A simulation-based heuristic for the improvement of on-demand mobility services

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Abstract

This study proposes a simulation-based heuristic for the optimization of (autonomous) ride-hailing services which is applicable to large-scale and real-world case studies. A software tool is provided as an extension of the existing agent-based simulation framework MATSim. The proposed optimization approach uses an outer loop to adjust ride-hailing service parameters and an inner loop to simulate transport users' reactions to the ride-hailing service. For the rural region of the Vulkaneifel (Volcanic Eifel) in Germany, in different simulation experiments, the fare, fleet size and service area are separately adjusted based on predefined control variables (90th waiting time percentile or number of ride-hailing users). The simulation experiments reveal that the ride-hailing service adjustment strategies have a significant impact on the level of service. Waiting times are successfully reduced by applying a fare surcharge during peak times, by increasing the ride-hailing vehicle fleet and by reducing the service area. For a 90th waiting time percentile of 600 sec, a fleet size of 120 vehicles is required and for 900 sec only half the fleet size is required. Besides optimizing an existing service, the proposed tool allows for a more accurate estimation of demand levels for future on-demand mobility services.

1 Introduction and problem statement

In the last years, several companies have provided App-based on-demand mobility services (e.g. UBER, Lyft, BerlKönig, CleverShuttle), also referred to as ride-hailing or demand responsive transit (DRT). In some cities or regions these services are an essential part of the public transport sector and it is impossible to imagine life without them. In other places, however, these services are rather an optional addition to the existing public transport system. The services then primarily compete with local taxi companies. The introduction of autonomous vehicles and the resulting elimination of personnel costs could lead to a reduction in operating costs 0.30 to 0.38 EUR per passenger-km (Bösch et al., 2018; Trommer et al., 2016), reducing user costs and further enhancing the attractiveness of ride-hailing services. Like regular transit operators, operators of on-demand mobility services need guidance on how to change their today's service in order to increase their profit, increase the number of users or reach a predefined level of service quality. In contrast, municipalities may need guidance on how to regulate the existing ride-hailing services in order to improve overall system welfare or follow a political agenda, e.g. a modal shift from private cars to environmental friendlier modes. This study provides a first methodological approach to address such questions for on-demand mobility services.

The optimization of public transit services has been addressed in several studies. The planning process in public transportation is usually divided into sequential planning phases, moving from a strategic to an operational level: network design, line and frequency planning, timetable development, vehicle scheduling, and crew scheduling (e.g. Ceder and Wilson, 1986; Borndörfer et al., 2007; Schöbel, 2012). In contrast, flexible mobility services heavily rely on a supervising structure. Often a controller is in charge with allocating resources (vehicles) to the collected trip requests, solving the so-called dynamic pickup and delivery problem (Cortés, 2003; Pagés et al., 2006; Fernandez et al., 2008; Cortés et al., 2008; Sáez et al., 2008). Consequently, for flexible on-demand mobility services, the optimization parameters and planning steps are very different from schedule-based public transit. Most relevant design elements are the service area, fleet size, pricing system, vehicle sizes, operation modes (e.g. with or without pooling) and rebalancing strategies. Autonomous vehicle technology provides additional chances and challenges that have been addressed in various studies (Narayanan et al., 2020).

For on-demand mobility services, Maciejewski and Bischoff (2015) looked into different fleet sizes and resulting waiting times. The authors find that above a certain threshold, increasing the fleet size only yields a minor change in service quality (see Fig. 5 in Maciejewski and Bischoff (2015), also see Fig. 6.1 in Bischoff (2019)). In Bischoff and Maciejewski (2016) and Bischoff (2019), simulation experiments are carried out for a fixed travel demand without mode choice. Thus, the impact of different fleet sizes on the attractiveness of the ride-hailing mode and the resulting number of users is not accounted for. Bischoff et al. (2018) developed a simulation-based heuristic to optimize the service area of on-demand mobility providers. Different decision criteria are used to adjust the ride-hailing service area and analyze the operator's profit: the average vehicle occupancy per zone, the revenues per zone or a combination of both. Again, a weakness in Bischoff et al. (2018) is that travel demand is fixed and mode choice reactions are not accounted for. In contrast, Zhao and Kockelman (2018) account for mode choice reactions and evaluate the impact of different pricing concepts for shared autonomous vehicles on total vehicle kilometers traveled. Mode choice reactions are also accounted for by Hörl et al. (2019) who address the estimation of demand levels and fleet sizes for on-demand mobility services. In a first setup, Hörl et al. (2019) vary the fleet size and keep the distance-based fare at a constant level. Consequently, the resulting number of trips increases monotonically with the fleet size. In a second setup, the distance-based fare is computed based on the operating cost for each fleet size level and resulting fleet utilization. In consequence, very large fleet sizes translate into high fares and the number of users decrease. In the dynamic fare case, a maximum number of 1.2 million trips is obtained for a fleet size of 25 thousand vehicles operating within the Boulevard Périphérique of Paris. Kaddoura et al. (2020a) also account for mode choice and use an agent-based approach to optimize on-demand mobility services. For a fixed fleet size, a user-specific congestion charge is added to the fare which controls the number of users. Simulation experiments are carried out for Berlin, Germany, and the impact of different pricing concepts on the overall transport system is analyzed. Vosooghi et al. (2019) use an agent-based simulation approach to investigate the modal split and vehicle kilometers traveled for different ride-hailing fleet sizes and vehicle types. For a parametric study, Vosooghi et al. (2019) find the vehicle fleet size and rebalancing to have a major impact on the ride-hailing demand level and performance. Kaddoura et al. (2020b) investigate the impact of pricing and service area design on mode shift effects towards on-demand mobility concepts. Both, the pricing and service area are found to be effective levers to achieve the desired mode shift effect and avoid cannibalization of the schedule-based public transit system. Neumann (2014) developed a co-evolutionary approach to identify profitable minibus services where the schedule adapts to the demand level forming a hybrid concept between conventional public transit and on-demand ride-hailing services. The approach had been successfully applied to the Nelson Mandela Bay Area Municipality in South Africa (Neumann et al., 2015) as well as in the metropolitan area of Berlin (Neumann, 2015).

Overall, the literature shows that there are only a small number of studies in which the optimization of ride-hailing services is addressed in the context of large-scale and real-world case studies. This study proposes a simulation-based approach for the optimization of (autonomous) ride-hailing services which is applicable to large-scale and real-world case studies. A software tool is provided as an extension of an existing agent-based simulation framework. The provided tool is expandable and configurable for various use cases and optimization objectives.

