reach the request origin before the latest pick-up time elapsed. The schedule which minimizes the increase in system time is selected as the schedule, from which the offer is derived. Hereby, we define system time as the duration to finish all tasks in the schedule. In case the customer accepts the offer and books the ride, this schedule is assigned to the vehicle; otherwise the schedule is discarded.
A special case is the creation of offers to intermodal requests. In this case the mobiTopp queries a response to a set of 10 possible transfer stations with the corresponding public transport travel times to the destination or from the origin for first- or last-mile trips, respectively. An offer is created for each possible transfer option and the option that minimizes the overall customer travel time (with public transport leg) is selected as the ride-pooling offer by the fleet simulation. Because the start time of the ride-pooling trips can be far in the future for last-mile requests, an additional heuristic to find feasible vehicle schedules has to be applied to create the offer and maintain suitable computational time. Instead of all feasible vehicles, the search for feasible schedules is only applied for the N_v^{LM} vehicles closest to the pick-up location at the earliest pick-up time according to their currently assigned schedule.
Once all customer requests have been processed, a re-optimization of fleet assignments is triggered. The applied global optimization algorithm is based on the work of (*8*). Details on the implementation can be found in (*46*). On a high level, the idea of the algorithm is to, firstly, create all feasible schedules for all vehicle and customer set combinations. Secondly, these schedules are rated by the objective function of system time defined above. Finally, an integer linear optimization problem (ILP) is solved to assign schedules that primarily maximize the number of customers served and secondarily minimizes the total system time of all vehicles. In scenarios with high demand for ride-pooling, we prune the search for schedules by restricting the number of possible vehicles per customer by N_v^{heu}. The selection of vehicles only keeps those with the smallest schedule objective function value after inserting a customer into the initially assigned schedule. Additionally, a rolling horizon approach is applied to further constrain computational time. In this approach, only customers are included in the global optimization with an earliest pick up time within the next 12 min. Finally, an optimization time out of 30 s is applied for solving the ILP (as implemented in the Gurobi software package (*47*)).
In the repositioning module, triggered every 12 min, idle vehicles are redistributed within the operating area to prevent local supply shortages. The operating area is divided into zones. Because the

demand is endogenous, no forecasts are available to base the repositioning algorithm on. Therefore an approach is implemented that tries to stabilize local vehicle densities. For each zone the number of available vehicles and incoming vehicles is counted and normalized to create the initial vehicle distribution. The temporal constant target vehicle distribution is based on the number of inhabitants and trip attraction factors per zone extracted from the mobiTopp model. Vehicle repositioning trips are then computed by applying the algorithm of (*48*). Lastly, in the maintenance module charging as well as activation and deactivation of fleet vehicles is managed. If a shift schedule is applied, vehicles are getting activated or deactivated at specific points in time according to this schedule. Vehicles that are deactivated are sent back to the closest not fully occupied depot and cannot be used to serve customers anymore. In case a vehicle schedule to serve customers is assigned at the time of deactivation, these customers have to be served before returning to the depot. If additional vehicles should be activated, those inactive vehicles with the highest charging states become available for customer transport. Each time vehicles are activated, the repositioning module is called to redistribute activated vehicles in the operating area. If the current vehicle range drops below 10%, vehicles are sent to the next unoccupied charging station. They are not available for service until they reach full range according to battery size and charging power of the station. For a simulation of an autonomous fleet, the charging logic remains the same. Besides that, autonomous vehicles are assumed to be available 24/7 and therefore are never deactivated.

CASE STUDY

An agent- and activity-based travel demand model of Hamburg, Germany was created using mobiTopp. In the model, the population of the city of Hamburg and its vicinity, tourists and business travelers are integrated. In total, around 4.9 million agents are modeled. Out of these, 4.1 million are inhabitants which are grouped in 2.1 million households. The inhabitants are based on a population synthesis, which integrates population data concerning age, gender and household sizes with a high level of spatial detail (see Figure 4 for the zone structure). Furthermore, car ownership, transit pass ownership, and the membership for various mobility services (incl. ride-pooling) are modeled using multiple data sources and discrete choice methods. Tourists and business travelers are added to the population using the touriTopp module (*49*). Activity plans are assigned to inhabitants and tourists using synthesized data from actiTopp (*50*) and activity schedules from surveys, respectively.

