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Distribution of passenger costs in fixed versus flexible station-based feeder services

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Abstract

This paper presents a comparative analysis of demand-responsive and fixed-schedule, fixed route operations for a simplified station-based feeder to mass transit scenario. Traffic dynamics, demand-responsive fleet coordination, and the behaviour of individual transit users are represented using a public transit simulation framework. Each operational strategy is simulated for varying levels of demand and two fleet compositions with respect to vehicle capacities and fleet size are compared. The services are evaluated based on resulting passenger waiting times, in-vehicles times and additional waiting time if one is denied boarding a fully occupied vehicle. Results indicate that dividing planned service capacity into larger fleets of smaller vehicles can provide a higher level-of-service to passengers. On an aggregate level, utilizing a fixed operational policy results in shorter and more reliable waiting times for levels of demand where there is slack in service capacity. In scenarios where planned service capacity is sometimes exceeded, the on-demand service provides a more even spatial distribution of passenger waiting times, relative to a fixed service.

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Keywords: demand-responsive feeder; simulation; automated vehicles; spatial equity

1. Introduction

Demand-responsive services connecting to mass transit have shown potential to improve the mobility and level-of-service for travelers with limited access to a private car and for those in suburban or rural areas without adequate access to high capacity public transport. However, such solutions are also widely viewed as expensive to operate due to difficulties in spreading the cost of a given trip over a greater number of passengers (Davison et al., 2014; Ferreira et al., 2007). With the elimination of driver costs (often estimated to contribute to roughly 50% of the operational cost

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of bus transit in developed countries, see for example Australian Transport Council (2006)) a demand-responsive transit service making use of automated buses or shuttles could potentially be implemented at a far lower cost per vehicle (Bösch et al., 2018). Lower prospective costs per vehicle and their potential for centralized fleet coordination have also inspired the developments of automated feeder pilots all over the world (Ainsalu et al., 2018). Automated vehicles, although being developed at a high pace, have at present not reached levels of automation and safety that allow for their broader deployment. Demand-responsive transit systems are also difficult to trial, due to their cost of implementation, as well as the uncertainty of demand for such systems in the presence of varying design and fleet coordination strategies.

For the remainder of this paper a fixed-route, fixed-schedule service is simply referred to as a *fixed* service. A flexible-route service that is instead dynamically scheduled based on current and/or future demand is referred to as a *flexible* or *on-demand* service. A good deal of analytical models have been devoted to the comparison of fixed and flexible feeder services. The study of Daganzo (1984) presents an early comparison of fixed and flexible operational models. A flexible, station-based jitney service (referred to as checkpoint dial-a-ride transit) was found to only barely outperform fixed operations under high demand levels, while demand-responsive, door-to-door operations outperformed other services under low demand levels. Li and Quadrifoglio (2010) developed a combined analytical and simulation modelling approach to determine under which circumstances with respect to level of demand and demand pattern it is beneficial to switch between fixed and flexible operational policies for a one-vehicle feeder transit service. This work was extended by Edwards and Watkins (2013) who studied multiple fixed versus demand-responsive feeder systems for varying network configurations (grid and ring-radial layouts). Based on resulting operator- and passenger costs, case studies found that flexible transit could better serve user needs when demand density is below a given threshold.

An alternative approach to explore system design considerations of flexible transit solutions is by application of simulation models. Winter et al. (2016) studied fleet size requirements and system performance with respect to passenger- and operational costs of an automated, station-based feeder/last-mile solution. A simulation model was applied to the demand data and network of an ongoing pilot study evaluating the potential of replacing a campus train service between two stations with an on-demand service. The tested fleets consisted of automated, electric shuttles with capacities of 2-40 passengers. Among the presented results, passenger generalized costs were found to dominate system costs. The most effective ways found to reduce system cost per passenger were to increase demand levels, increase demand stochasticity, utilize vehicles with capacities larger than 10 passengers per vehicle, and operate with shorter vehicle dwell times. Scheltes and de Almeida Correia (2017) investigated the utilization of single-person capacity, automated, electric vehicles in an on-demand feeder/last-mile solution between a mass transit station and multiple stations within a university campus. In a simulated case study with demand input based on a survey of user acceptance and OD, system performance was evaluated under several scenarios in terms of network structure (adding and removing links to the baseline network), booking scheme (instant versus pre-booking of vehicles) and operational strategies (vehicle rebalancing strategies, charging strategies). Results indicated that utilizing automated feeder/last-mile connections had potential in reducing both average travel time and waiting time when compared to active modes. Shared rides with vehicles of higher capacities were not evaluated in the study but were hypothesized to bring further advantages of both operational and economical economies of scale; however carrying with it increased complexity and requirements on an effective centralized routing algorithm for the demand-responsive fleet.

