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A Simulation Based Analysis for Combining On-Demand Passenger and Freight Transport

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Abstract

Serving both passenger and freight demand with the same vehicle fleet is an ambition that led to the development of several innovative vehicle concepts [1, 2]. This study proposes a simulation-based methodology to investigate the execution of freight tours with an On-Demand fleet of autonomous, modular vehicles while giving priority to passenger transport. Based on assumptions regarding the operational scheme, tour pricing and delivery time windows, the software Multi-Agent Transport Simulation (MATSim) is extended. The developed methodology is then applied to a Berlin-wide freight delivery scenario. The results show that when using a relatively large vehicle fleet, passenger wait time statistics barely change. A rough cost analysis for the freight operator suggests that there is a large saving potential when using autonomous On-Demand vehicles instead of an owned fleet. Because of the uncertainty of price composition, further studies to quantify this saving potential have to be made. As a sensitivity analysis, various fleet configurations are simulated to determine a fleet size, which is potentially suitable for a real world scenario.

Keywords: *Autonomous Vehicles, Mobility-On-Demand, Demand-Responsive Transport, Freight Transport, Parcel Delivery, Multi-Purpose Vehicle Fleets, Transport Simulation, Agent-based Simulation*

1. Introduction

This paper is an extended version of 'Simulation of On-Demand Vehicles that serve both Person and Freight Transport', which originally was published at ANT2022 (https://www.sciencedirect.com/science/article/pii/S1877050922004665).

In recent years, (autonomous) ride-pooling fleets as a part of Mobility-as-a-Service (MaaS) have been a focus of transportation research [3, 4]. While pooling services using conventional cars operate in various cities [3, 5], pilot projects on the operation of autonomous vehicle fleets are conducted [6]. As driver wages constitute a major part of operation costs [7, 8], automation might be the key factor for demand-responsive transport (DRT) systems to establish themselves in the long run. Serving the current urban passenger mobility demand with MaaS systems could reduce the overall number of vehicles in the system by a factor of ten compared to individual motorized transport [9]. Despite this fact, there still is unused capacity in MaaS systems, as passenger demand commonly shows strong peak times and many vehicles remain idle during off-peak times [10]. Apart from passenger transport, Mobility-On-Demand (MOD), which is to be differentiated from MaaS, also affects freight transport [11]: The market responds to the increasing demand related to e-commerce with short-term deliveries, made feasible through innovative technological concepts such as including drones and robots on the last mile and automates parcel lockers [12–14]. In Germany, the parcel delivery market has grown by 67% within 10 years and is expected to grow further [15]. Automation and digitization not only support the thrive of MOD, but are influencing the entire supply-chain, reducing operational costs and increasing system efficiency. Potentially, deliveries can be shifted into off -peak transport times in order to reduce delivery travel times and relieve the load on the transport network during peak times. Trying to combine the developments of automation, the increase in (commercial) transport demand, and the thrive of MOD and MaaS respectively, various institutions including major car manufacturers have developed automated, modular vehicle concepts that aim to serve multiple transport segments [1, 2]. A previous study [16] shows that these concepts provide the potential to reduce the overall number of vehicles in the system. However, the study is conducted in the context of private vehicle ownership and stronger effects are expected for commercial fleets. This is the starting point for the present study. In contrast to Schlenther et al. [16] [21], modular vehicles are assumed to be run as an MOD fleet, which requires different algorithms for operation (e.g. dispatch of vehicles to customers and parcels etc.). For that, vehicles are assumed to deliver either persons or parcels at a time. The simulation-based approach is applied to the use case of Berlin with synthetically generated demands for

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passengers and parcel delivery and impacts on passengers, fleet operators and freight tours are analyzed.

