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To Wait or to Cruise: The Trade-Off Between Waiting Time and Detours for Service Efficiency in Ride-pooling Systems

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Abstract

Empowered by modern communication technology, demand-responsive transport (DRT) in the form of ride-pooling has gained momentum. Thanks to its flexibility and convenience, it is considered as a promising alternative to conventional public transport and private mobility. In order to pool rides, detours may occur, and this usually leads to extra waiting times and ride durations for passengers. While many studies in the literature focus on improving vehicle scheduling, it remains interesting to explore how the extra time passengers spend in traveling can be converted into improved efficiency in a DRT system. In this study, we will try to answer this question by carrying out experiments in an agent-based simulation framework on a real-world scenario. Results from the experiments suggest that relaxing waiting time constraints is more effective in reducing the minimum required fleet size and, consequently, the operational costs of the DRT system compared to relaxing constraints on ride duration. On the other hand, relaxing ride duration constraints leads to a higher occupancy of vehicles during peak hours compared to relaxing the waiting time constraint. This, however, does not necessarily correspond to a more efficient service.

Keywords: demand-responsive transport (DRT); vehicle routing problem (VRP); agent-based transport simulation; ride-pooling;

1. Introduction

Demand-responsive transport (DRT) is a popular topic nowadays. In fact, if we take the terminology literally, then this is not something new. Regular taxis and paratransit buses in emerging countries such as the Jeepney system in the Philippines and the minibus systems in South Africa are also on-demand transport services, and they exist for a very long time (Zwick et al., 2022). What makes DRT a highly discussed topic, however, are the more recent app-based

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ride-hailing services. Thanks to its convenience, more and more people choose to use ride-hailing services to travel around (Tirachini, 2020). In this study, we limit the term DRT to only include these modern ride-hailing services. By introducing ride-pooling into DRT, we are actually getting a new mode of transport, filling the gap between conventional public transport service and taxi or private cars. With small vehicles or minivans, DRT with ride-pooling can be more flexible and efficient than an underutilized conventional public transport service. On the other hand, it is possible to make better use of the road resource than unit-capacity ride-hailing services and private cars. This not only serves traffic quality, but may also improve the environment (Greenblatt and Saxena, 2015; Zwick et al., 2021a).

In order to pool rides, vehicles need to cover some detours. This leads to extra waiting time and riding time onboard. Obviously, passengers would like to minimize the time travelled. While this is also in line with the interest of DRT operators, the operators also need to keep the operational costs low, such that attractive fares can be offered. A common way to reduce costs is to limit the fleet size and minimize the vehicle kilometers travelled. Lastly, the public interest of reducing traffic and environmental burden must be taken into account.

There are many studies that try to improve the service quality of the DRT system while maintaining acceptable costs. Alonso-Mora et al. (2017) have developed an optimization-based online ride-pooling algorithm, which is very effective in reducing the number of vehicles required to serve historical taxi demand in Manhattan, New York. Ruch et al. (2020) have quantified the benefits of various ride-pooling strategies in different scenarios under a realistic transport simulation framework. Kucharski and Cats (2020) have developed a ride-pooling strategy that takes the cost-benefit analysis of passengers into account and only considers the pooling possibilities that are attractive for the passengers. Trip pre-booking may be another way to improve the efficiency of the DRT system. According to some previous studies, cost reductions ranging from 20% to 40% can be expected, if the trips are pre-booked at least half an hour in advance (Lu et al., 2023a,b). Furthermore, the benefits of pre-booking can also be preserved in the cases where both spontaneous and pre-booked requests exist (Engelhardt et al., 2022). Apart from the vehicle-passenger matching algorithms, empty vehicle relocations (also known as rebalancing) can also improve the service quality (Pavone et al., 2012; Hörl et al., 2019; Bischoff and Maciejewski, 2020). With a better distributed fleet, more passengers can be picked up without waiting for too long, at the cost of additional empty kilometers.

In most of the above-mentioned studies, a fixed set of constraints regarding waiting time, ride duration and total travel time is assumed, with a main focus on the optimization of vehicles schedules. While the solutions proposed in those studies are highly valuable, there is also a need to investigate the implications of constraints on the DRT system. For example, how does the system react to shifts from longer admissible waiting times to longer admissible detours.

