An innovative pricing concept for ridehailing services based on the service quality of schedule-based public transit

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Abstract

Demand Responsive Transport (DRT) services are gradually changing urban transportation. DRT (also: ridehailing, on-demand mobility) describes a hybrid of regular public transit and personalized taxi services. In this study, an innovative dynamic DRT pricing scheme is developed and applied to a simulation model of the Greater Berlin area, Germany. The proposed pricing scheme applies a correction to the DRT fare: (a) DRT fares are increased if the corresponding trip can be well-served by conventional schedule-based public transit. (b) DRT fares are decreased if the schedule-based public transit alternative is insufficient. This pricing concept aims to reduce the cannibalization of schedule-based public transit by DRT. Furthermore, the pricing concept aims to reduce private car ownership in areas with poor public transit provision. The simulation experiments carried out for Berlin suggest that the strategy can effectively shift users from DRT to public transit, in particular during peak hours and in the city center and western Berlin area. Reducing DRT fares during times of poor public transit service is found to shift private car trips to the DRT mode. Total vehicle-distance traveled is observed to reduce by 3% in both urban and suburban areas. Overall, the findings indicate that the proposed DRT pricing scheme is a useful approach to shift users to more efficient and sustainable transportation modes.

1 Introduciton and problem statement

In recent decades, advances in mobile communication technology development are allowing new user-centric services to transform urban mobility. Using smartphone applications, travelers can easily send their location information and request a ride which may be shared with other travelers. Ridesharing services provided by Transportation Network Companies (TNCs), e.g., Uber, Lyft, and Didi, are commonly defined as Ridehailing or Demand Responsive Transport (DRT). DRT has the potential to combine the advantages of the private car mode and conventional schedule-based public transit. Thus, users may experience reduced monetary travel costs or an improved service quality. For cities, DRT holds potential to improve efficiency and environmental sustainability by reducing the overall vehicle-kilometers traveled. To achieve this goal, it is crucial that DRT mainly competes with the private car mode and single-passenger taxi services rather than with the schedule-based public transit.

Data from several studies suggest that DRT services increase traffic congestion. According to Schaller (2018), even if 50 percent of the rides are shared, 2.2 DRT vehicle miles are added for each reduced private car mile as most DRT users switch from non-auto modes to shared rides. A similar conclusion is found in Gehrke (2018), where ridehailing is described to add new car trips to the Boston region's roads which increases traffic congestion.

This paper attempts to bridge the gap between the ideal expectation and the practical use of DRT by proposing an innovative pricing concept. By taking advantage of DRT users' price-sensitivity, the mode shift from schedule-based public transit to DRT can be controlled by dynamically adjusting every DRT trip's price according to the real-time public transit service quality. To analyze the extent of the effects on a major city, a case study of the Berlin metropolitan area was modeled using a mesoscopic transport simulation framework.

The remainder of this paper is organized as follows. Section 2 provides a literature review. Section 3 briefly describes the agent-based simulation framework and presents the proposed DRT pricing schemes. Section 4 describes the Berlin case study, simulation parameters, and experiments. Section 5 describes the simulation results, Section 6 provides the discussion and Section 7 concludes this study.

2 Literature review

Several studies investigate the diverse operation strategies of (automated) DRT services. Some of these studies focus on how to better integrate DRT within the public transport system or how to replace schedule-based public transit services, without looking in detail at prices. For example, Bischoff and Maciejewski (2020) introduce a rebalancing algorithm for a DRT service, which optimizes the empty vehicle rebalancing process and improves DRT as a feeder mode to connect public transport. Leich and Bischoff (2018) use a simulation approach to replace existing buses by SAVs and observe higher operating costs and only small travel time gains in comparison to conventional buses.

Other studies explicitly address the impact of pricing schemes on DRT services. For example, Reza Vosooghi (2019) suggest that a standard 4-seats car remains the best option among all vehicles of ridesharing services when the price of ridesharing is designed as 20% lower than no-pooling scenario. Kaddoura et al. (2020a) study effects of an external cost pricing schemes for shared autonomous vehicles (SAV) and find that without a congestion charge for SAV users and private car users, the level of traffic congestion increases, air pollution levels decrease, and noise levels slightly increase in the inner-city area. In contrast, a congestion charge for SAV and private car users pushes users from SAVs to the walk and bicycle modes. In a similar fashion, Gurumurthy et al. (2019) also use the simulation framework MATSim to show how SAVs may best be introduced to a city or region. Results indicate that a road-pricing for both SAV and private cars in the peak periods is able to increase SAV demand and fleet-manager revenue. SAVs are able to earn around \$100 per SAV per day even after paying tolls at low-fare levels.

Some papers consider pricing strategies based on the intensity of demand for DRT services.

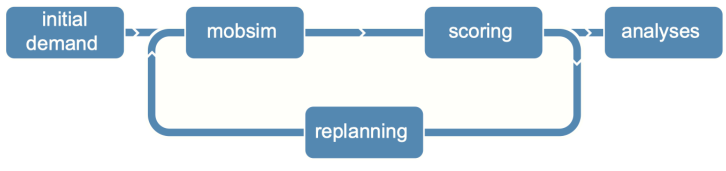


Figure 1: MATSim loop (Horni et al., 2016)

Bimpikis et al. (2019) study the use of spatial price discrimination to balance the demand when DRT serves passengers in a network of locations. Chen and Kockelman (2016) finds that pricing strategies that attempt to balance available SAV supply with anticipated trip demand can decrease average wait times by 19% to 23%. Based on a simulated case study of Berlin, Kaddoura et al. (2020b) suggest that a small service area and too low prices may result in an unwanted mode shift effect from walk and bicycle to DRT. A higher fares-setting and a larger DRT service area contribute towards an increase of the desired mode shift effect from car to DRT and reduces the mode shift from walking and bike to DRT.

To the best of the authors' knowledge, this paper is the first to propose a DRT pricing scheme, which is based on the real-time service quality of the alternative schedule-based public transit mode.

3 Methodology

3.1 Agent-based transport simulation framework

MATSim overview MATSim (Multi-Agent Transport Simulation, www.matsim.org) is an open-source software developed under the terms of the GNU General Public License[1], version 2 or later, published by the Free Software Foundation[2]. The core code and several extensions are available on GitHub[3].

In MATSim, each transport user is simulated as an agent. A typical MATSim simulation contains a configurable number of iterations, represented by the loop depicted in Fig. 1. It starts with an initial demand, which includes each agent's travel plans describing the daily activity patterns (e.g., home-work-leisure-home), the activity locations, the activity end time, and information about the trips between these activities. Applying an iterative, evolutionary approach, this initial demand is optimized individually by each agent. In each iteration, the travel plans are executed (mobsim), evaluated (scoring) and modified (replanning).

Mobsim: All travel plans are simultaneously executed. Numerous modes of transportation are supported by the MATSim core code and its extensions, which related to this study are *c*ar, *b*ike, *w*alk, *p*ublic transit, and *D*RT. Regarding mode *car*, MATSim applies a queueing model for the simulation of traffic congestion and vehicle movements (Gawron, 1998). For *bike* and *walk*, the scenarios involved in this paper will set them to teleported

[1]https://www.gnu.org/licenses/
[2]https://fsf.org
[3]https://github.com/matsim-org/matsim

modes. As for $p$ublic transit, MATSim supports very detailed modeling approach: Transit vehicles run along the defined transit line routes, picking up and dropping off passengers at stop locations accounting for the transit schedule, transit vehicles's capacities and maximum speeds. The detailed description of PT dynamics in MATSim can be found in Rieser (2010) and Rieser (2016). A detailed description of DRT is provided later in this section.

Scoring: For each agent, the executed plan is evaluated based on predefined utility functions and behavioral parameters (Nagel et al., 2016). The deterministic part of the utility is referred to as the $s$core.

Replanning: During replanning, agents are enabled to adjust their travel behavior, i.e. switch to another route, chose another departure time or use a different mode of transportation (see e.g. Balmer et al., 2005; Lefebvre and Balmer, 2007; Grether et al., 2009).

