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Publication date:
2020-05

Permanent link:
https://doi.org/https://doi.org/10.3929/ethz-b-000420103

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Conference paper STRC 2020

STRC | **20th Swiss Transport Research Conference**
Monte Verità / Ascona, May 13 – 15, 2020

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Abstract

Emerging ridepooling services promise to improve existing mobility systems and increase efficiency in road traffic. Private mobility companies and policymakers strive to find the right design of such services to meet customer needs and reduce traffic in urban areas. In order to analyse the effects of ridepooling systems and to predict implications, the agent-based simulation framework MATSim offers two extensions for the simulation of on-demand pooling services. Both use dynamic vehicle routing, but the interaction between service and customers on the one hand, and the pooling strategies on the other hand, differ. These differences between both extensions, their characteristics and the effects on service efficiency are pointed out here. The results show the influence of different pooling strategies on efficiency, mileage, mean travel and waiting times of the system. While the AMoD system generally leads to better results in high-demand scenarios, the DRT system has advantages in low-demand scenarios due to a predictive rebalancing system based on historical demand. The MATSim simulations are derived from demand data of a ridepooling company in Hamburg, Germany.

Keywords

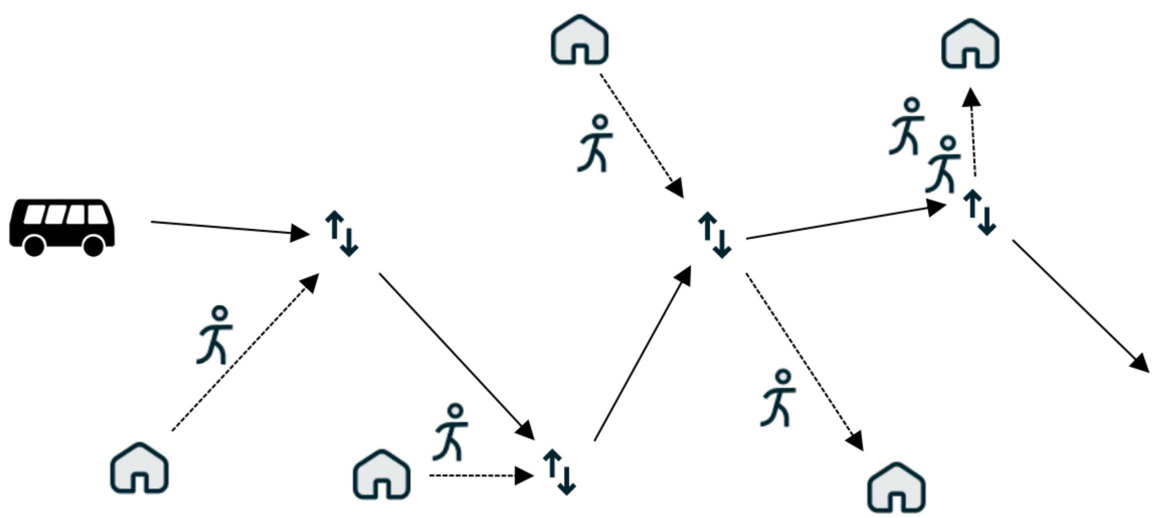
MATSim, ridepooling, on-demand mobility, demand responsive transport

1 Introduction

Several ridepooling services have been introduced world-wide in recent years by private mobility companies as well as public transport operators and public authorities. Ridepooling is not a new form of transportation as similar transport service complement urban transportation in many countries, such as for instance the minibus system in South Africa or the Dolmus system in Turkey (Neumann, 2014). The spread of digital communication technology however helped to improve the dispatching of customers and vehicles and lead to the establishment of Transportation Network Companies (TNCs) and app-based on-demand ridepooling services. Some of the best known TNCs offer pooled services as a cheaper alternative to their exclusive rides, for instance *UberPool* (LO and MORSEMAN, 2018), *Lyft Shared* (Lyft, 2020) or *GrabShare* (GrabShare, 2020). While those TNCs have gained large market shares in wide parts of the world, they face strong regulations of their ride-hailing business in the European and German mobility market. In Germany several exclusive ridepooling services have been introduced, e.g. *CleverShuttle* (CleverShuttle, 2020), *ioki* (ioki, 2020), *IsarTiger* (Münchner Verkehrsgesellschaft mbH, 2020) or *MOIA* (MOIA, 2020). Due to the current COVID-19 pandemic, some of these services are currently suspended.

