QUANTIFYING THE BENEFITS OF PRE-BOOKING IN DEMAND-RESPONSIVE SYSTEMS BASED ON REAL-WORLD SCENARIOS

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ABSTRACT

In this study, we explore the benefits of pre-booking in the demand-responsive transport (DRT) system under various demand densities and patterns. Systematic experiments have been carried out on two scenarios based on real-world data, within an agent-based transport simulation framework. Representing a small town in a rural region and the center of a metropolis, the two scenarios have different characteristics in terms of road network and population model. Within each scenario, simulations of DRT systems have been carried out under different demand densities. Simulation results suggest that pre-booking can improve the efficiency of the DRT system under all the setups. While the total cost savings induced by pre-booking is sensitive to the demand density, a relatively constant reduction in the fleet mileage can be realized in both scenarios under different demand densities. Another interesting outcome from the experiments is that when the demand density is the same, the DRT operation may be slightly more efficient in the small-town scenario. Therefore, when a small or medium size DRT system is considered to be introduced to service, the rural area may be a better choice than the city center, as long as there are sufficient demands.

Keywords: Demand-Responsive Transport, Pre-booking, Vehicle Routing Problem

INTRODUCTION

The demand-responsive transport service (DRT), also sometimes known as Mobility-on-Demand (MoD), is an emerging mode of transport. It is a flexible and efficient transport service (*1*). At the same time, it can also be used to improve the conventional public transport (PT) system, by providing first and last mile service (*2*). Some ambitious studies even propose to use the DRT system to replace part or all the private car trips in the cities (*3, 4*). The DRT system can be an efficient mode of transport not only in urban areas, but also in rural regions. For regions with low population density, where conventional high frequency PT service cannot be maintained, the DRT is one of the promising alternative solutions (*5, 6*).

When it comes to the operation of the DRT system, most of the studies in the literature focus on spontaneous demands. This is reasonable, because being able to serve spontaneous trips is one of the main advantages of the DRT system. But there are also prices for this spontaneity or convenience, especially when an efficient operation of the DRT system is desired. Incorporating ride-pooling in the DRT system is one of the frequently proposed ideas to improve the efficiency of the DRT system. Several advanced algorithms, such as (*7, 8*) have been proposed. But due to the nature of the problem, the computational tractability can easily be lost as the size of the DRT system grows. Furthermore, the benefits of ride-pooling in the spontaneous mode also depends on the scenarios (i.e., regions, road networks, demands). Ruch et al. (*9*) show that the good performance of various ride-pooling algorithms may not be fully reproducible in different scenarios. In the end, simple rule-based matching algorithms are usually used, both in real-world operations and in simulations.

Apart from the challenges in the optimization of the passenger assignment problems, empty vehicle relocations are usually needed in order to maintain a high level of service when serving spontaneous requests. In order to reach a balance of supply (i.e., available vehicles) and demand (i.e., passengers) across the service area, empty vehicles need to be sent from places with surplus in supply to areas with deficient supply (*10*). Various studies have shown that, while the service quality can be improved, a significantly higher fleet distance needs to be covered, when empty vehicle relocation process is enabled (*11–13*).

One way to overcome the above-mentioned drawbacks is to incorporate pre-booking into the DRT system. With pre-booking, there will be more time to perform the optimization process, which usually leads to a better system-wide passenger assignment plan. In addition, the frequency of empty vehicle relocation can be significantly reduced. If all the trips are pre-booked, the empty vehicle relocation is even no longer necessary. That means the efficiency of the DRT system can be improved, and the operational costs can be reduced. One recent study that explores the feasibility of transporting school children in rural areas by a fleet of minivans has shown that around 35% of the annual total costs can be reduced when the trips are pre-booked and offline optimization is performed beforehand (*14*).

In the conventional sense, pre-booking means the travel demands need to be submitted relatively long time in advance (e.g., one day before), and then the passenger assignment problem can be solved completely offline by vehicle routing problem (VRP) algorithms. This may not always be feasible, as serving spontaneous trips is sometimes desired in a DRT system. To mitigate this problem, we can reduce the length of required pre-booking time. By doing so, we can resume part of the spontaneity. For example, if a trip only needs to be pre-booked 30 minutes in advance, then the trip may still be considered somewhat spontaneous or semi-spontaneous, as the trip can be pre-booked while the passenger is getting ready for the departure. Some recent studies have shown that requesting passengers to pre-book their trips shortly before departure can also significantly improve the efficiency of the DRT system (*15, 16*).

Despite having the potential to greatly improve the efficiency of the DRT system at the cost of minimal inconvenience to the passengers, DRT system with pre-booking is less investigated than the other topics in the field. Most of the existing studies either focus on the special demands (such as school trips) or the characteristic of the solver in specific test bed scenarios. As is pointed out by a study, the statistics of the DRT system are sensitive to the scenarios and do not scale linearly to the demand density(*17*). Those factors may also impact the benefits of the pre-booking. To the knowledge of the authors, there is not yet a systematic study on the benefits of pre-booking under different operational conditions, such as the scale of the DRT service and the characteristics of the population in the service area.

In this study, we will quantify the benefits of pre-booking in DRT systems under different scenarios by conducting a set of comprehensive experiments. Agent-based transport simulations will be carried out based on scenarios derived from real-world data. With a small town in a rural region and the center of a metropolis, two scenarios with different road network structures and demands patterns are included in this study. Furthermore, within each scenario, simulations will be carried out based on different demand densities, which correspond to DRT operations in different scales.

