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# Transportation Equity in On-Demand Mobility: Balancing Level of Service and Access Through Agent-Based Simulations

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**Abstract**

Demand-responsive transit relies on a well-balanced demand-supply relationship and efficient service design. Beyond efficiency and budget considerations, policymakers designing such services often face the challenge of addressing conflicting goals, such as equitable access and level of service (LOS). While existing studies typically assume uniform service constraints within a single service, some public guidelines propose differentiated LOS based on metrics such as urban density. This study demonstrates and quantifies how the relaxation of LOS restrictions in the outskirts of the city can reduce the required supply, and thus costs, using an open agent-based transport simulation scenario for Berlin. The results highlight potential trade-offs between LOS equity and access equity, as policymakers may expand service areas for a given fleet size under relaxed constraints.



*Keywords:* ridepooling; on-demand transport; microtransit; transport equity; level of service

## 1. Introduction

On-demand ridepooling services are increasingly provided by central operators or as part of public transport, often referred to as microtransit and they promise to increase accessibility for previously underserved areas [6, 10]. These services may have various and possibly conflicting goals, such as economic viability, basic access to transit or complementing transit through feeder systems, among others. From an equity perspective, such services are often assumed to have fixed constraints such as maximum waiting time or detour/travel time that define the level of service (LOS) [2]. Typically, the unit cost of public services increases with the urban sprawl of a city [4], often leading to degraded service in less dense areas [12]. Similarly, the efficiency of ridepooling systems increases with demand

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density [7, 17]. As such, the question arises whether LOS has to be the same across a service area or whether it may be acceptable to expect higher flexibility of passengers traveling from or to the urban fringe to prevent prohibitive costs and possibly keep up basic access for a higher number of residents. While the question is of political nature, the present study aims to support decision making by showing how agent-based models may address such questions.

## 2. Methodology

We use the Multi-Agent Transport Simulation (MATSim) for our evaluation. MATSim is a mesoscopic agent-based transport simulation framework, which is widely used in academic studies [5]. Thanks to its efficient design, city- or region-wide scenarios can be simulated at the individual level within a relatively short period of time. As an open-source framework, the functionality of MATSim can be extended with various extensions. Among these, the DRT (demand-responsive transport) extension enables the simulation of DRT services [13]. The DRT extension also serves as a starting point for the implementation of heterogeneous insertion constraints.

The extension provides a default online request insertion strategy. When the agent departs, a travel request will be submitted to the DRT system. The strategy tries to find an insertion in the schedule of a vehicle in operation which, in the default setup, minimizes additional time spent driving. The insertion must obey several constraints to be considered feasible. If no feasible insertion is found, the request is rejected. The first constraint is the maximum wait time constraint. Each request $r$ must be picked up within $t_{wait,max}$, counting from the submission time $t_{sub}(r)$:

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

The second constraint is the latest arrival constraint, which we slightly adjust to allow the proper modeling of scenario constraints with minimum allowed detours.

The latest arrival includes the initial waiting time and any detours introduced by additional pickups and dropoffs along the route, constrained by the maximum allowed detour, which is calculated as:

$$t_{detour,max}(r) = \max(\ \alpha * t_{direct}(r),\ \ \beta) \tag{2}$$

where $t_{direct}(r)$ is the hypothetical direct travel time (i.e., without any detour) of request $r$.

The terms $\alpha$ and $\beta$ are parameters that determine how tight the detour constraint is, with $\beta$ functioning as the minimum allowed detour. As such, the latest arrival time of a request can be determined as:

$$t_{arrival,latest}(r) = t_{sub}(r) + t_{wait,max}(r) + t_{direct}(r) + t_{detour,max}(r) \tag{3}$$

Latest arrival and pickup times do not only apply to the request being inserted but also to all the requests already assigned to the vehicle that have not yet reached their destination. The third constraint is that a vehicle should never be overloaded at any time. In addition to the vehicle insertion strategy, the DRT extension provides several rebalancing strategies (i.e., empty vehicle relocation strategies). Inactive vehicles will be periodically distributed throughout the network to balance supply and demand. In this study, we use the simple yet effective rebalancing strategy proposed in [3].