2. Methodology

2.1. The MATSim framework

With MATSim (stands for Multi-Agent-Transport-Simulation; see https://github.com/matsim-org/matsim-libs/ and https://matsim.org/) there already exists a possibility to simulate large-scale traffic models. Its open-source implementation in Java offers high accessibility and expandability [17]. Each MATSim run has an initial (transport) demand, which is represented by a synthetic population of so-called agents, to begin with. Each agent possesses a certain number of daily plans, each consisting of activities, legs and a corresponding score. The score is the major criteria of whether a plan gets selected or not. After executing the actual daily plans in the physical traffic simulation, each performed plan receives a score. When the scoring process is done, a certain share of agents is allowed to adapt their executed plan. Through transformation the following (plan-)elements can be changed: departure time, route, transport mode or destination. Usually, the circle of traffic simulation, scoring and replanning is repeated until a stochastic user-equilibrium is achieved or the maximum number of iterations is reached.
One out of two MATSim extensions used in this study is the DRT module that is used for simulating demand-responsive transport services where vehicles are planned using dynamic routing algorithms [18]. Each vehicle in the DRT fleet has a schedule, that is re-computed by the optimization algorithm (optimizer) [19] in response to changes in the state of the system (demand, supply and traffic). Usually, ride requests are created by passengers at the event of their departure from their origin activity, only.
The second extension used is MATSim's freight module, with which tour planning of freight operators can be simulated. It introduces a structural representation of freight companies, the carrier agent, with vehicle fleet, depot(s) and delivery orders. Delivery orders contain a good's quantity, source, destination and delivery time window [20]. The actual planning of tours is done by jsprit [21], an open-source software, which iteratively solves vehicle routing problems. Therefore, a vehicle fleet and freight demand is needed, represented by services that hold information on customer time windows (See Section 3), within which the service has to be supplied.

2.2. Assumptions

Before combining the aforementioned freight and DRT extensions, three key assumptions had to be made.

1. For the policy cases, it is assumed that all carriers as the representation of freight companies do not possess their own vehicle fleet. Instead, they hire autonomous vehicles from a DRT fleet operator just like a usual DRT customer would do, too. Therefore, an arrangement between the two companies is needed, which settles the processing of a certain mandatory number of daily freight tours. On the freight companies side, said agreement ensures the delivery of their daily freight demand while saving a significant share of overhead costs. From the perspective of the DRT service providers, it offers a chance to reduce idle vehicle times by keeping them busy.
2. It is assumed that despite the additional demand induced by daily freight tours, the priority of the MOD company will remain on passenger traffic. This is because passengers are more time sensitive than the delivery of parcels. Additionally, nowadays companies like Uber, Lyft, etc. are already focused on offering passenger services, so it is expected that they want to keep said focus. The inclusion of freight traffic has the consequences that a vehicle can only be available for freight tours if it is not currently carrying a passenger. Moreover, it can never transport people and cargo at the same time. In this study, we assume modular vehicle concepts such that retooling is required before and after each freight tour.
3. In this research, the planning of freight tours is carried out offline, meaning beforehand, e.g. at midnight. This is mainly because of the complexity, which online tour planning would bring to the table. This research aims to explore the potential of using On-Demand-vehicles for person and freight transport, so it is held as simple as possible.

The addition of the freight demand under the above assumptions requires an adaption of the used dispatch algorithm within the DRT module. To be able to distribute freight demand among vehicles, taking into account the priority of passenger transport, an additional operational logic is needed, for switching vehicles between modes (passenger mode or freight mode). The freight tours are fed into the DRT optimizer through a separate request channel, as shown in Figure 1. From tour planning, the desired tour start time can be derived and offset by the time for retooling the vehicle. Tour requests are assumed to be submitted to the DRT optimizer with a look-ahead. For this work, we use a value of 7 minutes. In each time step, all passenger requests get handled first. If, after that, the share of idle vehicles in the DRT fleet is higher than a configurable value, unprocessed freight requests are handled in the order of their submission times until the share of idle vehicles is undercut or no freight request remains. This way, freight requests remain in the pipeline for a maximum duration of the submission look-ahead, before they are finally rejected. Otherwise, they would be performed later than planned. In this work, no replanning of (rejected) tours is conducted. The priority of passenger transport is imposed by scheduling freight requests only if a certain share of the fleet is idle. However, it means that a certain share of the fleet might remain unproductive even though there are more (freight requests). The value probably needs calibration for different use cases. For this work, a value of 50% is used.

