Modelling Commuting Activities for the Simulation of Demand Responsive Transport in Rural Areas

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Abstract: For the provision of efficient and high-quality public transport services in rural areas with a low population density, the introduction of Demand Responsive Transport (DRT) services is reasonable. The optimal design of such services depends on various socio-demographical and environmental factors, which is why the use of simulation is feasible to support planning and decision-making processes. A key challenge for sound simulation results is the generation of realistic demand, i.e., requests for DRT journeys. In this paper, a method for modelling and simulating commuting activities is presented, which is based on statistical real-world data. It is applied to Sjöbo and Tomelilla, two rural municipalities in southern Sweden.

1 INTRODUCTION

In minor municipalities and rural areas with low population density, it is challenging to provide high-quality Public Transport (PT) services that are also economically viable (Velaga et al., 2012). The small number of passengers often result in unsatisfactorily large distance to the nearest bus or train stations and low service frequency, resulting in low service utilization, making people turn towards private cars.

The need for private individual transport can be reduced by implementing Demand Responsive Transport (DRT), which has potential to improve the convenience of and access to PT (Mulley et al., 2012). By supplementing or replacing existing PT, DRT enables passengers to dynamically request pick-ups at specific locations, e.g., their homes, and be brought either directly to their destination or to a suitable PT stop, where they can continue their journeys.

In practice, DRT services have been introduced and tested in different cities and countries (Pettersson, 2019). However, many services were discontinued due to, e.g., poor scalability, integration issues, or insufficient service utilization. Still, PT providers and municipalities see DRT as a means to reduce PT costs due to its demand-based deployment. Passengers, in turn, may enjoy taxi-like accessibility of a bus. To assess the effects of introduction of DRT service, a simulation can be used. To make an assessment of a specific DRT design on a specific area, we need to model realistic traveller requests that correspond to the specifics of real-world requests such as the requested arrival time as well as pick-up and drop-off locations. This paper presents a method for generating artificial, synthetic, travel demand for the population of a municipality. It is applied to model DRT requests of commuters that use PT to reach their workplace. The method's feasibility to generate artificial commuting activities is demonstrated using the example of Sjöbo and Tomelilla, two neighbouring rural municipalities with approximately 32 700 inhabitants, which are located in southern Sweden.

In this paper we present a method for generating artificial, synthetic, travel demand with realistic service requests. The method is a mixture of the classic four-stage approach and agent based modelling, where 1) the amount of trips is predicted on a zone basis, 2) trips are distributed between zones with a gravity model, and 3) trip flows between zones are disaggregated to individual trips and parameters as time and exact location are assigned to them. The traffic assignment and mode choice steps are integrated in an agent-based simulation of a DRT fleet. The method is applied to model DRT requests of commuters that use PT to reach their workplace.

2 DEMAND RESPONSIVE TRANSPORT

An implementation of public DRT service may provide better travel opportunities and may be financially more viable comparing to regular PT, especially in low population density areas. The availability of technological advances such as smartphones, mobile Internet, and vehicle positioning systems, have further promoted the interest in such transportation concepts (Pettersson, 2019). In this section, we highlight current approaches for the implementation of DRT and outline the potentials of simulation for assessing different designs.

2.1 Approaches for DRT

DRT, sometimes also referred to as Flexible Transit Service or Dial-a-Ride transit, is a dynamic transportation service that is flexible in route or time, geared to the needs of the travellers (Mageean & Nelson, 2003). Examples of ongoing services are ViaVan[1], PickMeUp[2], or ArrivaClick[3].

There exists a variety of design options when planning DRT services. This includes, e.g., the number of allowed pick-up and drop-off points, routing options, booking time-windows, and vehicle settings (Daniels & Mulley, 2012). While door-to-door pick-up and drop-off are most convenient for customers, they might result in increased planning efforts, operational costs, route lengths, and travel times. Likewise, DRT services can be either offered only on the first- or last-mile to complement existing PT lines or for entire trips. Finally, the size of the time-window where customers are able to request journeys must be defined. While early requests simplify the planning of vehicles, it limits the travellers' flexibility and might affect the acceptance of the service. It is challenging to identify an individual and suitable design for a given target group and environment (Sharmeen & Meurs 2018).