Previous studies have provided important insights into how the design of automated, and non-automated fixed versus flexible feeder/last-mile transit relates to service performance in the presence of varying demand levels, demand patterns and network structures. To the best of our knowledge, however, the analysis of provided level-of-service in previous work has been based on system-wide aggregations and do not consider the distributional aspects of passenger benefits and costs. The studied feeder services in analytical studies, or those motivated by pilot studies of automated vehicles, also tend to focus on simplified service architecture, often either single-vehicle, single-person capacity fleets, or single-route designs. The study presented in this paper advances the comparison of fixed versus flexible operational policies with an analysis of spatial equity of passenger costs within the context of a station-based, multiple-route, shared-ride, feeder service. A public transit simulation framework is utilized to analyze the effects of operational model and fleet composition (with respect to vehicle capacities and number of vehicles) on passenger level-of-service measures in scenarios of low demand to high demand (where available capacity of the service is exceeded). The objective of this study is to investigate under what conditions demand-driven public transport by smaller connected vehicles can function as an alternative or supplement to fixed public transport.

The paper is organized as follows. In Section 2, the simulation framework that is used for our case study is described. In Section 3, the experimental set-up in terms of inputs and outputs to the simulation framework and variations that define the simulated scenarios are detailed. In Section 4, results from simulation runs are presented and compared. Finally, in Section 5, conclusions, discussion and suggestions for future research are given.

2. Methodology

In this study, an event-based public transit simulation model, BusMezzo, is used. BusMezzo (see Fig. 1) represents the progression of both individual vehicles as well as traveler agents and includes many important representations of public transit phenomena. The model has been shown to reproduce the phenomenon of bus-bunching (Cats et al., 2010) under various sources of uncertainty (passenger arrival process, dwell times, capacity constraints, travel times and vehicle scheduling) as well as represent passenger congestion effects (e.g., on-board crowding and denied boarding) (Cats et al., 2016). User input consists of demand input (arrival process and pattern) and network input (link, node and stop configurations and characteristics).

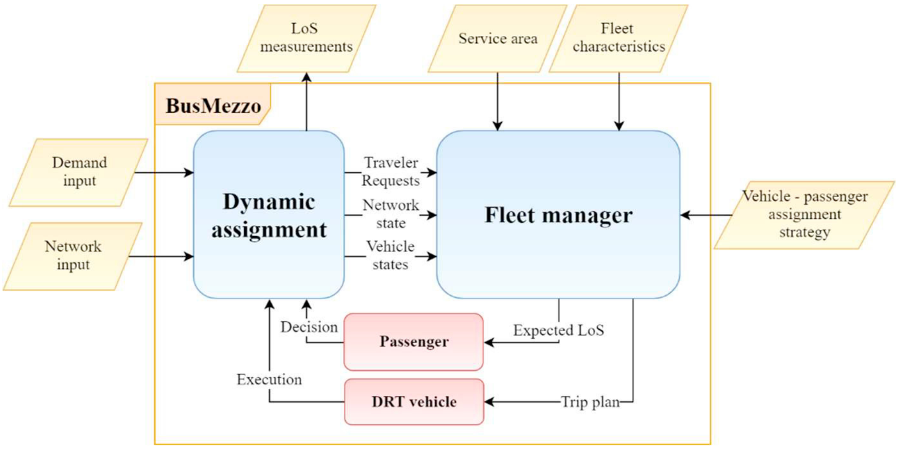

Fig. 1. Public transit simulation framework.

