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Simulation of fixed versus on-demand station-based feeder operations

David Leffler [a,*], Wilco Burghout [a], Erik Jenelius [a], Oded Cats [a,b]

[a] Division of Transport Planning, KTH Royal Institute of Technology, Brinellvägen 23, SE-100 44 Stockholm, Sweden
[b] Department of Transport and Planning, Delft University of Technology, P.O. Box 5048, 2600 GA Delft, The Netherlands

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ABSTRACT

The paper develops a simulation model and evaluates fixed versus on-demand operational designs of a station-based automated feeder service. The evaluation considers the operational cost and average passenger level-of-service trade-offs as well as distributional differences in waiting times. Two case studies are used to evaluate such trade-offs under different fleet compositions; (1) a simple circular network feeder service; (2) a case based on a real-world coordinated branched service in Stockholm, combining fixed-line services on the trunk portion with a flexible feeder service on the branches. Results for the circular network indicate that there are benefits in utilizing an on-demand operational policy for the lowest and highest demand levels tested. When fixed service capacity is exceeded, it is found that there are potential benefits in on-demand operations with respect to average level-of-service, as well as delivering a more even distribution of passenger waiting times. Results for the real-world case show that combining DRT on branches with fixed services on the trunk improves the overall median waiting times for all DRT scenarios and provides substantial improvements for passengers on the trunk, at the cost of more variable, and less equitable waiting times on the branches. For larger fleet sizes, generalized travel costs are reduced with and without rebalancing and level-of-service provided to branch-to-branch passengers is improved considerably by rebalancing idling vehicles to branch end-stops. The case studies demonstrate the usefulness of the simulation framework in evaluating trade-offs between fixed and on-demand service design variables and their effects on disaggregate level-of-service provided for stop-based feeder services.

1. Introduction

Demand-responsive transit (DRT) is a form of user-oriented public transport characterized by flexible routing and scheduling depending on passenger needs. The definition is broad and, depending on the source, can encompass services ranging from door-to-door shared taxi-like services (Fagnant and Kockelman, 2018), paratransit (Häll et al., 2015), or bus lines that allow for dynamic fleet management in response to evolving demand variations (Errico et al., 2013). One of the most typical applications of DRT is to provide connectivity from suburban areas with lower or dispersed population density to urban mass transit (see Potts et al. (2010) for a review of many practical examples in North America). Due to the operational costs of extending fixed-service transport at higher frequencies in such areas, DRT can improve accessibility to public transport with a more personalized service (Nelson et al., 2010).

* Corresponding author.
E-mail addresses: dleffler@kth.se (D. Leffler), wilco.burghout@abe.kth.se (W. Burghout), erik.jenelius@abe.kth.se (E. Jenelius), o.cats@tudelft.nl (O. Cats).

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Many DRT systems fail, however, due to poor implementation, planning and marketing (Enoch et al., 2006). There is also a widely held view that DRT systems are expensive solutions that come at a much higher cost to operators, and must be heavily subsidized if provided as a public service (Ferreira et al., 2007; Davison et al., 2014). This is often a result of an inability to spread the cost of a given trip over a greater number of passengers. Emerging technologies are often assumed to be key to efficient implementation of DRT solutions. Innovations in DRT provision over recent decades have gone hand-in-hand with the advancements of Intelligent Transport Systems (ITS) that make use of networks of sensors and connected vehicles to improve public transit situation awareness and real-time fleet coordination (Mageean and Nelson, 2003). More recently, the developments of automated vehicles (AVs) combined with increasingly convenient on-line alternatives to match shared vehicles and their customers, have inspired research in automated shared mobility solutions that are accessed on-demand. There are claims that AVs will enable more cost-efficient and user-friendly provision of DRT. With reductions of on-board crew costs (which is often estimated to constitute roughly 50% of the operational cost of bus transit in developed countries (Australian Transport Council, 2006; Davison et al., 2012)), an automated DRT service could potentially be offered at a lower per-vehicle operational cost (Bösch et al., 2018).

As data-collecting vehicles that can share information regarding both current and predicted traffic and demand conditions, AV fleets also offer promising opportunities for efficient real-time coordination. These prospects have motivated numerous pilot studies of automated feeder services worldwide, often utilizing lower passenger-capacity automated shuttles (Ainsalu et al., 2018). DRT systems are difficult to trial, however, due to their cost of implementation, as well as the time-frame required for demand to build up and for stable use patterns to emerge. Furthermore, while AVs with high levels of automation are rapidly developing, they have currently not reached levels of reliability and safety that allow for the broader application needed for offering on-demand services. Simulation is thus an important tool to evaluate the feasibility of an automated DRT system before implementation. Previous studies of fixed and demand-responsive feeder/last-mile solutions have extracted valuable relationships between service design variables and resulting level-of-service (LoS) and operational costs. However, investigations of LoS impacts on passengers tend to be based on average system performance and do not include equity and reliability considerations.

The performance of a public transit system may be assessed in terms of equity in the distribution across passengers of costs and benefits provided. In this context we particularly consider the spatial equality of travel conditions across different origin–destination (OD) pairs. A transit service is spatially unequal if travel conditions vary significantly depending on the OD of the traveler. In-vehicle crowding, expected waiting times and the risk of denied boarding may vary substantially along fixed transit lines (e.g., Leffler et al., 2017; Jenelius, 2018). However, studies of demand-responsive and fixed services have so far not compared their ability to achieve spatial equity in the provided LoS. Litman (2019) discusses two categories of equity in transportation: horizontal equity and vertical equity. Horizontal equity is defined as the distribution of costs or benefits between individuals or groups considered equal in abilities and needs, and vertical equity between individuals or groups that are considered to differ in terms of abilities and needs. Equality of travel conditions among OD pairs may be interpreted as an aspect of horizontal equity.

From the perspective of the passenger, route detours and flexible schedules can amplify uncertainty in waiting and in-vehicle times relative to traditional fixed route and schedule operations. Variations in the perceived reliability of the service can heavily influence mode and route choices of passengers when presented with multiple alternatives (Bhat and Sardesai, 2006; Carrel et al., 2013), which in turn contributes to the uncertainty of real-time demand predictions in the assignment of a DRT fleet to passenger trip requests.

At the core of any DRT operation is thus the problem of effectively assigning the on-demand fleet to passenger requests pre-booked, forecasted and/or received in real-time, while balancing LoS and operational cost objectives. In essence, this problem can be formulated as a dynamic variant of the well known vehicle routing problem (VRP). To maintain tractability in dynamic VRPs (which have been shown to be NP-hard), solution approaches tend to be based on metaheuristic and heuristic approaches (see for example the reviews of Pillac et al. (2013), Psaraftis et al. (2015)) and apply improvement heuristics that may converge to an optimal solution (e.g., Alonso-Mora et al. (2017)). Solution approaches may furthermore be characterized as reactive to currently known unassigned requests, or proactive by combining these with forecasted requests. What formulation or solution methodology is chosen, and its performance for a given DRT solution, depends on the inherent uncertainty in estimating current and future states of the DRT system as well as the objectives and real-time data available to the modeler. Reactive methods are often based on nearest neighbor heuristics, where the nearest available vehicles are iteratively assigned to known requests. Proactive strategies exploit statistical information available from historical data and assign empty-vehicle trips in anticipation of future supply and demand conditions (Babicheva et al., 2018). Strategies may be further enriched with other problem specific objectives or constraints (e.g., maximum allowable waiting time in Sheridan et al. (2013)).

Related work can be found in studies of station-based, one-way car-sharing services. At the operational level, emphasis has been put on devising proactive rebalancing strategies to redistribute vehicles as well as guarantee available parking spots where needed. Supported by many similar technological and societal trends as emerging station-based DRT systems, one-way car-sharing has experienced considerable growth around the world in recent decades, together with increased requirements on flexibility (e.g., in terms of reservation policy, pickup-up and drop-off points) and competition/integration with other modes of transportation (Illgen and Höck, 2019). Traditionally, the focus of rebalancing solutions has been on static optimization methods (e.g., for a longer time horizon and for deterministic demand) whereas more recent work, as well as car-sharing services in practice, have moved towards dynamic relocation that is closer to real-time (Repoux et al., 2019; Lu et al., 2020).

The objective of this study is to evaluate the LoS achieved by fixed and on-demand operational policies for AVs, including the equity of service across passengers. The potential benefits of utilizing demand-responsive AVs within a stop-based feeder service is examined as an alternative to fixed-service operations. The core purpose of the service is thus to provide transport from a fixed set of stops at various network demand centers to a local center that enables transfer to an urban mass transit network. This fixed set of stops and the set of service segments connecting them can be referred to as the service area of the feeder solution. To gain access to the on-demand feeder service, travelers will submit a request to a centralized coordinator of the on-demand fleet, referred to for the remainder of this paper as the fleet manager. Attributes associated with the travel request are at minimum a timestamp of when the request was submitted, a desired time of departure and a stop for pickup-up and drop-off. Travelers will submit a request upon arrival to a stop within the service area of the fleet manager. Requests are thus made known to the fleet manager in real-time without requirement of prior notification and travelers are assumed to desire departure at the earliest possible time when arriving to a stop.

The research contributions of this paper are: (1) the development of a modeling framework for station-based DRT and integrating this with an existing framework for fixed public transit, and (2) enabled by the microscopic modeling approach, an evaluation of trade-offs between overall LoS and equity among passengers dependent on the choice of fixed or on-demand operational policy.

The structure of the paper is as follows. Section 2 reviews the literature on the modeling and evaluation of DRT feeder services. Section 3 presents the simulation framework and modeling assumptions for comparison of fixed versus on-demand operational policies, as well as the theoretical framework for the reliability and equity analysis. Experimental design, parameter inputs and definitions of simulated scenario variations for a small theoretical feeder case as well as a larger real-world case are presented in Section 4. Computational results and analysis of fixed versus on-demand operational policies, as well as on-demand in cooperation with fixed line operations, are presented in Section 5. The paper concludes with an analysis of scenario outcomes followed by a discussion regarding study limitations and potential improvements in Section 6.

2. Literature review of modeling and evaluation of DRT feeder services

2.1. Fixed versus DRT feeder operations

A vital question in the operational planning of feeder services is under what conditions with respect to LoS provided and operational cost, to operate the feeder system as a fixed system or as a demand-responsive service. In contrast with previous studies of DRT without AV technology, the focus of recent research on shared automated vehicle (SAV) feeders leans more towards long-term resource planning (e.g. fleet-sizing) and developing dispatching algorithms to support centralized on-demand operations, rather than assessments of variable-type fixed versus demand-responsive operational policies in SAV feeder service design. Often using an analytical approach, earlier studies of feeder solutions have centered on the determination of cutoff points with respect to LoS and operational cost for switching between fixed versus flexible operational policies. Studies often evaluate feeder services characterized by a single transfer point, rectangular residential service area and pre-booked DRT services rather than real-time on-demand (Daganzo, 1984).

Diana et al. (2009) study the relative distance traveled of fixed versus on-demand DRT for grid and ring-radial mass transit network structures while maintaining comparable distributions of LoS provided to passengers. Kim and Schonfeld (2013) further explore the benefits of using mixed passenger capacity bus fleets and trade-offs between route-spacing under fixed operations and service area under DRT. Quadrifoglio and Li (2009) develop a continuous approximation model to determine when on-demand operations are preferable to fixed dependent on demand density for one and two vehicle fleets. This work is further applied and validated in Li and Quadrifoglio (2010) and utilized in Li and Quadrifoglio (2011) to evaluate optimal zone design. In the same stream of research Edwards and Watkins (2013) utilize the analytical model of Quadrifoglio and Li (2009) to evaluate systems that include stochastic passenger arrival rates and irregular transit schedules for a grid fixed transit network and varying feeder network layouts of Atlanta, Georgia. Trade-offs between increasing stop-spacing for fixed service operations and implementing a single-vehicle DRT feeder for each stop are compared. Badia and Jenelius (2020) study how the introduction of AV technology may shift the competitiveness of door-to-door services to higher demand densities.

2.2. Simulation based evaluation of DRT

Agent-based simulations, with real-time adaptive behavioral representation of passengers and dynamic transit operations, lend themselves well to studies of DRT (Ronald et al., 2015). Several agent-based frameworks combining solution methods of dynamic vehicle-routing problems (VRPs) underlying DRT operations with simulation of traffic and passenger interactions for the evaluation of DRT have been proposed over the last decade (see for example Maciejewski et al. (2017) and Narayan et al. (2020)). The focus and level of detail in suggested frameworks depend on application, ranging from case studies of simplified networks to large-scale simulations of several millions of vehicles.

Many on-demand services leveraging SAVs have been proposed and evaluated in the literature in recent years. Performance evaluations of these services go hand-in-hand with the development of modeling frameworks and solution procedures to dynamic VRPs (for extensive reviews of modeling components and impacts of different on-demand service designs see Narayanan et al. (2020), Markov et al. (2021), and Pillac et al. (2013), Psaraftis et al. (2015) for reviews of solution methods to dynamic VRPs). The most common strategy to evaluate DRT systems involving AVs is to modify existing agent-based simulation frameworks while relaxing assumptions regarding driver scheduling constraints and assuming full compliance to centralized planning and operational control. Impacts and sensitivities to estimated changes to labor cost structure, user adoption and projected AV fleet characteristics (e.g. fleet size, vehicle capacities, fuel efficiency) are evaluated through adjusted parameter settings or iterative optimization procedures.