We extend MATSim's DRT extension, such that constraints may not only be defined once for the whole service but are actually evaluated for each request. That is, $t_{wait,max}$, $\alpha$, and $\beta$ are now request dependent and, therefore, should be rewritten as $t_{wait,max}(r)$, $\alpha(r)$, and $\beta(r)$. Based on that, we employ a spatial differentiation of constraints based on the origin and destination of requests (note that any other differentiation such as by time, demographics, price, etc. would work as well). The aim here is to choose tight constraints for high-density core areas and looser constraints for remote areas at the urban fringe. With looser constraints, the passenger may need to wait longer and spend more time in the vehicle.

In this study, we focus on the supply side of the DRT system (i.e., fleet size) and thereby use fixed demand. By doing so, we no longer need to perform the iterative procedure commonly seen in studies based on MATSim. There are two advantages of doing this. First, without the iterative approach, the computational time can be significantly reduced and this enables us to carry out more experiments to extensively test and evaluate the impact of having heterogeneous constraints for the insertion strategy. Second, with fixed DRT demand, we can directly compare the service quality and fleet efficiency of the insertion strategy under flat (i.e., homogeneous) and spatial constraints.

In addition to rejection rates and wait times, we introduce a novel metric to quantify the degree of sharing observed in the simulation. This metric is based on the fraction of distance traveled per trip segment $s$ (i.e., the distance between pickup- or dropoff-related stops) and the corresponding occupancy $o$. The sharing factor $\phi_r$ is defined as

$$\phi_r = \frac{\sum_{s \in segments_r} d(s)}{\sum_{s \in segments_r} \frac{d(s)}{o(s)}} \quad , \tag{4}$$

where $d(s)$ denotes the distance of segment $s$ as a part of the ride of request $r$. In principle, a higher $\phi$ indicates a greater degree of sharing. It is important to note that, unlike a simple pooling rate, which measures the percentage of trips that share any portion of their time with another trip, the sharing factor accounts for both the actual duration (or distance) of shared segments and the occupancy (i.e., the number of trips sharing each segment). For the system efficiency $\eta$, we draw upon the indicator proposed by Liebchen [9], defined as the ratio of the passenger kilometers booked, $d_{PKB}$, to the vehicle kilometers traveled, $d_{VKT}$:

$$\eta = \frac{d_{PKB}}{d_{VKT}} \quad . \tag{5}$$

Note that $d_{PKB}$ is the direct theoretical distance without any detours. The average occupancy is based on the passenger kilometers traveled, $d_{PKM}$ and includes detours:

$$\omega = \frac{d_{PKM}}{d_{VKT}} \quad . \tag{6}$$

Finally, we introduce $\theta$ as the ratio between the hypothetical conventional public transport (PT) travel time, and the experienced travel time of accepted DRT trips for each request r:

$$\theta_r = \frac{t_{DRT,r}}{t_{PT,r}} \quad . \tag{7}$$

A value lower/greater than 1 means that the DRT trip is faster/slower than the respective hypothetical PT trip. We initially route every agent with a schedule-based transit router with the departure time set to the DRT submission time $t_{sub}(r)$. For the analysis, we run the same scenario with fixed demand with varying fleet sizes, i.e, varying supply, and compare selected metrics by whether flat or spatial constraints (SC) were used.

## 3. Scenario

We base our analysis on a publicly available DRT scenario for Berlin, Germany [11, 16]. The scenario contains DRT demand consisting of roughly 25,000 agents across a whole day. We divide the area into an outer and inner area (see figure 1) based on the *Ringbahn*, a roughly circular line of the local commute railway system. Between these areas we distinguish the applied DRT constraints, which we draw from values proposed in the position paper by the VDV (Verband Deutscher Verkehrsunternehmen, engl: Association of German Transport Companies) [15] in which there is a distinction between quality metrics based on urban density as shown in table 1. For requests traveling within the *Ringbahn* area, the *high* urban density constraints are applied (tight constraints). Requests starting or ending outside this area are subject to the *medium* urban density constraints (loose constraints). For trips between the two areas, the looser constraint set is used. In essence, these two service classes will differ in their $\alpha(r)$ and $t_{wait,max}(r)$ parameters, $\beta$ is constant across both classes. In each simulation, DRT vehicles with a seat capacity of eight will start the service from one of four depots in the scenario, each located at a strategical location: *Südkreuz*, *Ostkreuz*, *Gesundbrunnen*, and *Westkreuz*. In Berlin, these four locations are key interchange stations on the *Ringbahn*.

