Analysis of Schedules for Rural First and Last Mile Microtransit Services

Christian Truden[1[0000−0001−9018−4269]], Mario Ruthmair[2[0000−0002−2318−6667]], and Martin J. Kollingbaum[1[0000−0001−8170−8374]]

[1] Lakeside Labs GmbH, Lakeside 04b, 9020-Klagenfurt, Austria
{truden, kollingbaum}@lakeside-labs.at
[2] Alpen-Adria-Universität Klagenfurt, Department of Mathematics, Universitätsstraße 65-67, 9020-Klagenfurt, Austria
mario.ruthmair@aau.at

Abstract. Low and infrequent demand in rural areas poses a problem for public transport providers to run cost-effective services and individual car use is usually the main means of transportation. We investigate how microtransit services can be integrated with existing public transport solutions (bus, train) as a flexible shared mobility alternative in rural areas and how to make them attractive alternatives to individual car use. We combine large neighborhood search with agent-based modeling and simulation to validate generated schedules for a microtransit service in terms of vulnerability to tardiness in passenger behavior or service provision. This includes the study of how disturbances, such as delays in service provision or late arrivals of passengers affect the stability of a transport schedule concerning a reliable timely delivery to transfer stops. We explore how simulation can be utilized as a means to fine-tune provider policies, e.g., how long vehicles may wait for late passengers before they depart.

Keywords: mobility · agent-based simulation · ride-sharing

1 Introduction

Demand for transport in rural areas arises from the need to reach urban centers for work, schools, and the utilization of various services. Due to low population density, this demand usually peaks at particular times of a day. As a result, public transport provisions are concentrated around these times and otherwise operate with low frequency, and with transport services covering few select locations only. Individual car use is the main (and, often, only) means of transport available when ad-hoc demand arises. In particular, there is a lack of transport provisions for the first / last mile to / from public transport system corridors, where timetabled services are available at high frequency. There is a need to integrate microtransit services with existing (timetabled, high-volume) public transport systems to increase adoption of shared mobility solution in areas with low population density [6]. Improving access to and use of public transportation by refining the quality of the first / last mile connections is in the focus of many transport authorities around the globe [9]. New demand-responsive forms of transport gain popularity, in particular in urban centers, where ride-hailing services are now widely used. Microtransit systems are a demand-responsive ride-sharing option that are flexible in their service provision and are deployed in regions where public transport is not (or scarcely) available.

We investigate sustainable and reliable forms of rural passenger mobility. Shared transport modes are regarded as one of the measures to reduce carbon emissions in daily commuter traffic [4,7,10]. We are, therefore, interested in how to provide shared transportation in rural areas that can compete with private car use in terms of availability and convenience. This poses a challenge as using a car is typically the fastest and most convenient mode of transportation in rural areas.

In the modeling of transport scenarios, two complementary perspectives, capturing the passenger's and the service provider's view, respectively, can be distinguished, *a*) the *usage* behavior of customers using a transport system, which is captured in the form of basic transport requests or more complex activities (transport request chains). The main concern of a customer is to be transported without delay and in a reliable fashion; *b*) the *service provision*, where transport services may vary in terms of modality, purpose, flexibility (on-demand, timetabled), etc. The concern of a service provider is to optimize transport provision so that demand can be met. For demand-responsive services, customers may choose to request transport well ahead of the actual journey start time (*prebooked*), or make *ad-hoc* requests that may occur close to the actual required travel time.