The model contains all relevant travel modes that are currently available in Hamburg: besides the standard modes walking, bicycle, public transport, car as driver, car as passenger and taxi, also the shared mobility options bikesharing, e-scooter-sharing and carsharing are represented. All modes are modeled at high resolution, e.g. car and public transport use time-of-day- and day-of-week-dependent travel times, bicycle travel times are based on current bicycle infrastructure, and shared mobility services are offered in the actual business areas and with current prices. Moreover, the agent-based approach allows to consider mode availability restrictions, for example, only people with carsharing membership and driver license can use that mode. The applied mode choice model is estimated from joint revealed and stated preference data, mainly from a nation-wide household survey ”Mobilität in Deutschland" (MiD, Eng: "Mobility in Germany") and a specific MOIA user and non-user survey in Hamburg including a stated choice experiment (*23*). The model is calibrated with real-world travel behaviour, using mainly the survey MiD data from 2017 (*51*), which includes a large sample of travel patterns from residents of the city of Hamburg. We estimated and use a cross nested logit model as illustrated in Fig. 3, in which ride-pooling is part of several nests. Thereby, the interactions between ride-pooling and other modes can be modeled especially well.

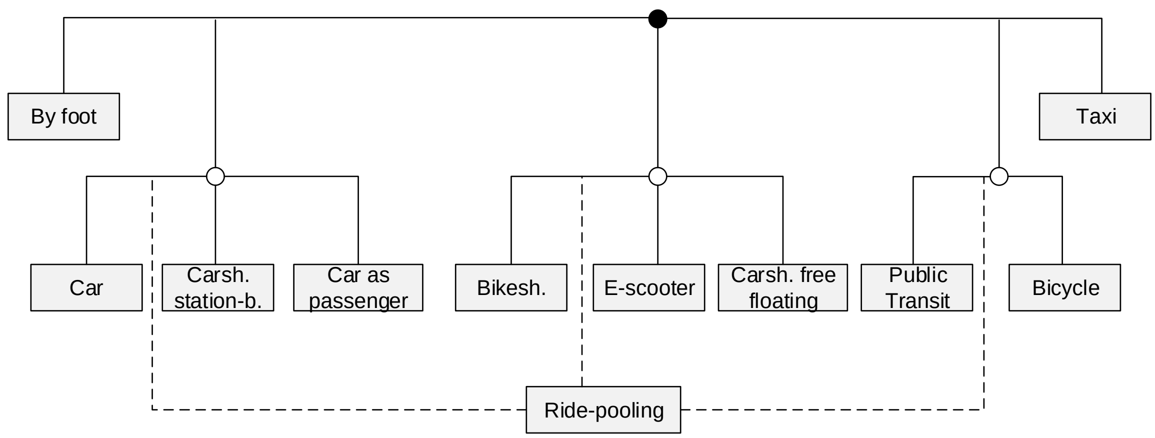

FIGURE 3: Nest structure of the cross nested logit model used for mode choice.

A special focus of the model is on ride-pooling. Real-world ride-pooling user and booking data were used to calibrate the demand and supply (fleet control) model in order to reproduce the actual MOIA ride-pooling service in Hamburg (see (*52*)). Best results to match data and simulation have been obtained by using the described fleet control model with request time constraints of 12 min for the maximum waiting time, 40% maximum relative detour compared to a direct trip and additionally 5 min absolute detour time. A boarding time of 2 min is assumed, which is longer compared to the actual service, but is used to accommodate breaking and acceleration processes and imperfect driver behaviour. The objective function "system time" is used with the goal to serve all customers as fast as possible, but it is worth mentioning that a more complex objective function is used in reality. Reproducing the real service, electric vehicles with a passenger capacity of 6 are simulated with a maximum range of 300 km. Depots with local charging stations are placed in the Hamburg network as operated today. In the case of large ride-pooling fleets, depot parking capacities as well as charging capacities are scaled up according to the scale factor of the increased fleet.