From the literature, we can see that people perceive waiting time and riding time onboard differently. Waiting time is often treated as less enjoyable than riding in a vehicle (Wardman, 2004). Waiting time in on-demand services, however, is not easy to interpret, as people not necessarily need to wait at the curbside and may proceed with their current activity after booking, accessing the stop just in time for the announced arrival time. Some people may even prefer to book somewhat in advance to get ready by dressing up or saying goodbye to their companions.Under this assumption, the disutility of waiting time can be significantly lower. The study by Alonso-González et al. (2020) even reports lower disutilities for waiting than for riding in a vehicle. Similarly, Schatzmann et al. (2023) show considerably lower disutilities for waiting time compared to travel time in a pooled choice model estimation using stated and revealed preferences from a large study of one of Europe's largest services in Hamburg. Meanwhile, working or resting while travelling on a DRT vehicle is considered comfortable by many people, and this means the disutility associated with ride duration can also be relatively low (Zhong et al., 2020). An in-depth overview of perceptions of waiting and travel time can be found in De Vos et al. (2023).

While it may be difficult to find a consensus on the value of time spending on waiting and riding a vehicle, we can still perform quantitative analyses on the overall system performance. We can investigate whether extending the permissible waiting time or ride duration would be more effective in reducing the necessary fleet size and vehicle kilometers of a DRT system. Based on this analysis, DRT operators may make better use of their resources. For example, if increasing maximum allowed ride duration is more effective, then operators may invest more budget improving the interior of vehicles and the seats. On the other hand, if a longer waiting time can release more burden on the fleet, then improving waiting facilities may be prioritized. Waiting facilities may be setup in collaboration with local shops and other business. Well-equipped DRT stops with seating can also be installed at some of the popular departure locations, such that passengers will have a better experience while waiting (Millonig et al., 2012).

In the actual operation of DRT systems, a certain level of minimum service quality related to travel time may be provided by the operators. For example, time windows for pickup and dropoff time are usually provided when passengers request for rides. For some operators, passengers may even decide between an earlier arrival time and a cheaper fare. With a defined minimum guaranteed service quality as constraints, the DRT operators can minimize the operational cost by optimizing the schedules of the vehicles.

In this study, we will explore how different levels of minimum service quality concerning travel time affect the DRT system. More specifically, we will independently adjust the constraints on waiting time and ride duration, and observe their impacts on the efficiency of the DRT system, including assessing the minimum required fleet size and the vehicle kilometers travelled (VKT). We will also look at the actual service quality experienced by passengers. The experiments are implemented within an agent-based transport simulation framework, and a real-world population model based on mobile-phone data is used. The data and the simulation framework are all open-sourced.

2. Methodology

In this study, we use MATSim, an agent-based transport simulation framework, to perform simulations and analysis (Horni et al., 2016). MATSim is an open-sourced mesoscopic agent-based transport simulation framework, where simulations can be carried out on detailed networks with efficient and relatively accurate traffic models. These characteristics make MATSim also suitable for simulating DRT systems. With the MATSim-DRT extension, operations of DRT systems can be simulated (Maciejewski et al., 2016).

In the MATSim-DRT extension, there is a default ride-pooling dispatching algorithm. The algorithm tries to greedily insert each travel request upon submission (t_{sub}) into one of the vehicles, while minimizing the total driving time of the DRT fleet. During the insertion, a couple of constraints have to be met. First, the maximum waiting time constraint defines the latest pickup time of a request:

$$t_{pickup,latest} = t_{sub} + t_{wait,max}, \tag{1}$$

Second, a request also needs to be transported to the destination before the latest arrival time defined as:

$$t_{arr,latest} = t_{sub} + \alpha \cdot t_{direct} + \beta, \tag{2}$$

where t_{direct} is the travel time of a direct trip by car; α and β are parameters that can be tuned. Finally, a vehicle's capacity should never be exceeded. If no suitable vehicle can be found for a particular request, then it may either be rejected or accepted with relaxed time-based constraints (i.e., pickup and/or drop-off exceed constraints), depending on the setup. In the latter case, a large penalty, proportionate to the amount of time the constraints are violated, will be imposed for each potential solution with violated time-based constraints. This will encourage the optimizer to prioritize the minimization of the violation of the time-based constraints.

