On-demand transport service as a feeder for public transport

Melvin Könitzer

Semester Project **June 2021**

Institut für Verkehrsplanung und Transportsysteme
Institute for Transport Planning and Systems

Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

On-demand transport service as a feeder for public transport

Melvin Könitzer
IVT
ETH Zürich
CH-8093 Zurich
melvink@student.ethz.ch

June 2021

Abstract

The growing demand for mobility is a challenge for the transportation networks of today's cities. Multimodal forms of mobility distribute the traffic flows better and allow for economical operations of a transport network. Public transport, as an efficient form of mobility, plays an important role in multimodal transportation systems. However, the access and egress stages, referred to as the first/last mile, are one of the most deterrent factors for public transportation usage. New technologies allow for on-demand automated taxi services which have the potential to solve the first/last mile problem and increase attractivity of intermodal trip making. According to the National Household Travel Survey of Switzerland of 2015, 14% of all trips with public transport as the main mode of the trip are conducted intermodally. Characteristics of intermodal ridership are medium age (25-64 years), above average income and good mobility tool ownership. This report explores the potential of a demand responsive transit (DRT) service in the greater area of Zurich and the possible impact on mode shares. Therefore, simulations are conducted with the agent-based simulation tool MATSim. The results confirm the results of the National Household Travel Survey. Unfortunately, issues were detected within the simulation framework, which could not be solved before the submission of this report. Therefore an outlook is provided how this project could be further developed to receive results which would allow for significant policy implications.

Keywords

Automated transit on demand; first/last mile; MATSim; eqasim; Transport policy

Suggested Citation

Könitzer, Melvin (2021) On-demand transport service as a feeder for public transport, Semester Project - Institut für Verkehrsplanung und Transportsysteme, Departement Bau, Umwelt und Geomatik, ETH Zürich

On-demand transport service as a feeder for public transport

Melvin Könitzer
IVT
ETH Zürich
CH-8093 Zurich
melvink@student.ethz.ch

Juni 2021

Zusammenfassung

Die steigende Nachfrage nach Mobilität bringt die Verkehrssysteme der Städte an ihre Grenzen. Multimodale Verkehrsnetzwerke können effizienter operiert werden, da die Verkehrsströme besser im Netzwerk verteilt werden. Die Basis dazu formt der öffentliche Verkehr, welcher im Vergleich zu den individuellen Verkehrsmitteln effizienter ist. Dabei hat die erste/letzte Meile hat einen grossen Einfluss auf die Nutzung des öffentlichen Verkehrs. Die Automatisierung von Fahrzeugen ermöglicht eine bessere Erschliessung des öffentlichen Verkehrs und somit die Nachfrage zu steigern. Dieser Bericht erkundet den Einfluss eines "demand responsive transit" (DRT) Service auf den Modal Split und inwiefern ein solches System die Attraktivität des öffentlichen Verkehrs als gesamtes steigern kann. Hierfür wird mittels der agenten-basierten Simulationssoftware MATSim ein solches System implementiert und die Nutzerdaten ausgewertet. Die Resultate aus den Simulationen haben gezeigt, dass der typische DRT-Nutzer mittleren Alters ist (25-64 Jahre), die überwiegende Mehrheit berufstätig ist (80%), sowie die Verfügbarkeit von Abonnements des öffentlichen Verkehrs und Fahrräder sehr hoch ist. Leider wurde festgestellt, dass die Simulationsdateien einen Fehler aufwiesen, welcher nicht vor Abgabe dieses Berichts behoben werden konnte. Bevor weitere Schlüsse aus den Resultaten gezogen werden, ist eine Analyse der Wartezeit Berechnung notwendig.

Schlagworte

automatisierter Verkehr; erste/letzte Meile; MATSim; eqasim

Zitierungsvorschlag

Könitzer, Melvin (2021) On-demand transport service as a feeder for public transport, Semester Project - Institut für Verkehrsplanung und Transportsysteme, Departement Bau, Umwelt und Geomatik, ETH Zürich

Acknowledgement

First of all and primarily I would like to thank Grace Khago and Dr. Milos Balac for their tireless support throughout the whole course of this project. Through their guidance I was able to learn several practical new skills which I am thankful for and am certain, that they will help me in my further studies. Furthermore, I want to thank Prof. Axhausen for giving me the opportunity to conduct a project under his supervision at the Institute of Transport Planning and Systems.

Secondly, I want to express my gratitude to everybody who has supported me throughout this semester and helped me with all kinds of inputs and discussions.

Contents

List of Figures

List of Tables

1 Introduction

Due to growing population and urbanization it has become increasingly challenging to accommodate the rising demand for mobility in cities and their transportation networks. Multimodal networks allow for an economical operation of a transportation system by spreading the demand across different modes. Additionally, new mobility models like shared mobility have emerged to expand the range of possible mode choices (de Freitas *et al.*, 2019). In this field, recent technological developments in vehicle electrification and automation open up new opportunities to sustainable solutions in public transportation. Thus, on the search for a solution for congested transportation systems, various programs are launched to push innovation in transportation in order to reduce the negative impacts of motorized individual transportation. For example the Smart City Challenge by the US Department of Transportation and the Mobility on Demand Sandbox program by the Federal Transit Administration in the United States (Lazarus *et al.*, 2018) or the Swiss "ETH-Mobility-Initiative"[1] which was announced in 2018, seeking for new solutions to transportation challenges by enhancing the collaboration between the national rail operator (SBB) and the Federal Institute of Technology (ETH). Lazarus *et al.* (2018) state that 82% of the projects which applied for funding in course of the Smart City Challenge included shared automated mobility. Thus, it is not surprising that studies (Yap *et al.* (2016), Huang *et al.* (2021), Andréasson (2012), Shen *et al.* (2018), Scheltes and Homem de Almeida Correia (2017)) and pilot projects (Soe and Müür (2020), Lervag (2020), *Pikmi* On-Demand Shuttle in Zurich[2]) are focused on shared on-demand automated vehicles (SAV), to examine their potential as a complement to public transportation. The main goal of these efforts is to overcome the first/last mile public transport problem and offer seamless on-demand door-to-door connections that will make public transport more competitive compared to motorized individual transportation.

In this report an automated on-demand transport system is designed to act as a feeder for public transport on the first/last mile. Therefore, an agent-based simulation is performed in MATSim (Horni *et al.*, 2016) for the greater Zurich area. The report is structured as follows. Section 2 comprises of the literature review on intermodality and possible solutions to overcome the first/last mile problem. In section 3 results from the data analysis of the National Household Travel Survey of 2015 (BFS and ARE, 2017) on intermodal travel behavior are presented. Section 4 describes the study set-up and MATSim simulation scenarios. Section 5 presents the results. Section 6 discusses the results and finally, conclusions for suitable policies are drawn in Section 7.

[1]https://ethz.ch/de/news-und-veranstaltungen/eth-news/news/2018/01/mobilitaets-initiative.html
[2]https://www.stadt-zuerich.ch/site/pikmi/de/index.html

2 Literature Review

The first/last mile problem is one of the most adverse factor of public transport (PT) attractiveness. Different solutions already exist (e.g. public bike-sharing) while others are only in their preliminary phases (e.g. shared automated shuttle services). While bike-sharing systems and their operation have been examined thoroughly through theoretical and empirical studies, to the knowledge of the author, only a scarce amount of results from pilot projects, studies and simulations are available for shared automated modes. In the following, the findings from different research on factors affecting mode choice in general and on possible solutions to the first/last mile problem are summarized and their implications for an intermodal service in Switzerland are assessed. de Freitas *et al.* (2019) give a general understanding of intermodal transportation in Switzerland, which is useful for assessing potential demand and suitable locations for the introduction of automated on-demand services. Urban areas seem to be favorable for intermodal transportation and young people are more likely to make intermodal trips than the elderly. However, the most important determinant for intermodal mobility behavior, is the ownership of transit mobility tools, i.e., integrating the on-demand service into the current public transport subscription scheme is viable to increase usage of the system as a feeder/distributor for PT.

In Reck and Axhausen (2020) values of travel time savings (VTTS) are calculated for a ridesourcing service to cover the first/last mile, highlighting which conditions would make the service attractive to users. The effects of transfers and waiting time have been studied and the results indicate that ridesourcing services only become attractive after a certain distance and only when subsidized. Subsidies and the subsidy scheme have been revealed to be an important asset to a shared first/last mile service. Without subsidies the VTTS are quickly exceeded by the costs of the ridesourcing service. Liu *et al.* (2019) emphasize the importance of reducing transfer times to a minimum to attract new users to PT. Similar statements resulted from an empirical study conducted in the area of Lausanne, where car drivers stated that the most detrimental factors to PT are longer travel times, ticket prices and transfers (Abou-Zeid *et al.*, 2012).

Efforts have been made to overcome the problem of the first/last mile by introducing shared bicycle systems to increase accessibility to PT (Liu *et al.*, 2021). In the study conducted by Fan *et al.* (2019) the mode choice of the population of Beijing is analyzed before and after the introduction of a public bike-sharing system. Results have shown that the density of bike-sharing facilities is a decisive factor for the success of the system. However, increasing the density by providing dock-less bicycles without fixed stations for access/egress, does not necessarily increase its usage. Reck *et al.* (2021) have found that stationary (e-)bike services are more likely to be incorporated into daily commute,

while free-floating vehicles such as e-scooters were mostly used for recreational trips. In conclusion, micromobility and public bike-sharing systems are not suitable to cause a large-scale mode shift from private modes to public transit, because they are mainly appealing for commuters, which already choose sustainable mobility modes like walking and cycling. Hence, competition is created between walking/private bicycle usage and the bike-sharing system, which means that the target of attracting users of private modes is missed. Additionally, adverse weather and reduced safety perception prevent car drivers from renouncing from driving and switching to cycling in large numbers. From this conclusion we can learn, that an effective system, which is a viable alternative to the car, must aim at providing similar comfort to incur a mode shift.
Other studies examine the influence of motorized demand responsive transportation systems in combination with PT. Interestingly, Ryley *et al.* (2014) have found on-demand services which serve airports and train stations to be the most cost-effective. The most important factors for car drivers to use the service or not are parking availability and costs. If the relation between parking costs and DRT service are chosen optimally, DRT can be favored over the car as a feeder to PT. In rural areas demand responsive transit replaced regular bus lines to cut operating costs, while maintaining minimum service for elderly, poor and mobility disabled. The greatest challenge was offering a service that was economically viable (Ryley *et al.*, 2014). Alonso-González *et al.* (2018) suggest a framework to investigate the increased accessibility of demand responsive services compared to conventional PT services. Results from their application of the framework to transportation systems in the UK show that journeys conducted by demand responsive transport took only half the time the journey would have taken with PT. Furthermore, it is suggested, that careful attention is paid to the integration of DRT into the PT system by adjusting DRT fees in order not to compete and replace conventional PT service but rather complement it on routes where PT cannot provide cost covering service, i.e., in rural areas or at times of low demand.
While automation offers many interesting opportunities for PT operators, it is just as much a threat. Becker (2020) showed that the costs for transportation will be reduced through the introduction of automated vehicles (AV). The reduction in costs has significant effects on bus and taxi operations as well as individual transportation (most pronounced in high-income countries, as Switzerland). Consequently, this effect is predicted to cause increased individual transport which leads to increased vehicle-kilometers travelled. Therefore, Becker (2020) advises to closely manage the introduction of AVs by appropriate policy implications to enforce mode shifts towards PT instead of individual transportation. Following this principle, the application of AVs is focused on shared shuttle services for which different studies and pilot projects have taken place, as indicated in the introduction. Soe and Müür (2020) have investigated the safety and security perception of users to use

automated shuttle service. In their survey they asked participants who used the automated shuttle service during a pilot project in Talinn, on their safety and security perception towards the new technology. The results are promising and suggest that the demand for automated shuttles exists and would not be restricted by safety or security concerns from potential ridership. Yap *et al.* (2016) have examined attitudinal factors as well and have found them to be of similar importance as travel time and costs. Another finding from Yap *et al.* (2016) regards potential ridership. While second class rail passengers perceived all other egress-modes (cycling, bus, tram, metro) as more positive than shared automated vehicles (SAV), first class passengers showed higher utility values and, therefore, can be regarded as a target group with increased potential to become customers of shared automated shuttle services. An interesting outcome of the study is that the additional productive time in an automated vehicle does not affect the utility positively, suggesting that stages were too short to use the time productively. From the socio-economic point of view, passengers with medium-income levels were most positive about the AV service. Huang *et al.* (2021) find that a first/last mile service with AVs can reduce travel times for access/egress stages and waiting times and, therefore, lower total travel time to become more competitive with private mobility modes. Shen *et al.* (2018) take an approach of integrating the SAV into the current PT system in Singapore and show that it can be beneficial to maintain high-demand bus routes and replace low-demand lines with SAVs. Additional decisive aspects to successful implementation of SAV are the vehicle fleet size and the operations logic (dispatching, charging, relocating) which both have large impact on the systems performance and hence, are especially of interest to operators (Scheltes and Homem de Almeida Correia (2017), Huang *et al.* (2021)).

In summary, the most relevant findings for the design of a new transport system for the first/last mile are the following. It is expected that micromobility and/or bike-sharing systems will not have the potential to change the mobility behavior significantly towards increased PT usage, due to lacking speed and comfort compared to the car. However, the shared and on-demand aspects of bike-sharing systems are valued positively. To overcome lacking speed and comfort, the aforementioned studies show promising results for SAVs to be a viable solution. SAVs as access/egress mode for PT seem most attractive in urban areas for young (predominantly female) users with medium income de Freitas *et al.* (2019), Becker (2020), Yap *et al.* (2016)). Other possible application areas for SAVs are rural areas where elderly, children and mobility disabled benefit from increased mobility. Although the economic viability for non-automated on-demand services in rural areas is questionable, automated vehicles could relax the operating costs and therefore enable a cost-effective service (Alonso-González *et al.* (2018), Becker (2020)). While reducing operating costs, SAV in most cases increase vehicle kilometers travelled due to the empty relocating trips

(Huang *et al.*, 2021). Therefore, a proper integration with well-functioning elements of the current PT system is desirable. This report contributes to the research of multi-modal mobility by examining the implementation of a DRT service in the greater area of Zurich, complementary to the existing PT network. Thereby, the service is designed to prevent PT substitution and enhance a mode shift towards PT, to contribute to a more sustainable transportation system.

3 Swiss Intermodality

To gain further insights into the mobility behavior of the Swiss population, the Swiss National Household Travel Survey data (Microcensus) from 2015 is analyzed (BFS and ARE, 2017). The data was collected through a survey of 57,060 participants who were asked about their socio-demographic attributes, mobility tool ownership, their trip making behavior, trip characteristics, etc. Therefore, conclusions can be drawn on Swiss intermodal trip making. The data was analyzed according to 5 different categories:

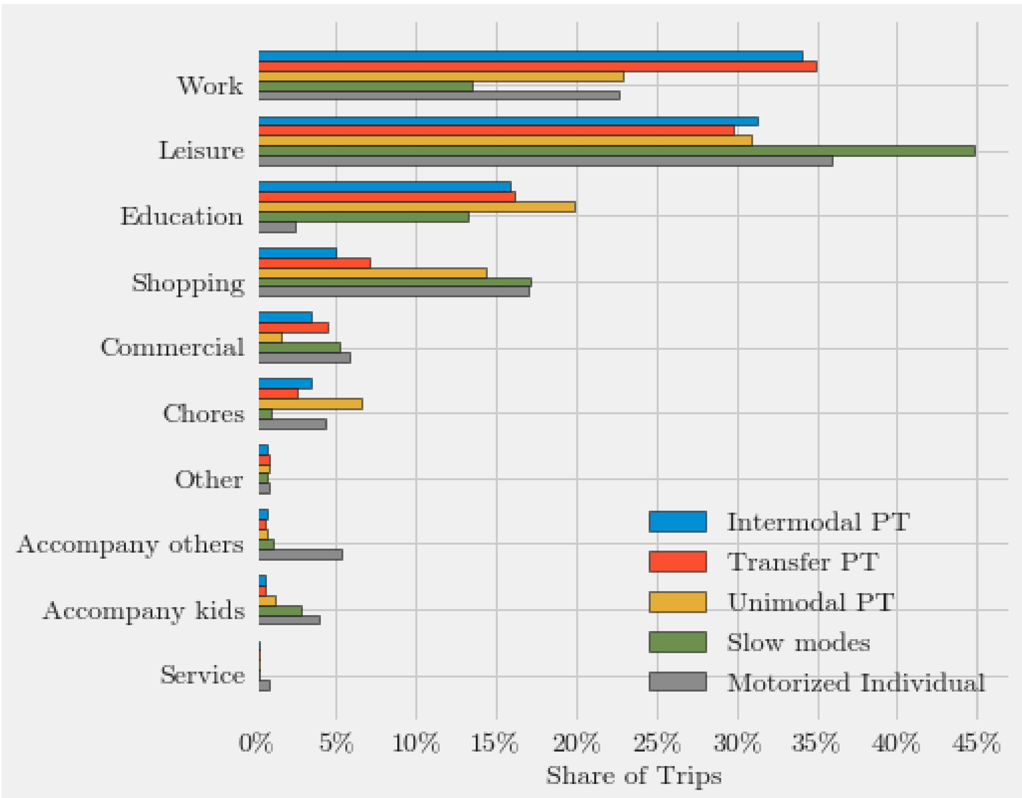
- *Intermodal PT*: PT trips with at least three stages excluding walk-PT-walk stages and either access or egress stage conducted by bike/mofa/light motorcycle/motorcycle (passenger)/car (passenger).
- *Transfer PT*: PT trips with at least three stages and at least one walking and two PT stages.
- *Unimodal PT*: PT trips with three stages or less. Trips consisting of three stages are of the scheme walk-PT-walk.
- *Slow Modes*: All trips with walk/bike as the main mode of the trip.
- *Motorized Individual Transport*: All trips with mofa/light motorcycle/car/motorcycle as the main mode of the trip (driver or passenger).

Since the greater area of Zurich will serve as study area for the simulations, the data analysis of the microcensus limits itself on the trips which were conducted within Switzerland. In this report, an intermodal trip is defined as a trip with at least three stages, where the main mode of the trip is PT and at least one of the access or egress stages was conducted with an other mode than PT or walk. The DRT service which is to be implemented in MATSim should complement, but not substitute PT stages. Trips which were a combination of low level and high level PT service (e.g. walk-bus-train-walk), were not considered intermodal but Transfer PT trips. Transfer PT trips comprise of various combinations of walk and PT stages. Unimodal PT examines the trips with PT as main mode and walk as access and egress. Therefore, the direct connections can be observed. The last two categories serve to compare PT travel behavior with other modes.

3.1 Intermodal trip characteristics

Analysis of the trips data yielded a share of 2% of intermodal trips, which represents 14% of all PT trips. The purposes for trip making are presented in Fig. 1. For the analysis of trip purposes, the transfers and home bound trips were excluded, since they are more of a necessity and have no significance in describing the motivation for conducting intermodal trips. The resulting distribution of trip purposes is illustrated in Fig. 1. The most intermodal trips were conducted to go to work, to engage in a leisure activity or are related to education (i.e., going to school, university). Consequently, most of the intermodal trips are related to commuting trips. It is noticeable that Transfer PT trips follow a similar distribution among trip purposes. Unimodal PT however has lower work shares and higher educational shares. Presumably, people tend to live closer to schools which allows the underaged to reach their educational facility more directly by PT, resulting in more unimodal PT trips. Multiple stages are unfavorable in shopping trips, since the newly acquired items have to be carried when transferring. Therefore, intermodal trips and Transfer PT trips have lowest shopping shares compared to other trip making behavior. Other trip making purposes only play a subordinate role.

Figure 1: Trip making purposes



The diurnal curve of intermodal trips in Fig. 3 confirms the previously assumed commuting character of intermodal trips. Two elaborated peaks during the morning and evening can be detected which underline the large share of work and education trips. As was the case for trip purposes, Transfer PT trips follow a similar distribution. When unimodal PT trips are considered, a third prolonged peak is observed during the afterPnoon implying lunch breaks and leisure travel. Trips of the individual category, on the contrary, show no distinct commuter peak. The surge between morning and evening peak observable in PT trips, cannot be detected. The number of trips remains high during the after-noon and is complemented by work and educational trips in the morning and evening (Fig. 3).

Noteworthy as well, is the difference in trip distances between the 5 categories (Fig. 10). The median for the PT trips are: intermodal trips - 29.7km, transfer PT trips - 16.9km and unimodal PT trips - 4.2km. In comparison the median of trips by slow modes is as short as 0.8km and of motorized individual transport trips 5.7km. So intermodal trips are by far the longest. The reason might lie in longer access/egress stages or longer trips requiring intermodal trip making. In addition, the distribution of trip distances is much larger for intermodal trips. The standard deviation for intermodal PT trips is 59km, 46km for transfer PT trips, 18km for unimodal PT trips, 4km for slow modes and 25km for motorized individual transport.