In our study, we investigate how microtransit systems can be integrated with existing public transport operations to meet transport demand. Certain behaviors in a population, such as passengers being late at agreed pickup locations, may lead to delays that make such a transport service unreliable. A balance has to be found in terms of providing a convenient service (all transport requests, including delayed departures for late passengers, are serviced) and a reliable service provision (reaching destinations in time). Whereas passenger behavior is beyond the control of a service provider, a provider can make particular decisions about its own service provision, such as allowing a certain waiting policy at stops that may influence the number of successfully serviced transport requests. This waiting policy may have to be calibrated to balance convenience with reliable service provision. We use agent-oriented simulation as a means to calibrate demand-responsive services in terms of convenience and reliability. Microtransit solutions follow a trip-sharing model, where multiple passengers are transported together on-demand to particular destinations. These systems are either flexible in terms of pickup and delivery locations (door-to-door) or operate within a network of possible, albeit fixed, locations (stops), where passengers can board and leave vehicles. We assume in our investigation a rural area with low population density, where a microtransit solution is introduced as a shuttle service to transfer people from their homes to a public transport system (train). In our rural transport scenario, therefore, people will conduct journeys with multiple legs and transfers in their commute, and where on-demand service elements are combined with timetabled public transport systems. Important aspects of service provision are *customer satisfaction* – a service provider has the capacity to provide a service when ad-hoc demand arises, and *trust* – customers can reach a destination in time (avoid being late for transfer to other modes of transport, or being late to work or school). We consider two performance indicators for microtransit systems to capture these two customer-specific notions, *a*) the percentage of transport requests made for a particular time horizon that can actually be serviced (capacity-related issue), and *b*) how many of these serviced transport requests are fulfilled in time (the passengers arrive at their destination at the specified time). Additional considerations are whether a customer with delayed pickup can still be delivered to their destination in time, or how much delay of a transport customers may accept before they switch to alternative modes of transportation. The main concern in this study is how *lateness* of customers or transport services has an impact on service provision and customer acceptance of these new transport modes. Given these considerations regarding performance, we distinguish passengers either arriving at a pickup location in a timely manner, or them being late. We consider passenger populations with a mix of these two behaviors and analyze how our planning approach can cope with late arrivals. We modeled this scenario as a multi-objective variant of the *dial-a-ride-problem* (DARP) [2,3], and developed a planning system based on a large neighborhood search heuristic for creating transport schedules for microtransit systems. The problem formulation aims at finding routes for a fleet of vehicles that satisfy transport requests of passengers. These requests are defined by *a*) a pickup location where passengers may board a microtransit vehicle and an associated pick-up time, and *b*) a destination location with an associated arrival time window. In our scenario, the destination location is a public transport stop, therefore, the time tables of the public transport services frequenting this stop may influence the chosen size of the arrival time window. We use agent-based modeling [16] to develop a simulation of a rural commuter scenario with a microtransit shuttle service. With this *agent-based modeling and simulation* (ABMS) approach, lateness of passengers or road disturbances can be simulated to verify whether a transport schedule can cope with these kinds of problems. With such a microsimulation approach, we investigate how planning results perform in terms of sensitivity to disturbances and in terms of stability with respect to arriving in time for transfers between modalities at stops, or in terms of transport capacities made available.

2 Related Work

Mobility solutions that are demand-responsive, such as ride-sharing or car pooling, are promoted as new forms of transport in urban and wider metropolitan areas to meet transport demand [7]. Riley et al. [12] present a real-time dispatching solution for a ride-sharing service with a rolling horizon that utilizes a column-generation approach. A computational study shows that their approach scales very well in practice. However, their approach is tailored towards large-scale systems used for highly populated urban areas such as New York City. In contrast to our approach, where pickup and drop-off time windows are essential for scheduling trips, the approach presented in [12] can neglect time windows due to a large number of available vehicles and, typically, relatively short travel times in the urban environment. In our study, a flexible microtransit service shuttles passengers to a train or bus station where they may transfer to a timetabled public service. Therefore, the choice of arrival time may be influenced by the time tables of public transport services that passengers want to reach. However, this is taken into account in a pre-processing phase where a set of typical transport requests are generated (synthetic population data), and not a concern of the actual planning and optimization algorithm we developed (variants of DARP, such as IDARP [11], in contrast, include a mix of flexible (bookable) and fixed timetabled services in the model). We use agent-based modeling [16] and microsimulation to investigate how a demand-responsive transportation service can be delivered efficiently ([1] provide a review of agent-based transportation systems). Microsimulation allows the modeling of individual behavior of agents (passengers, vehicles, etc.) in a particular transport system. Ronald et al. [13] discuss agent-based simulations for studying demand-responsive transportation systems.

3 Rural Commuter Scenario

A rural commuter scenario forms the basis for the investigation presented in this paper. This scenario is situated in an assumed rural area where a central transport corridor, consisting of a major motorway and a rail line, connects two urban centers. Public transport is concentrated in this corridor, whereas outside in the wider rural region, no such services are available. In this scenario, inhabitants of a rural area commute to a workplace in an urban center. They either use a car, leading to congestion and pollution, or find a way to use the rail line. There is usually no service for the first / last mile of daily commutes.