The iterative process is repeated until the scores stabilize. Assuming that the set of each agent's travel plans represents a valid choice set, the system state is an approximation of the stochastic user equilibrium (Nagel and Flötteröd, 2012). A detailed description of the agent-based transport simulation framework MATSim is described in Horni et al. (2016).

MATSim DRT overview The ridesharing services are simulated using the DRT contribution introduced in Bischoff et al. (2017). For the vehicle routing and assignment, the DRT-contribution uses the DVRP contribution presented in Maciejewski (2016) and Maciejewski et al. (2017) as backend. For a DRT trip, agents first submit a ride request which is then processed by the centralized dispatching system. Typically, the drive-task is assigned to the vehicle that takes the shortest additional time to complete the request taking into consideration waiting and in-vehicle time service constraints for both the new and already inserted requests. Besides, DRT vehicles are simulated like an ordinary car in terms of the traffic-flow simulation. DRT vehicles can cause congestion and are also affected by delays caused by other road users. After arriving at the destination stop, the agent will be charged based on the unshared travel distance of the ridership as well as based on the predefined minimum or base fare.

3.2 Proposed DRT pricing scheme

Overview This study proposes a dynamic DRT pricing scheme based on the real-time public transit service quality. For each DRT trip, the alternative public transit service quality for the same origin-destination and time of day is evaluated. Based on the evaluation results and predefined public transit service quality thresholds, the DRT trips will be classified as one of three public transit service level categories: high-level, mid-level, and low-level public transit service. Based on the calculated level-of-service, additional fares or discounts will be computed and then applied to the DRT customers accordingly.

With this approach, travelers in areas with high frequent service public transit will experience higher DRT fares, encouraging them to leave DRT and opt for other modes of transportation. Considering the convenient public transit options available, public transit will be their most likely selection. In contrast, in low-level public transit service areas or times, travelers are encouraged to use the DRT mode due to the relatively low fares.

In implementing the dynamic DRT pricing approach, the methods of public transit service quality assessment, the thresholds for public transit service quality, and the approach for calculating fare increases and discounts are the most critical components and need to be carefully considered. The corresponding details are described and presented in Section 3.2.1, 3.2.2, and 3.2.3.

3.2.1 Quantitative evaluation of PT service quality

Advanced GIS methods open data sources, and increasing processing capacity allow the direct comparison of different travel modes that can be easily presented to travelers for use in their daily travel behavior. Services like Google Maps, for example, can provide accurate, reliable, and timely predictions of travel time and travel distance for travelers across various modes of transportation.

Accurate prediction of travel times across several modes do not only make the travel of passengers more convenient, but also provides a useful tool for scientific research on modal performance and travel behavior. In many studies, comparing the travel times provided by public transit and other transportation modes are used to assess public transit service quality and to identify the disparities of public transit in accessibility (Frank et al., 2008; Salonen and Toivonen, 2013). The evaluation of public transit service quality in this study will be conducted in a similar way: For each DRT ride request, the ratio of the predicted PT travel time to the predicted DRT travel time will be used as the metric for assessing public transport service quality. This metric can be described as:

$$\phi = \frac{TT_{pt}^{pre}}{TT_{drt}^{pre}} \tag{1}$$

where TT_{pt}^{pre} is the predicted travel time by public transit and TT_{drt}^{pre} is the predicted travel time by mode DRT.

In this paper, the estimated travel times by public transit and DRT are calculated based on a door-to-door approach with same origin, destination, and departure time.

The public transit travel time, TT_{pt}^{pre} includes (1) walking time from origin to stop; (2) waiting time for the transit vehicle; (3) in-vehicle time; (4) transfer time (e.g. walking and waiting) if needed; (5) walking time from the arrived stop to the destination.

The DRT travel time, TT_{drt}^{pre} includes (1) walking time from the point of origin to the place to be picked up by DRT; (2) waiting time for DRT vehicle; (3) in-vehicle time; (4) walking time from drop-off location to destination.

3.2.2 Determination of PT service quality levels

After evaluating public transit service quality of equivalent DRT trips, the next step is to classify the public transit service level based on the calculated values of ratio ϕ. This step determines whether the trips belong to high-, mid-, or low-public transit service conditions and then applies the pricing adjustment accordingly.

In this paper, we will use two thresholds ϕ_h and ϕ_l to classify the service level of public transit. These two thresholds should be obtained by analyzing the empirical data and defined prior to the calculation of quality of service. For DRT trips where ϕ is less than ϕ_h, its public transit service level will be recognized as high-level. DRT trips where ϕ is greater than ϕ_l belong to low-level group.

Furthermore, travel-distance should also be considered when determining the threshold. From the perspective of DRT users, even if the ϕ value is small, the massive absolute time saved by using DRT still has substantial appeal. For example, a 20% reduction in travel time may be barely noticeable for a 5km trip, but quite substantial over a 50km trip when considering total time saved.

In summary, the determination of public transit service quality thresholds ϕ_h and ϕ_l should be predefined from empirical data. Both should show a downward trend as the travel distance increases (see Section 4, where procedures for determining thresholds for the Berlin case study are described in detail).

3.2.3 Calculation of optimized DRT fares

Penalty pricing scheme ($\phi < \phi_h$): For these DRT users, using public transit will not cause excessive time loss compared with using DRT. As a result, operators will increase the fare of DRT services, which can be described as a penalty due to their insisting on opting for DRT. Similar to how DRT fares are normally calculated, the penalty will be likewise charged based on the unshared (direct) trip distance, and the penalty per meter c_{pe} will be calculated according to Eq. 2.

$$c_{pe} = k_{pe} * c_B * \frac{\phi_h}{\phi} - c_B \tag{2}$$

where c_{pe} is the penalty distance fare in EUR per meter, k_{pe} is the penalty factor ($k_{pe} \geq 1$), and c_B is the basic distance fare of DRT service (EUR/m).

Reward pricing scheme ($\phi > \phi_l$): On the other hand, when ϕ is not only greater than ϕ_h, but also greater than ϕ_l, then public transit is slower and less attractive than DRT. At this point, the operator will appropriately lower the price of the DRT services, and this pricing strategy can be described as a reward pricing strategy.

$$c_{re} = -c_B * min(k_{lim}, k_{re} * \frac{\phi}{\phi_l}) \tag{3}$$

where c_{re} is the reward distance fare in EUR per meter ($c_{re} < 0$), k_{re} is the reward factor ($k_{re} > 0$), k_{lim} is the maximum reward limiting factor ($0 < k_{lim} \leq 1$), and c_B is the basic distance fare of the DRT service in EUR per meter.

Eq. 3 is proposed in this study to compute the DRT fare reduction. It should be noted that the c_{re} is negative as a fare deduction. Considering the cost of operating the vehicle for the DRT operator, there is a limit to the fare reduction that can be applied before the service becomes unprofitable, i.e., $-k_{lim} * c_B$. When $-k_{lim} = 1$, the applied reward can reach to $-c_B$. When this occurs, DRT services are free ($c_B - c_B = 0$) in the aspect of distance fare. The maximum reward limiting factor can be set to ensure that DRT operators remain profitable without unrealistic discounts.

Refer to the condition of $\phi_l > \phi > \phi_h$, there would be no specific pricing scheme implemented for customers. They will be charged only with the pre-defined base settings. A Java-based code implementation of the above DRT pricing algorithm has been published on GitHub, see GitHub (smart-drt-pricing, 2021, branch master, commit ID 4f7d2b8)[4].