In a recent study by Hörl et al. (2021), the introduction of single-passenger SAVs in the city of Zurich was simulated, also taking into account the feedback loop between demand for alternative modes (private car, public transit and active modes) and

LoS provided. Results indicate that, despite benefits to users, under a wide range of scenarios system impact is largely negative. To achieve a sustainable transport system that promotes sharing and active transport, the authors emphasize the importance of restricting pick-up and drop-off locations, regulating SAV pricing, promoting ride-sharing, and prioritizing the integration of SAV services with existing public transport. Markov et al. (2021) also demonstrate the process of simulating and evaluating a wider DRT service design space (e.g. door-to-door versus station-based services, instant booking versus pre-booking, ride-sharing versus no ride-sharing) for three distinct service areas in the city of Chicago. Trade-offs between passenger LoS and fleet efficiency KPIs, fleet size and levels of pre-booking are formalized in what the authors refer to as a *fundamental ride-sharing diagram*. Among the presented results, station-based service design is found to lead to substantial improvements to fleet utilization and improve ride-sharing potential at the expense of walking. The authors also underscore how shared DRT services can drastically reduce the number of vehicles required to satisfy urban mobility demand.

In relation to public transit, studies within this body of research can be categorized into: (i) those that evaluate SAV services independent of line-based public transit (as a replacement for individual-use taxis or privately owned cars) (Fagnant and Kockelman, 2014; Bischoff and Maciejewski, 2016; Liu et al., 2017; Martinez and Viegas, 2017; Markov et al., 2021), (ii) studies focusing on utilizing on-demand SAVs as a replacement to fixed public transit (Winter et al., 2018; Jäger et al., 2018; Narayan et al., 2019; Berrada and Poulhès, 2021) or a co-existing alternative (Liu et al., 2019; Winter et al., 2020; Hörl et al., 2021) at a city-wide scale, and (iii) studies of SAVs utilized as complement (e.g., feeder/last-mile) services to fixed public transit (Winter et al., 2016; Scheltes and de Almeida Correia, 2017; Moorthy et al., 2017; Salazar et al., 2018; Shen et al., 2018; Wen et al., 2018).

2.3. Emerging mobility services as complements to fixed public transit

A rapidly growing body of literature has been dedicated to the evaluation of emerging mobility services (ride-hailing, ride-sharing, and SAV services) as connectors to mass transit networks. Scheltes and de Almeida Correia (2017) and Salazar et al. (2018) evaluate personal use SAVs utilized in feeder couplings to fixed transit. Scheltes and de Almeida Correia (2017) study the performance of single-person capacity AVs within a station-based, on-demand feeder/last-mile system as an alternative to active modes. Based on survey data of user acceptance and OD patterns, system performance is simulated under varying scenarios of network structure, booking scheme and on-demand operational strategies. Salazar et al. (2018) propose a multi-commodity network flow model to formulate optimal passenger paths and vehicle routes for an on-demand AV ride-hailing system integrated with fixed public transit services at city-scale. Compared to on-demand AV ride-hailing and public transit existing as separate systems, the socially optimal performance of the integrated system was found to significantly improve travel times, require fewer vehicles, and results in lower emissions.

Winter et al. (2016) perform a simulation study examining the potential of replacing a fixed feeder service between two stations with an automated on-demand service. Using the demand data and network configuration of an ongoing pilot study, fleet size requirements and system performance are estimated. Higher demand levels, and utilizing vehicles with capacities larger than 10 passengers/vehicle are among the most effective ways found to reduce system cost per passenger. Moorthy et al. (2017) utilize a Life Cycle Assessment model to evaluate an SAV service providing feeder transit between an airport and fixed transit network. Results indicate that the integrated SAV system could greatly enhance sustainability of transit with a mode shift from private to public modes while maintaining a competitive average LoS provided.

At a larger scale, Shen et al. (2018) evaluate the introduction of on-demand SAV taxis as a replacement for low-demand bus feeder to metro routes in Singapore in an agent-based simulation study. Comparisons between personal use SAVs, and shared-trip SAVs, as well as an analysis of trade-offs between fleet size and profit margin per kilometer is provided. Wen et al. (2018) extend an agent-based simulation framework with a multi-modal discrete choice model to evaluate the feedback loop between service performance and demand for an integrated SAV + fixed transit service and alternative conventional modes. Results indicate that allowing for pre-booked requests, combining fare with transit and encouraging ride-sharing through the integrated SAV + fixed transit system can encourage more sustainable travel choices. Stiglic et al. (2018) develop an operational model for integrating (non-automated) ride-sharing services with mass transit as a feeder/last-mile solution using park-and-ride facilities. Sensitivities to driver matching flexibility (maximum acceptable detour), demand density, and mass transit service parameters are assessed through a simulated case study of a stylized transit network. The authors find that the integration of ride-sharing can reduce total system-wide vehicle-kilometers traveled (VKT).

3. Methodology

This section presents the simulation framework in Section 3.1, and details of the implemented on-demand vehicle-to-passenger assignment procedure in Section 3.2, as well as the theoretical framework for the LoS and equity analysis in Section 3.3. A summary of notation used is provided in Table 1.

3.1. Simulation model

To enable experimentation, a model for simulation of DRT services is developed. The module is embedded within the agent-based, dynamic public transit simulation framework BusMezzo (Toledo et al., 2010) to allow for consistent comparison between fixed and on-demand services. BusMezzo replicates transit operation phenomena including the propagation of headway variability and bunching. Demand can be provided in terms of OD pairs, and passengers are simulated as agents that can choose optimal

Table 1
Summary of notation.

Description	Notation
Level-of-service:	
In-vehicle time	t^{ivt}
Waiting time	t^{wait}
Waiting time if denied boarding	t^{denied}
Number of transfers	n^{trans}
Total waiting time	t^{twait}
Total travel time	t^{tt}
Value of in-vehicle time	β^{ivt}
Value of waiting time	β^{wait}
Value of waiting time if denied boarding	β^{denied}
Fixed cost penalty per transfer	β^{trans}
Weight passenger travel cost	c^{pcost}
Gini coefficient of total waiting time	G^{twait}
Total waiting time coefficient of variation	CV^{twait}
Operational costs:	
Vehicle size	s
Fleet size	f_s
Operating cost per vehicle-hour	g_s^{oper}
Capital cost per vehicle-hour	g_s^{cptl}
Unit fixed operating cost per vehicle-hour	c^{oper}
Unit size-dependent operating cost per vehicle-hour	b^{oper}
Unit fixed capital cost per vehicle-hour	c^{cptl}
Unit size-dependent capital cost per vehicle-hour	b^{cptl}
Percentage decrease in unit operational costs with vehicle automation	η
Percentage increase in unit capital cost with vehicle automation	ζ
Total vehicle-kilometers traveled	d^{vkt}
Operational cost per vehicle-kilometer	g_s^{km}

paths according to their maximal individual utility, considering real-time information and learning day-by-day (Cats et al., 2016). In addition to network-wide LoS measurements, it is possible to study the travel time, path and choices of each passenger separately within the network, as well as generalized costs of each passenger group. The framework is event-based and embedded within the mesoscopic traffic simulation model Mezzo (Burghout, 2004). The transit simulator has been used previously to compare and assess the performance of holding strategies, both schedule-based and regularity-based (Cats et al., 2011, 2012), multi-line holding control (Laskaris et al., 2018), as well as short-turning strategies (Leffler et al., 2017).

For the representation of on-demand services within this framework, a "fleet manager" functionality is developed and incorporated into BusMezzo, as displayed in Fig. 1. The purpose of the fleet manager is to act as an interface between travelers and the demand-responsive fleet and collect real-time information (travel requests, vehicles states and estimated travel times) necessary to dynamically assign centrally coordinated vehicles to trip plans. In this paper a "trip plan" is defined as a planned sequence of stop visits in order to serve a bundled group of passenger requests assigned to it. In this sense a trip plan also represents a "shareable" set of requests that satisfies potential LoS or vehicle-capacity constraints, as determined by the operator of the service and availability of supply. In defining the on-demand service, the fleet manager is provided as input a service area (i.e., a subset of stops within the transit network), fleet characteristics (i.e., vehicle types, starting positions and starting times) as well as a strategy used to coordinate the assignment of transit vehicles to traveler requests. The framework is implemented using an object-oriented programming approach to enable further enhancements and developments. Each entity in the simulation model (e.g. passenger, vehicle, fleet manager) is thus represented as an object with its related variables and functions.

Fig. 2 displays relationships between classes of the simulation framework associated with matching demand-responsive transit vehicles with travel requests. In short, the *FleetManager* keeps track of *TransitVehicle* and *Passenger* objects within a predefined service area, where the problem of matching travel requests with cooperating transit vehicles is partitioned and solved sequentially by supporting modules. A *FleetManager* is initialized with a set of one or several *TransitVehicle* and *Stop* objects, defining the corresponding fleet and service area of an on-demand service. Five supporting classes are defined as members of the *FleetManager*. The core responsibilities of these classes are:

- *RequestHandler* — receiving, bundling and sorting requests,
- *TripPlanner* — generating feasible trip plans for vehicles to serve currently known and/or forecasted requests,
- *Matcher* — performing a cost evaluation of candidate trip plans in order to create a matching with available vehicles,
- *Scheduler* — adjusting dispatch, pick-up, and drop-off schedules of matched vehicles,
- *Navigator* — provide shortest path estimations used by the other supporting classes.

Four of the supporting classes (all but the *Navigator*) may have one or several strategies (e.g., a *RequestHandler* may have access to one or several *BundlingStrategy* implementations) inheriting from an abstract class (colored orange in Fig. 2) containing shared methods and an interface for each vehicle-to-passenger assignment subproblem. To clarify, in this context the bundling of requests

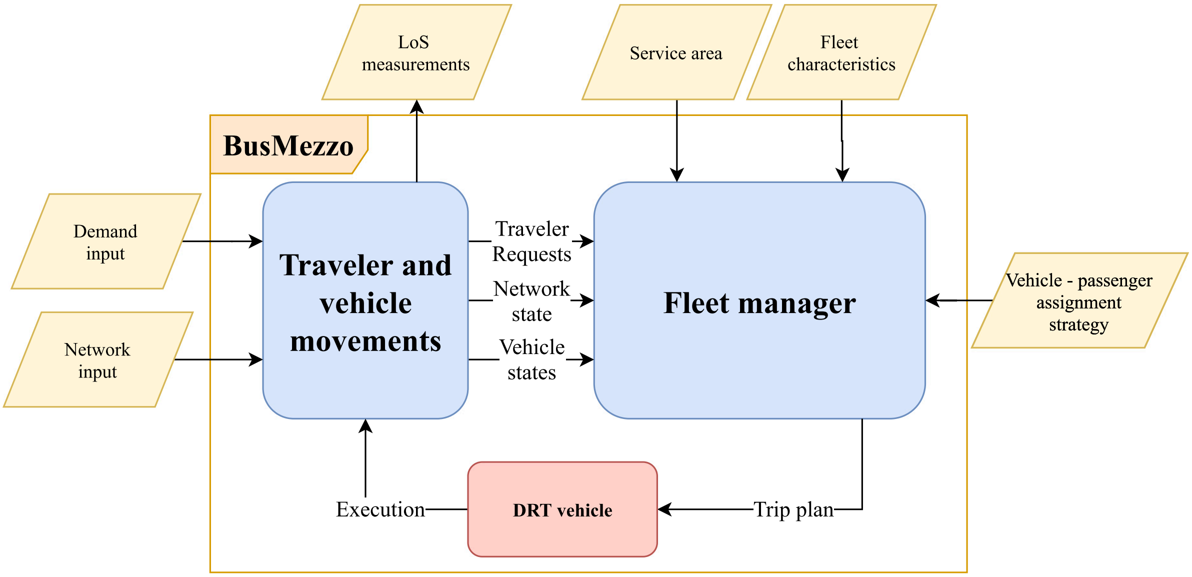

Fig. 1. High-level overview of the public transit simulation framework.

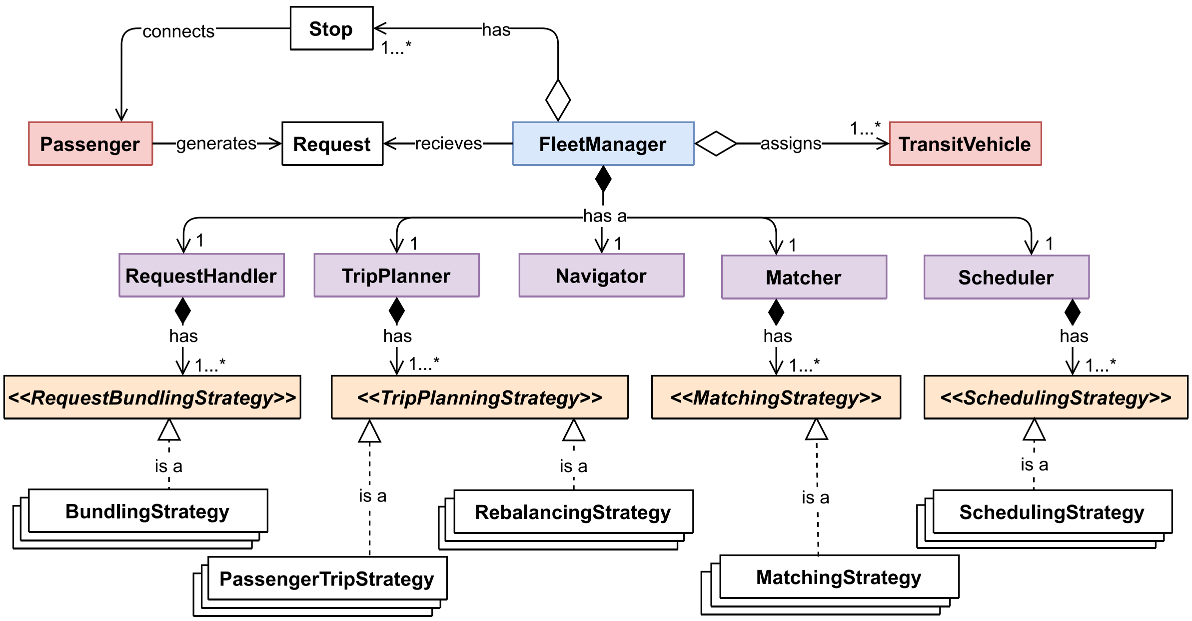

Fig. 2. Class diagram of *FleetManager* (blue) and member supporting classes (purple), with one or several strategies (orange). Arrows display relationships relevant for connecting *Passenger* and *TransitVehicle* agents (red). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

refers to grouping and filtering the set of all currently known and/or forecasted requests such that a subset of these is to be considered by the *TripPlanner*. A *RequestHandler* may thus also have no *BundlingStrategy*, meaning that all known requests are considered separately. The aim of this structure is to provide a more generic interface to experiment with alternative operational policies. The structure is considered flexible in the sense that it allows the *FleetManager* to switch between individual strategy components dynamically depending on, for example, resulting fleet utilization and LoS quality.