METHODOLOGY

In this study, the Multi-Agent Transport Simulation (MATSim) is used to perform the experiments. MATSim is an open-source framework for implementing large-scale agent-based transport simulations (*18*). The simulation framework is capable of performing detailed city-scale transport simulation within relatively short time. Within the MATSim framework, there is an extension called MATSim DRT Extension, which enables the simulation of the DRT service (*19*). In our experiments, we use different fixed DRT demands to perform the quantification. Therefore, we do not need the standard iterative process in order to reach the dynamic user equilibrium. This allows for the implementation of a more complex DRT operational strategy, as well as performing extensive experiments on multiple scenarios.

DRT optimizer for spontaneous trips

To simulate the DRT system with spontaneous trips (i.e., without pre-booking), we use the default passenger matching strategy, the extensive insertion search, in the MATSim DRT extension. The algorithm tries to insert each travel request into the schedule of a vehicle when the request is submitted, whenever it is feasible. An insertion is feasible if the following conditions are fulfilled: the maximum waiting time of the passengers, including the passenger being processed and the already accepted passengers waiting to be picked up, must not be exceeded; all the passengers must be transported to their destination on or before the latest arrival time; the vehicle must not be overloaded at any time. The latest arrival time $t_{arrival,latest}$ of each passenger is calculated as:

$$t_{arrival,latest} = t_{submission} + \alpha \cdot t_{direct} + \beta \qquad (1)$$

The term t_{direct} is the time it takes for a DRT vehicle to travel from the origin to the destination of the passenger directly. $t_{submision}$ is the submission time of the travel request. Parameters α and β are parameters that can be tuned. In this study, we set them to 2.0 and 900 seconds respectively.

For the maximum waiting time, we set it to 600 seconds (10 minutes) in this study. Note that the latest arrival time according to Equation (1) includes the waiting time. In other words, a long waiting time until pickup forces the travel time to be shorter. This looks like it is in the interest of travelers since it keeps overall times from booking to arrival predictable. It has, however, the consequence of relatively many rejections under high load.

If a request cannot be inserted properly, it will be rejected immediately. In order to reduce the rejection caused by the imbalanced distribution of the vehicles, the rebalancing operation (i.e., empty vehicle relocation) is enabled. The min-cost-flow rebalancing strategy proposed in (*12*) is used.

DRT optimizer for pre-booked trips

To simulate the DRT system with pre-booking, we use the rolling horizon approach proposed in (*16*). Instead of solving the VRP problem for the whole day, we divide a day into smaller pieces and solve them piece by piece. The schematic drawing of the rolling horizon approach is shown in Figure 1. There are two key parameters in the rolling horizon approach: the planning horizon length t_h and the update interval t_u. In this study, t_h is set to 30 minutes. That is to say, all the passengers departing in the next 30 minutes will be added to the VRP problem and an operational plan for the whole fleet will then be computed. It is worth mentioning that the horizontal lines in Figure 1, which represent the calculated plans, extend beyond the planning horizon t_h (i.e., see the horizontal line segments with fading color), this is because pick-ups and drop-offs may be scheduled after the end of the planning horizon, as long as they are within the pick-up or delivery time windows.

The update interval refers to the frequency at which we solve the VRP problems. Since the travel requests enter the system continuously, it is likely that there will be additional requests shortly after the horizon ends. As those requests are not considered during the optimization process, the end state of each plan is probably not ideal. Therefore, it makes sense to switch to a new plan before reaching the end of the current plan. Based on the findings in a previous study (*16*), we set t_u to 20 minutes in this study.

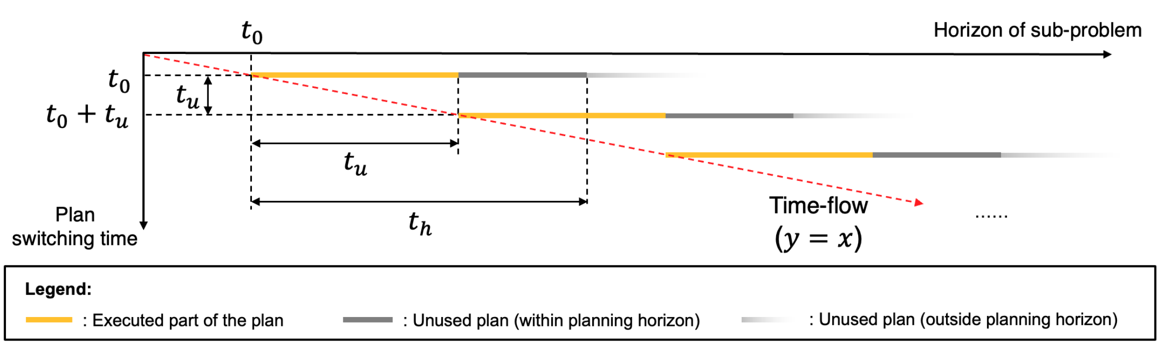


FIGURE 1: Schematic drawing of the rolling horizon approach

Within each planning horizon, we formulate the passenger assignment problem as an instance of the standard VRP problem, namely pick-up and delivery problem with time window (PDPTW). We integrate jsprit (*20*), an open-source VRP solver that uses ruin-and-recreate metaheuristic (*21*), with the MATSim DRT module to solve the problem within each planning horizon. Unlike the previous implemented integration of jsprit with MATSim in the context of freight transport (*22, 23*), where jsprit is called before the MATSim iterations, here jsprit runs alongside MATSim iterations, with two-way communication.