2 Methodology

2.1 Agent-based transport simulation framework

MATSim overview The proposed heuristic uses the agent-based and dynamic transport simulation framework MATSim[1] (Horni et al., 2016). In MATSim, transport users are simulated as individual agents. Each agent adapts to the transport supply (road network, ride-hailing service quality, fares) following an evolutionary iterative approach which consists of the following three steps:

1. The traffic flow is simulated. Private cars and ride-hailing vehicles interact on the same network based on a queue model which accounts for dynamic congestion and spill-back effects (see Fig. 3).

2. Each agent evaluates his/her daily (travel) plan taking into consideration (i) the utility from being at an activity and (ii) the travel-related disutility, including monetary cost components.

3. Some agents are enabled to adjust their behavior, e.g. switch to another route or mode of transportation. The other agents choose among their existing plans following a multinomial logit model.

MATSim ride-hailing module (DRT module) The simulation of on-demand mobility services uses an existing module for dynamic vehicle routing problems (Maciejewski,

[1]Multi-Agent Transport Simulation, see www.matsim.org

2016; Maciejewski et al., 2017) and an existing module for the simulation of ride-hailing services (Bischoff et al., 2017). Throughout the simulation, agents will try out different modes of transportation, including the ride-hailing mode. Users first walk to the next road segment (virtual DRT stop) within the ride-hailing service area and then request a ride. The trip request is then assigned to a vehicle which can serve the trip request while maintaining certain service quality criteria for the new passenger and the passengers that are already using or scheduled to use the same vehicle. The vehicle dispatching heuristic minimizes the total vehicle operation time for serving trip requests. If the ride-hailing system is at its capacity limit and trip requests cannot be served within the predefined service quality criteria, the request will not be rejected but assigned to the vehicle causing the least additional operation time. After the user arrives at the destination road segment (virtual DRT stop), the user walks to the destination.

2.2 Ride-hailing service optimization

The proposed ride-hailing service optimization heuristic uses an outer loop to adjust ride-hailing service parameters and an inner loop to simulate transport users' reactions to the service.

1. Provide some initial service parameters (fare, fleet size, service area).
2. Inner loop: Let the travel demand adapt to the ride-hailing service based on the iterative learning approach described in Sec. 2.1:
   (a) Traffic flow simulation
   (b) Plan evaluation
   (c) Plan selection and modification

   For the final iterations in the inner loop, innovative strategies (mode choice, departure time choice, route choice) are switched off and transport users only select a travel option based on their existing choice sets.
3. Compute a decision variable, e.g. the service level (90-percentile waiting time) per time of day, the number of users or the operator's profit.
4. Adjust some ride-hailing service parameters, e.g. increase or decrease a fare surcharge per time of day, increase or decrease the vehicle fleet or expand or reduce the service area. For the adjustment of ride-hailing service parameters, different controllers may be used, for example a simple approach with constant parameter changes or a proportional controller where the adjustment size depends on the deviation of the decision variable between the target value and the current value observed in the simulation.
5. Go to 2.

The ride-hailing service optimization module which may be used as an extension to MATSim is currently located on the following repository: `https://github.com/matsim-vsp/opt-drt`. For the simulation experiments carried out in this study the code version of 29 June 2020 (commit ID 8fe7d0a) was used. A first prototype of the ride-hailing optimization module is available since summer 2019.

3 Case study and simulation experiments

3.1 Case study: Vulkaneifel, Germany

In this study, simulation experiments are carried out for the sparsely populated rural region of the Vulkaneifel (Volcanic Eifel), Germany. The activity-based transport model is provided as an excerpt from the nation-wide MATSim model of Germany by Senozon Deutschland GmbH (`www.senozon.com`). The transport network is generated based on OpenStreetMap (`www.osm.org`) data and contains all roads in the Vulkaneifel and its surrounding area. Public transit supply is generated using GTFS data and contains all public transit lines in and around the Vulkaneifel area. The walk, bicycle and ride mode are simulated in a simplified way, neglecting interactions between users and assuming fixed mode-specific speed parameters. In addition to regular traffic surveys, the synthetic population is based on anonymized mobile phone data and includes all persons with an age of 14 or older that travel from, to or through the Vulkaneifel area. Travel patterns of the agents extend to all parts of Germany. To reduce the computational load, the least relevant agents, i.e. agents traveling very far and thus spending most time outside the area of interest, are removed together with the infrastructure they use. In consequence, with about 10 % of the agents removed, the infrastructure (network and transit schedule) still covers an area as far as Cologne, Koblenz, and the Mosel River. To travel between activity locations, in the base case, transport users are enabled to use the car, public transit, bicycle, ride and/or walk mode. Travel times within public transport mode result from access/egress times to/from the transit stop, waiting times and in-vehicle times based on simulation of real-world schedule data. In this simulation setup, buses and tramways do not interact with ride-hailing vehicles, private cars or bicycles. To reduce computation times, in this study, a 25% population sample is used and road capacities are accordingly reduced to 25% of the real-world capacity. For an in-depth information of the applied demand generation methodology, in particular the Mobility Pattern Recognition, see (Neumann and Balmer, 2020).

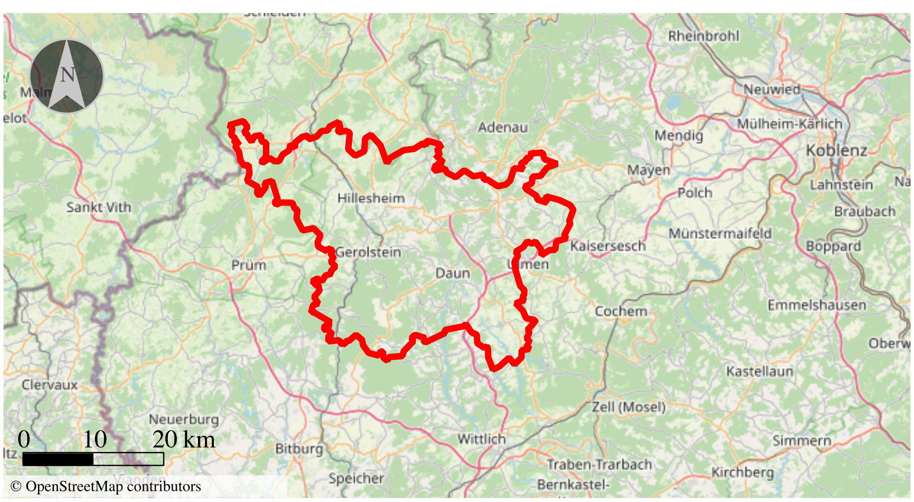


Figure 1: Vulkaneifel area; Background map: ©OpenStreetMap Contributors (www.osm.org)

3.2 Ride-hailing service and simulation setup

A ride-hailing service is added to the existing modes of transportation which may be used for trips or trip parts starting and ending within the service area. In different simulation experiments, initial ride-hailing parameters (service area, fleet size, fare) are set differently and are either fixed or changed throughout a single simulation run. The service allows for pooling (ride-sharing) and the vehicle capacity is set to 4 passengers. The fare is set to 1.50 EUR/km with a minimum fee of 4 EUR. In the first iteration, the vehicles are randomly distributed within the service area. Then, in each iteration, vehicles remain on the link where the last drop off took place in the iteration before. The pick-up and drop-off duration is set to 1 minute. Ride-hailing vehicles interact with other ride-hailing vehicles as well as private cars. In this study, the ride-hailing service may not be used as an access or egress mode within public transport trips.