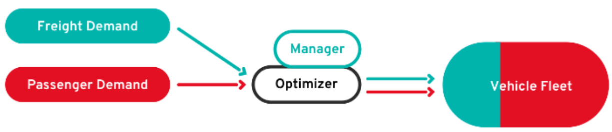

Figure 1. Structure of the proposed extension to the DRT module within MATSim

3. Simulation Setup

The dispatch algorithm presented in Section 2 for managing both passenger and freight demand is applied to the MATSim Open-Berlin-Scenario (https://github.com/matsim-scenarios/matsim-berlin/) with a sample size of 10% [22]. The parcel demand and DRT fleet are added, with the assumption that the additional traffic caused for freight purposes has no remarkable congestion effect, as the number of vehicles to serve it is relatively small. The following section describes the adaption of the scenario as well as additional assumptions that had to be made.

3.1. Vehicle Configuration

As mentioned before, an autonomous vehicle fleet is assumed for the present study. One exemplary vehicle concept is the U-Shift, which among others was developed by the German Aerospace Center (DLR). The U-Shift's drive unit (driveboard) works without a driver and is fully electric. It has an integrated lifting system through which the capsules designed for a wide variety of purposes can be picked up and dropped off. Possible use cases among others include public transport, parcel delivery or waste disposal [23]. Due to the detailed documentation of the concept, the U-Shift serves as a template for many vehicle-related parameters of this investigation. The dimensions of the cargo capsule are most decisive as they are crucial for how many packages per vehicle can be transported. The U-Shift's cargo capsule measures 2.60 x 1.25 x 2.40 m, which means there is space for 3 Euro pallets [23]. With a medium package size of 0.60 x 0.30 x 0.15 m [24] and taking into account that due to different package sizes not a 100% of the storage space can be used, the cargo capsule has a capacity of 216 packages. Regarding the vehicle's cost parameters an approach similar to Schlenther et al. [16] is used. In the aforementioned study, the cost rates (See "Base Case" in Table 2) are derived from a report based on the German Federal Transport Infrastructure Plan (BVWP) [16, 25].

3.2. Freight Demand

The freight demand used in this work arises from calculations by Thaller [26], based on studies by the Federal Association of Parcel and Express Logistics and the Institute for Applied Logistics at the University of Würzburg-Schweinfurt as well as on census data and statistics published by the Berlin-Brandenburg statistical office [26]. To model and later simulate the freight demand adequately in the urban area of Berlin similar to Schlenther et al. [16], it is distributed to freight depots inside the 23 city districts. For each district, a depot is established. The depots are served by 60 carrier agents, which are created based on Berlin's official regional statistical zones [27] in order to reduce computation time compared to 23 carrier agents (based on the city districts) serving rather big areas [16]. The mapping of the freight demand data to the 60 carrier agents results in a total number of 104,621 delivery services with service capacities from 1-12 parcels, which make for 394,800 parcels. In contrast to the spatial spread of the freight demand, the temporal distribution differs to Schlenther et al. [16], as first tests with the exact same time distribution of the freight demand resulted in unrealistically high duration and travel distances for freight tours. Therefore, the distribution of the home activity start times in the Open Berlin scenario [22] was analyzed and put into 4h-time bins (08:00-12:00; 12:00-16:00...) and 2h-time bins (08:00-10:00; 10:00-12:00...), respectively. With the relative weights of said distribution, the carrier services are then redistributed over the course of the day, see Figure 2. It is assumed that no deliveries are performed between midnight and 8 a.m.