It needs to be pointed out that in the default dispatching strategy, there is no explicit limit on the ride duration. If a request is picked up immediately after the submission, then it may stay onboard for a relatively long time. On the other hand, if a request is picked up by a vehicle after a relatively long waiting time, then the maximum duration that person can stay onboard the vehicle will be limited. In essence, the waiting time can be freely exchanged with the ride time as long as $t_{wait,max}$ is accounted for. This can lead to problems when the maximum waiting time may be relaxed, i.e. set to a high value (e.g., for less dense or rural regions). In this case, a passenger may face a high amount of detour if he or she is picked up early, as every insertion with an arrival before $t_{arr,latest}$ is legit.

As mentioned above, passengers have different perceptions on the value of waiting time and ride time. Therefore, we extend the dispatching strategy such that the ride duration of passengers can also be regulated.

To implement the maximum ride time or detour constraint, we first introduce an additional constraint on the pickup time. When a passenger submits the request, the dispatching algorithm will try to assign a vehicle. If the request is accepted, an expected pickup time will be transmitted to the passenger. In the original implementation, the actual pickup time may be delayed up to the latest pickup time defined in equation 1. The dispatching algorithm can take advantage of this and insert additional stops to pickup and drop-off other passengers before picking up that passenger. This leads to discrepancies between the initial scheduled pickup time and the actual pickup time for many passengers, also in the cases where there is no traffic congestion. Furthermore, as travel demands keep incoming, the actual pickup time of a passenger may also be delayed for multiple times. This usually leads to unsatisfying user experience.

The new pickup time constraint limits the maximum delay for a pickup since the initially scheduled pickup time. With this additional constraint, the latest pickup time now becomes:

$$t^{*}_{pickup,latest} = min\{t_{sub} + t_{wait,max}, t_{scheduled,initial} + t_{buffer}\} \tag{3}$$

where $t_{scheduled,initial}$ is the initially scheduled pickup time and t_{buffer} is the maximum delay allowed from the initially scheduled pickup time. The buffer can be set to 0, and in that case the dispatching algorithm will try to keep the promise and pickup the passenger at the initially scheduled pickup time. In the practice, a small buffer, such as 2 or 3 minutes can be given, in order to account for the uncertainties in traffic and other operational aspects. Furthermore, the additional pickups that cause minimal delay (e.g., pickups right along the way) can also be inserted beforehand.

With the new pickup time constraint, the user experience can be improved, as passengers will no longer suffer from constantly delayed estimated pickup times. Similar constraints can also be found in the real-world operation of DRT systems, which means the simulation may capture these services more realistically.

Apart from that, the introduction of the additional pickup time constraint also makes it easier to introduce the ride duration constraint under the existing structure of the optimization algorithm. When the buffer is small enough and there is no major disruption to the traffic, then the ride duration can be estimated as:

$$\hat{t}_{ride} = t_{arrival} - t^{*}_{pickup,latest} \tag{4}$$

Then we use a similar linear function as in equation 2 to calculate the maximum allowed ride duration $t_{ride,max}$:

$$t_{ride,max} = \lambda \cdot t_{direct} + \gamma \tag{5}$$

where λ and γ are parameters that can be tuned.

By replacing the $\hat{t}_{ride}$ with $t_{ride,max}$ and rearranging the equation, we can get the new latest arrival time $t^{*}_{arrival,latest}$ based on the maximum ride duration constraint:

$$t^{*}_{arrival,latest} = t^{*}_{pickup,latest} + t_{ride,max} \tag{6}$$

Since the term $t^{*}_{pickup,latest}$ is determined at the time when the request is submitted and scheduled and remains fixed, the latest arrival time $t^{*}_{arrival,latest}$ will also remain fixed. With this, the existing optimization algorithm can still be used to calculate the optimal vehicle-passenger assignments. We only need to replace the original pickup time and arrival time constraints with the new constraints introduced in equation 3 and 6.

In addition to the vehicle dispatching algorithm, the DRT system strategically relocates empty vehicles periodically to balance the vehicle supplies and the demands, such that the waiting time can be effectively reduced (Bischoff and Maciejewski, 2020).