All transport users are allowed to change their transport routes, departure times and modes of transportation. For each sub-tour, i.e. trip chains starting and ending at the same activity location, the transport mode may be changed to only car, only bicycle (chain-based modes) or a combination of public transit, ride-hailing, (private) ride and walk. Each agent's choice set is limited to 3 travel plans. All simulation experiments are run for a total of 600 iterations. During choice set generation (first 480 iterations), in each iteration the share of agents who change their mode, route and departure time is set to 10% per choice dimension. In the final 120 iterations, all agents select from their existing daily travel plans (choice sets) based on a multinomial logit model. Behavioral parameters for the ride-sharing service and the marginal utility of money are taken from a model which has been calibrated and validated against real-world ride-hailing trip data.

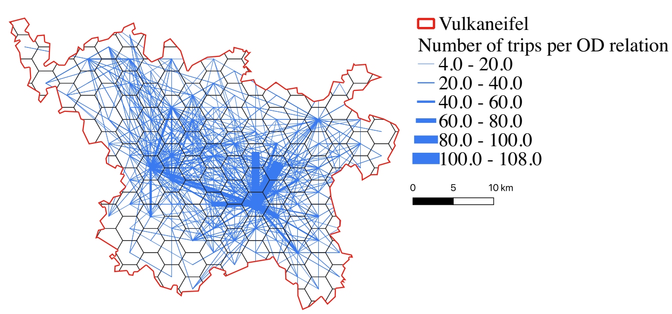


Figure 2: Number of ride-hailing trips per zone-based origin-destination relation (Simulation experiment DRT-0)

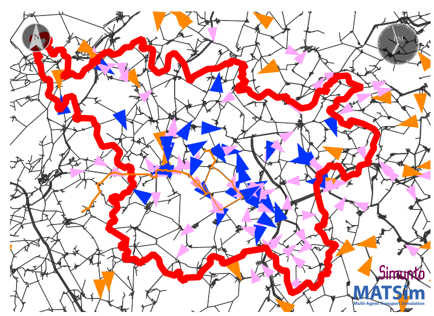


Figure 3: Network and simulated vehicles (blue: Ride-hailing vehicles; orange: public transit vehicles; purple: cars)

3.3 Simulation experiments

The following simulation experiments are carried out.

- **Fixed ride-hailing service (DRT-0):** In this simulation experiment the ride-hailing service optimization heuristic described in Sec. 2.2 is disabled. The ride-hailing fleet size is fixed to 50 vehicles. There is no fare surcharge and the service area is fixed to the entire Vulkaneifel region. This simulation experiment is considered as the base case and is used as a benchmark for the other simulation experiments in which the ride-hailing service is adjusted.

- **Fare adjustment (DRT-fare):** In this simulation experiment, only the fare strategy is applied and a simple control mechanism is applied which either increases or decreases a fare surcharge depending on the target waiting time (90th percentile) per 3-hour time bin:

  - DRT-fare-A: 300 sec
  - DRT-fare-B: 600 sec
  - DRT-fare-C: 900 sec

  The control mechanism increases or decreases the fare surcharge by 1 EUR/km applying the method of successive averages. The initial fare surcharge is 0 EUR. The fleet size is fixed to 50 vehicles and the service area is fixed to the entire Vulkaneifel region.

- **Fleet size adjustment (DRT-fleet):** In this simulation experiment, only the fleet size strategy is applied and a simple control mechanism is applied which either increases or decreases the fleet size by 10% (and a minimum of 1 vehicle) depending on the 90th waiting time percentile:

  - DRT-fleet-A: 300 sec
  - DRT-fleet-B: 600 sec
  - DRT-fleet-C: 900 sec

  The fleet is expanded by randomly selecting and cloning an existing ride-hailing vehicle, including the position in the network. The initial fleet size is set to 50 vehicles. There is no fare surcharge and the service area is fixed to the entire Vulkaneifel region.

- **Service area adjustment (DRT-area):** In this simulation experiment, only the service area strategy is applied and a simple control mechanism is applied which expands and reduces the service area by a certain number of hexagon grid cells depending on the number of ride-hailing users:

  - DRT-area-A: 1 DRT user
  - DRT-area-B: 10 DRT users
  - DRT-area-C: 20 DRT users

  For all hexagon grid cells where the demand level is below the threshold, 10 grid cells are randomly chosen to be removed from the service area. Also, 10 new hexagon grid cells are randomly chosen and then added to the service area. The hexagon grid cells have a spacing of 3 km. The initial service area is set to the entire Vulkaneifel region. There is no fare surcharge and the ride-hailing fleet size is fixed to 50 vehicles.

4 Results

4.1 Ride-hailing service parameters

The simulation experiments reveal that all ride-hailing service adjustment strategies have a significant impact on the level of service. Waiting times are successfully reduced by applying a fare surcharge during peak times, by increasing the vehicle fleet and by reducing the service area.

Fig. 4 shows the resulting ride-hailing fare surcharges per time of day in the final iteration. The fare surcharges depend on the predefined decision criteria (90th waiting time percentile). In simulation experiment DRT-fare-A, the waiting time threshold (90th percentile) is set to 300 sec and the resulting surcharges amount to more than 2.00 EUR during the afternoon and a bit less in the morning and evening. In the simulation experiments DRT-fare-B and DRT-fare-C, the waiting time thresholds are larger (600 sec and 900 sec) and resulting fare surcharges much lower in most time periods.

