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Potential Benefits of Demand Responsive Transport in Rural Areas: A Simulation Study in Lolland, Denmark

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Abstract: In rural areas with low demand, demand responsive transport (DRT) can provide an alternative to the regular public transport bus lines, which are expensive to operate in such conditions. With simulation, we explore the potential effects of introducing a DRT service that replaces existing bus lines in Lolland municipality in Denmark, assuming that the existing demand remains unchanged. We set up the DRT service in such a way that its service quality (in terms of waiting time and in-vehicle time) is comparable to the replaced buses. The results show that a DRT service can be more cost efficient than regular buses and can produce significantly less CO_2 emissions when the demand level is low. Additionally, we analyse the demand density at which regular buses become more cost efficient and explore how the target service quality of a DRT service can affect operational characteristics. Overall, we argue that DRT could be a more sustainable mode of public transport in low demand areas.

Keywords: demand-responsive transport; microsimulation; operational costs; emissions

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1. Introduction

Rural areas often suffer from poor public transport (PT) service quality as the costs of sustaining a good service frequency and area coverage become high due to the low demand density. Demand responsive transport (DRT) is one of the proposed solutions to provide a cost-effective PT service [1]. However, research shows that such expectations are often not met: many of the existing DRT attempts were not financially sustainable [2,3]. The environmental benefits of PT (compared to private cars) are well known [4]; in rural areas, DRT services have the potential to reduce CO_2 emissions (compared to buses) [5]. Additionally, DRT systems have been historically used as social service, for example, for people with disabilities, and social trips are seen as a strong niche for DRT services [1,6]. Altogether, DRT has the potential to improve the environmental and social sides of PT; however, the economic effects are less certain. In this study, based on real-world data, we examine a DRT service in a rural area mainly from economic and environmental perspectives.

DRT is a flexible transport mode in which travellers explicitly request a ride instead of relying on a schedule. A DRT service can minimise vehicles running empty when there is no demand and optimise the routes, thereby saving the time and distance travelled. The service can be organised in a variety of ways, ranging from fixed-lines running by request to free-floating fleets of vehicles serving the requests in a taxi-like manner [1,7]. The DRT concept was introduced in the 1960s, when travellers were required to call an operator well in advance. Nowadays, DRT schemes are still extensively used as special transport services geared towards increasing accessibility for traveller groups with limited mobility [6]. The development of information and communication technologies made it possible to route trips dynamically and to provide almost real-time responses to requests. Consequently, DRT has been re-evaluated as a transport option for the general population, and there is a growing trend to open DRT to the general public [8,9].

There is a variety of expectations (and potential purposes) associated with the introduction of DRT services. Some focus on providing universal access in cities, some see it as a replacement for bus lines with low ridership in rural areas, and others see DRT as a means for solving first and last-mile problems. From the point of view of public transport authorities, the goals for public transport lie in increasing patronage, reducing CO_2 emissions, improving cost efficiency, and increasing accessibility for people with disabilities [10,11]. One of the objectives of public transport actors (in the example of Sweden) is to "ensure that regional public transport is accessible for all groups of passengers" [10]. In practice, much effort is dedicated to providing a transport service to the general population, but relatively little attention is given to population groups with disadvantages (either economical, physical, or mental) [12,13]. DRT, unlike regular buses, has the potential to be utilised for both the general public and special groups [14]. Moreover, we argue that DRT is inherently better suited to provide the service required for special groups because it can provide a flexible level of service corresponding to the needs of travellers [15]. Door-to-door type of trips could be perceived as secure (when it is dark outside), which could motivate parents to allow their children to travel alone to their activities [16,17]. Moreover, the reduced walking time of door-to-door trips could be a factor that allows more elderly people to use PT [17,18].

The main purpose of this article is to explore how efficient DRT is compared to regular PT. Therefore, we explored a specific area in the municipality of Lolland in Denmark, but the results can be generalised to other territories with a similar demand distribution pattern. In our setup of the service, DRT can be a stand-alone service, carrying travellers within the service zone. In addition, DRT can serve first or last mile trips that connect travellers to regular PT for long-distance trips. We performed a single day microsimulation and obtained operational performance indicators (vehicle kilometres travelled (VKT), number of vehicles, and operational costs); traveller experience from the services (trip duration and deviation from the desired departure), and environmental impact (CO_2 emission and energy consumption). We compared the efficiency of DRT to the efficiency of the existing regular bus network in the area. To enable a fair comparison, we assumed the same demand for PT and DRT, and configured DRT to provide similar service quality to PT. Our results show that DRT can be more cost efficient and can produce less CO_2 emissions than regular PT. In further experiments, we analysed how well DRT can adapt its operations to the different target levels of the trip quality and found that relaxation of trip-level service quality provides rather limited opportunities for improving the performance. The main contributions of this article lie in the following points:

- The quantitative evaluation of the DRT service design (integrating DRT with regular PT) that has not been well studied by using simulation.
- The quantitative evaluation of the environmental impact of DRT and comparison of it to PT.
- The quantitative evaluation of how service quality impacts the performance of DRT.

This study presents some novel results. We show that DRT is capable of providing the target service quality within the service area, but changes in the PT supply of the neighbouring areas are required to satisfy the target service quality level for the long-distance trips. With the help of the joint analysis of cost-efficiency and environmental impact, we produce a finding that, to our knowledge, has not yet been published: the demand density at which DRT and PT have the same cost efficiency is lower than the demand density at which the services have the same environmental impact.

The rest of the article is organised as follows: Section 2 presents a short review of research in the area of DRT; Section 3 explains the simulation methods and models; Section 4 describes the study area and input data; the simulation scenarios and their results are presented in Section 5; the results and limitations of the study are further discussed in Section 6, and finally, Section 7 summarises and concludes the article.

2. Related Work

Autonomous mobility on demand (AMOD) is a concept that is very similar to DRT. The major difference is that AMOD vehicles have no drivers and operate autonomously, but the service follows the same main principle as DRT: serving trips based on explicit requests. In this overview, we consider AMOD, when ride-sharing is part of the service, as a DRT concept.

One popular research direction has been to study how low-capacity door-to-door DRT vehicles can replace private cars in urban environments. One study shows that in urban areas, a DRT vehicle without ride-sharing can replace up to nine private cars [19]. A study in Zurich and surrounding suburban areas shows that a stop-to-stop DRT service type can replace all private car trips, requiring a fleet size of only 3.7% of the number of private cars that are replaced. Additionally, DRT vehicles produce similar or up to 10% lower VKT. DRT (in a form of shared taxi) may improve waiting times for travellers and provide cheaper service than traditional taxis [20]. Dandl et al. [21] simulated DRT shuttles in a suburban area for employees of a large company. Their simulations show that DRT, in this scenario, can achieve a high degree of ride-share and fast travel times, which are only slightly worse than private cars. Additionally, such shuttles may reduce the total CO_2 emissions by up to 15–26%.

Other researchers explore the effects of replacing regular PT with DRT. In a small-scale simulation experiment comparing DRT and PT under the same conditions (demand and number of vehicles), DRT could serve more travellers than PT with the selected level of the quality of service (QoS) [22]. In contrast, Leich and Bischoff [23] estimate that replacing PT with autonomous DRT in a suburban area results in slightly worse travel times as well as in higher costs. A simulation study of light rail replacement by DRT reveals the trade-offs between the size of the DRT fleet and the resulting QoS and shows that almost four times more DRT vehicles are required [24]. In a simulation replacing all PT in a city with DRT, about two-thirds of the PT users switched to walking or cycling, while DRT attracted almost half of the car users and one-third of the bicycle users [19]. Altogether, DRT attracted slightly more trips than PT, significantly reducing car share. Oke et al. [25] show that DRT could absorb not only the PT demand but also some portion of car and carpool demand.