3. Experiments setup

To quantify how the different constraints on waiting time and ride duration affect the efficiency of the DRT system, we compare the minimum required fleet size and the VKT under different setups. To enable a fair comparison, we do not allow rejections. That is to say, no matter what constraints we use, the DRT system will always serve the same group of passengers in each scenario. The minimum required fleet size is determined based on the 95-percentile of waiting times: by varying the fleet size, we can identify the minimum required fleet size that brings the 95-percentile waiting time below the maximum waiting time constraint. Once the fleet size is fixed, we observe service efficiency, VKT and service quality of passengers by analyzing the average waiting time, ride duration and total travel time experienced by the passengers.

For the system efficiency η_{RP}, we draw upon the indicator proposed by Liebchen et al. (2020), defined as the ratio of the passenger kilometers booked (PKB), d_{PKB}, to the vehicle kilometers travelled (VKT), d_{VKT}:

$$\eta_{\mathrm{RP}} = \frac{d_{\mathrm{PKB}}}{d_{\mathrm{VKT}}} \tag{7}$$

Note that PKB is the *direct* theoretical distance without any detours.

We perform two sets of experiments. In the first set of experiments, we start from a setup with relatively strict constraints: $t_{wait,max} = 300$ (seconds), $\lambda = 1.5$ and $\gamma = 300$ (seconds). This corresponds to a relatively high lower bound on the service quality. We then gradually relax one of the two constraints and observe how it will affect the DRT system and the experience of passengers. When modifying the ride duration constraints, we only adjust the value of γ, such that it is comparable to the adjustment of the waiting time constraint ($t_{wait,max}$). In the second set of experiments, we fix the sum of $t_{wait,max}$ and γ to be 1,200 (seconds). Then we explore how different allocations of the buffer affect the DRT system and the experience of the passengers.

All other parameters remain fixed, of which some are summarized here. We employ a uniform fleet consisting of minivans with 8 passenger seats. The parameters α and β (see eq. 2) are set to very large values, such that they remain inactive. As the focus of this study is on the operation of the DRT system and due to computational reasons, we only simulate the DRT system and ignore any other modes of transport. This guarantees that the demand will remain constant when we adjust the operational parameters, and thus the results are comparable.

Figure 1 illustrates the geographical extent of the scenario. The scenario is extracted from the open Kelheim scenario (Schlenther et al., 2022). Kelheim is a small town in Bavaria, Germany, which currently has a small scale DRT service in operations. To avoid randomness due to the small sample size, we artificially increase the demand based on mobile phone data (Neumann and Balmer, 2020), leading to 8,513 DRT trips per day.

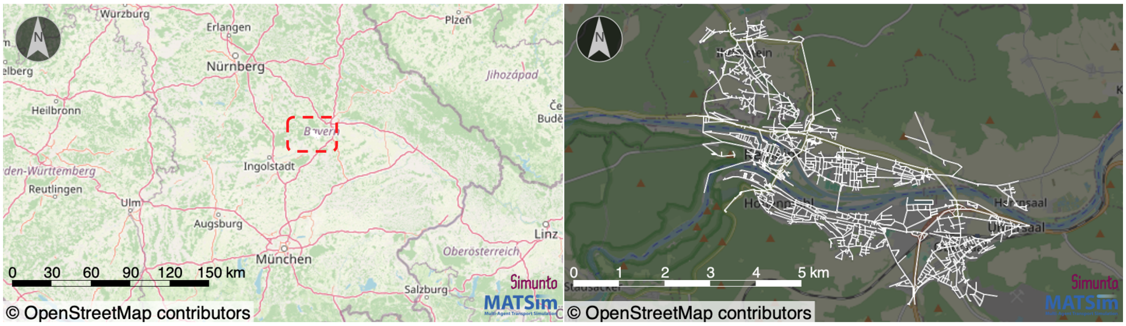

Fig. 1: Illustration of the scenario: Kelheim, a small town in Bavaria, Germany

4. Results and analysis

The key results for the first set of experiments are summarized in table 1 and figure 2. In the table, Δ values are calculated based on the "Base case", where both the waiting time constraint and the ride duration constraint are tight.

