An Individual-based Simulation Approach to Demand Responsive Transport

Sergei Dytckov, Fabian Lorig, Johan Holmgren,
Paul Davidsson, Jan A. Persson

Department of Computer Science and Media Technology
Internet of Things and People Research Center
K2 – The Swedish Knowledge Centre for Public Transport
Malmö University, 205 06 Malmö, Sweden
{sergei.dytckov, fabian.lorig, johan.holmgren,
paul.davidsson, jan.a.persson}@mau.se

Abstract. This article demonstrates an approach to the simulation of Demand Responsive Transport (DRT) – a flexible transport mode that typically operates as a combination of taxi and bus modes. Travellers request individual trips and DRT is capable of adjusting its routes or schedule to the needs of travellers. It has been seen as a part of the public transport network, which has the potential to reduce operational costs of public transport services, to provide better service quality for population groups with limited mobility and to improve transport fairness. However, a DRT service needs to be thoroughly planned to target the intended user groups, attract a sufficient demand level and maintain reasonable operational costs. As the demand for DRT is dynamic and heterogeneous, it is difficult to simulate it with a macro approach. To address this problem, we develop and evaluate an individual-based simulation comprising models of traveller behaviour for both supply and demand sides. Travellers choose a trip alternative with a mode choice model and DRT vehicle routing utilises a model of travellers' mode choice behaviour to optimise routes. This allows capturing supply-side operational costs and demand-side service quality for every individual, what allows for designing a personalised service that can prioritise needy groups of travellers improving transport fairness. By simulating different setups of DRT services, the simulator can be used as a decision support tool.

Keywords: Demand Responsive Transport · Simulation

1 Introduction

Demand Responsive Transport (DRT) describes a range of transport services where the vehicles' routes are dynamically planned based on trip requests by travellers. Most commonly, DRT is realised as a minibus taxi-like service, where a fleet of vehicles is serving travel requests in a door-to-door manner within a specified area. In contrast to conventional taxis, ride-sharing among multiple travellers is one of the features that allows reducing operational costs of DRT.

However, DRT may take more restricted forms closer to regular Public Transport (PT) bus service. For example, it can be a corridor service with defined start and final stops but flexible intermediate stops between them [36]. Most commonly, DRT is applied in two forms: as a special transport service for population groups with mobility limitations or as replacement of regular bus service in rural low-density areas [49].

In this work, the main characteristics of DRT are: 1) Service is open for everyone – it is not a special transport service but DRT may adapt to requirements of a specific population group or purpose. 2) A traveller has to inform the system about pick-up and drop-off points – this differs the service for traditional PT. 3) The service responds to changes in demand by either altering its route and/or its schedule. 4) The fare is charged on a per passenger and not a per vehicle basis. Thus taxi is not DRT, yet, DRT trips can be executed by taxi vehicles.

There is growing interest to use DRT for the general public and with the real-time serving of requests. However, many trial cases of new DRT systems were discontinued due to a variety of reasons including insufficient financial results, poor marketing, low integration to the regular public transport network or lacks in the service design [10]. Pettersson [40] concludes that new technologies do not seem to improve the success of DRT services by itself and we argue that the service needs to better adapt to conditions of a specific geographical area and population to be successful.

The potential of DRT services has been extensively studied through simulations [5,25,30,34,38,42–44,47,52]. Still, each case is unique and the DRT service needs to be designed in accordance with the conditions of the specific case. In case of the DRT service Kutsuplus in Helsinki, Finland, a simulation was built prior to the implementation of the physical service showing that DRT is more efficient than PT at high demand levels [21]. After the service was discontinued, the final report shows that the demand prediction was inaccurate [16]. A realistic simulation could help decision-makers (politicians, authorities and PT actors) to assess the effectiveness of a DRT service and the whole PT network before doing expensive trials.

DRT in its nature is similar to other on-demand transport modes, like shared autonomous vehicles, and simulation of them can be done very similarly. We focus on DRT to highlight non-private use of service vehicles, ride-sharing and social goals of the service that DRT is usually associated with. With the simulation, we want to find a balance between social benefits and operational costs. According to a study in UK [23], actors see social objectives as the main reason to introduce DRT. We want to help decision-makers to understand what design of a DRT service is most beneficial to the target demand groups and how to achieve synergies between different target groups to enable better DRT performance.

In this article, we suggest and demonstrate an approach to the simulation of DRT and analyse benefits and disadvantages of such an approach. When developing the simulation, there were the following two goals: 1) To develop a simulation capable of providing decision support for decision-makers; 2) To study how DRT, if seen as a part of PT network, may affect the mobility opportunities and what population groups may benefit the most. We are developing an agent-based simulation approach where the traveller behaviour is in the centre of simulation and DRT is directly connected to PT. Our approach allows for simulating a DRT system where social objectives are optimised when routing vehicles, what allows tuning of the service towards the needs of the travellers.

2 Related Work

Traditionally, DRT is used as paratransit service, or as a replacement for low-demand bus lines in rural areas [49]. But there is a trend that travellers change their travel behaviour towards less predictable travels and expect more personalised service, what opens up a potential for flexible transport services such as DRT [39]. In a series of interviews, Davison et al. identify existing market niches that DRT occupies and opportunities for future market penetration [7]. They also note that unsuccessful DRT cases are often caused by the realisation of inappropriate DRT scheme for the target purpose. To overcome this issue, the suitability of a DRT design should be evaluated in advance to their implementation. In this regard, this section presents different approaches for the simulation, analysis and design of on-demand transport services and relates them to the approach we present in this paper.