## 4. Results

Table 2 presents simulation results for different fleet sizes differentiated by whether the SC were used or not. We limited the results to include only scenarios where the global acceptance rate is greater than 20 %. For a given fleet size, we observe that global acceptance rates are considerably higher in the SC scenarios. Similarly, empty kilometer share, $\eta$, $\phi$ and $\omega$ improve when using SC. However, these improvements come at the cost of elevated wait times,

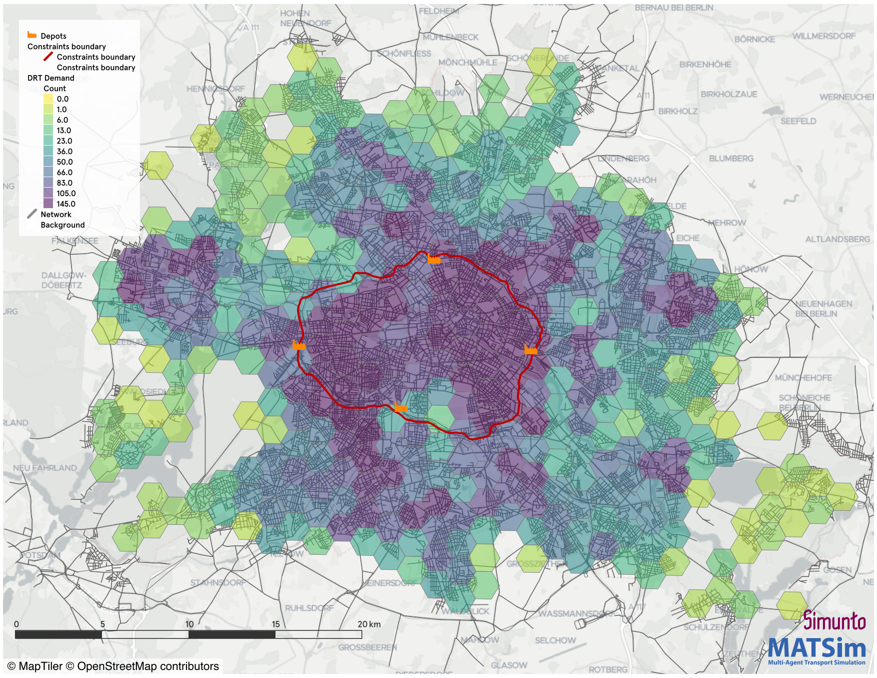



Fig. 1: Aggregated DRT demand in the Berlin scenario (graduated by deciles). The area delineated by the red line depicts the boundary between inner and outer DRT constraints employed in the study. The orange symbols show the four depot locations of vehicles.

Table 1: (Target) Level of service metrics in relation to urban density as proposed by Verband Deutscher Verkehrsunternehmen e.V. (VDV) [15].

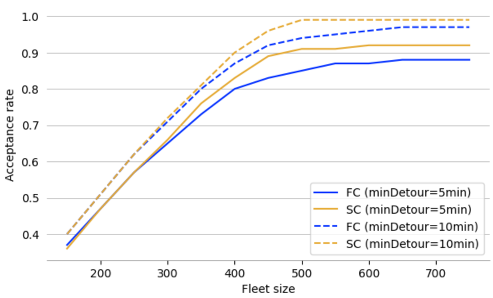
| | Urban density | | |
|---|---|---|---|
| Metric | high | medium | low |
| Maximum waiting time ($t_{wait,max}$) | 15 Min. | 25 Min. | 50 Min. |
| Mean waiting time | 7,5 Min. | 15 Min. | 30 Min. |
| Acceptance rate | $> 95\%$ | 80%-95% | 70%-90% |
| Admissable detour factor $\alpha$ ($\beta = 5$ mins always acceptable) | max. 30% | max. 50% | max. 100% |
| Fleet size | 1 vehicle per 5.000 inhabitants | 1 vehicle per 5.000-10.000 inhabitants | 1 vehicle per 100 km$^2$ |

which are consistently higher for the SC scenarios, although this difference decreases with larger fleet sizes and less undersupply. $\omega$ increases more strongly than $\eta$, indicating that the detour distance increases in the SC scenarios.