Rather than replacing regular PT, DRT can function as an additional travel mode complementing existing services. According to Segui-Gasco et al. [26], different configurations of DRT (e.g., cheap and accessible DRT for the general public, a shared taxi service with higher costs and smaller vehicles, or a balanced option in between) affect how many travellers shift their travel modes from buses and private cars to DRT. Their study reports, on the one hand, reduced trip time compared to buses and high mode shift from bus to DRT and, on the other hand, an increase of total VKT for all the studied DRT configurations.

DRT can also be seen as an expansion of regular PT. A common approach is to use DRT as a first-mile connector. Introducing such a service in suburban areas has the potential to attract up to 43% of car users [27]. The integration of DRT into PT increases the total share of PT compared to the case of DRT as a competing or replacement service [25,28].

Many researchers have compared the performance of regular PT and DRT using an analytical approach. One common approach is to define a rectangular service area where DRT serves either the first or the last mile connecting the area to a PT hub in the border region [29,30]. Another approach is where DRT operates between two terminals in a corridor fashion [31–34]. In both approaches, DRT travels with a certain headway on a central path, deviating from it to pick up new travellers at their origin points. An analysis of generalised costs (comprising operational costs and user costs) reveals that there is an optimal headway for DRT [35]. The optimal costs depend on the demand density, and most of the studies agree that regular PT is more efficient at high-demand levels (typically more than 10–50 trips/km^2/h), whereas flexible services are more efficient with lower demand [29–34].

DRT is a flexible service where service quality can vary significantly. To our knowledge, the importance of this aspect on operational characteristics is not commonly studied. Service quality is often set to a specific level, and a particular scenario is studied (see e.g., [20,22,36]). In many studies, DRT service is configured to provide as good a QoS as possible, and the resulting service quality is the output of the simulation [19,25,28,37]. Fewer researchers investigate how different QoS levels affect the system performance [26,27,38]. Some researchers have proposed simulation frameworks to find an equilibrium of supply and demand [39] or to optimise service parameters [40].

The role of PT in reducing CO_2 emissions from transport because of shared use is widely accepted. Most research focuses on the development of cleaner engines for vehicles and on incentives for the mode switch from private cars to PT (e.g., [41]). The optimisation of PT itself for reducing emissions has also become a topic of discussion [42–45]. Studies show that DRT systems could help with emission reduction, especially in the areas with low demand [5,46]. More literature on emissions can be found in the related concept of shared autonomous vehicles (e.g., [47,48]). However, such systems are typically assumed to work in a taxi-like manner without ride-sharing. The impact of DRT systems on emissions is rarely analysed. Specifically, there is a lack of studies investigating emissions caused by different DRT designs.

DRT services can be configured very differently, and the effectiveness of different DRT designs needs to be evaluated. Numerous research efforts are dedicated to the analysis of stand-alone DRT systems, whereas the integration of DRT into PT is relatively new and requires additional studies. The integration is mostly studied with analytical methods that use rather crude assumptions on the operational characteristics and demand. However, the integration is rarely studied with simulation, which allows for more flexible analyses of potential scenarios. With the simulation study we present in this article, first, we add to the understanding of the particular understudied service design that combines the replacement of buses with DRT as well as the integration of DRT into the PT system. Second, we add to the under-researched aspect of DRT, CO_2 emissions. Third, we analyse how different levels of service quality affect system performance.

3. Methods

To investigate the efficiency of DRT, we conducted a simulation study. For this study, we made use of an individual-based model in which travellers dynamically request DRT trips, which triggers a re-optimisation of vehicle schedules for the DRT service.

It is possible to approximate the results of the service work (QoS for travellers, VKT, and operational costs) on a macro level (e.g., [49]), but this requires a number of coarse assumptions on how both service and demand operate. Microsimulation is an alternative approach allowing for a more precise estimation of vehicle costs and QoS for travellers. Such precision has its price in the form of high computational requirements, which requires researchers to utilise heuristics to solve vehicle routing problems.

We argue that for a DRT service that positions itself as individualised PT, it is important to understand and adapt to customer needs (see further discussion in [15]). Additionally, for a service type that has historically shown a large degree of failed trials [2], it is important to fine-tune the service configuration for the specific niche in the area. The major contribution of this study is the comparison of operational costs and CO_2 emissions of DRT and fixed bus services. To achieve this, we set up the DRT service in a way that provides travellers with a similar QoS as with fixed buses. To ensure that the QoS is similar, we resorted to microsimulation as the main method. Microsimulation allows accounting for the large headways between bus departures, which is particularly important for the trips with a transfer between DRT and regular PT.

We built a simulator based on open-source tools. We used the multi-modal travel planner OpenTripPlanner (OTP, opentripplanner.org, accessed on 1 March 2022) to schedule trips with PT and used jsprit (jsprit.github.io, accessed on 1 March 2022), a library for solving vehicle routing problems (VRP), to route DRT vehicles. Additionally, we utilised

OpenSourceRoutingMachine (OSRM, project-osrm.org, accessed on 1 March 2022) to prepare data for the VRP solver. We connected these tools to a custom event-driven simulator (github.com/serdyt/DRTsim/tree/lolland_dep_tw, accessed on 1 March 2022) that implements traveller and service models and orchestrates the rest of the tools. More details can be found in [15].

In the rest of this section, we describe the four main sub-models in our study: a traveller model dealing with the expected QoS for travellers (in Section 3.1), a service model optimising vehicle routes (in Section 3.2), and cost and CO_2 emission models, which are applied in the post-processing of the simulation (in Sections 3.3 and 3.4).

3.1. Traveller Model

In the simulation experiments presented in this article, we simulated only the current PT travellers of the study area. Travellers behave according to the fixed behaviour of plan, choose, and execute. We assumed that travellers actively plan their trips and perform a mode choice according to available alternatives (disregarding previous experiences with a service that the travellers could potentially have).

In our simulation, travellers plan their trips one hour prior to the expected departure time. This helped us preserve the dynamic nature of the inflow of trip requests to the DRT system. The DRT service and our simulation have no problem processing real-time trip requests (pick up as soon as possible), but this introduces more strict QoS requirements to DRT (less flexibility to route DRT vehicles). We assumed that in the case of fixed PT (especially in rural areas with long headways), travellers have to plan their trips in advance; thus, we found it fair to add this restriction explicitly to DRT.

When choosing between available travel alternatives, travellers use a simple rule-based model capturing only two of the main aspects of the QoS: trip time and deviation from the desired departure time. While more sophisticated (and realistic) mode choice models have been developed for DRT (e.g., [50]), our simple model allowed us to focus on QoS levels and specify a fixed level of demand, ignoring problems of demand elasticity and mode switch.

The mode choice model is depicted in Figure 1. Given the desired departure time, a traveller accepts a DRT trip that starts within the time window and lasts no longer than a direct trip time by car multiplied by a direct time multiplier (DTM). The time window of departure is constructed to be symmetric around desired departure times. The model is applied for DRT trips, and the values for parameters are extracted from the PT trip alternative. In the main part of this study, the time window is the same for all travellers and equals one hour. The size of the time window is based on the headway between bus departures on most of the regular bus lines in the area. The maximum trip duration is individual and equals to the duration of the fastest PT trip the person could get that starts within the time window. In other words, a DRT trip is allowed to be as long as an alternative PT trip (before PT removal). This way, we set up the quality of service for DRT to be close to PT.

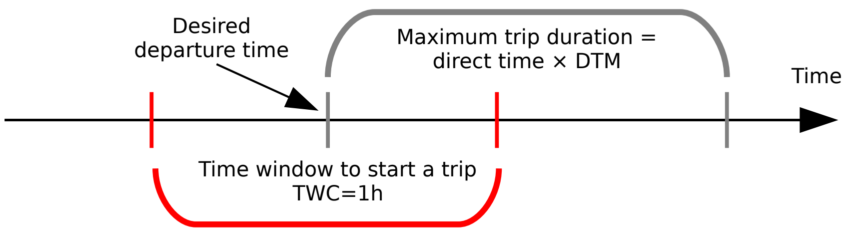


Figure 1. Illustration of the time window model for trip acceptance.