To model the demand-responsive fleet BusMezzo is extended with a “fleet manager” functionality. The key purpose of the fleet manager is to function as the vehicle-to-travel request assignment platform for the on-demand service. A travel request is defined by the information a traveler sends to the fleet manager when requesting a ride with an on-demand service. Attributes associated with a travel request are a pick-up and drop-off location and a time window (desired time of departure and arrival) for when the ride should be provided, but may furthermore include additional specifications (e.g. number of travelers or vehicle type). The fleet manager thus functions as an interface between travelers and the demand-responsive fleet, and collects real-time information (e.g. traveler requests, vehicle states and estimated travel times) to dynamically assign connected demand-responsive vehicles to trips. In contrast, passengers utilizing a fixed service will wait until the next available vehicle arrives to their origin stop and do not have any direct influence over the routing and scheduling of the fixed fleet before boarding.

In defining the on-demand service the fleet manager requires as input the service area (i.e., stops that are served by the on-demand fleet), fleet characteristics (vehicle types, starting positions and starting times) as well as a strategy used to coordinate the fleet. In this paper, the fleet manager utilizes a greedy and reactive (i.e., no forecasted requests are considered) vehicle-to-travel request assignment strategy to coordinate the flexible fleet. In short, the strategy seeks to assign the closest (in terms of expected travel time) on-call vehicle to the origin stop of the OD with the highest number of unassigned requests. The current time window of an unassigned request is not considered in this process.

Furthermore, each OD is assigned at most one vehicle per call to the assignment algorithm without consideration of capacity. This means that once a vehicle has been assigned to a group of unassigned requests with the same OD a second vehicle will not be sent to serve this OD until the first has arrived and unserved demand remains. An attempt to assign available on-demand vehicles to requests is triggered whenever a new request is received by the fleet manager and when an on-demand vehicle has completed an assigned trip.

A passenger's experienced level-of-service is operationalized by observing the amount of time a passenger spends in different segments of their trip and then converting this to a generalized travel cost term via value-of-time estimates. Trip components included in the output of the simulation framework for each passenger agent are walking time (t^{walk}), waiting time (t^{wait}), additional waiting time if one is denied boarding (t^{denied}), in-vehicle time (t^{ivt}) and number of transfers (n^{trans}). The resulting travel cost of a passenger is then given by selected appropriate weighting parameters (β^{walk}, β^{wait}, β^{denied}, β^{ivt}, β^{trans}) and calculating the weighted sum of each of the trip components.

3. Experimental setup

The feeder service this paper focuses on is a stop-based, ridesharing service with a centrally controlled demand-responsive fleet. We devise a simple application to allow us to disentangle the relationships between fleet composition, demand levels and operational model with a focus on passenger costs. The simulation framework is applied to the network and operations displayed in Fig. 2.

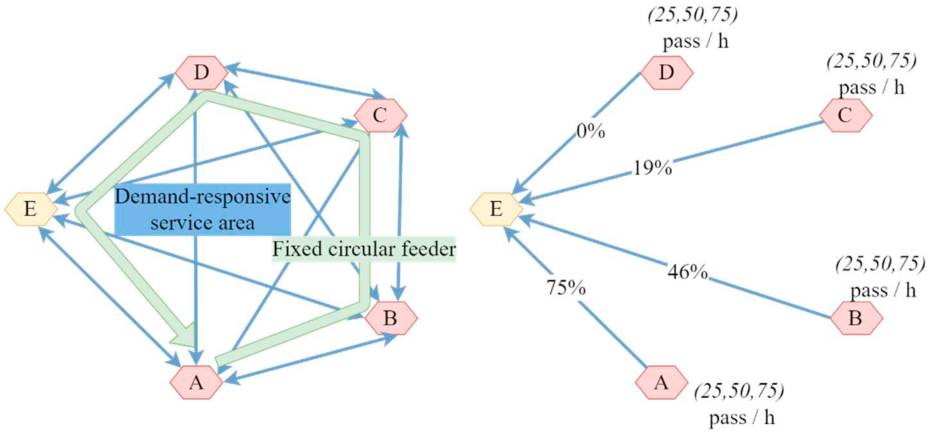

Fig. 2. (Left) Feeder network with origin stops A, B, C, and D travelling to transfer stop E. Fixed circular feeder route is A->B->C->D->E->A. Demand-responsive service area is all direct connections between stops A, B, C, D and E. (Right) Demand rates with destination E and in-vehicle time reductions for direct routes relative to circular feeder.