2.2 Simulation of Demand for DRT

Computer simulation is considered well-suited to analyse and compare different DRT design options prior to their implementation (Deflorio et al., 2002). It allows, for instance, for the identification of optimal zones, time-windows, or fleet size (Quadrifoglio et al., 2008). Prior to the real-world rollout of Kutsuplus pilot study in Helsinki, Finland, between 2012 and 2015 (HSL, 2016), Jokinen et al. (2011) simulated the DRT to assess its cost effectiveness. The applied trip demand model was based on a Poisson point process, which does not consider local travel conditions, e.g., residences of passengers or existing road- or PT networks (Hyytiä et al., 2010).

Yu et al. (2016) and Ke et al. (2017) apply neural networks for predicting passenger demand. A drawback of this approach is the required size of the training dataset. To overcome this, Ke et al. extract 1 000 000 random orders from an existing DRT service. Hence, this approach is most feasible for improving an existing service, while it is challenging to apply for future services or services in different environments.

Another approach for the generation of artificial, realistic, activities of persons include activity-based demand generation (ABDG), where intelligent agents proactively request journeys according to predefined behaviours. Rieser et al. (2007) demonstrate the combination of ABDG and traffic simulation using the MATSim simulator. The feasibility of ABDG has also been shown in other domains, e.g., smart homes (Renoux & Klügl, 2018). Moreover, population synthesis is a class of statistical approaches for predicting decision-making, which can be also applied to transport scenarios (Müller & Axhausen, 2010). Still, both machine learning and agent-based approaches require detailed high-quality data on individuals and motivations for a specific behaviour.

Deflorio (2011) outlines how the space-wise and time-wise dispersion of travel demand in DRT scenarios can be simulated. The author presents the use of Monte-Carlo methods and assumes that the number of requests per area is known and that detailed data in the current use of PT is available. Based on this, Deflorio derives probability distributions for estimating commuting behaviour on a zone-level.

We may conclude that simulation has been proven suitable for investigating DRT design and utilization. Unrealistic representation of demand, disconnected from the real-world demand for DRT simulations, is, however, a weak point of many simulations. We argue that case-studies of realistic environment are required to understand how to get more benefits from DRT in a specific area.

3 CASE STUDY OF SJÖBO AND TOMELILLA

In a case study, we simulated DRT usage, aiming to identify how DRT can be implemented with

[1] https://www.viavan.com/

[2] https://pickmeup.oxfordbus.co.uk/

[3] https://www.arrivabus.co.uk/arrivaclick/

maximum benefit, in the two rural municipalities of Sjöbo and Tomelilla. They are located in the Skåne County in the southern Sweden. They are the home to approximately 32 700 inhabitants, and they lie in the rural part of Skåne with a distance of 40–75 km to larger cities Kristianstad, Trelleborg, Lund, and Malmö. As of 2019, Sjöbo and Tomelilla have no regular, local, public transport, but they are connected with 9 bus lines: 6 with connection to close-by municipalities and 3 express lines to the above-mentioned cities, yet, with only a small number of stops in central Sjöbo and Tomelilla. Tomelilla also has a railroad connection. As a part our simulation study, we developed a method to generate a realistic demand of DRT journeys.

3.1 Available Data Sources

It is generally known that modelling activities are highly dictated by the availability of data in a selected region. To estimate the demand for DRT services, data on living and working conditions of the investigated municipalities are required. *Statistics Sweden* [4] (SCB), the national statistics agency, provides aggregated socio-demographical characteristics in order to ensure the privacy of individuals.

To derive more detailed information, data from different registers must be combined. The Swedish SAMS (Small Areas for Market Statistics) areas, which divides municipalities and cities into areas with an approximately equal number of inhabitants, is a typical basis for aggregation publicly available data. In our case study, the travel analysis zones are defined by SAMS. There are 17 zones in Sjöbo and 20 zones in Tomelilla. Other studies make use of these areas as well, such as the *investigation of travel habits* (RVU, 2018). We base our study on RVU from year 2013 as we have full access to the dataset. RVU contains detailed travel information on 24 483 individuals in Skåne including their travel origin and destinations, specified on SAMS zone level, reasons for travel, and travel times, as well as information on their availability of other transport means, e.g., car or bike.

Geographical Sweden Data [5] (GSD) is a public database that contains data on the position and purpose of buildings, e.g., residential house, industrial facility, or public building. While residential houses serve as home for commuters and thus tend to be the origin of commuting activities, industrial and public buildings are usually worksites and thus the destination of commuters.