In the present case study, two different scenarios are studied. The **base scenario** represents a situation in the near future, in which the current developments are extrapolated. These developments include measures that are not present today, such as expanded freeways, new bicycle facilities, and improvements in the public transport system. Furthermore, the inhabitants are extrapolated towards the year 2028 based on a current prognosis. However, the ride-pooling service area illustrated in Fig. 4 remains in a scale comparable to today's MOIA service area covering mainly the inner parts of the city (192 m^2). Using a fleet size of maximally 500 vehicles over the course the whole day and a potential user base of around $300,000$ people, the service is scaled up by a factor of two compared to today's size. Because not all vehicles are active during the whole day in the real service and the time dependent number of active vehicles is recreated from real data, at most 220 vehicles are available during the morning peak. Furthermore, the costs for using ride-pooling are the same as they are today for the MOIA service: Each customer has to pay a base

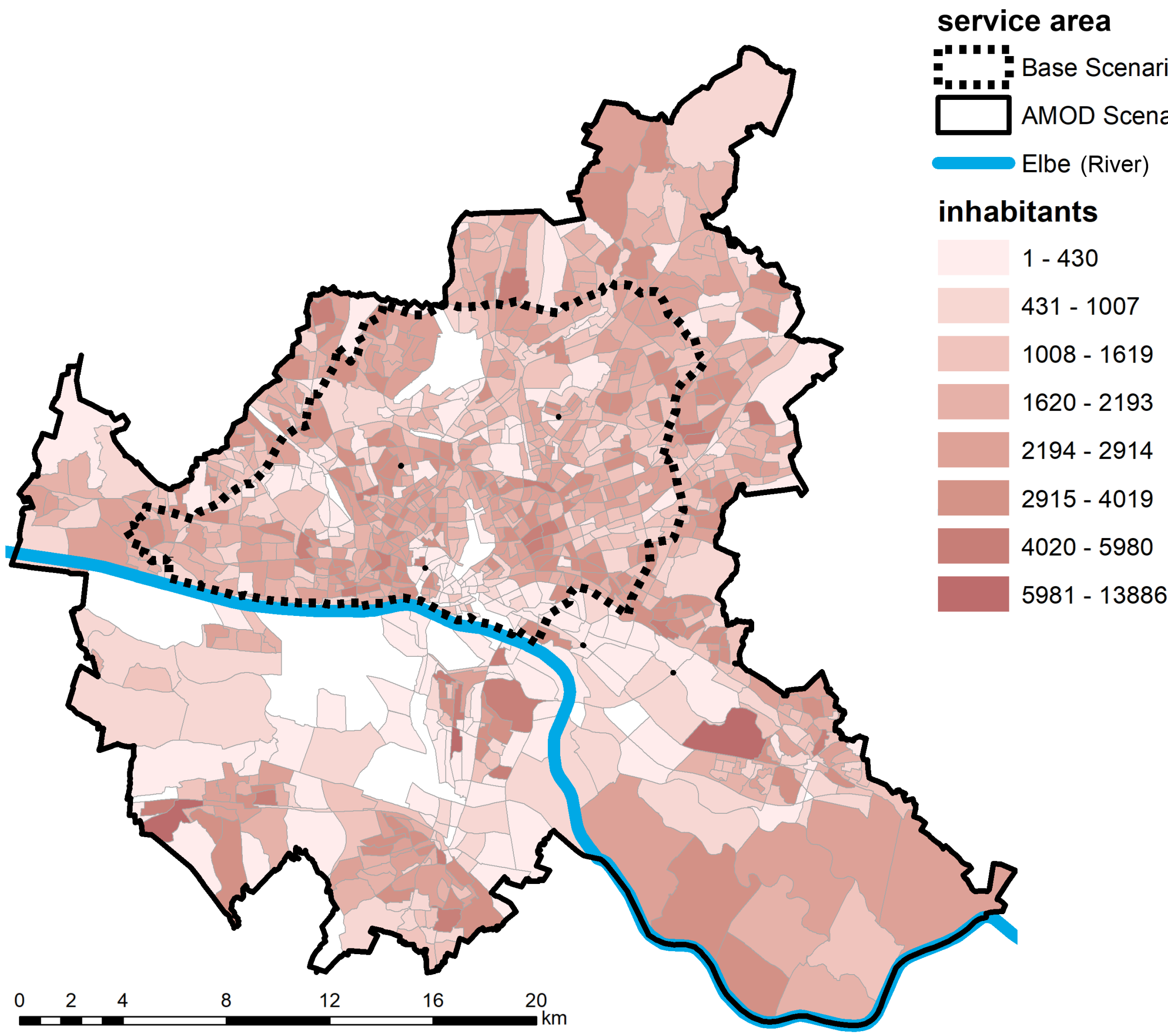

FIGURE 4: Model planning area with the zone structure, number of inhabitants per zone, and the ride-pooling service areas of both scenarios. The service area in the AMOD scenario is equal to the city boundaries of Hamburg. For the sake of simplicity, only the city of Hamburg is shown, however, also the inhabitants from the surrounding area are modeled.

fare of 4.30€, which includes the first 2km of the trip. Each additional km costs 0.5€. Fares for groups and time dependent pricing is implemented.