Figure 2: Diurnal curves for (a) Intermodal PT (b) Transfer PT, (c) Unimodal PT, (d) Slow modes, (e) Motorized individual modes

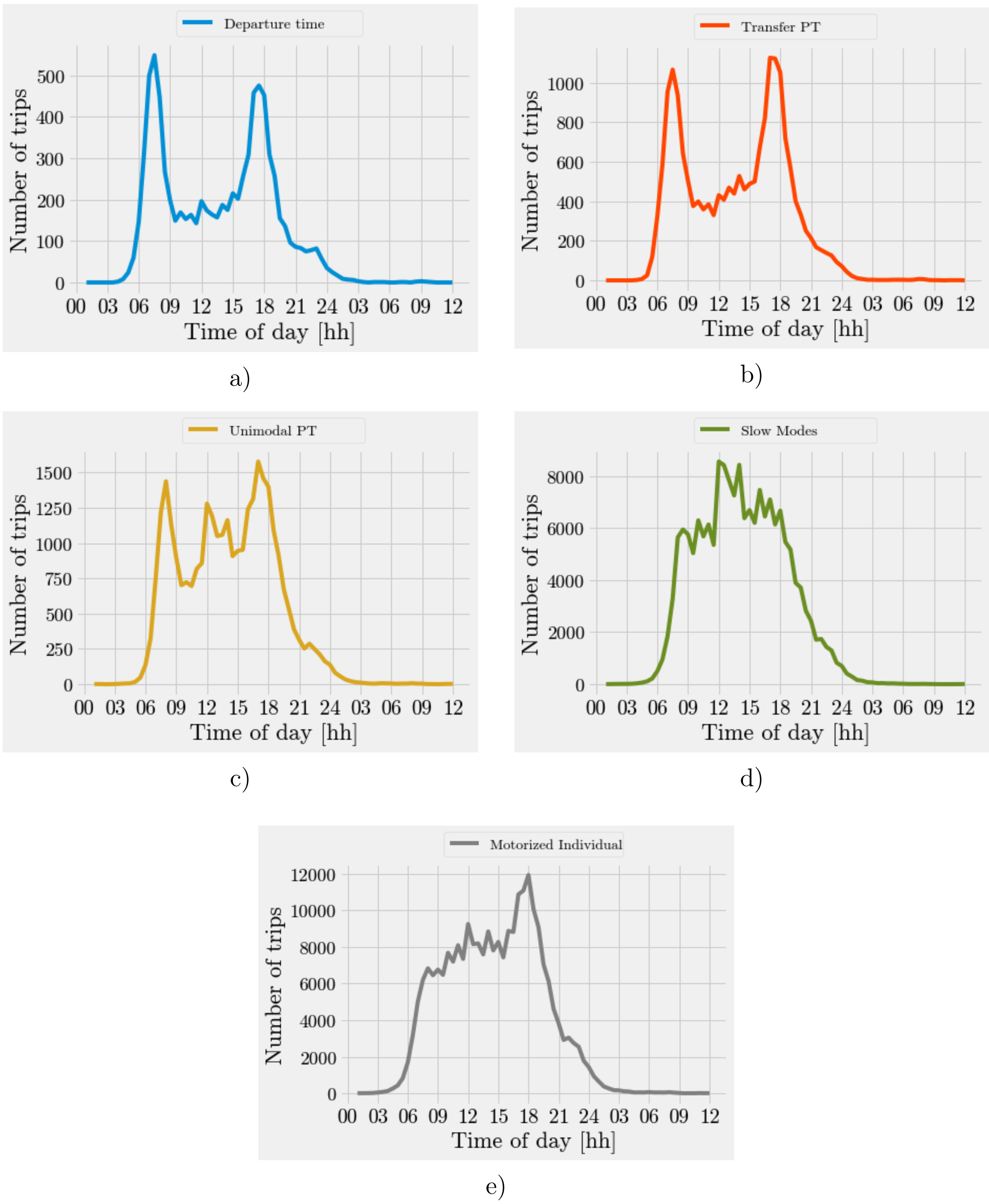
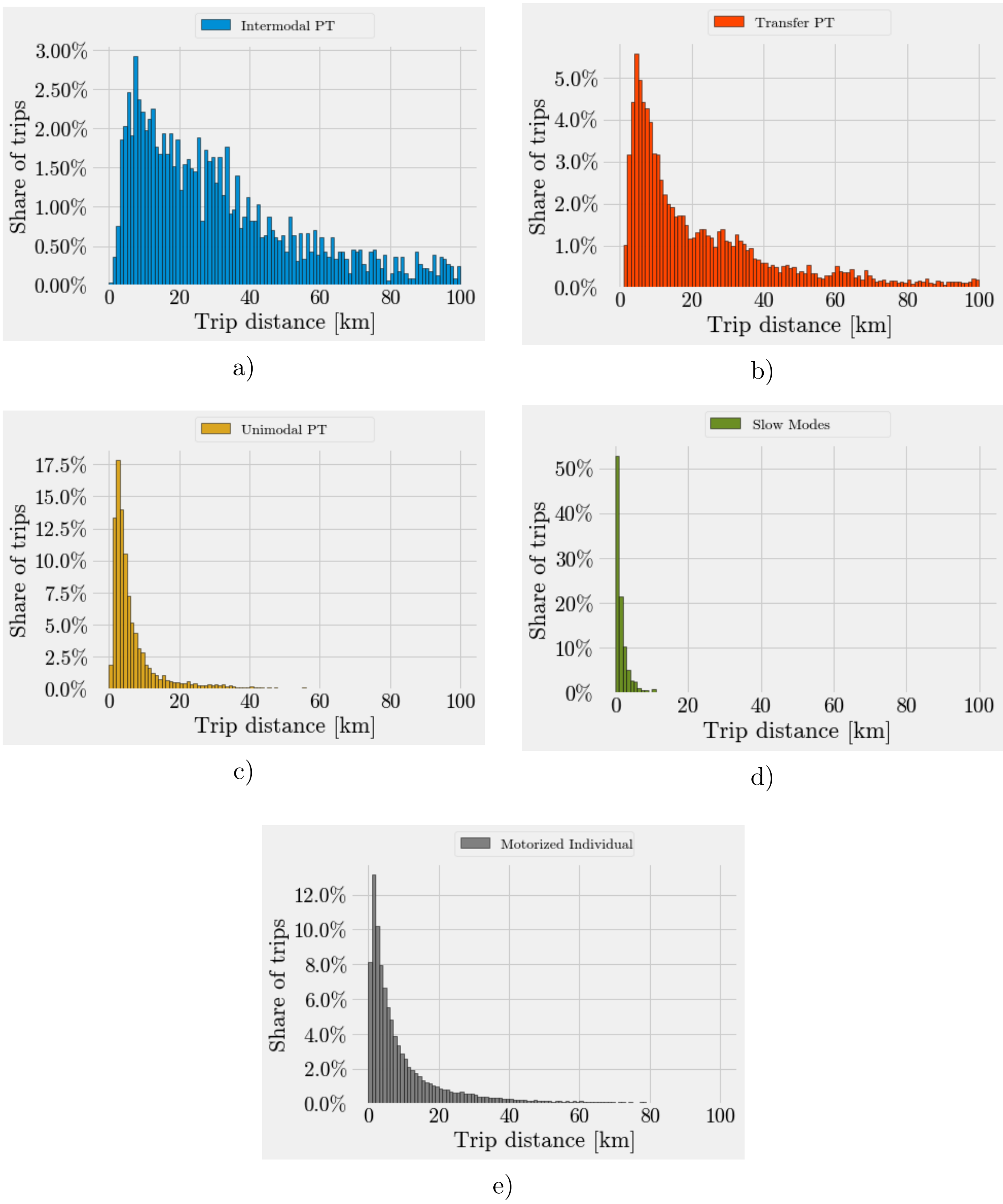


Figure 3: Trip distance distribution for (a) Intermodal PT (b) Transfer PT, (c) Unimodal PT, (d) Slow modes, (e) Motorized individual modes



Mode chains provide deeper insight into intermodal trip making. Table 1 lists the top 10 mode chains out of 1,338. Walk forms the majority of intermodal accessing and egressing stages as it applies to almost all trips. The PT mode which is predominantly accessed is the train which is part of 82% of the mode chains. Second comes the bus which is accessed in 41% of the cases and the tram comes in third with a share of 21%. The high share of train and bus being accessed/egressed is possibly from trips in suburban/rural areas where train and bus stops form the majority and are less accessible as tram stations in the urban context. In 39% of the trips the bike was used as access/egress. With regard to the design of an automated on-demand feeder system the stages conducted by car and as car passengers rides are interesting. Combined, these modes appeared in 59% of the trips. Hence these trips describe the direct competitor to the automated DRT feeder service and could possibly be substituted to decrease the mode share of motorized individual transport, leading to a more sustainable transportation system.

Table 1: 10 most popular mode chains

Mode Chain	Share
walk-train-bike	5.47%
bike-train-walk	5.04%
car (passenger)-train-walk	3.22%
walk-train-car (passenger)	3.16%
walk-train-car	1.76%
bike-train-train-walk	1.73%
car-train-walk	1.64%
bike-train-bike	1.58%
walk-train-train-bike	1.55%
walk-train-walk-car	1.12%
Remaining (1,328 chains)	73.73%

Source: BFS and ARE (2017)

To gain further understanding of the motivation for intermodal trip making, the mode choice purposes are analysed. Unfortunately, most participants replied with "Simplest Solution" or "No other choice" which does not allow to draw meaningful conclusions, since the interpretation for the definition of the simplest solution is very individual. Amongst the well-known supply elements (i.e. travel time, travel cost, comfort) the most important is travel time. In addition, a higher number of intermodal participants stated that subscription availability and the lacking of parking at their destination motivate their PT usage.

3.2 Accessibility

Analysis of the trip shares between areas of different degrees of urbanization (according to EUROSTAT definition: 1 = Cities/densely populated areas, 2 = Towns and suburbs/intermediate density areas, 3 = Rural areas / thinly populated areas)[3] reveals that intermodality is more often observed in towns and suburban areas (Table 2). The pattern for intermodal PT has a specific difference from non-intermodal PT. While the Transfer and Unimodal PT trips have their peak shares in cities, intermodal trips are mostly conducted within suburbs and between suburbs and the city. It is most likely that this occurrence, to some degree, stems from the decreasing quality of public transport and as a result other modes than walk are chosen for the access and egress stage. Trips originating or destined for rural areas showed the lowest share of trips in general. However, it must be taken into account that totally the majority of trips take place in resp. between suburban areas. PT and slow modes are dominant within cities. Inhabitants of cities enjoy higher quality of PT service with more direct connections, hence unimodal PT is the dominant form and there is less need for intermodality. Also distances are short, wherefore slow modes have a high share of intra-city trips. Motorized individual transport is predominantly conducted in the suburban areas, like intermodal trips. Additionally, there is a slight tendency for usage from the suburbs to rural areas which is the opposite for intermodal trips. This is most probably due to the lower accessibility to PT in rural areas. Furthermore, it is interesting to see that trips between regions of different degree of urbanization are often made by PT (mostly Intermodal PT) while unimodal forms of mobility (slow modes and motorized individual transport) have a focus on areas of the same degree of urbanization.

As mentioned before, the PT accessibility decreases with decreasing urbanization. The PT quality class is a measure developed by the Swiss Federal Institute for Spatial Planning to express accessibility to PT in specific areas. The rating is as follows (für Raumentwicklung ARE, 2011):

- Class A = Very good accessibility
- Class B = Good accessibility
- Class C = Moderate accessibility
- Class D = Low accessibility
- No Class = Marginal or no accessibility

[3] https://ec.europa.eu/eurostat/web/degree-of-urbanisation/background

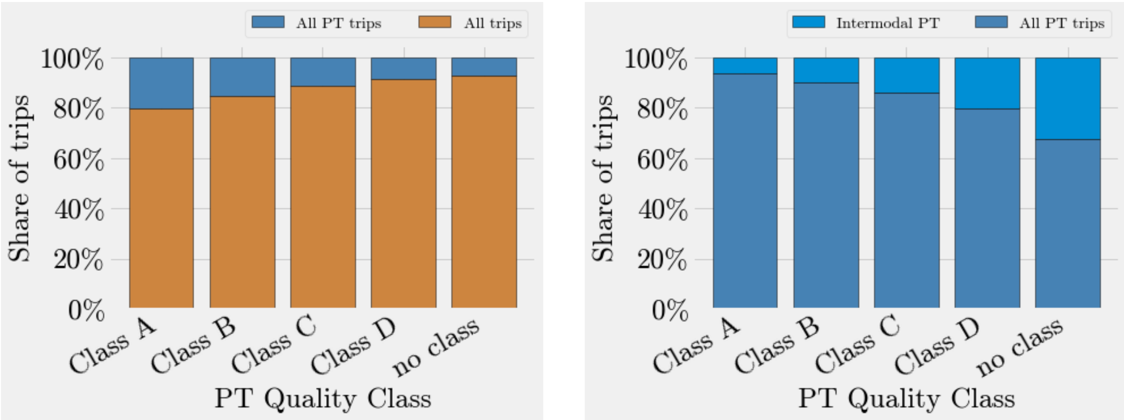
Table 2: Share of trips between areas of different degrees of urbanization

	Intermodal PT			Transfer PT			Unimodal PT		
Destination \ Origin	1	2	3	1	2	3	1	2	3
1	13.8%	17.2%	5.1%	32.3%	16.7%	2.8%	43.1%	6.4%	0.9%
2	17.4%	23.5%	6.6%	16.6%	19.7%	3.6%	6.1%	29.5%	3.9%
3	5.2%	6.5%	4.8%	2.9%	3.8%	1.6%	0.8%	3.8%	5.4%
	Slow Modes			**Motorized Individual**			**All trips in Total**		
Destination \ Origin	1	2	3	1	2	3	1	2	3
1	28.3%	0.3%	0.0%	11.8%	5.1%	1.4%	20.7%	4.1%	1.0%
2	0.3%	54.3%	0.5%	5.0%	45.8%	8.6%	4.0%	46.4%	5.1%
3	0.0%	0.5%	15.6%	1.5%	8.7%	12.1%	1.0%	5.1%	12.5%

Source: BFS and ARE (2017)

There is a tendency for intermodal trips to occur in regions where the PT quality class, at the place of residency, is lower. In areas with low PT quality, accessibility and frequency of PT is lower which promotes intermodal trip making. Fig. 4 shows that the share of intermodal trips decreases with decreasing PT quality class. The same is valid for all PT trips. However, the chart (b) in Fig. 4 implies that with decreasing PT quality class the share of intermodal PT trips increases, when PT is used as main mode.

Figure 4: Influence of PT Quality Class at the place of residence on trip making behavior, (a) Share of PT trips of all trips & (b) Share of intermodal trips of all PT trips

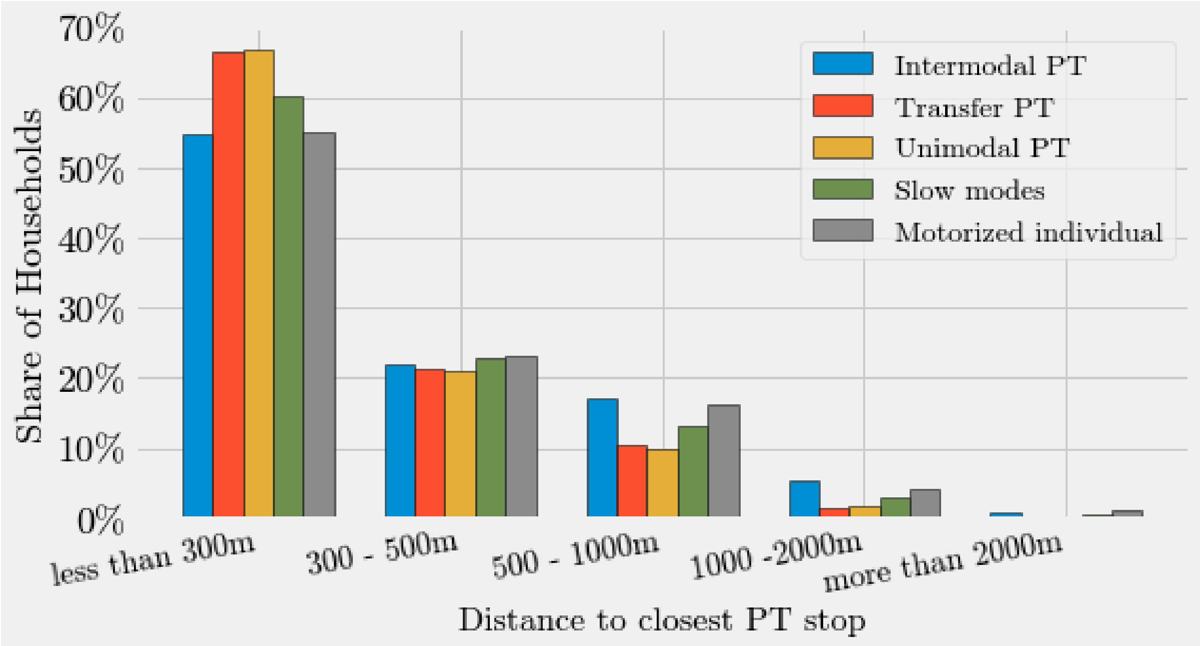


a) b)

In conclusion, when absolute numbers are considered, the majority of intermodal PT trips are conducted in areas of high PT quality class, because simply more PT trips are conducted in these areas. On the other hand, in areas of lower PT quality classes the share of intermodal trips is higher, because of lower accessibility.

Transfer and Unimodal PT users in general are more likely to live closer to a PT stop implying that the better accessibility to PT increases PT usage, or as examined in Becker (2020) the implication might also be that PT users choose their place of residence closer to PT stations. In comparison, intermodal trip makers and motorized individual transport users both live farther from PT stops(Fig. 5). This confirms the assumption made before that decreasing PT quality (i.e., lower accessibility) favors intermodal trip making. With increasing distances from PT stops and thus decreasing accessibility the ridership decreases rapidly for all trip makers. It can be concluded that living farther from PT stops promotes the usage of motorized individual transport, or from the other perspective, accessibility plays a subordinate role in the considerations of these trip makers when choosing the place of residence. They are less dependant on PT, since they have already been using motorized individual transport before moving.

Figure 5: Distance to the closest PT station from the place of residence



3.3 Socio-economic characteristics

The socio-economic/demographic attributes and mobility tool ownership which characterises intermodal trip making are outlined in Table 3. The intermodal ridership is predominantly used by young people and has significantly decreasing ridership for persons aged above 64 years. Females are slightly more likely to conduct intermodal trips than males (53.1% vs. 46.9%).

[4]In some cases the values do not add up to 100% due to rounding.