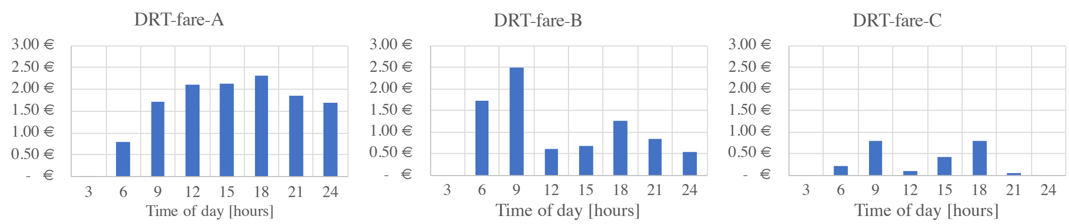


Figure 4: Fare surcharge in EUR/km per time of day

In Fig. 5, the vehicle fleet size is shown over the iterations for the simulation experiments in which the fleet size is adjusted: DRT-fleet-A, DRT-fleet-B and DRT-fleet-C. For the low waiting time threshold of 300 sec, in simulation experiment DRT-fleet-A, the vehicle fleet is increased until the very end and there is no stable outcome. In contrast, for the higher waiting time thresholds (90th percentile 600 sec and 900 sec), a relaxation of the fleet size is observed at a level of approximately 120 vehicles in experiment DRT-fleet-B and 60 vehicles in experiment DRT-fleet-C.

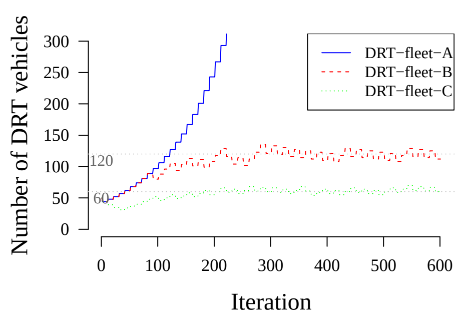


Figure 5: Fleet size per Iteration

Fig. 6 shows the resulting ride-hailing service area in the final iteration for the simulation experiments in which the service area is adjusted: DRT-area-A, DRT-area-B and DRT-area-C. Increasing the demand threshold yields a concentration of the ride-hailing service area to the more densely populated area within the Vulkaneifel, including the towns of

Daun, Gerolstein, and Hillesheim.

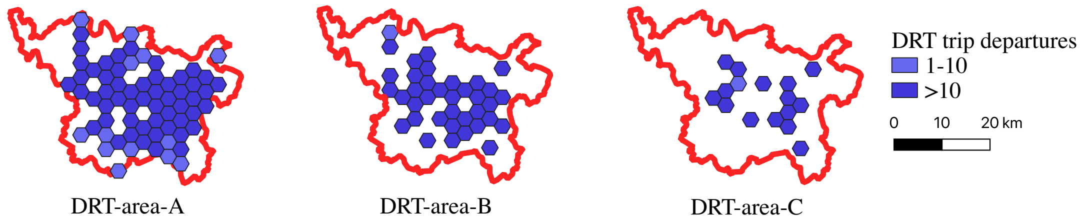
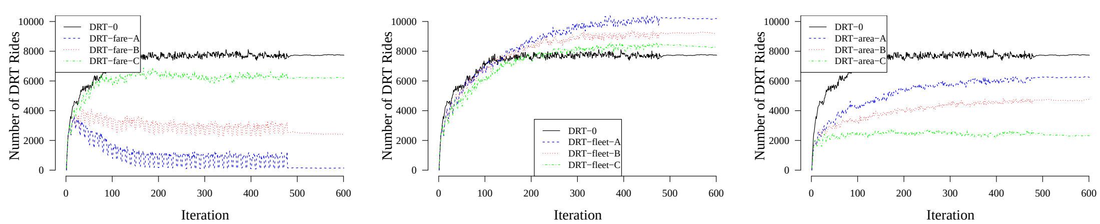


Figure 6: Resulting ride-hailing service areas

4.2 Ride-hailing demand and service quality

The ride-hailing service parameters and adjustment criteria have a different impact on the number of ride-hailing trips and the service quality. Time-dependent fare surcharges control the number of ride-hailing users and improve the resulting ride-hailing service quality for the remaining ride-hailing users. Most ride-hailing users are observed to switch from ride-hailing to the (private) ride and bicycle mode. The users remaining within the ride-hailing mode experience an average reduction in travel time of 144 sec in experiment DRT-fare-C and 307 sec in experiment DRT-fare-B. The vehicle fleet size and service area have a direct impact on the service level: A larger fleet size translates into more and faster available ride-hailing vehicles which reduces waiting times and attracts additional ride-hailing users, mainly from the public transit and bike mode. Thus, waiting times increase until the ride-hailing vehicle fleet size is again increased. Fig. 7 shows the number of ride-hailing trips per iteration. In experiment DRT-fleet-B and DRT-fleet-C, at some



(a) DRT-fare (b) DRT-fleet (c) DRT-area

Figure 7: Number of ride-hailing Rides per iteration

point the gradient flattens and the resulting number of ride-hailing users (and ride-hailing vehicles) stabilizes. Even though the ride-hailing demand is at a higher level, the users previously using the ride-hailing mode experience a decrease in average travel time per trip of 254 sec in experiment DRT-fleet-B and 84 sec in experiment DRT-fleet-C. Reducing the service area has a similar effect: Some agents are no longer allowed to use the ride-hailing mode for trips starting or ending in certain low-demand areas. Most of these users switch to the ride and bike mode. Thus, the existing ride-hailing vehicles focus more on the urbanized centers which yields a higher availability of ride-hailing vehicles in those areas. For the remaining ride-hailing users the average travel time per trip is reduced by 150 sec in experiment DRT-area-A and 250 sec in experiment DRT-area-B.

Fig. 8 shows the number of ride-hailing trips for each simulation experiment in the final iteration. In the base case simulation experiment DRT-0, the ride-hailing users amount to 7728 trips. The simulation experiments in which the fare is increased (DRT-fare) and the service area is reduced (DRT-area), the number of ride-hailing trips is significantly reduced. In contrast, the simulation experiments, in which the ride-hailing vehicle fleet size is adjusted (DRT-fleet) the ride-hailing users increase to 10,200 trips in experiment DRT-fleet-A, 9,228 trips in experiment DRT-fleet-B or slightly increases to 8,256 trips in experiment DRT-fleet-C.