[4] http://www.statistikdatabasen.scb.se/

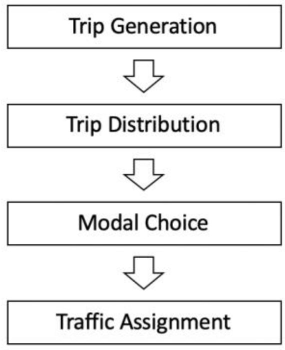

Figure 1: Transportation modeling process.

4 MODELLING COMMUTING ACTIVITIES

To investigate and assess the suitability of different DRT design choices, a model is required that allows for the dynamic planning and scheduling of DRT vehicle routes based on trips requested by travellers. In this section, a method for the generation of artificial commuting activities, i.e., work trips (home-work-home sequences), is presented. We used a stepwise approach on the transportation modelling process for forecasting travel demand presented by Johnston (2014) (cf. Figure 1). In our study, steps 3 and 4 are implemented in a simulation model.

Due to reasons of data privacy, it is difficult to obtain detailed and reliable data on travellers' habits, routines, and commuting activities. Thus, the required information must be deduced from other information sources, such as interviews, surveys or census. In these sources, data is often aggregated, e.g., for defined regions or groups, to ensure anonymization of the surveyed individuals, as it is the case in Sweden, where travel surveys are aggregated to the level of SAMS zones. The goal of the presented method is to build a transport demand model, based on statistical data, that allows for the estimation of an origin-destination (O-D) matrix on the number of commuting activities between multiple areas. Moreover, the start and end location as well as the time of each request need to be estimated in order to enable realistic simulation of DRT use.

4.1 Trip Generation

The goal of the trip generation step is to estimate the travel demand, i.e., the number of trips that start (have origin O_i) and end (have destination D_i) in each of the

[5] https://www.geodata.se/geodataportalen/

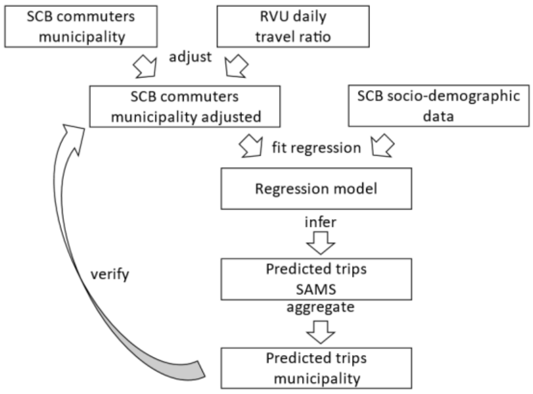

Figure 2: Trip generation method

predefined zones i. We use the terms production and attraction, which are used to describe traffic flows, where households "produce", and workplaces "attract" trips or commuters. This step does not yet connect of origins and destinations (where from and where to trips are made). In the case of lacking individual survey data, such information can be deduced or predicted based on socio-demographic and household data (De Dios Ortúzar & Willumsen, 2011). Due to limited availability of data, we limited the application of presented methodology to one purpose of journeys, which is commuting to work. Moreover, we explore a target group, commuters, that is not typically eligible to use DRT services. As home-work-home sequences start and end at the same location, they will be generated as one tour, consisting of two distinct trips. The return trip home is not counted towards production of a zone of a workplace.

An approach that can be used for estimating the relationship between attraction and production of regions (zones) and socio-demographic data is linear regression trip generation models (De Dios Ortúzar & Willumsen, 2011). The benefit of regression is that it is simple, it produces interpretable results, and works sufficiently well with a medium sized dataset.

When using regression models to estimate travel demand in terms of ingoing and outgoing work trips, it might occur that the sum of all respective trips over all zones is not equal. According to De Dios Ortúzar and Willumsen (2011), the assumption can be made that the overall sum of outgoing trips (T) is correct because the amount and quality of data on housing is typically better, and the number of ingoing trips is adjusted accordingly by factor f for all destination zones D_j with

$$f = {}^{T}/_{\sum_j D_j} .$$

For our case study, we build a regression model to predict the number of trips produced and attracted by the municipalities of Skåne. Then we apply the model to predict the amount of trips in each SAMS zone of the target municipalities. To produce sane non-negative results, we used lasso regression with zero intercept and strictly positive coefficients. We used demographical (different statistics on population size) and land use data (amount of buildings by type) out of which data on the day population (considering the workplace of individuals), night population (considering the residence of individuals) was significant and not strongly linearly correlated. The dependent variable for fitting, the number of outgoing journeys, is calculated based on SCB data on commuters between municipalities and adjusted by the average daily trip ratio extracted from the RVU 2013 survey (cf. Figure 2).