The *FleetManager* monitors associated *TransitVehicle* state changes (e.g., 'unassigned', 'assigned', or 'driving') throughout the simulation. A *Passenger* intending to use an on-demand service in real-time is connected to a *FleetManager* when a decision has been made to wait at a *Stop* within the on-demand service area. Once connected, the *FleetManager* will await a *Request* submission from this *Passenger* containing desired specifications for the trip.

3.2. On-demand vehicle-to-passenger assignment

To model on-demand operations for the service settings and experiments considered in this paper, a greedy nearest-neighbor heuristic is implemented, similar to those described in Babicheva et al. (2018), Sheridan et al. (2013). The assignment of vehicles to trip plans is a version of the general assignment problem:

$$\min \sum_{v=1}^{m} \sum_{tp=1}^{m} c_{v,tp} x_{v,tp} \tag{1}$$

subject to

$$\sum_{v=1}^{m} x_{v,tp} = 1, \forall tp \in \{1...m\} \tag{2}$$

$$\sum_{tp=1}^{m} x_{v,tp} = 1, \forall v \in \{1...m\} \tag{3}$$

$$x_{v,tp} \in \{0,1\}, \forall v \in \{1...m\}, \forall tp \in \{1...m\}, \tag{4}$$

where the decision variables $x_{v,tp} = 1$ if and only if vehicle v is assigned to trip plan tp and $c_{v,tp}$ is the cost associated with assigning vehicle v to trip plan tp. Constraints (2) ensure that each vehicle is assigned to only one trip plan, and (3) that each trip plan is assigned to only one vehicle. Constraints (4) ensure that only whole assignments are performed. Typical cost functions are based on vehicle distance or travel times to the pickup point of the trip plan, but any separable cost function may be used.

In this paper we employ a heuristic that seeks to either maximize the number of treated requests, or minimize the cumulative waiting times for trip plans. The sequence of steps to assign trips and to re-position empty (on-call) vehicles, is described in Algorithm 1. The input to the algorithm is a set of trip plans. Starting from the set of trip plans generated by the *FleetManager* the algorithm first sorts them according to the selected ranking function. The two alternative objective functions considered in this article are:

$$RankByRequests(tp) = \left| R_{tp} \right| \tag{5}$$

$$RankByCumulativeWaitingTime(tp) = \sum_{r \in R_{tp}} t_r^{wait} \tag{6}$$

where tp is the trip plan, R_{tp} is the set of requests assigned to tp, and t_r^{wait} is the time that has elapsed since the desired departure time for request r. The first objective function ranks the trip plans by the number of passenger requests assigned to them. The second objective function ranks the trip plans by the cumulative waiting time for all requests assigned to that plan. The purpose is to balance the number of requests with the waiting times, expanding on the method in Sheridan et al. (2013) where a maximum waiting time is imposed.

After sorting the trip plans, the algorithm takes the highest ranking trip plan tp and attempts to assign it to an on-call vehicle at the starting point, if any are available. If not, the nearest on-call vehicle v is found, an empty trip is generated to the start point of tp and tp is chained immediately after this empty trip.

Algorithm 1 Trip assignment

```
procedure AssignTrips
    SortedTripPlans ← SortTripPlansByRankingFunction
    repeat
        tp ← top(SortedTripPlans)
        if OnCallVehicle v at start of tp then
            assign v to tp
            remove tp from SortedTripPlans
        else
            find nearest OnCallVehicle v to start of tp
            create EmptyTrip etp
            assign v to etp
            chain tp to etp
            remove tp from SortedTripPlans
        end if
    until SortedTripPlans is empty
end procedure
```

Two events are set up to initiate the process of matching groups of travel requests to transit vehicles: (1) when a passenger makes a decision to stay at a stop and submits a request, and (2) when a transit vehicle finishes a trip with no future assignments (it becomes on-call). In addition, an event to redistribute on-call vehicles to stops within the service area of the *FleetManager* may be included at scheduled time intervals. The assignment procedure is reactive in the sense that it considers only known requests

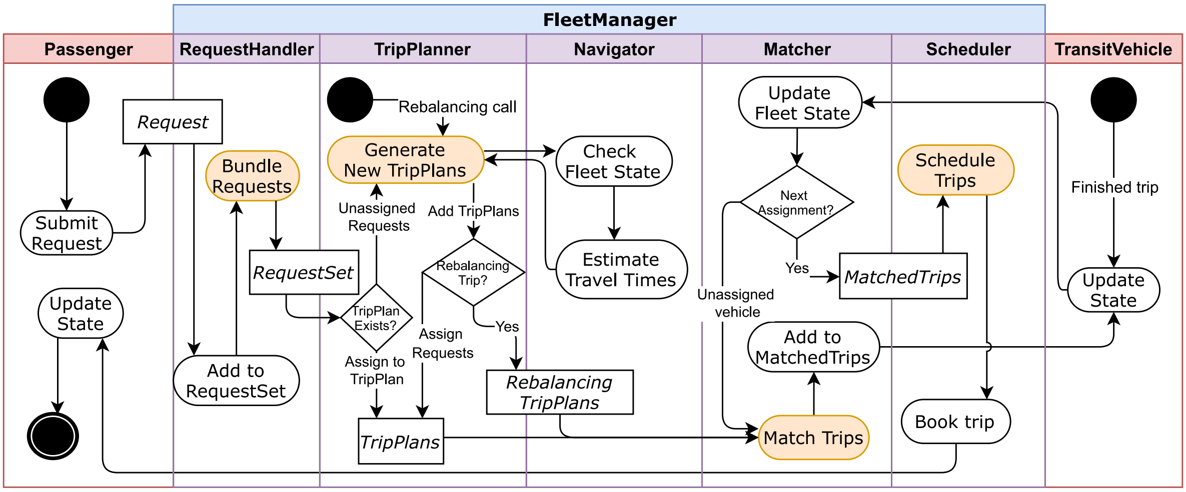

Fig. 3. An activity diagram for greedy vehicle-to-passenger assignment. Column headers and coloring correspond to classes displayed in Fig. 2. Activities are displayed as rounded rectangles, diamonds as conditional branches, and straight rectangles as data structures passed between classes. Orange activities are associated with strategies of the containing class. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

and no forecast requests are considered. The presented framework can be readily extended to incorporate predictive algorithms such as the index-based redistribution in Babicheva et al. (2018), network-wide matching algorithms (Kucharski and Cats, 2020) and other supply-deficit type algorithms such as (Salazar et al., 2018; Psaraftis et al., 2015), as well as re-optimizing strategies such as (Alonso-Mora et al., 2017).

To describe how the greedy heuristic is sequenced within the described framework, an activity diagram is presented in Fig. 3. The passenger activated initial state is displayed to the top left of Fig. 3. When a decision has been made to use an on-demand service within the service area of the *FleetManager*, the *Passenger* submits a *Request* to the *RequestHandler*, which verifies that the destination of this request is contained within the on-demand service area and adds it to a *RequestSet* containing all currently known unassigned requests.

The *RequestHandler* groups requests by calling a *BundlingStrategy* that sorts the *RequestSet* by requests with shared ODs that are currently unassigned to a trip plan. The *TripPlanner* has a set of *TripPlans* that have not yet been matched by the *Matcher*. The *TripPlanner* first attempts to insert unassigned requests into existing trip plans. For requests for which no suitable trip plan is available, a *PassengerTripStrategy* is called. The *PassengerTripStrategy* will generate new trip plans, assigns these to associated requests, and adds them to the set of *TripPlans*. When all requests in the *RequestSet* have been assigned, the *TripPlans* set is passed to the *Matcher* to be assigned to suitable vehicles.

The transit vehicle activated initial state is displayed on the top right of Fig. 3. When a *TransitVehicle* finishes a trip, its state is updated, which triggers a fleet state update in the associated *FleetManager* of the vehicle. If the vehicle has a chained trip scheduled it will proceed to serve this trip, otherwise it changes its state to on-call and passes itself to the *Matcher*. The *Matcher* applies a *MatchingStrategy*, such as the one described in Algorithm 1, to match the most suitable vehicle to each trip in *TripPlans*, and generate *EmptyTrips* chained by the selected *TripPlans* if needed. After each successful matching the matched trip plan is added to the set of *MatchedTrips*. The *Scheduler* then schedules the planned dispatch for each trip in *MatchedTrips*, and notifies the *Passenger*.

A rebalancing call may also trigger the generation of a new trip plan at regular time intervals, as displayed at the top of the *TripPlanner* column. In this case, the trip plan is not generated to serve unassigned requests, rather to redistribute supply in anticipation of future requests. The *RebalancingStrategy* of the *TripPlanner* will attempt to balance available supply between stops within the service area of the *FleetManager*. If a rebalancing trip is found, this is added to a separate set of *RebalancingTripPlans* which is passed forward to the *Matcher* and *Scheduler*.

3.3. Level-of-service and equity evaluation

From the passengers' perspective, the performance of a public transport system can be evaluated in terms of the generalized travel cost of the passengers. The travel costs are dynamic and stochastic as they depend on systematic and stochastic temporal variations in travel demand and supply. In this paper generalized cost is evaluated based on a combination of three factors: in-vehicle time, waiting time and number of transfers. A distinction is made between waiting time for the first vehicle that a passenger wishes to board and additional waiting time if a passenger is denied boarding until their next opportunity to board. The total travel time t_i^{tt} of each passenger i is thus defined as the sum of in-vehicle time t_i^{ivt}, waiting time t_i^{wait} and denied waiting boarding time t_i^{denied}. The

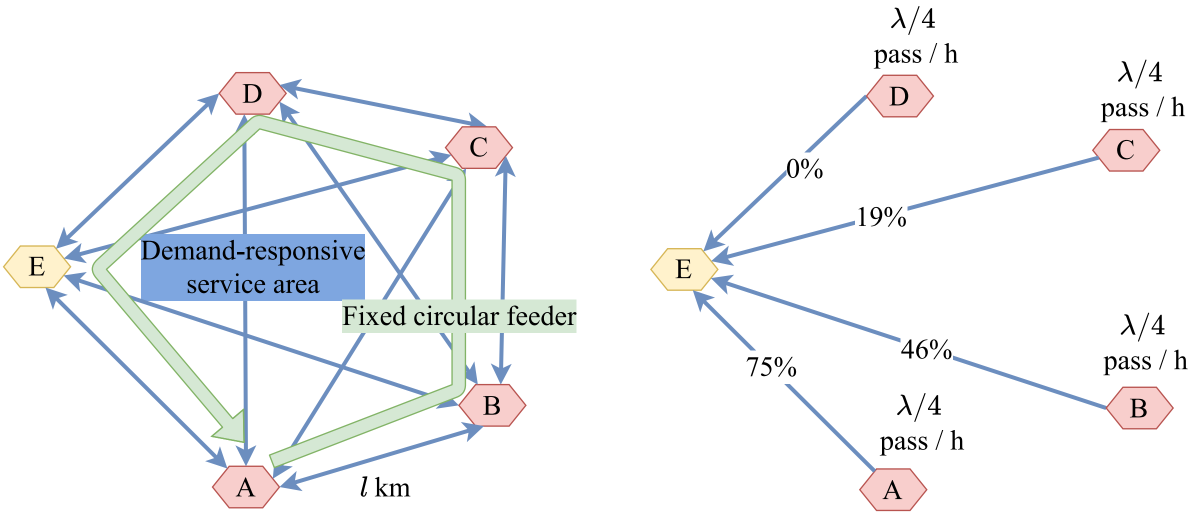

Fig. 4. (Left) Feeder network with origin stops A, B, C, and D traveling to transfer stop E placed in the shape of a regular pentagon. The length of links connecting pairs of stops along the perimeter of the network is controlled by the parameter l. The fixed circular feeder route is A→B→C→D→E→A. The demand-responsive service area is comprised of 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 the fixed circular feeder are noted next to nodes and links, respectively.

number of transfers required by a passenger to reach their final destination is denoted n_i^{trans}. The travel cost (c_i^{pcost}) is calculated by selecting corresponding weighting parameters ($\beta^{wait}, \beta^{denied}, \beta^{ivt}, \beta^{trans}$) and summing over each weighted trip component,

$$c_i^{pcost} = \beta^{wait} t_i^{wait} + \beta^{denied} t_i^{denied} + \beta^{ivt} t_i^{ivt} + \beta^{trans} n_i^{trans}. \tag{7}$$

A key difference between fixed and on-demand operations is in the perceived reliability of waiting times for the service. The total waiting time (i.e., $t^{twait} = t^{wait} + t^{denied}$) coefficient of variation (CV^{twait}) is used as a metric to compare differences in reliability between operational policies. While there are many ways of assessing LoS reliability, the CV is a well-defined and commonly used metric that can also serve as a good proxy for several other reliability measures (Pu, 2011).