[4]https://github.com/matsim-vsp/smart-drt-pricing

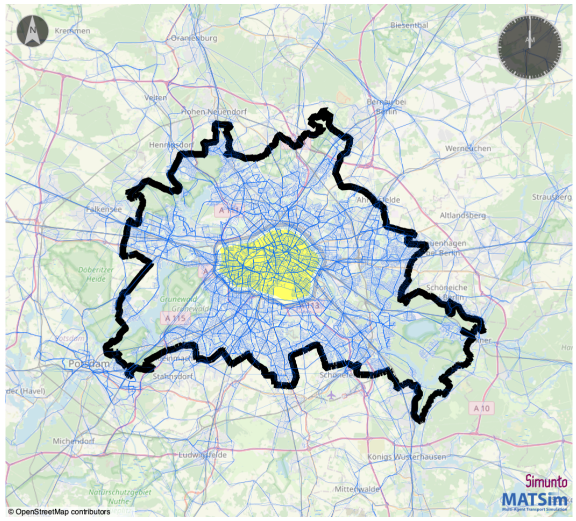


Figure 2: Case study: Greater Berlin area. Black line: DRT service area boundary (entire Berlin area). Blue lines: Road network. Yellow area: inner-city center area

4 Case studies and simulation experiments

The proposed smart DRT pricing strategies are applied to the real-world simulation model of the Greater Berlin area generated by Ziemke et al. (2019) based on the methodology developed by Ziemke et al. (2015). Transport supply cover all major and minor roads in the Greater Berlin area, including all public transit lines. Travel demand is modeled as individual agents, including commuters and non-commuters using the car, public transit, bike, ride, and walk modes. For computational efficiency, in this study a 10% population sample is used and road capacities are accordingly reduced to account for realistic congestion effects.

As a result, the entire scenario includes a total of 471,002 agents and 1,823,235 trips, with an average of 3.7 trips per person per day. The model is calibrated with reference to surveys of various real traffic data , i.e, car counts, modal split and trip-distances (Ahrens, 2009; infas and DLR, 2010). The applied Berlin case study is publicly available via GitHub (MATSim-Berlin, 2020, branch 5.5, commit ID f60e7bf)[5].

4.1 DRT setup

DRT is added as a new mode of transportation and can be used within the service area (Fig. 2) during the entire day. A total of 10,000 DRT vehicles are available, each with a maximum capacity of four passengers. Before the start of the first iteration, the service vehicles are evenly distributed in the service area. After completing a service, the vehicles will stay at the drop-off link until they are assigned to a new task. After one iteration has ended, the vehicle's location is recorded and applied directly to the beginning of the next iteration. In this study, the DRT mode can not be used as an access or egress mode in combination with public transit.

The basic fare of DRT services consists of two components: a minimum fare of 2 EUR

[5]https://github.com/matsim-scenarios/matsim-berlin

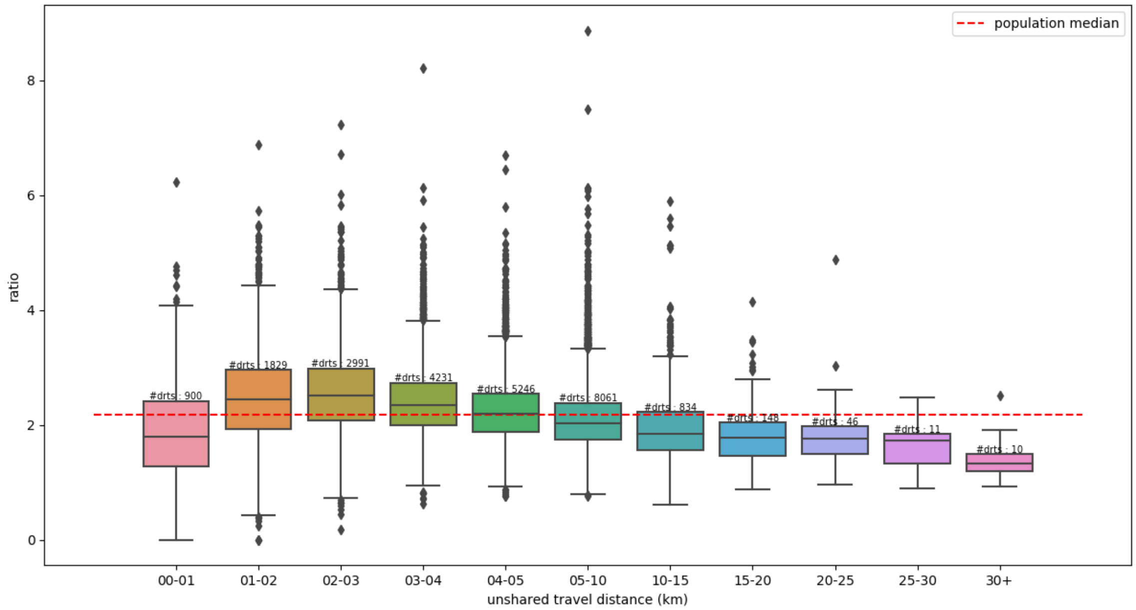


Figure 3: Distribution of ϕ in base case

and distance-based fare of 0.35 EUR/km. The choice of the base fare is future-oriented, and assumes that all DRT vehicles will be autonomous which reduces the operating costs and allows DRT to become a common mode for travelers' daily commutes.

4.2 Simulation experiments: base case

In the base case (Exp. bc), no dynamic DRT pricing strategy is implemented. Agents using DRT are only charged with the predefined fare setting mentioned in Section 4.1.

Table 1: Statistics of ϕ in base case

count	mean	25th-pctl	50th-pctl	75th-pctl
24307	2.26	1.82	2.18	2.61

Although there is no application of dynamic DRT pricing strategies in the base case, the estimated travel time by DRT (TT_{drt}^{pre}) and by public transit (TT_{pt}^{pre}) and the resulting ratio value ϕ were collected and recorded during the simulation for each DRT trip. This data was collected in order to determine thresholds for the public transit service quality levels (ϕ_h) and (ϕ_l). The data is also valuable for comparing the base case with other experimental cases to verify the results of the pricing approach's implementation.

Tab. 1 shows the summary statistics for ϕ in the base case without dynamic DRT pricing. Among the entire 24,307 DRT trips, the average public transport travel time is 2.26 times that of DRT unshared travel time. Moreover, according to Fig. 3, which shows the relationship between the ϕ and unshared travel distance[6] (d_u). With the increase in the d_u, the ϕ basically indicates the expected downward trend as stated in Section 3.2.2.

The only exception is the 00-01 km segment, where a relatively small ϕ is observed. This

[6]Same value as travel distance with mode car, obtained from built-in API of DRT extension module

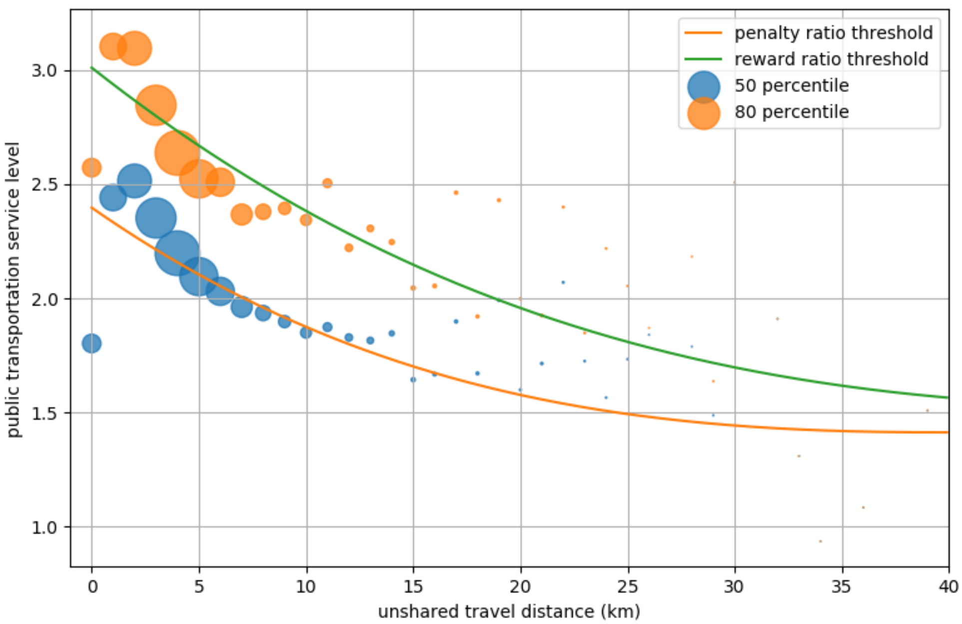


Figure 4: Thresholds in for DRT pricing approach. The size of the circle corresponds to the number of DRT trips in each travel distance bin

may be due to higher proportion of travel times involving walking and waiting times for those short trips, thus reducing the disparities in travel time between the DRT and public transit modes.