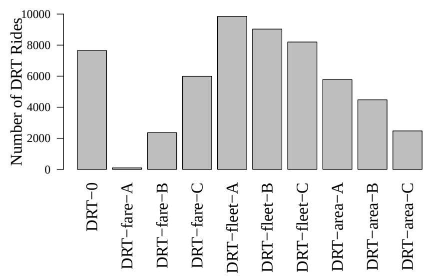
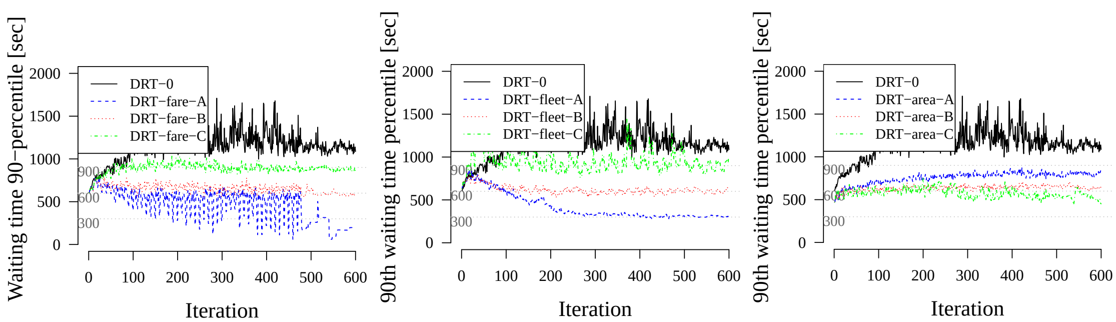


Figure 8: Number of rides in the final iteration

Fig. 9 shows the 90th waiting time percentile per iteration in the base case (DRT-0) and the different ride-hailing adjustment simulation experiments. In the simulation experiments DRT-fare and DRT-fleet, the 90th waiting time percentile is used as the decision criteria, thus, the observed 90th waiting time percentile quickly drops below or close to the level of the target value, i.e. 300 sec, 600 sec, and 900 sec. An interesting fact is that, in experiment DRT-fleet-A, the 90th waiting time percentile is never reached and stays slightly above the target value of 300 sec. Thus, the vehicle fleet is constantly increased (see Fig. 5).



(a) DRT-fare (b) DRT-fleet (c) DRT-area

Figure 9: 90th waiting time percentile per iteration

In Fig. 10, the resulting waiting time distribution, including the 90th percentile, is shown for each simulation experiment. The waiting times exhibit a right-skewed distribution with several outliers in the higher value range. In all simulation experiments in which the ride-hailing service is iteratively adjusted, the waiting times are significantly reduced compared to the base case simulation experiment DRT-0.

In simulation experiment DRT-fare-A, the ride-hailing demand is on a very low level, thus, except for a few outliers, waiting times are below 300 sec. In experiment DRT-fare-B and DRT-fare-C, the 90th waiting time percentile is slightly below the target value 600 sec and 900 sec, respectively.

In simulation experiment DRT-fleet-A, DRT-fleet-B and DRT-fleet-C, the 90th waiting time percentile is only slightly above the target value 300 sec, 600 sec and 900 sec, respectively. Since the controller either increases or decreases the vehicle fleet, in simulation experiment DRT-fleet-B and DRT-fleet-C, the fleet size oscillates around the final number (see Fig. 7b) and therefore also the 90th waiting time percentile fluctuates around the target value (see Fig. 9b).

The simulation experiments DRT-area-A, DRT-area-B, and DRT-area-C reveal that a smaller ride-hailing service area reduces the 90th waiting time percentiles from 1086 sec in experiment DRT-0 to 806 sec in experiment DRT-area-A or 451 sec in experiment DRT-area-C.

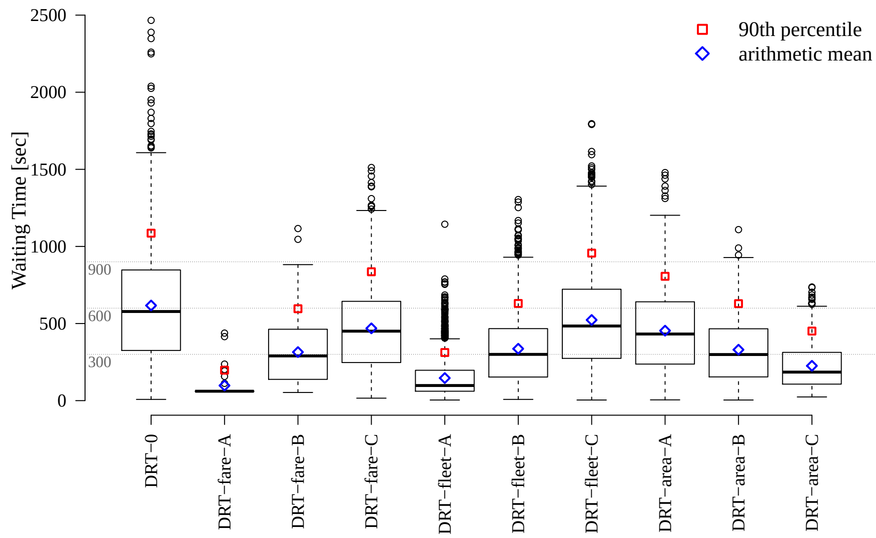
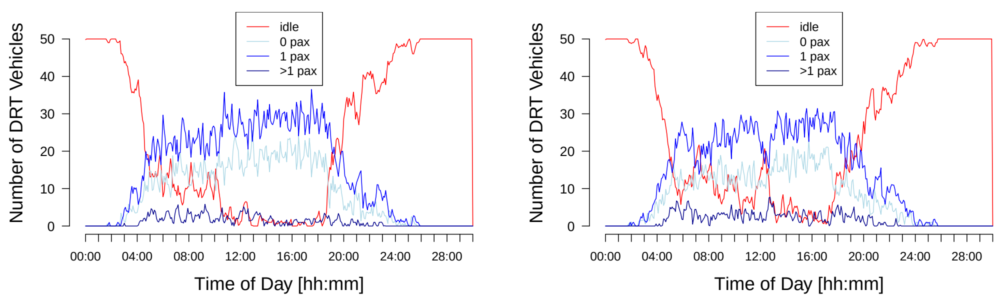


Figure 10: Ride-hailing Waiting Times in the final iteration (25% population sample); box: 25th percentile, median and 75th percentile; lower whisker: 25th percentile − 1.5 × box length; upper whisker: 75th percentile + 1.5 × box length; black circles: outliers; red : 90th percentile; blue: arithmetic mean

5 Discussion

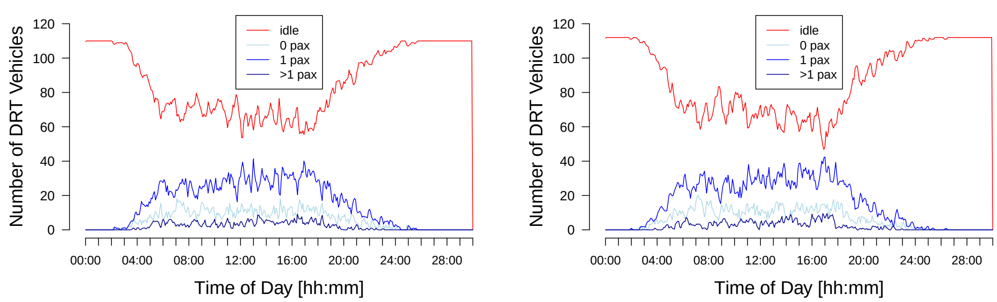
5.1 Estimation of ride-hailing potentials