The CV can also be used as an inequality measure (e.g., Allison, 1978; Jenelius, 2010). The CV is closely related to the Gini coefficient (Gini, 1912), which is sometimes used to quantify equity in public transit (e.g., Delbosc and Currie (2011), Jang et al. (2016), Rubensson et al. (2020)). As a complement to the CV the Gini coefficient of total waiting times (G^{twait}) is used to compare the distribution of total waiting times under fixed and on-demand operational policies.

$$G^{twait} = \frac{1}{2n^2 \bar{t}^{twait}} \sum_{i=1}^{n} \sum_{j=1}^{n} |t_i^{twait} - t_j^{twait}|,$$

where n is the total number of passengers in the evaluated time period, t_i^{twait} is the total waiting time experienced by passenger i, and $\bar{t}^{twait}$ is the average total waiting time over all passengers $1, \ldots, n$. G^{twait} can interpreted as an inequality metric, ranging from 0% (perfect equality of total waiting times for all passengers) to 100% (perfect inequality of total waiting times).

4. Case study set-up and implementation

This section describes the implementation and assumptions used to analyze and compare the performance of fixed and on-demand feeder operations in two case studies. The first case focuses on a circular feeder network and is described in Section 4.1. The second case study extends this to a real-world network in Stockholm, Sweden, focusing on the use of DRT to feed a common trunk line in Section 4.2.

4.1. Case 1: Circular feeder network

To isolate the effects of fixed versus on-demand feeder policies, a case study aimed at capturing key features of a real-world circular feeder network structure is devised. The simulation framework is applied to the network, operations and demand pattern displayed in Fig. 4.

As shown in Fig. 4 (left), the feeder network takes the shape of a regular pentagon with stops at vertices. All stops are connected by bidirectional links. The size of the network is controlled by l, the length of each link on the perimeter of the network. Two operational policies (displayed on the left-hand side of Fig. 4) for feeder services are simulated. Based on estimations of operational cost reductions with vehicle automation, comparable fleet compositions consisting of AVs or non-AVs are evaluated under both operational policies. Simplifying assumptions used for analysis are characterized below.

4.1.1. System definition and assumptions

Demand is inelastic with respect to the LoS provided. Demand is asymmetric with all passengers destined to transfer stop E. The number of transfers are thus considered the same for both fixed and on-demand feeder services. The temporal distribution of passengers arrivals is Poisson with average rate λ. Passengers are thus assumed to arrive at stops independent of expected vehicle arrivals. The spatial distribution of passenger arrivals is uniform among stops A-D as displayed in Fig. 4 (right). Passenger access and egress time at stops are assumed to be the same for both services.

Passenger boarding follows a first-in-first-out regime. Passengers that may be left behind if denied boarding, or that experience longer waiting times, remain at the stop and wait for the next available vehicle. Passengers have no intrinsic preference for a specific vehicle type or operational policy.

Operational speeds are constant for all links, and vehicle types. Layover times between trips are considered negligible. Both services utilize the same fixed boarding/alighting points. The number of stops and the spacing between them is considered constant. Dwell times and boarding/alighting time per passenger are assumed the same for both operational policies and vehicle types. Fare is assumed equal between both services. Differences in external effects between operational policies and vehicle types are considered negligible.

Fixed service vehicles visit stops sequentially along perimeter links of the service region in a cycle (stops A→B→C→D→E→A in Fig. 4). Vehicles operate on schedules according to a fixed headway policy.

On-demand service vehicles serve requests as direct trips to the transfer stop with no detouring. On-demand vehicles are coordinated using the greedy assignment procedure described in Section 3.2 with the ranking function described in Eq. (5) that prioritizes the largest group of unassigned requests. No strategy for rebalancing on-call vehicles without a trip currently assigned to them is applied. In-vehicle time reductions for direct routes relative to the fixed circular feeder are displayed in Fig. 4 (right). Passengers transmit a request with their OD and time of arrival upon arrival to a stop and not at any intermediate points between them. Passengers do not cancel requests once sent, and requests are always accepted by the fleet manager of the on-demand service independent of system state.

A potential reduction in operational cost per hour for a fixed transit service with vehicle automation is estimated to motivate an increase in fleet size. The operational cost estimates are based off the model developed by Zhang et al. (2019). Using similar notation, the operating cost per vehicle-hour (g_s^{oper}) and capital cost per vehicle hour (g_s^{cptl}) for an AV of size s (seating and standing capacity) is given by

$$g_s^{oper} = (1-\eta)c^{oper} + b^{oper}s \tag{8}$$

and

$$g_s^{cptl} = (1+\zeta)c^{cptl} + b^{cptl}s \tag{9}$$

respectively. The parameters c^{oper} and c^{cptl} correspond to unit fixed operating, and capital costs per vehicle-hour respectively. Parameters b^{oper} and b^{cptl} correspond to unit size-dependent operating, and capital costs per vehicle hour respectively. The parameter η is defined as a percentage decrease in unit operational costs due to the reduction in labor costs when replacing a non-AV with an AV with a high level of automation. The parameter ζ corresponds to a percentage increase in unit capital cost due to changes in acquisition costs of AVs. Using these cost estimates, vehicle-size dependent fleet-sizes, denoted f_s, with comparable operational cost per hour are estimated.

4.1.2. Parameter set-up

To explore relative performance sensitivities to demand intensity, total passenger arrival rates λ is set to 25–300 passengers/hour over one simulated hour. Fixed and on-demand fleets have the same operational speeds of 30 km/h on all links in the network. Perimeter links (e.g., A→B or A→E in Fig. 4) have a length of 1.5 km. Diagonal distances (e.g., A→D or C→E in Fig. 4) are thus approximately 2.4 km. Given this network and demand configuration, two buses with capacities of 50 passengers/vehicle are required to provide a 12-minute headway policy for the fixed circular feeder route with a maximum service capacity of 250 passengers/hour. Using this as a base case, we estimate the planned operational cost per hour for this service and evaluate the potential of expanding the existing fleet size with a larger fleet of AVs.

In the study of Zhang et al. (2019), the operating cost parameters c^{oper} and b^{oper} are estimated based on a sum of time-related operating costs and distance-related operating costs. The distance-based operating cost per vehicle-kilometer (g_s^{km}) for the on-demand service is estimated by assuming that distance-based costs are the same between AV and non-AV vehicle types. Assuming time-based operating and capital costs are the same between fixed and on-demand operations, this estimate is then used to evaluate differences in operational cost between fixed and on-demand services as a result of total VKT required to serve all passengers (d^{vkt}).

The estimated reduction in operational and capital costs used in the study by Zhang et al. (2019) depend on expected operational speeds of 15 km/h for urban transit. Given the same data (Australian Transport Council, 2006) but with an expected operational speed of 30 km/h, the estimated intercepts and slopes of the relationships in Eqs. (8) and (9) are c^{oper} = 39.24 €/vehicle/hour, b^{oper} = 0.145 €/vehicle/hour, c^{cptl} = 1.4 €/vehicle/hour, and b^{cptl} = 0.099 €/vehicle/hour, using a conversion rate of 1AUD = 0.63€.

With the reasoning that crew costs could be eliminated by utilizing fully AVs, η is estimated to be 53%. This is given by the ratio between per-hour labor costs (20.79 €/vehicle/hour independent of vehicle capacity) and the estimated fixed operating cost per vehicle hour c^{oper}. Note that there may be additional changes in operational costs besides driving crew costs that are not included (e.g., vehicle insurance, fleet operator costs, or vehicle maintenance). The parameter for ζ is set to 50%, assuming an increase in

Table 2
Experiment design parameters.

Description	Notation	Value	Unit
Network and Demand input:			
Length of network perimeter link	l	1.5	km
Length of network diagonal link		2.4	km
Service area size		3.9	km^2
Demand intensities	λ	25,50,100,200,300	pass/h
Service input:			
Vehicle speeds		30	km/h
Vehicle sizes	s	25,50	(veh,pass/veh)
Fleet sizes dependent on vehicle-size (s=25,50)	f_s	4,2	veh
Fixed service headway dependent on fleet-size (f_s=4,2)		6,12	min/veh
Operator costs:			
Percentage decrease in unit operational costs with vehicle automation	η	53	%
Percentage increase in unit capital cost with vehicle automation	ζ	50	%
Unit fixed operating cost per vehicle-hour	c^{oper}	39.24	€/veh/h
Unit size-dependent operating cost per vehicle-hour	b^{oper}	0.145	€/veh/h
Unit fixed capital cost per vehicle-hour	c^{cptl}	1.4	€/veh/h
Unit size-dependent capital cost per vehicle-hour	b^{cptl}	0.099	€/veh/h
Distance-based operating costs dependent on vehicle size (s=25,50)	g_s^{km}	0.54, 0.66	€/km
Passenger costs:			
Value of in-vehicle time	β^{ivt}	5.9	€/h
Value of waiting time	β^{wait}	$2 \cdot \beta^{ivt}$	€/h
Value of waiting time if denied boarding	β^{denied}	$7 \cdot \beta^{ivt}$	€/h

acquisition cost due to the additional equipment required to enable automated driving, but also speculating that current costs of AVs will decrease if mass production is achieved. Plugging the estimated values into Eqs. (8) and (9) gives us the vehicle-size dependent operational cost per vehicle-hour for both non-AVs (i.e., η and ζ are 0%) and for AVs when operated as a fixed service.

With this it is estimated that two non-automated buses of capacity 50 passengers/vehicle can be replaced by approximately four AVs of capacity 25 passengers/vehicle, for the same operational cost per hour and while keeping planned service capacity the same when operated as a fixed service. With a fixed operational policy the scheduled headway with a doubled fleet size is thus reduced to 6 min. Operational cost per kilometer are estimated at $g_{25}^{km} = 0.54$ €/km for vehicles of size 25 and $g_{50}^{km} = 0.66$ €/km for vehicles of size 50 using the same data from Australian Transport Council (2006).

For consistency, the value of in-vehicle time $\beta^{ivt} = 5.9$ €/h for peak hour bus transport recommended in Australian Transport Council (2006) is used. The weight of perceived waiting time is set to double that of in-vehicle time, $\beta^{wait} = 2 \cdot \beta^{ivt}$, based on the study of Wardman (2004). The value of waiting time due to denied boarding $\beta^{denied} = 7 \cdot \beta^{ivt}$ is used based on the study of Cats et al. (2016). Travel costs associated with transfers for this case study are the same for both of the simulated service designs, and are hence omitted in the comparison. A summary of the parameters used in numerical experiments for Case 1 is presented in Table 2.

In summary a total of 20 scenarios are simulated: two vehicle sizes ($s \in \{25, 50\}$ passengers/vehicle with corresponding fleet size f_s) and five demand levels (combined rates of $\lambda \in \{25, 50, 100, 200, 300\}$ passengers/h) for fixed and on-demand operational policies. In Section 5 each scenario is denoted by FC(f_s, s, λ) for fixed operations and DRT(f_s, s, λ) for on-demand operations. Passengers are generated over one simulated hour. Output statistics are calculated for both on-demand and fixed scenarios for the time period starting with the first passenger arrival and until all passengers have reached their destination. Prior to the first passenger arrival a warm-up time is included to distribute fixed service vehicles with an even headway along the circular route. Given the stochastic nature of the simulation (the random passenger arrivals), each scenario is simulated with 400 replications. This results in a smaller than 1% relative standard error for all mean estimates.

4.2. Case 2: Stockholm case study

In the second case study we apply the DRT feeder operations to the Stockholm area, specifically to lines 176 and 177 which form a trunk-and-branches network connecting rural parts of the Drottningholm and Ekerö islands to the more central parts of Stockholm, running between Solbacka and Skärvik on the west side and Mörby in the northeast. In Fig. 5 the two branches and trunk are shown. The timetables of the two lines are planned such that they run as a trunk line on the shared part of the line, but irregularities and bunching regularly occur. In Laskaris et al. (2018) this network was used to study multi-line holding control for the trunk part in order to improve coordination and regularity. In this paper we investigate instead the possibility of restricting the fixed service to the trunk portion of the network, while operating a flexible service on the branches. In theory this could improve the regularity of the service on the trunk line and provide a more robust and adaptive service on the branches, also allowing rebalancing of service across the branches in case of asymmetric demand. As in Laskaris et al. (2018) we focus on the eastbound direction of the service.

In Fig. 6 the demand profile for both lines is shown. The distribution of total demand on the branches and on the shared corridor is displayed in Table 3. Empirical data for the demand and travel times of the lines were obtained from the Stockholm public transport

Fig. 5. Lines 176 and 177 in Stockholm. The purple portion is common for both lines (trunk portion). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Source: Laskaris et al. (2018)

Table 3
Demand distribution breakdown for line 176 and line 177.
Source: (Laskaris et al., 2018).