3.2. Service Model

The DRT service in our model knows exactly the model for trip acceptance of travellers. The service has a hard constraint to provide a trip that satisfies the traveller's restriction.

If no such trip could be scheduled, the trip is considered unrouteable, and no DRT alternative is provided to the traveller.

During the simulation, trip requests arrive sequentially to the system. Each time a new request arrives, the schedule of already scheduled vehicles can be modified. We utilised a simple insertion heuristic to reduce the computational load. The algorithm preserves the order of pick-up and deliveries of already scheduled travellers when a new trip should be inserted. The timing of the trips can change, but the VRP solver ensures that the time window of departure and maximum trip duration constraints of all trips in the schedule are satisfied. The vehicle routing algorithm optimises a generalised cost consisting of driving time for vehicles, a penalty for activating a new vehicle, and a penalty for not serving a request. The penalty for not serving a request is much larger than the penalty for activating a new vehicle, which in turn is much larger than the driving cost. This way, the algorithm prioritises the activation of as few vehicles as needed to serve all the trip requests.

3.3. Operational Costs

To estimate the cost of both bus and DRT services, we used three cost models obtained from different sources. One cost model is based on contracts procured by the Swedish public transport agency Västtrafik. Another is based on the costs of special services provided by the Swedish public transport agency Skånetrafiken. The third cost model is adapted from Estrada et al. [51], where vehicle costs for large buses were obtained based on data of a bus operator in Barcelona, Spain. Table 1 shows the models.

Table 1. Cost models.

	Model 1	**Model 2**	**Model 3**		
	Temporal Cost, EUR/h	**Distance Cost, EUR/km**	**Vehicle Cost, EUR/day**	**Temporal Cost, EUR/h**	**Distance Cost, EUR/km**
bus	112.9	—	57.1	52.2	1.5
DRT	34.5	1.95	9.4	43.3	0.3

The first model is based on the contract cost of a bus on rural lines. All costs are recalculated from SEK to EUR according to the average conversion ratio of 0.094 in the year 2020. The average cost is EUR 112.9 per hour which comprises all operational costs, including driver salary, fuel costs, maintenance costs, and profit margin. In other words, these are the costs of having a bus line for the regional budget (covered with public funds and travellers' fees). We extracted the operating time for buses from the timetables for buses in our study area. The buses that operate only at the morning and afternoon peak time were considered idle at the depot in the middle of the day and had zero cost at that time.

Based on similar data on PT contracts for the special service vehicles, we estimated the average cost of operation to be EUR 34.5 per hour. We also assumed the costs of DRT vehicles to be similar to the costs of special service vehicles, as they are typically minibuses, which corresponds to the type of DRT vehicles used in this article. For the calculation of the costs, we assumed that all DRT vehicles (the maximum number of vehicles utilised) are available between 5 a.m. and 8 p.m. The full cost is applied for the time when a vehicle is riding. When on-demand vehicles are on hold in a depot, a cost coefficient of 0.7 is applied.

The second cost model for DRT derives from the dataset on the cost of 89,000 special transport trips that happened in November 2019 and November 2020 in the Scania region. We used the cost of trips performed by special transport vehicles (non-light motor vehicles) as an approximation of the cost for DRT. This model estimates the overall costs based on the cost of EUR 1.95 per kilometre.

The third cost model for buses is adapted from [51]. We assumed an average lifetime of 12 years for the vehicles and approximated the costs for eight-seat vehicles, assuming a second-order polynomial trend. The total cost in this model is the sum of three components:

fixed cost of owning a vehicle, temporal cost of riding a vehicle (includes the cost for drivers), and distance-based costs.

3.4. Emission Model

To compare the environmental impact of regular PT and DRT, we utilised The Handbook of Emission Factors for Road Transport (HBEFA) tool [52], the part that is openly available online (hbefa.net, accessed on 1 March 2022). The CO_2 emissions depend on a large variety of factors (engine type, fuel type, vehicle mass, road gradient, and driving pattern). The HBEFA tool provides emission factors for different countries, based on data about vehicle type and road conditions received from local transport administrations. We took the emission factors for Sweden. The HBEFA does not have a dedicated vehicle group for regional buses or minibuses. We assumed that the emission factor for regional buses is a mean value between city buses and coach buses (long-distance buses) as the vehicle type and driving pattern of regional buses is somewhat in-between. For DRT, we used the category of light-duty vehicles, which includes minivans and minibuses. The emission factors are shown in Table 2 and are limited to CO_2 emission factors for diesel-powered vehicles and energy consumption for electric vehicles. In the analysis of our experiments, we assume fleets of either 100% combustion engine vehicles or 100% electric vehicles.

Table 2. Emission models.

	Diesel Engine CO_2 Emissions, g/km	**Electric Engine MJ/km**
bus	807	4.27
DRT	221	0.88

4. Area, Data, and Data Processing

We studied the western part of the municipality of Lolland that is situated on the western part of the island Lolland in Denmark (see Figure 2a). The municipality had approximately 40,500 inhabitants in the year 2021 (da.wikipedia.org/wiki/Lolland_Kommune, accessed on 1 March 2022). It has a well-developed public transport network with over 20 local bus lines, and a railroad connects it with the eastern islands Falster and Zealand.

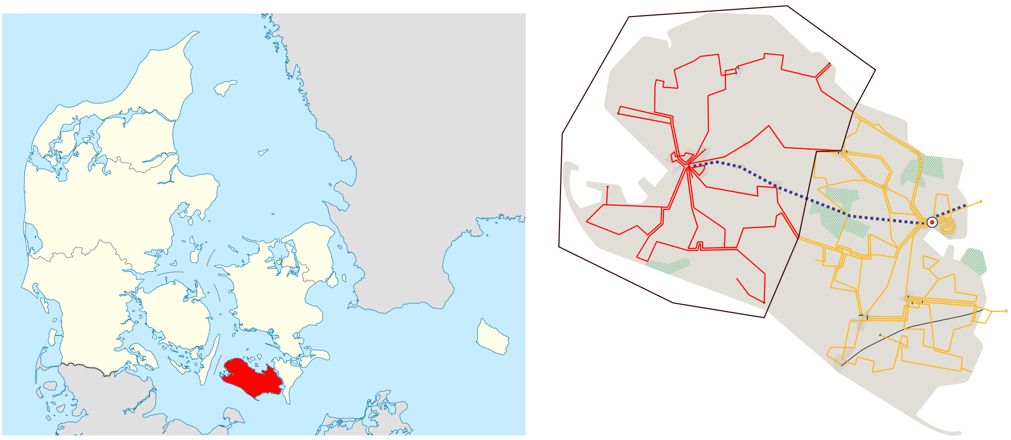
The interest in DRT within the region is raised by the PT actors, including the local PT operator Movia, which provided the main dataset for the study. We consider the target area of Lolland representative of a rural Danish area. Additionally, the location of the area on a peninsula is convenient for simulation and analysis as the number of options for cross-border trips is limited.

The study area is highlighted in Figure 2b by the black border, and it comprises about half of the Lolland municipality. We selected this area to reduce the computational load for simulation (by limiting the number of simulated trips) and to reduce the amount of data for manual processing. The red lines depict the bus lines that were replaced by DRT, while the yellow lines are the untouched bus lines. Note that four bus lines are crossing the border of the study area. Those lines were partially disabled when replaced by DRT.