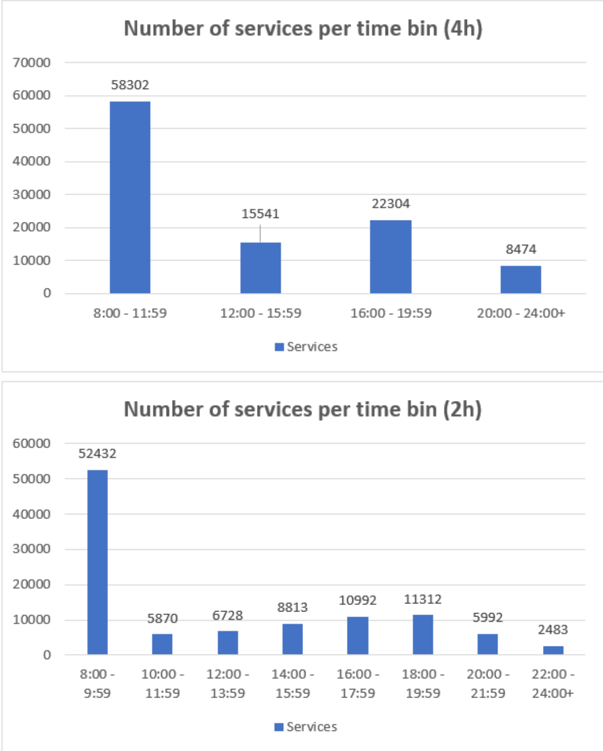

Figure 2. Service distribution from 08:00 to 24:00 in 4h / 2h-time bins according to the synthetic population's activities

3.3. DRT Fleet and Demand

Since the original MATSim Open-Berlin-Scenario only considers the bicycle, pedestrian and public transport modes [22], for further investigations, DRT has to be added as a transport mode. The DRT system is configured using recent methodologies including rebalancing [28] and a heuristic to estimate the fleet size necessary to obtain a 95th percentile of passenger wait at 7 minutes [29]. The service area is set to the city of Berlin, the passenger price to 1 € per ride plus 0.20 € per kilometer. The results are represented by 118,994 rides realized by a fleet of 7450 vehicles (with a sample size of 10 %, see above). The fleet size seems to be rather overestimated, as the peak for the share of vehicles busy with serving customers is at around 30%.

3.4. Simulated Scenarios

To be able to understand the impact of the additional freight demand on the traffic system, the DRT customers and operators, it is necessary to compare to a base case, in which the freight tours are realized by a separate fleet. In this case the freight operator possesses a vehicle fleet with human drivers. Additionally, there are two policy cases. In both, the newly implemented operation logic described in Section 2 is used. The autonomous DRT fleet not only serves the passenger demand, which is kept constant throughout all simulations, but the parcel demand as well. The only difference between the two policy cases is the time bin size, in which the vehicles deliver parcels. Whereas in "Policy Case 4h" the time bin size and therefore temporal distribution of Figure 2 of 4h is used, "Policy Case 2h" uses time bins of 2h. This means, the only difference of "Policy Case 4h" to the base case is that the freight demand is served by the DRT fleet and the freight operator abolishes his own fleet. Firstly, the DRT fleet size is kept constant at rather high level, in order to investigate the feasability of the combined service of passenger and freight demand. This is described in Section 4. In Section 5, various fleet sizes are simulated in order to determine the relation of fleet size, passenger demand, freight demand, wait times and the rejection rate.

4. Fixed Fleet Size Analysis

To measure the impact of the fleet abolition by the freight operator, three points of view are taken. First, an analysis from a general perspective on the autonomous vehicle fleet is carried out. Next, an analysis on how the delivery of the additional freight demand influences the DRT-users. Finally, a focus on the economic impact is set. Every scenario defined in Section 3 is considered.

4.1. Impact on vehicle fleet

An analysis of the fleet's general utilization shows that the share of vehicles that remain idle throughout the entire day, drops from 14% in the base case and "Policy Case 4h" to around 2% in "Policy Case 2h". Therefore, a look into the fleet-utilization over the course of the day is useful. In Figure 3 every DRT-related action of a fleet vehicle is marked as" x pax" (x indicating the number of passengers on board) or "RELOCATE" (due to fleet rebalancing). The remaining action types are freight-related. It can be seen that for both policy cases the peak hours of freight demand and passenger demand seem to overlap at around respectively 08:00-12:00 and 08:00-10:00. This overlap causes a greater demand for vehicles at this period of time, which then leads to fewer idle vehicles in general. Taking into account the high share of delivery services at this time of day (56%, see Figure 2) and the general fact that Berlin's daily traffic typically shows a distinctive peak hour in the morning [10], the overlap could have been expected in advance of the actual simulation.