Table 1: Experiment 1, Kelheim scenario: effect of relaxing different constraints

Setup	Min fleet size	Δ_{fleet}	VKT [km]	Δ_{dist}	η_{RP}	$\Delta_{\eta_{\mathrm{RP}}}$
$t_{wait,max}$ = 300, γ = 300 (Base case)	92	-	29625	-	1.104	-
Relaxing maximum waiting time constraint ($t_{wait,max}$)						
$t_{wait,max}$ = 450, γ = 300	78	-15.2%	28375	-4.2%	1.153	+4.4%
$t_{wait,max}$ = 600, γ = 300	74	-19.6%	28265	-4.6%	1.158	+4.9%
$t_{wait,max}$ = 750, γ = 300	73	-20.7%	28052	-5.3%	1.166	+5.6%
$t_{wait,max}$ = 900, γ = 300	70	-23.9%	27756	-6.3%	1.179	+6.7%
Relaxing maximum ride duration constraint (γ)						
$t_{wait,max}$ = 300, γ = 450	88	-4.3%	28428	-4.0%	1.151	+4.3%
$t_{wait,max}$ = 300, γ = 600	85	-7.6%	27790	-6.2%	1.177	+6.6%
$t_{wait,max}$ = 300, γ = 750	82	-10.9%	27028	-8.8%	1.211	+9.7%
$t_{wait,max}$ = 300, γ = 900	79	-14.1%	26531	-10.4%	1.233	+11.7%

We can observe that the minimum required fleet size and the VKT decrease as we relax the waiting time or ride duration constraints. Furthermore, the relaxation of the waiting time constraint has a greater impact on the required fleet size than the relaxation of the ride duration constraint. In other words, if we want to reduce the operational cost by reducing the fleet size, then having a longer waiting time constraint will be more effective. When it comes to the VKT reduction, a relaxation of the ride duration constraint has a slightly larger impact on the VKT in general. The service efficiency lies in the range of 1.1 to 1.2 which is in line with earlier findings for rural Bavaria (Zwick et al., 2021b). The efficiency increases with both relaxations but relatively stronger for the ride duration constraint.

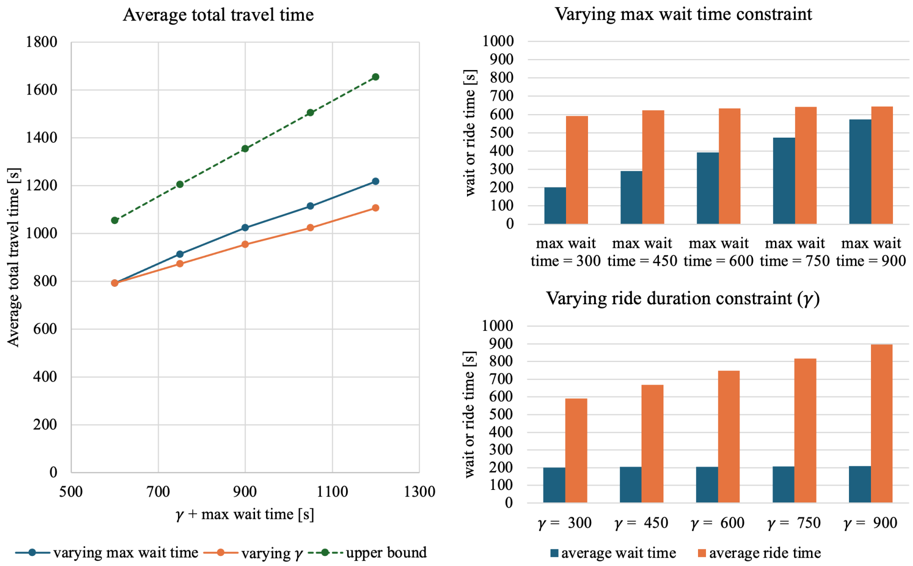

Fig. 2: Experiment 1, Kelheim scenario: actual service quality experienced by passengers under different setups

On the customer side, the average total travel time (i.e., waiting time plus riding time) increases as the constraints are relaxed because the vehicle scheduling algorithm is taking advantage of the relaxed constraints and tries to serve more passengers per kilometer travelled. Relaxing the waiting time constraint leads to a higher increase in the total travel time. If we split the total travel time into waiting time and ride duration, we can see that while relaxing the ride duration constraint (i.e., γ) and keeping the waiting time constraint constant, the average waiting time experienced by the passengers remains constant. Contrarily, when we relax the waiting time constraint and keep the ride duration constraint constant, we can observe a slight increase in the average ride duration experienced by the passengers.