The developed methodology, in particular the ride-hailing vehicle fleet adjustment approach, may also be used to estimate the number of potential users of a newly introduced ride-hailing mode. A variable fleet size which depends on the demand level allows the consideration of a constant service quality throughout the simulation process. In contrast, a constant fleet size seems difficult for the following reason: During the iterative learning process, the number of ride-hailing users changes and so does the service quality. During the phase of choice set generation, in every iteration a certain number of agents try out the new mode of transportation. Users for which the ride-hailing mode seems attractive in some early iterations for low demand levels may eventually switch back to their previous mode of transportation once the demand level increases, waiting times increase and the service becomes less reliable. That is, the rather expensive ride-hailing service turns from a premium mode to a much less attractive service. Thus, the resulting ride-hailing demand may neglect certain users, in particular those with a high willingness to pay for a fast and reliable transport service. Fig. 11 shows the occupancy time profile in iteration 400 and the final iteration 600 for simulation experiment DRT-0. During peak times, the vehicle fleet reaches the capacity limit. That is, during peak times all ride-hailing vehicles are moving on the network serving trip requests and there are no idle vehicles. Note that vehicles with 0 pax are on its way to the next pick-up location of their assign request. Fig. 12 shows the same plots for simulation experiment DRT-fleet-B in which the fleet size is adjusted in order to keep a constant service level. The plots exhibit that in order to guarantee a 90th waiting time percentile below 600 sec, in the applied Vulkaneifel case study, the ride-hailing vehicle fleet needs to be large enough to provide a minimum of approximately 60 idle vehicles at any time. A possible way out is to set the vehicle



(a) Iteration 400 (b) Iteration 600

Figure 11: Ride-hailing occupancy time profile in simulation experiment DRT-0



(a) Iteration 400 (b) Iteration 600

Figure 12: Ride-hailing occupancy time profile in simulation experiment DRT-fleet-B

fleet size to a very high level. On the one hand, this will prevent the ride-hailing service from reaching the capacity limit and will always guarantee a high level of service quality. On the other hand, however, this will underestimate waiting times because there is an unrealistically high availability of ride-hailing vehicles. Most ride-hailing vehicles will be idle throughout the day or only serve a single trip request. Once the ride-hailing vehicle fleet is reduced to a more realistic number, waiting times will increase and some users will switch from the ride-hailing mode to other modes of transportation.

5.2 Challenges with larger numbers of ride-hailing users

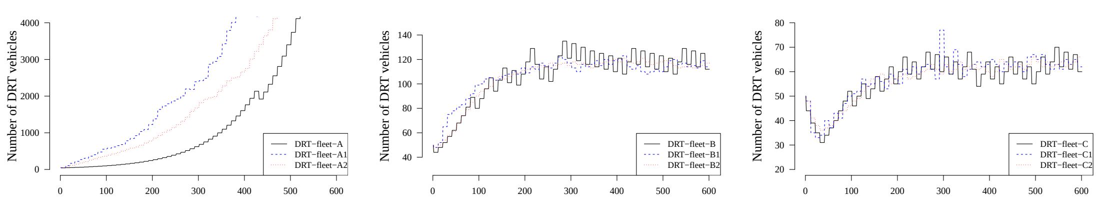
In the context of sensitivity analysis, the minimum and distance-based fare was reduced to look into the impact of autonomous driving technologies and the elimination of driver costs. Consequently, ride-hailing demand levels are on a much higher level which also leads to some challenges for the proposed ride-hailing service optimization approach.

Proportional ride-hailing fleet size controller Depending on the initial fleet size, a fixed change in fleet size by 10% may require a large number of iterations until the vehicle fleet is at a sufficient high level. Larger fleet size adjustments may reduce the number of required iterations, however, results in strong oscillations around the final fleet size level. A reduction in simulation time and a stable fleet size level is obtained using a proportional controller which computes the relative change in fleet size as follows:

$$n_{i+1} = (t_i - t_{target})/t_{target} \cdot K_p \cdot n_i \,, \tag{1}$$

where i denotes the iteration, n is the number of vehicles, t_i is the 90th waiting time percentile in iteration i, t_{target} is the target 90-percentile waiting time and K_p is a tuning parameter. Additional simulation experiments are carried out for the new proportional controller: Simulation experiment DRT-fleet-A1, DRT-fleet-B1 and DRT-fleet-C1 with $K_p = 1.0$ and DRT-fleet-A2, DRT-fleet-B2 and DRT-fleet-C2 with $K_p = 0.5$.

Fig. 13 shows the changes in vehicle fleet size for the simple controller described in Sec. 3.3 and the new proportional controller. Again, for the current ride-hailing operation mode, the target 90th waiting time percentile of 300 sec can not be reached and the ride-hailing fleet size is constantly expanded (see Fig. 13a). In all other simulation experiments, the simple controller and proportional controller show a similar fleet size adjustment over the iterations and the final ride-hailing fleet size is approximately at the same level. The tuning parameter K_p slows down the adaptation speed which only has a minor impact in Fig. 13b and Fig. 13c but a huge impact in Fig. 13a where the initial fleet size is far too small for the target waiting time of 300 sec.



(a) DRT-fleet-A (b) DRT-fleet-B (c) DRT-fleet-C

Figure 13: DRT fleet size adjustment: Proportional Controller

Speeding-up simulation times For larger service areas or ride-hailing demand levels, also simulation times may significantly increase. The proposed ride-hailing optimization heuristic is compatible with the speed-up approach presented in Kaddoura et al. (2020b) and, thus, allows for large-scale applications. In the speed-up approach by Kaddoura et al. (2020b), a detailed ride-hailing assignment is only simulated in certain iteration intervals, e.g. every 10 or 30 iterations, and in between ride-hailing users are simply teleported applying estimates based on the waiting time, the travel speed, and the travel distance from previous iterations. Each iteration with a detailed ride-hailing assignment then updates the estimates. To improve the existing speed-up approach and reduce oscillations between the detailed ride-hailing assignment simulations, a simple moving average approach was added which takes into consideration the most recent iterations with simulated ride-hailing. This is in particular relevant for ride-hailing fleet sizes that are reduced to just the number of required vehicles to obtain a predefined service level. To make the speed-up approach compatible with the proposed ride-hailing optimization approach, the iteration interval of the outer loop in which ride-hailing service parameters are adjusted only need to match the iteration interval in which the speed-up approach runs a detailed ride-hailing simulation. Also, adjusted ride-hailing service parameters, for example time-specific fare surcharges, need to be passed on to the ride-hailing speed-up approach.