3.1 Transportation Network

In the modeling of this scenario, we assume that a demand responsive mobility system is available for servicing the first / last mile travel of a rural population. A microtransit service will serve fixed locations where passengers may be picked up or transported to. We assume that there are stops specific to the microtransit service, but that also existing public transport stops (e.g. railway stations, bus stations) are frequented by such a service. This is necessary to allow a transition of passengers from a demand-responsive to a public transport system. We, therefore, distinguish two types of stops: *i*) Public Transport (PT) stops are provided by transit authorities; *ii*) Microtransit (MT) stops specific to such a mobility service. Microtransit stops are used on-demand – they are only frequented when passengers request transport from such a location. There are two main reasons that drive the creation of a network of such stops, *a*) it is demand-oriented – because of a certain population density, or through the initiative of local authorities, MT stops are established, or *b*) there are special points of interest that warrant good accessibility. In the considered region, there are 5 PT (train stations) and 97 MT stops. The road network of the rural region under consideration is represented by a travel matrix with distances and travel times (computed by OSRM [5] based on OpenStreetMap) between each pair of PT and MT stops with the default OSRM car profile.

3.2 Vehicle Fleet

The vehicle fleet of the microtransit service is comprised of small buses with limited seating. Vehicles are specified by the following parameters: *a*) number of passenger seats, and *b*) availability, i.e., earliest start time, latest end time, depot location. This microtransit fleet is deployed demand-responsive and, therefore, is not subject to fixed service times. However, we assume that the complementary public transport system is deploying services according to fixed timetables and, therefore, the scheduling of public transport resources cannot be changed.

3.3 Transport Demand

Transport demand arises through passengers (alone or in groups) issuing *transport requests*. A transport request is characterized through an OD-pair, describing a single journey from an origin to a destination location. In our current study, a passenger may issue multiple transport requests in one booking. Such a set of transport requests is then regarded as related and either all of them can be scheduled for transport at the requested times and from / to the requested locations, or all of them are rejected (no partial scheduling of a set of requests is allowed). Several such requests may form a *transport request chain*, if the destination of one request is the origin of the next and there is a timely correlation between arrivals and departures. However, they can also be unrelated in terms of timing and locations. In principle, transport requests are either pre-booked well before a defined planning horizon, or they are placed on short notice (ad-hoc transport requests). For now, we consider only a set of pre-booked requests. In our study, a pre-processing step is generating a set of such request chains (*synthetic population*) that represent the typical travel behavior of a particular rural population as close as possible. Such a pre-processing step is necessary as data about actual transport demand is not available. In the generation of such a synthetic population, we assume that passengers book a chain of requests, describing situations where passengers are taken from an MT stop to the closest PT stop (representing the commute from a rural microtransit stop to a selected public transport stop), from where the public transport system will get them to their work place (or any other destination), and the corresponding return request between these chosen stops. Passengers will start their journey at an MT stop, and, with a scheduled return request, also end their journey at the same MT stop.

For generating the first (*outgoing*) OD-pair in such a transport request chain (passengers commute to a train station), we assume that *a*) each origin stop in a generated OD-pair is a randomly chosen MT stop in the pilot region, *b*) each destination stop in a generated OD-pair is the PT stop closest to the MT stop (shortest Euclidean distance). In order to use these scenarios in the planning and simulation work, we limit what public transport is available to commuters. We assume that passengers start their commute in a time period between 05:00 and 09:00 in the morning from Monday to Friday. Timetable information at public transport stops is used in the calculation of the required arrival time windows for the microtransit services at such a PT stop. The arrival time window is currently set to 10 min and is correlated with timetabled departures of transport services at the PT stop. The pick-up time of the microtransit service is calculated from this arrival time window, using minimal duration of a transport request as well as its maximum allowed duration (ride time limit) between the two selected stops. For the generation of the corresponding *return* transport request, we assume that the origin and destination of the first request are used in reverse. Commuters returning from a train station to the original MT stop are assumed to do this in a time period from 15:00 - 19:00 in the evening from Monday to Friday.

The approach for generating a synthetic population presented here is currently limited to commuter trips, as no reliable data about other types of trips exist in the chosen rural area of study. Given that our work aims at showing the use of agent-based simulation for shaping policies for mobility service provision in general, we do not consider this focus on a particular type of trips a limitation. Clearly, in the long run, for a successful service also trips for shopping or recreational activities and trips leading to journeys local to the rural area (coordinated with the timetabled services) have to be included in policy-shaping procedures.