The resulting model is presented in Table 1. There is not enough data in the RVU surveys to compare the model with the trips between SAMS zones, so the data were aggregated back to the level of municipalities and the predicted aggregated data is compared to the original data of production of municipalities from SCB. $R2_{adj}$=0.99988 with a mean deviation in the amount of trips of 70 trips and standard deviation of 155.

Likewise, the number of buildings that might serve as workspace, the day population in the public and economic sector, the number of inhabitants that are between 25 and 44 years (age range according to SCB division) are used to construct an attraction regression model (cf. Table 2). $R2_{adj}$=0.9998, where the average deviation of predicted attraction aggregated to municipalities from SCB data is 94 trips with standard deviation of 293.

The results of the production model show that employees of private sector produce more trips than of public sector. However, the situation is opposite in relation to attraction. An explanation can be that the number of industrial buildings explains attraction better that the amount of registered people.

4.2 Trip Distribution

After estimating the total number of work trips that have their origin or destination in a specific zone, the next step is to generate a trip matrix, which contains information on the number of trips (T_{ij}) that occur between all possible pairs of considered zones as well as within zones. A common approach for estimating the number of trips between different zones is the use of gravity models, which is based on the assumption that a correlation exists between the number of travellers between two zones and the number of trips originating and ending in the respective zones. As there is enough data to rely on both attraction and

Table 1: Production regression model.

	Coefficient	**Std. Error**	***t*-value***
Employees Public Sector (Night pop.)	0.5158	0.018	28.324
Employees Economic Sector (Night pop.)	0.6993	0.010	68.610
Employees Economic Sector (Day pop.)	0.0372	0.008	4.949

*all P values are less than 0.001

production values, we may use the tri-proportional fitting method:

$$T_{ij} = A_i O_i B_j D_j f(c_{ij})$$

with two balancing factors A_i and B_j for ensuring both the origin and destination constraints

$$A_i = {}^{1}\!/_{\sum_j B_j D_j f(c_{ij})} \,,$$

$$B_j = {}^{1}\!/_{\sum_j A_i O_i f(c_{ij})} \,,$$

and a *deterrence function* $f(c_{ij})$ that fits a modelled distribution of tours into the observed trip length distribution in RVU. The process happens cyclically: first origins O_i and destinations D_j are balanced with balancing factors A_i and B_j , then the deterrence function $f(c_{ij})$ is adjusted to fit the resulting modelled trip length into observed trip length distribution.

In our case study, for balancing production and attraction rates, attraction rates are scaled to the level of productions. The distance of a shortest-path car trip between the SAMS zones is used to assess travel costs. Length of trips within the zones is taken a as a half of distance to a closest zone. Deterrence function is balanced to represent distribution of trip lengths observed in RVU. Number of trips is rounded to nearest integer after each balancing operation.

The trip matrix does only contain aggregated information on the number of journeys, not on individual travels. For the modelling of realistic DRT requests, this is not sufficiently detailed, as the temporal and spatial occurrence of requests might influence the success of different DRT design options. The desired arrival time of each traveller must be considered as well as information on the start and endpoint of the trip that is as accurate as possible. Each trip $t_i \in T$ is represented by a tuple $<o_i, d_i, t_i>$, with origin (o_i), destination (d_i), and desired arrival time (t_i).

GSD land use datasets are used to randomly assign each traveller with a residential building of its origin zone, from where the work trip is requested and a workplace with company or public buildings, to which the journey is requested. The point in time for which the traveller decides to request a DRT journey is determined based on the RVU survey. Probability distribution fitting can be used to derive adequate probability distributions of travel start or end times as well as on the working hours based on data acquired by the survey (cf. Figure 3). Through this, realistic travel and work behaviour of an arbitrary number of inhabitants can be modelled.

Table 2: Attraction regression model.