5.3 Operator's profit

In this study, the 90th waiting time percentile is used as decision variable to adjust the ride-hailing vehicle fleet size. This may be interpreted as a ride-hailing service provider which is regulated by the state or city administration and is forced to ensure a certain service quality. In order to reflect an unregulated and profit maximizing mobility service provider, the proposed approach allows for different control variables, including the operator's profit. In the following, the operator's profit is estimated based on the revenues, the fleet size, the vehicle-km, and some rough assumptions regarding the cost rates: Daily fix costs are assumed to be 17.88 EUR per vehicle (Planco et al., 2015, see p. 284, Tab. 8-32)[2]. Staff costs are assumed to be 17.64 EUR per hour (Planco et al., 2015, see p. 284, Tab. 8-37). Staff time is calculated by summing up each ride-hailing vehicle's daily operating time using the first and last vehicle movement on the network. Variable vehicle operating costs are assumed to be 0.35 EUR/km. With these assumptions regarding the cost rates,

Table 1: Estimation of the daily operator's profit (the numbers are upscaled to a 100% scenario sample)

Simulation experiment	DRT-0	DRT-fleet-A	DRT-fleet-B	DRT-fleet-C
Revenues [EUR]	124,888	154,945	142,789	131,138
Number of ride-hailing vehicles	200	19,304	448	240
Vehicle fix costs (17.88 EUR/vehicle) [EUR]	3,576	345,156	8,010	4,291
Staff time [hours]	3,628	15,118	6,886	4,233
Staff costs (17.64 EUR/hour) [EUR]	63,991	266,686	121,464	74,672
Total vehicle-km	108,100	100,708	109,264	110,636
Vehicle operating costs (0.35 EUR/km) [EUR]	37,835	35,248	38,242	38,723
Total costs [EUR]	105,402	647,090	167,717	117,685
Profit [EUR]	19,486	−492,145	−24,927	13,453

[2] see p. 284, Tab. 8-32, "Vorhaltungskosten ohne Fahrpersonalkosten" (fix costs without personnel costs) for a VW Golf 1.4 Trendline per year divided by 365, with "Allgemeine Kosten" (overhead costs) of 5.291 EUR/year for the vehicle fleet management]

in experiment DRT-0, the operator's profit is positive. A larger fleet size translates into higher costs, but also increases the number of ride-hailing users that yield higher revenues. In experiment DRT-fleet-A, the operator makes large losses due to the large number of ride-hailing vehicles. In experiment DRT-fleet-B, the increase in fleet size translates into higher costs, thus the profit is reduced compared to experiment DRT-0. In experiment DRT-fleet-C, the profit slightly decreases compared to experiment DRT-0 and is still positive. There are only a few more vehicles, thus, operating cost only slightly increase and the ride-hailing service attracts more users which yields an increase in revenues.

A service with autonomous vehicles would eliminate staff costs for drivers. If staff costs were excluded from Tab. 1, both experiments DRT-fleet-B and DRT-fleet-C would yield an increase in profit compared to DRT-0.

6 Conclusion and outlook

This study proposes a simulation-based heuristic for the optimization of ride-hailing services which is applicable to large-scale and real-world case studies. A software tool is provided as an extension of the existing agent-based simulation framework MATSim. The proposed optimization approach uses an outer loop to adjust ride-hailing service parameters and an inner loop to simulate transport users' reactions to the ride-hailing service. For the rural region of the Vulkaneifel (Volcanic Eifel) in Germany, in different simulation experiments, the fare, fleet size and service area are separately adjusted based on predefined control variables (90th waiting time percentile or number of ride-hailing users). The simulation experiments reveal that the ride-hailing service adjustment strategies have a significant impact on the level of service. Waiting times are successfully reduced by applying a fare surcharge during peak times, by increasing the ride-hailing vehicle fleet and by reducing the service area. Time-dependent fare surcharges reduce the number of ride-hailing users and improve the resulting ride-hailing service quality for the remaining ride-hailing users. A larger fleet size translates into more and faster available ride-hailing vehicles which at first reduces waiting times and attracts additional ride-hailing users, mainly from the public transit and bike mode. Thus, waiting times increase until the ride-hailing vehicle fleet size is again increased. At some point the gradient flattens and the resulting number of ride-hailing users (and ride-hailing vehicles) stabilizes. For a 90th waiting time percentile of 600 sec, a fleet size of 120 ride-hailing vehicles is required and for 900 sec only half the fleet size is required. In addition to optimizing an existing service, the proposed tool allows for a more accurate estimation of demand levels for future ride-hailing services. The tool guarantees a certain ride-hailing quality of service throughout the simulation process and regardless of the number of ride-hailing users.

In future studies, the proposed methodology will be applied to additional case studies, including urban areas, e.g. Berlin, Gladbeck, with larger population sizes. In addition, future studies will address the impact of vehicle rebalancing strategies on resulting ride-hailing service parameters, in particular the required fleet size to obtain a desired service level. Further research will also deal with the interaction between ride-hailing services and regular taxi services, or two competing ride-hailing service providers. The latest developments in the proposed ride-hailing optimization tool allow for a multi-mode ride-hailing application.

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References

Bischoff, J. *Mobility as a Service and the transition to driverless systems*. PhD thesis, TU Berlin, Berlin, 2019.

Bischoff, J. and M. Maciejewski. Simulation of City-wide Replacement of Private Cars with Autonomous Taxis in Berlin. *Procedia Computer Science*, 83:237–244, 2016. ISSN 1877-0509. doi: 10.1016/j.procs.2016.04.121.

Bischoff, J., M. Maciejewski, and K. Nagel. City-wide shared taxis: A simulation study in Berlin. In *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, Oct. 2017. doi: 10.1109/itsc.2017.8317926.

Bischoff, J., I. Kaddoura, M. Maciejewski, and K. Nagel. Simulation-based optimization of service areas for pooled ride-hailing operators. *Procedia Computer Science*, 130:816–823, 2018. doi: 10.1016/j.procs.2018.04.069.

Borndörfer, R., M. Grötschel, and M. Pfetsch. A Column Generation Approach to Line Planning in Public Transport. *Transportation Science*, 41(1):123–132, 2007. doi: 10.1287/trsc.1060.0161.