The constraints for the PDPTW are similar to those in the DRT optimizer for spontaneous trips. Since the trips are now pre-booked, we replace the term submission time ($t_{submission}$) with the earliest departure time ($t_{departure,earliest}$). With this, the pick-up time window is defined in Equation (2), where γ is set to 10 minutes to match the value of maximum waiting time in the spontaneous trips optimizer. The delivery time window is defined in Equation (3), where α and β are also set to the same values as in the spontaneous trips optimizer.

$$t_{pickup} \in [t_{departure,earliest}, t_{departure,earliest} + \gamma] \tag{2}$$

$$t_{delivery} \in [t_{departure,earliest}, t_{departure,earliest} + \alpha \cdot t_{direct} + \beta] \tag{3}$$

In order to make this setup work, passengers should pre-book their trips at least 30 minutes before the departure. In this study, we assume compulsory pre-booking, such that we can estimate the maximum potential benefits of pre-booking. It may also be interesting to explore the mixed case, where both pre-booked and spontaneous trips present. Yet, that is a complex problem and is, therefore, not included in this study. There are attempts to study the efficiency gain at different proportion of pre-booked trips. But most of them simply put two types of trips side by side, and the benefits of the pre-booking under such setup are not very promising. For example, in the study (*15*), the efficiency of the DRT system may even decrease as the proportion of the pre-booked trips increases. This suggests that an additional mechanism is necessary, in order to efficiently serve spontaneous trips and pre-booked trips at the same time. Developing such a mechanism can be a future research topic. Moreover, in our study, a trip only needs to be pre-booked 30 minutes before the departure, making pre-booking compulsory is therefore not a very strong assumption. This value also coincides with the minimum advance booking time in some of the commercial ride-hailing service providers, such as Uber[1].

EXPERIMENTS AND ANALYSIS

The DRT operation strategies with and without pre-booking are investigated in two different scenarios with varying demand densities, respectively. In this section, we first elaborate on the scenarios used for the present study. The simulation results are then analyzed and discussed.

The Kelheim DRT scenario

The Kelheim DRT scenario is generated based on the MATSim Open Kelheim scenario (*24*). This scenario represents the region of Kelheim county in Bavaria in Germany. Mobile phone trajectories and region specific survey data form the basis of the demand model (*25, 26*). Therefore, it includes synthetic agents, who (on a given day) travel into, out of or through the study area. This includes long-distance travelers. Overall, the transport model contains 42,455 agents, meaning that the model depicts the study area with a scale of 25 % (compared to the number of residents). Additionally, long-haul freight traffic is included in the model, which is done by an extraction of

[1] `https://help.uber.com/riders/article/scheduling-a-ride-in-advance?nodeId=63165ec1-0910-409e-972f-0b8d8df1a605`

relevant trips (domestic and international) from the German-wide freight traffic model by (*27*). All simulated vehicles are travelling on a supplied transport network, which is generated based on Open Street Map data (*28*). The MATSim Open Kelheim scenario contains the transport modes car (car as a driver), ride (car as a passenger), bike, walk and public transport (pt).

In the course of the KelRide project,[2] a conventional DRT service (KEXI) is added to the above transport model (*24*). Here, the term "conventional" refers to the service with human-driven vehicles. The service has been in operation since 2020. To date, there are 3 conventional minivans providing DRT service from 6:00 to 22:00, Monday to Saturday. As for the pricing, a single trip costs 2 or 3 Euro, depending on the origin and the destination of the trip. Real-world operational data since June 2020 has been partially made open-sourced by the KelRide project consortium, and there are currently around 160 rides per day.

Based on the real-world DRT system, a set of hypothetical DRT demands in the area are generated. First, a DRT service area is derived from the actual operational scheme of the KEXI service. The service area size is 24.1 km^2. Figure 2 shows the service area of the Kelheim Scenario on the map. We go through all the trips in the population file of the scenario and determine if the trip is feasible for DRT. A trip is feasible if both ends of the trip are within the service area. Furthermore, trips that are too short (i.e., below 500 meters) are also considered infeasible, as they are generally not suitable for the DRT service and may add unnecessary burden to the system. In the hypothetical demands model, we extend the service hours to cover the whole day (i.e., 24 hours) and provide door-to-door service.

The above-mentioned process results in 8513 potential DRT trips throughout the day in the 25% scenario. Note that the open Kelheim scenario is based on the 25% population model, therefore 25% is the maximum demand density we can achieve. When all the potential trips in the 25% scenario are served by the DRT system, it is equivalent to 25% of all the trips happening in the service area in the 100% scenario are served by the DRT system, which is already a relatively high mode share regarding real world applications. Therefore, it is reasonable to accept that as the upper bound in this experiment, and we can sample down the demands from there to generate a sequence of demands, representing various adoption rate of the DRT service. To avoid confusion, we will use the absolute adoption rate of the DRT system against the 100% scenario. For example, 5% demands refers to 5% of trips in the real-world population (i.e., 100% scenario) are served by the DRT system.

Starting from the 25% scenario, we generate a sequence of demands, where fewer users decide to use the DRT service, namely, 15%, 10%, 5%, 1% and 0.5%. As mentioned above, there are currently around 160 trips per day in the actual KEXI operation. This is similar to the number of trips in the 0.5% demands. In other words, in the current operation, around 0.5% of the trips within the service area are served by the DRT system (i.e., the KEXI service).

When down-sampling the DRT demands, we used 5 different random seeds for each case. This can reduce the impact of the randomness on the outcome of the DRT service. In addition, it also serves as a good representation of the day-to-day fluctuation of the travel demands.