3.4 Constraints

The following constraints are considered in planning and execution of the transport schedules: *a*) the number of used seats in a vehicle cannot be exceeded, and *b*) the time windows and ride time limit defined by the passengers cannot be exceeded. Currently, multi-modality and, consequently, transfer times for changes between different modes of transportation are not considered by the optimization algorithm.

4 Approach

For the study of demand responsive transport systems, we use a combination of combinatorial optimization and microsimulation. In a first step (Fig. 1), an optimization algorithm takes a set of transport requests of customers and constructs a transport schedule for a fleet of vehicles. For each vehicle, a route is defined as a timed sequence of stops with additional information about performed transport requests. Currently, we only consider transport requests that

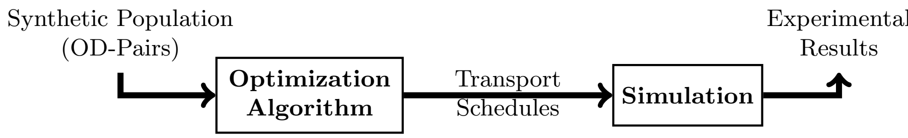

Fig. 1. Evaluation of transport schedules.

are pre-booked in advance of the actual journey. In a second step, this transport schedule is executed in a simulation environment and tested under various conditions, introducing stochastic events such as late arrivals or disturbances. Agent-based modeling [16] is used to create a simulation of the rural area where passengers request transport at particular times and microtransit systems operate on a network of stops (pickup and delivery locations for passengers).

4.1 Optimization Algorithm

We generate feasible vehicle schedules by solving the considered DARP variant with a greedy heuristic to construct initial solutions, followed by a large neighborhood search (LNS) to improve them with respect to the following three objectives: *i*) maximizing the number of accepted requests, *ii*) minimizing the total distance driven by all vehicles, and *iii*) minimizing the total excess ride time of passengers exceeding their request's direct travel time. These goals have been selected to achieve both high customer satisfaction and carbon emission reduction in service provision. The latter is based on the assumption of a linear relationship between emissions and the total distance driven that is widely accepted in the literature [4,10]. Since we are dealing with three potentially conflicting objective functions, we need to adapt classical single-objective meta-heuristics to work with multiple objectives. We decided to use a large neighborhood search (LNS) similar to the one in [14], since it is considered to be one of the state-of-the-art heuristics for a wide class of vehicle routing problems. Additionally, we use some ideas from a bi-objective LNS in [8]. To preserve diversification throughout the search, we maintain a pool of non-dominated vehicle schedules that is continuously improved and updated. Initial schedules are constructed as follows: *i*) we sort all transport requests by ascending latest arrival times, *ii*) iteratively select the (initially empty) best schedule in our pool (based on the objective ordering above), *iii*) extend it with the current request in all feasible ways, and *iv*) add all obtained solutions to our pool. Deciding the feasibility of an insertion is non-trivial for the DARP and done by using the method described in [2]. The obtained solutions are then iteratively improved via LNS by *i*) randomly selecting one of the schedules in our pool, *ii*) removing random transport request chains from it, *iii*) trying to insert to it as many not yet served request chains as possible (by using greedy and regret insertion), and *iv*) feeding all intermediately obtained schedules back to the pool. These steps are repeated for 100 iterations.

4.2 Agent-based Modeling

Microsimulation is used for the evaluation of the transport schedule generated by the optimization algorithm. In a process of agent-based modeling, we identify the stakeholders in the chosen rural transport scenario, such as passengers and vehicle fleets of service providers. In the execution of a transport schedule, concerns regarding delivery (passengers reach their connections in time) are investigated through simulation.

The following agent types are considered: *i*) *passengers* who require transport (and issue single transport requests or book whole transport chains), *ii*) *vehicles* that conduct these transports (following the transport schedule), *iii*) *stops (PT and MT)* that are agentified in this scenario, in order to model and control arrival, pickup and delivery procedures of passengers and vehicles at PT and MT-transit stops, respectively, and a *iv*) *disturbance agent* that is used to introduce randomness into the execution of the transport schedules.