2.1 Simulation of On-Demand Transport Modes

Traditionally, transport is studied using macro-models that simulate traffic flow based on different characteristics such as flow or density to estimate the utilisation or congestion of larger street segments [15]. They approximate the dynamics of interactions between actors. Ramezani and Nourinejad show how macroscopic fundamental diagrams can be used to optimise the dispatching of taxis taking into account traffic conditions [41]. Macroscopic fundamental diagrams relate vehicle density and flow rates in a traffic network and need to be generated using real traffic data or other individual-based simulation approaches. Yang, Wong and Wong used an analytical modelling approach to find an equilibrium state of the taxi market for different scenarios of managing taxi [56]. While this approach allows for maximising social objectives (amount of trips, waiting time and costs), it is difficult to use it for the evaluation of service quality for heterogeneous travellers or for optimising the service for specific groups of travellers. This is because macroscopic approaches do not explicitly model interactions between actors.

Micro-simulations, in contrast, focus on modelling the behaviour of individual autonomous units such as travellers and DRT vehicles. Numerous of micro-simulation studies have been presented on on-demand modes of transport such as autonomous shared vehicles, which operate similar to DRT. In both cases, the used simulation methodology is very similar. One major difference is that ride-sharing is not considered in the majority of studies on autonomous shared vehicles. Instead, vehicles are only shared between users [3, 18, 26, 29, 50]. Ride-sharing is an important feature of DRT, hence, in the remainder of this section, we present only studies on DRT and on-demand mobility with ride-sharing.

2.2 Analysis and Design of On-Demand Transport Modes

In attempts to analyse theoretical advantages of on-demand transport modes, most simulation studies explore modelled service on unrealistic road networks [34] with randomly generated demand [33, 38], by serving all the recorded trips by DRT [1, 30] or by defining an arbitrary number of trips [1, 5, 11]. The goal of these studies is to estimate the required amount of vehicles and costs for DRT. Only a limited amount of studies considers realistic environments and demand [8, 25, 46, 48]. As we aim to provide a decision for DRT introduction to a specific area, we need to consider both realistic road network and demand model.

We consider DRT as a service that complements PT rather than replacing or competing with it. In our vision, DRT is integrated into the PT network. In most of studies of DRT (e.g., [25, 38, 43, 44, 46, 52]) and other on-demand transport modes (e.g., [3, 11, 18, 30, 31]) PT is considered a separate standalone service, sometimes in direct competition to other existing transportation services. On-demand transport, such as autonomous vehicles, are often seen as a leading mode in future transportation but it has potential to increase demand due to reduction of travel costs, new user groups and recontextualisation of trip time [53]. Improving roads does not solve road congestion, although the degree of effect is in discussion [4, 19]. PT is more efficient in moving high volumes of travellers [28]. The generalised costs of public transport for society is half the cost of private transport when considering external costs such as air pollution, climate change and road accidents [20]. Thus, we see the ride-sharing aspect of DRT and connection of DRT to PT (that could also help to promote PT), as a potential way forward for improving transport equity and sustainable future and focus our efforts on building a simulation that helps to estimate the effects of a scenario with DRT integrated with PT.

An important aspect of our study is the integration of DRT into PT network. In literature, DRT is often opposed to PT. For instance, Leich and Bischoff show that replacing PT with DRT results in marginal benefits [25]. However, the combination of PT and DRT may be more efficient than solely PT when the demand level is low. With higher demand, in contrast, PT becomes more efficient [27]. To achieve a higher level of social welfare, the same vehicle fleet may be used as demand-responsive or as regular timetabled transport depending on demand level [45]. A combination of DRT and PT may be more efficient if DRT vehicles are allowed to drive travellers to any of the available PT transfer stations [24]. Shen, Zhang, and Zhao presented a simulation approach to study the integration of autonomous vehicles into the public transport network [48]. These studies show that DRT integrated into PT network may be more efficient than PT or than PT and DRT as competing services.

3 Simulation of Demand Responsive Transport

The overarching goal of our work is to develop a simulation tool that can provide decision support to decision-makers in the process of designing a DRT system for a specific area. The simulation helps to evaluate different service options: level of route flexibility, target population groups or geographical coverage. We see DRT as a service that may actively optimise its behaviour at the vehicle routing phase towards social objectives. In line with this, we see DRT as a part of public transport (PT) and strive to find a way to optimise the connection between the services, as PT plays an important role in sustainable transportation (where social aspects are as important as economical) [28]. We see a need to develop a simulation approach capable of simulating DRT together with PT and capturing not only economical characteristics but also social value that a DRT service could bring.

Traditional paratransit DRT services require booking of a trip at least one day in advance. To make DRT attractive for other population groups, we consider a flow of requests to the DRT service with real-time requirements (meaning that trip is requested to be executed as soon as possible) or with small booking time (a trip is executed at the same day as request). This assumption makes the demand dynamic what is a challenge for the simulation process. The dynamic nature of DRT makes it more difficult to simulate it with conventional macro-simulation approaches. Macro-simulations have to approximate travel times and do not allow to capture the details of service quality, making it harder to estimate the social value of a DRT service. Thus, we apply agent-based micro-simulation that allows for modelling individual behaviour.

3.1 Simulation approach

The overall simulation process is shown in Figure 1. When a traveller, which is modelled as an autonomous agent, is planning a trip, he or she requests the service (through a trip planner) to find available travel options. The service generates trips that include DRT as well as the combination of DRT and PT and other conventional travel options. Then traveller chooses one of the options and books it if it involves DRT. If DRT is booked, the service updates its vehicles' routes and vehicles execute them. Travel requests come into the system dynamically during the day and vehicles' routes can be modified even when a vehicle is already executing journeys.