The Manhattan scenario (Midtown + Lower Manhattan)

Manhattan is a popular scenario for the studies on the operation of DRT service. Many studies, such as (*7*), use Manhattan as the test bed for newly developed DRT operational strategies. Moreover,

[2] `https://kelride.com/`

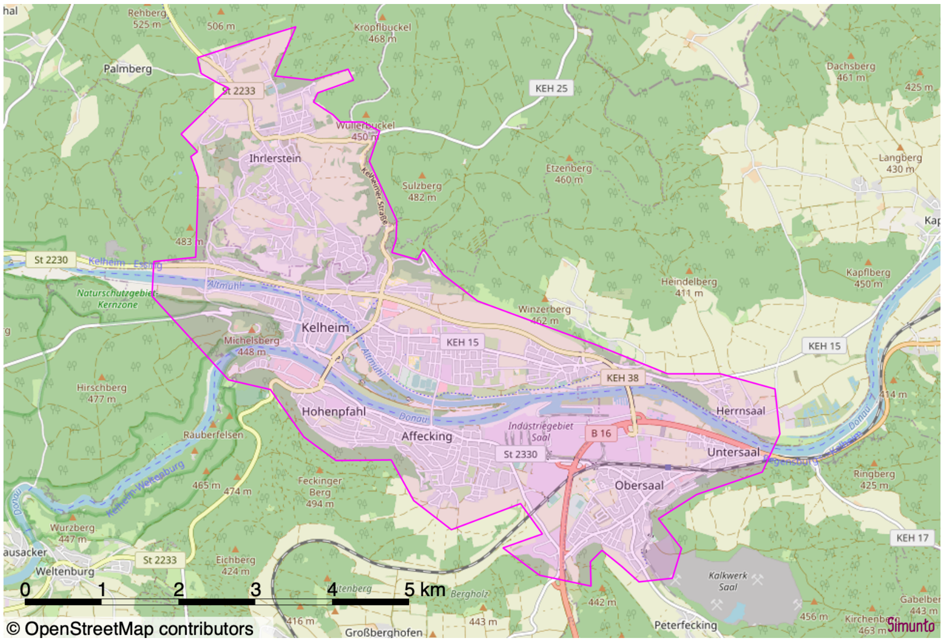


FIGURE 2: The service area of Kelheim Scenario on the map

the New York taxi data is openly available. Thus, in this study, we also perform experiments on the Manhattan scenario. As opposed to the Kelheim scenario, which models a small town in a rural region, the Manhattan scenario locates in the most densely populated area of a metropolis. With two different types of scenarios, we can also gain a deeper insight on the benefits of the pre-booking in different DRT systems.

In the MATSim DRT scenario library (*29*), there is a New York Manhattan scenario for DRT studies. The scenario is generated based on the actual operational data of the Yellow Taxi Cab data in Manhattan[3]. The data from the website is disaggregated onto the network generated from Open Street Map (*28*). This leads to 84,421 DRT requests within Manhattan throughout the day.

We have chosen the area consisting of Midtown and Lower Manhattan (Downtown) as the service area of our DRT system in this study. This is because the total surface area of that two districts (around 23 km^2) is similar to the size of service area in the Kelheim scenario (24.1 km^2), which makes it a suitable scenario to perform comparison. That two districts are also the busiest areas of the Manhattan island. Figure 3 illustrates the service area of the DRT system on the Map. After the service area is determined, the Manhattan scenario is generated by extracting feasible trips from the New York Manhattan scenario in the MATSim DRT scenario Library. The same extraction criteria are used as in the Kelheim scenario. In our Midtown and Lower Manhattan scenario (hereinafter referred to as Manhattan scenario), there are 38,113 DRT requests.

Then we perform the down-sampling of the trips. As suggested by previous studies, the density of the travel demands has an impact on the DRT service (*17*). To enable a better comparison between the Kelheim scenario and the Manhattan scenario, we sample down the Manhattan scenarios to achieve a same sequence of demand densities. In the 25% Kelheim scenario, the demand density is around 350 requests per kilometer square per day. To reach a similar demand