In the **AMOD scenario**, the general setting is the same as in the base scenario. However, it is assumed that ride-pooling is operated with an autonomous fleet, which is modeled by the costs for the users being only one quarter of the current prices. As a consequence of the cheaper service, the service area has expanded to the entire city of Hamburg and the user base has grown to 1 million people. Additional depots for the larger service area are added in the outskirts of Hamburg for a spatially balanced distribution. The fleet size is calculated based on the potential demand (see next section). It is important to mention that the crucial parameters for decision-making remained the same in all scenarios, corresponding to the manifestations obtained during the calibration. Only the before-mentioned framework conditions were changed to design the simulation study as realistic

mode	trips Base Scenario	AMOD Scenario	modal split Base Scenario	AMOD Scenario
By foot	325,393	324,942	23.69%	23.67%
Bicycle	185,461	181,539	13.50%	13.23%
Car	271,938	265,296	19.80%	19.33%
Car as passenger	66,493	63,221	4.84%	4.61%
Public transit	512,814	511,964	37.34%	37.30%
Taxi	4,206	3,140	0.31%	0.23%
Sharing services	5,644	5,005	0.41%	0.36%
Ride-pooling	1,455	17,413	0.11%	1.27%

TABLE 1: Number of main trips per mode and trip-based modal split in both scenarios. This is filtered to trips that take place completely in the city of Hamburg (start and destination in Hamburg). Intermodal access and egress legs are not included.

as possible.

To retrieve suitable fleet size, we first performed a simulation run where the ride-pooling supply was considered unlimited. This was undertaken through simulating the ride-pooling mode statically inside of mobiTopp. The resulting demand for ride-pooling was afterwards used in a fleet simulation run to estimate the number of vehicles needed during the highest peak times.

RESULTS

Having an integrated model, we are able to analyze the impact of the ride-pooling service on the rest of the transport system. The current results are based on modeling the morning commuting peak during a week-day, starting from 6 AM to 9.30 AM. The number of main trips (i.e., access and egress legs are not included) for all modes is depicted in Table 1. Compared to the base scenario, in the AMOD scenario the share of trips using the ride-pooling service among all trips that take place in Hamburg increases from 0.11% to 1.27%. People use all other modes less, but the modes are impacted to different degrees. With a relative change of roughly -0.47 percentage points, the mode car loses most trips. Public transport, despite having the highest share among all trips, only loses 0.04 percentage points in the modal split. The autonomous ride-pooling service has a multitude of effects on public transport usage. On the one hand, the new service competes with the line-based public transport. On the other hand, this service can also be used as a first/last mile service to high-capacity public transport lines which results in better accessibility and hence a more attractive public transport. Additionally, a tour effect could become observable when evaluating longer time periods: travelers, who previously used the private vehicle to get to an activity and back, can use the ride-pooling service to get to the activity, and might use public transport on the way back as the private vehicle is no alternative for the return trip (consistency of vehicle location). All in all, Table 1 shows that the ride-pooling system can be viewed as one more alternative to the private vehicle complementing public transport. It is also noteworthy that there are hardly changes to the active modes, which shows that a base fare is still effective, even if it is just approximately one euro. Together with some waiting time and a possible detour, ride-pooling is not attractive for very short trips, which is good from a system point of view.

The operating area was also enlarged for the AMOD scenario, creating the possibility of

mode	Base Scenario	AMOD Scenario	relative change
By foot	0.96	0.95	-0.7%
Bicycle	3.39	3.34	-1.3%
Car	8.51	8.37	-1.6%
Car as passenger	6.42	6.25	-2.6%
Public transport	8.03	8.06	0.4%
Taxi	4.28	3.90	-8.8%
Sharing services	3.87	3.57	-7.7 %
Ride-pooling	6.43	8.24	28.2%

TABLE 2: Mean trip lengths by mode in both scenarios in km and the relative change. This is filtered to trips that take place completely within the city of Hamburg. Intermodal access and egress legs are not included.