With the simulation approach that integrates a model of travel behaviour, we may evaluate a DRT service with a complex behaviour of the service that balances between economical and social goals providing suitable mobility options for everyone. DRT service routes the vehicles according to its optimisation goals which can be formulated multi-objective optimisation problem. The economical objective of DRT is to minimise its operational costs, the major part of which are the number of vehicles running and distance driven. The value of a travel can be represented by its utility (or disutility) and the social objective is to maximise the utility for travellers (or minimise the disutility). Such a numeric representation

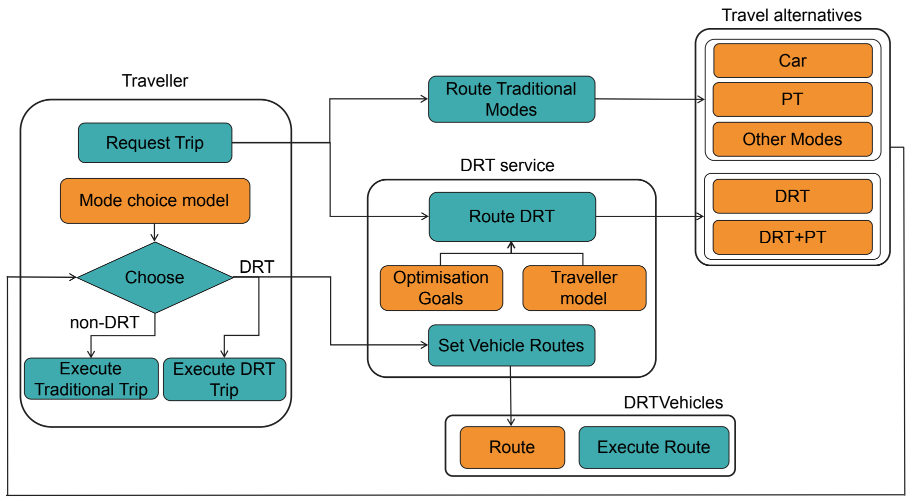

Fig. 1. Overview of the simulation approach.

allows for integrating social objective into the optimisation function for vehicle routing, allowing, in turn, to balance between economical and social objectives when routing DRT vehicles.

In a micro-simulation, we have an opportunity to model the utility a trip provides to a traveller and even model traveller choice (a probability that accepts the proposed DRT trip). Accounting for that, the service may provide sub-optimal trip alternatives (from the point of view of a traveller), which still will be likely accepted by travellers, to improve the overall performance. Additionally, this allows implementing a heterogeneous service scheme, meaning that different population groups or purposes of travel may be routed differently according to the needs of people and priority of service. For example, trips to work or hospital require specific arrival times that must be kept, while shopping trips may be more flexible. Persons with movement limitations may be of higher priority for the service and minimising walking distance is of higher priority than total travel time for them. A DRT service can be designed with hard restrictions to target the needs of specific population groups (e.g. by setting predefined stop points, restricting who can use the service). If such restrictions are applied on the stage of routing trips, there is an opportunity to use ”soft” restriction putting priority to the trips the service is intended to serve, but still allowing other trip types, what could help with the service overall efficiency.

Travel behaviour (the actions of actual travellers) includes both the demand model, trip planning and mode choice. This behaviour is different and individual for each of the agents and depends on socio-demographic factors (e.g. age, family status, employment, or income) but also on geographical factors such as the place of residence as described in [9]. Demand and mode choice are complex multilevel problems in real life and include long-term decisions on home and workplace locations. Moreover, car ownership dictates everyday mode choice. Still, we separate demand modelling from mode choice for simplicity. By doing that, we can focus on the parameters of the system that we can simulate (influence of travel time to acceptance ratio) but ignore the connection of long-term decision (housing location and car ownership) to the availability of transport options. We implicitly assume that DRT would be perceived as PT and will not change the long-term housing and work decision but may help to decrease car use. We may argue that in short-term, while DRT is being adopted, it is unlikely that it will significantly affect long term decisions. This delimitation allows us to use travel surveys or otherwise recorded real-world data to approximate the behaviour of travellers if DRT was implemented.

3.2 Evaluation of the approach

The benefit of such a request-oriented simulation approach is that the system might take into account personal and contextual information from travellers and generate trip alternatives according to both the needs of the travellers and system optimality, allowing the maximisation of social objectives. Alternatively, when travellers' behaviour is modelled realistically, one may use this approach to optimise service parameters such as travel cost, amount of vehicles or expected profits [30, 34].

The drawback of this approach is that it relies heavily on the mode choice modelling while there is a very limited amount of data to build such models. Still, this opens up opportunities to study what type of behaviour shift is needed an efficient DRT operation. A benefit of our approach is that it allows explicit mode choice in each situation and that travellers are not required to use a service with insufficient quality, reducing the service load, thus, converging towards a transport equilibrium state. That is also a drawback of our approach – it represents a single day. If a traveller received service with sufficient quality in one day it does not guarantee that on a different day service would be able to provide the exact same quality.

Multiple similar simulations in the area of conventional and on-demand transportation have been done with MATSim [17,18,31]. The philosophy of MATSim lies in the co-evolution of supply and demand. Travellers in MATSim plan the trip mode at the beginning of a simulation cycle, evaluate their results after each day and replan their journeys for the next day. The problem with DRT simulation in MATSim is that a person requires to select DRT not knowing trip characteristics as waiting and travel time. And while in the evolutionary cycle the demand will adjust to the supply, a significant amount of simulation cycles are required to find the equilibrium.

In a way, travellers in MATSim learn average service quality and make an informed choice based on the average utility of DRT service. However, separating mode choice from building routes could result in a large amount of sub-optimal and unrealistic trips being accepted travellers, especially when a connection of

DRT and PT is utilised. This brings down the potential of DRT and slows down the process of converging to the equilibrium state.

Our approach could benefit from MATSim philosophy: in multi-day simulations, travellers could accumulate the knowledge on service quality and utilise it in the decision process. Yet, simulation of DRT is a computationally expensive process: building routes and solving vehicle routing problems is NP-hard and should rely on heuristics for large-scale simulations. In our simulation experiments, the computational bottleneck was in constructing time-distance matrices between travellers and vehicles to build a vehicle routing problem. To relax this problem, a workaround has been made by [46]. The authors use MATSim to find a near-equilibrium state based on approximate time provided by DRT and then simulate this state in a custom simulator with advanced fleet management and routing.