Input Data and Data Processing

In this study, we modelled only the existing public transport users. The travel dataset is provided by the PT operator in the region Movia (moviatrafik.dk, accessed on 1 March 2022) and comprises an origin–destination (OD) matrix of PT trips having their origin or destination within Lolland municipality. The trips start and finish on PT stops (i.e., the access and egress part of the trips is not included). The data is from the pre-pandemic situation of November 2019. The OD matrix is computed by Movia and is mostly based on ticketing data. The popular Danish travel card Rejsekort requires travellers to check-in and out at their origin and destination, which makes the estimation of travel flows very precise. However, in some cases, mostly on small bus lines, the only available data are the recordings of bus drivers. Due to the low precision, we have excluded such bus lines from the simulation and subsequent analysis when comparing scenarios with and without bus lines. This concerns lines 771, 772, 773, 774, 791, and 792. According to the dataset, these lines serve around 20 travellers a day at 29 departures. This data does not allow us to realistically estimate the replacement of these lines with DRT, although such lines seem well suited for the replacement.

The input dataset includes an average number of trips between the pairs of bus stops in one-hour time bins. To generate the demand for a one-day simulation, we sampled 4525 trips, which is the expected value of the total number of trips. The probability of an OD pair and time bin to a trip is proportional to the flow size between the corresponding stops within the specific time bin.



(**a**) (**b**)

Figure 2. (**a**) The location of Lolland island (image obtained from https://commons.wikimedia.org (accessed on 1 March 2022) under Creative Commons Attribution 3.0 Unported license https://creativecommons.org/licenses/by/3.0/ (accessed on 1 March 2022)). (**b**) The study area (black border) within Lolland municipality and the bus lines (red) replaced by DRT.

In the next step, we generated the desired departure time for a person (with a precision of one second) within the time bin according to the extrapolated distribution of trip departure shown in Figure 3a. This allowed us to compare between waiting times for different services. Setting the desired departure time to the beginning of the respective hour could give an unrealistic advantage to DRT service. A sampled time distribution is shown in Figure 3b.

Figure 3c shows the OD matrix for the time bin between 7 a.m. and 8 a.m. Each blue line represents an origin–destination pair, and the weight of the lines is proportional to the number of trips. The main attraction points are the main towns: Nakskov, Maribo, Rødby, Horslunde, and Nykøbing Falster—the largest city of the neighbouring municipality. The prevalence of the few major OD pairs is also seen in Figure 3d, which shows the distribution of direct trip distances in the input dataset. The peak at the 10–15 km bin corresponds to the distance from Nakskov to a big portion of the local villages; the peak at 25–30 km bin corresponds to the trips Nakskov–Maribo; the peak at 50–55 km bin corresponds to the trips Nakskov–Nykøbing Falster.

The spatial trip pattern within the study area can be described as radial, where most of the trips are performed to or from Nakskov. These trips can be performed by DRT directly. We use the term *direct trips* for the trips within the study area and term *long-distance trips* to highlight the trips crossing the border of the study area and requiring a transfer between DRT and PT. A large proportion of long-distance trips is captured by the rail line and is not affected by the simulated switch of buses to DRT. Other long-distance trips require a transfer from DRT to PT.

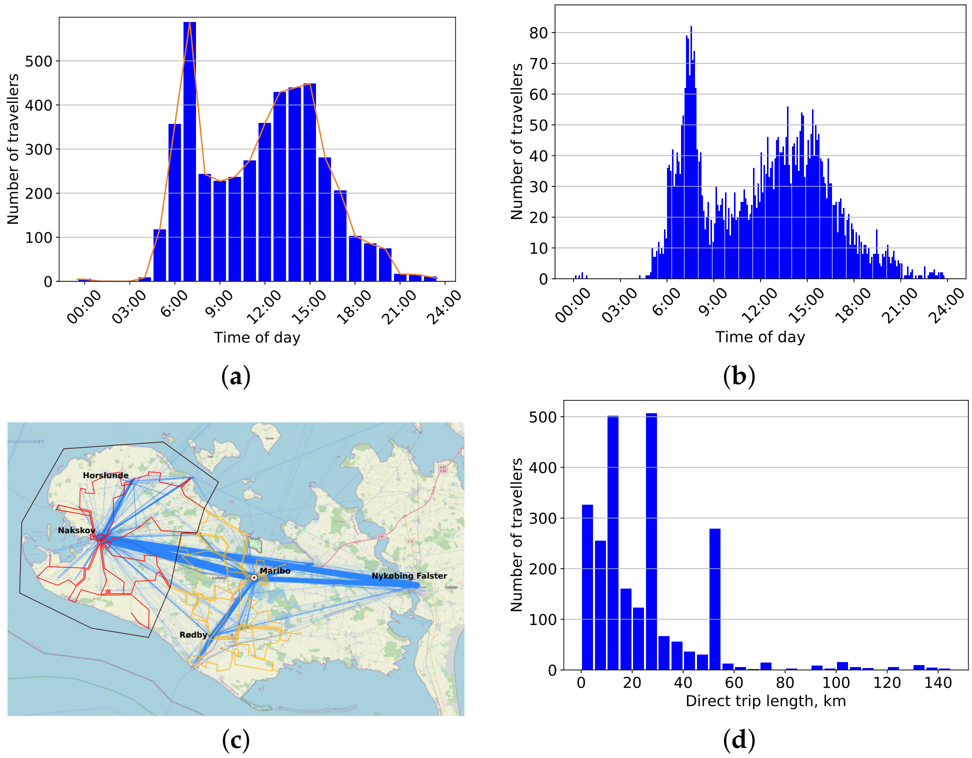


Figure 3. (**a**) Distribution of trips over time in the input dataset (blue bars) and linear interpolation of them (yellow line). (**b**) A sampled desired departure time used in the simulation. (**c**) The spatial distribution of trips for time bin 07:00 (background image obtained from OpenStreetMap, licensed under the Open Database License https://opendatacommons.org/licenses/odbl/ (accessed on 1 March 2022)). (**d**) The distribution of trip distances.

We obtained public transport timetables for November 2019, in the form of General Transit Feed Specification (GTFS, developers.google.com/transit/gtfs, accessed on 1 March 2022) files, through Movia. The road network was obtained from OpenStreetMaps (openstreetmap.org, accessed on 1 March 2022). The route planner excluded the aforementioned PT lines with unavailable data. When lines need to be removed partially, the trip planner excluded stops related to the part of the line that needs to be removed. This way, the trip planner can still route a trip with those bus lines, but only the part of the route where stops are available. We did not alter the timetables of the partially removed bus lines.

5. Simulation Scenarios and Results

This section describes the scenarios of simulation experiments and their results. In all the scenarios, we removed all the fixed bus lines from the study area and replaced them with a free-floating DRT fleet consisting of eight-seat minibuses. All local lines have been removed completely, and the lines passing through the borders of the study area were removed partially (namely bus lines 725, 780, 717, and 716). We allocated specific bus stops—namely, the closest bus stops to the study area border—as transfer zones between DRT and the partially removed bus lines, while any railway station was a valid transfer point. We examined operational characteristics (VKT, number of vehicles, operational cost, and emissions) and traveller experience (detour and deviation from the desired departure time) for buses and DRT.

We simulated three scenarios. In all the scenarios, we assumed that the demand for DRT is the same as the demand for buses. In the baseline scenario, we analysed in depth how the existing demand is served by either DRT or PT. In the second scenario, we adjusted the demand level between 50% and 150% of the baseline demand and analysed how the main performance indicators depend on the demand level. In the third scenario, we looked only at DRT and adjusted the parameters of the traveller model to see whether DRT can handle trips with a very high QoS level and how much can be gained from relaxing QoS.

To account for the day-to-day variations, we generated five input demand files and provided the average results from five simulation runs. Simulations with different demand samples produced a very close result, which can be seen in the results in Section 5.1. The DRT service had access to as many vehicles as needed, but we only considered actually utilised vehicles in the calculation of costs. DRT was configured to serve the trips within the study area as a trip without transfers, while long-distance trips were served by the combination of DRT and regular PT.