The results of the second set of experiments are summarized in table 2 and figure 3. In this set of experiments, the results are compared against the "Reference case", where the constant part of the buffer is equally shared between the waiting time constraint and the ride duration constraint, and Δ values are computed based on that case.

Table 2: Experiment 2, Kelheim scenario: effect of different buffer allocations

Setup	Min fleet size	Δ_{fleet}	VKT [km]	Δ_{dist}	η_{RP}	$\Delta_{\eta_{\mathrm{RP}}}$
$t_{wait,max} = 300, \gamma = 900$	79	+14.5%	26531	+1.0%	1.233	-1.0%
$t_{wait,max} = 450, \gamma = 750$	72	+4.3%	26265	+0.0%	1.246	-0.0%
$t_{wait,max} = 600, \gamma = 600$ (Reference case)	69	-	26262	-	1.246	-
$t_{wait,max} = 750, \gamma = 450$	70	+1.4%	26630	+1.4%	1.229	-1.4%
$t_{wait,max} = 900, \gamma = 300$	70	+1.4%	27756	+5.7%	1.179	-5.4%

From the results, it can be seen that to reach a smaller minimum required fleet size, it is desirable to allocate adequate buffer to the waiting time constraint. And to minimize total VKT, an adequate buffer should be allocated to the ride duration constraint. This is in line with the results from the first set of experiments. In the end, an equal split of the total buffer of 1200 seconds between $t_{wait,max}$ and γ leads to a good performance from the perspective of the operator in this scenario. On the service quality side, the average total travel time experienced by the passengers increases slightly as we move towards a more relaxed waiting time constraint and a tighter ride duration constraint.

In addition to the daily aggregated values, we also look at the occupancy profiles of the vehicles throughout the day. Figure 4 illustrates the occupancy profiles of the both "extreme" setups, with $t_{wait,max} = 300, \gamma = 900$ and $t_{wait,max} = 900, \gamma = 300$, respectively. From the figures, it can be seen that if we allocate more slack time to the ride duration constraint, more vehicles will be occupied by more passengers during the peak hours (i.e., more pooling is happening). On the other hand, despite the fact that more seats in vehicles are occupied, it does not necessarily

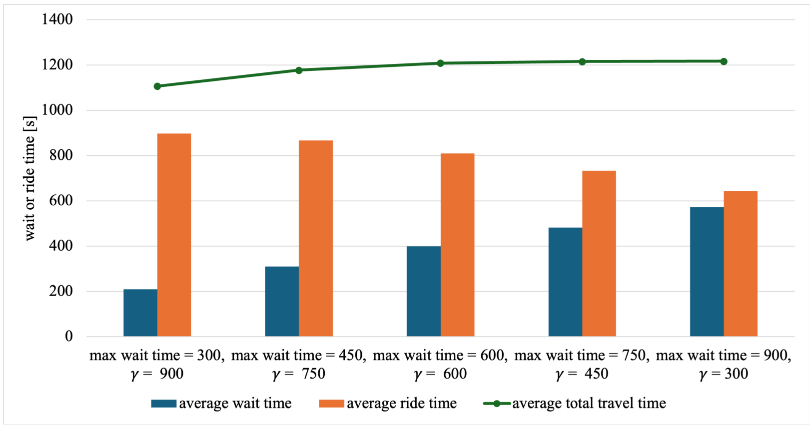

Fig. 3: Experiment 2: average travel and waiting times experienced by passengers

correspond to a reduced minimum required fleet size or service efficiency. For example, a passenger kept on board for longer may increase vehicle occupancy, but also increases detours that would not exist in a direct trip.