4.3 Simulation Experiments: policy cases

Penalty case: Exp. p_1.0 In this scenario, the dynamic DRT pricing strategy proposed in this paper will be applied, but only the part related to penalties. In other words, for DRT trips with poor public transit service, there is no corresponding price discount to reward the users. The detailed penalty mechanism has been described in Section 3.2.3, and the selected values of k_{pe} and ϕ_h are given here:

$$k_{pe} = 1.0 \tag{4}$$

$$\phi_h = \begin{cases} -0.00001d_u^3 + 0.00142d_u^2 - 0.06539d_u + 2.39697, & d_u \leq 40 \\ 1.41337, & d_u > 40 \end{cases} \tag{5}$$

where d_u is the unshared travel distance with DRT vehicles in km.

In the penalty case, the threshold ϕ_h is set by the distribution of ϕ according to the base case. As an experiment, the threshold value ϕ is set at the overall median level. Meanwhile, according to the analysis in the previous section, the distance factor of DRT trips must be considered when setting the threshold value, so Eq. 5 is proposed.

Eq. 5 is obtained by fitting the median value of ϕ in the base case contained within each kilometer, e.g., 0-1 km, 1-2 km, etc. A corresponding scatterplot is shown in Fig. 4. Since there is no DRT trip exceeding 40 km in the base case, the DRT trip over 40 km has a fixed value of $\phi_h = 1.41337$, i.e., when $d_u = 40km$, the calculation result from Eq. 5.

As a result, a total of 10,932 DRT trips in base case had corresponding high-level public transit service quality. This amount accounts eventually for 44.97% of all DRT trips in the base case, which is on par with a median level as is desired.

Reward case: Exp. r_0.5 Similar to Exp. p_1.0, the scenario considers only one type of pricing adjustment. In this scenario, when adjusting DRT fares, only the reward strategy will be applied.

As an experiment, the value of k_{re} and k_{lim} are both set to 0.5 (see Eq. 6), which means that for DRT trips, the maximum discount is half of the base cost. Moreover, the 80th percentile of the ϕ in Exp. bc is adopted as the reward threshold.(see Eq. 7 and Fig. 4). As a result, a total of 5023 DRT trips in the base case met the conditions for accepting rewards, accounting for 20.67% of all DRT trips.

$$k_{re} = k_{lim} = 0.5 \tag{6}$$

$$\phi_l = \begin{cases} -0.000006d_u^3 + 0.00119d_u^2 - 0.07407d_u + 3.00593, & d_u \leq 40 \\ 1.557759595, & d_u > 40 \end{cases} \tag{7}$$

where d_u is the unshared travel distance with DRT vehicles in km.

Final Case: Exp. p_1.0_r_0.5 In the final case, both the penalty strategy and reward strategy are in effect. As an integration of Exp. p_1.0 and Exp. r_0.5, the computation of DRT fare in the final case is following the Eq. 2, Eq. 3, Eq. 4, Eq. 5, Eq. 6, and Eq. 7.

5 Results

5.1 DRT trip number and fares

The differences in the number of DRT trips between Exp.bc and the other three policy cases are highlighted in Tab. 2.

One key finding is that the proposed DRT pricing strategy can significantly reduced the demand for DRT services while public transport provided comparable or better performance. Conversely, dynamic DRT pricing effectively increased the number of DRT services when public transport provided worse service.

Table 2: DRT trip number in each simulation experiment

	bc	p_1.0	r_0.5	p_1.0_r_0.5
num of DRT trips	243,070	213,390	263,910	223,360
high-PT-service-level	109,320	**68,910**	91,600	**54,430**
middle-PT-service-level	83,520	86,350	91,800	86,660
low-PT-service-level	50,230	58,130	**80,510**	**82,270**

Exp. p_1.0: A total of 213,390 trips finally adopted DRT as the mode of transportation for travel, i.e., a reduction of 12% compared with the base case. Tab. 2 demonstrates that this reduction mainly results from the penalty pricing strategy on DRT trips: compared with Exp.bc, the number of DRT trips with high-grade public transit service dropped sharply from 10,932 to only 6,891, i.e., a 36.96% reduction. For those with mid- and low-level public transit services that are not directly affected by the smart pricing scheme, a slight increase can be observed. Thus, the penalty pricing strategy can reduce the attractiveness of DRT to users with high-grade public transport accessibility by increasing DRT fares. Service vehicles can also be diverted to serve users, to whom public transit can hardly be seen as a reasonable alternative.

Exp. r_0.5: Compared with the base case, the number of DRT trips increased by 20,840 (8.57%) to 263,910. As expected, the newly added DRT trips mainly occur under the condition of a lower public transit services level, because these trips can benefit from the reward strategy by being exempted from certain fees. Just in terms of low-grade PT service alone, the number of DRT trips increased by nearly 60% (from 50,230 to 80,510) in reward case compared with Exp. bc.

Exp. p_1.0_r_0.5: The impacts observed above are confirmed in this scenario as well. Compared with Exp. bc, the number of DRT trips under high-level public transit service decreased by 54,890 (-50.21%), while the number of DRT trips under low-PT service quality increased by 63.78%, i.e., an increase of 32,040 trips. Finally, a total of 22,336 DRT trips appear in Exp. p_1.0_r_0.5. Consistent with the expectation, this value is between Exp. p_1..0 and Exp. r_0.5, while compared with base case, it is reduced by 19,710 (8.1%), indicating that under this experiment parameters penalties have a stronger effect on traveler behavior than the rewards.

Tab. 3 shows the revenue statistics under different pricing strategies. In terms of total daily revenues (total revenue = basic revenue + penalty revenue + reward revenue), the highest revenue is observed in Exp. r_0.5. However, in the aspects of average values, whether per km or trip, Exp. r_0.5 is the lowest compared with other cases.

Table 3: Revenue statistics

	bc	p_1.0	r_0.5	p_1.0_r_0.5
total revenue [EUR]	538,591.0	520,591.1	569,911.9	503,448.6
basic revenue [EUR]	538,591.0	501,097.7	590,754.5	511,071.1
penalty revenue [EUR]	0.00	19,493.4	0.00	14,008.3
reward revenue [EUR]	0.00	0.00	-20,842.7	-21,630.7
avg. revenue per distance [EUR/km]	0.43	0.44	0.39	0.41
avg. revenue per trip [EUR]	2.22	2.44	2.16	2.25

The final case (Exp. p_1.0_r_0.5) implements both strategies simultaneously, and obtains the lowest revenues under all experiments. This is because fewer users are willing to pay fines under the combined effect of the entire pricing strategy, but more users are attracted to travel with DRT through discounts. In consequence, operators will charge lower penalties (14,008.3 EUR) than the discounts (21,630.7 EUR) they offer. In addition to the decrease in the number of DRT trips, a revenue loss can be estimated (about 35000 EUR less compared with Exp. bc).

5.2 Temporal changes of DRT trips

As described in the previous sections, the DRT dynamic pricing strategy proposed in this paper is based on the service quality of public transport. In general, the service quality of public transportation should follow a predictable temporal and spatial pattern. For example, buses and trains arrive at more frequent intervals during peak periods than during off-peak periods, and the accessibility of public transit in the city center is often better than the lower density city suburb. Hence, it can be reasonably hypothesized that after the implementation of the pricing strategy, the DRT services should also be affected accordingly. To measure these effects, impact of the pricing schemes on DRT's temporal and spatial distribution needs to be analyzed and is presented as follows.