	Coefficient	**Std. Error**	***t*-value***
Inhabitants with Age between 25-44	0.2051	0.029	7.003
Number of Industrial Buildings	0.9510	0.197	4.833
Employees Public Sector (Day pop.)	0.6471	0.025	25.617
Employees Economic Sector (Day pop.)	0.5360	0.026	20.234

*all P values are less than 0.001

To validate the generated commuting trips, they can be compared to real-world survey data. To this end, attraction and production rates estimated by the regression models can be compared to SCB data on commuters per municipality and the resulting O-D matrix can be validated against data from the RVU survey.

In Table 3, the commuting tours of the generated O-D matrix are compared against data from SCB. As SCB data on commuters is not available for the considered year, datasets from two surrounding studies have been linearly interpolated. A deviation between SCB and RVU data can be observed, which might be due to the origin of the data. While RVU data was acquired directly by surveying travellers, SCB commuting data might be based on estimations from other surveyed data, e.g., residence and workplace of individuals. Hence, we assume that RVU data we used as basis for our regression model is more representative and scale the interpolated SCB data according to RVU data with a derived factor of 0.65 such that they can be compared to the data we simulated.

It can be observed that the simulated number of outgoing, incoming, and intra-zonal tours deviates between 3 and 20% from data that is provided by SCB. It is also important to notice that SCB data only exists on a municipality level, while the simulated data from all zones within the municipality was cumulated for the comparison.

4.3 Modal Choice

As a result of the previous two steps, an O-D matrix is generated, which estimates the flows of commuters between the investigated zones. In the classical transportation forecasting model, the selected travel mode is determined by statistical choice models, e.g., direct demand models.

To allow for more sophisticated and individual decision-making, the use of agent-based modelling (ABM) is suitable (DeAngelis & Diaz, 2019). Instead of forecasting the use of PT and DRT based on, for instance, travel time diversion curves or by means of utility functions, travellers in ABM proactively and individually select the travel mode that seems most suitable considering their current personal situation, environment, and desires. This is done through agent function F, which determines a decision on whether or not to accept an offered DRT trip (action A={accept, reject}) from information that is provided on the offered journey (e.g., estimated departure, travel, or arrival time) as well as on the traveler's individual circumstances (perceptions P; e.g., access to car, age, or income).

$$F_i: P^* \rightarrow A$$

In transportation, econometric utility-based models are the dominate modelling approach, where the most widely used is multinomial logit model (McFadden, 1973). There are other approaches, such as Machine learning based methods (Chen et al., 2017, Daisik et al., 2017). They have a potential to

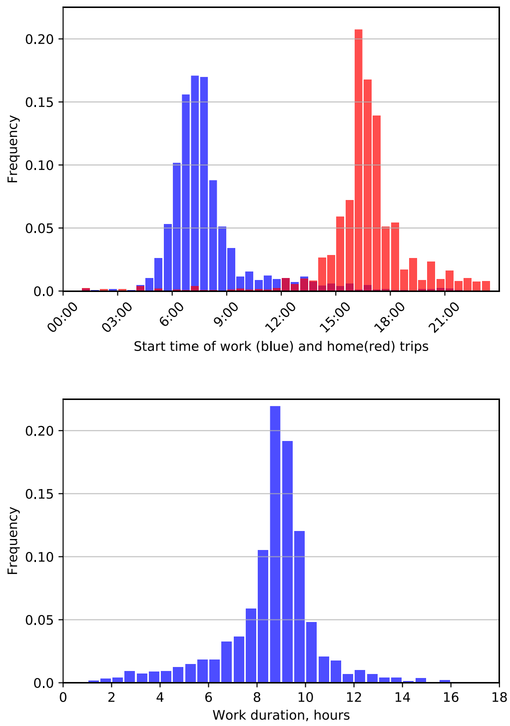

Figure 3: Probability distribution of a) work and home trip start times b) work length distribution.

Table 3: Comparison of simulated O-D matrix and SCB commuter data.

	Simulated Data	Interpolated SCB Data	Dev. in Percent
Sjöbo			
- outgoing	2 955	3 050	-3.2%
- incoming	1 633	1 296	+20.6%
- within	2 957	2 680	+9.3%
Tomelilla			
- outgoing	1 803	1.863	-3.3%
- incoming	1 434	1 173	+18.2%
- within	2 242	2 044	+8.8%

produce good results, but they require large dataset for training. In this case study, we do not possess data to produce a complex model for choice of DRT.