Two alternative operational strategies for feeder services (as depicted on the left-hand side of Fig. 2) are simulated for three levels of demand. For each demand level, passenger arrivals are modelled as Poisson processes with arrival rates of 100, 200 and 300 passengers/hour, respectively. The demand is generated over one simulated hour and is uniformly distributed (as shown on the right-hand of Fig. 2) among the origin stops A, B, C, and D, with transfer stop E as their destination. Vehicles in the simulated fixed and flexible fleets run at the same speeds (36 km/h) on all links in the network. The distance between stops via links on the perimeter of the network (e.g., A to B or A to E) is 1.5 km. The diagonal distance (e.g., A to D or B to E) is 2.4 km. Dwell times are modelled as a deterministic linear function of the number of boarding and alighting passengers for both vehicle types and for all stops.

Three service designs are considered. First, a fixed-route and fixed-schedule circular feeder consisting of a fleet of two buses with a capacity of 50 passengers/vehicle that operates on a 12-minute headway. Second, an on-demand service with a service area consisting of five stops (A, B, C, D and E in Fig. 2) and a fleet size of 10 minibuses with a capacity of 10 passengers/vehicle. Finally, the same 10 minibuses as in the on-demand case are applied to the fixed circular feeder instead, increasing the frequency of this service to a headway of 2.4 minutes. The total maximum fleet capacity is thus the same for all scenarios. Table 1 displays a summary of the compared scenarios.

Table 1: Summary of the scenarios considered.

Scenario ID	*Fleet size; Headway*	*Vehicle capacity*	*Operational strategy*
FC2	2 vehicles; 12 minutes	50 passengers/vehicle	Fixed circular
DRT10	10 vehicles	10 passengers/vehicle	On-demand
FC10	10 vehicles; 2.4 minutes	10 passengers/vehicle	Fixed circular

In the on-demand scenario there are no pre-booked requests, i.e. passengers will send a request to be picked up as soon as possible upon arriving to their stop of origin. No requests are rejected by the fleet manager and a simulation run will continue until all passengers have reached their destination. Given that all passengers are destined to the transfer stop E and do not have any incentive other than to wait for the most direct route available, the number of transfers is the same for both fixed and flexible feeder services and is hence omitted from the comparison of level-of-service results. Access and egress time to stops is assumed also the same for all simulated scenarios and walking time is thus omitted. The analysis of level-of-service thus focuses on remaining variables of trip segments that may differ, namely: t^{ivt}, t^{wait} and t^{denied}.

In the evaluated scenarios, we conceptually consider a service in which automated vehicles have reached levels of automation to allow for application at operational speeds similar to that of conventional fixed bus transit. Passengers are assumed to interact with a driverless vehicle in the same way they would a conventional vehicle. The value-of-time weights, $(\beta^{ivt}, \beta^{wait}, \beta^{denied}) = (0.04, 0.07, 0.245)$ in SEK/second, are used for weighting travel time components for level-of-service comparison. These weights were selected based on previous studies (Cats et al., 2016; Wardman, 2004) and imply that t^{wait} and t^{denied} are evaluated as inducing almost twice, and six times the per-second cost to passengers as t^{ivt}, respectively.

4. Results

The following section presents results of the simulated scenarios and analysis. Section 4.1 presents results and comparison of scenarios FC2 and DRT10. In Section 4.2, results and comparison of scenarios FC10 and DRT10 are provided.