Figure 1 shows the ridepooling process for one vehicle and three different customers that share a similar route to reach their destination. We consider a stop-based service that requires customers to walk to and from a pre-defined stop to use the service.

Figure 1: Ridepooling process with pre-defined stops



There has been a great variety of research in the field of (autonomous) shared on-demand mobility, its impact on the transportation system and the (dis-)advantages for customers. Many simulation frameworks and operational strategies have been introduced to assess the effects of (pooled) on-demand mobility, mostly in the context of autonomous mobility (Bischoff *et al.*, 2017; Hörl, 2017; Ruch *et al.*, 2020; Hyland and Mahmassani, 2018; Alonso-Mora *et al.*, 2017). As simulations frameworks differ as well as assignment and pooling strategies, the results of different pooling strategies are difficult to compare. Two of the frameworks were introduced as extensions of the Multi-Agent Transport Simulation MATSim (Horni *et al.*, 2016). This facilitates the comparison of them which we will do in this work. Ruch *et al.* (2020) implemented different pooling strategies into the Autonomous Mobility on-Demand (AMoD) extension and found that in urban environments the strategy of Alonso-Mora *et al.* (2017) performs best in terms of sharing rate and saved mileage, which is why we focus on this strategy here. The second pooling strategies, developed by Bischoff *et al.* (2017), was introduced as the MATSim extension for demand responsive transport (DRT). A main difference of the two modules is the assignment or rejection of requests to vehicles that happens immediately after the submission of a request in the case of the DRT module, whereas the AMoD module saves all requests for a predefined timeframe and assignment optimisations take place every 30 seconds, including the possibility of re-assignments.

We compare the two pooling strategies in regards to computation time, efficiency, service level and (empty) mileage with different fleet sizes using demand data from the ridepooling service MOIA in Hamburg. Section 2 gives a further explanation of the simulation framework and the pooling strategies as well as the input data. The results are presented in section 3 followed by a discussion of the results in section 4.

2 Simulation Configuration

This section describes the simulation framework MATSim, the implemented pooling extensions and their functionality and the demand and supply data that serves as input for the simulation.