Passenger and Vehicle Agents Both passenger and vehicle agents execute information derived from the transport schedule. Vehicle agents receive a schedule comprised of a sequence of stops where passengers are either picked up or delivered at particular times. Assuming a microtransit system using a fleet of mini-buses, such a vehicle usually has a capacity of around eight seats. In addition, mini-buses require, in contrast to city buses with large seating and standing capacities, a one-to-one seat assignment. Passenger agents receive information about their chain of transport requests (scheduled according to the passenger's transport requests), they are required to arrive at a specified stop at a given time (within a time window) so that they can board a mini-bus. Vehicle agents, passenger agents and stop agents interact when arrival events occur at a particular stop. Vehicle agents perform the following actions: *a*) transfer between stops (starting from a depot), such a transfer ends with an arrival event at a stop, *b*) arrive / register at a stop, *c*) start waiting time at stop (wait for a period of time or until arrival events of registered passenger agents occur), *d*) drop off passenger agents according to transport schedule (seats become available, passenger agent is un-registered from the vehicle agent), *e*) pickup of all registered passenger agents (passenger agent is regarded as occupying a seat on the mini-bus and is registered by the vehicle agent), *f*) depart / un-register from stop when all pickup requests fulfilled or waiting time expires. Passenger agents perform the following actions at the pickup location: *a*) depart from home; *b*) arrive / register at stop; *c*) start waiting time at stop (record waiting time); *d*) wait for arrival event of vehicle that fulfills transport request (information received from stop agent); *e*) board vehicle (register with vehicle, occupy seat); *f*) un-register from stop; *g*) start recording transfer time. Passenger agents perform the following actions at the drop-off location: *a*) stop recording transfer time; *b*) arrive / register at stop (stop agent acknowledges arrival). At this point in the process, passenger agents either leave the stop (they un-register) to reach their final destination on foot, or they start the next leg of their request chain, where the current stop is the next pickup location.

Stop Agents Stop agents act as arbitrators between passenger and vehicle agents and keep track of the registration and waiting of both agents at a particular stop of the transport network. Agents that are not registered with stop agents, are regarded "in transit". A stop agent keeps track of the passengers arriving, waiting, and departing at this stop.

4.3 Disturbance Events

A separate system agent, the so-called *Disturbance Agent*, generates disturbance events. In the first instance, two events are considered: *a*) longer (or shorter) travel times than expected, leading to delays or early arrival, and *b*) tardiness of passenger or vehicle agents when leaving from a location. Arrival delays are modeled implicitly. Each time a vehicle is in transit between two locations of the transport network, the disturbance agent adds a random delay (or reduction) to the travel times. Hence, a vehicle can arrive later (or earlier) than planned at its next destination. We assume that the travel times recorded in the travel matrix (representing the transport network) are not biased, i.e., they represent the expected value of the underlying (unknown) distribution of the travel times, where travel times for each vehicle and each trip are independent, which is a reasonable assumption in case that travel times depend on the condition of the vehicles, a driver's skills, or minor roadside obstacles (slower vehicles impeding the traffic, red lights) [15]. For now, extreme events such as traffic accidents, blocked roads, or mechanical failures of the vehicles are not considered.

Influences on Passenger Agents We distinguish two types of passenger agents: *a*) *punctual*, showing little to no tardiness, *b*) *tardy*, being late most of the time. Assuming that a passenger has a scheduled pickup time α at a MT-stop that is β walking minutes from his / her home address, the arrival of the passenger is determined by two random processes. *a*) *Departure from home / work.* follows a normal distribution $X \sim \mathcal{N}(\mu, \sigma^2)$. Punctual (tardy) passengers leave at $\mu = \alpha - \beta - \gamma$ with a standard deviation of $\sigma^2 = 2\,\text{min}$, where γ defines the "slack" of the passenger leaving earlier. Punctual passengers allow a slack of $\gamma = 5\,\text{min}$, while tardy passengers only allow $\gamma = 3.5\,\text{min}$. *b*) *Walking time to the stop* deviates from the expected walking time following a truncated normal distribution $X \sim \mathcal{N}(\mu, \sigma^2, a, b)$, where $a, b \in \mathbb{R}$ define upper/lower bounds. For punctual customers we assume the parametrization $\mu = 0$, $\sigma^2 = 10\,\%$, $a = -5\,\%$, $b = 5\,\%$ and for tardy customers we assume $\mu = 0$, $\sigma^2 = 15\,\%$, $a = -5\,\%$, $b = 5\,\%$. The actual arrival time at the pick-up location $\hat{\alpha}$ is determined by adding up both random values. In Fig. 2 we show the empirical density of the punctuality $(\hat{\alpha} - \alpha)$ of passengers at the pick-up locations. We notice that $0.65\,\%$ of the *punctual* and $5.38\,\%$ of the *tardy* passengers arrive later than the scheduled pick-up time α. Further, we assume that passengers wait up to 5 min after the scheduled pick-up time for the vehicle to arrive before they abort the request.