To implement an initial decision-making of the traveller, we compare a planned DRT travel time (d^t) against the assumed travel time by car (c^t) and a factor of maximum acceptable deviation (dev) from this travel time is suitable, e.g.,

$$F_i(d^t) = \begin{cases} \text{accept, if } d^t < (c^t \cdot dev_i) + c_i \\ \text{reject, else.} \end{cases}$$

This factor describes the relative delay that the traveller is willing to accept in favour of DRT transportation regarding the length of a direct trip. c_i is a constant value that is added to the previously determined deviation time. Both delays can either be individual values for each traveller i, e.g., depending on its access to other means of transportation, or equal for all travelers. Also, the delay can refer to the entire work trip, from home to workplace, or only on the DRT leg, e.g., from home to the first PT stop.

4.4 Traffic Assignment

Finally, as a last step of the methodology, the choice of the route takes place (Patriksson, 2015). This step considers overload and congestions that might occur if all travellers chose the same route for their journey. In the presented case study, the focus lies on DRT and PT in a low-density area. Thus, it can be assumed that PT services will not deviate from their planned route and that significant delays due to increased traffic density will not occur. Still, the number of DRT vehicles as well as their capacity are limited. Accordingly, trip request put a load on the DRT service resulting in increased waiting and travel times for travellers due to detours to serve multiple clients. The trips with the large detours will likely be rejected by travellers, which prevents overload of the DRT service itself in a self-regulatory way.

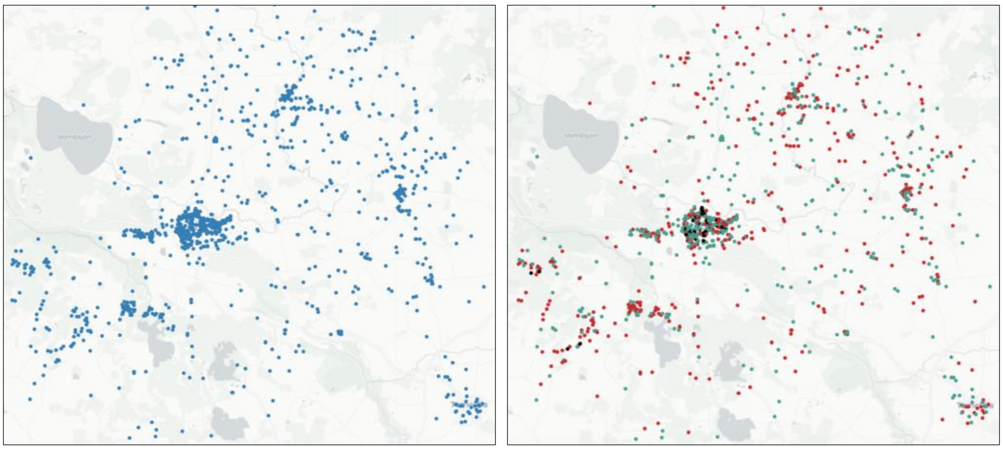

Figure 4: Distribution of start points of DRT journeys a) potential travellers and b) subset of simulated requests that were accepted (green), rejected (red), and ignored due to its closeness to PT stops (black).

An important assignment task that must be solved and optimized in DRT scenarios is the dynamic planning and scheduling of the DRT vehicles. Each of the travellers' requests must be allocated to one of the vehicles and both pick-up and drop-off must be scheduled in accordance with maximum deviation restriction. This results in a vehicle routing problem with paired pickups and deliveries, i.e., the *dial-a-ride* problem, with the goal of minimizing the total costs of transportation

$$\min \sum_{k \in K} \sum_{(i,j) \in V} c_{ij} x_{ij}^{k}$$

according to (Parragh et al., 2008), with a set of vehicles K and set V of available edges leading from node i to node j. c_{ij} is defined as the costs to pass edge (i,j) and $x_{ij} \in \{0,1\}$ being 1 only if edge (i,j) is used by vehicle k. The costs might consider both the time and distance of the journey.

This optimization problem is dynamic, as request may come in a real-time. When a traveller requests a trip, a state of the service (position of vehicles, planned routes) are determined by previous travel requests. The resulting characteristics of a trip (travel and waiting times) can be compared to the expectations of the requesting traveller to evaluate whether the person will use DRT to make a trip. Simulation of DRT service and traveller behaviour allows to realistically estimate operational characteristics of a service. Furthermore, data is generated that allows for the assessment and comparison of the performance and utility of different DRT designs.