5.1. Simulation Scenario 1: Remove All Local Buses

In this scenario, we estimated how DRT can replace the bus lines in the study area. The goal of this experiment is to put PT and DRT in the same conditions. To implement this, for each trip request, we found the fastest trip on PT according to the GTFS and measured the trip time, which was applied as a maximum trip duration constraint when routing DRT vehicles. In other words, after DRT replaces buses, the trip duration for the travellers can become better or remain the same, but it cannot become worse. For the time window size, we used one hour (±30 min from the desired departure time) for the base case, as this is the resolution of the input data and the frequency of the most fixed bus lines in the area. However, in some cases, the delay between departures is more than an hour. If the desired departure time of a trip was not in the time window, we considered that such a trip could not be satisfied. This is mostly relevant to regular PT because DRT is allowed to activate additional vehicles when active vehicles cannot pick up a traveller. For example, unsatisfied trips could appear at the first and last departures of a bus on a line. Some long-distance DRT + PT trips could not be satisfied due to long transfers. When a trip could not be satisfied, we assumed that it was either executed by a private car or not executed at all, so we did not consider such travellers in the further analysis. The number of unsatisfied trips was on average 0.8% of all the trips in the baseline case.

The simulation results in Table 3 show the mean mode split for five simulation runs with different samples of demand. We may see that DRT can satisfy most of the demand. The few unsatisfied trips are attributed to overnight long-distance trips, which the simulation cannot route, or a few occasions of too early trips, when the demand is specified for the hour without a PT departure. Even when all of the buses are removed, about half of all trips are still performed by the railway connecting the two largest towns. These people are not given the option to ride with DRT.

Table 3. Modal split in the base case simulation.

Total Trips	Unsatisfied Trips	PT Trips	DRT Trips Local	DRT + PT Trips
2562	9.6	1278.4	1020	229

The comparison between DRT and buses in Table 4 shows that DRT requires 28.6 8-seat vehicles on average, which is 79% more than the 16 buses used nowadays. (The number of buses is estimated based on timetables.) DRT vehicles produce more than twice more VKT. However, the CO_2 emissions (and energy consumption for electric vehicles) for DRT are lower because DRT vehicles are smaller. Cost models 1 and 3 (see Table 1) estimate lower costs for DRT than for buses. This is due to the drastic difference in temporal costs in model 1 and the large difference in distance-based costs in model 3. However, we did not simulate drivers and breaks that drivers are legally required to have, but it is included in model 1. Adding the break time for drivers (or switching drivers at some stops) would increase the total driving time, VKT, and the number of required vehicles. Thus, such a low cost is likely an underestimation. Cost model 2 gives the highest cost for DRT; however, this value may be an overestimation as the model is based on a service with a demand density approximately five times lower than in the study area. A higher demand density would allow the routing algorithms to improve the occupancy on DRT vehicles and thus reduce the cost. Additionally, cost model 1 does not account for the possibility of contracting a varying number of vehicles during the day (e.g., 30 vehicles during the peak time and 15 at the off-peak time), which would reduce the costs. The standard deviation (STD) row in Table 4 shows that the difference is rather low between simulation runs with different input samples.

Table 4. Main results of the base case simulation.

	# Vehicles	VKT	Service Hours	Cost/Trip, EUR Model 1	Cost/Trip, EUR Model 2	Cost/Trip, EUR Model 3	CO_2 Emissions, t	Energy GJ
bus	16	3953	130	11.7	-	10.5	3.19	16.9
DRT	28.6	9733	247	10.3	15.1	10.6	2.05	8.6
STD DRT	2.1	408	8.7	0.6	0.5	0.4	0.1	0.4

Figure 4 shows that buses are more efficient in utilising the vehicles. DRT vehicles produce more empty running time, and riding with only one traveller is more common (see Figure 4a,b). We did not model buses running empty to or from the depot; for DRT, the amount of time spent on this is about 1% of the total active time. Buses do utilise their larger capacity, which is unlimited in simulation, but there are 17 min of ride time with more than 30 travellers on board (out of 130 bus ride hours in total). Figure 4c,d show that buses reach the efficiency of 12 travellers per vehicle hour during the morning rush hour, while DRT reaches the value of 4 travellers per vehicle hour. Additionally, occupancy on bus lines is slightly underestimated because we did not simulate the travellers on the partially removed bus lines that could be using the lines in the parts outside the study area.

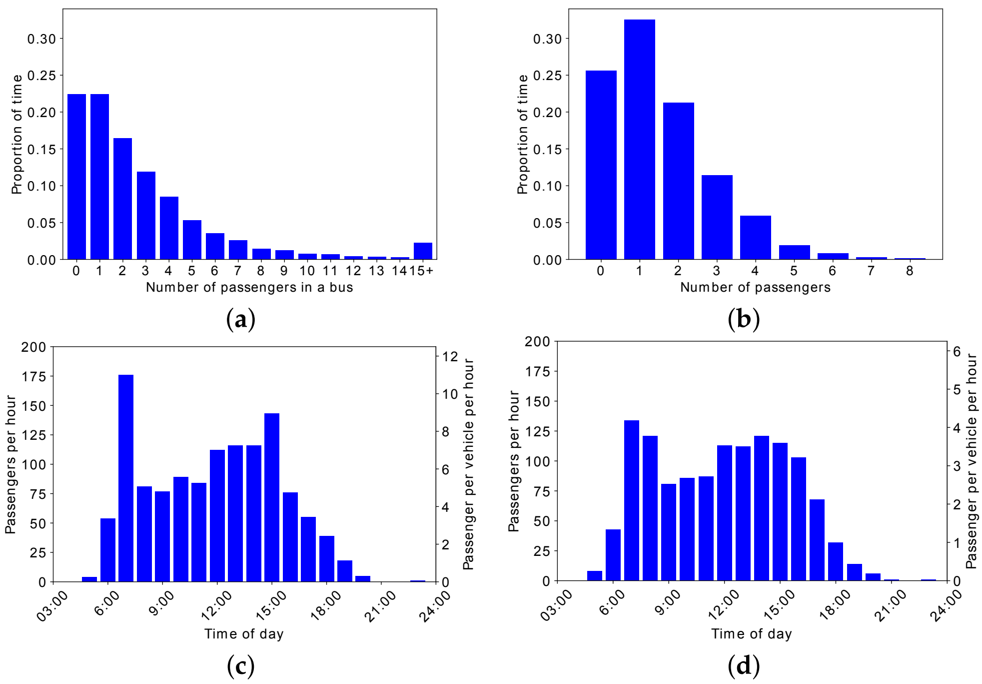


Figure 4. Ride-sharing ratio in (**a**) buses and (**b**) DRT. Travellers per hour served by (**c**) buses and (**d**) by DRT.

Figure 5 shows the deviation from the desired waiting time experienced by travellers. The desired departure time was distributed within the respective departure hours, and the time interval of ±30 around the desired departure time defines the time window when a trip can start. This enabled us to observe waiting or early departure time with relation to the desired departure time in the middle (the 30 min mark). The distribution of waiting time for buses in Figure 5a is close to uniform with a slight skew toward late departures. The distribution for DRT trips in Figure 5b has a prominent peak for very early departures. Unfortunately, the routing algorithm does not allow us to specify a soft penalty for the deviation from the desired departure time, only a hard constraint of the departure being within the time window. The algorithm routes early departures when possible. With that in mind, a more advanced algorithm could have transferred the peak to the middle of the chart (i.e., travellers could receive a trip when they actually want to go). There is a potential for DRT to improve on this aspect of QoS over the conventional PT. However, this hypothesis needs to be confirmed. On the other hand, there is a large peak in the number of travellers getting the latest possible departure time. This helps the system to spread out the load during peak hours. This can be observed in Figure 4c,d: the 07:00 peak is very prominent for buses, but it is more spread out to 07:00–08:00 for DRT.