Influences on Vehicle Agents Vehicle agents have the following behavior. The vehicles leave from a location towards the next location according to their

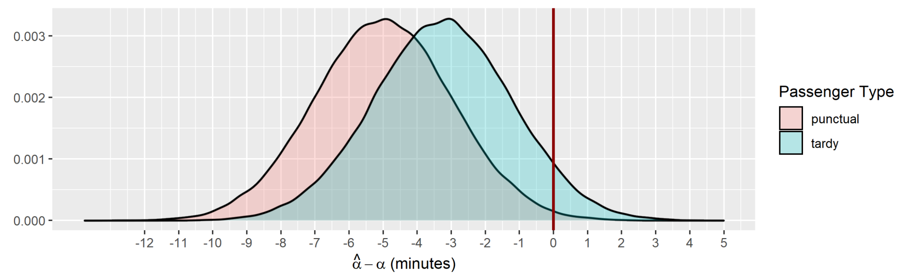

Fig. 2. Empirical density of punctuality for the two passenger types *punctual* and *tardy*, n =100 000 samples each. The punctuality is determined as the difference between the scheduled pick-up time α and the actual arrival time at the pick-up location $\hat{\alpha}$.

schedule once a) all passengers that are scheduled for pick-up have arrived, or, b) the scheduled boarding time (plus a waiting time $\omega \geq 0$) of the passenger(s) has passed and the passenger(s) have not arrived. However, their arrival times are subject to random influence through the disturbance agent. Clearly, travel times must always have positive values. In our experiments, we assume that they follow a *truncated Normal distribution.* $X \sim \mathcal{N}(\mu, \sigma^2, a, b$, where $a, b \in \mathbb{R}$ define upper/lower bounds. The bounds ensure that only "reasonable" values are sampled. The expected values mu (for each edge of the travel matrix) are obtained from the OSRM routing engine [5]. For now, we assume the following parameters $\mu = 0$, σ^2 =15 %, a =−10 %, b =20 %. Obviously the parameterization must be individually adjusted for other rural regions of study for which simulations would be done.

5 Analysis

We study how disturbances, such as tardiness of passengers and delayed services, affect the provision of a transport service with respect to transfers at stops and timely delivery at destinations. In the analysis performed, the focus is on the effect of passenger tardiness on service lateness at destinations and the number of transport requests that are aborted (rather than determining appropriate fleet sizes through simulation). Clearly, the punctuality of the passengers affects the efficiency and stability of the service. In particular, services should not arrive late at destinations. However, service providers may have a choice to wait for tardy passengers in order to maximize the number of transport requests that are serviced. Of interest is the sensitivity of a transport schedule for a microtransit service to a population of tardy passengers and delays in service provision. A proper management of a demand responsive mobility system, in particular timely delivery at transfer stops to other modes of transport, is important to ensure customer satisfaction and to establish trust in the reliability of the microtransit service. Demand-responsive services have a certain flexibility in terms of departure from stops as they are not bound to a fixed time table and may leave as soon as all booked passengers have boarded. Time savings like these may compensate for delays occurring further downstream of the remaining journey. This allows service providers to operate according to a waiting policy at departures. The present analysis shows the effect of a waiting time policy on numbers of transport requests serviced and what kind of lateness at destinations can be expected.

5.1 Experimental Setup

For our analysis, we consider 10 randomly sampled instances that contain 100 transport request chains each that are served by a fleet of 10 vehicles (minibuses), each with a capacity of 8 passenger seats. For each instance, we consider all those transport schedules from the pool of solutions for which all 100 chains have been accepted. Further, we perform 100 simulation runs for each transport schedule.

Passenger Agent Populations The punctuality of the passengers affects the efficiency and stability of a transport service. To elaborate this point in more detail, we run our simulations with different "populations" of passenger, i.e., different mixes of *punctual* and *tardy* passengers. We compare the simulation results for the following three population types: *a*) 20 % *punctual* passengers (and 80 % *tardy* passengers), *b*) 50 % *punctual* passengers, *c*) 80 % *punctual* passengers. For each population, a total of around 1.34 million transport request chains have been generated in our experiments.