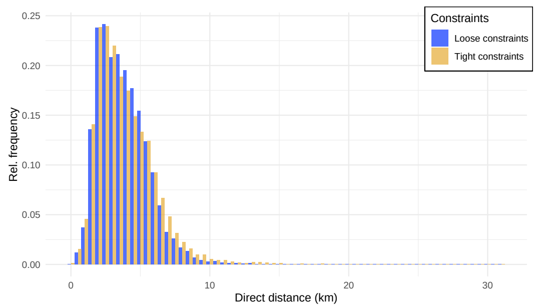
Figure 2a summarizes the differences of acceptance rates for all simulated fleet sizes. We observe that in heavy undersupply, when acceptance rates are low, the difference is hardly visible. However, for acceptance rates above 80 %, we see an increasing improvement for the SC scenarios. For the example of a given acceptance rate of 85 %, a fleet size of 500 vehicles may be reduced to roughly 425 vehicles, which means a reduction of 15 %. For a 90 % acceptance rate, this reduction would be roughly from 650 vehicles down to 450 vehicles, a saving of 30 %. This would imply substantial savings in investments and operating costs. We also observe that even with large fleets we do not reach 100 % acceptance rates. A potential reason is the notably high share of short trips (see figure 2b). The mean direct trip distance (without detours) is only 3.9 km, which is quite low. Given that in the VDV definition these short trips will only have an allowed detour of 5 minutes, it becomes hard to efficiently serve them. In a setup where we deviate from the VDV-based minimum allowed detour of 5 minutes and set it to 10 minutes, acceptance rates increase considerably, as can be seen by the dotted lines in figure 2a. As this can be in-

Table 2: Simulation results ordered by fleet size. 'SC' is an indicator variable, for whether spatial constraints were used. At $n >= 650$ we do not observe improvement in acceptance without relaxing detour constraints.

| Vehicles | Acc. rate | Wait $p_{50}$ [s] | Wait $p_{95}$ [s] | $\eta$ (avg) | $\omega$ | Empty ratio | $\phi$ (avg) | $\theta$ (avg) | SC |
|---|---|---|---|---|---|---|---|---|---|
| 400 | 0.80 | 553 | 864 | 0.75 | 0.83 | 0.29 | 1.22 | 0.72 | false |
| 400 | 0.83 | 747 | 1391 | 0.76 | 0.88 | 0.28 | 1.28 | 0.86 | true |
| 450 | 0.83 | 496 | 849 | 0.75 | 0.84 | 0.28 | 1.21 | 0.69 | false |
| 450 | 0.89 | 646 | 1333 | 0.76 | 0.89 | 0.27 | 1.27 | 0.81 | true |
| 500 | 0.85 | 445 | 832 | 0.75 | 0.83 | 0.28 | 1.21 | 0.67 | false |
| 500 | 0.91 | 546 | 1270 | 0.76 | 0.89 | 0.27 | 1.27 | 0.77 | true |
| 550 | 0.87 | 405 | 819 | 0.74 | 0.83 | 0.29 | 1.21 | 0.65 | false |
| 550 | 0.91 | 469 | 1199 | 0.76 | 0.89 | 0.27 | 1.27 | 0.73 | true |
| 600 | 0.87 | 382 | 801 | 0.75 | 0.83 | 0.28 | 1.21 | 0.64 | false |
| 600 | 0.92 | 428 | 1149 | 0.76 | 0.89 | 0.27 | 1.27 | 0.71 | true |
| 650 | 0.88 | 367 | 791 | 0.76 | 0.85 | 0.27 | 1.21 | 0.63 | false |
| 650 | 0.92 | 404 | 1103 | 0.78 | 0.90 | 0.26 | 1.26 | 0.69 | true |




(a) Acceptance rate of SC vs FC (flat constraints) by fleet size.