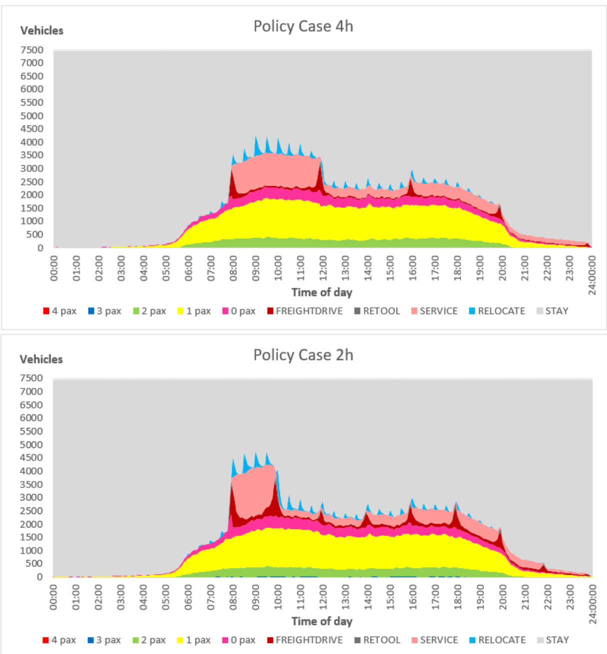

Figure 3. DRT vehicle occupancy over the course of the day in the policy cases

4.2. Impact on DRT-passengers

As pointed out in Section 2, serving the passenger demand remains the vehicle fleet's main focus despite the freight demand being added. Therefore, it is interesting to check whether DRT passengers are impacted by the addition of the freight demand and if yes, how. The statistics shown in Table 1 suggest that there is no big impact, although the average wait time compared to the base case increases by respectively 3 and 6 seconds. The average in vehicle travel times and average travel distances of the policy cases do only present negligible changes. Regarding the number of rejected passengers, an increase of respectively 61 and 87 rejections can be observed, but compared to number of served passengers in each case it can be considered negligible as well.

Table 1. DRT-customer statistics per scenario

Case	avg. wait time [s]	avg. in vehicle time [s]	avg. travel distance [m]	served passengers	rejected passengers
Base Case	176	827	4171	119050	153
Policy Case 4h	179	827	4169	118953	214
Policy Case 2h	181	828	4172	118887	240

4.3. Financial impact

From the operators' perspectives it is highly interesting to put a spotlight on the fleet's driven distance. In the base case, the autonomous vehicle fleet covers 454,769 km. Through the addition of the parcel demand, this value rises to 484,955 km in "Policy Case 4h" and 513,234 km in "Policy Case 2h". As the kilometers driven for passenger services stay similar to the base case this increase can be attributed to the added freight tours. A comparison of the driven freight distance in the two policy cases shows that the distance traveled approximately doubles. Thus, the driven freight distance increases from 28,927 km in "Policy Case 4h" to 55,265 km in "Policy Case 2h", which is due to the narrowing of delivery time windows from 4h to 2h, because the freight operator then has to plan shorter and more tours at the same time. Whereas in "Policy Case 4h" roughly the same number of tours was planned and completed as in the "Base Case", the number of planned tours in "Policy Case 2h" is more than doubled (see Table 2). Further, it is the only investigated case, in which freight tours were rejected (15%) The average duration of tours per case are located around the respective size of time bins (4h/2h), which is due to jsprit's nature of obeying the vehicles' time limitations, which equal the corresponding time bins.

With the above statistics, a rough look at the freight operator's cost can be made. For this purpose, based on the cost rates given in Table 2, the number of tours performed and elapsed tour duration, the total cost for the "Base Case" is calculated. Table 2 reveals that more than 67% of the freight operator's cost is related to driver wages. Thus, automation by itself brings a huge saving potential. In order to distinguish effects from automation from fleet abolition, a "Base Case automated" that was not simulated is introduced, which is equivalent to the "Base Case" without driver wages, i.e. time costs. For the policy cases, the same way cost rate is assumed, meaning that additional costs for technological advances (like a modular vehicle concept) are balanced with savings on fuel and energy and other effects. Then, the total costs of the freight operator in the policy cases