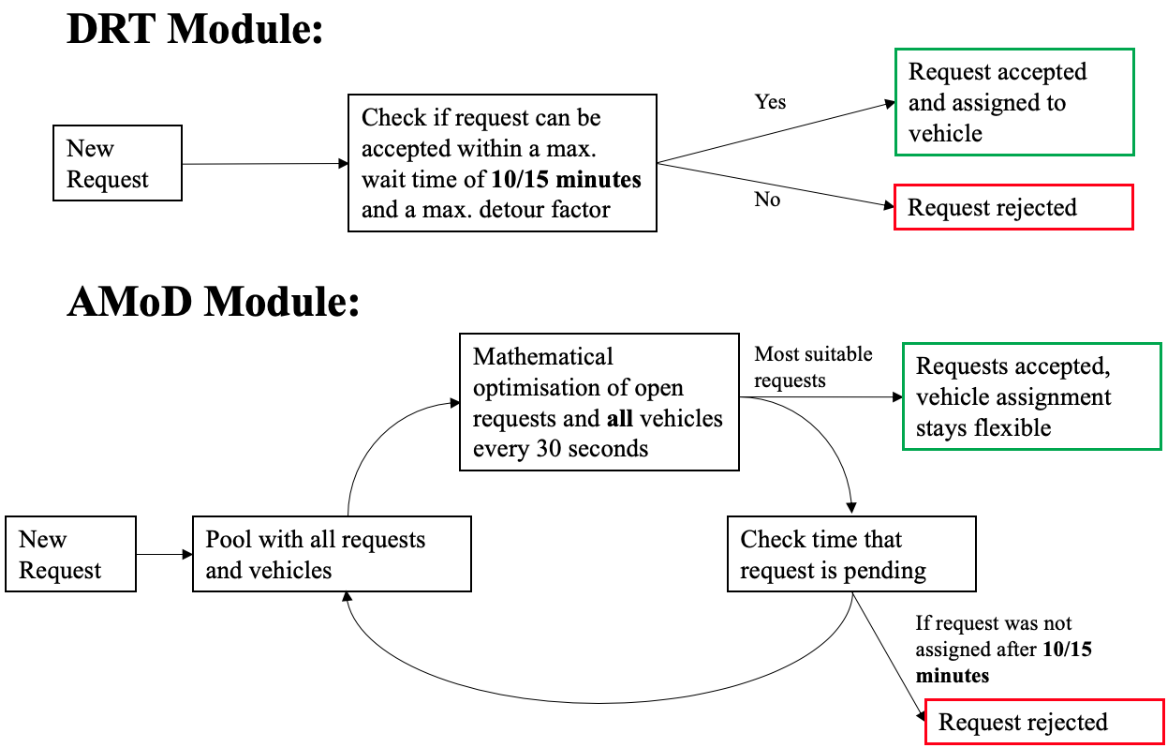
2.1 Simulation Framework MATSim

The multi-agent transport simulation MATSim is capable of modelling large-scale transport scenarios on a microscopic level Horni *et al.* (2016). In general, a daily plan with all activities and trips between the activities of each agent of a synthetic population is simulated. In an iterative approach, each agent aspires strives to optimise its daily schedule by reducing travel times and extending the execution of activities.
Despite the possibility to simulate entire populations and different modes, we only focus on the ridepooling trips of one day and do not make use of the mode choice feature of MATSim, as information about the whole population of Hamburg is not yet available. Compared to the simulation of an entire synthetic population, this setup leads to faster computation times and an easy reproducibility for different spatial environments, since the amount of required information is greatly reduced. In recent years, different MATSim extensions have been developed to simulate different types of on-demand mobility (Maciejewski, 2016). In this study, we make use of the ridepooling extensions *DRT* (Bischoff *et al.*, 2017) and *AMoD* (Ruch *et al.*, 2020) extension that are both based on the DVRP extension that was developed by Maciejewski *et al.* (2017) and designed to solve the dynamic vehicle routing problem.

2.2 Pooling Extensions

For the simulation of ridepooling services in MATSim, the minimal requirements are a street network with traffic flows, a fleet of dynamic vehicles and customer demand. The dynamic transport system can be integrated into existing MATSim models and interact with other modes. This allows to benchmark the simulation of vehicle routing against other modes and for instance analyse and compare efficiencies or external effects.
During the simulation, future requests and future vehicle states are not known in advance, but are allocated to each other live and dependent on the system state. This ensures, that the system in the simulation behaves like a real-world system and cannot pool any requests in advance without a request being submitted. Figure 2 shows the booking processes for the two MATSim extensions considered. The process within the DRT module is as follows: Each time a new request is submitted, the system checks if a vehicle can serve the request within a maximum wait time and considering a maximum detour time of the uncompleted rides. In this work we analyse scenarios with a maximum wait time of 10 and 15 minutes and a maximum detour of 5 minutes + 50 % of the direct ride time. If more than one vehicle can serve the request, the most feasible based on the parameters

Figure 2: Booking Process in the DRT and the AMoD module



vehicle capacity, vehicle availability, wait time and detour time is elected to serve the request (Bischoff *et al.*, 2017).