Table 3: Comparison of socio-demographic attributes and mobility tool ownership[4]

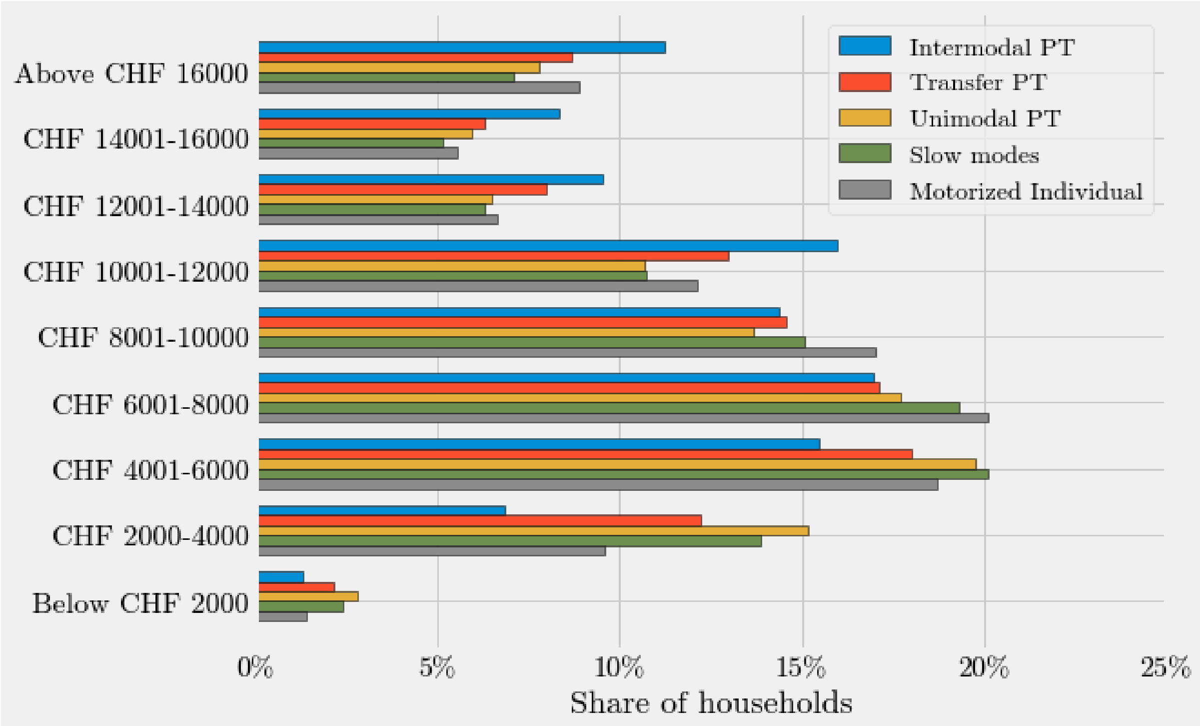
Attribute		Intermodal PT	Transfer PT	Unimodal PT	Slow modes	Motorized Individual
Age	< 18 years	17.6%	17.2%	22.2%	18.4%	10.5%
	18 - 24 years	19.5%	19.0%	14.9%	7.1%	7.7%
	25 - 44 years	25.5%	25.8%	23.9%	23.6%	27.9%
	45 - 64 years	27.0%	24.8%	23.2%	30.4%	36.5%
	65 - 79 years	9.6%	11.0%	12.2%	16.8%	14.9%
	≥ 80 years	1.0%	2.2%	3.6%	3.8%	2.5%
Gender	Female	53.1%	54.5%	57.0%	52.7%	47.7%
	Male	46.9%	45.5%	43.0%	47.3%	52.3%
Income	< CHF 2,000	1.3%	2.2%	2.8%	2.4%	1.4%
	CHF 2,000 - 4,000	6.8%	12.2%	15.1%	13.9%	9.6%
	CHF 4,001 - 6,000	15.5%	18.0%	19.8%	20.1%	18.7%
	CHF 6,001 - 8,000	16.9%	17.1%	17.7%	19.3%	20.1%
	CHF 8,001 - 10,000	14.4%	14.6%	13.7%	15.1%	17.0%
	CHF 10,001 - 12,000	15.9%	13.0%	10.7%	10.8%	12.1%
	CHF 12,001 - 14,000	9.5%	8.0%	6.5%	6.3%	6.7%
	CHF 14,000 - 16,000	8.3%	6.3%	5.9%	5.2%	5.6%
	> CHF 16,000	11.3%	8.7%	7.8%	7.1%	8.9%
Household Size	1 Person	12.1%	18.1%	19.3%	15.7%	13.4%
	2 Persons	27.9%	27.8%	26.3%	31.8%	34.4%
	3 Persons	17.6%	18.0%	16.9%	16.1%	16.5%
	4 Persons or more	42.4%	36.2%	37.5%	36.4%	35.7%
Mobility Tools	Drivers license	77.7%	65.6%	64.0%	81.7%	93.61%
	Car availability	56.6%	49.5%	51.2%	73.8%	84.9%
	Bike availability	80.7%	70.4%	66.5%	70.4%	69.8%
	PT subscriptions	19.4%	20.1%	19.5%	12.1%	9.4%
	1. class	7.9%	6.3%	5.1%	6.1%	7.0%
	2. class	92.1%	93.7%	94.9%	93.9%	93.0%

Source: BFS and ARE (2017)

In terms of income, intermodal trip makers have higher household income than all other trip makers. Above a monthly household income of CHF 10,000 intermodal households have the highest shares. In the medium income range PT is slightly below slow modes and motorized individual transpot. For low income households intermodal trip making and motorized individual transport have the lowest share. The relationship between income and trip making behavior is depicted in Fig. 6.

Household size was found to have a minor effect, yet it was interesting to observe that intermodal trip making had the highest share of households with 4 people and more. A

Figure 6: Household income distribution

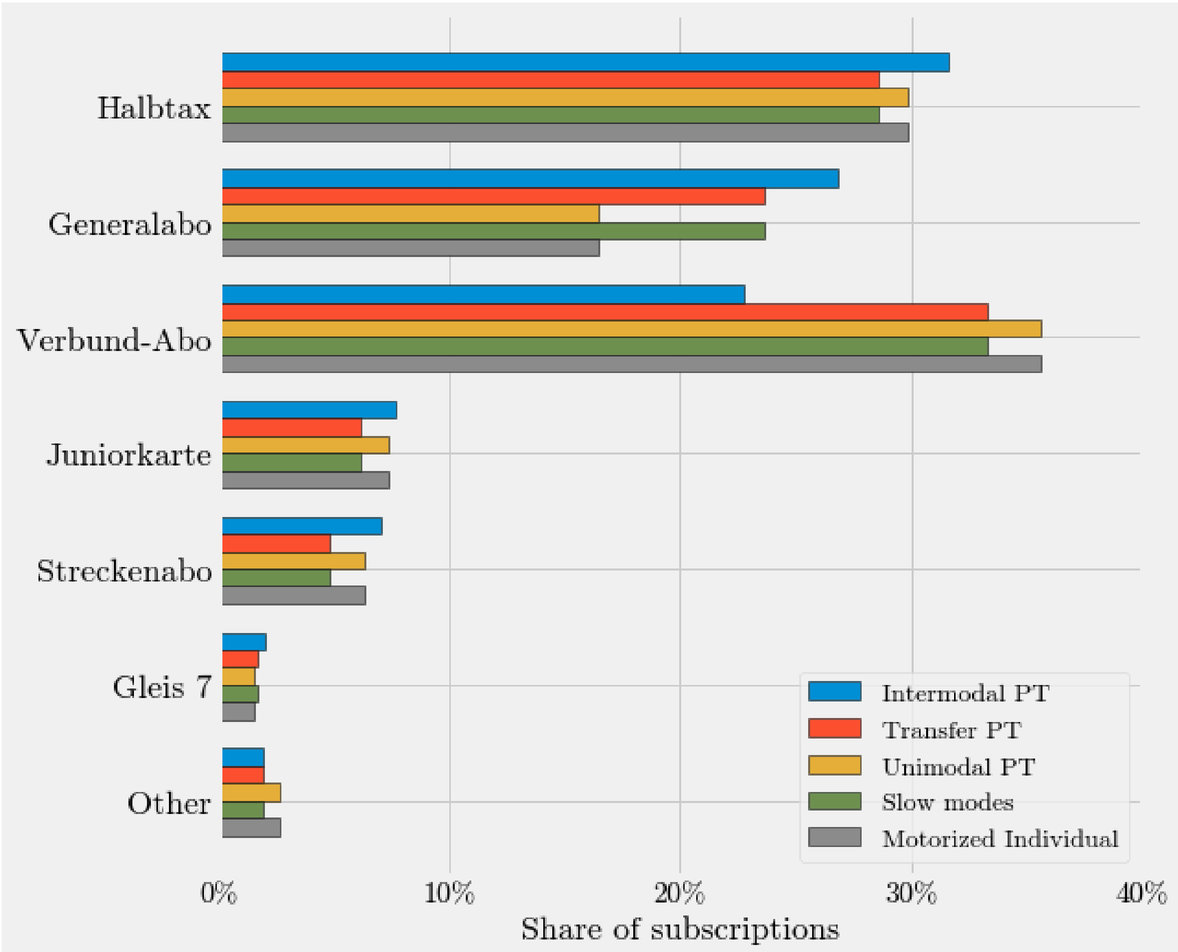


possible explanation is that the competition for modes between members of a household call for adaptation of the household member towards other forms of mobility, resulting in intermodal trip making.For 3 person households the trip making behaviors are equally balanced, while for 2 person households the individual modes (slow and motorized) have higher shares and for 1 person households the non-intermodal PT trip shares are highest. In Becker (2020) the mobility tools are attested significant importance for mode choice. The microcensus data reflects this importance. Intermodal trip makers have lower driver license ownership and car availability than individual trip makers, however the share is higher compared to other PT trip makers. Bike availability was highest for intermodal trip makers from which can be inferred that it is used more often for intermodal trip making. In terms of PT subscription ownership, compared to individual modes, approximately twice as many intermodal trip makers had any kind of PT subscription. Halbtax[5], GA[6] and Verbund[7] subscriptions are the most popular forms of subscriptions for any trip making behavior. Intermodal trip makers have the highest share of GA ownership and at the same time the lowest share of Verbund subscriptions. The Halbtax shares are more or elss equally high for all trip behaviors, intermodal shares being slightly above others.

[5]The Halbtax subscription allows for PT usage at half the price in Switzerland.
[6]The GA allows for PT usage free of charge in Switzerland
[7]The Verbund subscriptions allow for PT usage free of charge in a specified area of a PT provider, e.g. NetzPass in Canton of Zurich

The relations are shown in Fig. 7. The high share of GA ownership could presumably stem from the flexibility of intermodal trip makers, to choose any mobility tool available. The GA gives the intermodal trip maker the highest degree of freedom in his choice and therefore suits best intermodal trip making. It can be concluded that the integration of the PT service into one PT subscription is an important asset to intermodal trip makers.

Figure 7: Share of subscriptions amongst different trip making behaviors



4 Methodology

In order to derive policy implications for an automated on-demand feeder transport system, simulations of such a system are performed with the agent-based transport simulation framework MATSim (Horni *et al.*, 2016). The DRT alternative is added with the constraint that agents can only use the service in combination with public transport. The study area where the DRT system is run, is depicted in Fig. 8. In the subsequent paragraphs, the simulation set-up and the DRT service is described in more detail.

Figure 8: Study area in which the DRT feeder service was tested.

4.1 Simulation set-up

The households and the population with their trips and activity chains were generated according to the eqasim framework (Hörl and Balac, 2021), which was developed to ensure reproducibility of agent-based studies. To reduce the computational effort required for the simulations, they were run with a reduced population of 10%. In the first iteration the agents start their activity plans and base their mode choice on the multinomial logit model. The parameters of the mode choice model used in this report are taken from Hörl *et al.* (2018) and supplemented by the mode parameters for the DRT service. Table 4 gives an overview of the parameters used.

Table 4: Parameters of the discrete mode choice model

Mode	Parameter	Value	Unit
Car	α_{car}	0.827	
	$\beta_{travelTime,car}$	-0.0667	[min^{-1}]
Public Transport	α_{pt}	0.0	
	$\beta_{numberOfTransfers}$	-0.17	
	$\beta_{inVehicleTime}$	-0.0192	[min^{-1}]
	$\beta_{TransferTime}$	-0.0384	[min^{-1}]
	$\beta_{accessEgressTime}$	-0.0804	[min^{-1}]
Bike	α_{bike}	-0.1	
	$\beta_{travelTime,bike}$	-0.0805	[min^{-1}]
	$\beta_{age,bike}$	-0.0496	[a]
Walking	α_{walk}	0.63	
	$\beta_{travelTime,walk}$	-0.141	[min^{-1}]
Others	β_{cost}	-0.126	[CHF^{-1}]
	γ	-0.4	
	$\theta_{averageCrowflyDistance}$	40	[km]
Calibration	$\theta_{parkingSearchPenalty}$	6	[min]
	$\theta_{accessEgressWalkTime}$	5	[min]

Source: Hörl *et al.* (2018)

Since the mode choice parameters for DRT are not included in Hörl *et al.* (2018) it was roughly derived from the mode choice parameters used in Hörl *et al.* (2021). Therefore, $\beta_{inVehicleTime,feeder}$ was taken from Hörl *et al.* (2021) and adjusted so to match the mode choice parameters listed in Table 4. Comparing it to the mode choice parameters in Table 4, the resulting value for $\beta_{inVehicleTime,DRT}$ is in the range of $\beta_{accessEgressTime}$ for PT and perceived more positively than walking. Therefore, it is assumed to be a suitable approximation to describe DRT in-vehicle time. For $\beta_{waitTime,DRT}$ the value of $\beta_{transferTime}$ for PT in Table 4 was used. The wait time parameter is part of the utility function which influences the agent's mode choice. The average wait time is calculated dynamically for a specific zone and time frame. When average wait time for a mode increases, usage of the mode becomes less attractive and agents might replan in the next iteration if a more attractive plan can be executed. Alternatively, it is also possible that agents even cannot start their trip with the planned mode in the first place, because the average wait time for a certain mode, in the zone the agent wishes to travel, exceeds a threshold and therefore the agent is rejected from the service. However, in this simulation set-up no maximum average wait time was defined. The mode choice parameters for DRT are summarized in Table 5.

Table 5: Mode choice parameters for DRT

Mode	Parameter	Value	Unit
DRT	$\beta_{inVehicleTime,DRT}$	-0.087	[min^{-1}]
	$\beta_{waitTime,DRT}$	-0.0384	[min^{-1}]

Another characteristic parameter is the Value of Time (VOT), which is calculated with the mode choice parameters according to Eq. (1).

$$VOT_{DRT} = \frac{\beta_{inVehicleTime,drt}}{\beta_{cost}} = -0.69\ \frac{CHF}{min} = 41.4\ \frac{CHF}{h} \tag{1}$$

Further constraints were imposed on travel distances to ensure that the DRT service is used as a feeder service and isn't used as a substitute for PT. Firstly, the agents were required to travel a minimum distance of 500m with DRT. Secondly, the initial Search-Radius was set to 2000m and the maximum Search-Radius to 3000m, while allowing the agents to extend their search radius by 1000m. The requirement for the maximum Search-Radius was, to enable as many agents as possible to at least access a train station by DRT. Therefore, the measurement tool in the federal map viewer of Switzerland[8] was used, to draw circles with the major train stations at the center, to see if the whole study area

[8] www.map.geo.admin.ch

was covered.
The price for the service was determined after the method used in Hörl *et al.* (2021). The cost-covering price for an automated taxi system in the city of Zurich is calculated, by considering operator costs and deriving the necessary price to cover these costs. The cost calculations by Bösch *et al.* (2018), adapted in Hörl *et al.* (2021) are used as reference. The fleet costs are then determined by Eq. (2).

$$C_{fleet} = c_{perDistance} * d_{fleetDistance} + c_{perTrip} * n_{numberOfTrips} + c_{perVehicle} * n_{fleetSize} \tag{2}$$

In this report the AV cost parameters are adapted from Räth *et al.* (2021) for a vehicle with 4 seats:

- $c_{perDistance} = 0.2\ CHF/vkm$
- $c_{perTrip} = 0.375\ CHF$
- $c_{perVehicle} = 33.6\ CHF\ (per\ day)$

It must be noted that the simulated DRT service didn't enable ridesharing, despite having 4 seats. The remaining parameters of Eq. (2) are derived as follows. For the fleet distance and number of trips, it is assumed that the expected demand roughly corresponds to the proportional share of access and egress stages of the microcensus data (BFS and ARE, 2017). The share is calculated based on the share of the population living in the study area and the whole Swiss population, which the microcensus data reflects. Finally, the fleet size of 50 vehicles is then chosen as a best-guess which provides reasonable cost/km for the passenger and is adequate for the expected demand. Hörl *et al.* (2019) provided a guideline as to what could be a reasonable per-km cost for an AV service. The price calculation is done according to Eq. (3).

$$p_{DRT} = \frac{C_{fleet}}{d_{customerDistance}} = 0.85\ CHF/km \tag{3}$$

For reasons of simplicity, the distance dependant cost was kept constant throughout the simulations, despite changing values for fleet size which would inevitably affect fleet costs and therefore service prices. From these basic prerequisites different scenarios were generated which are described in the next section.

4.2 Scenarios

The developed scenarios differ in terms of 4 different parameters. Cost, discounts, constraints to the application of the service, and fleet size.

The cost parameter takes two different values. The first consisting of only a distance fare of 0.85 CHF/km, as mentioned in the previous section. Secondly, a base fare of 1 CHF/trip is added to the costs to examine the changing trip behavior. Scenarios with odd numbers (Scenario 1, 3, 5) do not include a base fare, scenarios with even numbers (Scenario 2,4,6) include the base fare. The hypothesis is made that by including a base fare, shorter trips are reduced since the base fare would increase the price per kilometer disproportionally (i.e. for trips between 500m - 1000m the price per kilometer increases by 235% and 118% respectively). Shorter trips are being discouraged to motivate agents to use more efficient modes for access and/or egress in areas where the accessibility of such is sufficient. The focus is on supplementing PT and increasing accessibility for less connected areas, rather than increasing service quality in already well connected areas. Besides, a base-fare can ease the financial expenses for the operator by compensating for empty relocation rides of the AV.
As stated in Loder and Axhausen (2018), mobility tool ownership is decisive for activity patterns and mode choices. Therefore, the effects of PT subscription ownership is examined by considering the scenario of service integration into existing PT subscriptions. For scenarios with integration, DRT services are free of charge for GA-/Verbund-/Strecke-subscriptions and half-fare with Halbtax. Thereby, it is possible to understand the importance of the integration of mobility services into one single ticket in order to increase its accessibility and attract as many users as possible. The third parameter defines in which locations the DRT service can run and comes in three different variants. The maximum variant allows DRT trips from anywhere in the network to any PT stop in the study area (Scenarios a & b). In the second variant, agents can travel from anywhere to PT stops of category 1 & 2[9] (Scenarios c & d). Lastly, agents are only allowed to travel to train stations, which would mainly aim at connecting rural areas to rail services (Scenarios e & f). The fleet size is varied for 25/50/100 vehicles to understand the influence of fleet size on the DRT service. Scenarios 1 & 2 are run with 25, scenarios 3 & 4 with 50 and scenario 5 & 6 with 100 vehicles. To detect a change in modal split inferred by the DRT service, a base scenario without DRT, is specified, against which the DRT scenarios can be compared. Table 6 provides an overview of all 36 DRT scenarios.

[9]PT stops are categorized according to the frequency of PT service and the PT mode, by which the stops are served. For more information it is referred to für Raumentwicklung ARE (2011)

Table 6: Scenarios run with MATSim

	Base fare	PT subscription integration	Accessibility	Fleet size
Scenario 1a	No	Yes	Anywhere / Any PT stop	25
Scenario 1b	No	No	Anywhere / Any PT stop	25
Scenario 1c	No	Yes	Anywhere / PT stop category 1 & 2	25
Scenario 1d	No	No	Anywhere / PT stop category 1 & 2	25
Scenario 1e	No	Yes	Anywhere / Train stops	25
Scenario 1f	No	No	Anywhere / Train stops	25
Scenario 2a	Yes	Yes	Anywhere / Any PT stop	25
Scenario 2b	Yes	No	Anywhere / Any PT stop	25
Scenario 2c	Yes	Yes	Anywhere / PT stop category 1 & 2	25
Scenario 2d	Yes	No	Anywhere / PT stop category 1 & 2	25
Scenario 2e	Yes	Yes	Anywhere / Train stops	25
Scenario 2f	Yes	No	Anywhere / Train stops	25
Scenario 3a	No	Yes	Anywhere / Any PT stop	50
Scenario 3b	No	No	Anywhere / Any PT stop	50
Scenario 3c	No	Yes	Anywhere / PT stop category 1 & 2	50
Scenario 3d	No	No	Anywhere / PT stop category 1 & 2	50
Scenario 3e	No	Yes	Anywhere / Train stops	50
Scenario 3f	No	No	Anywhere / Train stops	50
Scenario 4a	Yes	Yes	Anywhere / Any PT stop	50
Scenario 4b	Yes	No	Anywhere / Any PT stop	50
Scenario 4c	Yes	Yes	Anywhere / PT stop category 1 & 2	50
Scenario 4d	Yes	No	Anywhere / PT stop category 1 & 2	50
Scenario 4e	Yes	Yes	Anywhere / Train stops	50
Scenario 4f	Yes	No	Anywhere / Train stops	50
Scenario 5a	No	Yes	Anywhere / Any PT stop	100
Scenario 5b	No	No	Anywhere / Any PT stop	100
Scenario 5c	No	Yes	Anywhere / PT stop category 1 & 2	100
Scenario 5d	No	No	Anywhere / PT stop category 1 & 2	100
Scenario 5e	No	Yes	Anywhere / Train stops	100
Scenario 5f	No	No	Anywhere / Train stops	100
Scenario 6a	Yes	Yes	Anywhere / Any PT stop	100
Scenario 6b	Yes	No	Anywhere / Any PT stop	100
Scenario 6c	Yes	Yes	Anywhere / PT stop category 1 & 2	100
Scenario 6d	Yes	No	Anywhere / PT stop category 1 & 2	100
Scenario 6e	Yes	Yes	Anywhere / Train stops	100
Scenario 6f	Yes	No	Anywhere / Train stops	100

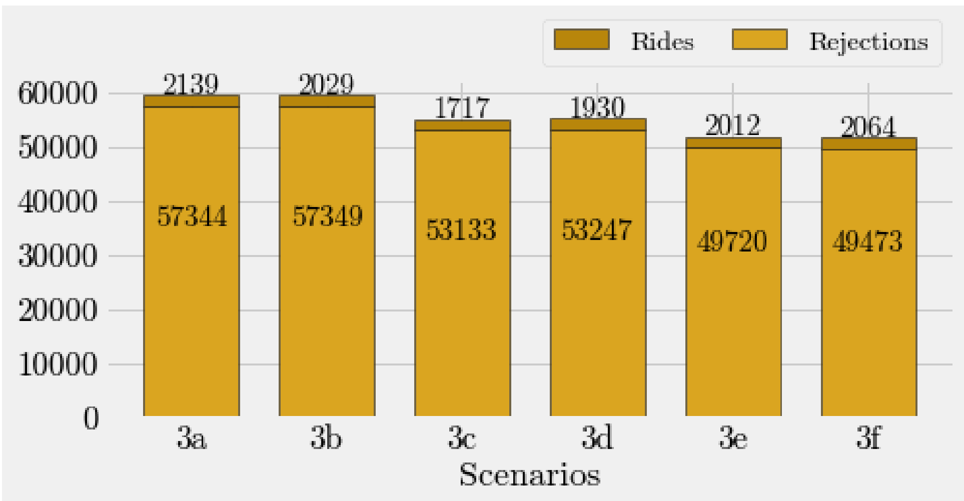
5 Results

The following section reports the results of the simulations. Beforehand, it must be stated, that the results are similar over all scenarios. Most differences arise due to the smaller and larger fleet size. For simplicity, scenario 3 is chosen for the representation of the results by the means of bar charts and tables. Scenario 3 is chosen, since the cost parameter for said scenario is based off assumptions, which were implemented in scenario 3. This means, results of scenario 3 are thought to represent the most accurate results. Plots of the other scenarios are added to Appendix A. First, the DRT service performance and trip characteristics are described, which are identified from the number of rides, the trip distances, the empty ratio of the vehicle distance, the temporal distribution of trips, and the spatial distribution of trips. Secondly, the mode share including the DRT service is shown and lastly the characteristic socio-economic attributes of a DRT user are described.