are set to total costs in "Base Case automated", deducted by the way costs and divided by the number of tours performed in order to determine the break-even point for the fix costs per tour.
The results suggest that, assuming the same vehicle cost rates, the abolition of the fleet has no effect on the costs per tour in the "Policy Case 4h", where vehicle time windows were not touched for tour planning. As the number of tours is roughly twice as high for "Policy Case 2h", the costs per tour are roughly halved. However, in the policy cases, the freight operator would not have to entirely account for fleet overhead costs and only pay them partially via a fixed fare per tour, charged by the DRT operator. Moreover, taking into account that DRT passengers only pay a fraction of the calculated fixed cost (Compare cost components of Section 3 and Table 2) it can be assumed that the actual cost rate per tour (or fee paid by freight operator to the DRT operator) is lower than in the base case, leading to a saving potential for the freight operator.

Table 2. Cost analysis based on operated tours per scenario. Total costs for the policy cases are defined to equal to 'Base case automated' in order to determine the break-even point for costs per tour. Variable costs consist of (1) distance costs of 0.2522 €/km and (2) of driver wages which are 17.64 €/h for 'Base case' and 0 €/h for all other cases. Values marked with (*) are input values for the corresponding scenario.

	Base Case	Base Case automated	Policy Case 4h	Policy Case 2h
total cost [€]	252,208	82,598	(*) 82,598	(*) 82,598
distance cost [€]	7,117	7,117	7,295	13,938
time cost [€]	169,611	0	0	0
fixed cost [€]	75,480	75,480	75,302	68,660
# completed tours	2,487	2,487	2,509	5,074
fixed cost rate [€/tour]	(*) 30.35	(*) 30.35	30.01	13.53

4.4. Discussion

As the researched scenario lays in the future, it strongly depends on multiple parameters based and assumptions. Figure 3 shows that even at peak hours the share of idle fleet vehicles is never less than 45% and 36%, respectively. This means that the simulated autonomous fleet is rather too large, which is why there is almost no impact by the additional freight tours on the DRT passengers. In Section 5, the fleet size is varied in order to understand how large the impact on passengers really is.
Further, the parameters used for the cost analysis are to be questioned. Although it makes sense to adopt the fi x, way and time cost used for tour planning one could imagine the fleet owner (i.e. DRT operator) altering the prices. As described in Section 4, in this use case, there is an immense difference between fixed cost rates in tour planning and passenger transport. Additional studies with alternative pricing schemes for freight tour planning would assist to find a realistic and reasonable price equilibrium. On the other hand, the cost analysis displays the huge potential for savings when using an autonomous multi-purpose vehicle fleet.
Regarding the service distribution displayed in Figure 2, it has to be remarked that in a scenario taking place in the future such distribution which is based on the agents' home activities might not be realistic. With delivery boxes being used more and more, the customers do not need to be at home to receive their packages. This bears the chance to spread the freight tours all over the day, e.g. using off -peak hours in passenger traffic. This way the impact of freight tours on passengers can be kept low while also operating with a fleet of smaller size because peak hours of freight and passenger-tours will not overlap anymore.
Finally, the chosen form of offline tour planning does not provide much flexibility. It is a legit solution when thinking of the already mentioned delivery boxes, whereto parcels are delivered usually successful, but still online tour planning offers more opportunities to react dynamically. E.g. one could implement a certain number of unsuccessful deliveries or even canceled tours which have to be re-planned during the day (online). The strongest argument for online tour planning is an additional ability to reply to changes in passenger demand as well as the ability to model same day (good) deliveries. With historical fleet utilization data just like in Figure 3 favorable, off -peak time slots for freight tours can be found in advance. In addition, quick reactions to increased demands are possible by just pushing freight tours to a likely less requested time slot in the future.

5. Impact Analysis of Fleet Size

As shown above, the investigated fleet in section 4 is large enough to serve freight tours additionally to the passenger demand without having a big impact on the average wait time of passengers. One reason for that is the assumed fleet size, which is rather large. This chapter aims to understand more of the impact of fleet size and the ratio of vehicles reserved for passenger demand on the rejection rate of freight tours as well as on wait times of passengers.