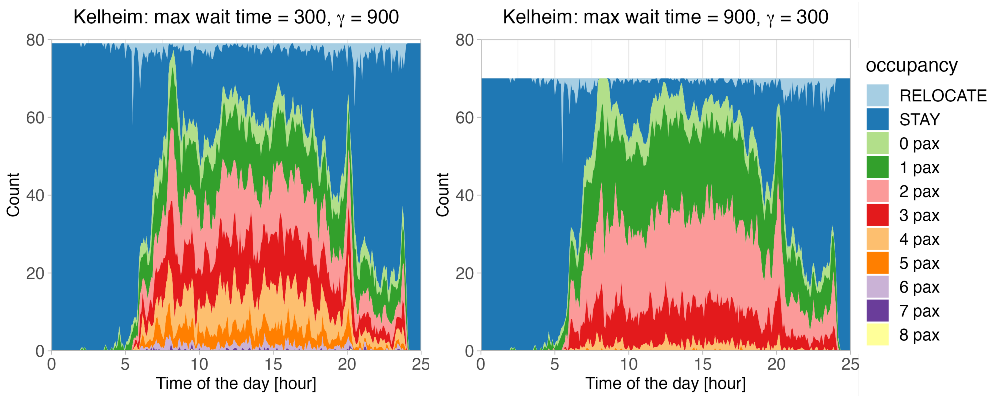

Fig. 4: Occupancy profiles of the fleet under different setups

5. Conclusion and Outlook

In this study, we have explored the impact of having different levels of minimum guaranteed service quality on the DRT systems and the passengers. In particular, we explicitly separate travel time into waiting time and ride duration. Two separate constraints are then imposed on the waiting time and the ride duration. We have carried out experiments in three scenarios based on real-world data, with different geographical characteristics and population distribution.

Results from the experiments indicate that the waiting time constraint has a more significant impact on the minimum required fleet size compared to the ride duration constraint. On the passenger side, the average total travel time experienced by the passengers increases more rapidly as we relax the waiting time constraint. When it comes to the vehicle occupancy, relaxing the ride duration constraint leads to higher occupancy rates compared to the case where we relax the waiting time constraint. This, however, does not necessarily correspond to a reduced minimum required fleet size, but may reduce VKT and increase service efficiency. Based on the results from this study, we can conclude that fleet efficiency can be improved if passengers can tolerate a higher maximum waiting time or ride duration. While a more relaxed ride duration is slightly better in terms of VKT and system efficiency, it does require considerably more vehicles to maintain the quality of the service. Given that the cost for keeping up more vehicles at the same time is likely more expensive than the small reduction in VKT, accepting higher waiting times instead of longer ride duration may be a sensible choice and DRT operators should prioritize enhancing the waiting experience, for example weatherproofing stop facilities . Building upon the findings of Schatzmann et al. (2023), when being faced with the decision to either allow longer waiting times or longer ride durations, customers would probably prefer the former.

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References

Alonso-González, M.J., van Oort, N., Cats, O., Hoogendoorn-Lanser, S., Hoogendoorn, S., 2020. Value of time and reliability for urban pooled on-demand services. Transportation Research Part C: Emerging Technologies 115, 102621. doi:10.1016/j.trc.2020.102621.

Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., Rus, D., 2017. On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. Proceedings of the National Academy of Sciences 114, 462–467.

Bischoff, J., Maciejewski, M., 2020. Proactive empty vehicle rebalancing for demand responsive transport services. Procedia Computer Science 170, 739–744. doi:10.1016/j.procs.2020.03.162.

De Vos, J., Ermagun, A., Shaw, F.A., 2023. Wait time, travel time and waiting during travel: existing research and future directions. Transport Reviews 43, 805–810. doi:10.1080/01441647.2023.2220206.

Engelhardt, R., Dandl, F., Bogenberger, K., 2022. Simulating ride-pooling services with pre-booking and on-demand customers. arXiv preprint arXiv:2210.06972 .

Greenblatt, J.B., Saxena, S., 2015. Autonomous taxis could greatly reduce greenhouse-gas emissions of us light-duty vehicles. Nature climate change 5, 860–863.

Hörl, S., Ruch, C., Becker, F., Frazzoli, E., Axhausen, K.W., 2019. Fleet operational policies for automated mobility: A simulation assessment for zurich. Transportation Research Part C: Emerging Technologies 102, 20–31.

Horni, A., Nagel, K., Axhausen, K.W. (Eds.), 2016. The Multi-Agent Transport Simulation MATSim. Ubiquity, London. doi:10.5334/baw.

Kucharski, R., Cats, O., 2020. Exact matching of attractive shared rides (exmas) for system-wide strategic evaluations. Transportation Research Part B: Methodological 139, 285–310. doi:10.1016/j.trb.2020.06.006.