A benefit of our implementation is that we designed the system based on DRT connected to PT. There are several extensions in MATSim: public transport, on-demand transport, multi-modal trips and carsharing. They allow adding this functionality to MATSim. For instance, one could expand the DRT route planning algorithm to plan the connection between DRT and PT. But so far, to our knowledge, existing studies in MATSim include DRT-like ride-share [35, 38, 52] and they do not utilise the MATSim philosophy of co-evolution. We also have not found examples where on-demand transport is connected with regular PT in the same network.

3.3 Simulation Prototype

This section describes the prototype of our simulator, focusing on how trip routing flow is implemented. We are developing an open-source simulator[1] based on other open-source projects. As we do not have a requirement to create a precise traffic micro-simulation so vehicle movement is implemented as event-driven simulation. Vehicles teleport between picking up and delivering travellers according to travel times estimated by the trip planner. If a vehicle needs to be rerouted when it is moving, its current position can be extracted from the planned route.

The trip generation flow is depicted in figure 2. Processing of trip requests starts from OpenTripPlaner[2] (OTP) and it is a central tool for generating trip alternatives for requests. It uses Open Street Maps[3] and PT timetables in the format of General Transit Feed Specification (GTFS) to find multi-modal trip alternatives that can combine car, walking, public transport, bicycle. Routing a direct trip by DRT is straightforward: we build a vehicle routing problem, calculating time and distance matrix between all the trip start and trip end positions with the help of Open Street Routing Machine[4] (OSRM) which works significantly faster than OTP and solve the resulting vehicle routing problem

[1] https://github.com/serdyt/DRTsim
[2] https://www.opentripplanner.org
[3] https://www.openstreetmap.org/
[4] http://project-osrm.org

with jsprit[5]. Finding a DRT+PT trip involves two steps: first, with the use of OTP, we find a trip with the "kiss and ride" mode, when a traveller is assumed to be driven from a starting position to a bus stop as a passenger in a car; then, we replace the car leg with DRT building a vehicle routing problem and solving it with jsprit in the same way as with the direct DRT trip.

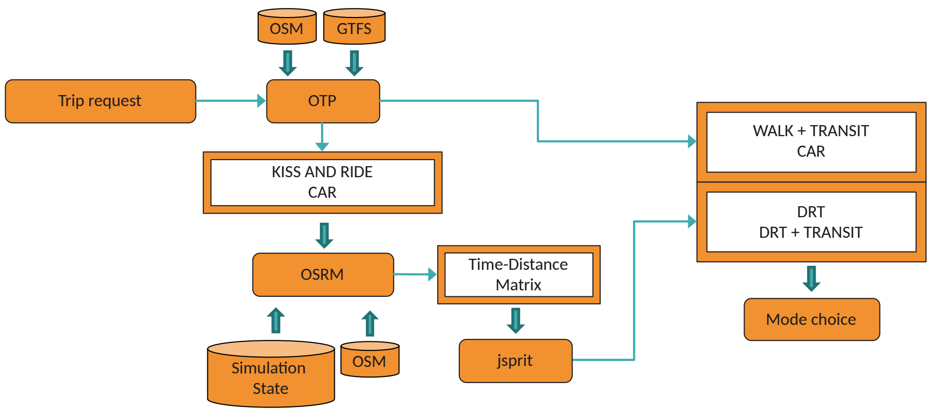

Fig. 2. The process diagram of routing trip alternatives.

Building a naïve optimisation problem including all of the currently active requests resulted in a computational bottleneck limiting the scalability. A time-distance matrix between all the geographical points involved is required to solve the optimisation problem. The size of such a matrix is quadratic to the number of requests R: $O(R^2)$, as each new request adds new origin and destination to the matrix. In our first experiments (described in more details in the section 3.4), planned vehicle routes involved on average 19 travellers per vehicle, what means OSRM needs to find all to all shortest paths between 600 points (for 30 vehicles), which took around 15 seconds to compute, what limits the simulation possibilities. A smarter algorithm for data preparation for vehicle routing problem is required, like in [1], filtering out the vehicles that cannot be utilised in serving of a new request.

3.4 Experiments

The prototype was evaluated with a simulation experiment on the municipality of Sjöbo in southern Sweden. Travel demand for commuters (travellers going to the workplace and back with either home or work activities located in the target area) was modelled based on a regional Swedish survey of travel habits [14] with modified four-step modelling approach [9]. Trip attraction and production were modelled with a linear regression model. Trips were distributed into the

[5] https://github.com/graphhopper/jsprit

origin-destination matrix with tri-proportional fitting. The trip matrix was disaggregated into individual trips by sampling locations of houses and workplaces. Additionally, the desired time of the trip was assigned based on the recorded distribution of work trips. A sample of about 15% of the total amount of commuters was simulated, what corresponds to the current public transport ridership in the target area. The demand was served by 30 DRT vehicles executing door-to-door trips withing the borders of target municipality and door-to-PT transfer if the trip crossed the borders of the municipality. Travellers request a trip two hours in advance to the approximated trip start time. When routing vehicles, service used the desired time of arrival for trips to work and the desired time of departure for trips from work as a hard constraint. Both service and travellers were using the same model of traveller behaviour: a DRT trip is accepted if

$$t_{DRT} < t_{CAR} \times 1.5 + 15min. \tag{1}$$

In other words, travellers accept a DRT trip if service was able to generate a DRT trip within this time window, where either arrival or departure times are fixed. The service is allowed to modify confirmed trips even at runtime as long as the trip duration would fit in the specified time windows of each traveller.