	Line 176		Line 177	
	Passengers per vehicle trip	Share of total demand	Passengers per vehicle trip	Share of total demand
Total demand	147	100%	144	100%
Demand on branch	14	9.5%	7	4.9%
Demand on shared transit corridor	133	90.5%	137	95.1%
Corridor demand generated at branch stops	40	27.2%	44	30.6%
Corridor demand generated at corridor stops	93	63.3%	93	64.5%

authority (SLL) and specified as input to the simulation model. As can be observed in Fig. 6 and Table 3, the two lines have similar demand profiles where passengers board along both the branch and the trunk but alight mostly along the trunk.

4.2.1. System definition and assumptions

In this study, lines 176 and 177 are merged into a single corridor (or trunk) line starting from the first common stop (stop 20 for line 176 and stop 13 for line 177) and ending at Mörby station. The branches, consisting of stops 1–19 (line 176) and 1–12 (line 177) are now operated by a flexible service. To characterize the variability of vehicle running times, travel times between stops are sampled from log-normal distributions. These distributions are parameterized by the scheduled travel time as the mean and a 10% standard deviation of the mean, calculated from AVL data. As in Laskaris et al. (2018), only unidirectional demand is considered to focus evaluation on the first-mile use case. The propagation of trip delays across sequential fixed service trips by the same vehicle is not considered. Fixed service vehicles are in other words modeled with perfect even headways at dispatch points according to schedule, while on-trip delays (e.g., bunching due to passenger congestion effects and variability of travel times between stops) can still occur. For flexible service vehicles, with routes and schedules assigned in real time, delays will propagate to future trips by the same vehicle.

Passengers using the flexible service to a destination on the trunk will transfer at the start of the trunk line and continue their trips to their final destinations. Similar to the operation of the on-demand service in Section 4.1, passengers will request on-demand trips to the transfer stop if their final destination lies on the corridor or to their final destination if it lies on a branch. In contrast

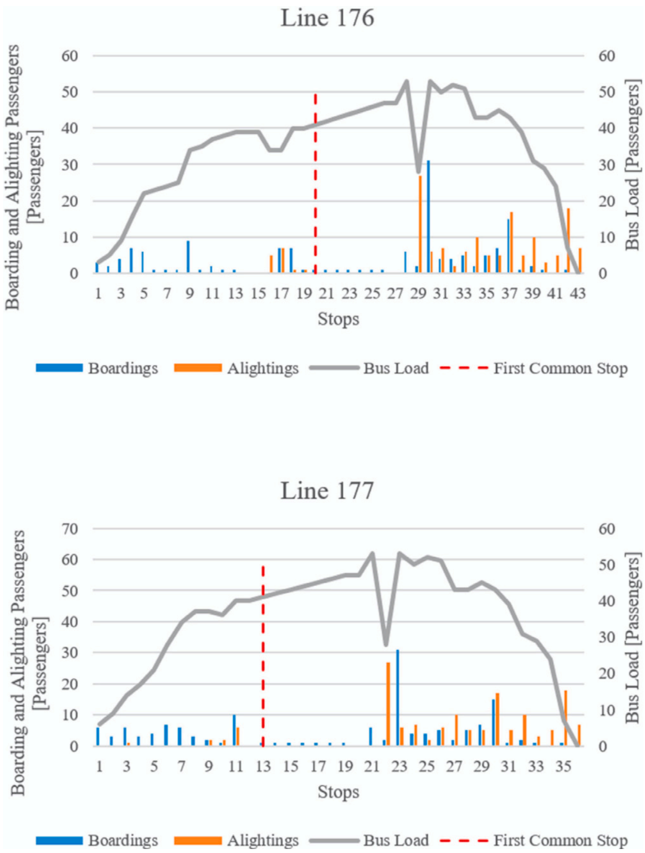

Fig. 6. Demand and load profiles for lines 176 and 177 in Stockholm. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Source: Laskaris et al. (2018)

to Case 1, however, flexible vehicles may also be assigned additional requests while already en-route, taking advantage of the more linear organization of the stops on branches. The insertion of an additional request into an existing trip plan is considered feasible if both pickup and drop-off do not require an assigned vehicle to backtrack from already planned stop visits downstream towards the transfer stop, and if the forecasted load of the vehicle based on already assigned requests does not exceed its maximum passenger capacity.

To focus the evaluation of the flexible service as a true replacement of a public transit service in this study, LoS constraints are not included to instead evaluate what kind of LoS can be achieved for existing public transit demand. All requests are accepted, and requests are not canceled, but passengers may opportunistically board another vehicle than the one that was assigned to their trip, if that vehicle arrives earlier and serves the passenger destination (transfer) stop. This will then be notified to the fleet manager.

4.2.2. Parameter set-up

The baseline service against which we compare the DRT services, is the fixed-line service as is currently in operation (and from which the demand and performance data were retrieved), without the improved holding control proposed in Laskaris et al. (2018). Buses in the baseline scenario are dispatched from end stops Solbacka and Skärvik according to a 10-minute even-headway policy. Dispatch times and stop visits are planned such that a joint 5-minute headway is coordinated (in the absence of bunching) from the first common stop on the trunk.

When shortening the service to the trunk line, while keeping the same frequency, the fixed bus fleet can be reduced by a total of 10 buses, each with capacity for 100 passengers. We redistribute these 1000 seats in two DRT fleet scenarios, one consisting of 50 vehicles with a capacity of 20 and one of 100 smaller vehicles with capacity 10. With the same operational cost assumptions as described for Case 1 in Section 4.1.2, a smaller fleet is also considered. Using the operational cost parameters in Table 2 and cost relationships with and without vehicle automation in Eqs. (8) and (9), it is estimated that 10 non-automated buses of capacity 100 passengers/vehicle can be replaced by approximately 26 AVs of capacity 20 passengers/vehicle for the same operational cost per hour.

We compare the two different ranking functions for the nearest neighbor algorithm: based on serving the maximum number of served requests (Eq. (5)) and based on serving the OD trip plans with maximum cumulative waiting time for the assigned requests

Table 4
Scenario definitions for case study 2.

Scenario	Fixed fleet	DRT fleet	DRT capacity	Algorithm
Fixed	38	0	–	–
26x20 maxR	28	26	20	#Requests
50x20 maxR	28	50	20	#Requests
100x10 maxR	28	100	10	#Requests
26x20 cumWT	28	26	20	CumulativeWait
50x20 cumWT	28	50	20	CumulativeWait
100x10 cumWT	28	100	10	CumulativeWait
26x20 maxR-rb	28	50	20	#Requests+Rebalancing
50x20 maxR-rb	28	50	20	#Requests+Rebalancing
100x10 maxR-rb	28	100	10	#Requests+Rebalancing
26x20 cumWT-rb	28	26	20	CumulativeWait+Rebalancing
50x20 cumWT-rb	28	50	20	CumulativeWait+Rebalancing
100x10 cumWT-rb	28	100	10	CumulativeWait+Rebalancing

(Eq. (6)). Intuitively, the latter should provide a more equitable reassignment of empty vehicles, since it is sensitive to both the number of requests and the waiting times.

Results are also provided with and without the application of a simple rebalancing strategy for on-call vehicles not currently assigned to any trip. For scenarios where rebalancing is applied, checks are performed at 1-minute intervals throughout the simulation. If available, on-call vehicles are redistributed to end stops Solbacka and Skärvik such that an equal supply (the total number of on-call vehicles at the stop plus the number of vehicles en-route to this stop) at these stops is maintained. The configuration of the 13 scenarios is presented in Table 4.

For each scenario we report the results for the following passenger groups: branch-to-branch passengers (B2B), branch-to-corridor (B2C), corridor-to-corridor (C2C), as well as overall (Total). Passengers in the B2C group will experience an additional transfer cost when replacing fixed service branches with an on-demand feeder service. The additional transfer cost used in calculating generalized travel costs of travelers in the B2C category is equal to 5 min of in-vehicle time (Balcombe et al., 2004). Using the same value of in-vehicle time as in Case 1 (see Table 2), the fixed cost penalty per transfer $\beta^{trans} = 0.49€$ is applied in calculating generalized travel costs for all on-demand scenarios.

We focus on the same KPIs as previously defined as the main LoS criteria: average and standard deviations for passenger costs, waiting times, and in-vehicle times. In addition we consider the Gini coefficient, the CV and percentiles of waiting times, in order to investigate the equity effects of the scenarios for the various passenger groups.

All results are averaged over 50 simulation replications per scenario, for which the relative standard error of the mean was smaller than 1% for all reported KPIs. Passengers are generated over 2.5 simulated hours. Output statistics are calculated for both on-demand and fixed scenarios for all trips that started and completed within the passenger generation period. Prior to the first passenger arrival a warm-up time is included to distribute fixed service vehicles with an even headway along fixed lines in all scenarios. On-demand vehicles are initialized as on-call uniformly distributed at all branch stops.

5. Results and analysis

In this section we analyze the results for both the simplified and the real-world case studies. The results for Case 1 (circular feeder network) are presented in Section 5.1 and the results for Case 2 (Stockholm case study) are analyzed in Section 5.2.

5.1. Case 1: Circular feeder network

The simulated scenarios are evaluated based on metrics of passenger cost, individual passenger travel time components and total VKT. Table 5 displays the computed averages ($\bar{t}$) and standard deviation (σ) of all t^{ivt}, t^{wait} and t^{denied} over all simulation replications. Furthermore, average and standard deviation of passenger total travel time ($\bar{t}^{tt}$, σ^{tt}), weighted travel cost per passenger ($\bar{c}^{pcost}$, σ^{pcost}) and total VKT ($\bar{d}^{vkt}$, σ^{vkt}) are displayed.

For convenience, using the equivalent fixed service scenario as a reference, the relative change with on-demand operations is shown in Table 6.

As displayed in Table 6, with more direct routes in-vehicle times are on average 47% shorter in all DRT scenarios, resulting in shorter average total travel times for all levels of demand and for both fleet compositions. Average VKT also decreases with on-demand operations for all scenarios with a larger fleet size. However, total waiting times as well as weighted passenger travel costs are in general higher for all DRT scenarios, with the exception of the highest level of demand.

Table 5
Summary of simulation results for all scenarios.

Scenario	Performance metrics					
$(f_s,\ s,\ \lambda)$	$\bar{t}^{ivt};\ \sigma^{ivt}$ [s]	$\bar{t}^{wait};\ \sigma^{wait}$ [s]	$\bar{t}^{denied};\ \sigma^{denied}$ [s]	$\bar{t}^{tt};\ \sigma^{tt}$ [s]	$\bar{c}^{pcost};\ \sigma^{pcost}$ [€]	$\bar{d}^{vkt};\ \sigma^{vkt}$ [km]
FC(4,25,25)	454; 203	180; 105	–	634; 229	1.22; 0.44	112.77; 0.04
FC(4,25,50)	458; 205	181; 105	–	639; 231	1.23; 0.44	111.13; 0.03
FC(4,25,100)	459; 205	180; 105	–	639; 230	1.23; 0.44	112.60; 0.02
FC(4,25,200)	466; 207	180; 105	7; 51	653; 228	1.32; 0.65	111.02; 0.02
FC(4,25,300)	469; 208	181; 104	324; 682	974; 587	4.81; 7.16	133.92; 0.02
DRT(4,25,25)	238; 55	302; 304	–	540; 313	1.28; 0.95	59.12; 9.26
DRT(4,25,50)	240; 56	351; 304	–	591; 312	1.43; 0.95	77.42; 8.18
DRT(4,25,100)	243; 56	378; 295	–	620; 303	1.52; 0.92	88.91; 7.20
DRT(4,25,200)	248; 56	398; 291	–	646; 299	1.59; 0.90	96.35; 6.53
DRT(4,25,300)	253; 56	413; 296	3; 52	669; 306	1.67; 1.05	99.09; 5.61
FC(2,50,25)	458; 204	358; 208	–	817; 291	1.77; 0.71	59.38; 0.02
FC(2,50,50)	460; 206	362; 207	–	822; 291	1.79; 0.70	59.33; 0.02
FC(2,50,100)	465; 208	362; 208	–	827; 293	1.79; 0.71	59.31; 0.01
FC(2,50,200)	477; 212	360; 209	3; 48	840; 294	1.85; 0.84	59.30; 0.01
FC(2,50,300)	484; 213	363; 209	276; 632	1123; 567	4.87; 6.63	74.56; 0.01
DRT(2,50,25)	238; 55	421; 371	–	659; 377	1.64; 1.15	53.03; 5.85
DRT(2,50,50)	241; 55	505; 395	–	746; 400	1.91; 1.22	61.88; 3.89
DRT(2,50,100)	244; 56	546; 392	–	789; 398	2.04; 1.21	65.54; 2.78
DRT(2,50,200)	252; 56	587; 404	–	838; 408	2.18; 1.25	66.94; 2.20
DRT(2,50,300)	259; 56	617; 418	–	876; 422	2.28; 1.29	66.62; 2.19

Table 6
Relative differences under on-demand operations using the equivalent fixed scenario as a reference. Δ^{ivt} denotes the difference in average in-vehicle time, Δ^{twait} difference in average total waiting time, Δ^{tt} difference in average total travel time, Δ^{cost} difference in average passenger cost and Δ^{vkt} difference in average VKT.