4.1 Comparison of fixed-service buses with flexible minibuses

In a comparison of aggregate system performance of the fixed buses with flexible minibuses, averaged travel times and costs over all passengers from 100 simulation runs of scenarios FC2 and DRT10 are presented. In Fig. 3, 'FC2 Low' corresponds to the FC2 scenario with the lowest level of demand and each of the other scenarios is abbreviated in a similar fashion. To the left in Fig. 3, averages of in-vehicle time (blue), waiting time (red), and additional waiting time due to denied boarding (orange) are displayed. On average, passengers in the DRT10 scenario experience lower waiting times for all levels of demand relative to FC2. In the high demand scenario, passengers will in some cases experience longer waiting times due to a denial of boarding, as well as longer loading/unloading times at each stop. Along with the reduction of in-vehicle time provided by direct routes, the DRT10 feeder service consistently outperforms that of FC2. This is further emphasized when travel time components are converted to weighted travel costs, as seen on the right-hand side of Fig. 3. Generalized passenger travel costs are on average lower in the DRT10 scenario for all simulated levels of demand.

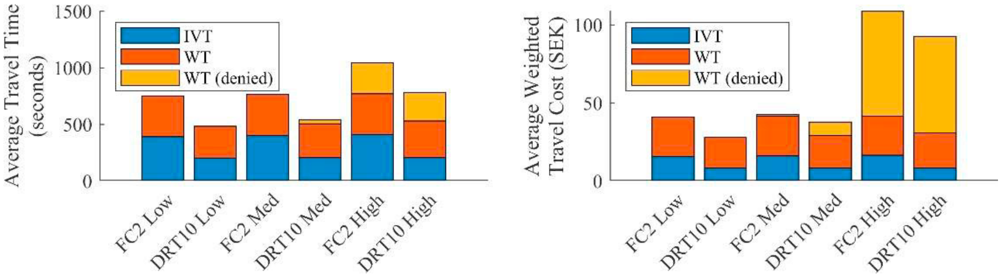

Fig. 3. Average nominal travel times (left) and weighted travel costs (right) for scenarios FC2 and DRT10.

To further investigate differences in passenger experiences in terms of fairness and service reliability, passenger total waiting time (i.e., t^{wait} $+t^{denied}$) distributions for scenarios FC2 and DRT10 are displayed. In Fig. 4, for low and medium levels of demand the waiting times for the FC2 scenario are on average longer but are more consistent in terms of lower maximum waiting time (headway of the service) and lower standard deviation relative to DRT10. For the high level of demand where passengers are sometimes denied boarding, however, one can observe a group of passengers in the FC2 scenario that experience longer waiting times. Both standard deviation and average of passenger waiting times for this level of demand is higher for the FC2 scenario relative to DRT10.

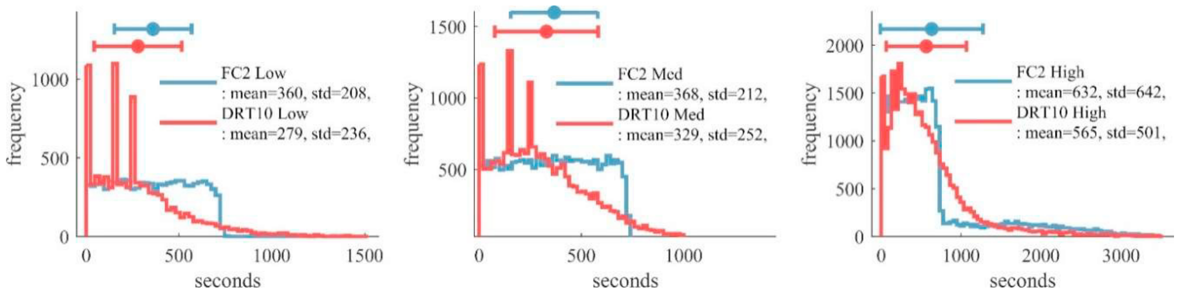

Fig. 4. Passenger total waiting time distributions per demand level (low - left, middle – medium, right - high) for FC2 (blue) and DRT10 (red). Error bars show the mean and ± 1 standard deviation of each distribution.