	Base Scenario	AMOD Scenario	Difference
Person km	32,776,838	32,618,109	-158,729
Private vehicle km	14,361,220	14,227,264	-133,956
Ride-pooling fleet km	10,464	129,078	118,614

TABLE 3: Aggregated figures of person and vehicle mileage.

longer ride-pooling trips. Indeed, the mean trip length for ride-pooling increases by 26.8%. As shown in Table 2, the mean distances by most other modes decreases, thus the ride-pooling service attracts relatively long trips from these modes in the AMOD scenario. The largest change can be observed with the modes taxi and the other sharing services. Interestingly, the mean trip distance of public transport does not decrease, but even increases slightly. This is partially due to the phenomenon that the average trip length of intermodal public transport trips in combination with ride-pooling are longer in the AMOD scenario compared to the base scenario.

In Table 3 the main aggregated figures concerning total mileage are depicted. With increased availability of ride-pooling by the larger service combined with decreased fares, it is observable that the accumulated person distances decreases by roughly 0.5%. Looking at the private vehicle trips a decline of 134 thousand km can be observed. Combined with an increase in fleet km of 119 thousand km by the enlarged ride-pooling service, the total driven distance by passenger cars is reduced by 15 thousand km (0.1% compared to the overall driven distance of passenger cars in the base scenario).

Table 4 illustrates the ride-pooling fleet's key performance indicators for the two different simulation scenarios. While 2000 travelers chose the ride-pooling service in the base scenario, 10 times more customers booked the offer in the AMOD scenario, as a consequence of the extended user base due to the cheap fares. The base scenario was simulated with 500 vehicles (with manual drivers) and 3500 (autonomous) vehicles were utilized in the AMOD scenario. Even though the fleet size was increased only by factor of 7, the number of ride-pooling travelers increased by a factor of 10. In both scenarios, over 98% of agents that requested a trip also received an offer, showing that vehicle supply is still sufficient. Another indicator for the scaling property of

	Base Scenario	AMOD Scenario
Number Travelers	2,000	20,704
Created Offers [%]	98.8	98.5
Avg. Rel. Detour [%]	31.9	35.2
Avg. Wait Time [min]	5.9	5.0
Avg. Travel Time [min]	22.1	27.1
Avg. Occupancy [per/km]	1.3	1.7
Empty Vkm [%]	28.7	15.9

TABLE 4: Key performance indicators of the ride-pooling operator for the different scenarios. The number of travelers is distinct to Table 1 as here intermodal legs and possible companion riders are included.

ride-pooling can be observed when evaluating average vehicle occupancy and empty mileage that increase from 1.3 to 1.7 and decrease from 28.7% to 15.9%, respectively. These positive scaling properties can be explained by an increase of pooling possibilities with a higher number of customers and by a higher density of vehicles, which implicates less empty pick-up trips as well as a reduced need for spatial rebalancing. For the same reasons, the effects for customers are on the one hand a reduced waiting time by statistical closer positioning of fleet vehicles, while on the other hand the detour times increase because of the higher number of pooled trips. The average travel time of ride-pooling customers increases from 22.1 min in the base scenario to 27.1 min in the AMOD scenario due to the increased detour time and, additionally, longer trip distances in the larger operating area.

The effect of increased occupancy and decreased empty mileage can also be observed in Figure 5 where the different occupancy states of the ride-pooling vehicles are depicted over the time of the morning peak. Because of more pooling options and higher vehicle density, the fraction of emptily driving vehicles decreases and the fraction of vehicles with higher occupancy states increases when comparing the AMOD with the base scenario. The white areas in the plots reflect idle vehicles which is smaller in the AMOD scenario indicating a higher utilization of the fleet. This can be traced back to (i) the fleet size being scaled by only a factor of 7 compared to a demand factor of roughly 12 and (ii) longer vehicle trips induced by the larger operating area. On the other hand, the black curve in in Figure 5(a) illustrates the number of active vehicles in the base scenario reflecting driver shift schedules of the real service. It can be seen, that most of the idle vehicles are not available for service and that especially between 7 and 8 AM nearly full utilization of active vehicle is reached, which indicates a ride-pooling supply shortage. Nevertheless, since still most agents receive offers from the ride-pooling service this supply shortage is not very distinctive.