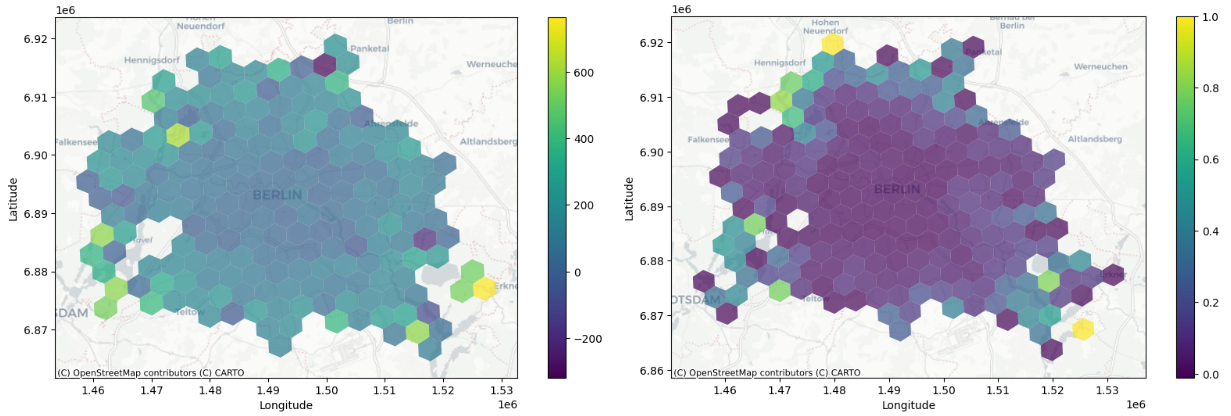

(b) Direct trip distance distribution for tight and loose constraints.

Fig. 2: Acceptance rate comparison for different fleet sizes. The direct trip distance distribution reveal short average trip lengths, which are hard to serve using tight constraints.

terpreted as a general relaxation of constraints, the difference between the loose and tight constraints becomes smaller.

Figure 3 shows the spatial distribution of differences in median wait times and acceptance rates between the FC and SC scenario, exemplary for a fleet of 550 vehicles. In the SC setup, the acceptance rate experiences a higher increase in the outskirts. At the same time, the median waiting time also increases more in the outskirts. That is to say, with the SC setup, more people in the outskirts area will be able to use the DRT service, at the cost of a slightly reduced service quality.

When looking at the values obtained for $\theta$, we observe that the average ratio of DRT to PT travel times is always lower than 1 in all scenarios, meaning that the service is an attractive service for many agents. However, $\theta$ is consistently higher in the SC scenarios. This is expected for two reasons: for one, the relaxation of constraints allows longer wait and in-vehicle travel times, increasing the DRT travel time for some of the agents. In addition, the SC service allows many agents on the edge of the service area to travel at all. Since these trips are rather difficult to serve (and were therefore not even accepted in the FC scenario), these trips pull down the average of theta. Figure 4 shows the spatial distribution of zonal averages of $\theta$, again on the example of the 550 vehicle scenarios. While the zonal average remains below 1 for most zones in the SC scenario, many outer zones get closer to 1 or even exceed it in some zones. It should be noted, however, that the mean may be distorted by outliers. A complete picture of the overall distribution of $\theta_r$ is shown in figure 5. Even in the SC scenario, 84.6% of agents travel faster (and potentially more comfortably) with DRT than with PT. However, in the SC scenario, roughly twice as many (15.4% vs. 7.4%) agents experience a DRT travel time that would likely be slower than the respective PT connection.




(a) Difference in median waiting time, when using SC (positive values imply increase for SC).

(b) Difference in acceptance rate, when using SC (positive values imply increase for SC).

Fig. 3: Spatial comparison of n=550 vehicles. We see increased acceptance rates compared to FC, but also increased median wait times in outlying areas. Aggregation based on uber H3 cells on resolution level 7 (`https://www.uber.com/en-DE/blog/h3/`).