For the experiments, the simulation received data on 1900 real-world trips as input. Approximately 1450 of these trips were executed with DRT on a simulated day by a fleet of 30 vehicles. As shown in Figure 3, most of the time (39%) there was no ride-sharing and only one passenger was on board of the DRT vehicle. Only in 19% of vehicles' travel time, two or more travellers were present. At the same time, when using 30 vehicles, the rejection ratio was around 24% (rejection happened when the DRT service could not provide a trip within the time window, according to equation 1). This low performance may be explained by the non-uniform distribution of demand, as shown in Figure 4. Vehicles were ready to operate during the whole 24-hour period but travellers show two distinct peaks in the demand. The demand during peak hours is 3.4 times higher than average

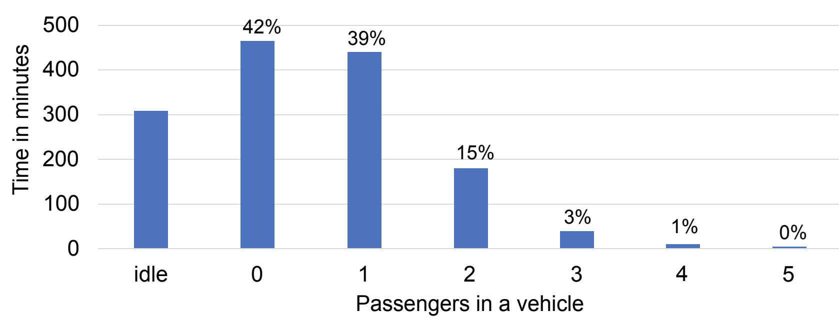

Fig. 3. Amount of time a certain number of people (0 to 5) was in the DRT vehicles. "Idle" represents the time vehicles spent in a depot. Values above the bars show the percentage of total travel time the vehicles were running with the corresponding amount of passengers ignoring idle time.

daily demand so there is little possibility for ride-sharing outside peak hours and many vehicles are idling. At the same time, the high rejection ratio around 24% indicates that 30 vehicles cannot handle the peak level of the demand.

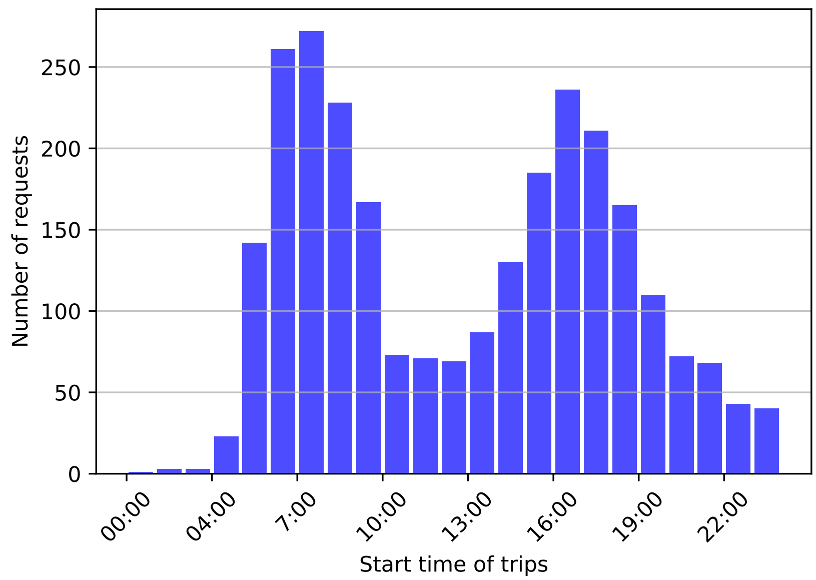

Fig. 4. Distribution of requested trip times.

We have conducted a sensitivity analysis serving the same demand with different amount of vehicles as shown in Table 1. We extracted the key performance indicators to compare the scenarios. They are:

- **Rejection ratio**: The percentage of the trips that travellers rejected (or trips violating the time windows restriction, equation 1). This is an indicator of service quality and lower values are more desirable.
- **Travellers per vehicle**: The average amount of travellers served by a vehicle during one day. This is an indicator of service efficiency and higher values are more desirable.
- **VKT per vehicle**: The number of kilometres travelled per vehicle. This is an indicator of service operational costs and lower values are more desirable.
- **Extra travel time**: Average extra time spent in DRT trip, compared to a direct trip by a car. This is an indicator of service quality and lower values are more desirable.
- **Direct vehicle kilometre per DRT vehicle kilometre**: The ratio of the length of the direct trips (trip by a direct path from origin to destination) to the actual length of DRT trips.

- **Direct travel minutes** (not explicitly shown in Table 1): The total time of direct trips, if they are executed by a car. Excludes detour time from travel time. This is an indicator of service efficiency and lower values are more desirable.
- **Direct minutes per hour**: The amount of direct travel minutes executed by an average DRT vehicle in an hour. This is an indicator of service efficiency and higher values are more desirable. For example, this value is always equal to 1 for private cars, as car always executes a direct path; the value is equal to 2 if two travellers (family members) are going to the same place in the same car; the value is equal to 0.5 if a taxi needs to ride 30 minutes to pick up a traveller and ride 30 minutes to the destination.

In Table 1, we see that the system behaves according to expectations: when more vehicles are utilised, it is possible to serve more travellers and the rejection ration decreases. At the same time, the average number of travellers and number of vehicle kilometres per vehicle decreases together with the number of direct minutes per hour, indicating that the cost efficiency of service is decreasing. Extra travel time, however, stays approximately the same as it is restricted by the mode choice model. We should note that extra travel time in DRT slightly increases together with the number of vehicles in the scenarios with 20, 30 and 40 vehicles, but drops in the scenario with 50 vehicles. When the amount of vehicles is low and service is overloaded, the service selects the trips that can be executed most efficiently. When the amount of vehicles is increasing to the level when the service has an opportunity to serve most inconvenient trips, there is less room for ride-sharing and more trips are executed in a taxi manner.