5 RESULTS

To simulate the request of DRT journeys by commuters for Sjöbo and Tomelilla and to estimate the travel times for each requested journey, two tools are combined. First, *OpenTripPlanner*[6] is used to identify suitable multi-modal trips based on a road network (*OpenStreetMap*[7]) and PT timetables. To provide efficient DRT services, requests can be grouped and served together, so that pick-ups and drop-offs of other potential passengers must be considered when estimating travel times. To this end, we used *jsprit*[8], a vehicle routing problem solver, to find optimal routes for a set of requests.

We assume that individuals are allowed to request DRT services for trips with a distance of more than two kilometres. It may be a direct trip by DRT within the borders of the two municipalities or a connecting trip by DRT to a PT stop if a person commutes out of or into the studied municipalities. Moreover, we assume that travellers are not willing to accept DRT legs with an estimated travel time of more than 1.5 times the travel time of using direct car transport plus 15 minutes, i.e., $dev_i = 1.5$ and $c_i = 15$. For example, a car trip of 15 minutes will only we replaced by a DRT trip if this trip does not take longer than 38 minutes. The simulated requests are shown in Figure 4, where each blue point represents the start point of a work trip.

[6] https://www.opentripplanner.org/

[7] https://www.openstreetmap.org/

[8] https://jsprit.github.io/

The simulation was run with 30 vehicles (minibus with 8 seats) and for the morning of a workday, i.e., outward journeys. DRT trips could be successfully offered to 990 travellers and the rejection rate was 27%. In average, there were 42.6 travellers per vehicle and the total distance driven by all vehicle was 18 444 km (average of 614.8 km per vehicle). 47 trips were not served as they were too short (≤2 km).

On the right side of Figure 4, the simulated requests are shown. Here, green dots represent requests that were accepted by the travellers as the estimated travel time was satisfactorily for them. Red dots mark requests that were rejected or trips that could not be routed by the planning and scheduling engine. This might be due to unavailability of adequate PT connections or capacities of DRT vehicles. Black dots represent travellers that are excluded from the system due to their closeness to PT stops. In the simulation, this occurs in some parts of the city centre.

6 CONCLUSIONS

In this paper, we presented an approach for the modelling of realistic commuting activities, which can be used for the assessment and comparison of DRT designs. In contrast to many other existing approaches, requests for DRT journeys are generated on a level of individuals, such that individual pick-ups and drop-offs at the home or workplace of the commuters can be simulated. To show the feasibility of the approach, a case study is presented of Sjöbo and Tomelilla, two municipalities that are located in the rural area of southern Sweden.

The case study presented in this paper is only a first step towards showing the feasibility of the generated requests. The results do not yet allow for assessing the effectiveness or viability of a DRT service. For this purpose, a more advanced simulation study must be conducted in which different designs are systematically compared. The intention of the presented simulation experiments is to show the feasibility of the approach. For the design of an efficient DRT service, extensions of the presented simulation are reasonable. There is a need in more advanced mode choice model, that considers further attributes of the travellers that influence their decision towards the use of DRT services, e.g., climate protection awareness, availability of car, or age. Accordingly, the route scheduling should not only focus on operational costs but also optimize quality of the service for passengers. In this case study, road congestions were not considered as we investigate rural areas. However, in urban conditions, congestion is an important factor. Still, the presented case study indicates where potential DRT requests occur and when rush hours can be expected. Also, a first estimation of the number of required vehicles can be made based on the number of requests.

The generation of demand for DRT is a key component of a simulation framework for investigating the suitability of different DRT design decisions. We plan to not only simulate commuters that use DRT on their way to work but also other types of travel, for instance, school, medical, or leisure trips.

Our overall goal is to provide decision-makers with a tool that can be used to explore and assess, how to plan and execute an efficient and high-quality DRT services. The development of a modelling and simulation framework facilitates the conducting of comprehensive simulation studies of DRT services. This includes the consideration of specific local conditions such as the distribution of inhabitants or existing PT lines but also of different performance measures on the utilization of vehicles or average travel times. This allows for the thorough investigation of different design decisions and parameters, to identify whether and how they affect efficiency, viability, and acceptance of DRT for specific scenarios.

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