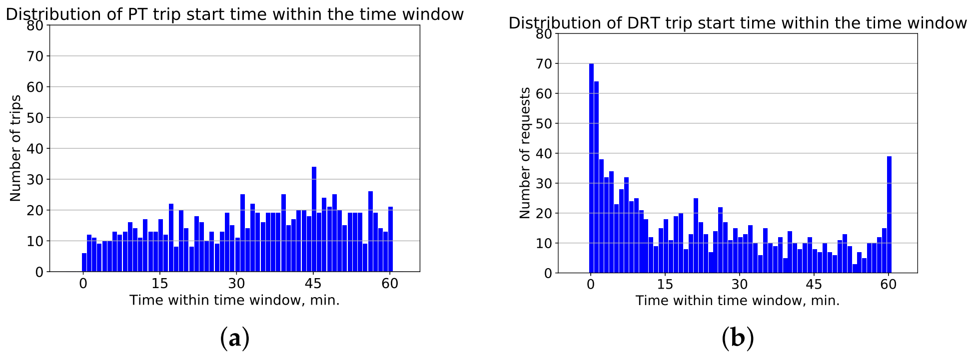


Figure 5. Distribution of start time of trips on (**a**) buses and (**b**) DRT.

5.2. Simulation Scenario 2: Scaled Demand

To check the efficiency of DRT, we performed a second set of experiments with the demand scaled between 50% and 150% from the original demand size. We assumed buses would follow the same schedule. As traveller capacity in buses is large and often under-utilised, they can absorb additional demand without increasing VKT and CO_2 emissions, with an exception for the 150% demand case, when two extra buses were added to one route in the morning peak due to the demand of more than 60 trips per departure. This can be seen in Figure 6b, but it does not visibly affect VKT and the other results. In the 50% demand scenario, the occupancy level on buses becomes very low on most of the lines (down to 1–5 travellers per departure), and on average, 13% of all departures per day serve zero travellers. However, it is impossible to reduce the required number of buses or cancel some departures without declining some travellers a trip due to day-to-day variability. DRT handles the lower demand more efficiently by reducing the number of utilised vehicles, as seen in Figure 6b. The number of DRT vehicles grows approximately linearly with the demand. Together with the number of vehicles grows the VKT of DRT. It grows linearly at almost the same rate. The required number of vehicles in the scenario with 50% of the demand is close for regular buses and DRT (16 and 18 vehicles, respectively). The VKT could be projected to equalise between the services at the demand level of 25%.

Despite the larger number of vehicles and higher VKT value in all the simulated scenarios, DRT can be significantly more cost-efficient than regular buses according to Figure 6a. This result can be explained by the cost models 1 and 3, which show that DRT vehicles are significantly cheaper to operate. We can observe that additional demand improves the efficiency of both services. DRT is cheaper to operate when demand is low, and the service cost decreases linearly with the increase of the demand. However, regular PT scales much better with the growing demand and becomes more cost efficient than DRT with higher demand levels, although the reduction of cost begins to diminish with the additional demand. The cost models 1 and 3 produce very close results for both service types, while cost model 2 predicts roughly 40% higher cost of DRT compared to the other models. The point at which the operational costs of DRT and regular buses are equal falls into the region 75–125% of the baseline demand (900–1380 travellers).

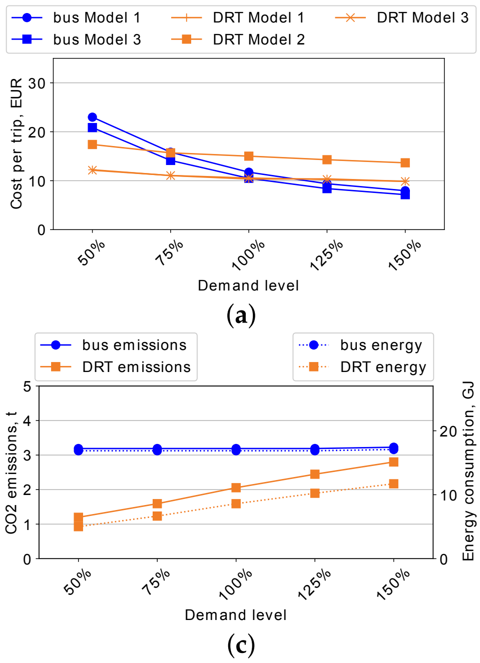


Figure 6. Simulation results for different demand levels: (**a**) cost per trip, (**b**) number of vehicles (left axis) and vehicle kilometres traveller (right axis), and (**c**) CO_2 emissions of vehicles with diesel engines (left axis) and energy emission of vehicles with electric engines (right axis).

The results presented in Figure 6a show that DRT could be more cost efficient than regular buses in situations with low demand levels, but when demand level rises, regular PT takes the lead. This is consistent with the literature, which analytically estimates the point when both systems have the same efficiency to be around 10–50 trips/km^2/h [31–34]. In our study, the initial demand level (100%) corresponds to 16.6 travellers/km^2/h, if we assume a 1 km^2 of service area around the bus stops. The cost efficiencies of DRT and regular buses are the same in the range of the demand of 12.4–21 trips/km^2/h, according to Figure 6a.

Although DRT produces significantly more vehicle kilometres, Figure 6c shows that there is a significant saving in emissions or energy consumption when using DRT. CO_2 emissions and energy consumption scale linearly from VKT according to the emission model. Electrification increases the savings that DRT could bring compared to buses. Electrical DRT vehicles save more energy (compare the gap between CO_2 emissions and energy consumption of both services), and energy consumption scales slightly better than CO_2 emissions. Similarly to the operational costs, the reduction in emissions happens because the DRT service uses smaller vehicles, which produce more than three times less CO_2 and require less energy per kilometre.

5.3. Simulation Scenario 3: Service Quality Variations for DRT

The following experiments explored how different DRT QoS policies affect service performance. We modified the parameters of the acceptance model for travellers together with the routing restrictions of the DRT service. We considered only the travellers who have chosen DRT or DRT + PT option in the baseline scenario (experiment 1). In this experiment, we continued to assume that the DRT service knows exactly the travellers' acceptance thresholds and provides the trips that would satisfy them.

In the baseline experiment, the time window was fixed to one hour. In the first part of this experiment, we modified the size of the time window between 15 min (i.e., a time window of ±7.5 min around the desired departure time) and 1.5 h (i.e., ±45 min).

The results presented in Figure 7a show that relaxing the time-window size allows the system to improve the cost efficiency, which decreases almost linearly with the increase of the time-window size. Additionally, Figure 7d indicates that the number of DRT vehicles and their resultant VKT both start to reduce when the size of the time window is increased to one hour. The CO_2 emissions and the energy consumption decrease accordingly, as seen in Figure 7b. When the time-window size is increased, the DRT system receives more opportunities for route optimisation.