Fig. 5 shows the variation of the temporal distribution of DRT trips compared with the base case. It can be clearly seen that the changes in DRT trip amounts follow a certain temporal pattern, which is:

Exp. bc vs. Exp. p_1.0: Under the penalty pricing strategy, the demand for DRT decreases greatly, but this effect is more significant in peak hours. For midnight, when public transit service is poor, the consequence of eliminating DRT demands has less impact.

Exp. bc vs. Exp. r_0.5: In contrast, an increase in DRT demands is more likely to occur during the non-peak periods, i.e., from midnight to 7 am and from 8 pm to midnight. The demand enhancement for DRT services between 10 am and 6 pm is less substantial.

When the two strategies are executed together, the effect is even more pronounced. Between 6 am and 8 pm, when public transport is considered very dense, the demand for DRT decreases, while during midnight and early morning hours, the number of DRT services increases due to the implementation of the reward pricing strategy.

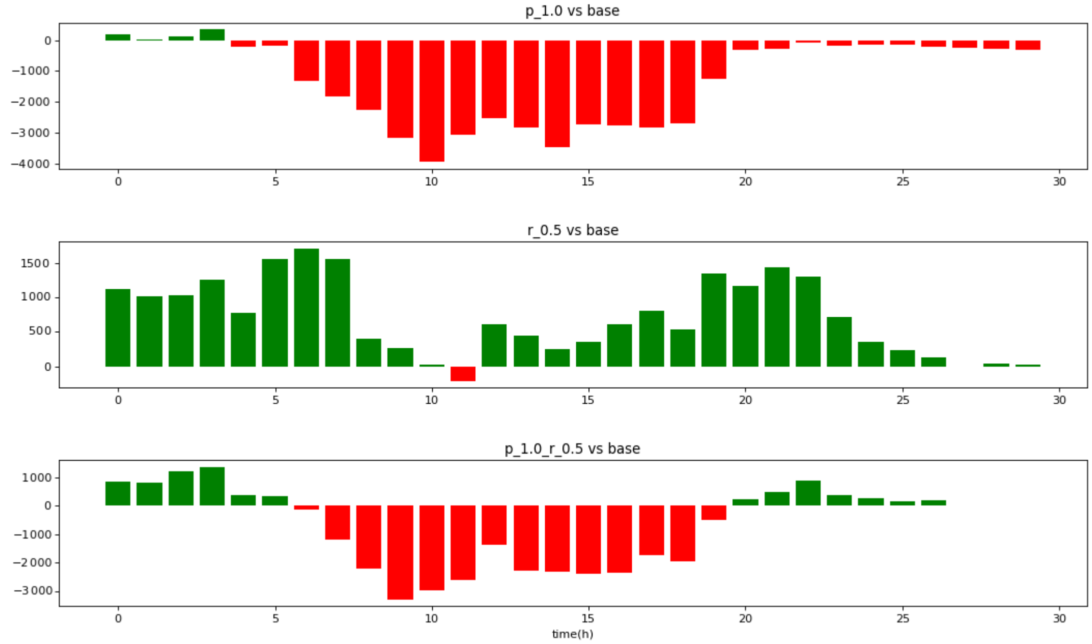


Figure 5: Hourly changes in the number of DRT trips

5.3 Spatial changes of DRT trips

In the previous section, the temporal changes in demand for DRT caused by the dynamic pricing schemes are presented and discussed. Even within a given time period, however, a spatial variation of changes in the DRT demand is observed which stresses the uneven distribution of public transport services in the city. Public transit generally offers better service in densely populated city centers compared to low-density outskirts. The dynamic pricing model reflects this discrepancy.

The Ringbahn is a 37.5 km long railway line of the Berlin S-Bahn network that functions as a rough border of the inner-city Berlin area. For this paper, the area within the Ringbahn is classified as Berlin city center, while the area outside the Ringbahn is classified as city outskirts (see Fig. 2).

The variation of OD data of DRT trips between the urban center and the outskirts can be an essential factor in studying the impact of the pricing schemes on DRT spatial characteristics. To eliminate the effect of time-of-day, analysis is limited to the morning period from 8 am to 11 am. The absolute change in the number of DRT trips during this time interval compared to Exp.bc is indicated in Tab. 4.

The dynamic pricing strategy proposed in this paper significantly reduces the use demand of DRT during peak hours in the city center. In Exp. p_1.0, where the penalty pricing strategy is implemented, the number of DRT trips, whose starting point and ending point are both inside the city center, decreases by about 27%. In the Exp. r_0.5, the number of DRT trips in all other OD-relations except center-to-center increased, confirming the ability of the reward strategy to improve the attractiveness of DRT in urban suburbs.

Finally, in the Exp. p_1.0_r_0.5, where the two pricing strategies work together, the amount of DRT trips occurring in the city center is greatly reduced by 2860 trips compared to the

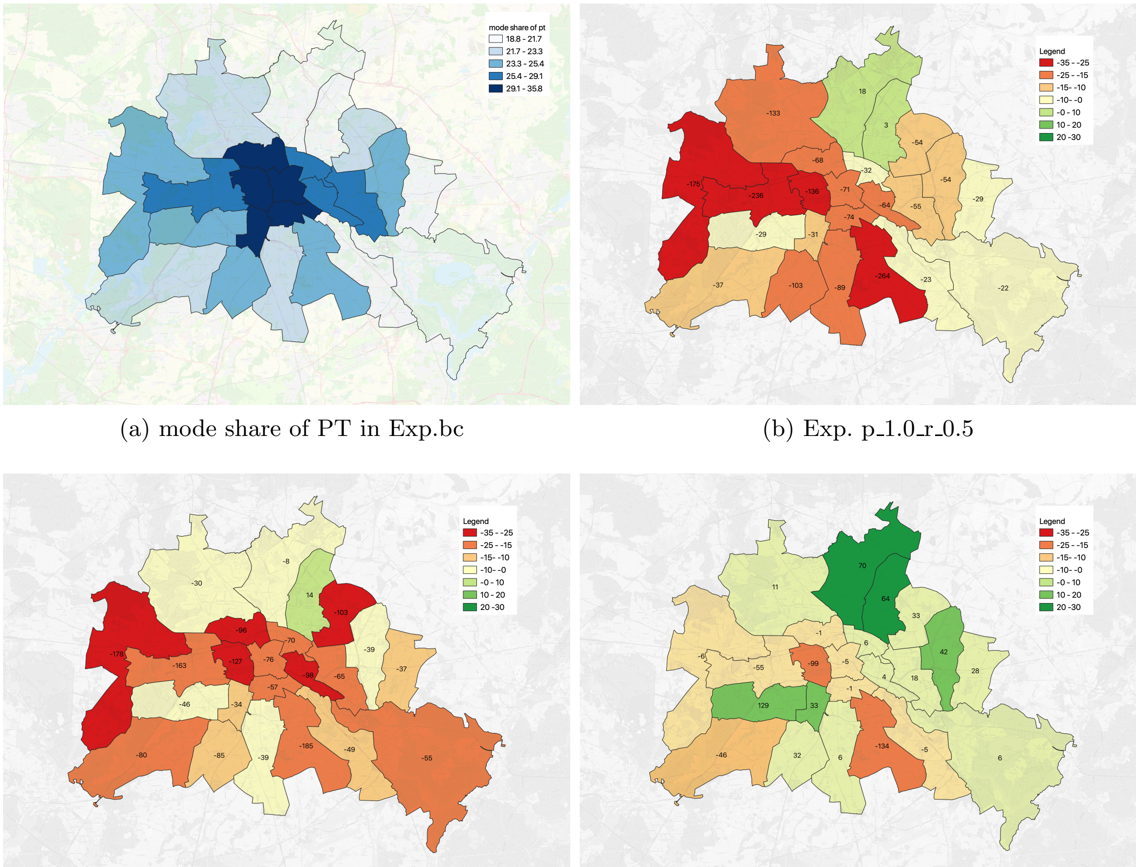
Table 4: Changes of DRT trips in city-center and city-outskirts during 8 am-11 am

from	to	bc	compare to Exp.bc		
			p_1.0	r_0.5	p_1.0_r_0.5
center	center	9430	-2540 (-26.93%)	-1150 (-12.19%)	-2860 (-30.32%)
center	outskirts	4760	-390 (-8.19%)	+530 (+11.13%)	-410 (-8.61%)
outskirts	center	4820	-570 (-11.83%)	+290 (+6.01%)	-690 (-14.32%)
outskirts	outskirts	32780	-4950 (-15.10%)	+970 (+2.95%)	-4530 (-13.81%)

base case level of 9430 trips. This reduction (-30.32%) reaches the most significant value among all OD-relations of all the experiments.