Lateness at the Destination A late departure at pick-up locations, caused by vehicles being late or waiting for tardy passengers may lead to late arrivals at destinations. We measure this as the *lateness* ℓ, which is the difference between the actual (maybe late) arrival of the passenger at the destination and the end of the arrival time window (of 10 min length). We report this late arrival time (in minutes and seconds) at the destination for all requests (*outgoing* and *return*). In that sense, $\ell = -10\,\text{min}$ means arriving at the beginning of the arrival time window, while $\ell = 5\,\text{min}$ means arriving 5 min after the end of the time window (being late).

Results - Vehicles with zero Waiting Time At first, we assume that vehicles do not wait for the passengers beyond the scheduled pick-up time, i.e., waiting time $\omega = 0\,\text{min}$. We summarize the aborted transport requests in Table 1 and report the lateness (passengers arriving late at their destinations) in Table 2. Additionally, we illustrate the lateness in Fig. 3. We notice that there are between 5.4 % and 10 % incomplete transport chains, depending on the population mix, while the q_{95} quantiles for the lateness range from 1 min 27 s to 1 min 40 s. The 25 % quantile q_{95} is around -13 min meaning that these passengers arrive 3 min prior to the arrival time window. Also, there is no excessive lateness with the

q_{95} being at around 4 min. Overall, the rate of aborted requests seems to be inversely proportional to the percentage of punctual passengers. Similarly, we notice that the passenger population mix also influences the lateness. Although we can clearly observe this effect in Fig. 3, it is limited as we can only report lateness for completed transport requests. Depending on how much slack for transferring to the next means of transportation at the destination was added when defining the arrival time windows, these results seem very promising due to the absence of excessive lateness or overly early arrivals. However, with the percentage of aborted requests being rather high the reliability of the service (even if this is induced by the tardiness of the passengers) is not guaranteed. In an effort to reduce the number of aborted requests, the service provider may introduce a waiting policy such that the drivers, who are represented by the vehicle agents in the ABM, may wait for the passenger to arrive past the schedule arrival time, i.e., $\omega > 0$ min. If such a policy is put in place, it is pertinent to provide additional date what a driver may allow in terms of lateness and still will be able to compensate for the passenger's lateness up to a certain amount of time.

Table 1. Percentage of aborted transport request chains reported for the three population types, $\omega = 0$ min. We report the percentages of transport request chains aborted at the *outgoing* or *return* transport request, and the completed transport chains. A chain being aborted at the *return* transport request prerequisites that the corresponding *outgoing* transport request was successful.

punctual (%)	aborted *outgoing* (%)	aborted *return* (%)	both completed (%)
80	3.56	1.82	94.6
50	4.74	3.06	92.2
20	5.83	4.22	90.0

Table 2. Lateness ℓ reported for the three population types, $\omega = 0$ min. The percentage of (completed) transport requests with $\ell > 0$ is reported, and the 25 %, 50 %, 75 %, 95 %, 99 % quantiles are reported as well. Given are combined numbers for all completed *outgoing* and *return* transport requests (if completed).

punctual (%)	$\ell > 0$ (%)	q_{25} (mm.ss)	q_{50} (mm.ss)	q_{75} (mm.ss)	q_{95} (mm.ss)	q_{99} (mm.ss)
80	10.804 66	-13.53	-7.58	-2.45	1.27	4.07
50	12.118 65	-13.20	-7.31	-2.15	1.34	4.10
20	13.265 74	-12.52	-7.10	-1.51	1.40	4.14