5.1 DRT trips

The number of rides conducted with DRT, depend most of all on the fleet size. The distribution over all sub-scenarios a - f is similar for all other scenarios 1 - 6, but the number of conducted rides varies greatly with fleet size. Table 7 lists the customer statistics for all scenarios.

Figure 9: Requests and rides in scenario 3



The requests exceed the executed rides by far. The number of requests for scenarios a & b are highest, for scenarios e & f lowest and for scenarios c & d values lie in between. This is what could be expected since the agents have the least options to take DRT to.

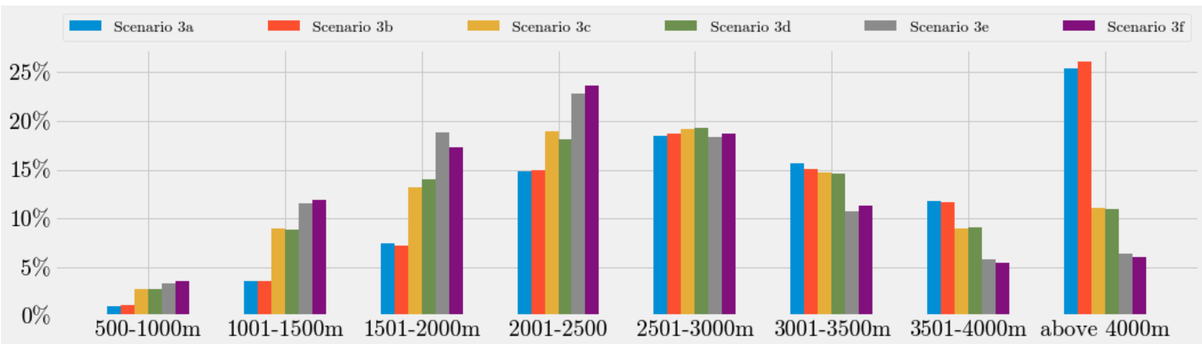
Table 7: Customer statistics for the DRT service

Scenarios	Requests	Rides	Rejections	Rejection Rate	Vehicle Kilometers	Empty Distance Ratio
Scenario 1a	61,346	1,096	60,250	98%	10,761 km	62%
Scenario 1b	61,346	1,096	60,250	98%	10,761 km	62%
Scenario 1c	57,135	874	56,261	98%	6,949 km	64%
Scenario 1d	57,125	899	56,226	98%	6,964 km	63%
Scenario 1e	53,889	888	53,001	98%	6,773 km	66%
Scenario 1f	53,818	881	52,937	98%	6,721 km	66%
Scenario 2a	61,249	977	60,272	98%	9,540 km	61%
Scenario 2b	61,346	1,096	60,250	98%	10,761 km	62%
Scenario 2c	57,135	874	56,261	98%	6,949 km	64%
Scenario 2d	57,228	934	56,294	98%	7,514 km	65%
Scenario 2e	53,907	926	52,981	98%	7,205 km	67%
Scenario 2f	54,010	974	53,036	98%	7,387 km	66%
Scenario 3a	59,483	2,139	57,344	96%	18,470 km	57%
Scenario 3b	59,378	2,029	57,349	97%	17,603 km	57%
Scenario 3c	54,850	1,717	53,133	97%	11,538 km	58%
Scenario 3d	55,177	1,930	53,247	97%	13,026 km	58%
Scenario 3e	51,732	2,012	49,720	96%	12,647 km	60%
Scenario 3f	51,537	2,064	49,473	96%	13,013 km	60%
Scenario 4a	59,508	2,078	57,430	97%	18,183 km	58%
Scenario 4b	59,417	2,028	57,389	97%	17,378 km	57%
Scenario 4c	54,998	1,805	53,193	97%	12,406 km	59%
Scenario 4d	54,887	1,732	53,155	97%	11,883 km	59%
Scenario 4e	50,931	1,864	49,067	96%	11,832 km	61%
Scenario 4f	51,599	1,865	49,734	96%	11,560 km	60%
Scenario 5a	56,389	3,532	52,857	94%	27,359 km	52%
Scenario 5b	56,610	3,679	52,931	94%	28,544 km	52%
Scenario 5c	51,800	3,188	48,612	94%	19,362 km	54%
Scenario 5d	51,855	3,312	48,543	94%	20,181 km	54%
Scenario 5e	48,457	3,386	45,071	93%	19,400 km	56%
Scenario 5f	48,843	3,603	45,240	93%	20,736 km	56%
Scenario 6a	55,712	3,230	52,482	94%	24,897 km	53%
Scenario 6b	55,959	3,320	52,639	94%	25,615 km	52%
Scenario 6c	51,813	3,396	48,417	93%	20,520 km	54%
Scenario 6d	51,960	3,263	48,697	94%	20,082 km	55%
Scenario 6e	48,548	3,494	45,054	93%	20,334 km	57%
Scenario 6f	48,981	3,613	45,368	93%	21,101 km	57%

What wasn't anticipated is the excessive rejection rate of 93% and higher. Scenarios with a greater fleet size have a higher productivity but still cannot serve the requested demand. Thereby, it is also noticeable that the requests decrease with increasing fleet size. Rather surprising the number of rides were lowest in scenarios c/d, where agents only could use DRT to PT stops of category 1 & 2. It was expected that rides in scenarios e/f would decrease proportionally to the decrease of requests. Another surprising outcome is, that PT subscriptions did not seem to have a significant effect on ridership. Differences in ridership between scenarios a/b, c/d & e/f are only marginal. In certain scenarios the rides are higher when all agents pay for the service and cannot benefit from a PT subscription (e.g. Scenarios 1f, 2d, 2e, 4c, 6c, 6e). The vehicle kilometers and empty distance ratio give an insight on the fleets performance. While the fleets total travel distance increases with the fleet size, the empty distance ratio decreases. The greater the fleet size the better the coverage of the service area and therefore the lesser the distances to the next pick-up. For the sub-scenarios a-f empty rides increase in all cases. Since less PT stops are accessible by DRT, empty stages to the next pick-up location are longer.

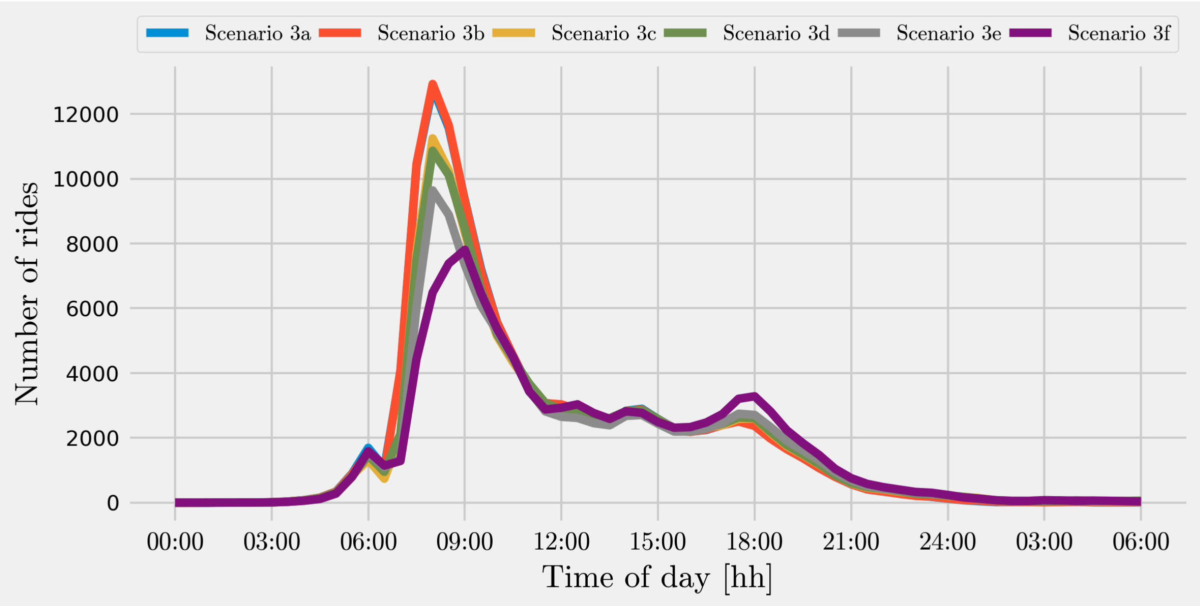
Looking at trip distances traveled with the DRT mode, it can be observed that for all scenarios most trips are made within the range of 2000-3500m (Fig. 10). For trips shorter than 2000m and longer than 3500m less rides are registered. Short trips between 500-1000m are made the least. However, there are outliers in scenario a & b where a disproportionate share of rides exceeded 4000m. The distribution suggests that the DRT service did provide better accessibility in areas where the next PT stop exceeded usual walking distances and did not substitute PT in well accessible areas, Otherwise shares of shorter trip distances should be higher. Nevertheless, this relationship has yet to be confirmed.

Figure 10: Trip distances in scenario 3



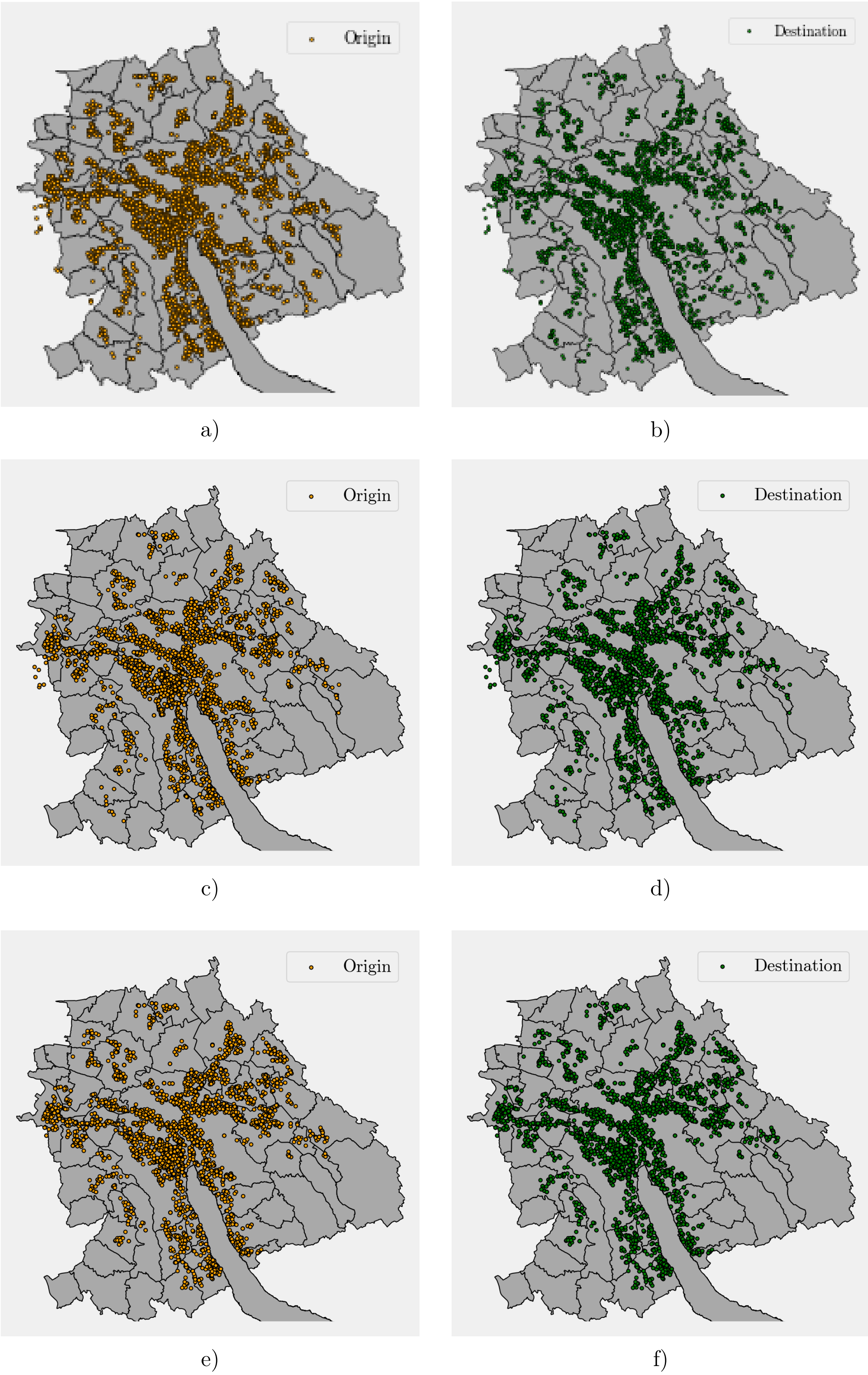
As the overwhelming majority of purposes for trip making with DRT was found to be work related (median over all scenarios = 72 %), it was expected, that a clear morning and evening peak could be identified. However, the temporal distribution of all requested DRT rides (incl. rejected rides, Fig. 11) shows, that the highest share of trips were requested during the morning peak. Thereafter, the number of rides drops and only a slight increase in trips is recorded during the evening peak hours.

Figure 11: Diurnal curve of all requested rides (incl. rejections) in scenario 3



The origin and destinations of DRT trips are aggregated for all scenarios with the same application area (i.e. Any PT stop (a & b), stop category 1 & 2 (c & d) or train stops only (e & f)) and are illustrated in Fig. 12. The orange dots depict the origins of a DRT stage, whereas green dots represent destinations. The difference between the three is small, nonetheless it is visible that the spread of the trips decreases with increasing restriction of the service area (i.e. from left figure to the right). Most pronounced is the loss of ridership in the south-eastern part of the study area which means rural ridership is lost when DRT service is restricted to train stations.

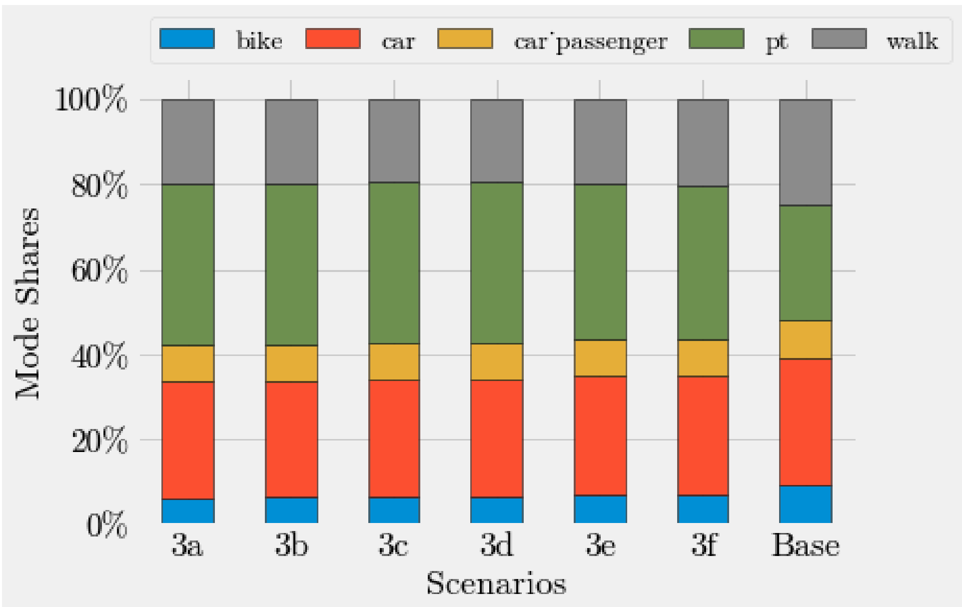
Figure 12: Origin and Destinations if DRT service accessible from any PT station (a) & (b), PT stops of category (c) & (d) and only train stops (e) & (f).



5.2 Mode shares

The results for the mode shares do not vary significantly from scenario 1 - 6. However, there is a slight variation within the sub-scenarios. Fig. 13 shows the mode shares for scenario 3. It represents the mode shares according to trips conducted, therefore the DRT service itself is not listed since DRT always is part of a trip. What Fig. 13 reveals, is that in comparison to the base scenario, the PT share could be, on average, increased (+ 9.9%) and car trips (- 2.6%), bike trips (- 2.5%) as well as walk trips (- 5.0%) decreased. So to say, the goal to incur a mode shift towards PT and lower car usage has been achieved. Nonetheless, car passenger trips have not been reduced, whereas walking and bike shares yet have decreased which is not desireable. The mode shares for all scenarios are listed in Appendix A.6.

Figure 13: Mode shares in scenario 3 and base scenario without DRT for comparison



The PT trips can further be divided into groups according to the modes used in access and egress. Therefore, the trips have been split into its stages which allowed for an exact analysis of the mode chains. Trips which used DRT in access and/or egress stages represent the vast majority with shares ranging between 94 and 98%. The DRT service is the first choice for the access and egress stages of PT trips.

5.3 Socio-demographic attributes

The attributes of the DRT users in the simulation are presented in Table 8 and compared to the non-DRT users.

Table 8: Comparison of socio-economic attributes between DRT users and non-DRT users

Attribute		DRT-Users	Non-DRT Users
Age	<18	1.8%	12.0%
	18-24	8.1%	7.2%
	25-44	47.6%	35.1%
	45-64	41.2%	30.6%
	65-79	1.1%	10.5%
	>80	0.1%	4.7%
Male		73.5%	52.9%
Female		26.5%	47.1%
Employment Rate		82.3%	65.4%
PT Subscription		35.0%	29.7%
(GA/Verbund/Strecke)		.	.
Halbtax		22.0%	26.2%
No Subscription		43.0%	44.1%
Bike Availability		52.6%	47.6%
Car Availability		69.5%	68.3%
Drivers License		86.2%	85.9%

Similar to the intermodality data from the microcensus, the simulation indicates that the age of users of the DRT service as well peaks in the mid-range between 25-64 years. These age groups combined account for 88.8% of all DRT users. Hence, only a small proportion of DRT users consists of the other age groups. Contrary to the microcensus is the share of male DRT riders, which amount almost to three quarters, whereas the intermodal trip makers were most favorably female (53.1%). When considering GA/Verbund/Strecke subscriptions, 35% of DRT users owned a PT subscription but on the other hand just 22% possessed a Halbtax which is less than the non-DRT user. This relation between DRT/Non-DRT and Intermodal/Non-intermodal is in line with the microcensus data. However, the Halbtax has proven to be more dominant in the microcensus data. Mobility tool availability is similar for both, only bike availability is higher for DRT users which as well reflects the microcensus data and the intermodal trip makers. Car availability and drivers license are similar for DRT and Non-DRT.

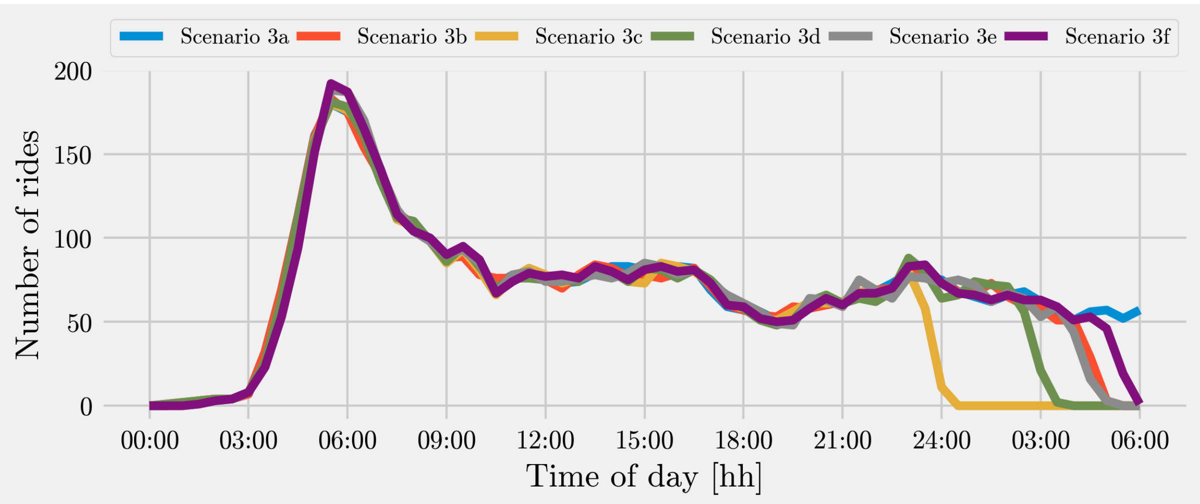
6 Discussion

As was seen in Section 5, the ratio of executed rides and ride requests are out of balance, with rejection rates at 94% and above. The temporal distribution of the rides has also raised some suspicions, regarding the integrity of the results. Therefore, in this section these peculiarities are addressed and investigated more closely. Furthermore, the scenario parameter costs, subscription integration, application restrictions and fleet size are outlined in the last subsection of this chapter.