The booking process within the AMoD module does not only consider a request at the time it is submitted, but optimises the overall system regularly, taking into account all requests that have not yet been picked up or rejected. The algorithm does not directly respond to an incoming request, but adds it to a pool of all pending requests and vehicles. A mathematical assignment optimisation takes place every 30 seconds and takes into account all vehicles in service and all requests that were not yet served or rejected. The maximum wait time after the assignment of a vehicle is 5 minutes and the maximum delay due to detours is 10 minutes. An optimisation strategy defines the most suitable requests based on the status of the system and the given constraints, accepts them and assigns them to the most suitable vehicle. Until the customer is picked up, the assigned vehicle can be reconsidered in every optimisation step. All requests that cannot be assigned in an optimisation step remain in the pool of open requests. If requests remain in the pool for more than 10 or 15 minutes, they are rejected and not considered any further. All other requests are considered again in the next optimisation step. As Ruch *et al.* (2020) have found that in urban environments, the *High-Capacity Dispatcher* of Alonso-Mora *et al.* (2017) performs best in terms of mileage reduction and sharing rate, we focus on this strategy implemented in the AMoD module.

Both extensions include a rebalancing strategy to reallocate idle vehicles to areas with a high expected demand and thus improve the service level. They have been introduced and described by Bischoff and Maciejewski (2020) and Alonso-Mora *et al.* (2017). While the rebalancing strategy of the AMoD module only takes into account the current demand, the rebalancing strategy of the DRT module takes the demand from previous iterations into account. Consequently we simulate only one MATSim iteration for the AMoD module and three MATSim iterations for the DRT module. Since the demand does not vary from iteration to iteration, the DRT system has better information where to reallocate the vehicles.

2.3 Input Data

The input data is obtained from the German ridepooling service MOIA (2020) that operates in Hamburg since April 2019. We take 12,427 requests that MOIA had on a particular day during the ongoing ramp-up phase and serve it with different fleet sizes from 50 to 300. It should be expected that modal choice decisions specifically affected from the current COVID-19 pandemic will change in regards to shared mobility systems. We only consider single bookings instead of group bookings and therefore define the size of the vehicles to have 4 seats although MOIA operates with 6-seaters in Hamburg.

Figure 3 shows the service area of the ridepooling service by the time the study took place and the used street network taken from OpenStreetMap (OpenStreetMap Contributors, 2020). The area covers an area of roughly 200 km^2 and covers the most densely populated areas of Hamburg. The highest demand occurs in the central parts of Hamburg around the lakes Inner and Outer Alster and at the airport. After matching all virtual stops of MOIA with the MATSim street network, roughly 7,000 MATSim stops remain. In general, customers reach a stop within 250 metres of their location. The time to pick up and drop off customers is defined to be 30 seconds.

3 Results

The ridepooling strategies are compared in terms of experienced service levels for the customers, produced mileage and occupancy of the fleet. We consider five different scenarios: The DRT strategy without rebalancing strategy and a maximum wait time of