In addition to generally dividing Berlin into city-center and city-outskirts, the changes in the demand for DRT in each borough of the urban area also play a significant role in the spatial effects of the DRT pricing schemes.

Compared with the base case, the variation of DRT volume in each urban district is presented in Fig. 6(b)(c)&(d). Again, only trips between 8 am and 11 am are considered.



(a) mode share of PT in Exp.bc

(b) Exp. p_1.0_r_0.5

(c) Exp. p_1.0

(d) Exp. r_0.5

Figure 6: Changes in number of DRT trips in every districts during 8 am to 11 am (These numbers refer to the 10% population sample.)

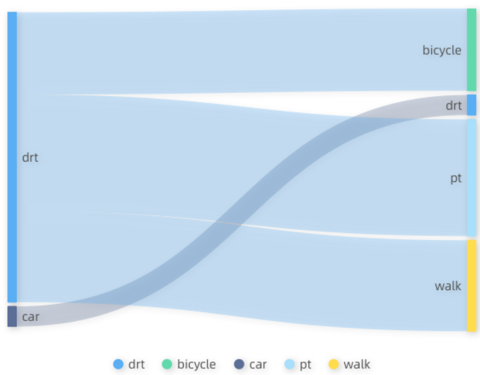
As a reference, the mode share value of public transport in each district in Exp. bc is shown in Fig. 6(a), which can also be used as an indicator to estimate the level of public transit service.

As expected, the effect of the penalty strategy is greater in areas with higher public transit mode-share values. On the contrary, the reward strategy can effectively increase the DRT demand in areas where public transit is not widely-used. In particular, by comparing Fig. 6(b) and Fig. 6(a),a highly consistent rule in color can be observed. DRT usage drops a lot in downtown districts and West Berlin where public transit mode-share is high. But for the areas where, public transit is relatively less used, e.g., East Berlin and North Berlin, only a slight reduction and even a rise of the number of DRT trips can be observed.

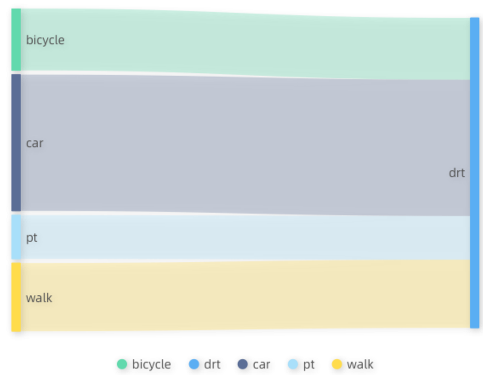
5.4 Mode shift effects

This section focuses on the mode shift effects brought by the DRT pricing strategy. The results are depicted in Fig. 7, which shows the aggregated person-specific mode shift effects of mode DRT resulting from comparisons between base and policy cases.

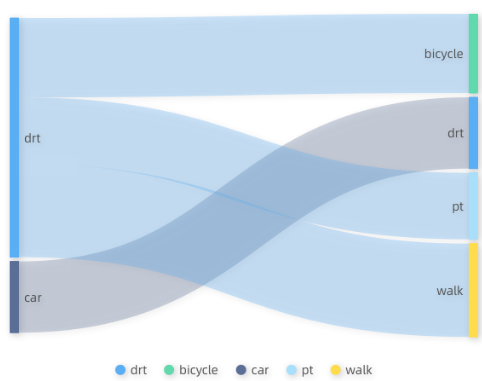
The data suggests that the penalty pricing strategy effectively encourages DRT users



(a) from Exp. bc to Exp. p_1.0



(b) from Exp. bc to Exp. r_0.5



(c) from Exp. bc to Exp. p_1.0_r_0.5

Figure 7: Aggregated mode switch analysis of DRT trips from Exp. bc to policy cases. Trips that do not interact with the DRT mode are not shown. Trips in which the transport mode remains DRT are also not shown. The line width corresponds to the overall mode switch effect in both directions, e.g. trips that are shifted from mode car to DRT minus the trips that are shifted from DRT to mode car.

to switch to public transportation. In the penalty strategy cases, DRT users switch to public transit as well as to bicycle and walk and there are no additional DRT-to-car mode shifts. The reward pricing has also, as expected, encouraged a large number of car users to switch to DRT. As the penalty and reward strategies are both implemented in the final case, 28,080 DRT trips were replaced with sustainable modes such as bicycle, public transportation, and walking. Simultaneously, 8,370 car users switch to DRT, resulting in a total combined reduction of 19,710 DRT trips.

The aggregated mode shift of all modes are depicted in Tab. 5. For each simulation experiment, the mode-specific trip share considers only potential DRT trips (i.e., trips inside the DRT service area).

For public transit, the reward strategy and the penalty strategy have a similar effect on increasing its use, with 42,860 and 42,760 trips, respectively. When the two strategies are implemented simultaneously, PT use increases even more, with 61,370 new public transit trips representing an increase of 1.94%.

For private vehicles, the reward strategy had the most significant effect on its decline in usage, which is in keeping with the original intention of the reward strategy to shift car users to DRT by lowering the DRT price. The reduction of the number of car users is also maintained in Exp.p_1.0_r_0.5. Compared with base case, , this scenario reduced car trips by 48,390, which is similar to Exp. r_0.5's reduction of 53,830 car trips.

The dynamic DRT pricing strategy directly encouraged only 8,370 car users to switch to DRT, while an overall reduction of nearly 50,000 car trips is observed with the overall mode counts analysis. This difference can be explained as the car was set as a chain-based-mode in advance. In MATSim simulation, each sub-tour, i.e., trips chains starting and ending at the same activity location, can be performed only with a chain-based-mode like a car or a combination of other non-chain-based-modes. For example, agents in the simulation must use a car to travel back from work to home if they had previously used car to travel from home to work. Therefore, when one trip within the sub-tour switched car to DRT due to the incentives offered in the reward strategy, the other trips in the same sub-tour were also forced to shift from car travel to other modes. Moreover, the results indicated public transit is more likely to be the alternative for the rest trips in the sub-tour, as the number of PT trips is increased greatly by 61,370, while only 10% came from DRT directly because of the penalty strategy.

Table 5: Modal split analysis

	Exp.bc	Compare with Exp.bc					
	total number	p_1.0		r_0.5		p_1.0_r_0.5	
bicycle	1,442,700	-9,590	-0.66%	-26,050	-1.81%	-10,710	-0.74%
car	2,735,990	-17,900	-0.65%	-53,830	-1.97%	-48,390	-1.77%
drt	243,070	-29,680	-12.18%	+20,840	+8.55%	-19,710	-8.08%
pt	3,172,870	+42,860	+1.35%	+43,760	+1.37%	**+61,370**	+1.93%
walk	3,076,190	+14,350	+0.46%	+15,300	+0.50%	+17,430	+0.56%

5.5 Vehicle-kilometers traveled

By comparing the data in the Tab. 6, it can be seen that Exp. p_1.0 indeed has the shortest DRT mileage, and the lowest VKT of car is also observed in Exp. r_0.5, as the mode share indicates in Section 5.4. The most desirable VKT value, however, exists in the Exp. p_1.0_r_0.5, where the penalty and reward pricing strategies are implemented simultaneously. Here, the total VKT reaches 16,100,550km, which is reduced by nearly 3% compared with the base case.