The length of the ride-pooling customer trips is shown in Figure 6. While in the base scenario an average trip length of 6.43 km is measured, it is increased to 8.24 km in the AMOD scenario (also see Table 2). Especially the fraction of trips longer than 15 km is enlarged due to the larger operating area. Nevertheless, in both scenarios the lion's share of trips is shorter than 10 km. Intermodal trips are shorter than 5km in nearly all cases. This is reasonable since the total fare is cheaper in most cases if the whole trip is composed of a long succeeding or preceding public transport leg. Nevertheless, only a fraction of 8.5% in the base scenario and 3.5% in the AMOD scenario of the ride-pooling trips is used as an access or egress trip to public transport. The

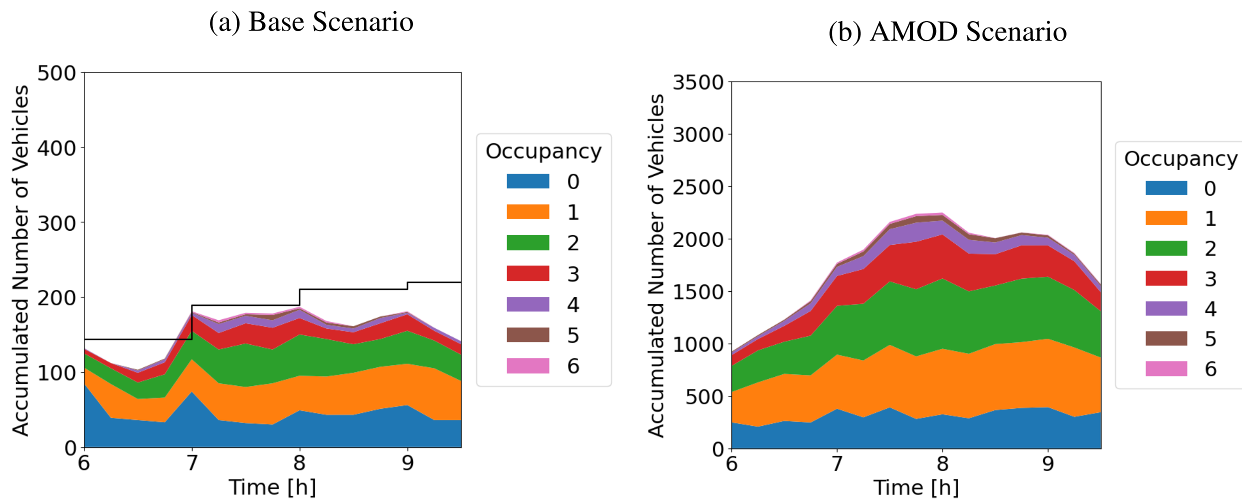

FIGURE 5: Ride-pooling fleet occupancy states for the different scenarios. The black curve in the base scenario illustrates the number of active ride-pooling vehicles. The slight overstepping of the active vehicle curve can be traced back to smoothing of the occupancy curves.

reasons are twofold: on the one hand, thousands of long trips previously made by private vehicle are replaced in the AMOD scenario; on the other hand, due to small fares many of these trips become monomodal ride-pooling trips rather than intermodal trips. Evaluating the composition of intermodal trips in first and last mile trips, a higher share is observed for last mile trips. One reason is the evaluation of the morning peaks and agents tend to travel from outside Hamburg into the ride-pooling service area to finish their trip with a ride-pooling leg. Another reason is a bias of the model towards last mile trips: because of scheduling the customer far in the future, the ride-pooling optimization can often find seamless connections for the last-mile trip, whereas an on-demand first-mile trip typically contains a waiting period.