Figure 3: Overview of Service Area and Stop Network

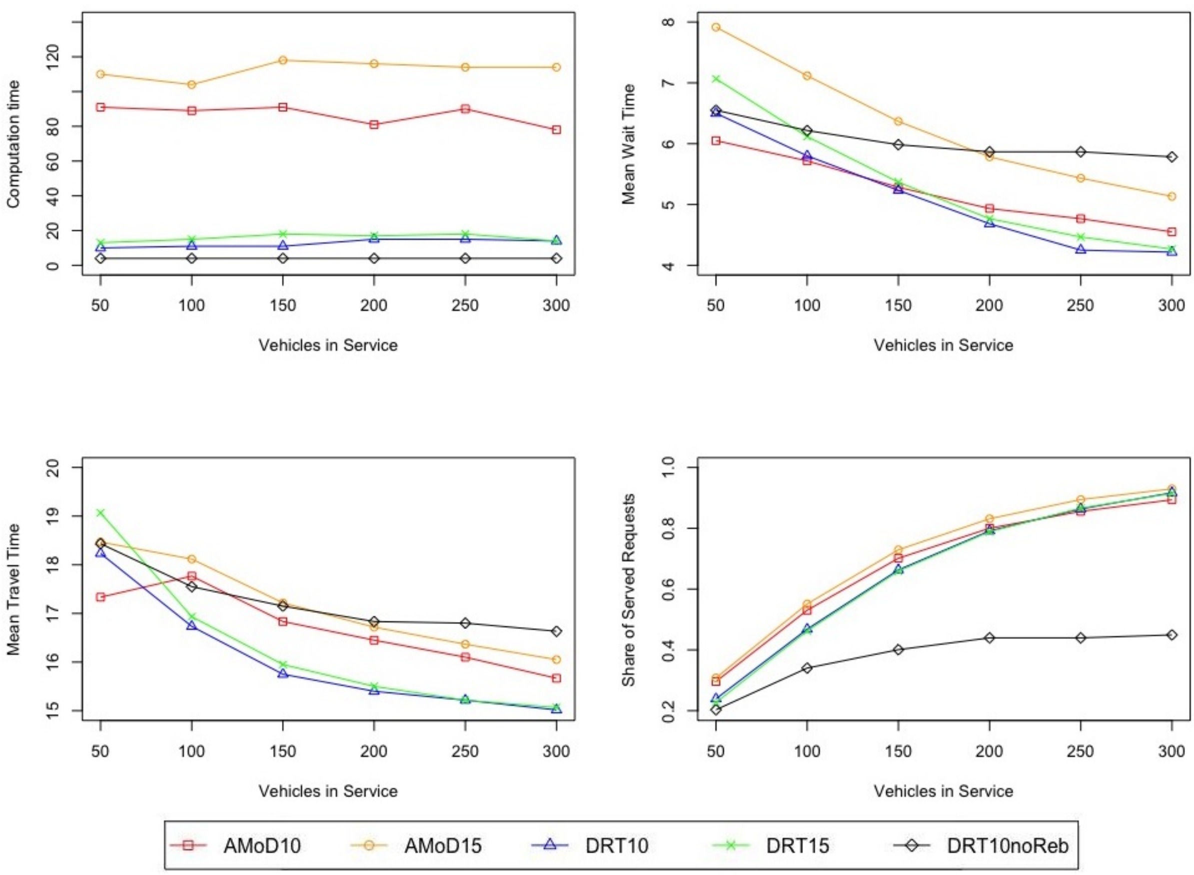
10 minutes, the DRT strategy with rebalancing strategy and a maximum wait time of 10 and 15 minutes and the AMoD strategy with pending requests remaining in the request pool for 10 and 15 minutes.

The computation time for both strategies is shown in a plot in Figure 4. The DRT system without rebalancing only requires one iteration, which only takes four minutes in all scenarios. To make use of the rebalancing strategy, we simulate three iterations which increases the total computation to 10 to 18 minutes. The used "High Capacity Dispatching" strategy of the AMoD module requires much longer computation times between 78 and 118 minutes. If pending requests are saved for a longer time, computation increases even further because the optimisation problem becomes more complex.

3.1 Service Level

We measure the service level of the ridepooling service through the share of requests that could be served and the experienced wait and travel time. Figure 4 shows the mean wait time, mean travel time, the share of served requests and the computation time for each scenario. All pooling strategies can provide shorter wait times with a bigger fleet size,

Figure 4: Service Level Results and Compuation Time for different Fleet Sizes and Pooling Strategies



which has been expected as vehicles are better distributed throughout the city, especially in areas with high demand, and customers may be reached faster. Without rebalancing, the mean wait time does not decrease a lot with a larger fleet because the distribution effect is smaller and badly located vehicles remain where they are until they are assigned to a new request. Customers face slightly higher wait times in the AMoD system than in the DRT system.