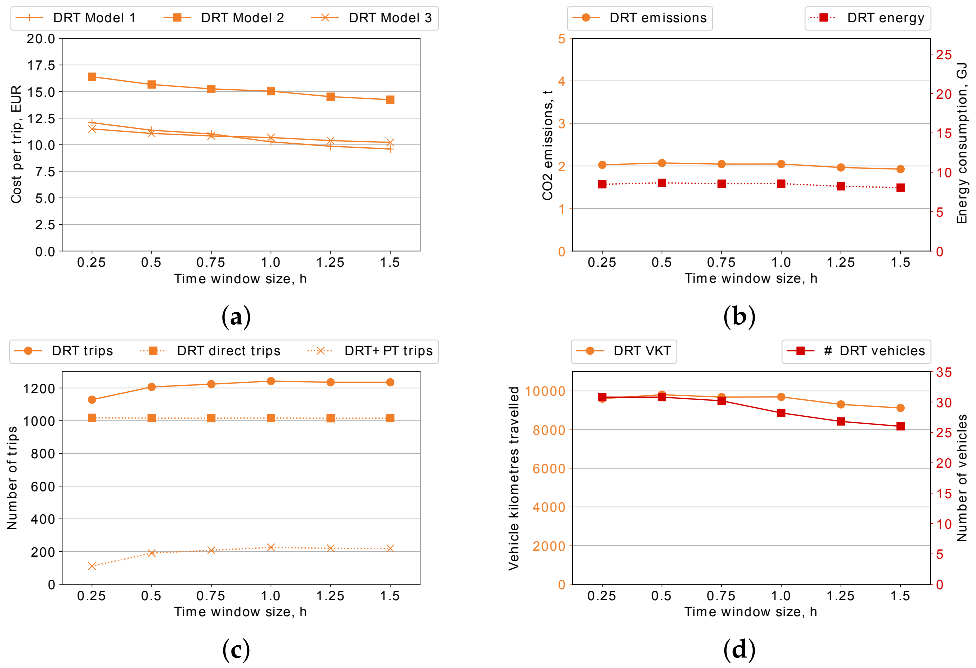


Figure 7. Simulation results for the time-window size between 15 min and 1.5 h: (**a**) cost per trip, (**b**) CO_2 emissions for vehicles with diesel engines (left axis) and energy consumption for vehicles with electric engine (right axis), (**c**) number of trips on DRT, and (**d**) vehicle kilometres travelled (left axis) and number of vehicles (right axis). For (**b**,**d**), the colour of axes corresponds to the colour of line belonging to that axes.

Another factor affects the results when the size of the time window is lower than one hour. Figure 7c shows that the DRT service has no issues with serving all the direct trips within the service zone, even with the smallest time-window sizes. However, a large number of long-distance trips could not be satisfied when the time window is reduced below one hour: the number of trips goes down to 111 out of the potential 225 trips. Such a large number of trips not served is explained by the low frequency of the transfer trip outside of the service zone. That is, even if the DRT system can pick up travellers within a short time window, there could be no connecting bus or train to finish the trip. The reduction of demand balances out the reduction of efficiency due to decreased time-window size; this flattens the charts in the region from 0.25 h to 0.75 h in Figure 7d. However, the cost per trip in Figure 7a keeps steadily increasing when the size of the time window decreases below 0.75 h.

The time-window size affects the DRT performance moderately. The increase of time-window size by 300% from 0.5 h (we chose 0.5 h because the results do not show a significant decrease in the number of DRT trips) to 1.5 h allows activating 4.8 less vehicles on average (a decrease by 16%), decreasing the total VKT by 7% and decreasing costs by 8–16% (depending on the cost model).

The second parameter of the service quality we studied is the maximum allowed trip duration that we could manage with the direct trip multiplier parameter (DTM). In the baseline scenario, the maximum allowed trip time was individual for every trip. In this experiment, we defined the same trip QoS level for all the trips. Again, only the travellers who used DRT in the baseline scenario are simulated for this experiment. We varied the DTM between 1.1 and 1.9 (the trip is allowed to be longer than a direct trip by a car by 10–90%), while the time window size is fixed to 1 h. The results concerning the effects of varying DTM depicted in Figure 8 are similar to those of varying time-window size in Figure 7.

Figure 8c shows that DRT adapts well even to the strongest restrictions to the allowed detour and serves all the local trips in the area. However, a large proportion (46%) of long-distance trips requiring a transfer between DRT and PT could not be served with the target service quality. This is mainly explained by the slower average riding speed of regular buses. Even if DRT can provide a fast connection for a part of a trip, the target trip time for the whole trip is often not achievable due to slower moving buses. Another issue is the transfer time when the long-distance trip requires multiple transfers. DRT is capable of synchronising delivery time with the departure time of a bus or a train, but scheduled lines can synchronise only a limited number of departures.

The cost per trip shown in Figure 8a decreases when the DTM increases. All cost models estimate that the increase of DTM beyond 1.5 brings a much lower improvement of costs than the increase of DTM between 1.1 and 1.5. Figure 8d also shows that the system is unable to utilise DTM values larger than 1.5 to reduce the number of active vehicles. However, there are improvements in VKT and corresponding improvements in CO_2 emission or energy consumption reduction (see Figure 8b).

Changes in the maximum allowed trip duration have a similar impact on the service efficiency as the time-window size. The change of DTM from 1.3 to 1.9 (300% increase of allowed detour from 0.3 to 0.9) causes a reduction in costs by 8–13%, VKT by 7%, emissions by 8%, and the required number of vehicles by 12%.

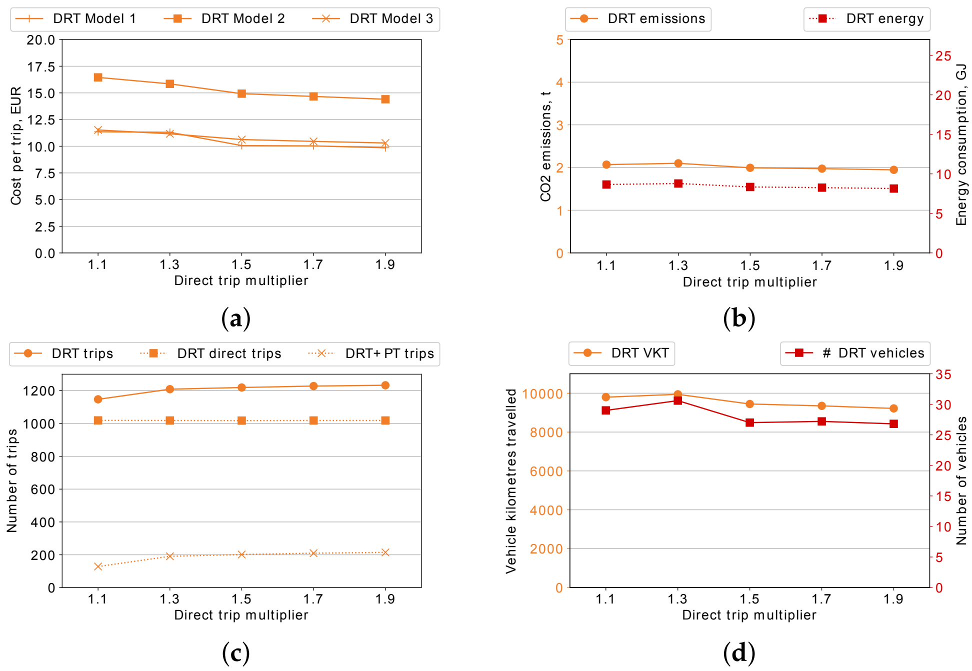


Figure 8. Simulation results for the direct time multiplier size between 1.1 min and 1.9 h: (**a**) cost per trip, (**b**) CO_2 emissions for vehicles with diesel engines (left axis) and energy consumption for vehicles with electric engine (right axis), (**c**) number of trips on DRT, and (**d**) vehicle kilometres travelled (left axis) and number of vehicles (right axis).

6. Discussion and Limitations

The simulations show that replacing PT with DRT has the potential to reduce costs and CO_2 emissions. However, it should be noted that accurately estimating the actual costs of on-demand service is challenging. For instance, drivers' salaries could be different due to additional responsibilities, and fixed costs of vehicles could be allocated differently in case the vehicles can be utilised in a different service during the off-peak time (e.g., as a taxi or for special service trips). Additionally, our cost models are based on data from different countries with different workforce costs, policies, supply, demand, and PT network structures. Hence, the values in our study are only approximations of the actual costs.