CONCLUSION

The case study at hand investigates the possible impacts of an autonomous ride-pooling service by advancing a currently operating ride-pooling service in an European city, namely Hamburg, Germany. The automation was modeled by a reduction of ride-pooling prices to $1/4$, an increased operating area and user base and continuous vehicle availability. However, all crucial mode choice parameters remained the same in both scenarios. This study differs mainly in three aspects from existing studies: Firstly, and in contrast to studies from North American cities, the public transport system is widely used (mode share of approximately 35%). Hence, different modal shifts and in particular a different effect on public transport usage could be expected. Secondly, we used a comprehensive approach with detailed modeling of both, demand and supply side by combining an agent-based travel demand model coupled with a fleet simulation. These interdependencies are crucial when investigating on-demand mobility, as people react sensitively to delays in waiting and travel time. This aspect is often disregarded when assuming a given travel demand. Thirdly, the travel behavior for ride-pooling is based on data from a large customer-base from an existing service. Current users can assess the usage much better than people who have never experienced such a service and respond in a hypothetical mode choice experiment. Consequently, the behav-

(a) Base Scenario (b) AMOD Scenario

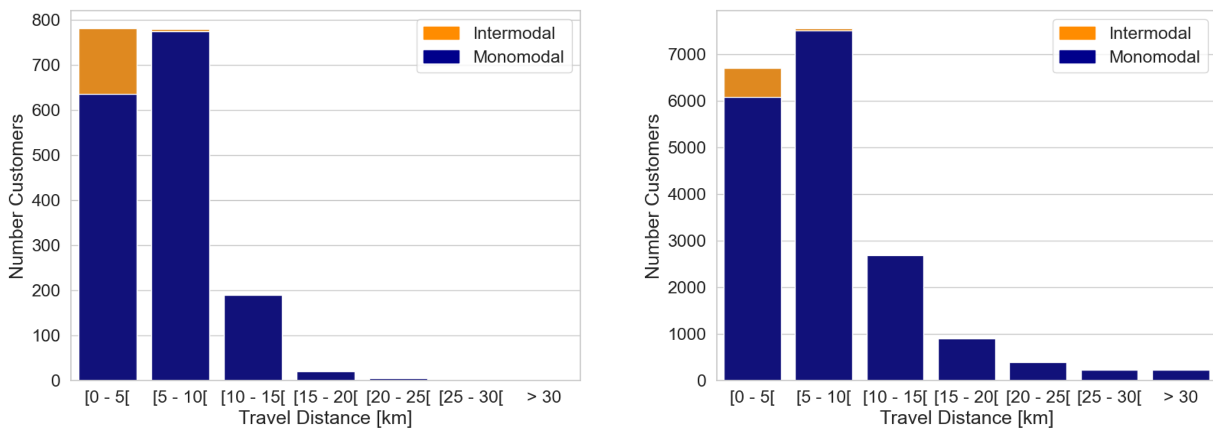

FIGURE 6: Travel distances of ride-pooling customers.

ior predicted is more profound as responses are less biased due to misunderstanding or wrong appraisals.

In the scenario with an autonomous fleet, ride-pooling demand increases by a factor of 10. As a consequence, positive scaling effects like a higher average occupancy and less deadheading can be observed. A key result is that the effects of decreasing and increasing public transport demand approximately equalize. Moreover, the modal share of the active modes is practically unchanged, which indicates that a base fare, a waiting and possible detour time are sufficiently repulsive for short trips. Finally, the number of private vehicle trips are reduced thereby showing the potential of ride-pooling to actually complement public transport and decrease negative externalities of private vehicles. However, even though demand scaled by a factor of 10, the overall effects are still comparatively small.

In future work, regulatory measures will be studied to push the equilibrium further away from the private vehicle mode. For example, increased parking costs or a road toll have the potential to affect user decision towards more sustainable transportation modes (*53*). Additionally, a more pronounced integration of the ride-pooling system with the public transport system, e.g. with different pricing schemes within the city and the outer regions, will be evaluated. Finally, the simulation period will be expanded to one week to gain a better understanding of the dynamics for different times of day and days of the week.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: Gabriel Wilkes, Roman Engelhardt, Nadine Kostorz, Florian Dandl, Peter Vortisch, Klaus Bogenberger, Martin Kagerbauer; data collection: Gabriel Wilkes, Roman Engelhardt, Nadine Kostorz, Florian Dandl; analysis and interpretation of results: Gabriel Wilkes, Roman Engelhardt, Nadine Kostorz, Florian Dandl; draft manuscript preparation: Gabriel Wilkes, Roman Engelhardt, Nadine Kostorz, Florian Dandl. All authors reviewed the results and approved the final version of the manuscript.

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