6.1 Investigation of scenarios 1 - 6

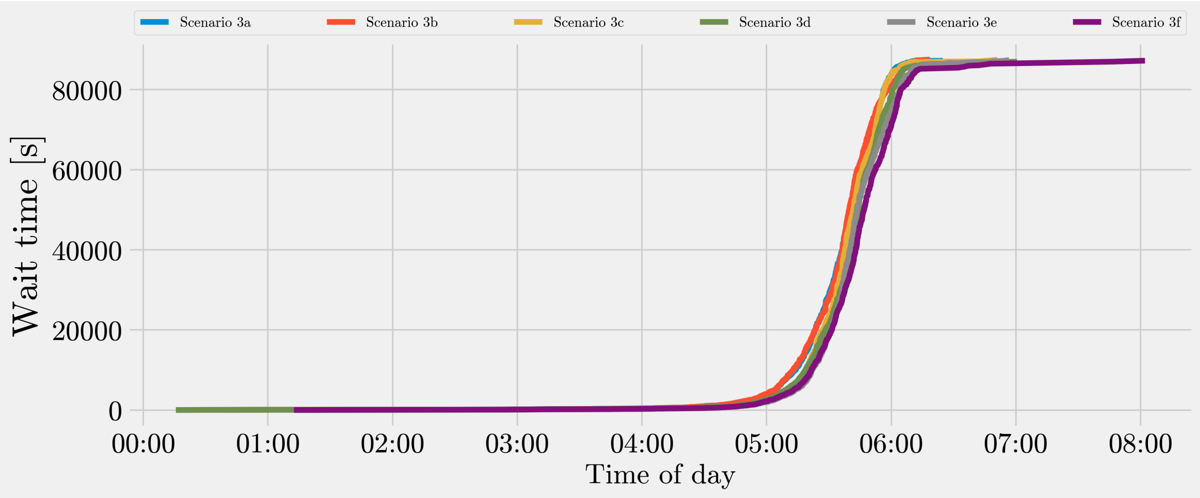
In a first step, the temporal distribution of the actual DRT pick-up times is analyzed. The results confirm the morning peak hours to be the busiest. On the other hand, the rides do not drop as sharply and most sub-scenarios remain at a similar level until close to the end of the simulation. This means, that there must be significant wait time, which causes a shift of the rides from the morning to later in the day.

Figure 14: Departure times for executed DRT trips in scenario 3



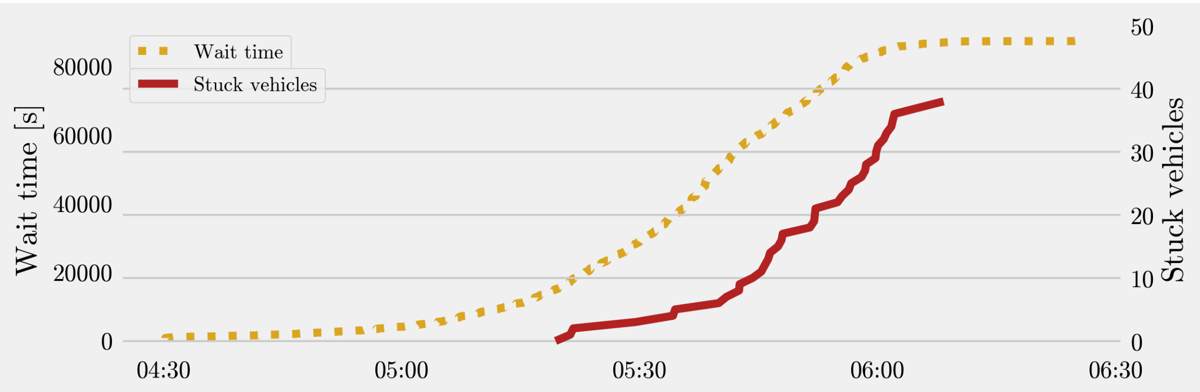
Plotting waiting time for the executed rides, it becomes clear, why there is a discrepancy between requested departure time and actual pick-up time. The temporal distribution of the rides as in Fig. 14 stems from the excessive wait time, which increases sharply between 05:00 and 06:00 Fig. 15.

Figure 15: Wait time for DRT service in scenario 3



As Fig. 15 illustrates, agents requesting a DRT service at around 6 a.m. were left waiting for the rest of the duration of the simulation and only arrived late at night. This explains why the share of rides does not decrease during the evening and night hours, as the requests do (Fig. 11). On the other hand, it raises questions as to why agents experience that excessive wait time and why agents didn't replan to other modes and still stayed waiting for the service? These questions are partially answered by analysing the DRT trips file. The DRT service starts its operation normally and serves a couple of agents during the early morning hours. After some time has passed, vehicles inexplicably stop running at their next pick-up. Consequently, the fleet size is reduced and wait times for the agents increase. Fig. 16 shows the connection between the number of vehicles getting stuck and the increasing wait time for the agents.

Figure 16: Relationship between stuck vehicles and waiting time in scenario 3a



The service doesn't seize entirely. A part of the fleet still operates. Table 9 shows the share of the remaining fleet compared to total fleet size for all scenarios. It can be seen, that the share of the fleet, which remains operational, is smaller for larger fleet sizes, which means more vehicles seize operations, when the fleet is larger.

Table 9: Remaining operational fleet

	a	b	c	d	e	f
Scenario 1	48%	48%	40%	16%	32%	40%
Scenario 2	28%	48%	40%	24%	48%	40%
Scenario 3	22%	34%	26%	16%	20%	16%
Scenario 4	22%	24%	20%	22%	12%	16%
Scenario 5	7%	8%	14%	9%	16%	12%
Scenario 6	17%	15%	14%	12%	10%	10%

Source:

What additionally should be noticed is, that the wait time increases already before the vehicles stop running. Possibly, there is an error caused by the wait time. However, initially the wait time increases because the fleet neither can serve the demand at full capacity. Therefore, additional scenarios are generated to test a much larger fleet size which might be able to limit the initial wait time and prevent the vehicles from getting stuck.

6.2 Scenarios 7 & 8

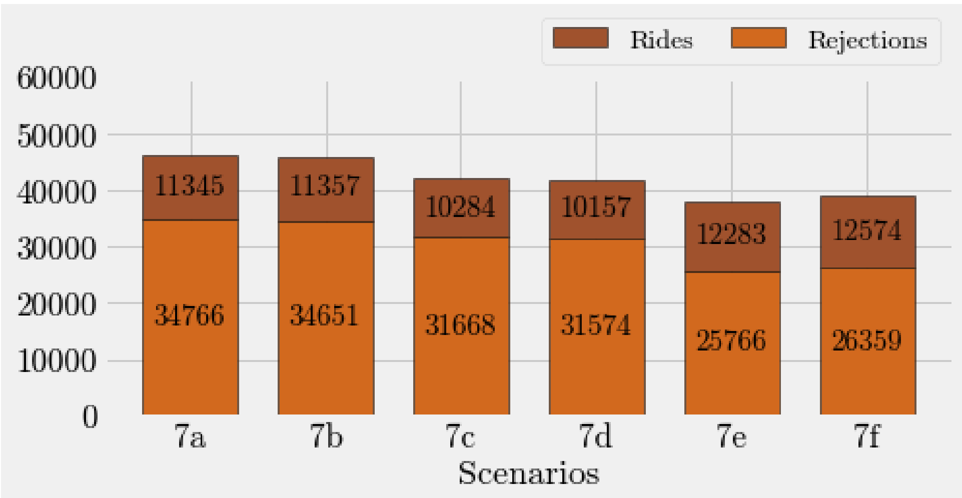
For scenarios 7 and 8, sub-scenarios a - f are created just as in the previous scenarios. The only parameter altered is the fleet size. The parameters are described in Table 10. As can be seen, the fleet size was increased five fold, compared to the largest fleet size in scenarios 5 & 6, which results in 500 vehicles. This number was set arbitrarily. The idea was to examine if it was the design of the service that caused the large waiting times for the DRT trips or if there is another basic underlying problem in the simulations configuration file or framework, which causes these delays and therefore inefficient operation of the DRT service.

Table 10: Additional scenarios 7 & 8 with increased fleet size

	Base fare	PT subscription integration	Access from / to	Fleet size
Scenario 7a	No	Yes	Anywhere / Anywhere	500
Scenario 7b	No	No	Anywhere / Anywhere	500
Scenario 7c	No	Yes	Anywhere / PT stop category 1 & 2	500
Scenario 7d	No	No	Anywhere / PT stop category 1 & 2	500
Scenario 7e	No	Yes	Anywhere / Train stops	500
Scenario 7f	No	No	Anywhere / Train stops	500
Scenario 8a	Yes	Yes	Anywhere / Anywhere	500
Scenario 8b	Yes	No	Anywhere / Anywhere	500
Scenario 8c	Yes	Yes	Anywhere / PT stop category 1 & 2	500
Scenario 8d	Yes	No	Anywhere / PT stop category 1 & 2	500
Scenario 8e	Yes	Yes	Anywhere / Train stops	500
Scenario 8f	Yes	No	Anywhere / Train stops	500

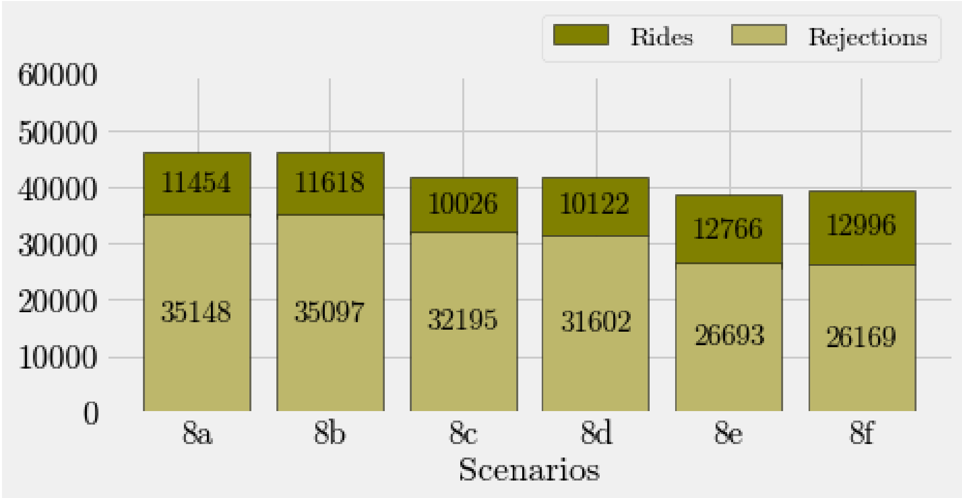
Once more the rides and requests are analyzed for both scenarios. From Fig. 17 and Fig. 18 it becomes clear that the alteration of the fleet size increased the number of rides, however the pattern is similar but not exactly the same.

Figure 17: Requests and executed rides in scenario 7



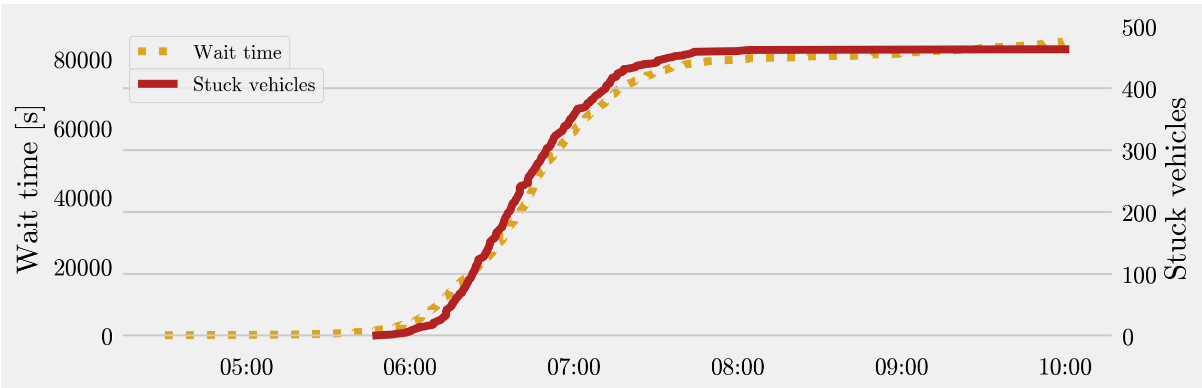
While the number of requests still decreases, depending on the application area of the DRT service, the number of rides are highest for scenarios e & f in both scenarios 7 & 8. This is an interesting finding, because they represent the cases with the highest ratio of executed rides compared to total requests. This means that in these scenarios the DRT service has been the most efficient. Unfortunately, the rejection rate is still very high.

Figure 18: Requests and executed rides in scenario 8



This indicates that the problem of vehicles getting stuck amid the simulations remains. To verify this assumption, the wait time and number of stuck vehicles are plotted, just as for scenarios 1 - 6 (Fig. 19).

Figure 19: Relationship between stuck vehicles and waiting time in scenario 7a



The comparison to scenarios 1 - 6 reveals that the share of vehicles, which do not get stuck and remain operational has decreased once more. Therefore, the tendency for larger fleet sizes to experience more vehicles getting stuck, is confirmed. Table 11 shows that the remaining operational fleet is below 10% for both scenarios 7 & 8. It can be concluded, that a larger fleet size does not solve the prevailing problem of vehicles getting stuck. The error must lie somewhere in the simulations framework.

Table 11: Remaining operational fleet

	a	b	c	d	e	f
Scenario 7	7.2%	5.8%	6.8%	6.8%	6.6%	5.2%
Scenario 8	8.2%	6.2%	5.0%	7.0%	8.4%	5.6%

6.3 Influence of scenario parameters

From the scenarios, the influence of costs, service integration, application area and fleet size are examined. The interpretations of the results need to be handled with caution, since the results have shown to be counter-intuitive.
The price and base fare both seem to have potential to be increased, considering the large number of requests and the arbitrary distribution of rides between both cost scenarios (with/without base fare). It should nonetheless be taken into account that the larger fleet size of scenarios 5-8 require more financial resources than was calculated for the reference scenario 3. Hence, the price would anyway need to be recalculated, if larger fleets would be operated. In Hörl *et al.* (2019) the cost for individual motorized transportation was said to be at 0.7 CHF/km and was hence considered to be the upper bound for an automated mobility on demand (AMoD) service. The DRT service cost of at 0.85 CHF/km is 20% more expensive. Against this background, the similarity of the results in both cost scenarios and the large number of requests is surprising. Possibly, the error lies in the inaccurate calculation of the β value for the DRT service and/or the cost calculations. Comparing the assumed values for $n_{numberOfTrips}$ (= 1,400) and $d_{fleetDistance}$ (= 3,900 km), which were used for the derivation of C_{fleet} in Eq. (2), it is noticed that both values are underestimated (roughly -40% for rides and -380% for fleet distance). A possibility to derive more accurate costs would be to iteratively recalculate the costs, by feeding back the simulation output into the cost equation Eq. (2). With the preceding discussion of the influence of the price, it is not a surprise that the integration of the DRT service into the PT subscription did not influence ridership. The price is low enough for the PT integration to only marginally influence the mode choice. Thus, no statement on its influence can be made but it still would be interesting to consider this parameter in consequent simulations, when a more accurately elaborated price has been determined.

The restrictions for the application of the DRT service limit the accessibility of the service and hence affects the service negatively. Requests decrease and it can be seen that clusters of riders disappear in rural areas , when the service is limited to train stations, compared to scenarios a & b where DRT can be used anywhere (Fig. 12). This implies that in rural areas there might not necessarily be a connection by rail, which suits the needs of the residents and DRT cannot increase its attractiveness enough. However, DRT might potentially increase ridership on rural bus lines by offering better accessibility to such. On the other hand, the downside of unrestricted DRT service is increased vehicle kilometers and higher empty mileage which results in higher operating costs.
The fleet size altered the performance of the system by providing higher capacity and reduced the empty distance ratio, due to the better coverage of the area and therefore shorter distances to the next pick-up. It must be noted that in this report, the price for the service was not varied with the fleet size. Therefore, requests would probably decrease slightly, if fleet size is increased, since the price would increase with increasing fleet size (Eq. (3)). With regards to the high number of requests it is not expected that there would be significantly less rides. On the other hand, the true performance of the system is unclear, because it must be assumed that there is a bug in the simulation files which causes parts of the fleet to seize operations. This has to be properly examined, once the framework has been fixed of errors. Unexpected was that larger share of vehicles got stuck, when the fleet size was increased. This again cannot be explained by the output data and the simulation files, therefore, must be examined.

6.4 Implication of socio-demographic attributes

The analysis of socio-economic attributes have revealed, that the DRT ridership is concentrated around medium ages ranging from 25 to 64 (89%) and is predominantly male (73%). However, the data might be biased because the data represents the trip makers according to the requests with a peculiar distribution (Fig. 11). Furthermore, the employment rate of DRT users was found to be higher (82.3%) compared to Non-DRT users (65.5%). The implication thereof is, that DRT usage is strongly related to work commuter trips. The young people and the elderly aged 65 and above, are not drawn to the service. Therefore, the assumption that DRT would offer increased mobility to these age groups is not confirmed.
As previously discussed, PT subscription integration did not return the expected increase in ridership. Yet, DRT users more often possessed a PT subscription compared to Non-DRT users. There are two possible explanations, why the integration did not

yield differences in ridership. First, the PT subscription only offered a marginal benefit to the agents, because the price was too low. Second, to detect an increasing ridership, due to the benefits of PT integration, the agents would have to be able to acquire PT subscriptions during the simulations, which they did not. In reality, a user of motorized individual transport might choose to get a PT subscription, because he now finds PT convenient in combination with DRT. In the simulations this behavior is not detected and therefore also no rise in ridership can be distinguished in cases with or without PT integration. In case of the microcensus data, PT subscription ownership was higher for PT trip makers in general, compared to non-PT. The availability of other mobility tools is similar between DRT and Non-DRT users except for bike availability which is 5% higher for DRT users. Assuming that higher bike availability favors intermodality, it can be concluded that before the DRT service was introduced, the agents used the bike but replaced it with DRT once it became available. This is also what the mode share data in Fig. 13 suggests.

7 Conclusion

The results gathered in this report shed valuable light on important aspects of DRT services and its simulation in the different context. The last part of this report, summarizes the findings and describes possible improvement for the simulation of a DRT service and the limitations to this report.
In summary, the service is valued highly by the agents. The agents are willing to pay prices exceeding the costs for motorized individual transport. The socio-demographic attributes imply that the DRT ridership is male, employed and aged 25 - 64. Share of PT subscription ownership are higher for DRT users. However, the integration of the service into PT subscriptions does not alter the DRT ridership. The application area has proven to be an important parameter and it must be chosen carefully, to exploit the full potential of DRT services. It was found that if the service is run from any PT station requests for the service are highest and empty distance ratios are reduced. This in turn requires a larger fleet size to serve the demand, which increases operator costs due to increased vehicle kilometers. From the microcensus data (BFS and ARE, 2017) there is evidence that intermodality takes place in suburbs rather than cities. Following the policy implications given by Räth *et al.* (2021) for an AToD service in Zurich, it would be interesting for further simulations to include a scenario, which prohibits DRT service within a certain area of the city where accessibility to PT is already guaranteed and benefits from a DRT service are only marginal. The focus would then be on connecting suburbs to the urban PT stops at the cities boundaries. The goal is to capture more shares of suburban car traffic while reducing the financial efforts and resources to maintain a DRT service, because a smaller area has to be served. By focusing on increasing accessibility in suburbs and rural areas, the performance of regional bus lines and thus its attractiveness could be increased and attract new demand. Additionally, it would be interesting to test relocating algorithms to alter the performance of the system.

There are some limitations to this study and room for improvement, which must be addressed. First of all, as mentioned in Section 6.3 the determination of the price and the mode choice parameters can be done in a more sophisticated way. The same statement is valid for the fleet size, which is related to the service cost by the cost equation Eq. (2). This relation could be further examined and optimized to find the ideal fleet size for the most efficient operation. It is suggested that the fleet size is varied to maximize the ride/request ratio and minimize C_{fleet}. In an iterative process the results from the simulations could be fed back into the cost equation Eq. (2) until an equilibrium is found, where cost and fleet size are optimized.