The main assumption we used in this study is that the demand does not change when buses are replaced with DRT. In practice, the demand may change significantly when DRT is introduced, especially when DRT is replacing bus lines [8]. Analysing the potential change in demand is not the goal of this article; rather, its goal is to estimate the DRT service efficiency in a somewhat realistic, but still hypothetical, environment. We organised DRT in a way that the trip quality (i.e., when the trip starts and how long the trip is) stays approximately the same. We argue that this would ensure the traveller's experience and, consequently, the demand stay the same. However, we had limitations in the algorithms for controlling the pick-up time of DRT within the allocated time window, as discussed in Section 5.1. The resulting distributions of deviation from the desired departure time differ significantly between DRT and PT. In general, the waiting time and service reliability are crucial factors in service satisfaction [53,54] and for potential ridership [50,55]. In our baseline experiment, travellers could perceive the day-to-day reliability of DRT to be lower than the reliability of regular buses, as there is no guarantee that the trips would start at the same time on different days. We argue that a time window of one hour allows for a fair comparison of operational characteristics, but user satisfaction could be lower, negatively affecting the demand. Another change in the service that would affect the demand is the requirement to request trips in advance.

To make the comparison between DRT and buses, we transported travellers between the existing bus stops. This type of DRT service is generally more efficient but does not utilise the possibility of door-to-door trips. A door-to-door type of service could attract new traveller groups, such as the elderly or young people, who may have problems with long walking distances to bus stops. On the other hand, navigating through smaller streets and overall longer detours would make a door-to-door type of service less cost-efficient and make the service produce more VKT and CO_2 emissions.

The models that we used have certain limitations in their applicability and some components could be improved to achieve more precise results. One limitation is that the traveller model does not enable a realistic estimation of the demand for PT or DRT under particular circumstances. A rule-based model, taking into account only waiting and travel time, is too simplistic to realistically predict a modal split. A probabilistic mode choice model could be used for this purpose, as demonstrated in [50], for example. Another component affecting the precision of the results is the lack of a model for drivers. In our simulation, we assumed DRT vehicles to be driven without the need for breaks or returns to a depot for a change of drivers. This leads to an overestimation of the DRT service efficiency. In the future, when automated vehicles are fully established, this issue in our model would be automatically resolved as drivers would not be required. In addition, the automation of vehicles would significantly change the costs, as drivers are a great portion of the total costs of transport today. Bosch et al. [56] show that smaller vehicles benefit more from the shift towards autonomous vehicles. Thus, DRT can become more cost efficient for higher demand levels than today. Additionally, we utilised a common insertion heuristic for routing DRT vehicles, which could be improved. Allowing the algorithm to switch travellers between vehicles or incorporating other state-of-the-art features like demand forecasting and fleet re-balancing could help to further improve DRT efficiency.

When we modified the demand, we assumed that bus schedules are unchanged. A common practice, in reality, is to decrease bus frequency to consolidate the demand and save costs when the demand level is low. On the one hand, optimising regular buses for low demand would lead to a reduction of VKT and CO_2 emissions, a consolidation of demand, and consequently a higher utilisation of buses as well as a reduction of costs per trip. On the other hand, increasing the headway between buses could affect the demand negatively. When demand increases, the frequency of buses is normally increased to accommodate more travellers, which would lead to an increase in both costs and CO_2 emissions for regular PT. However, there is an optimal range in the headway of buses that minimises a generalised cost (or maximises profits), as can be seen in [57,58], for example.

The data that we based our study on has overall high quality according to its sources, as the OD matrix is based on the good quality data from tap-in and tap-out automatic data collection system. However, we had to exclude a few small bus lines without the automatic data collection system from the simulation and analysis due to missing data on the demand. Nevertheless, this does not affect the main finding: dependence of operational characteristics from the demand density. The OD matrix that we used does not have any information about individuals or the access or egress parts of the trips. Therefore, we limited this study to a stop-to-stop type of DRT. The input OD matrix could be algorithmically expanded (for example, by combining the OD matrix with geographical data on buildings and their types) to study the efficiency of the door-to-door type of DRT.

Door-to-door types of DRT have long been in use in a form of special services. The efficiency of DRT for larger demand densities is important to evaluate. The findings in this article enable PT actors to estimate in what areas DRT service can be economically viable. An important finding of this work is that the demand level equalising operational costs between DRT and PT is significantly lower than the demand density equalising the environmental impact. The savings in CO_2 emissions (or energy) by DRT could become an increasingly important factor in the future both for decision-makers when planning what type of service to initiate in a certain area and for travellers when choosing between alternative travel modes.

In addition to the economic potential and environmental benefits we addressed in this article, DRT systems have the potential to improve the accessibility to the population groups that have problems using conventional PT. This has been historically shown through their use in special services. Further evaluation is required of DRT services combining general and special trips. Other situations when DRT could potentially be beneficial over regular PT include the restrictions that we experienced during the COVID-19 pandemic. DRT, by design, is a service with a predictable number of travellers in the vehicles, which enables travel agencies to control crowdedness. Travel restrictions and recommendations for teleworking decrease the demand, potentially making even densely populated areas into areas with low demand and making DRT an attractive alternative in more geographical areas. This shows the potential of DRT services, but the benefits and shortcomings of different types of DRT in different conditions should be further evaluated.

7. Conclusions

The simulation results show that DRT can potentially replace buses in the simulated area. A DRT service would require significantly more vehicles, which in turn would result in significantly more vehicle kilometres. However, DRT is comparable with the costs of regular PT. Additionally, despite high vehicle kilometres, CO_2 emissions from DRT are expected to be significantly lower due to lower emissions per kilometre for smaller DRT vehicles. Electrification also benefits DRT more than buses: the gap in energy consumption between DRT and buses is larger than the gap in CO_2 emissions.

The analysis of different demand levels shows that DRT is significantly more cost efficient and environmentally friendly in the scenarios with low demand. However, in the scenarios with higher demand, regular buses become more cost efficient as large buses can absorb the demand without significant changes in the schedule or number of vehicles. Emission-wise, when demand increases, DRT vehicles produce proportionally more VKT and CO_2 emissions, while regular buses (if schedules are not modified) stay at the same level of VKT and emissions. Electrification again benefits DRT as energy consumption grows slightly slower than CO_2 emissions. Importantly, the demand density at which DRT equalises in cost-efficiency with regular PT is significantly lower than the demand density at which the environmental impact of DRT reaches the level of PT.

Our analysis shows that DRT can easily provide a service with a very high quality (regarding pick-up and trip time), which gives the system the potential to attract more demand or to prioritise certain trips requiring, for example, strict arrival time. Additionally, DRT (especially the door-to-door variant) has the potential to improve accessibility to PT for certain population groups. Kids who have to rely on their parents to deliver them to sports training or the elderly who may have issues with walking long distances could benefit from secure door-to-door trips.

The demand density at which DRT and regular PT have the same cost efficiency is estimated to be in the range 12.4–21 trips/km^2/h (75–125% of existing demand), which is in line with the mathematical modelling results in the literature. Our study focused primarily on operational costs, whereas most of the literature used generalised costs comprising both operational costs and traveller costs [30,32–34]. However, as we set up our simulations to equalise traveller costs for the DRT and regular PT, we could compare the numbers. Additionally, we assumed that the schedules for regular PT do not change if demand changes, whereas other studies optimised this, improving the cost efficiency of regular PT. This makes the results of the simulations with scaled demand more favourable for DRT than they would be in reality.

We have found that DRT can provide high service quality levels (in terms of time-window size and allowed trip duration) for direct trips. However, it is hard to satisfy the required trip quality for long-distance trips that require transfers between DRT and PT (or multiple transfers on PT). The effects on efficiency metrics (cost, VKT, and number of vehicles) caused by the quality of service parameters (trip duration and time window) are similar in magnitude. The magnitude of these effects is not high. For example, changing the service quality from almost taxi-like (allowed travel time is equal to 1.1 of direct trip time) to rather slow trips almost twice as slow (allowed travel time is equal to 1.9 of direct trip time) allows the DRT service to reduce the total operating costs by only about 11–13%. We speculate that costs could be further reduced with higher demand levels and better optimisation strategies.

The results of our simulations show that in rural areas with rather low and spread out demand, DRT has the potential to improve cost efficiency and reduce the environmental impact of PT. Moreover, DRT has the potential to improve accessibility for vulnerable population groups, improving social equity of public transport.

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