Liebchen, C., Lehnert, M., Mehlert, C., Schiefelbusch, M., 2020. Ridepooling-Effizienz messbar machen. Der Nahverkehr 9, 18–21. URL: https://www.kcw-online.de/media/pages/veroeffentlichungen/effizienz-von-ridepooling/d9df2621f8-1600861812/dnv_2020_009_mehlert_etal_kcw-liz.pdf.

Lu, C., Maciejewski, M., Wu, H., Nagel, K., 2023a. Demand-responsive transport for students in rural areas: A case study in vulkaneifel, germany. Transportation Research Part A: Policy and Practice 178, 103837. doi:10.1016/j.tra.2023.103837.

Lu, C., Schlenther, T., Meinhardt, S., Nagel, K., 2023b. Quantifying the benefits of pre-booking in demand-responsive systems based on real-world scenarios. Preprint, TU Berlin, Transport Systems Planning and Transport Telematics.

Maciejewski, M., Horni, A., Nagel, K., Axhausen, K.W., 2016. Dynamic transport services. The multi-agent transport simulation MATSim 23, 145–152.

Millonig, A., Sleszynski, M., Ulm, M., 2012. Sitting, waiting, wishing: Waiting time perception in public transport, in: 2012 15th International IEEE Conference on Intelligent Transportation Systems, IEEE. pp. 1852–1857.

Neumann, A., Balmer, M., 2020. Mobility pattern recognition (mpr) und anonymisierung von mobilfunkdaten. White paper, Senozon Deutschland GmbH and Senozon AG. URL: https://senozon.com/wp-content/uploads/Whitepaper_MPR_Senozon_DE-3.pdf.

Pavone, M., Smith, S.L., Frazzoli, E., Rus, D., 2012. Robotic load balancing for mobility-on-demand systems. The International Journal of Robotics Research 31, 839–854. doi:10.1177/0278364912444766.

Ruch, C., Lu, C., Sieber, L., Frazzoli, E., 2020. Quantifying the efficiency of ride sharing. IEEE Transactions on Intelligent Transportation Systems 22, 5811–5816.

Schatzmann, T., Zwick, F., Axhausen, K.W., 2023. Investigating the preferences for the use of urban ridepooling, in: 11th Symposium of the European Association for Research in Transportation (hEART 2023), IVT, ETH Zurich.

Schlenther, T., Lu, C., Meinhardt, S., Rakow, C., Nagel, K., 2022. Autonomous mobility-on-demand in a rural area: Calibration, simulation and projection based on real-world data. Accepted for WCTR 2023. preprint available at https://svn.vsp.tu-berlin.de/repos/public-svn/publications/vspwp/2022/22-17/SchlentherEtAl2022KelRideAVServiceAreas.pdf.

Tirachini, A., 2020. Ride-hailing, travel behaviour and sustainable mobility: an international review. Transportation 47, 2011–2047. doi:10.1007/s11116-019-10070-2.

Wardman, M., 2004. Public transport values of time. Transport Policy 11, 363–377. doi:10.1016/j.tranpol.2004.05.001.

Zhong, H., Li, W., Burris, M.W., Talebpour, A., Sinha, K.C., 2020. Will autonomous vehicles change auto commuters' value of travel time? Transportation Research Part D: Transport and Environment 83, 102303. doi:10.1016/j.trd.2020.102303.

Zwick, F., Kuehnel, N., Axhausen, K.W., 2022. Review on theoretical assessments and practical implementations of ride-pooling, in: 22nd Swiss Transport Research Conference (STRC 2022), STRC. URL: 10.3929/ethz-b-000548675.

Zwick, F., Kuehnel, N., Moeckel, R., Axhausen, K.W., 2021a. Agent-based simulation of city-wide autonomous ride-pooling and the impact on traffic noise. Transportation Research Part D: Transport and Environment 90, 102673. doi:10.1016/j.trd.2020.102673.

Zwick, F., Kuehnel, N., Moeckel, R., Axhausen, K.W., 2021b. Ride-pooling efficiency in large, medium-sized and small towns - simulation assessment in the munich metropolitan region. Procedia Computer Science 184, 662–667. doi:https://doi.org/10.1016/j.procs.2021.03.083.