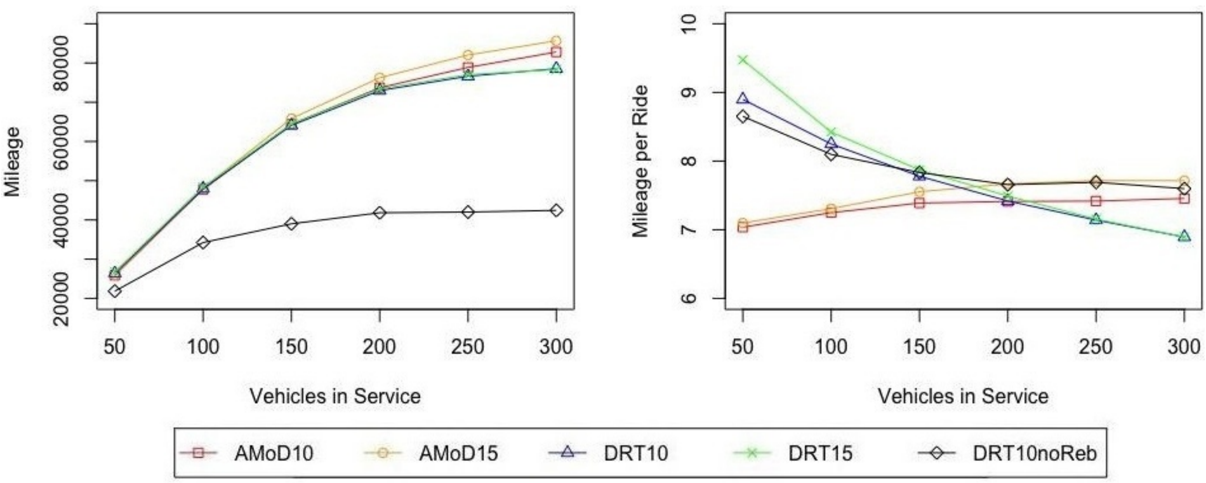
The travel times show a similar pattern and generally decreases with larger fleet sizes as more vehicles are availabe for the same amount of requests and consequently less detouring takes place. The effect is again smaller for the scenario without rebalancing and travel

times are slightly higher in the AMoD system than in the DRT system.
The share of served requests increases as expected with an increasing number of vehicles. The effect is smallest for the scenario without rebalancing strategy and the share of served requests remains below 50 %. All other strategies are able to serve more than 80 % of the requests with fleet sizes above 200 vehicles. The AMoD system is able to serve more customers than the DRT system in all scenarios with less than 200 vehicles whereas with high fleet sizes both strategies serve a similar amount of customers.
Overall, the strategies offer a similar service level to the customer. The low amount of shared rides in a system without rebalancing shows the importance of such feature.