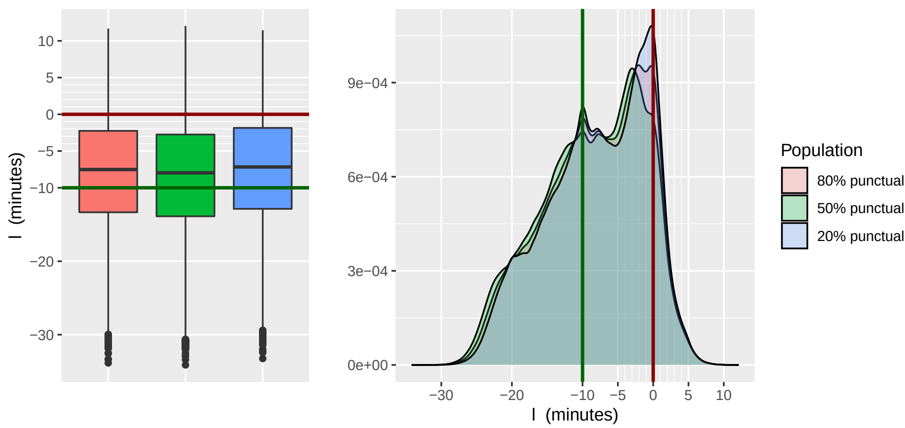

Fig. 3. Illustration of the lateness ℓ for the three population types (for the completed transport requests). The green (red) line marks the beginning (end) of the arrival time windows of the requests. All time windows are of 10min length.

Results - Vehicles with Waiting Times up to 10min We repeat our experiments with waiting times $\omega = \{1\,\text{min}, 2\,\text{min}\ldots, 10\,\text{min}\}$. The data show that the quantile values for ℓ increase for growing ω. However, this effect is rather modest as the values grow no more than a minute when ω is increased from 0min to 10min. In Fig. 4, we illustrate the percentages of aborted requests for changing ω. However, we notice a minimum for the *return* requests at $\omega = 2\,\text{min}$, that is followed by an increase for $\omega > 2\,\text{min}$. The *outgoing* requests show a similar behavior but the increase for $\omega > 3\,\text{min}$ is less strong. In that sense, the tardiness of passengers at pickup influences arrival times at destinations, depending on the chosen waiting time ω. All later arrivals lead to aborted requests (chains). Overall, we observe a consistent effect of the passenger population mix in terms of punctuality across all experiments, i.e., lateness at passenger destinations and percentage of aborted requests is always negatively affected by a lack of punctuality of the passengers. Passengers being tardy at their pickup location usually lead to aborted transport requests, which can be counteracted by introducing a vehicle waiting policy that increases the number of serviced requests. In summary, we see that introducing a waiting policy is beneficial to avoid aborted transport requests, while the effect on the lateness ℓ is rather small and therefore acceptable. The above results suggest that our approach can be a valuable decision-support tool for mobility providers that want to fine-tune their vehicle waiting policy in order to maximize the number of serviced transport requests.

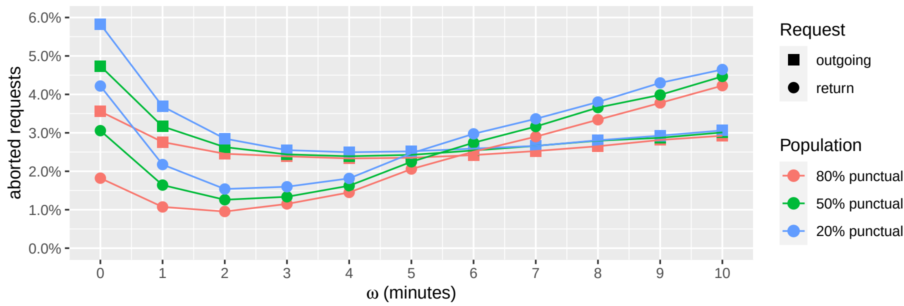

Fig. 4. Percentages of aborted transport request chains compared for different vehicle wait times $\omega = 0, 1, \ldots, 10$ min. We distinguish if a transport request chain is aborted at the *outgoing* or the *return* request.

6 Conclusion

We modeled a rural commuter scenario as a set of agents, where transport resources, passengers and elements of the transportation network (stops) are modeled as agents. At this stage of the project, generated requests represent passenger travel between dedicated stops of different mobility systems (on-demand transit, public transport). In a process of generating representative sets of passenger transport requests, these transport system stops are selected according to criteria such as whether they are the most plausible entry / exit points into a transport system that are closest to a person's start or to their vicinity to a person's intended destination, or their reachability from rural population centers, or whether they are public transport stops that allow a transfer from a microtransit system to a public transport system. We analyzed how late arrival of passengers and / or transport impacts on service quality (reaching transfer stops or final destinations in time). Our study shows that introducing a vehicle waiting policy is beneficial for service provision, resulting in less aborted trips. In future research, agent-based modeling and simulation (ABMS) will be used to investigate additional aspects, such as bottlenecks in service provision, how to optimize traffic and passenger flows, or how changes in procedures impact on the performance of an overall mobility system.

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