[3] `https://www.nyc.gov/site/tlc/about/tlc-trip-record-data.page`

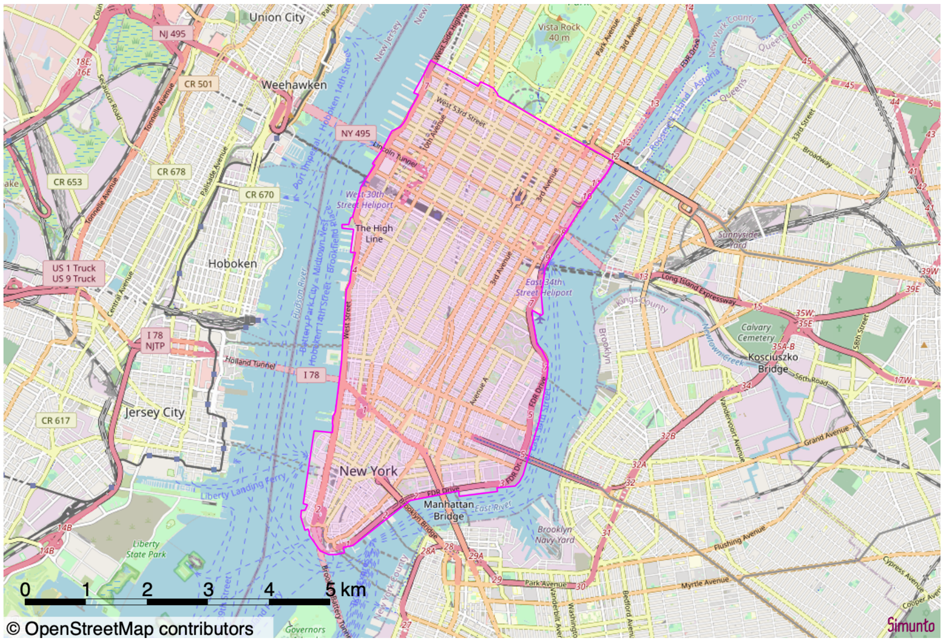


FIGURE 3: The service area of Manhattan Scenario on the map

density, the trips in Manhattan need to be down-sampled to 21.1%. Subsequently, a sequence of further down-sampled Manhattan scenarios, namely 12.7%, 8.5%, 4.2%, 0.85% and 0.42% are generated to match the sequence of demand densities in the Kelheim side. Same as in the Kelheim scenarios, 5 random seeds are used to generate each down-sampled case.

Evaluation criteria (KPIs)

In order to compare the performance, a systematic evaluation scheme needs to be defined. In the experiments, we will mainly focus on the key aspects that relate to the operational cost, the efficiency of the road usage and the service quality. The evaluation criteria used in the experiments are summarized below:

- **Required fleet size**: minimum required fleet size to serve all the requests without breaking the constraints (i.e., pick-up and drop-off time windows, vehicle capacity constraints). In this study, we use a fleet of minivans, each with 8 passenger seats, to serve the DRT requests. In order to identify the minimum required fleet, we gradually increase the fleet size, until a point where all the requests can be served (i.e., no rejection).
- **Total fleet distance**: the total driving distance of the fleet, including empty drive and passenger-carrying distance.
- **Distance efficiency**: the ratio between total customer direct network travel distance and the fleet distance. This value shows how efficient the DRT fleet is. A value greater than one indicates that the DRT system is more efficient, in terms of travel distance, compared to the hypothetical case that all the passengers drive their private cars to cover the same trips. This value can also serve as an indicator of the profitability of the service.
- **In-vehicle delay**: the average extra time a passenger spends onboard the vehicle due to ride-pooling (i.e., detours, stopping time to pick-up / drop-off other passengers). The value is normalized to the duration of the direct trip. If the passenger is directly driven

from the origin to destination, it results to 0%.
- **Vehicle level statistics**: average number of travel requests served per vehicle per day; average driving hours per vehicle per day; average driving distance per vehicle per day.
- **Cost**: the daily operational cost for the DRT system. More details for the cost calculation will be introduced in the cost calculation section below (Section 4.4). Furthermore, we also compare the average cost per request, which is another indicator of the profitability of the DRT system.

Cost calculation model

We build the cost model based on the cost analysis report from the German Federal Ministry for Digital and Transport (*30*). The vehicle costs mainly consist of three parts: the fixed costs, the operational costs and the personnel costs. The fixed costs are incurred by the fleet (e.g., capital investment, insurance, administrative) and are independent of the vehicle operations. In Germany, there are around 250 working days per year, and that value is used to calculate daily fixed costs from the annual values. The operational costs cover the energy (including energy infrastructures) and the maintenance costs. The more distance the fleet covers, the higher the operational costs will be. The personnel costs cover the salaries of the drivers. The costs are summarized in Table 1. The unit is in Euro.

Since the cost analysis report (*30*) is based on the value of money in year 2012, the values in the table are converted to the value of money in 2012, when necessary. Since we are comparing the cost across different scenarios, we will focus on the relative values between different scenarios. For the same reason, we also use the same cost structure to perform the cost analysis for the Manhattan scenario. The main goal here is therefore not to provide a price estimation for the Manhattan DRT system, rather we use the Manhattan scenario to show the impact of different road networks and population models on the DRT system.

Summary of experiment results

The outcome of the simulation runs for the Kelheim scenario are summarized in the Table 2 - 3 below. Note that the results, except for the 25% case, represent the average value of 5 simulation runs based on different input plans generated from different down-sampling seeds.

The results of the Manhattan scenario are summarized in the Table 4 - 5. In the Manhattan scenario, all the values in the table are the average value of 5 simulation runs based on different input plans generated from different down-sampling seeds.

As we are interested in the benefits of pre-booking, several plots are made to demonstrate the comparison between the DRT system with spontaneous trips and that with pre-booked trips, under different scenarios. Figure 4 shows the benefits of pre-booking in terms of savings in the total costs (Figure 4a) and the total fleet mileage (Figure 4b). Figure 5 illustrates the average number of requests a vehicle serves during one day under different setups. Figure 6 shows the average cost of each request under different setups.

Analysis of the results

From the experiment results, we can see that the benefits of the pre-booking can be realized in both Kelheim and Manhattan scenarios. The benefits can also be realized under different demand densities. When the demand density is greater than 200 departures per square kilometer, then the savings of total daily cost can reach 35% – 40%. This value is on par with the savings brought

TABLE 1: Cost calculation

	Values	Units / Remarks
	Vehicle Information	
Vehicle type	Mercedes Vito Tourer	Base Edition 114 CDI
Listed price [Euro]	35349	Euro
	Fixed costs	
Capital costs	1754	Euro per year
Administration costs	3176	Euro per year
Sum	4930	Euro per year
Daily fixed costs	19.72	Euro per working day
	Operational costs	
Deprecation and maintenance	15.01	Euro per 100 km
Energy costs	8.35	Euro per 100 km
Sum	23.36	Euro per 100 km
	Personnel costs	
Working hours per vehicle per day	24	Hour
Hourly salary cost	17.64	Euro per hour
Daily cost per vehicle	423.36	Euro per day