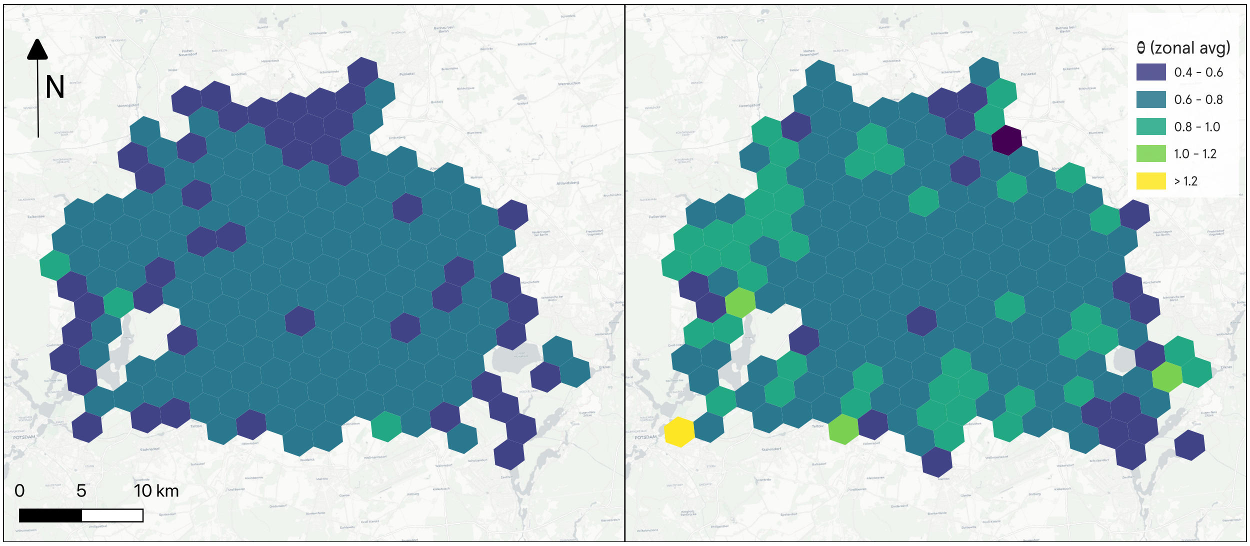



Fig. 4: Zonal averages of $\theta$ for the scenario with n=550 vehicles. The average $\theta$ increases in the outskirts in the spatial constraints scenario (right) when compared to the flat constraints scenario (left). Aggregation based on uber H3 cells on resolution level 7.

## 5. Conclusions

A limitation of the current study is the assumption of fixed demand. Obviously, demand would react to service quality deterioration, as people can be quite sensitive to longer detours and waiting times, although waiting time increases may be considered less severe than increased detours [14]. Another limitation is that the rebalancing algorithm is not adjusted to reflect different spatial service constraints. In principle, expected (unmet) demand in the outskirts triggers a reaction similar to demand in the center of the service area. However, since constraints are relaxed, the supply/demand ratio may possibly be reduced, with fewer vehicles being sent to the outskirts through rebalancing. By doing that, vehicle-per-population targets such as those defined by the VDV could be taken into account. The direct trip distances in the open Berlin scenario are rather short (avg. 3.9 km) when compared to observed trip distances of an urban ridepooling service in Hamburg, with an average distance of 7.7 km as reported by Kuehnel et al. [8]. As a result, the five minute minimum allowed detour suggestion by the VDV led to a visibly