Before going on with the same simulation framework as was used in this report, the problem of the stuck vehicles must be addressed. There seems to be an issue within the code of the simulation that causes the vehicles to stop their operation. The reason for this behavior could not be determined yet. The calculation of average wait time and the possible influence thereof on rejections is subject to further investigations.

8 References

Abou-Zeid, M., R. Witter, M. Bierlaire, V. Kaufmann and M. Ben-Akiva (2012) Happiness and travel mode switching: Findings from a Swiss public transportation experiment, *Transport Policy*, **19** (1) 93–104.

Alonso-González, M., T. Liu, O. Cats, N. Van Oort and S. Hoogendoorn (2018) The potential of demand responsive transport as a complement to public transport: An assessment framework and an empirical evaluation, *Transportation Research Record*, **2672** (8) 879–889.

Andréasson, I. J. (2012) Personal rapid transit as feeder-distributor to rail, *Transportation Research Record*, **2275**, 88–93.

Becker, F. (2020) Multidimensional mobility behavior today and in a future with automated vehicles – Investigating the choices of modes, mobility tools, and residential locations, *Doctoral Thesis - Institut für Verkehrsplanung und Transportsysteme, Departement Bau, Umwelt und Geomatik, ETH Zürich.*

BFS and ARE (2017) Verkehrsverhalten der Bevölkerung - Ergebnisse des Mikrozensus Mobilität und Verkehr 2015, *Bundesamt für Statistik and Bundesamt für Raumentwicklung.*

Bösch, P. M., F. Becker, H. Becker and K. W. Axhausen (2018) Cost-based analysis of autonomous mobility services, *Transport Policy*, **64**, 76–91.

de Freitas, L. M., H. Becker, M. Zimmermann and K. W. Axhausen (2019) Modelling intermodal travel in Switzerland: A recursive logit approach, *Transportation Research Part A: Policy and Practice*, **119**, 200–213.

Fan, A., X. Chen and T. Wan (2019) How have travelers changed mode choices for first/last mile trips after the introduction of bicycle-sharing systems: An empirical study in Beijing, China, *Journal of Advanced Transportation*, **2019**.

für Raumentwicklung ARE, B. (2011) ÖV-Güteklassen - Berechnungsmethodik ARE.

Horni, A., K. Nagel and K. W. Axhausen (2016) *The multi-agent transport simulation MATSim*, Ubiquity Press, London.

Huang, Y., K. Kockelman, V. Garikapati, L. Zhu and Y. S. (2021) Use of shared automated vehicles for first-mile Service: Micro-simulation of rail-transit connections in Austin, Texas, *Transportation Research Record*, **2675** (2) 135–149.

Hörl, S. and M. Balac (2021) Introducing the eqasim pipeline: From raw data to agent-based transport simulation, *Procedia Computer Science*.

Hörl, S., M. Balac and K. W. Axhausen (2018) Pairing discrete mode choice models and agent-based transport simulation with MATSim, *Arbeitsberichte Verkehrs- und Raumplanung*, **1373**, 19.

Hörl, S., F. Becker and K. W. Axhausen (2021) Simulation of price, customer behaviour and system impact for a cost-covering automated taxi system in Zurich, *Transportation Research Part C: Emerging Technologies*, **123**, 102974.

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

Lazarus, J., S. Shaheen, S. E. Young, D. Fagnant, T. Voege, W. Baumgardner, J. Fishelson and J. S. Lott (2018) Shared automated mobility and public transport, *Road Vehicle Automation 4*, 141–161.

Lervag, L.-E. (2020) Automated shuttle services in public transport; Lessons learned from the Smart Feeder Research Project in Norway, *European Transport Conference 2020, Milan, Italy.*

Liu, Y., J. Chen, W. Wu and J. Ye (2019) Typical combined travel mode choice utility model in multimodal transportation network, *Sustainability*, **11** (549).

Liu, Z., X. Jia and W. Cheng (2021) Solving the last mile problem: Ensure the success of public bicycle system in Beijing, *Procedia - Social and Behavioral Sciences*, **43**, 73–78.

Loder, A. and K. W. Axhausen (2018) Mobility tools and use: Accessibility's role in Switzerland, *Journal of Transport and Land Use*, **11** (1) 367–385.

Reck, D. J. and K. W. Axhausen (2020) Subsidized ridesourcing for the first/last mile: How valuable for whom?, *European Journal of Transport and Infrastructure Research*, **20** (4) 59–77.

Reck, D. J., H. Haitao, S. Guidon and K. W. Axhausen (2021) Explaining shared micromobility usage, competition and mode choice by modelling empirical data from Zurich, Switzerland, *Transportation Research Part C: Emerging Technologies*, **124** (102947).

Ryley, T. J., P. A. Stanley, M. P. Enoch, A. M. Zanni and M. A. Quddus (2014) Investigating the contribution of demand responsive transport to a sustainable local public transport system, *Research in Transportation Economics*, **48**, 364–372.

Räth, M., Yves M. Balac, S. Hörl and K. W. Axhausen (2021) System level policies for Automated Transit On-Demand Services: A case study for Zurich, Switzerland, *Transportation Research Part A: Policy and Practice*, (1).

Scheltes, A. and G. Homem de Almeida Correia (2017) Exploring the use of automated vehicles as last mile connection of train trips through an agent-based simulation model: An application to Delft, Netherlands, *International Journal of Transportation Science and Technology*, **6** (1) 28–41.

Shen, Y., H. Zhang and J. Zhao (2018) Integrating shared autonomous vehicle in public transportation system: A supply-side simulation of the first-mile service in Singapore, *Transportation Research Part A: Policy and Practice*, **113**, 125–136.

Soe, R.-M. and J. Müür (2020) Mobility acceptance factors of an automated shuttle bus last-mile service, *Sustainability*, **12** (13).

Yap, M. D., G. Correia and B. van Arem (2016) Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips, *Transportation Research Part A: Policy and Practice*, **94**, 1–16.

A Plots of Scenarios 1 - 8 from MATSim simulation results

A.1 Requests and Rides

Figure 20: Requests and rejections in scenario 1 and 2

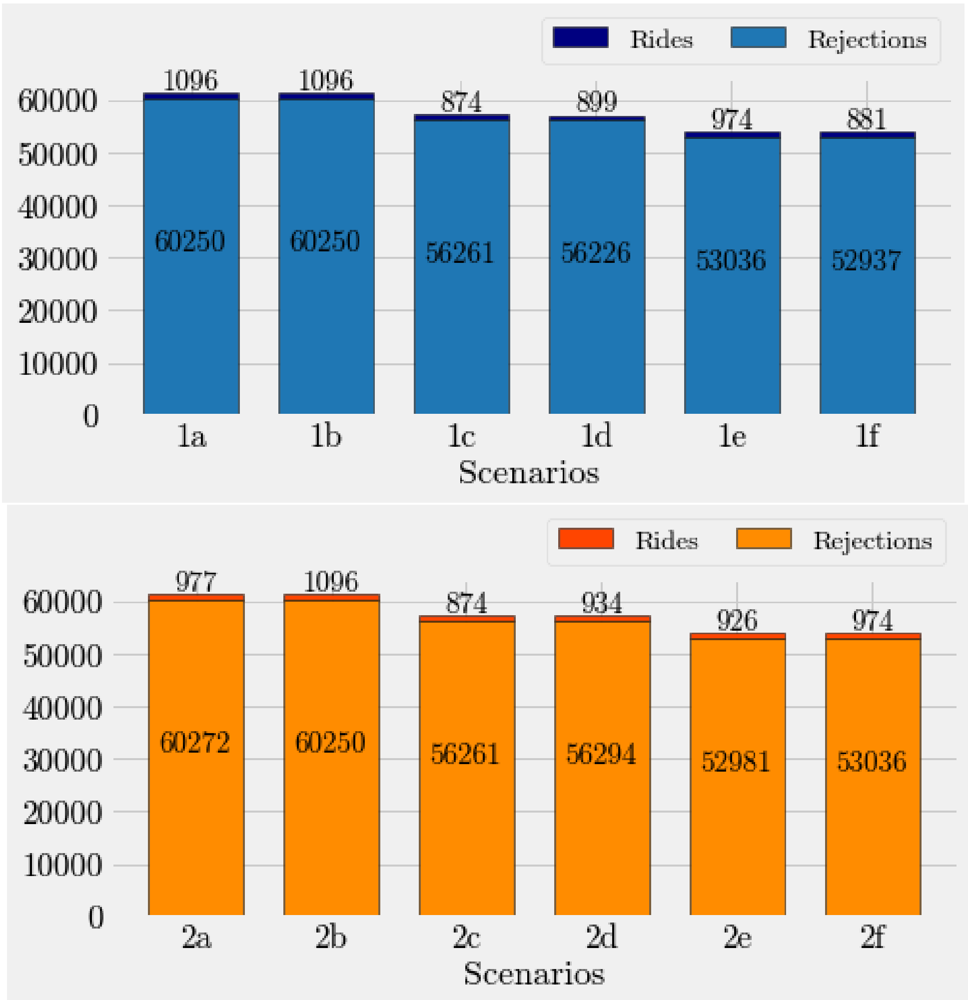


Figure 21: Requests and rejections in scenario 3, 4 and 5

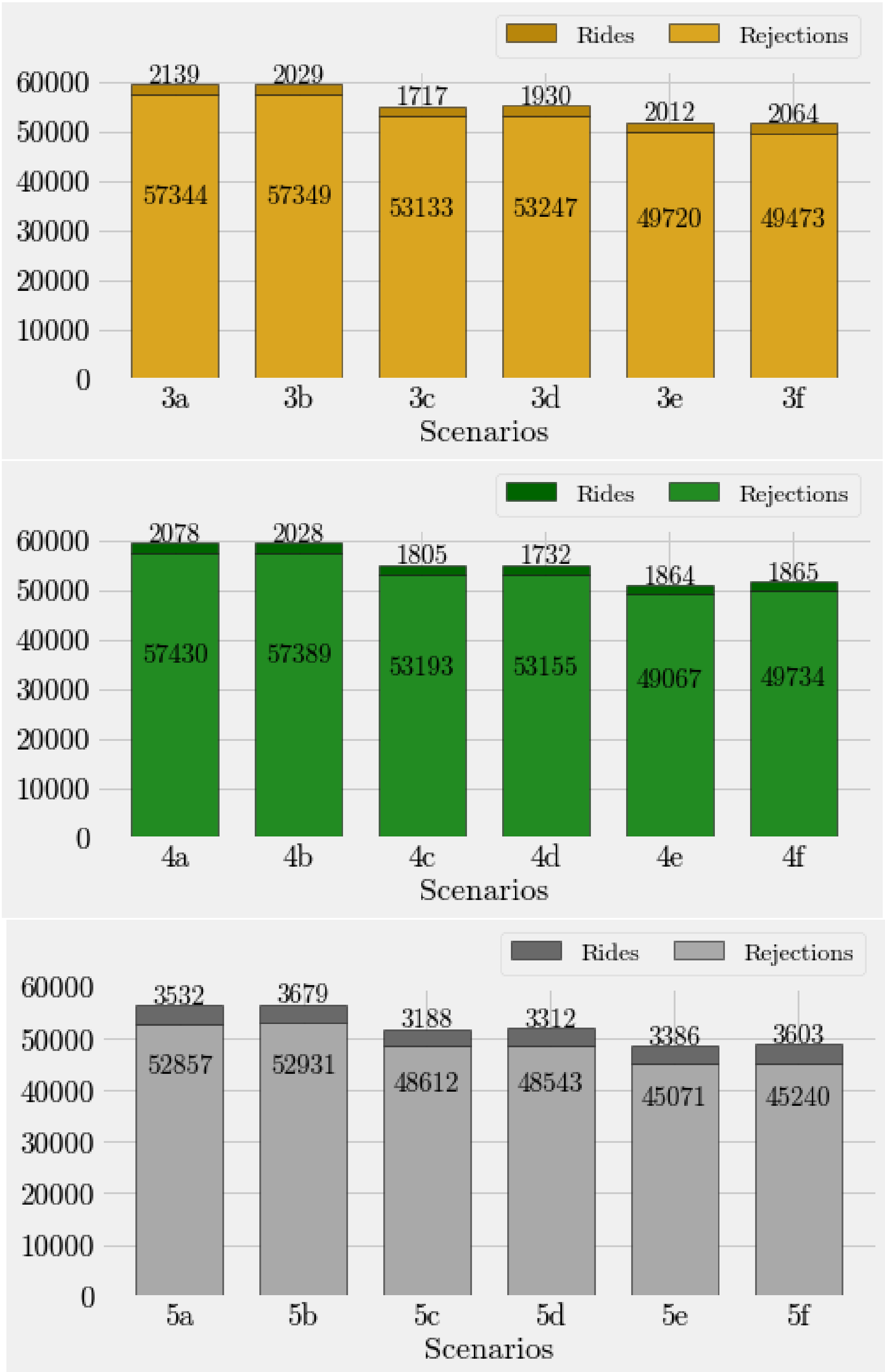
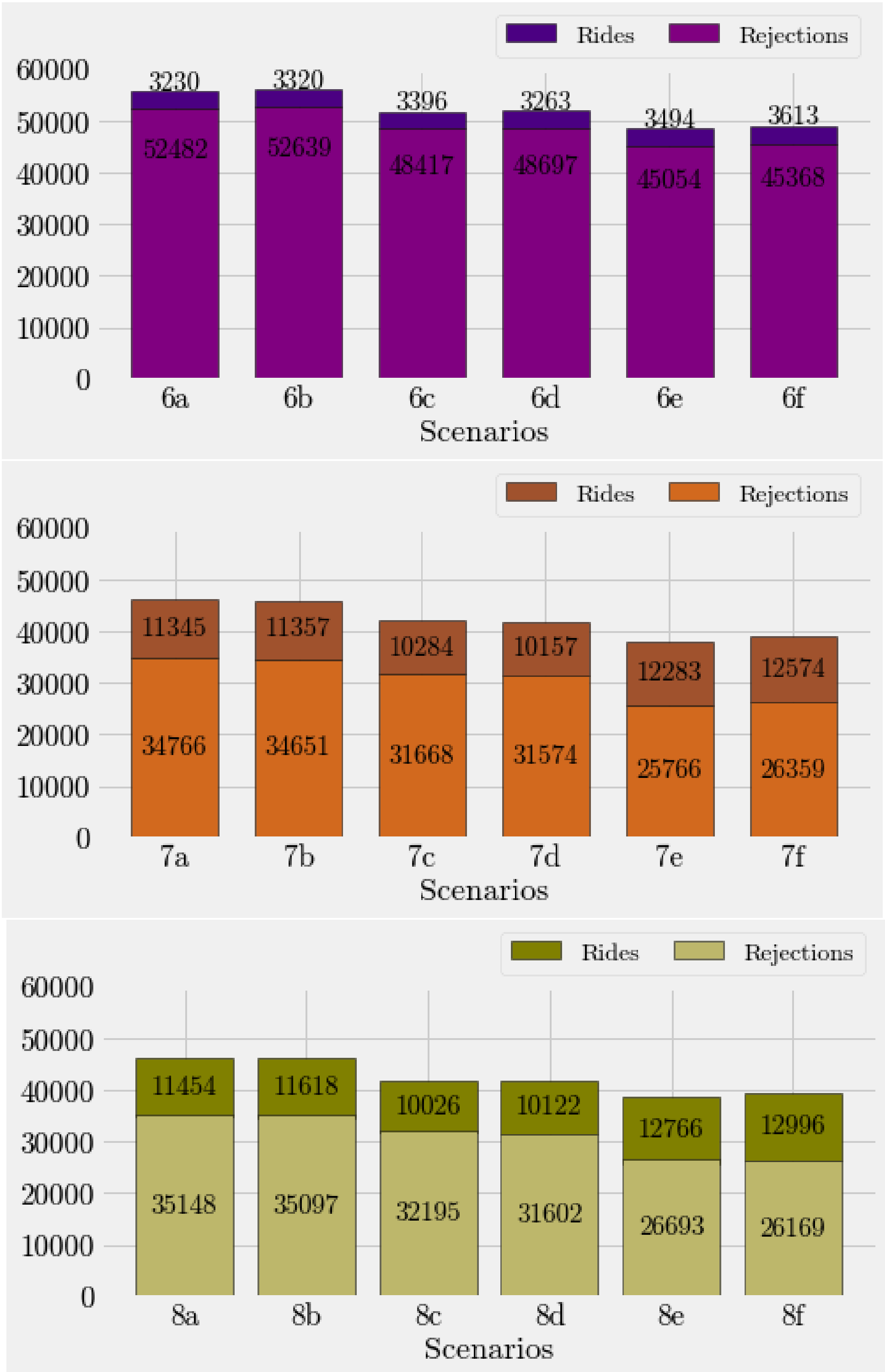


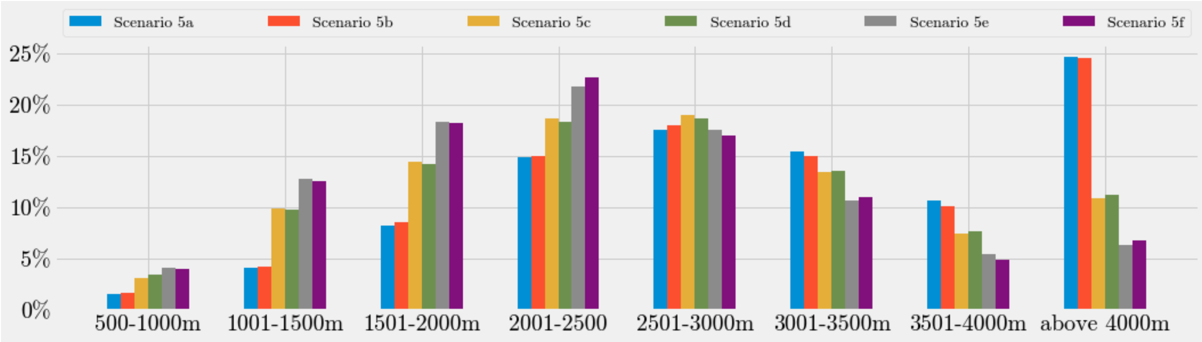
Figure 22: Requests and rejections in scenario 6, 7 and 8

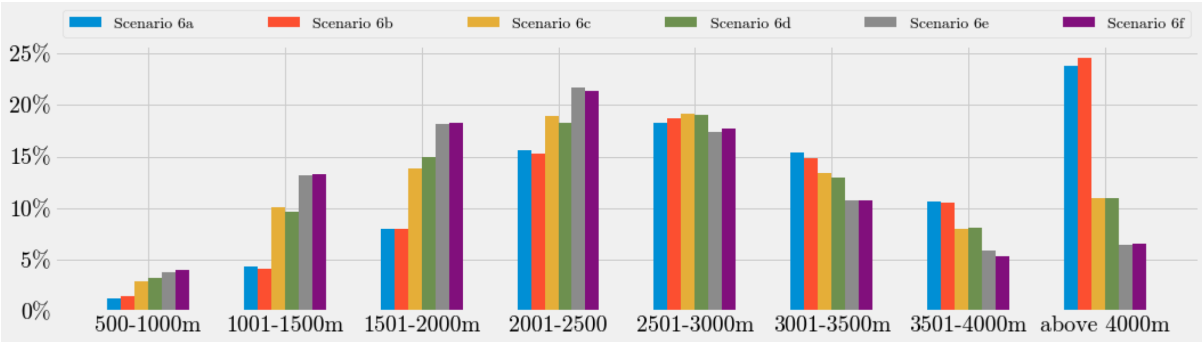


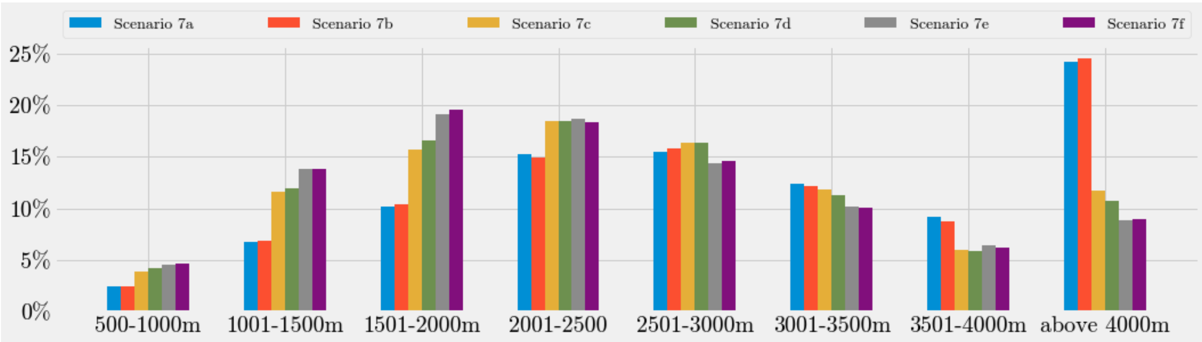
A.2 Distribution of DRT trip distances

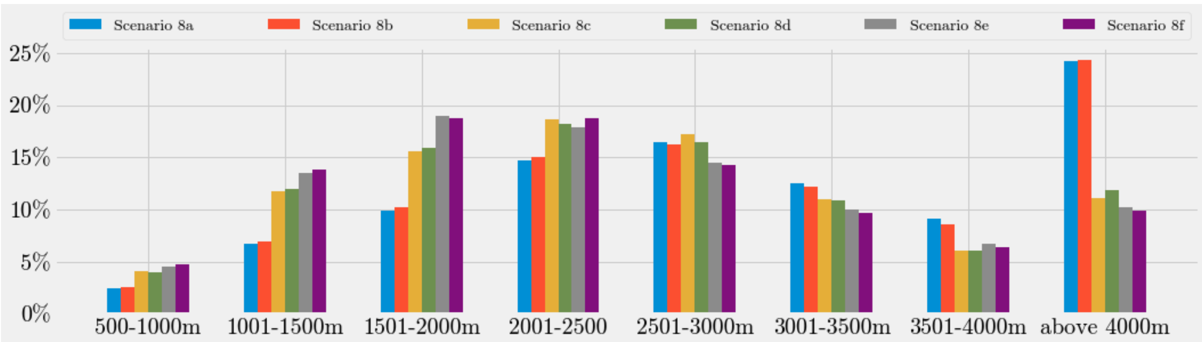
Figure 23: DRT trip distances in scenarios 1 - 4