TABLE 2: Summary of the system-wide results in Kelheim Scenarios

Scenario	Number of trips	Demand density [per km^2 per day]	Required fleet size	Fleet distance [km]	Distance efficiency	Cost [Euro/day]
			Without pre-booking			
0.5%	171	7	3.4	1083	0.618	1749
1%	341	14	5.4	1872	0.708	2811
5%	1703	71	15.6	6240	1.053	8307
10%	3406	142	28.8	10719	1.222	15158
15%	5108	212	40	15000	1.310	21077
25%	8513	354	57	22707	1.442	30333
			With mandatory pre-booking			
0.5%	171	7	3	794	0.842	1507
1%	341	14	4	1362	0.973	2077
5%	1703	71	10.6	4454	1.475	5693
10%	3406	142	18	7558	1.733	9665
15%	5108	212	24.4	10363	1.897	13128
25%	8513	354	36	15690	2.088	19459

by the pre-booking in the school transport service from study (*14*). This indicates that the good performance of pre-booking can also be realized in a general demand pattern.

While the savings in the total costs are sensitive to the demand density, the savings in total fleet distance remain more stable under different demand densities (see Figure 4). Reductions of the total fleet distance have positive impact on the traffic and the environment. Therefore, enabling pre-booking in the DRT system also has positive social impact, regardless of the demand density.

Next, we will take a closer look at the impact of the demand density on the benefits of pre-

TABLE 3: Summary of performance analysis in Kelheim Scenarios

Scenario	Mean direct dist. [km]	Mean onboard delay	Mean cost per trip [Euro]	Vehicle level average daily values		
				Trips	Dist. [km]	Driving hours
Without pre-booking						
0.5%	3.91	40%	10.10	50.3	318.6	7.42
1%	3.89	64%	8.15	63.1	346.7	8.21
5%	3.86	119%	4.82	109.2	400.0	9.91
10%	3.85	137%	4.40	118.3	372.2	9.39
15%	3.85	146%	4.08	127.7	375.0	9.52
25%	3.85	156%	3.52	149.4	398.4	10.22
With mandatory pre-booking						
0.5%	3.91	114%	8.70	57.0	264.8	6.23
1%	3.89	136%	6.02	85.3	340.5	8.21
5%	3.86	157%	3.30	160.6	420.2	10.73
10%	3.85	163%	2.81	189.2	419.9	10.93
15%	3.85	165%	2.54	209.3	424.7	11.15
25%	3.85	165%	2.26	236.5	435.8	11.52

TABLE 4: Summary of the system-wide results in Manhattan Scenarios

Scenario	Number of trips	Demand density [per km^2 per day]	Required fleet size	Fleet distance [km]	Distance efficiency	Cost [Euro/day]
Without pre-booking						
0.42%	161	7	3.8	874	0.554	1879
0.85%	325	14	5.8	1477	0.661	2900
4.2%	1602	70	15.4	4914	0.984	7922
8.5%	3241	141	28.4	8618	1.133	14511
12.2%	4841	210	44	12052	1.213	22190
21.1%	8042	350	68.6	18275	1.334	34482
With mandatory pre-booking						
0.42%	161	7	2.6	624	0.776	1292
0.85%	325	14	4	1051	0.928	2007
4.2%	1602	70	10.8	3582	1.350	5586
8.5%	3241	141	18.4	6213	1.572	9542
12.2%	4841	210	25.6	8548	1.711	13254
21.1%	8042	350	39.6	12829	1.900	20415

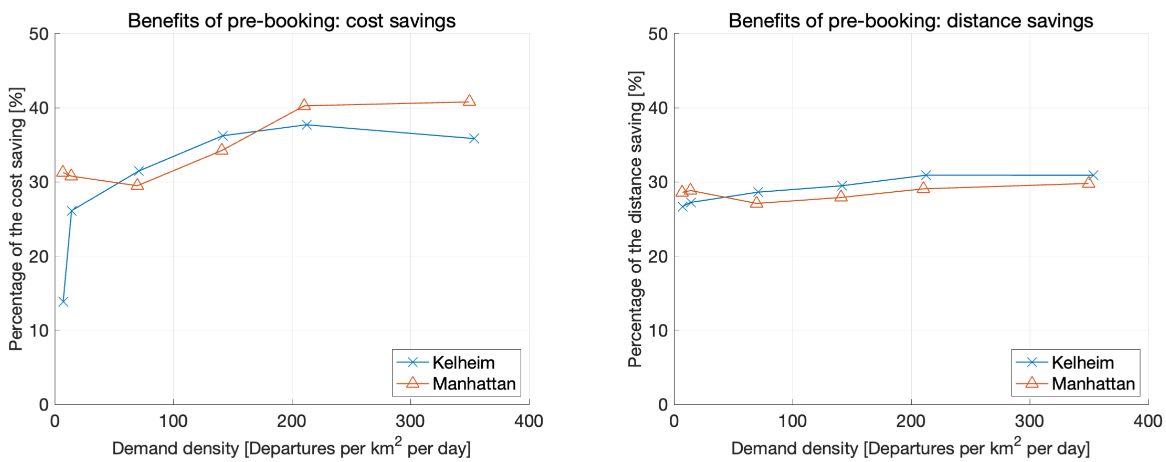
booking, as well as on the whole DRT system. The first thing we can notice is that as the demand density increases, the number of trips served by each vehicle per day also increases. Consequently, the average work load of each vehicle (i.e., driving hours and distance) also increases. This is the case both with and without pre-booking, and in both Kelheim and Manhattan scenario.