Table 1. Sensitivity analysis

Number of vehicles	20	30	40	50
Rejection ratio, %	42	24	12	4
Travellers per vehicle	55	48	42	36
VKT per vehicle	772	671	585	516
Extra travel time, %	33.1	33.3	34.5	33.7
Direct VKT per DRT VKT	0.85	0.85	0.84	0.85
Direct minutes per hour	44	38	33	28

4 Discussion and future work

Multiple optimisation issues need to be solved during the simulation. The trip planner needs to find trip alternatives, rank them to provide most promising alternatives to a traveller, find and rank possible DRT to PT transfers (which again involves a loop of searching for PT alternatives) and solve a vehicle routing problem. According to our goal, to balance social objectives, the model of traveller behaviour is included in all of the aforementioned operations. This results in the distribution of the behaviour model making it less transparent and harder to comprehend and potentially inhibits knowledge transit to decision-makers. To prevent this, the same model of traveller behaviour should be used on different steps of finding trip alternatives and better analysis and visualisation tools need to be developed to understand the impact of DRT design decisions on social objectives.

OTP uses heuristics and trip ranking to limit the amount of generated trip suggestions. When filtering out trip alternatives, OTP uses parameters like walk and transfer reluctance, that define how walking is perceived comparing to in-vehicle time or waiting time. These parameters are hidden from a final user (decision maker) but it also opens up an opportunity for contextualised and personalised travel planning that takes into account these parameters. A benefit of OpenTripPlaner is that it would be straightforward to integrate context-aware travel planing into the simulation.

The second optimisation engine is jsprit that optimises vehicle routes according to a cost function. In the first experiments, we used the default cost function that minimises operational costs.

$$C = C_{const} + \sum_{v \in Vehicles} C_{distance} + C_{time} \tag{2}$$

Reduction of transportation cost with sharing a ride is only a part of the DRT objective. This optimisation function does not allow for direct optimisation of social objectives such as quality of service. Especially for investigating the viability of a DRT service, a trade-off between the service costs and the quality of service needs to be made by the decision-maker. Thus, extending the simulation with this respect would be desirable.

To account for social objectives, we need to model traveller behaviour on this level to predict traveller satisfaction from a trip. Behaviour in transport modelling (most often in form of mode choice) is dominated by econometric utility-based models [2, 22]. To build such a model, we need to have real-world statistics on usage of the service. As we don't have access to such data, we are limited to either stated preference surveys (similar to [30, 51]), or approximate value of time (similar to [18] or [12, 54]).

As a temporary measure, we implemented rule-based behaviour. A person interested in DRT accepts a proposed journey if travel time is within an interval of $m \times t_{direct\ travel} + c$, where the constant c accounts for time that would be spent for parking a car and multiplier m represents tolerance to detours. There are two alternatives to how to apply this formula: to the whole trip or the DRT leg only. If we consider car users then it is meaningful to compare direct car time to the whole trip, yet the people already using PT could prefer to other transportation modes to access PT stops like being a passenger in a car, using a car to drive to PT stop or scooters or bikes. While such a time window puts a restriction to trip length, it does not penalise the increase in travel time and does not account for other trip characteristics like waiting time, transfer convenience, on-route rescheduling. Improvements to optimisation function open up more elaborate multi-objective optimisation.

We use routes built by OTP to teleport vehicles between pick-up and drop-off locations, according to the approximated travel time of vehicle path. We use OTP output for navigators to track vehicle positions during the route, but in a rural area, where long straight roads do exist, it is preferable to turn a vehicle in between navigation points. It should be possible to connect a high precision micro-simulator like SUMO with Traffic Control Interface [55] that simulates exact positions of vehicles at each moment in time.

PT in general and DRT in our view serves social purposes among others. To measure how mobility levels are affected by DRT we need to have metrics measuring that. Accessibility is one of the typical metrics. [37] identify high-level metrics like route length or amount of activity centres linked by PT network, but it is not directly applicable to DRT. At the best case, a person may receive a taxi level of service. But in a heavily loaded system, possibilities for each request would be limited by previous requests and a dynamic state of the service (position of vehicles and their routes).

Another interesting approach for optimisation of DRT is the dynamic allocation of stop points. If DRT is working in a non-door-to-door manner, fixed stop points are typically assigned and travellers are forced to walk to the closest stop point. There is an opportunity to utilise the flexibility of DRT to optimise the position of pick-up points if they are dynamically allocated [6, 13, 32]. Similarly, when DRT has a connection to PT, DRT to PT transfer points can be optimised what increases overall efficiency [24].

5 Conclusions

In this article, we present an agent-based simulation approach to DRT that introduces a traveller behaviour model into DRT service planning process allowing the service to adapt to the needs of the target population groups or utilise contextual information for trip planning. Such an approach requires an appropriate travellers' behaviour model (mode choice) so that travellers realistically choose DRT only when it is convenient for them. Our simulation focuses on the scenarios when DRT service is open to the general public, but it may prioritise some population groups and adapt to their needs. It allows optimising between social goals (providing mobility means for target population groups) and economical goals (minimising operational costs).

We evaluate this simulation approach and compare it to the alternatives. The weak point of macro-simulations and analytical approaches is in the approximation of detour time for DRT. A simulation approach implemented in MATSim may better capture service quality that users learn in time but may struggle to implement a feedback loop for adjusting route optimisation algorithms. The approach we present allows using contextual data to provide personalised trips according to the needs of travellers. It allows evaluating DRT service with soft priorities without hard restrictions, thus contributing to transport fairness and allows dynamically adjusting supply-side parameters and optimisation of service parameters. A combination of two approaches may be beneficial, but would result in a very high computational load. Here, further studies are required. The integration of DRT and PT into one service is the second highlight of this article – it allows more realistic and more practical DRT service designs. Most works consider DRT as a separate service, we argue that to capture the transfers between services, allows optimising both service performances.