3.2 Mileage

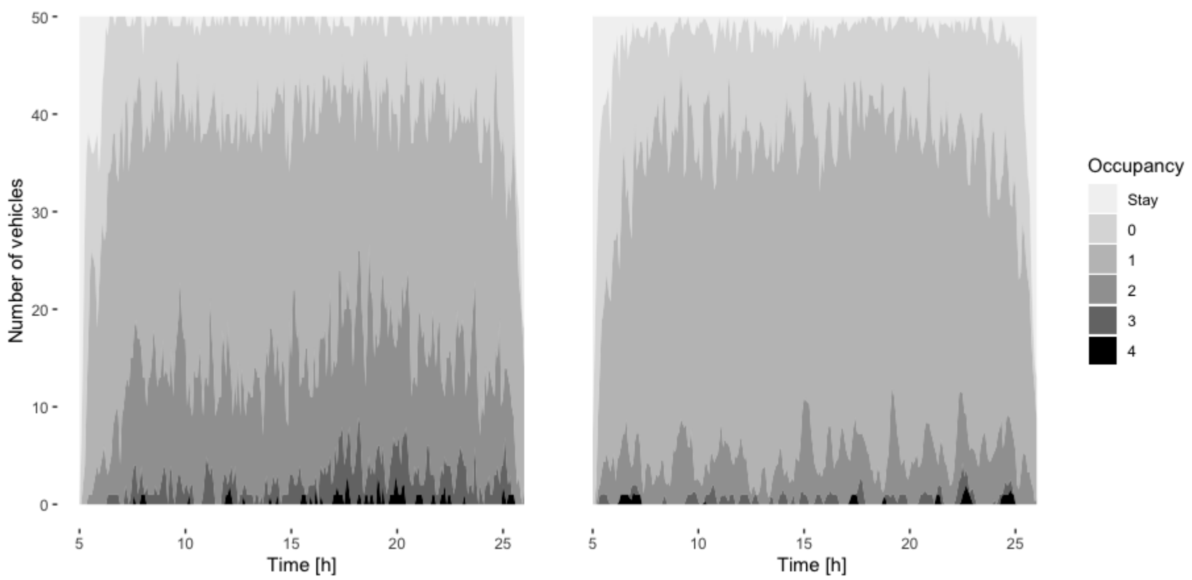
Produced overall and empty mileage are important indicators for the effect on traffic load and congestion and should be as low as possible. Figure 5 shows the overall mileage and the mileage divided by the number of served rides for each pooling strategy. The

Figure 5: Mileage results for different Fleet Sizes and Pooling Strategies



produced mileage is lowest for the strategy without rebalancing since less rides are served and many vehicles stay parked for a long time of the day. The other strategies show a similar pattern but with higher fleet sizes, the AMoD system produces more mileage. As the mileage depends on the number of served rides, we also consider the produced mileage per ride. The average direct distance of all rides is approximately 7 km. Major differences may be observed between the two systems. While the mileage per ride in the DRT system constantly decreases with higher fleet sizes, it remains stable for the AMoD system. The configuration of each strategy, i.e. different waiting/queuing times, does not have a high

Figure 6: Vehicle occupancy over the course of the day for the AMoD (left) and DRT (right) system with a fleet of 50 vehicles