4.2 Comparison of fixed versus flexible minibuses

In the previous section, scenarios differed with respect to both the mode of operations as well as vehicle capacities. In the following section, utilizing a larger fleet of lower capacity minibuses to increase the frequency of the fixed circular service is compared against the same on-demand operations as before. Fig. 5 displays the averages of travel time components and weighted travel costs, this time for comparison of the FC10 scenario with the DRT10 scenario. With a quintuple increase in service frequency, average waiting times in the FC10 scenario are substantially lower relative to DRT10 for all levels of demand. For low and medium levels of demand, average waiting times are reduced to the degree that they compensate for the longer riding times required by the circular route and result in a lower average total travel time compared to DRT10. When converted to travel costs FC10 outperforms DRT10 for low and medium

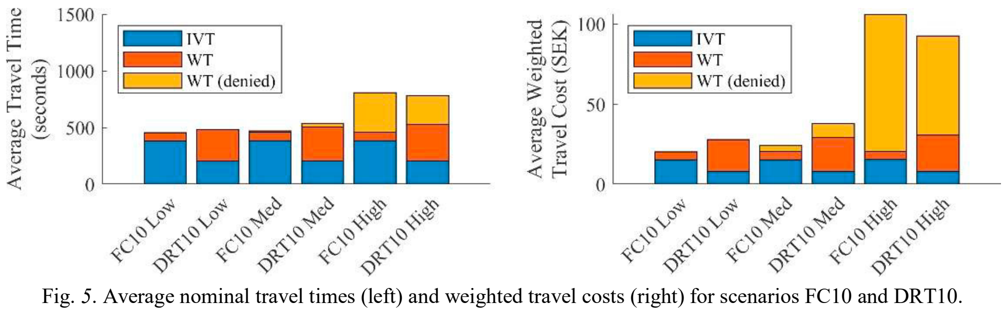

Fig. 5. Average nominal travel times (left) and weighted travel costs (right) for scenarios FC10 and DRT10.

levels of demand. For the high level of demand, however, due to additional waiting times caused by a denial of boarding, DRT10 still outperforms FC10.

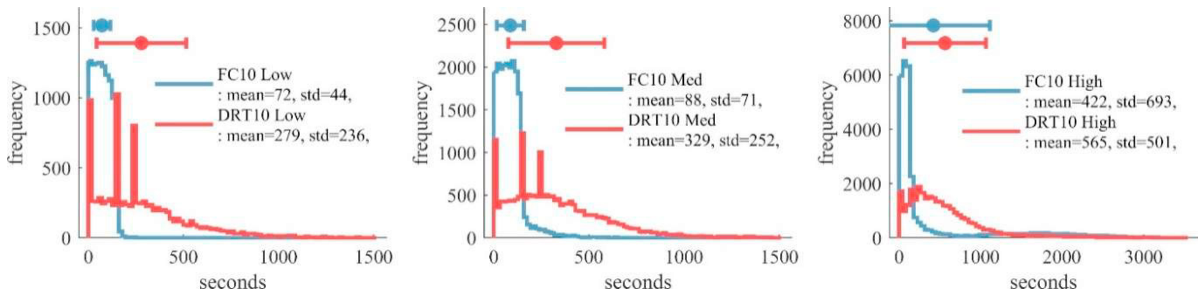

Fig. 6. Passenger total waiting time distributions per demand level (low - left, middle – medium, right - high) for FC10 (blue) and DRT10 (red). Error bars show the mean and ± 1 standard deviation of each distribution.

Fig. 6 displays the total waiting time distributions for all passengers over 100 runs, this time comparing the FC10 scenario with DRT10. As shown on the left-hand side, the waiting times for the low and medium levels of demand have consistently decreased in the FC10 scenario. However, when service capacity is exceeded for the high demand level one can again observe a, albeit smaller, group of passengers that experience much longer waiting times in the FC10 scenario relative to DRT10 such that the standard deviation of waiting times is still greater for FC10.