Another interesting fact is that the distance efficiency crosses the 1.0 value as the demand density increases in all the cases. Here, the value 1.0 means that the total distance covered by the DRT fleet is equal to the sum of the direct travel distance of each individual trip, if private cars are used. Therefore, as a rule of thumb, if the DRT trips are introduced to replace private car trips, some threshold value in the demand density needs to be reached in order to achieve a positive impact on the traffic and environment. The inclusion of pre-booking can effectively reduce this threshold value of the demand density.

A higher distance efficiency and a higher number of daily trips served by each vehicle also

TABLE 5: Summary of performance analysis in Manhattan Scenarios

Scenario	Mean direct dist. [km]	Mean onboard delay	Mean cost per trip [Euro]	Vehicle level average daily values		
				Trips	Dist. [km]	Driving hours
Without pre-booking						
0.42%	3.01	30%	11.67	42.4	230.0	6.54
0.85%	3.00	49%	8.92	56.0	254.6	7.26
4.2%	3.02	106%	4.95	104.0	319.1	9.21
8.5%	3.01	125%	4.48	114.1	303.5	8.80
12.2%	3.02	133%	4.58	110.0	273.9	7.96
21.1%	3.03	142%	4.29	117.2	266.4	7.75
With mandatory pre-booking						
0.42%	3.01	114%	8.02	61.9	240.0	6.81
0.85%	3.00	129%	6.18	81.3	262.9	7.57
4.2%	3.02	148%	3.49	148.3	331.6	9.66
8.5%	3.01	152%	2.94	176.1	337.7	9.87
12.2%	3.02	154%	2.74	189.1	333.9	9.77
21.1%	3.03	156%	2.54	203.1	324.0	9.49

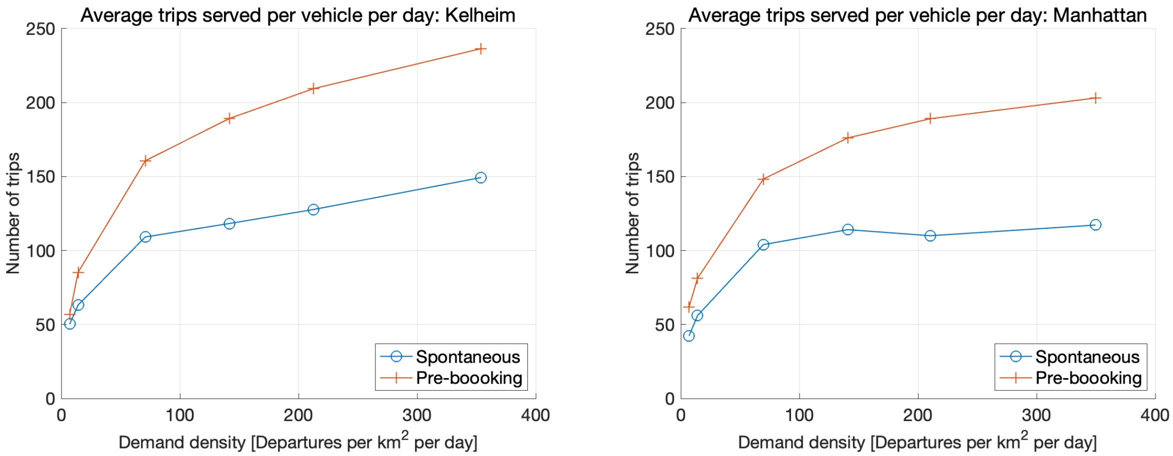


(a) Costs savings (b) Distance savings

FIGURE 4: Benefits of Pre-booking under different setups

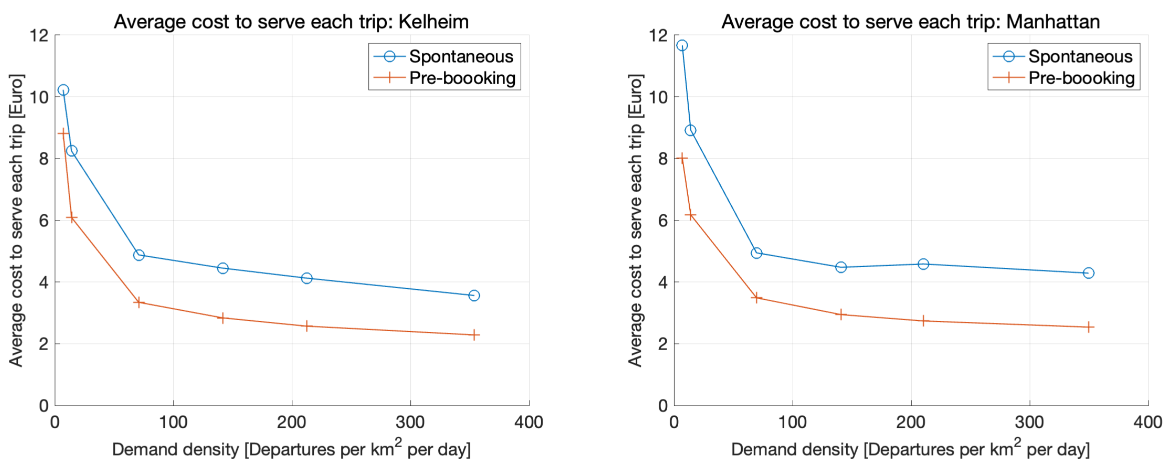
contribute to a lower average price per trip. With a higher demand density, the average cost to serve each passenger can be reduced. If the DRT operator desires to remain profitable, then the average fare collected from the trips needs to be greater than the average cost to serve each passenger. To make the fare attractive while keeping the operator making a profit (or at least not suffering from a major deficit), a certain amount of demand density is needed. When the demand density reaches a bottleneck, pre-booking can be enabled to further reduce the burden of the DRT operation and thus keep the fare more competitive.