We developed a prototype of simulation based on open-source tools OpenTripPlanner, jsprit and Open Source Routing Machine and identified opportunities for future work and possible extensions. Finally, we conducted a simulation study of commuter trips to demonstrate the approach. This simulation study indicates that it is challenging to achieve high efficiency of a service just by increasing the number of DRT vehicles to serve the demand. Additionally, we identify the direct trade-off between cost-effectiveness and service quality.

Acknowledgements. This work has been partially funded by the Interreg ÖKS fund within the Intelligent Mobility of the Future in Greater Copenhagen project.

References

1. Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., Rus, D.: On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. Proceedings of the National Academy of Sciences **114**(3), 462–467 (2017)
2. Ben-Akiva, M., Bierlaire, M.: Discrete choice methods and their applications to short term travel decisions. In: Handbook of transportation science, pp. 5–33. Springer (1999)
3. Boesch, P.M., Ciari, F., Axhausen, K.W.: Autonomous vehicle fleet sizes required to serve different levels of demand. Transportation Research Record **2542**(1), 111–119 (2016)
4. Cervero, R.: Road expansion, urban growth, and induced travel: A path analysis. In: Dialogues in urban and regional planning, pp. 310–343. Routledge (2006)
5. Charisis, A., Iliopoulou, C., Kepaptsoglou, K.: Drt route design for the first/last mile problem: model and application to Athens, Greece. Public Transport **10**(3), 499–527 (2018)
6. Czioska, P., Kutadinata, R., Trifunović, A., Winter, S., Sester, M., Friedrich, B.: Real-world meeting points for shared demand-responsive transportation systems. Public Transport **11**(2), 341–377 (2019)
7. Davison, L., Enoch, M., Ryley, T., Quddus, M., Wang, C.: Identifying potential market niches for Demand Responsive Transport. Research in Transportation Business & Management **3**, 50–61 (2012)
8. Deflorio, F.P., Dalla Chiara, B., Murro, A.: Simulation and performance of DRTS in a realistic environment. In: Proceedings of the 13th Mini-Euro Conference on Handling uncertainty in the analysis of Traffic and Transportation systems and the 9th Meeting of the Euro Working Group on Transportation Intermodality, Sustainability and Intelligent transport systems. pp. 622–628 (2002)
9. Dytckov, S., Lorig, F., Davidsson, P., Holmgren, J., Persson, J.: Modelling commuting activities for the simulation of demand responsive transport in rural areas. In: Proceedings of the 6th International Conference on Vehicle Technology and Intelligent Transport Systems - Volume 1: VEHITS. pp. 89–97 (2020)

10. Enoch, M., Potter, S., Parkhurst, G., Smith, M.: Why do demand responsive transport systems fail? In: Transportation Research Board 85th Annual Meeting (2006)
11. Fagnant, D.J., Kockelman, K.M.: Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas. Transportation **45**(1), 143–158 (2018)
12. Fosgerau, M., Hjorth, K., Lyk-Jensen, S.V.: The danish value of time study. Tech. report (2007)
13. Gökay, S., Heuvels, A., Krempels, K.H.: On-demand ride-sharing services with meeting points. In: Proc. 4th int. conf. on vehicle technology and intelligent transport systems. pp. 117–125 (2019)
14. Hedlund, J.: This is how we travel in Skåne – travel survey 2018. Report, https://utveckling.skane.se/publikationer/rapporter-analyser-och-prognoser/resvaneundersokning-i-skane/, [in Swedish]
15. Helbing, D., Hennecke, A., Shvetsov, V., Treiber, M.: Micro-and macro-simulation of freeway traffic. Mathematical and computer modelling **35**(5-6), 517–547 (2002)
16. Helsinki Regional Transport: Kutsuplus–final report (2016), https://www.hsl.fi/en/news/2016/final-report-kutsuplus-trial-work-develop-ride-pooling-worth-continuing-8568
17. Hörl, S.: Agent-based simulation of autonomous taxi services with dynamic demand responses. Procedia Computer Science **109**, 899–904 (2017)
18. Hörl, S., Balac, M., Axhausen, K.W.: Dynamic demand estimation for an AMoD system in paris. In: 2019 IEEE Intelligent Vehicles Symposium (IV). pp. 260–266. IEEE (2019)
19. Hymel, K.M., Small, K.A., Van Dender, K.: Induced demand and rebound effects in road transport. Transportation Research Part B: Methodological **44**(10), 1220–1241 (2010)
20. Jakob, A., Craig, J.L., Fisher, G.: Transport cost analysis: a case study of the total costs of private and public transport in Auckland. Environmental Science & Policy **9**(1), 55–66 (2006)
21. Jokinen, J.P., Sihvola, T., Hyytiä, E., Sulonen, R.: Why urban mass demand responsive transport? In: 2011 IEEE Forum on Integrated and Sustainable Transportation Systems. pp. 317–322. IEEE (2011)
22. Koppelman, F.S., Bhat, C.: A self instructing course in mode choice modeling: multinomial and nested logit models. Transportation Research Board (2006)
23. Laws, R., Enoch, M.P., Ison, S.G., Potter, S.: Demand-Responsive Transport schemes in England and Wales and considerations for their future. In: Transportation Research Board 87th Annual Meeting (2008)
24. Lee, A., Savelsbergh, M.: An extended demand responsive connector. EURO Journal on Transportation and Logistics **6**(1), 25–50 (2017)
25. Leich, G., Bischoff, J.: Should autonomous shared taxis replace buses? A simulation study. Transportation Research Procedia **41**, 450–460 (2019)
26. Levin, M.W., Kockelman, K.M., Boyles, S.D., Li, T.: A general framework for modeling shared autonomous vehicles with dynamic network-loading and dynamic ride-sharing application. Computers, Environment and Urban Systems **64**, 373–383 (2017)
27. Li, X., Quadrifoglio, L.: Feeder transit services: choosing between fixed and demand responsive policy. Transportation Research Part C: Emerging Technologies **18**(5), 770–780 (2010)
28. Litman, T.: Evaluating public transit benefits and costs. Victoria Transport Policy Institute Victoria, BC, Canada (2015)