Bösch, P. M., F. Becker, H. Becker, and K. W. Axhausen. Cost-based analysis of autonomous mobility services. *Transport Policy*, 64:76–91, May 2018. doi: 10.1016/j.tranpol.2017.09.005.

Ceder, A. and N. Wilson. Bus Network Design. *Transportation Research Part B-Methodological*, 20(4):331–344, Aug. 1986. ISSN 0191-2615.

Cortés, C. *High coverage point to point transit (HCPPT): A new design concept and simulation-evaluation of operational schemes*. PhD thesis, University of California, Irvine, 2003.

Cortés, C., A. Núñez, and D. Sáez. Hybrid adaptive predictive control for a dynamic pickup and delivery problem including traffic congestion. *International Journal of Adaptive Control and Signal Processing*, 22(2):103–123, Mar. 2008. ISSN 0890-6327. doi: 10.1002/acs.1005.

Fernandez, J., J. de Cea, and R. Malbran. Demand responsive urban public transport system design: Methodology and application. *Transportation Research Part A-Policy And Practice*, 42(7):951–972, Aug. 2008. ISSN 0965-8564. doi: 10.1016/j.tra.2007.12.008.

Hörl, S., M. Balac, and K. Axhausen. Dynamic demand estimation for an AMoD system in Paris. In *2019 IEEE Intelligent Vehicles Symposium (IV)*, pages 260–266, July 2019. doi: 10.1109/IVS.2019.8814051. URL `https://www.researchgate.net/publication/334637984_Dynamic_demand_estimation_for_an_AMoD_system_in_Paris`.

Horni, A., K. Nagel, and K. W. Axhausen, editors. *The Multi-Agent Transport Simulation MATSim*. Ubiquity, London, 2016. doi: 10.5334/baw.

Kaddoura, I., J. Bischoff, and K. Nagel. Towards welfare optimal operation of innovative mobility concepts: External cost pricing in a world of shared autonomous vehicles. *Transportation Research Part A: Policy and Practice*, 136:48–63, 2020a. doi: https://doi.org/10.1016/j.tra.2020.03.032.

Kaddoura, I., G. Leich, and K. Nagel. The impact of pricing and service area design on the modal shift towards demand responsive transit. *Procedia Computer Science*, 170:807–812, 2020b. doi: 10.1016/j.procs.2020.03.152.

Maciejewski, M. Dynamic Transport Services. In Horni et al. (2016), chapter 23. doi: 10.5334/baw.

Maciejewski, M. and J. Bischoff. Large-scale Microscopic Simulation of Taxi Services. *Procedia Computer Science*, 52:358–364, 2015. ISSN 1877-0509. doi: 10.1016/j.procs.2015.05.107. URL `http://www.sciencedirect.com/science/article/pii/S1877050915009072`.

Maciejewski, M., J. Bischoff, S. Hörl, and K. Nagel. Towards a Testbed for Dynamic Vehicle Routing Algorithms. In Bajo, J., Z. Vale, K. Hallenborg, A. P. Rocha, P. Mathieu, P. Pawlewski, E. Del Val, P. Novais, F. Lopes, N. D. Duque Méndez, V. Julián, and J. Holmgren, editors, *Highlights of Practical Applications of Cyber-Physical Multi-Agent Systems: International Workshops of PAAMS 2017, Porto, Portugal, June 21-23, 2017, Proceedings*, pages 69–79. Springer International Publishing, 2017. ISBN 978-3-319-60285-1. doi: 10.1007/978-3-319-60285-1.

Narayanan, S., E. Chaniotakis, and C. Antoniou. Shared autonomous vehicle services: A comprehensive review. *Transportation Research Part C: Emerging Technologies*, 111:255–293, 2020. doi: 10.1016/j.trc.2019.12.008.

Neumann, A. *A paratransit-inspired evolutionary process for public transit network design*. PhD thesis, TU Berlin, Berlin, 2014.

Neumann, A. Why closing an airport may not matter – The impact of the relocation of TXL airport on the bus network of Berlin. *Procedia Computer Science*, 52C:896–901, 2015. ISSN 1877-0509. doi: 10.1016/j.procs.2015.05.160.

Neumann, A. and M. Balmer. Mobility Pattern Recognition (MPR) und Anonymisierung von Mobilfunkdaten. White paper, Senozon Deutschland GmbH and Senozon AG, 2020. URL `https://senozon.com/wp-content/uploads/Whitepaper_MPR_Senozon_DE-3.pdf`. V1.0.

Neumann, A., D. Röder, and J. W. Joubert. Towards a simulation of minibuses in South Africa. *Journal of Transport and Land Use*, 8(1):137–154, May 2015. doi: 10.5198/jtlu.2015.390.

Pagés, L., R. Jayakrishnan, and C. Cortés. Real-time mass passenger transport network optimization problems. *Transportation Research Record*, 1964:229–237, 2006. ISSN 0361-1981.

Planco, ITP, and TUBS. Grundsätzliche Überprüfung und Weiterentwicklung der Nutzen-Kosten-Analyse im Bewertungsverfahren der Bundesverkehrswegeplanung. Endbericht FE Projekt Nr. 960974/2011, Planco GmbH, Intraplan Consult GmbH, TU Berlin Service GmbH, 2015. Im Auftrag des BMVI. Auch VSP WP 14-12, see `http://www.vsp.tu-berlin.de/publications`.

Sáez, D., C. Cortés, and A. Núñez. Hybrid adaptive predictive control for the multi-vehicle dynamic pick-up and delivery problem based on genetic algorithms and fuzzy clustering. *Computers & Operations Research*, 35(11): 3412–3438, Nov. 2008. ISSN 0305-0548. doi: 10.1016/j.cor.2007.01.025.

Schöbel, A. Line planning in public transportation: models and methods. *OR Spectrum*, 34:491–510, 2012. doi: 10.1007/s00291-011-0251-6.

Trommer, S., V. Kolarova, F. E., L. Kröger, B. Kickhöfer, T. Kuhnimhof, B. Lenz, and P. Phleps. Autonomous Driving: The Impact of Vehicle Automation on Mobility Behaviour. Institute for Mobility Research (ifmo), 2016.

Vosooghi, R., J. Puchinger, M. Jankovic, and A. Vouillon. Shared autonomous vehicle simulation and service design. *Transportation Research Part C: Emerging Technologies*, 107:15–33, 2019. doi: 10.1016/j.trc.2019.08.006.

Zhao, Y. and K. Kockelman. Anticipating the regional impacts of connected and automated vehicle travel in Austin, Texas. *Journal of Urban Planning and Development*, 144(4), 2018. doi: 10.1061/(ASCE)UP.1943-5444.0000463.