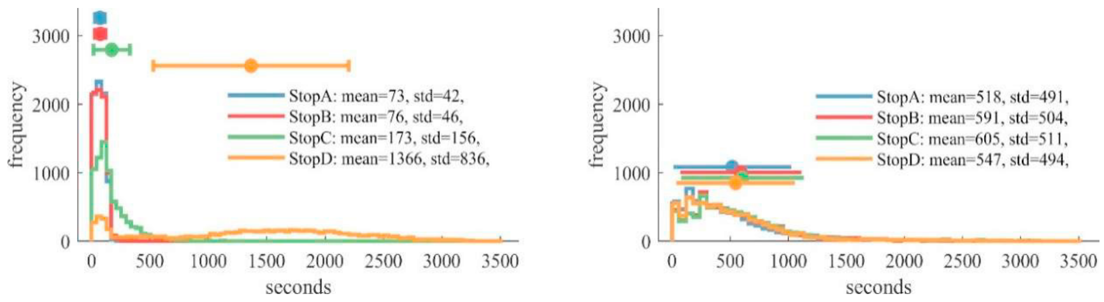

Fig. 7. FC10 (left) vs DRT10 (right) total waiting time distributions per origin stop for high demand. Error bars show the mean and ± 1 standard deviation of each distribution.

To highlight this difference in greater detail, Fig. 7 displays total waiting time distributions per origin stop for scenarios FC10 and DRT10 under the highest level of demand. It is evident from this figure that the limits in capacity most heavily affect the stop furthest downstream before the transfer stop on the fixed circular route. In contrast, the shape of the distribution for the flexible service remains similar for all stops, as all stops are equivalent and interchangeable in terms of supply provision.

5. Conclusions and discussion

The anticipation of fully automated vehicles accompanied with an increase in the availability and usage of shared mobility options has inspired the development of many innovations in on-demand transit design. In this study, a public transit simulation framework is utilized to evaluate the application of smaller automated vehicles operated as a fixed or on-demand feeder service. In addition to aggregate level-of-service measures, a qualitative analysis of the spatial equity of passenger costs is provided. Simulation results for a simplified network and homogenous demand pattern indicate that dividing planned fleet capacity into larger fleets of smaller vehicles can provide a higher level-of-service in a feeder-to-mass transit scenario. Whether these should operate as a fixed or flexible service depends on demand level however, as neither operational model consistently outperforms the other. For the demand levels tested, utilizing a larger fleet of smaller vehicles to increase the frequency of a fixed-route, fixed-schedule circular line is far more effective in improving waiting times and service reliability for passengers in the lower and medium demand scenarios, than if the same vehicles are operated as an on-demand service. A flexible service, evaluated based on passenger waiting- and in-vehicle times, is on the other hand fairer in terms of waiting time distributions per passenger origin in scenarios of higher demand where capacity is sometimes exceeded. The feasibility of flexible feeder services, benchmarked against traditional fixed operational policies depends on what measurements are included in their evaluation. With the inclusion of fairness, defined in terms of the distribution of waiting time costs across passengers and its spatial variation, the assessment of system performance highlights an additional tradeoff between fixed and flexible services. Note that the way an on-demand fleet is coordinated can significantly affect overall system performance. The simplified strategy used for coordinating the fleet in this paper is in most cases likely to underperform compared to an on-demand service that takes both anticipated demand and individual vehicle capacities into account. By definition, the greedy algorithm of the flexible service can also discriminate based on the location of highest demand. Without consideration of pick-up and drop-off time windows, it is likely that the performance of the flexible service is sensitive to alternative demand patterns as well. The resulting level-of-service output of the simulated on-demand operational model should thus be viewed as a lower bound on potential performance.

This paper leaves several avenues open for future research. Investigation of fixed, flexible and hybrid operational models in the presence of alternative demand patterns could provide further insight into the connection between feeder service reliability dependent on passenger origins and transit network structure. An analysis of operational costs could also provide deeper insight into tradeoffs of the solutions. Another research direction is to test the performance of competing fixed and flexible feeder services. User acceptance and perceptions of automated vehicles, as well as on-demand public transit services are likely to differ from conventional public transit however. The incorporation of a dynamic mode choice model for combined or competing fixed and flexible services that takes into account level-of-service, and in particular the reliability of both services, is an interesting line of future research.

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