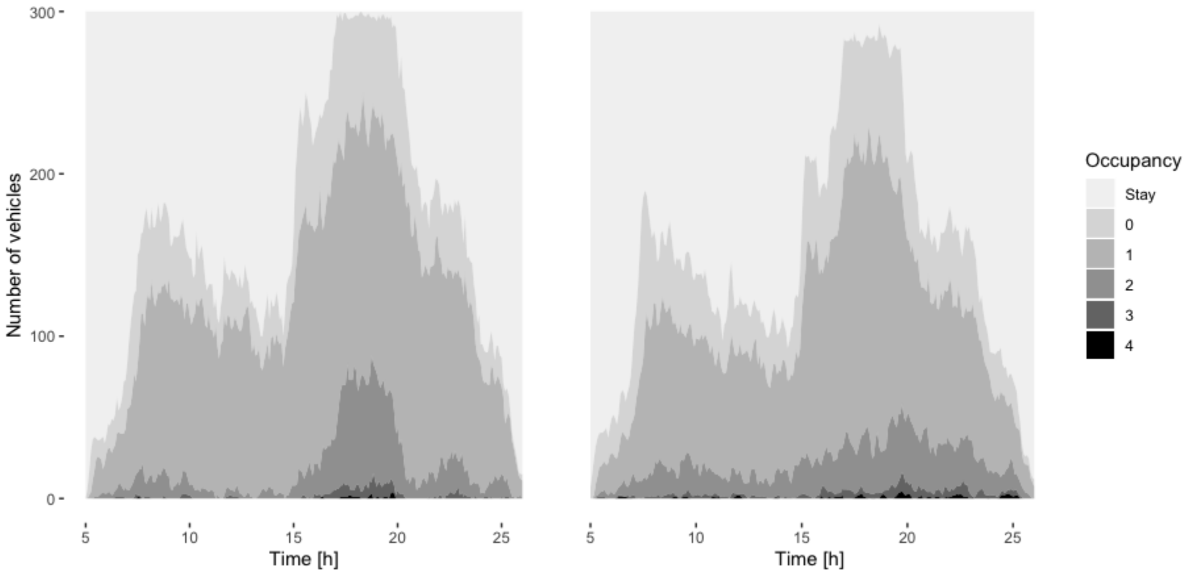


impact on the pattern. Nevertheless, different configurations of the pooling algorithms could lead to an acceptance of rather short or long trips which affects the result as long as not all requests are served. Both pooling strategies can be adapted in this regard.
The share of empty mileage is between 21 and 26 % in the AMoD and DRT scenario with rebalancing, without major differences between the two systems. Without rebalancing the share of empty mileage is only 15 % for all fleet sizes as the empty reallocation drives are not conducted.

3.3 Occupancy

The vehicle occupancy is an important indication how many rides are pooled and whether the vehicle size is appropriate. This analysis shows at which times the fleet operates at its capacity limit with the both pooling strategies. Figure 6 shows the fleet occupancy over the course of the day with 50 vehicles with a requests saved for up to 15 minutes in the AMoD case and a maximum waiting time of 15 minutes in the DRT case. The colours show how many vehicles transport a certain amount of different bookings at the same time. If vehicles have the status *Stay* they park and await the next request and if the status is *0* they are either rebalancing or on their way to a customer. The fleet is busy throughout the day in both cases. In the AMoD scenario, more vehicles transport 2, 3

Figure 7: Vehicle occupancy over the course of the day for the AMoD (left) and DRT (right) system with a fleet of 300 vehicles



or 4 different bookings simultaneously than in the DRT system in which vehicles rarely transport more than 2 bookings at the same time. This is also reflected in the higher share of served rides of the AMoD strategy, shown in Figure 4. This result indicates that the AMoD algorithm perform more efficiently in scenarios with very high demand and low supply.

Figure 7 shows the fleet occupancy when the service operates with 300 vehicles. A small peak in demand can be observed in the morning with almost 200 busy vehicles, and a large peak in demand occurs between 5 and 10 pm when almost all vehicles are busy. In the DRT system, a small share of vehicles is always staying and waiting for an order. In the evening peak, the occupancy of the AMoD fleet increases and almost 100 vehicles transport 2 or more bookings at the same time whereas only about 50 vehicles of the DRT fleet do so. In contrast, the DRT system seems to have higher occupancy rates than the AMoD system at times with little demand and many idle vehicles. This may be a consequence of the demand information from the first iterations that are taken into account when vehicles are rebalanced.

4 Conclusion

In this work two state of the art pooling strategies, implemented in the simulation framework MATSim, are compared based on demand data of the ridepooling company MOIA in Hamburg. Overall, both strategies lead to similar results in terms of travel and waiting times, but the service efficiency differs for different demand and supply situations. In high demand situations the AMoD systems is able to pool more requests than the DRT system and rejects less passengers. This leads to higher customer satisfaction and revenue for the operator. In low demand situations with many idle vehicles, the DRT system transports more customers. This might be a consequence of the rebalancing system that takes into account historical demand from previous iterations and therefore allocates idle vehicles optimally. The results of the system without a rebalancing strategy show the high importance of such policy that should be fed with historical demand data. The mileage analysis shows a clear trend that with an increasing fleet size, the DRT system is able to transport the same amount of requests with less kilometres travelled. This trend will be further analysed with larger fleet sizes and different demand scenarios. The high computation time is a downside of the AMoD environment and it would be necessary to adjust the algorithm to simulate larger scenarios.
Further studies will evaluate the system behaviour in different demand and supply scenarios. We also consider to implement the functionality into existing MATSim models and evaluate the interaction with other transport modes and the mode choice behaviour of the customers.

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