5.1. Simulation Setup

In this section, the fleet size is set to 6 different values. For each, we vary the ratio of vehicles that is reserved for passenger demand between 0.5 and 0.25 (in previous sections this was kept constant at 0.5). Additionally, for each of the 6 fleet sizes, a base case is simulated, which is equivalent to a reservation ratio of 1. This results in 18 simulations overall. The fleet size values are determined based on the occupancy of the original base case, where only passenger demand is served and the autonomous fleet has a maximum occupancy of 2347 vehicles at peak times. Including a buffer, 2500 vehicles represent a fleet occupancy of 100%. The simulated fleet sizes are then increased by 1250 up until 5000 (2500, 3750, 5000). If relocating vehicles are considered, too, the maximum occupancy lays at 3200 (2979 + buff er) vehicles. For this case similar steps are taken (3200, 4800, 6400).

5.2. Results

Figure 4 displays the resulting passenger wait time and rejection rate of freight tours for each simulation. It is pointed out that in general the smaller the fleet the higher the average wait time of DRT passengers. In contrast, the passengers' average travel time and average distance only seem to be impacted marginally by the reduced fleet sizes. For both passenger and freight transport, the scenario with 2500 vehicles is the most extreme one: It features very expressive values for the average customer wait time and rejection rate of freight tours. As explained in the previous paragraph, this is the case where, during the peak hours, the fleet is occupied to almost 100% with serving the passenger demand only, so the large increase is not surprising. From a fleet occupancy standpoint, the scenario with 3750 autonomous vehicles and a reservation ratio of 0.25 is interesting. Here, the percentage of occupied vehicles in peak hours is almost at 100% while about 28% of the planned freight tours are rejected. This of course impacts passenger wait times: compared to the base case an increase of 83 seconds is observed. Although the fleet's occupancy is on a rather high level, due to increased average passenger wait time and significant number of rejected tours this scenario is not to be considered ideal. Comparing all scenarios simulated in this section, the one with 4800 autonomous fleet vehicles and a reservation ratio of 25% offers both a rather low increase of average passenger wait times (+25s) and a high percentage of executed freight tours (94%), while at the same time around 80% of fleet vehicles are occupied in peak hours. With regard to the given passenger and freight demand, the aforementioned scenario seems to be the most suitable configuration for a real-world usage. A comparison shows that the passenger wait times and freight tour rejection rate are at the same level as for the 5000 vehicles scenario whereas the increase of both performance indicators for the 3750 vehicles scenario is much stronger (see Figure 4).

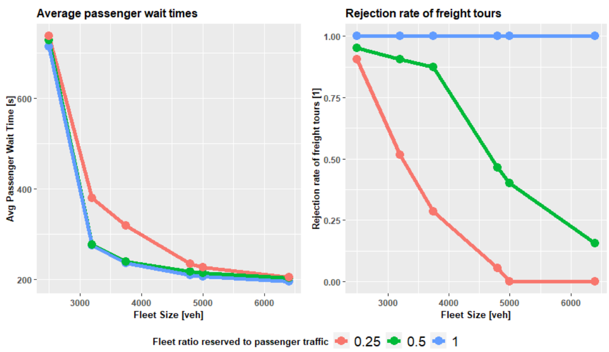

Figure 4. Passenger wait times and rejection rate of freight tour in all scenarios

6. Conclusion

This research proposes a methodology to simulate autonomous On-Demand vehicle fleets that serve both freight and passenger transport. The vehicle fleet's utilization can be increased in comparison to passenger-only operation. It is shown that it is possible to serve freight and passenger demand with a single multi-purpose autonomous vehicle fleet. Moreover, this operation pattern possibly offers savings for freight operators while On-Demand fleet operators may also take advantage of additional and possibly regular income by providing the freight company with vehicles. As pricing schemes remain unclear, the quantity of savings is still a matter to be researched. In the investigated use case for parcel delivery in the city of Berlin, the impact of the additional freight demand on passengers is minimal when assuming a large fleet size. In this case, average wait times, travel distances and travel times are held at the same quality. An additional study including different fleet size configurations shows that, with help of a systematic approach, a fleet configuration, which combines rather high occupancy with low increases of average passenger wait times and freight tour rejections, can be found.

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