Table 6: Vehicle-kilometers traveled (km)

	bc	p_1.0	r_0.5	p_1.0_r_0.5
Car	15,285,910	15,126,430	14,828,150	14,858,900
DRT	1,244,540	1,187,280	1,464,120	1,241,650
Total	16,530,450	16,313,710	16,292,270	**16,100,550**

5.6 Travel Time

Tab. 7 shows the change in travel time of several sets of mode shifts, e.g., from DRT to PT and from car to DRT.

Table 7: Changes in average travel time (seconds) per trip

from	to	Change	
drt	pt	+517.55	+37.19%
car	drt	+77.96	+6.24%
car	car	-3.18	-0.17%
drt	drt	-38.98	-3.23%

While the pricing strategies proposed in this paper, especially the penalty pricing strategy, play a significant role in promoting DRT users to switch to public transit, travel times increased as users switched modes. As shown in Tab. 7, the travel time for DRT users switching to PT increased by an average of 517s, nearly 9 minutes.

Travel time for users switching from car to DRT increased by less than 80s, representing only a 6.24% increase compared to the base case.

For users remaining within the car mode, the change in travel time per trip may be used as an indicator for traffic congestion. The introduction of the pricing schemes showed a slight reduction in traffic congestion, as travel times for car users decreased by 3.18s in Exp. p_1.0_r_0.5 compared to the base case. A larger travel time reduction (40s, 3.23%) was observed for the DRT mode.

6 Discussion

In the following sections, we further explore the applicability of the proposed DRT pricing approach to gain a better understanding of how to successfully implement it within existing DRT systems.

6.1 Determination of computation parameters

The relevant parameters, i.e., the thresholds (ϕ_h, ϕ_l) and the factors (k_{pe}, k_{re}, k_{lim}) of the penalty and reward pricing computation, should be determined in advance for the calculation of the surcharge or discount of each DRT trip. The setting of these parameters will then further affect the result of the final pricing strategy to a large extent. For example, as a reference, the parameter setting adopted in this case study is more focused on penalty strategy than reward, so that the reduction of DRT demand in the case of developed public transportation is much greater than the increase with low-level public transit conditions. Finally, as shown in Section 5.1, DRT operators suffer a certain loss (-21,630.7 EUR) in their revenues.

However, given that the impact of both the penalty and reward strategies have successfully met our expectations, it remains possible that with the right parameters a DRT operator might be able to implement an incentive strategy that reduces urban congestion without associated revenue loss. Alternatively, the parameters might be set to maximize DRT operator revenue. In other words, the determination of those parameters should depend on the purpose of the study or the interests of stakeholders.

As the impacts of the pricing parameters is closely related to the specific traffic characteristics of each city, the emphasis of this study is on the overall price strategy and the verification of its impact. The specific methodology to calibrate the parameters for a specific objective function is an important area for future research that is beyond the scope of this paper.

6.2 The DRT base fare level

As described in Section 4.1, the DRT service implemented in this study is future-oriented. With the introduction of autonomous vehicles, operational costs are expected to be significantly reduced to rates lower than the today's DRT services. To reflect this potential cost reduction, a low base fare of 0.35 EUR/km and a minimum fare of only 2 EUR per ride is used.This raises questions about the effectiveness of the proposed DRT pricing approach for today's DRT fare levels. Therefore, further simulation experiments are carried out with a higher fare levels of 1.5 EUR/km as distance-fare and 4 EUR as the minimum fare per ride, which is in line with the fare setting of BerlKönig, a DRT service in Berlin (high-base-fare scenario). All other settings are identical with the case study described in Section. 4.1(low-base-fare scenario).

The results in the high-base-fare scenario are quite different from the previous low-base-fare results. In the high-base-fare scenario, the reward strategy yields an increase of less than 1500 (0.2%) DRT trips compared to the base case, whereas the low-base-fare scenario yields an increase of 20840 (8%) DRT trips.

In the high-base-fare case, transport users who choose the rather costly DRT mode have no convenient public transit travel alternative. As a reference, the average ϕ in the base case of the high-base-fare scenario is 3.02, while it is 2.26 in the low-base-fare scenario. The reward strategy leads to reduced DRT fares that are therefore not sufficient to attract many users as the low-level public transit service level is still set as the 80 percentile of ϕ in this base case. Compare to the low-base-fare scenario, this setting will affect much fewer travelers in the city.

To attract more travelers to the DRT mode, the threshold for the low-level PT service quality must be reduced. This will, however, have two consequences: (1) revenues of the DRT operator will significantly decrease and (2) there will also be large number users who switch from public transit, walking and bicycle to the DRT mode which is considered as an undesired effect.

In the high-base-fare scenario, the penalty strategy significantly reduces DRT demand (-27.8%), however, the previous DRT users are observed to switch to car and not to public transit; the number of car users increase by about 20,000 trips. That is, the proposed DRT pricing scheme is not effective in the high-base-fare scenario as DRT services are too expensive to compete with the public transit mode, in particular for daily commuting. Since most DRT users have no convenient public transit travel alternative, the second best option is to switch (back) to the private car mode. As DRT fares increase in the penalty case, most DRT users make use of that option and switch to car.

The dynamic DRT pricing approach proposed in this paper will have a more significant effect when the base fare of DRT is greatly reduced to the point that it becomes a viable option for daily commuting. When applied to situations with the current, higher DRT fare, the dynamic DRT pricing strategy should be based not on PT service quality but rather other modes with which DRT directly competes, e.g., private car, traditional taxi, or other DRT services providers.

7 Conclusion and outlook

In this study, an innovative DRT pricing strategy is proposed in which DRT fares are corrected based on the quality of the alternative schedule-based public transit service. This pricing strategy aims to reduce traffic congestion and to encourage a mode shift from car to DRT as well as from DRT to public transit.

First, the relative public transit service level for each DRT trip is calculated as the ratio of the predicted travel time by public transit and travel time by DRT. By comparing this ratio with the pre-defined thresholds, DRT trips are classified as one of three public transit service level categories: high-, mid-, or low-level PT service. For DRT trips belonging to the high-level PT service level group, surcharges were applied to DRT fares to encourage travelers to switch from DRT to public transit. For DRT trips in the low-level public transit service category, DRT fares were discounted to encourage travelers to switch from car to DRT.

In order to evaluate the impact of the proposed DRT pricing strategy on the DRT operator and the overall urban traffic, the agent-based simulation framework MATSim is used and several simulation experiments are carried out for the real-world case study of the Greater Berlin area, Germany. The simulation experiments include one base case and three different DRT pricing strategies.

In Exp. p_1.0, only the penalty strategy is implemented, which significantly shifts DRT users to public transit. An analysis of the temporal and spatial changes in DRT demand shows a reduction in the number of DRT trips during peak hours and in the inner-city area (see Section 5.2 and Section 5.3).

The effect of the reward pricing strategy is investigated in Exp. r_0.5. A mode shift from car to DRT is observed in areas and times where public transit is underdeveloped. As a result, the total number of car trips decrease by 53,830 compared to the base case, while DRT trips increase by 20,840. Both shifts result in significant reductions in traffic congestion.

In the final case (Exp. p_1.0_r_0.5), the two pricing strategies are implemented simultaneously. The combined impacts were larger than each strategy by itself, with an increase of 61,370 public transit trips and a 3% reduction in car and DRT distance travelled (16 million km) compared to the base case. Although the total revenue for DRT operators is reduced by 503,440 EUR in this pricing strategy, the unit revenue per trip (2.25 EUR) is higher than in Exp. bc (2.22 EUR).

In general, the proposed DRT pricing scheme effectively provides a solution to the dilemma how to control the mode shift effect and realize advantages of DRT services as a substitute for private cars and at the same time avoiding the cannibalization of PT. As there are already sophisticated applications to estimate the travel time across different traffic modes, the proposed pricing approach may easily be incorporated into DRT smartphone applications.