29. Liu, J., Kockelman, K.M., Boesch, P.M., Ciari, F.: Tracking a system of shared autonomous vehicles across the Austin, Texas network using agent-based simulation. Transportation **44**(6), 1261–1278 (2017)
30. Liu, Y., Bansal, P., Daziano, R., Samaranayake, S.: A framework to integrate mode choice in the design of mobility-on-demand systems. Transportation Research Part C: Emerging Technologies **105**, 648–665 (2019)
31. Loeb, B., Kockelman, K.M., Liu, J.: Shared autonomous electric vehicle (SAEV) operations across the austin, texas network with charging infrastructure decisions. Transportation Research Part C: Emerging Technologies **89**, 222–233 (2018)
32. Lyu, Y., Lee, V.C., Ng, J.K.Y., Lim, B.Y., Liu, K., Chen, C.: Flexi-sharing: A flexible and personalized taxi-sharing system. IEEE Transactions on Vehicular Technology **68**(10), 9399–9413 (2019)
33. Ma, T.Y.: On-demand dynamic Bi-/multi-modal ride-sharing using optimal passenger-vehicle assignments. In: 2017 IEEE Int. Conf. on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe). pp. 1–5. IEEE (2017)
34. Ma, T.Y., Klein, S.: Integrated microtransit services with chance-constrained dynamic pricing and demand learning. arXiv preprint arXiv:2001.09151 (2020)
35. Maciejewski, M., Nagel, K.: Simulation and dynamic optimization of taxi services in MATSim. VSP Working Paper 13-0 (2013)
36. Mageean, J., Nelson, J.D.: The evaluation of demand responsive transport services in Europe. Journal of Transport Geography **11**(4), 255–270 (2003)
37. Miller, P., de Barros, A.G., Kattan, L., Wirasinghe, S.: Analyzing the sustainability performance of public transit. Transportation Research Part D: Transport and Environment **44**, 177–198 (2016)
38. Navidi, Z., Ronald, N., Winter, S.: Comparison between ad-hoc demand responsive and conventional transit: a simulation study. Public Transport **10**(1), 147–167 (2018)
39. Nelson, J.D., Wright, S., Masson, B., Ambrosino, G., Naniopoulos, A.: Recent developments in flexible transport services. Research in Transportation Economics **29**(1), 243–248 (2010)
40. Pettersson, F.: An international review of experiences from on-demand public transport services. working paper (2019)
41. Ramezani, M., Nourinejad, M.: Dynamic modeling and control of taxi services in large-scale urban networks: A macroscopic approach. Transportation research procedia **23**, 41–60 (2017)
42. Ronald, N., Thompson, R., Haasz, J., Winter, S.: Determining the viability of a demand-responsive transport system under varying demand scenarios. In: Proc. 6th ACM SIGSPATIAL Int. Workshop on Computational Transportation Science. pp. 7–12 (2013)
43. Ronald, N., Thompson, R.G., Winter, S.: Comparison of constrained and Ad Hoc demand-responsive transportation systems. Transportation Research Record **2563**(1), 44–51 (2015)
44. Ruch, C., Lu, C., Sieber, L., Frazzoli, E.: Quantifying the benefits of ride sharing. Working Paper (2019), https://www.research-collection.ethz.ch/handle/20.500.11850/367142
45. Sayarshad, H.R., Gao, H.O.: Optimizing dynamic switching between fixed and flexible transit services with an idle-vehicle relocation strategy and reductions in emissions. Transportation Research Part A: Policy and Practice **135**, 198–214 (2020)

46. Segui-Gasco, P., Ballis, H., Parisi, V., Kelsall, D.G., North, R.J., Busquets, D.: Simulating a rich ride-share mobility service using agent-based models. Transportation **46**(6), 2041–2062 (2019)
47. Shen, C.W., Quadrifoglio, L.: Evaluation of zoning design with transfers for paratransit services. Transportation research record **2277**(1), 82–89 (2012)
48. Shen, Y., Zhang, H., Zhao, J.: Integrating shared autonomous vehicle in public transportation system: A supply-side simulation of the first-mile service in Singapore. Transportation Research Part A: Policy and Practice **113**, 125–136 (2018)
49. Spielberg, F., Pratt, R.H.: Traveler Response to Transportation System Changes Handbook, Third Edition: Chapter 6: Demand-Responsive/ADA. No. Project B-12A FY'99, The National Academies Press (2004)
50. Spieser, K., Treleaven, K., Zhang, R., Frazzoli, E., Morton, D., Pavone, M.: Toward a systematic approach to the design and evaluation of automated mobility-on-demand systems: A case study in Singapore. In: Road vehicle automation, pp. 229–245. Springer (2014)
51. Te Morsche, W., Puello, L.L.P., Geurs, K.T.: Potential uptake of adaptive transport services: An exploration of service attributes and attitudes. Transport policy **84**, 1–11 (2019)
52. Viergutz, K., Schmidt, C.: Demand responsive-vs. conventional public transportation: A MATSim study about the rural town of Colditz, Germany. Procedia Computer Science **151**, 69–76 (2019)
53. Wadud, Z., MacKenzie, D., Leiby, P.: Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. Transportation Research Part A: Policy and Practice **86**, 1–18 (2016)
54. Wardman, M.: Public transport values of time. Transport policy **11**(4), 363–377 (2004)
55. Wegener, A., Piórkowski, M., Raya, M., Hellbrück, H., Fischer, S., Hubaux, J.P.: TraCI: an interface for coupling road traffic and network simulators. In: Proc. 11th communications and networking simulation symposium. pp. 155–163 (2008)
56. Yang, H., Wong, S.C., Wong, K.I.: Demand–supply equilibrium of taxi services in a network under competition and regulation. Transportation Research Part B: Methodological **36**(9), 799–819 (2002)