Scenario FC→DRT	Relative differences				
	Δ^{ivt} [s]	Δ^{twait} [s]	Δ^{tt} [s]	Δ^{pcost} [€]	Δ^{vkt} [km]
(4,25,25)	−48%	68%	−15%	5%	−48%
(4,25,50)	−48%	94%	−8%	16%	−30%
(4,25,100)	−47%	110%	−3%	24%	−21%
(4,25,200)	−47%	113%	−1%	20%	−13%
(4,25,300)	−46%	−18%	−31%	−65%	−26%
(2,50,25)	−48%	18%	−19%	−7%	−11%
(2,50,50)	−48%	40%	−9%	7%	4%
(2,50,100)	−48%	51%	−5%	14%	11%
(2,50,200)	−47%	62%	0%	18%	13%
(2,50,300)	−46%	−3%	−22%	−53%	−11%

5.1.1. Weighted travel costs

For comparison of absolute and relative differences in average travel cost components for passengers, Fig. 7 displays average weighted travel costs per passenger trip for the larger fleet (top row) and smaller fleet (bottom row) respectively. Unsurprisingly, weighted travel costs are lower when a larger fleet is deployed for both operational policies and for all levels of demand. Average in-vehicle times across levels of demand stay relatively stable for all the simulated scenarios. Average waiting time is also stable between demand levels for the fixed service when there is slack in service capacity (i.e., for scenarios with demand intensity $\lambda < 250$ passengers/hour). The core source of differences in average passenger costs between fixed and on-demand operational policies thus stems from differences in waiting times.

While the on-demand service results in total travel times that are on average shorter (see Table 6), average waiting times are generally longer and grow with demand level relative to the fixed service. When evaluated at double the weighted travel cost relative to in-vehicle time, the discount in total travel time does not compensate for increases in required waiting times. However, for the highest level of demand, when the planned service capacity of the fixed fleet is exceeded, a substantial number of passengers are denied boarding, which has a large impact on weighted travel costs for these scenarios.

5.1.2. System cost

Table 7 displays a summary of average system cost components for each of the simulated scenarios. The average system cost (z^{sys}) for each scenario is defined as the sum of the corresponding average time-based and distance-based operational costs (z^{oper})

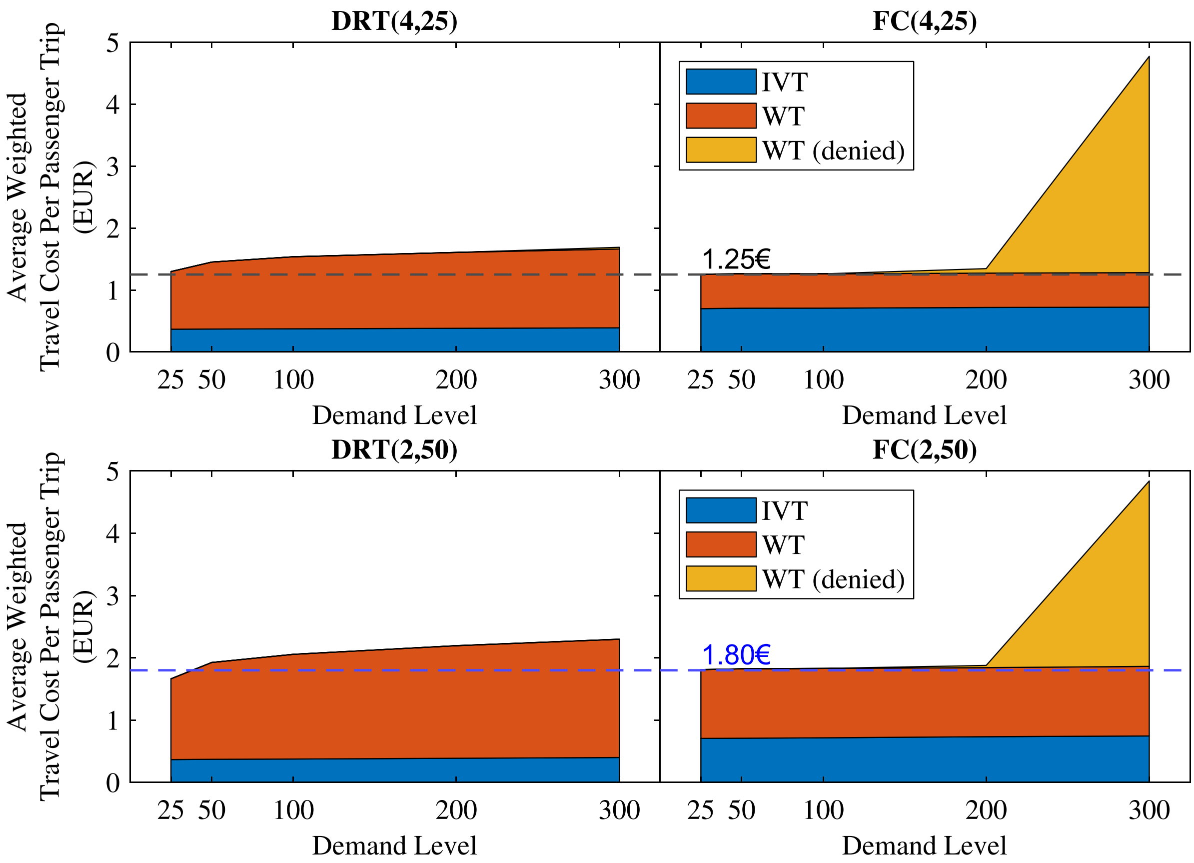

Fig. 7. Average weighted travel cost per passenger for all scenarios. The top row corresponds to results from the scenario with 4 vehicles of size 25 passengers/vehicle, and the bottom row corresponds to scenarios with 2 vehicles of size 50 passengers/vehicle. The left column corresponds to results with on-demand operations and the right column fixed operations. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

and average total passenger cost (z^{tpcost}). Average total passenger costs are given by the average weighted travel cost per passenger trip ($\bar{c}^{pcost}$) multiplied by the demand level of a given scenario. Since both time and distance required to serve all passengers are dependent on operational policy and demand level, the average operating hours required to serve all passengers ($\bar{t}^{oper}$) and the difference in average distance based costs for each on-demand scenario relative to fixed (δ^{dcost}) are also presented.

Fig. 8 displays the relative change in system cost with on-demand operations using the equivalent fixed scenario as a reference. For both fleet compositions, the on-demand policy results in a lower average system cost only for the lowest demand level under the maximum fixed service capacity. On-demand operations outperforms fixed service operations with respect to both average operational cost and total passenger costs only for the lowest demand level and the smaller fleet of larger vehicles. When planned fixed service capacity is exceeded, on-demand operations substantially reduces average system cost.

5.1.3. Waiting time distributions

To investigate differences in service reliability with respect to waiting times for each operational policy, total waiting time CVs are displayed in Fig. 9 for each level of demand. The relative variance of waiting times for the fixed service is always lower than for the on-demand service with the exception of when passengers are denied boarding. With higher rates of passenger arrivals, greedy and reactive routing and scheduling results in a relative variance of waiting times that decreases with higher levels of demand for both fleet compositions.

To evaluate the distribution of waiting time costs, Table 8 displays the Gini coefficients of total waiting time distribution for all scenarios. Across all demand levels under maximum service capacity the fixed policy results in a more equitable distribution of waiting time among passengers relative to on-demand operations. Inequality of passenger total waiting times increases drastically for the fixed service for the highest demand level, indicating that a decrease in the availability of the service affects passengers very unevenly. For the on-demand case the induced increase in total waiting times with higher demand is instead distributed more evenly among all passengers.

In Fig. 10, distributions of total waiting time are displayed for the lowest and highest demand scenarios, which represent the largest difference in total waiting time equality. The reactive fleet coordination strategy utilized in on-demand operations is reflected

Table 7
System cost components for all scenarios.

Scenario	System cost components					
$(f_s,\ s,\ \lambda)$	δ^{dcost} [€]	$\bar{t}^{oper}$ [h]	$\bar{c}^{pcost}$ [€/pass]	z^{oper} [€]	z^{tpcost} [€]	z^{sys} [€]
FC(4,25,25)	–	1.16	1.22	124	31	154
FC(4,25,50)	–	1.19	1.23	127	62	188
FC(4,25,100)	–	1.20	1.23	128	123	251
FC(4,25,200)	–	1.21	1.32	129	264	393
FC(4,25,300)	–	1.37	4.81	146	1443	1589
DRT(4,25,25)	−29	1.20	1.28	99	32	131
DRT(4,25,50)	−18	1.28	1.43	118	72	189
DRT(4,25,100)	−13	1.35	1.52	131	152	283
DRT(4,25,200)	−8	1.39	1.59	140	318	458
DRT(4,25,300)	−19	1.41	1.67	131	501	632
FC(2,50,25)	–	1.22	1.77	129	44	173
FC(2,50,50)	–	1.27	1.79	134	90	223
FC(2,50,100)	–	1.30	1.79	137	179	316
FC(2,50,200)	–	1.31	1.85	138	370	508
FC(2,50,300)	–	1.40	4.87	148	1461	1609
DRT(2,50,25)	−4	1.24	1.64	127	41	168
DRT(2,50,50)	2	1.37	1.91	146	96	241
DRT(2,50,100)	4	1.42	2.04	154	204	358
DRT(2,50,200)	5	1.46	2.18	160	436	596
DRT(2,50,300)	−5	1.48	2.28	151	684	835

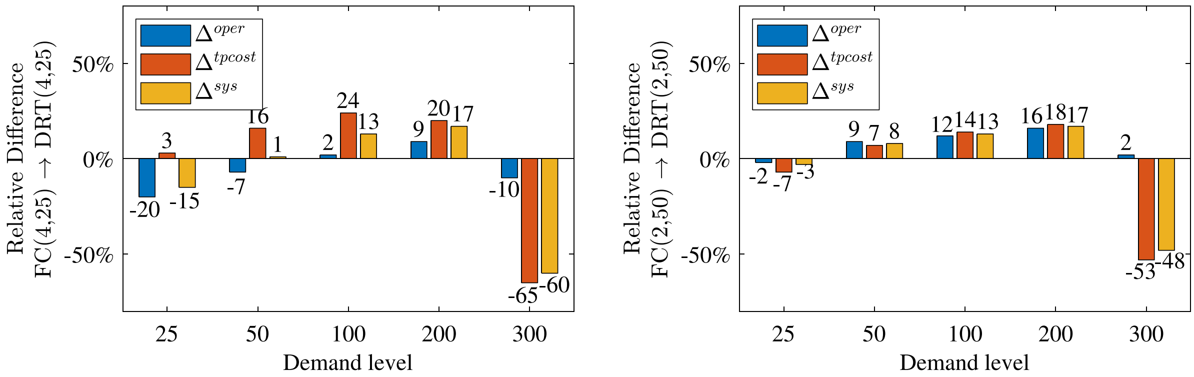

Fig. 8. Relative differences in system cost with on-demand operations using the equivalent fixed scenario as a reference for the (4,25) fleet (left) and the (2,50) fleet (right). Δ^{oper} denotes the difference in average operational cost required to serve all passengers, Δ^{tpcost} the difference in average total passenger cost and Δ^{sys} the difference in average system cost. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 8
Gini coefficients of total waiting times.

Scenarios	Demand level				
	25	50	100	200	300
FC(4,25)	34%	33%	34%	34%	60%
DRT(4,25)	47%	44%	42%	40%	39%
FC(2,50)	33%	33%	33%	34%	49%
DRT(2,50)	43%	41%	39%	39%	38%

in three peaks in waiting time frequencies for this service, most clearly seen for the lowest level of demand (left). Each peak corresponds to the current closest location of a DRT vehicle when a new request has been received. The peak at zero total waiting time corresponds to when a vehicle is already at the origin of the passenger, 180 s when the closest vehicle is at a neighboring stop to the origin of the passenger, and 235 s when the closest vehicle is at diagonal stop to that of the passenger's origin. From the distributions in Fig. 10 (right) it is apparent that the reduction in available service capacity most heavily influences only a portion of the passengers for the fixed service. With a fixed circular feeder that serves stops sequentially, passengers furthest downstream towards the transfer stop are most heavily effected by a decrease in service availability and are continuously denied boarding until

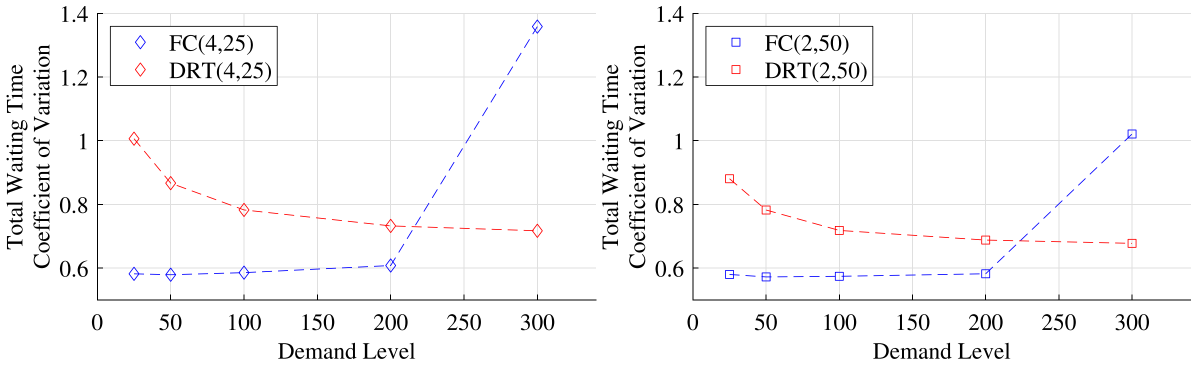

Fig. 9. Total waiting time coefficient of variation per demand level for fixed (blue) and on-demand (red) operational policies for the (4,25) fleet (left) and (2,50) fleet (right). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