In future research, the methodology to calibrate the parameters of the proposed DRT pricing approach can be addressed. Furthermore, the simulation setup will be extended to account for situations in which DRT can be used as an intermodal mode of transportation in combination with PT which allows for additional DRT fare correction strategies. Another next step is to apply the proposed DRT pricing scheme to investigate today's DRT services and explores ways to achieve the desired mode shift effect towards more efficient and sustainable modes of transportation.

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References

Ahrens, G.-A. Endbericht zur Verkehrserhebung Mobilität in Städten – SrV 2008 in Berlin. Technical report, Technische Universität Dresden, 2009. `http://www.stadtentwicklung.berlin.de/verkehr/politik_planung/zahlen_fakten/download/2_SrV_endbericht_tudresden_2008_berlin.pdf`.

Balmer, M., B. Raney, and K. Nagel. Adjustment of activity timing and duration in an agent-based traffic flow simulation. In Timmermans, H., editor, *Progress in activity-based analysis*, pages 91–114. Elsevier, Oxford, UK, 2005.

Bimpikis, K., O. Candogan, and D. Saban. Spatial Pricing in Ride-Sharing Networks. *Operations Research*, 2019. doi: 10.1287/opre.2018.1800. URL `https://doi.org/10.1287/opre.2018.1800`.

Bischoff, J. and M. Maciejewski. Proactive empty vehicle rebalancing for Demand Responsive Transport services. *Procedia Computer Science*, 170:739–744, 2020. doi: 10.1016/j.procs.2020.03.162.

Bischoff, J., M. Maciejewski, and K. Nagel. City-wide shared taxis: A simulation study in Berlin. In *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, Oct. 2017. doi: 10.1109/itsc.2017.8317926.

Chen, T. D. and K. M. Kockelman. Management of a Shared Autonomous Electric Vehicle Fleet: Implications of Pricing Schemes. *Transportation Research Record*, 2016. doi: 10.3141/2572-05. URL `https://doi.org/10.3141/2572-05`.

Frank, L., M. Bradley, S. Kavage, J. Chapman, and T. K. Lawton. Urban form, travel time, and cost relationships with tour complexity and mode choice. *Transportation*, 2008.

Gawron, C. An Iterative Algorithm to Determine the Dynamic User Equilibrium in a Traffic Simulation Model. *International Journal of Modern Physics C*, 9(3):393–407, 1998.

Gehrke, S. A Survey of Ride-Hailing Passengers. *TREC Friday Seminar Series.*, (152), 2018. URL `https://pdxscholar.library.pdx.edu/trec_seminar/152/`.

Grether, D., Y. Chen, M. Rieser, and K. Nagel. Effects of a Simple Mode Choice Model in a Large-scale Agent-Based Transport Simulation. In Reggiani, A. and P. Nijkamp, editors, *Complexity and Spatial Networks. In Search of Simplicity*, Advances in Spatial Science, chapter 13, pages 167–186. Springer, 2009. doi: 10.1007/978-3-642-01554-0.

Gurumurthy, K. M., K. M. Kockelman, and M. D. Simoni. Benefits and Costs of Ride-Sharing in Shared Automated Vehicles across Austin, Texas: Opportunities for Congestion Pricing. *Transportation Research Record*, 2019. doi: 10.1177/0361198119850785. URL `https://doi.org/10.1177/0361198119850785`.

Horni, A., K. Nagel, and K. W. Axhausen, editors. *The Multi-Agent Transport Simulation MATSim*. Ubiquity, London, 2016. doi: 10.5334/baw.

infas and DLR. Mobilität in Deutschland 2008 – Ergebnisbericht. Schlussbericht für Forschungsprojekt FE Nr. 70.801/2006, Institut für angewandte Sozialwissenschaft, Deutsches Zentrum für Luft- und Raumfahrt, 2010. URL `http://daten.clearingstelle-verkehr.de/223/`.

Kaddoura, I., J. Bischoff, and K. Nagel. Towards welfare optimal operation of innovative mobility concepts: External cost pricing in a world of shared autonomous vehicles. *Transportation Research Part A: Policy and Practice*, 136:48–63, 2020a. doi: https://doi.org/10.1016/j.tra.2020.03.032.

Kaddoura, I., G. Leich, and K. Nagel. The impact of pricing and service area design on the modal shift towards demand responsive transit. *Procedia Computer Science*, 170:807–812, 2020b. doi: 10.1016/j.procs.2020.03.152.

Lefebvre, N. and M. Balmer. Fast shortest path computation in time-dependent traffic networks. In *Swiss Transport Research Conference (STRC)*, Monte Verita, Switzerland, 2007. URL `http://www.strc.ch`. See `http://www.strc.ch`.

Leich, G. and J. Bischoff. Should autonomous shared taxis replace buses? A simulation study. VSP Working Paper 18-05, TU Berlin, Transport Systems Planning and Transport Telematics, 2018. URL `http://www.vsp.tu-berlin.de/publications`.

Maciejewski, M. Dynamic Transport Services. In Horni et al. (2016), chapter 23. doi: 10.5334/baw.

Maciejewski, M., J. Bischoff, S. Hörl, and K. Nagel. Towards a Testbed for Dynamic Vehicle Routing Algorithms. In Bajo, J., Z. Vale, K. Hallenborg, A. P. Rocha, P. Mathieu, P. Pawlewski, E. Del Val, P. Novais, F. Lopes, N. D. Duque Méndez, V. Julián, and J. Holmgren, editors, *Highlights of Practical Applications of Cyber-Physical Multi-Agent Systems: International Workshops of PAAMS 2017, Porto, Portugal, June 21-23, 2017, Proceedings*, pages 69–79. Springer International Publishing, 2017. ISBN 978-3-319-60285-1. doi: 10.1007/978-3-319-60285-1.

Nagel, K. and G. Flötteröd. Agent-based traffic assignment: Going from trips to behavioural travelers. In Pendyala, R. and C. Bhat, editors, *Travel Behaviour Research in an Evolving World – Selected papers from the 12th international conference on travel behaviour research*, pages 261–294. International Association for Travel Behaviour Research, 2012. ISBN 978-1-105-47378-4.

Nagel, K., B. Kickhöfer, A. Horni, and D. Charypar. A Closer Look at Scoring. In Horni et al. (2016), chapter 3. doi: 10.5334/baw.

Reza Vosooghi, Jakob Puchinger, M. J. A. V. Shared autonomous vehicle simulation and service design. *Transportation Research Part C: Emerging Technologies*, 107, 2019. doi: https://doi.org/10.1016/j.trc.2019.08.006. URL `http://www.sciencedirect.com/science/article/pii/S0968090X19304449`.

Rieser, M. *Adding Transit to an Agent-Based Transportation Simulation: Concepts and Implementation*. PhD thesis, TU Berlin, Berlin, 2010.

Rieser, M. Modeling Public Transport with MATSim. In Horni et al. (2016), chapter 16. doi: 10.5334/baw.

Salonen, M. and T. Toivonen. Modelling travel time in urban networks: comparable measures for private car and public transport. *Journal of Transport Geography*, 2013. doi: 10.1016/j.jtrangeo.2013.06.011. URL `http://www.sciencedirect.com/science/article/pii/S096669231300121X`.

Schaller, B. The new automobility: Lyft, Uber and the future of American cities. 2018.

Ziemke, D., K. Nagel, and C. Bhat. Integrating CEMDAP and MATSim to increase the transferability of transport demand models. *Transportation Research Record*, 2493:117–125, 2015. doi: 10.3141/2493-13.

Ziemke, D., I. Kaddoura, and K. Nagel. The MATSim Open Berlin Scenario: A multimodal agent-based transport simulation scenario based on synthetic demand modeling and open data. *Procedia Computer Science*, 151: 870–877, 2019. doi: 10.1016/j.procs.2019.04.120.