As nothing is perfect, there are also drawbacks of pre-booking. On top of the potential inconvenience caused by the need of planning a trip some time in advance, passengers are also likely to spend more time on-board. This is because the DRT system will exploit every possible opportunity to fit in extra passengers into each vehicle. This will lead to longer detours and longer onboard delay. Nevertheless, passengers will still be able to arrive at their destination before the



(a) Kelheim scenario (b) Manhattan scenario

FIGURE 5: Average number of trips served per vehicle per day under differetn setups



(a) Kelheim scenario (b) Manhattan scenario

FIGURE 6: Average cost per trips under different setups

latest arrival time.

One of the highlights of this study is that we include two scenarios with different geographic characteristics in the road network and the population model. By looking at the scenarios side-by-side, we can acquire some extra observations. The network of the Manhattan scenario is denser and more regular than the Kelheim scenario (see Figure 7). Furthermore, there are also many one-way roads in the Manhattan scenario. If we compare the average cost per trip, we can realize that, given the same demand density, the trips in Kelheim are generally slightly cheaper to serve (except for one case), despite having a longer average direct distance. This suggests that the spatial-temporal distribution of the trips in Kelheim scenario is actually more favorable for ride-pooling than the Manhattan scenario. This could be explained by the fact that the number of points-of-interest is rather low in Kelheim, which is typical for a small town. This means that a higher share of requests can be pooled.

It needs to be pointed out that the precondition for this statement is the same demand density level. Apparently, as one of the busiest districts in the world, Manhattan has a much higher trip density than Kelheim. Even the number of taxi trips in Manhattan is higher than the number of all the trips in Kelheim (i.e., including all the modes of transport). That is to say, in the end, Manhattan still has a greater potential for DRT systems, because of its considerably higher potential demand density. But in order to realize that potential, the DRT system should also be operated at an adequately large scale. Therefore, for small or medium size operators, who possess relatively small fleets and can only serve a limited number of trips per day, the more favorable spatio-temporal distribution of demands, in terms of ride-pooling, in rural regions like Kelheim may not be a trivial matter.

(a) Kelheim Scenario (b) Manhattan scenario

FIGURE 7: Side-by-side view of the road networks of the two different scenarios

CONCLUSION AND OUTLOOK

The first and the most important conclusion based on our experiments and analysis is that the benefits of pre-booking can be realized in both investigated scenarios. With an adequately high demand density, incorporating pre-booking into the DRT system will effectively reduce the total costs to maintain and operate the system. The savings are on a similar level as suggested by a previous study on the special case of school transport (*14*). In addition to the cost savings, pre-booking also has a positive impact on the system and its externalities. The travel distance of the whole fleet can be reduced by more than 25%. This also applies to the cases where demand density is low. Such reduction will not only relieve part of the burden on the road network, but also reduce the energy consumption.

A side outcome from the study is that the demand density also plays an important role in the efficiency of the DRT system. In order to make the DRT system more efficient than private cars, in terms of total driving distance, a certain demand density needs to be reached. When the demand density is too low, then the DRT system may produce a greater overall mileage than private cars. If this happens, pre-booking can be used to mitigate the negative impact.

Another interesting remark based on the comparison between the Kelheim scenario and the Manhattan scenario is that rural scenarios may be even more lucrative for small or medium size DRT operators. This is because, given the same demand density, the average cost to serve a trip in the Kelheim scenario is actually cheaper than that in the Manhattan scenario. Note that this is not because of the different cost parameters, as we use the same cost calculation model for both cases. Therefore, when a DRT system can only serve a limited number of trips, which corresponds to a limited demand density, then the popular Manhattan scenario may not be the best choice. On the contrary, it may be easier to make profits in small towns like Kelheim. For transport planners, the same argument may also apply. When a DRT system of certain size is considered to be introduced to service, the rural area may be a better choice than the city center, as long as there are sufficient demands.

One interesting direction for future investigation is the optimization of shifts of drivers in the DRT system. Currently, we assume that a driver needs to be in the vehicle during the whole day. This leads to very high personnel costs per day, which contribute to around 80% of the total daily costs. This value is actually in line with the actual situation in taxi operation, where the salary of the driver contributes to a very large part of the total costs (*31*). In the results of this study (i.e., in Table 3 and 5), we can see that the average driving time of a vehicle is less than 50% of the total service hours. This means, during the non-peak hours, parts of the fleet may temporarily exit the service, which will reduce the personnel costs. Alternatively, vehicles could also be used to transport goods like parcels during off-peak hours, as suggested by (*32*).

Another future research direction is to include autonomous vehicles into the analysis. The main goal of the KelRide project is to complement the conventional KEXI service with autonomous vehicles, which can provide a weatherproof and reliable transport service. The autonomous segment operates in parallel to the conventional service, but has a different service area and pricing scheme. Currently, the autonomous vehicles provide free DRT service within a small service area (in the old town and its surrounding area). Speed limits of 20 km/h are currently imposed to assure the safety. There are plans to extend the service area and to increase the speed limit (*24*). Including the operation of autonomous vehicles under different setups, such as various service areas and different speed limits, into the analysis is an interesting future research topic.

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