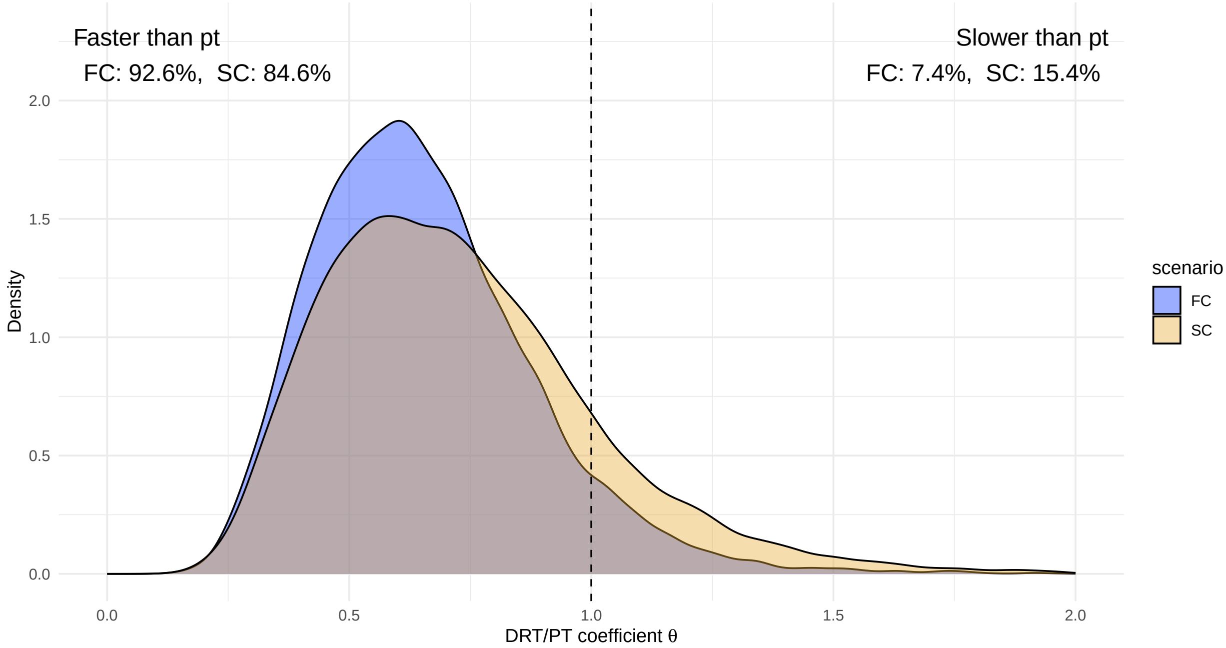



Fig. 5: Density plot of the distribution of $\theta_r$ in the 550 vehicle FC and SC scenaris.

lower acceptance rate (see figure 2b), and should be increased in such cases. The current spatial differentiation was quite arbitrarily chosen to reflect the circular commute railway line.

Future work could differentiate more systematically, e.g., on the basis of population or demand density. However, similar to traditional transit tariff zones, easily communicable zones should be favored to appropriately inform customers. Instead of spatially segregating constraints or quality metrics, the same per-request constraint approach can be used to vary constraints temporally (e.g., tighter/looser constraints in off-/peak-hours). In addition, tighter constraints may be offered in exchange for a premium paid by the customer. Future research could look into the trade-off between service area extent and spatial LOS to understand how much more demand could be covered for a given fleet size. In contrast to the door-to-door service shown in this study, most microtransit services use a virtual stop network which imposes access and egress walk trips to the customers. Similarly to our study, this stop network could also be adapted by providing different stop densities in different areas, potentially increasing the chance of shared rides or reducing the need to drive in slow residential roads.

According to [12] (and as can be seen in the spatial distribution of $\theta$ in the FC scenario above), the travel time of the alternative modes (i.e., PT or walk) are considerably longer in the outskirts. The increased access to the DRT service in the SC scenario represents a significant improvement in accessibility for residents of these areas, despite the slight reduction in service quality compared to the FC case. Therefore, the SC setup has a positive impact on accessibility overall.

The present study is meant to provide initial insights about the potential trade-off between LOS and required supply in on-demand transport systems. When faced with the problem of designing services under limited subsidies/investments, decision makers may opt to offer no service at all to more remote areas by limiting the service area of a service - in which case inequality of access would be high. With relaxed LOS requirements, services may cover larger areas with the same supply, giving access to a -degraded- basic service to more people. The extent of such policies is a political question, which may be informed by agent-based models. From an equity perspective, access considerations should not only be limited to ”spatial remoteness” but should include societal aspects [1].

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## Declaration of Interests

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