Figure 24: DRT trip distances in scenarios 5 - 8









A.3 Temporal distribution of DRT rides

Figure 25: Temporal distribution of DRT rides in scenario 1 and 2

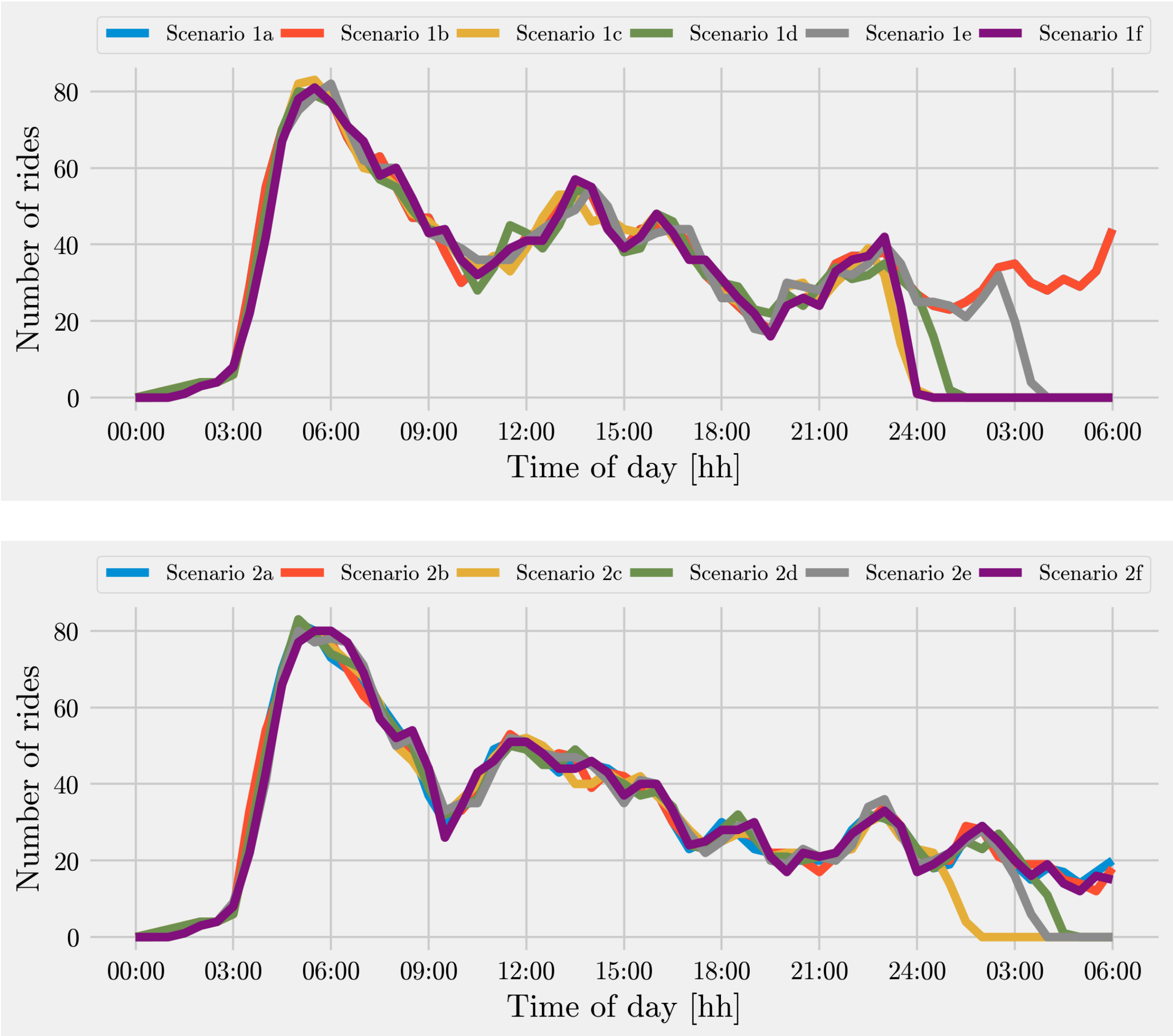


Figure 26: Temporal distribution of DRT rides in scenario 3 - 5

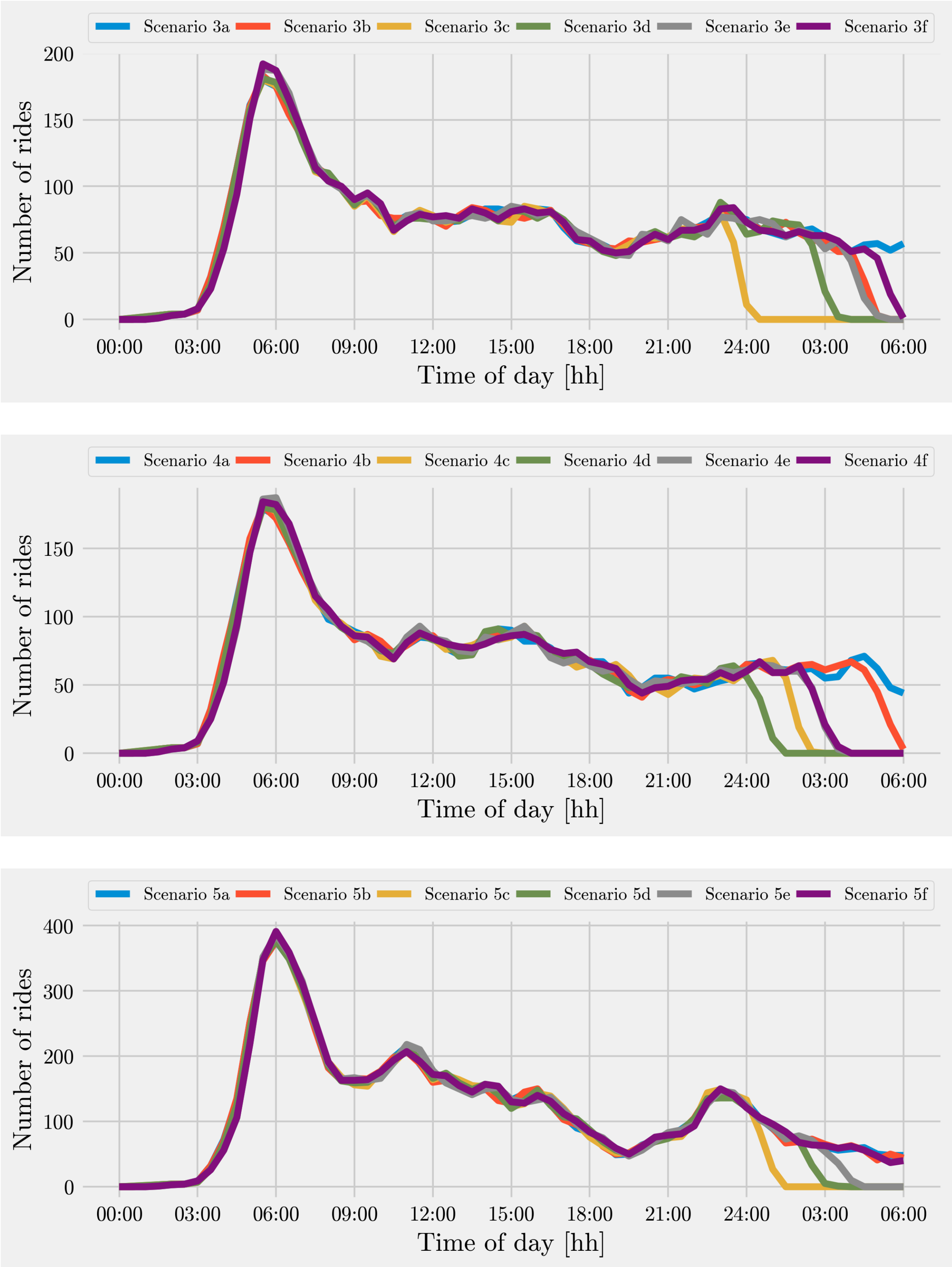
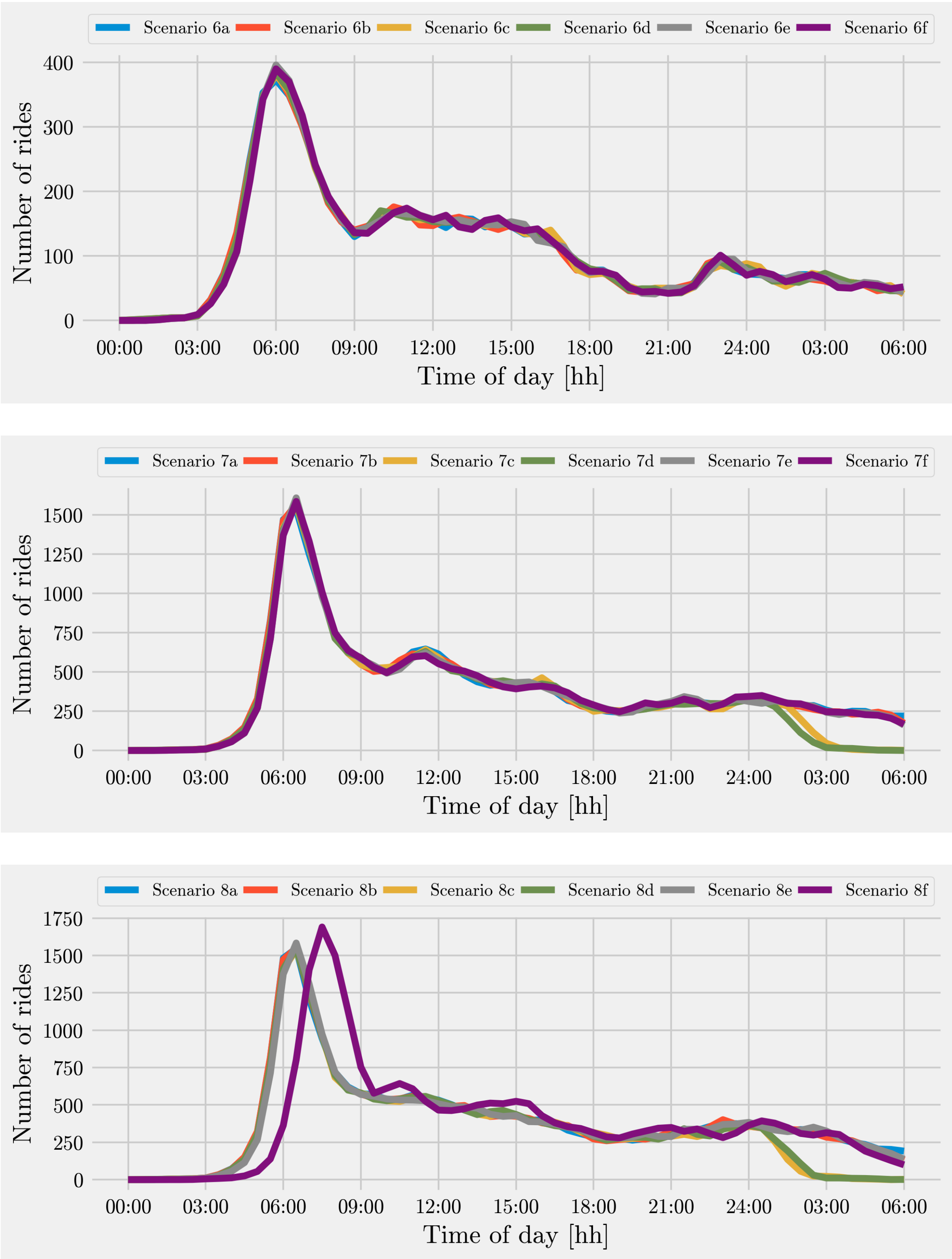
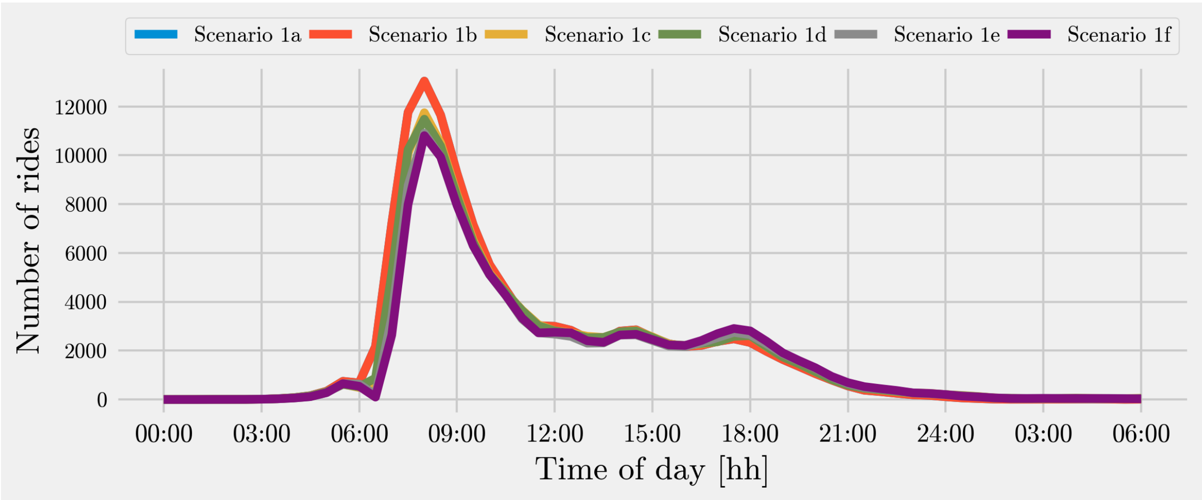


Figure 27: Temporal distribution of DRT rides in scenario 6 - 8



A.4 Temporal distribution of requests for DRT trips

Figure 28: Requested departure times for DRT trips in scenario 1 and 2



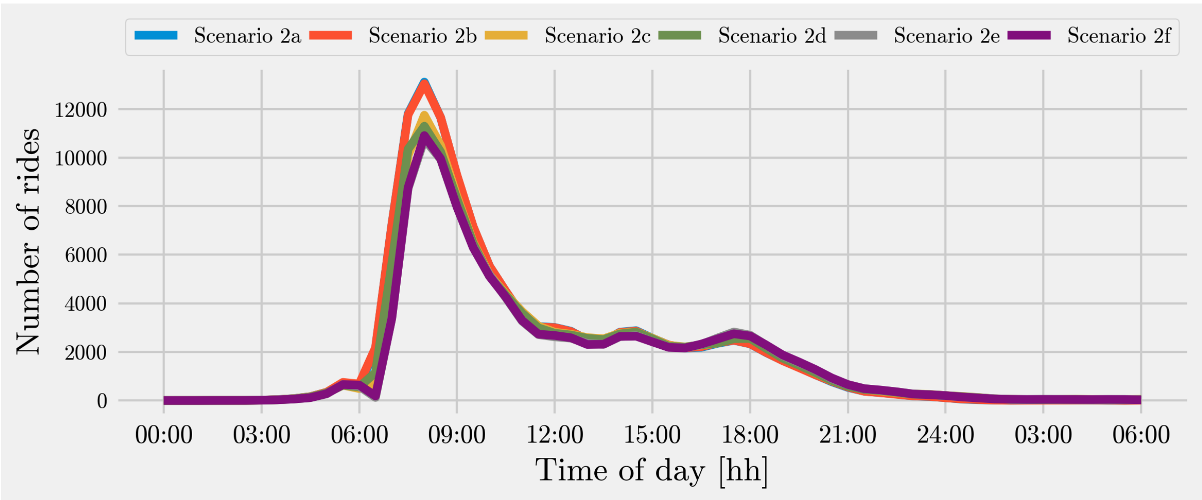
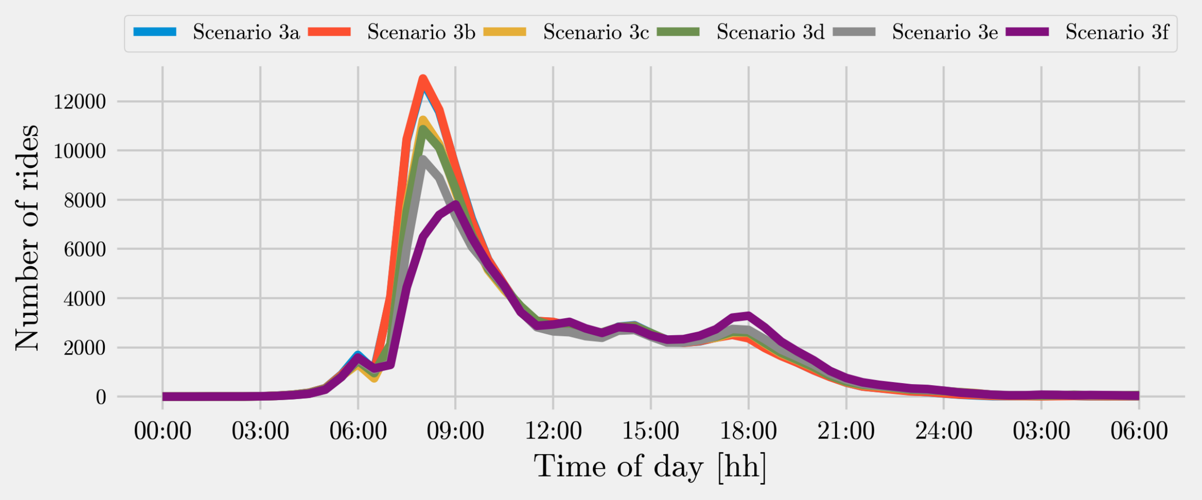
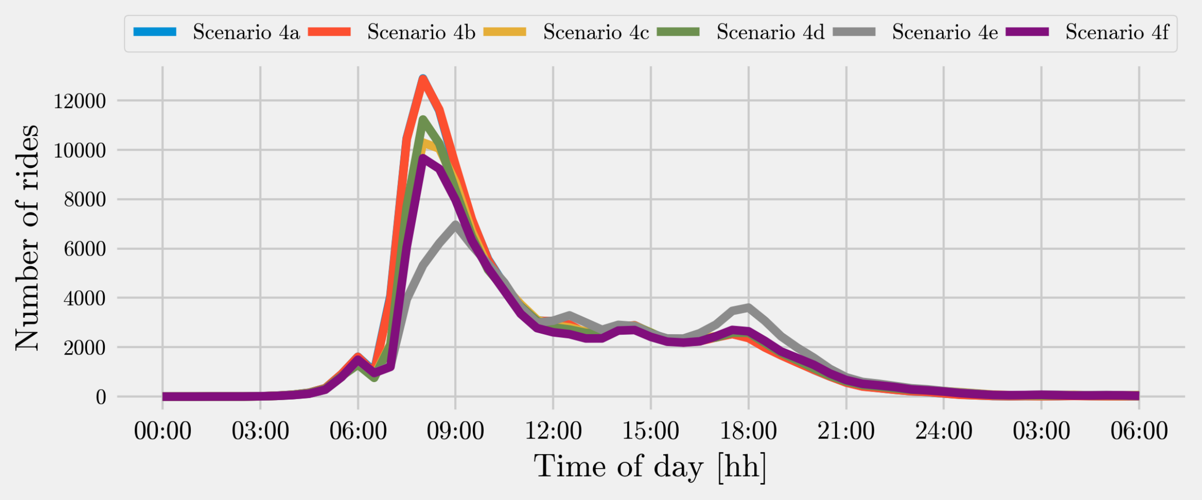