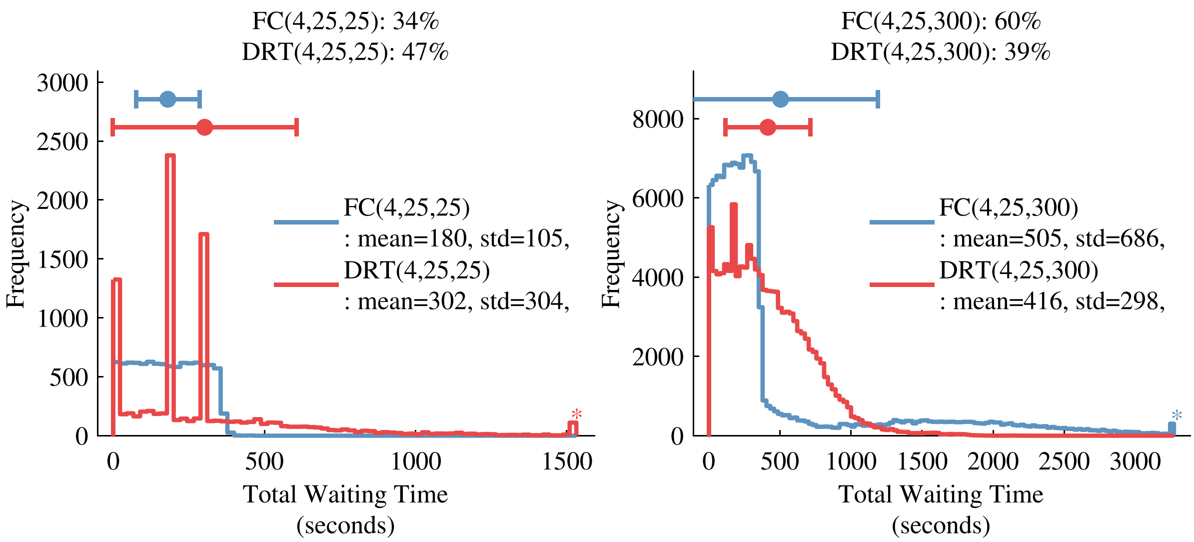

Fig. 10. Passenger total waiting time distributions for FC(4,25) (blue) and DRT(4,25) for the lowest (left) and highest (right) demand levels. Bars above each histogram display the mean and ±1 standard deviation of each distribution. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

demand subsides. With an operational policy where all stops are interchangeable in terms of supply provision, the shape of the waiting time distribution remains the same for all stops for the on-demand service. As seen in Fig. 10, both average and standard deviation of total waiting time is lower for the fixed service relative on-demand operations. For the highest demand level this is reversed, with a lower average and standard deviation of total waiting times for the on-demand service.

5.2. Case 2: Stockholm case study

In this section the results of the second case study are discussed. All results are the average over 50 simulation replications for each scenario. The computations were performed on an Intel I7 processor with 16GB of ram. Each replication required on average 45 s and all 650 replications for all 13 scenarios took 29250 s to complete. Table 9 reports the main passenger LoS results.

Starting with the overall results (Total), the number of transported passengers decreases from 2205 to 2190 with the smallest fleet of 26 vehicles with 20 seats (26x20) and the maxR sorting criterion. The cumWT marginally increases this value to 2195. The addition of rebalancing slightly increases this to 2196 (maxR-rb) and 2207 (cumWT-rb). When increasing the fleet size to 50 vehicles, the number of passengers transported increases to 2251 for the first three variants and 2257 for the cumWT-rb. The largest fleet size of 100 vehicles only yields more passengers transported (2263) for the two rebalancing variants (maxR-rb and cumWT-rb).

Regarding the overall waiting times, the median waiting time for the fixed service is 256 s. All DRT scenarios improve on this, ranging from 203 s for the 26x20 cumWT-rb variant, to 168 s for the two rebalancing variants of the largest fleet. The average waiting times, however, are higher for the smallest fleet size, ranging from 283 to 295 s versus 268 s for the fixed service. The two larger DRT fleet sizes clearly improve on the fixed service with average waiting times ranging from 229 s to 183 (again for the

Table 9
Summary of simulation results per passenger category and scenario.

	Scenario	$\bar{n}^{pass}$ [pass]	$\bar{t}^{wait}$; σ^{wait} [sec]	$med(t^{wait})$ [sec]	CV^{wait}	G^{wait}	$max(t^{wait})$ [sec]	$\bar{t}^{ivt}$ [sec]	$\bar{c}^{pcost}$ [€]
Total	Fixed	2205	268; 176	256	0.66	38%	725	1427	3.12
	26x20 maxR	2190	283; 359	199	1.27	51%	4414	1395	3.4
	26x20 cumWT	2195	283; 356	199	1.26	51%	4219	1394	3.39
	26x20 maxR-rb	2196	296; 385	202	1.3	52%	4370	1389	3.45
	26x20 cumWT-rb	2207	295; 379	203	1.29	52%	4158	1397	3.44
	50x20 maxR	2251	228; 211	186	0.92	44%	1671	1387	3.09
	50x20 cumWT	2251	229; 213	187	0.93	44%	1758	1392	3.1
	50x20 maxR-rb	2251	225; 216	185	0.96	44%	2315	1386	3.07
	50x20 cumWT-rb	2257	225; 213	185	0.95	44%	2245	1396	3.09
	100x10 maxR	2251	218; 196	183	0.9	43%	1636	1384	3.14
	100x10 cumWT	2251	218; 196	183	0.9	43%	1636	1384	3.14
	100x10 maxR-rb	2263	183; 136	168	0.74	40%	1218	1384	2.94
	100x10 cumWT-rb	2263	183; 136	168	0.74	40%	1218	1384	2.94
C2C	Fixed	1476	253; 174	237	0.69	39%	720	1152	2.65
	26x20 maxR	1490	167; 111	154	0.67	38%	598	1147	2.35
	26x20 cumWT	1497	166; 112	153	0.67	38%	575	1145	2.34
	26x20 maxR-rb	1491	167; 112	154	0.67	38%	585	1141	2.34
	26x20 cumWT-rb	1500	167; 112	154	0.67	38%	585	1148	2.35
	50x20 maxR	1492	165; 108	153	0.66	37%	570	1135	2.32
	50x20 cumWT	1490	165; 109	153	0.66	37%	583	1141	2.32
	50x20 maxR-rb	1491	166; 109	154	0.66	37%	559	1139	2.32
	50x20 cumWT-rb	1498	166; 110	154	0.66	37%	571	1149	2.34
	100x10 maxR	1496	165; 108	154	0.66	37%	562	1143	2.33
	100x10 cumWT	1496	165; 108	154	0.66	37%	562	1143	2.33
	100x10 maxR-rb	1497	164; 108	153	0.66	37%	570	1140	2.32
	100x10 cumWT-rb	1497	164; 108	153	0.66	37%	570	1140	2.32
B2C	Fixed	581	298; 177	294	0.59	34%	676	2191	4.4
	26x20 maxR	558	504; 507	360	1.01	43%	3755	2132	5.92
	26x20 cumWT	560	513; 509	365	0.99	43%	3681	2128	5.94
	26x20 maxR-rb	556	561; 533	407	0.95	42%	3788	2133	6.21
	26x20 cumWT-rb	564	556; 545	398	0.98	43%	3647	2135	6.13
	50x20 maxR	594	342; 253	281	0.74	37%	1653	2116	5.06
	50x20 cumWT	596	346; 260	283	0.75	37%	1749	2117	5.06
	50x20 maxR-rb	587	364; 280	299	0.77	37%	2101	2122	5.12
	50x20 cumWT-rb	590	362; 273	298	0.75	36%	2012	2125	5.14
	100x10 maxR	587	322; 241	267	0.75	37%	1622	2101	5.2
	100x10 cumWT	587	322; 241	267	0.75	37%	1622	2101	5.2
	100x10 maxR-rb	593	271; 162	254	0.6	31%	1218	2107	4.85
	100x10 cumWT-rb	593	271; 162	254	0.6	31%	1218	2107	4.85
B2B	Fixed	148	296; 172	295	0.58	34%	615	1167	2.79
	26x20 maxR	141	734; 787	505	1.07	52%	3790	1097	4.53
	26x20 cumWT	137	718; 763	499	1.06	51%	3438	1110	4.48
	26x20 maxR-rb	148	690; 781	438	1.13	54%	3623	1087	4.24
	26x20 cumWT-rb	143	672; 727	434	1.08	53%	3564	1088	4.22
	50x20 maxR	165	394; 398	251	1.01	53%	1527	1036	2.97
	50x20 cumWT	164	387; 393	249	1.02	53%	1527	1041	2.96
	50x20 maxR-rb	173	267; 380	104	1.42	65%	2021	1021	2.5
	50x20 cumWT-rb	169	270; 378	108	1.4	65%	1953	1035	2.53
	100x10 maxR	169	353; 378	216	1.07	56%	1502	1030	3.13
	100x10 cumWT	169	353; 378	216	1.07	56%	1502	1030	3.13
	100x10 maxR-rb	174	47; 61	14	1.29	61%	316	1014	1.74
	100x10 cumWT-rb	174	47; 61	14	1.29	61%	316	1014	1.74

largest fleet size, with rebalancing). Maximum waiting times are worse for all DRT scenarios, but improve with larger fleet sizes and for the 100x10 vehicle case through the use of rebalancing.

It is important to note here that especially with the larger fleet sizes, the differences between the cumWT and maxR sorting criteria are minimal, due to the fact that vehicles are being rebalanced, the reactiveness of the algorithm (triggered by each request and each vehicle becoming available), and the assignment of requests to trip plans for en-route vehicles. There is rarely more than one trip plan that needs to be assigned at any time, thus the sorting criterion has little impact. With the smaller fleet size there is a small but noticeable difference between the two criteria.

Table 10
Waiting time percentiles over all passengers for fixed and maxR scenarios.

Scenario	1	5	25	50	75	95	99
Fixed	3.6	18.4	110.9	256	410.4	561.1	626.9
26x20 maxR	3.5	19.9	100.3	199.2	320.8	916.7	1777.1
26x20 maxR-rb	3.6	19.8	100.4	202.2	332.4	989.4	1917.4
50x20 maxR	3.2	18.8	95.1	186.4	289.4	614.7	1132.7
50x20 maxR-rb	2.3	14.2	90.3	184.9	289.7	575.3	1116.5
100x10 maxR	2.6	17.3	91.7	182.8	283.4	570.4	1063
100x10 maxR-rb	1.8	10.3	77.5	167.7	262.7	407.4	595.5

The average in-vehicle time for the fixed service is 1427 s and between 1384 and 1395 s for the DRT scenarios. The superior performance of the DRT service is due to the fact that it does not need to stop at intermediate stops on the branches, unless there are passengers to pick up en-route.

In terms of generalized costs per passenger, the smaller fleet size variants perform worse than the fixed service (3.39–3.45€ vs. 3.12€), but the medium and largest fleet sizes perform similar, or better (2.94€ for the 100x10 scenarios with rebalancing).

5.2.1. Waiting time distributions per passenger category

Regarding the distributional effects, the CV for the waiting time is lowest for the fixed service (possibly due to the optimistic regular departures) at 0.66, and is almost double that for the smallest fleet scenarios. The larger fleet sizes improve on this but even the largest fleet size, with rebalancing, has a higher CV (0.74) than the fixed service. The Gini coefficients show a similar pattern, where the fixed service may be optimistic at 38%, whereas the 26x20 scenarios have the highest values at 51%–52% and increasing the fleet size reduces this to 44% for the 50x20 scenarios and 40% for the 100x10 scenarios with rebalancing.

Looking at the various passenger groups, starting with passengers boarding and alighting on the corridor (C2C), the average and median waiting times are drastically lower for all scenarios compared to the fixed service, with average waiting times ranging from 253 s for the fixed service to 164 s for the 100x10 scenarios with rebalancing. The maximum waiting time, CV and Gini coefficients show that the DRT scenarios have a small positive effect on the waiting times for C2C passengers.

For the passengers boarding on a branch and alighting on the corridor (B2C), the waiting times are higher and more variable when compared to the fixed service with the exception of the 100x10 scenarios with rebalancing. The number of passengers served increases from 558 to 593 with increasing fleet size. Gini coefficients improve for the 100x10 case with rebalancing, with CV on-par with fixed. For the B2C travelers, maximum waiting times as well as generalized travel costs (including the additional transfer penalty) increase for all on-demand scenarios. Despite improvements on the trunk or the branches independently, B2C passengers experience an increase in generalized travel costs for all scenarios tested when compared to fixed.

For the passengers boarding and alighting on the branches (B2B), the DRT scenarios without rebalancing reduce the LoS with higher and more variable waiting times. The cumWT algorithm improves on this for the 26x20 and 50x20 fleets, but practically no difference is observed for the 100x10 vehicle case. With rebalancing, waiting time results improve considerably for the B2B passenger group. For the 50x20 and 100x20 vehicle cases, average waiting time is improved to the degree that it is now better than fixed. The 100x10 fleet scenarios stand out as being heavily improved by rebalancing. The number of passengers served increases with an average waiting time of 47 s and a median waiting time of 14 s. The maximum waiting time for this scenario also improves drastically when compared to fixed from 615 s to 316 s. CV and Gini coefficients for these scenarios worsen, however, and are in general inferior to fixed for all DRT scenarios.