Figure 29: Requested departure times for DRT trips in scenario 3 - 5





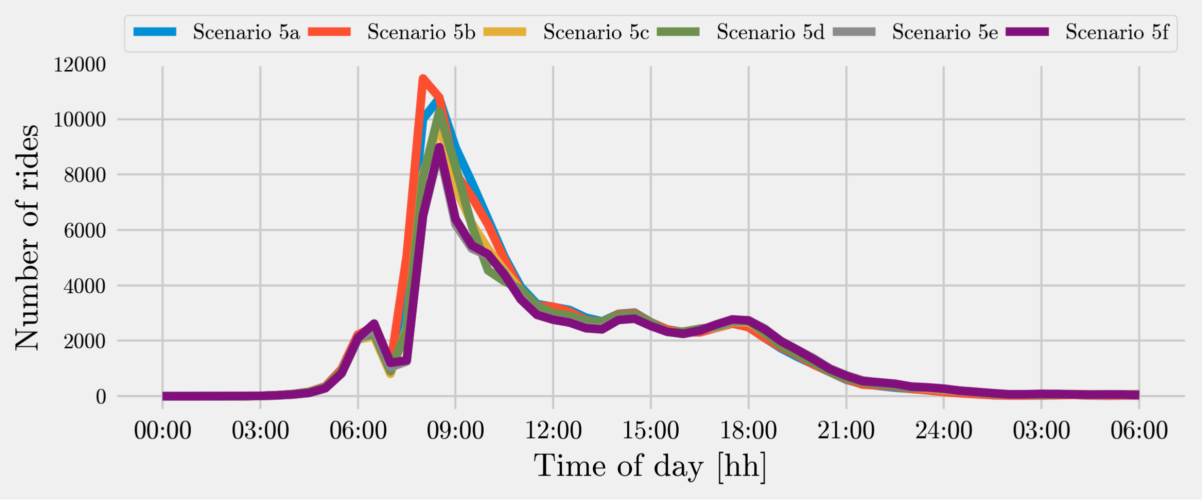
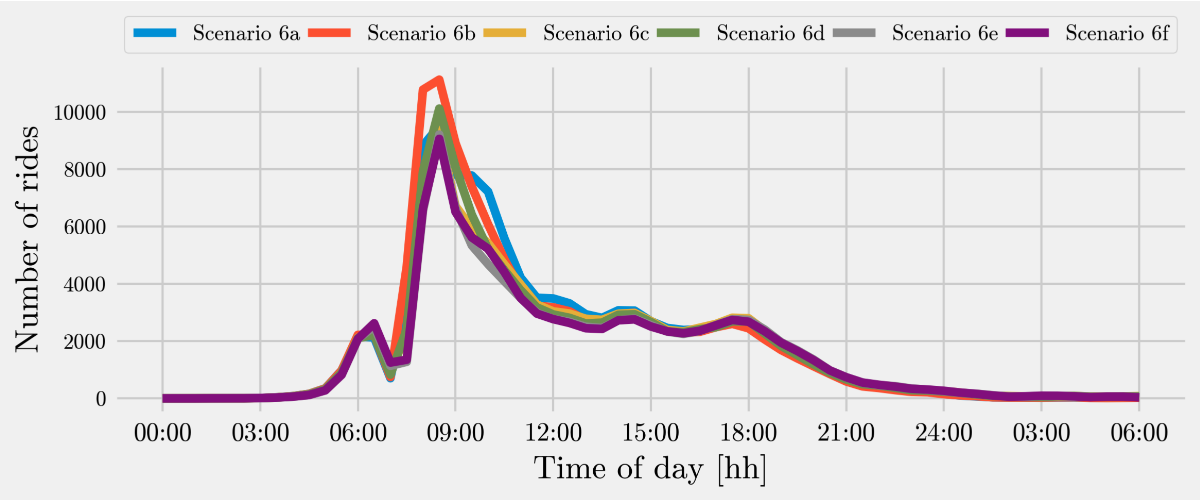
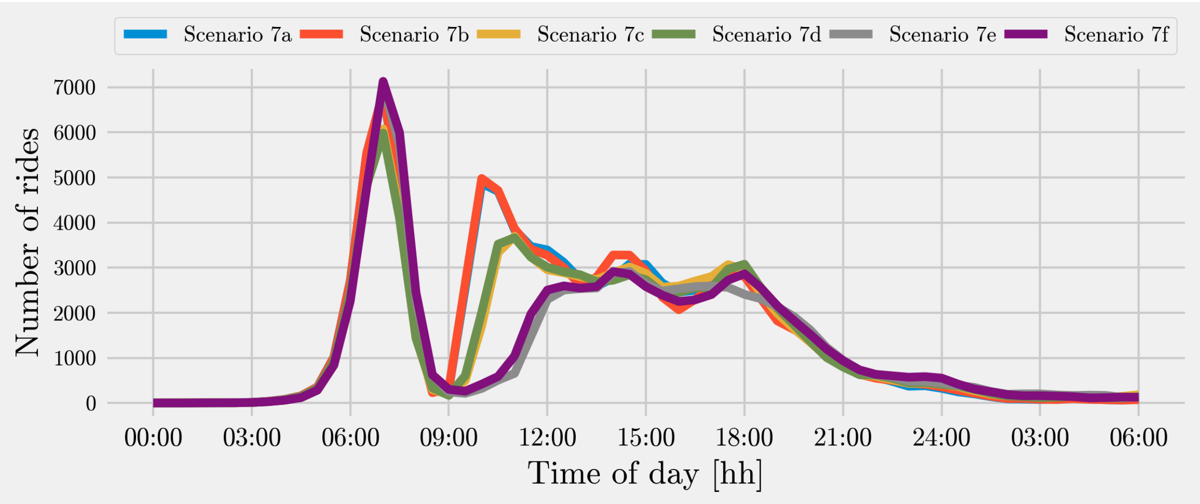
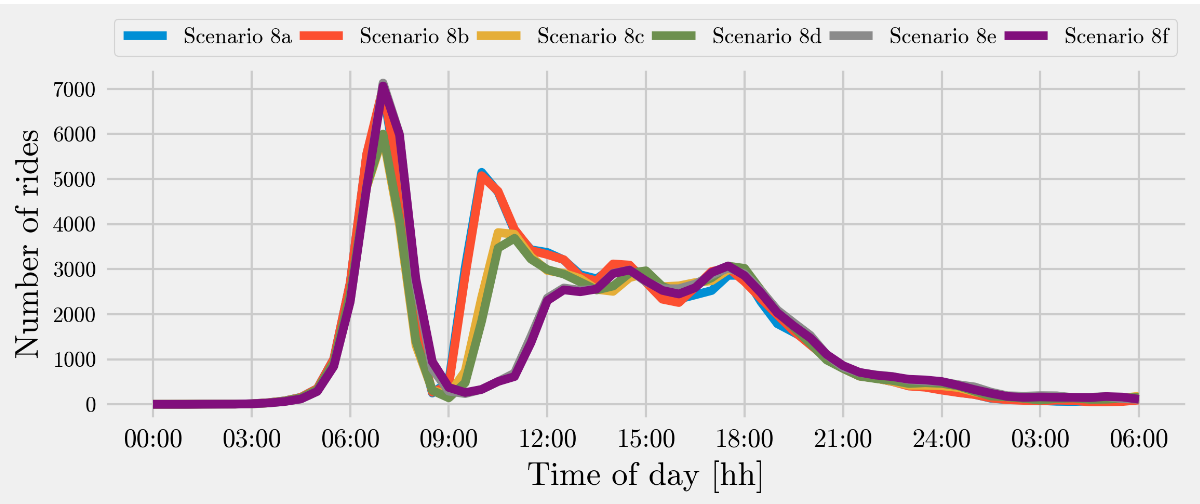


Figure 30: Requested departure times for DRT trips in scenario 6 - 8







A.5 Evolution of wait time for DRT trips

Figure 31: Evolution of wait time for DRT trips in scenario 1 - 3

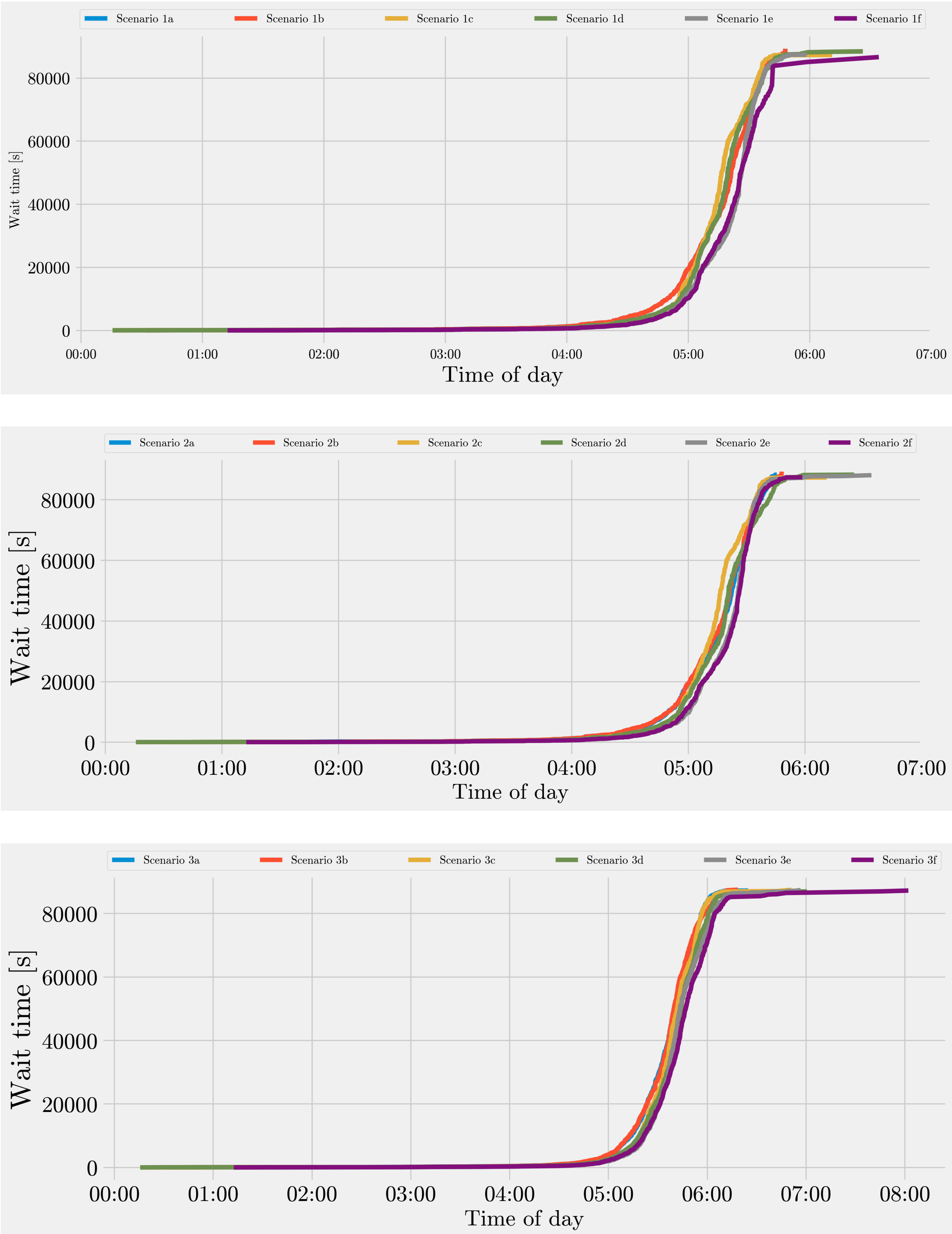
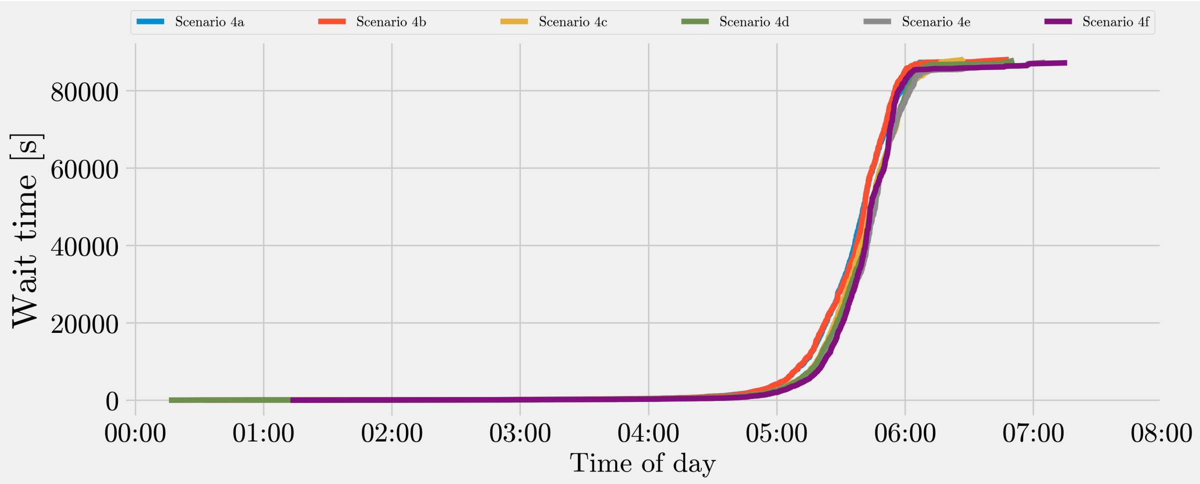
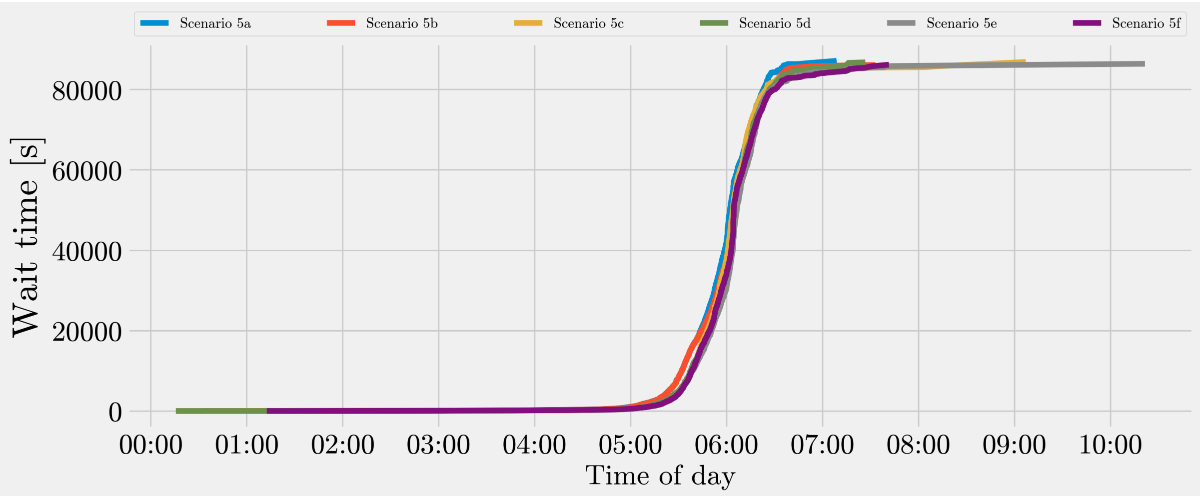
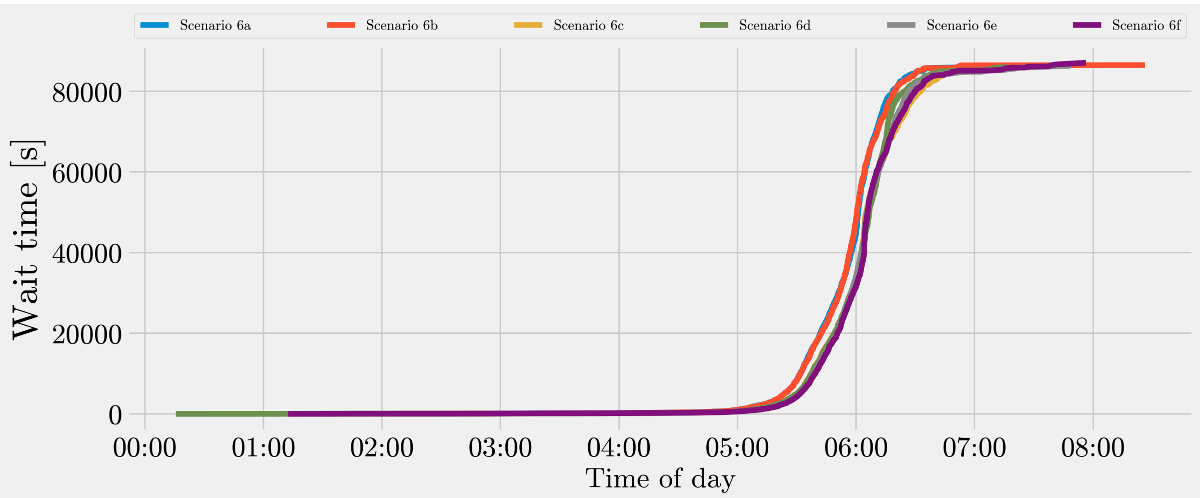


Figure 32: Evolution of wait time for DRT trips in scenario 4 - 6







A.6 Mode Shares

Table 12: Mode shares in scenarios 1-4 in [%]

	Bike	Car	Car Passenger	PT	Walk
Base Scenario	9.1	30.0	8.7	27.2	24.8
Scenario 1a	6.3	27.2	8.7	37.9	19.8
Scenario 1b	6.3	27.2	8.7	37.9	19.8
Scenario 1c	6.6	27.4	8.7	37.7	19.7
Scenario 1d	6.6	27.4	8.7	37.6	19.7
Scenario 1e	7.0	27.8	8.7	36.5	20.0
Scenario 1f	7.0	27.8	8.7	36.4	20.0
Scenario 2a	6.3	27.2	8.7	37.9	19.8
Scenario 2b	6.3	27.2	8.7	37.9	19.8
Scenario 2c	6.6	27.4	8.7	37.7	19.7
Scenario 2d	6.6	27.4	8.7	37.7	19.7
Scenario 2e	7.0	27.8	8.7	36.5	20.0
Scenario 2f	7.0	27.8	8.7	36.5	20.0
Scenario 3a	6.3	27.2	8.7	37.9	19.8
Scenario 3b	6.4	27.2	8.7	37.9	19.8
Scenario 3c	6.5	27.4	8.7	37.7	19.7
Scenario 3d	6.6	27.4	8.7	37.7	19.7
Scenario 3e	7.0	27.8	8.7	36.5	20.0
Scenario 3f	7.1	27.8	8.7	36.2	20.2
Scenario 4a	6.3	27.2	8.7	37.9	19.9
Scenario 4b	6.4	27.2	8.7	37.9	19.8
Scenario 4c	6.6	27.4	8.7	37.6	19.7
Scenario 4d	6.5	27.4	8.7	37.7	19.7
Scenario 4e	7.0	27.9	8.7	36.0	20.4
Scenario 4f	7.0	27.8	8.7	36.5	19.9

Table 13: Mode shares in scenarios 5 - 8 in [%]

	Bike	Car	Car Passenger	PT	Walk
Scenario 5a	6.3	27.2	8.7	37.9	19.9
Scenario 5b	6.3	27.2	8.7	37.9	19.9
Scenario 5c	6.6	27.4	8.7	37.6	19.7
Scenario 5d	6.6	27.4	8.7	37.6	19.7
Scenario 5e	7.0	27.8	8.7	36.4	20.0
Scenario 5f	7.0	27.8	8.7	36.5	20.0
Scenario 6a	6.3	27.2	8.7	37.8	20.0
Scenario 6b	6.3	27.2	8.7	37.9	19.9
Scenario 6c	6.6	27.4	8.7	37.5	19.8
Scenario 6d	6.6	27.4	8.7	37.7	19.7
Scenario 6e	7.0	27.8	8.7	36.4	20.0
Scenario 6f	7.0	27.8	8.7	36.5	20.0
Scenario 7a	6.4	27.2	8.7	37.6	20.1
Scenario 7b	6.4	27.2	8.7	37.5	20.2
Scenario 7c	6.6	27.4	8.7	37.6	19.8
Scenario 7d	6.6	27.4	8.7	37.3	20.0
Scenario 7e	7.1	27.9	8.7	36.1	20.2
Scenario 7f	7.1	27.9	8.7	36.1	20.2
Scenario 8a	6.3	27.2	8.7	37.6	20.1
Scenario 8b	6.4	27.2	8.7	37.6	20.1
Scenario 8c	6.6	27.4	8.7	37.4	19.9
Scenario 8d	6.6	27.4	8.7	37.3	20.0
Scenario 8e	7.0	27.8	8.7	36.5	19.9
Scenario 8f	7.0	27.8	8.7	36.5	19.9

A.7 DRT access & egress stages in PT trips

Table 14: Share of PT trips with DRT in access or egress (in [%])

	a	b	c	d	e	f
Scenario 1	0.98	0.98	0.95	0.95	0.93	0.93
Scenario 2	0.98	0.98	0.95	0.95	0.94	0.93
Scenario 3	0.98	0.98	0.95	0.95	0.93	0.93
Scenario 4	0.98	0.98	0.95	0.95	0.93	0.94
Scenario 5	0.98	0.98	0.95	0.95	0.93	0.93
Scenario 6	0.98	0.98	0.95	0.95	0.93	0.93
Scenario 7	0.98	0.97	0.95	0.95	0.93	0.93
Scenario 8	0.98	0.98	0.95	0.95	0.93	0.93