In Fig. 11 the waiting time distributions for the fixed and maxR algorithm with and without rebalancing scenarios and passenger groups (Total, C2C, B2C, and B2B) are plotted. In general the overall effects observed in Table 9 can be seen here as well. The main improvements in service regularity are found on the corridor portion (C2C) where the fixed service shows a larger dispersion than the DRT scenarios. For B2C and B2B travelers, waiting time distributions tend to be heavily right-skewed with a tail of longer waiting times, most clearly observed for the 26x20 fleet.

For the 26 vehicle fleet, waiting times in relation to fixed operations worsen for B2C and B2B travelers, with higher average- and more variable waiting times. With the addition of a rebalancing strategy for this fleet composition, marginal improvements to waiting times are achieved for B2B travelers at the expense of the B2C travelers. For the 50x20 and 100x10 fleets without rebalancing, a lower average and median waiting time is achieved on an aggregate (Total) level, nevertheless still with long tail-ends for B2C and B2B travelers. The addition of rebalancing for the 50x20 fleet improves waiting times for the B2B travelers to the degree that averages for this group now surpass the fixed scenario. However, this still comes at the expense of B2C travelers. The clearest change with rebalancing is observed for the 100x10 scenario, where waiting time averages and spread improve for B2C travelers and even more drastically for B2B travelers. This indicates that the previous assignment without rebalancing was inefficient, with many vehicles grouping at the transfer stop. Proactively rebalancing these vehicles to branch start stops result in LoS provision with considerably lower average waiting times and smaller spread within and across all passenger groups.

Table 10 displays waiting time percentiles for fixed and maxR scenarios (with and without rebalancing). As mentioned before, all median (50th percentile) waiting times for DRT are lower than for the fixed service. At the 75th percentile, waiting times are also better for all DRT scenarios. At the 95th the 50x20 and 100x10 scenarios are either on-par with or, for the 100x10 case with rebalancing, better than fixed. At the 99th percentile, only the 100x10 fleet with rebalancing outperforms fixed operations.

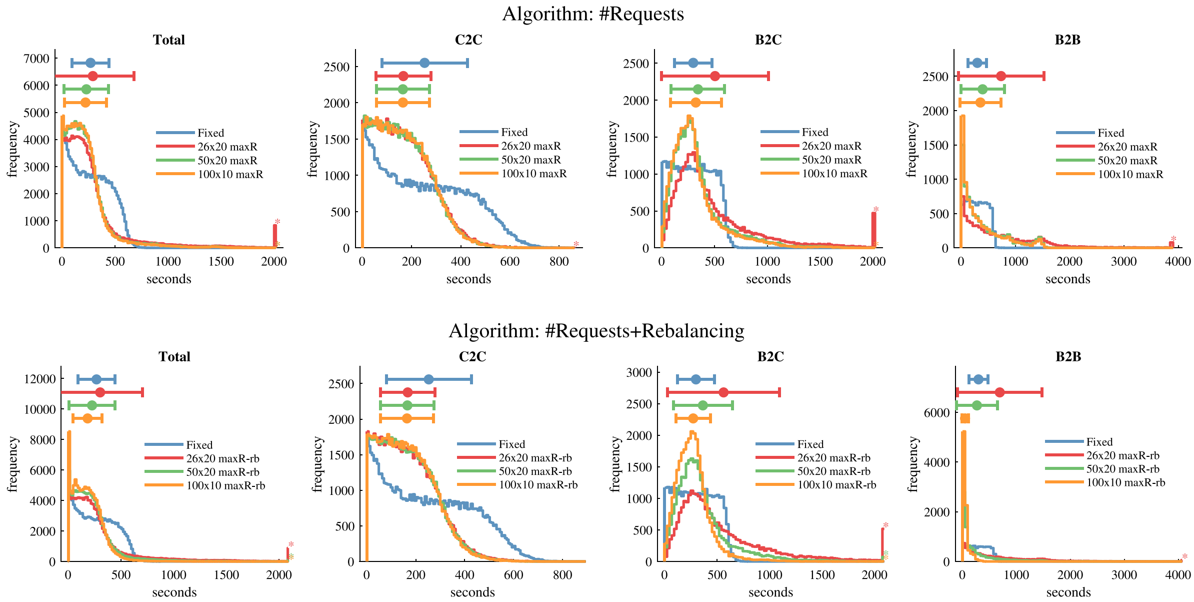

Fig. 11. Passenger total waiting time distributions with and without rebalancing for passenger groups (Total, Corridor-to-Corridor, Branch-to-Corridor, and Branch-to-Branch), for all tested scenarios. Bars above each histogram display the mean and ±1 standard deviation of each distribution. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 11
Total, occupied, and empty VKT results of DRT vehicles for each scenario.

Scenario	$\bar{d}^{vkt}$; σ^{vkt}	Occupied	Empty
26x20 maxR	2363; 34	35%	65%
26x20 maxR-rb	2362; 36	33%	67%
50x20 maxR	4018; 97	31%	69%
50x20 maxR-rb	4086; 96	32%	68%
100x10 maxR	4582; 184	33%	67%
100x10 maxR-rb	5394; 202	37%	63%

The results from Table 10 indicate that while the variability of waiting times is in many scenarios larger on the branches, there is still a high probability of experiencing on-par or better waiting times in comparison with strictly fixed operations. Nevertheless, the CVs and Gini coefficients of waiting times in Table 9 suggest that fixed service operation is difficult to compete with in terms of reliable and equitable service over all passengers, and for passengers with origins on branches. However, it is worth noting that these metrics may be interpreted in the context of LoS achieved. An example of this is for the B2B travelers in the 100x10 scenario with rebalancing. The average, median, standard deviation and maximum of waiting times for B2B travelers, as well waiting times overall at the 99th percentile for the 100x10 scenario with rebalancing, are far better than fixed, with a greater number of travelers served. While this might be interpreted as a superior LoS provided, the relative average and variance of waiting times is still far higher for B2B travelers resulting in a less equitable service overall.

5.2.2. Fleet utilization

In Table 11 the VKT results for DRT vehicles are presented. As mentioned in Section 4.2, the results presented are for demand in the eastbound direction, hence trips in the westbound direction will always be empty. As expected, VKT increase with fleet size as well as through the use of rebalancing for the larger fleets. Similar fill ratios are observed across the fleet sizes, vehicle types and assignment algorithms tested. Empty trips increase for the smallest fleet size with the use of rebalancing to end stops. In contrast, the ratio of empty trips decreases with rebalancing from 69% to 68% in the 50x20 case, and from 67% to 63% in the 100x10 case. These results indicate that the fill ratio of the vehicles may be improved by more efficient ride-sharing algorithms. In addition, the linear alignment of the stations and the lack of short-cuts between the branches limits the opportunity of DRT operations to provide faster service than the fixed lines, which are expected to be prevalent under most other circumstances.

6. Conclusions and discussion

This paper presents a simulation framework encompassing essential components for modeling demand-responsive transit services designed for prototyping a wide variety of demand-responsive operational policies. This framework is embedded within an existing public transit simulation model that has previously been utilized in evaluating fixed transit services and that includes a detailed representation of adaptive passenger behavior. The combined framework allows for quantifying LoS and operational cost impacts of demand-responsive services under alternative operational settings and enables consistent comparison of such services with fixed transit alternatives. A nearest-neighbor on-demand operational strategy with two candidate objective functions is implemented within this framework together with a strategy for rebalancing idling vehicles.

The framework is evaluated using two case studies. The first case study consists of a simplified circular feeder network where two fleet compositions are simulated under varying conditions of demand intensity. With estimated reductions in labor cost with vehicle automation, the two fleet compositions are considered comparable with respect to both operational cost per hour as well as expected service capacity at fixed service frequencies. The second case study is based on passenger and operations data of lines 176 and 177 in the Stockholm area, and replaces the branch portions with on-demand flexible services while maintaining the fixed operations for the trunk portion. Passengers on the branch portion with a destination on the trunk would book a flexible trip to a transfer point and then transfer to the fixed-line service. In total, 13 scenarios are evaluated, contrasting comparable fleet compositions based on expected operational costs or service capacity, as well as alternative redistribution strategies.

Results for the circular network case indicate that the increase in fleet size with smaller AVs can improve passenger LoS regardless of the operational policy. This naturally comes with an increase in total VKT per passenger, in particular for fixed service operations where vehicles drive continuously regardless of the demand level. In comparing operational policies, fixed operations provide on average a higher LoS to passengers for most levels of demand where there is slack in service capacity. On-demand operations are in such circumstances more competitive with respect to passenger costs with decreasing demand level. For the lowest demand level and a smaller fleet, the on-demand service provides an on average higher LoS to passengers for lower VKT per passenger. Average system costs also improve under on-demand operations for the lowest demand levels. This result is consistent with previous comparisons of fixed versus on-demand feeder operations under alternative network geometries.

A key difference in fixed versus on-demand services is service reliability. The greedy on-demand strategy results in a relative variance of waiting times that decreases with increasing demand levels but that is still higher than for fixed operations for all demand levels below maximum service capacity. Total waiting time Gini coefficients also indicate that a fixed service is more equitable for lower demand levels. Limitations in available capacity for the highest demand level, however, most heavily affect passengers downstream when stops are served sequentially. Average weighted travel costs are in this case dominated by costs associated with waiting time due to denied boarding. In contrast, the distribution of total waiting times under limited service capacity is spread equally among passenger groups when utilizing the on-demand operational policy. While this result is specific to the assumptions made in this case study, the analysis highlights differences in the dispersion of negative effects that may be worth considering in an evaluation of fixed versus on-demand operations for comparable transit network structure and demand patterns.

Results from the real-world case study show that service performance on the corridor section is greatly improved with the DRT combined with fixed services, in terms of average and median travel times as well as generalized travel costs. Without the application of rebalancing, service on the branches suffers from longer waiting times, in particular for the smaller fleet size of 26 vehicles. All DRT services improve on median as well as 75th percentile waiting times, and the larger 50 and 100 vehicle fleet sizes result in improved average generalized travel costs with or without rebalancing.

Notwithstanding, the maximum waiting times as well as CV and equity (Gini coefficient) are better for fixed services, even when compared against the best performing DRT scenario with the 100 vehicle fleet and rebalancing. However, at the 95th and 99th percentile, waiting times over all passengers for this best performing DRT scenario outperform fixed services, as well as the average and standard deviation of waiting times for each of the separate passenger categories. This highlights the importance of evaluating equity also as a potential trade-off to overall improvements to LoS.

The presented real-world case study offers insights into the performance of reactive DRT services within a similar context, network topology and demand pattern. Results indicate that there are benefits to LoS overall when fixed branches are replaced with DRT, at the expense of transferring passengers and a less equitable and reliable distribution of waiting times. More extensive simulations varying key design variables (i.e., stop locations, fleet size and characteristics, assignment strategies) as well as demand distributions are required however to derive more direct analytical results and assess system performance under various circumstances. Together with alternative objectives in the DRT assignment, the equity dimension of this study could also be explored more in depth by also explicitly optimizing for this in an iterative simulation-based design process.

It is important to note that the fixed service was modeled only in a single direction (eastbound). Consequently, the interaction effects of round-trip services, which often lead to late departures at the start of trips, are not taken into consideration. Thus, the service regularity of the fixed service is optimistic. Moreover, the performance of an on-demand transit system is highly dependent on the strategy used to assign service vehicles to travel requests. The nearest-neighbor greedy algorithm used in this article is purely reactive and steers towards either maximum number of requests served, or balancing between minimizing maximum waiting times and maximizing the number of requests served, by ranking trip plans by cumulative waiting time for the assigned requests. Our modeling framework can in the future be extended to include predictive type of algorithms as well as algorithms that more effectively pursue ride-pooling and (en-route) re-optimization of schedules. Additionally, future work should consider time windows of traveler requests, as well as model DRT operations in the opposite direction (distribution).

This paper also makes use of a simple, rule-based rebalancing strategy adapted to the topology of the studied network. The DRT results for both case studies would presumably improve with more sophisticated redistribution strategies, which would mean that the reported results provide a conservative, lower bound on their potential performance. Advanced rebalancing strategies that make use of predictions of future station supply/demand ratios, for example those developed in studies of station-based, one-way car-sharing services (e.g. Repoux et al. (2019)), have shown potential to improve LoS provided to users. Although the studied problems are not the same, similar methods inspired by these principles may be applied to station-based DRT problems. Therefore, another interesting line of future work could be to further experiment with alternative proactive rebalancing strategies within the presented simulation framework. Babicheva et al. (2018) show that, especially for high demand cases, simpler nearest-neighbor strategies are more robust, with minimal calibration. Investigating such trade-offs for both synthetic and real-world cases is another interesting future research direction.

DRT operations were simulated without request rejections or cancellations to target service evaluation for existing fixed public transit demand. In studies of DRT services, LoS constraints on accepted requests (for example based on maximum allowable waiting time, crowding, or in-vehicle detour constraints) can still be important, however. These could be used both as a representation of a traveler's willingness to share/request a ride, or to enable the DRT service operator to increase operational efficiency by rejecting more costly requests in favor of those that are more easily bundled into a shared trip. To further evaluate DRT feeder services with respect to the trade-offs between operational efficiency and service availability, as well as in the presence of other alternative modes, evaluating DRT assignment with LoS constraints is an interesting line of future work.

The current study also assumes identical stop placement for the compared services focusing solely on differences in route and timetable operations. In addition to these dimensions, optimal stop placement dependent on demand pattern, operational policy and fleet composition, can aid in evaluating 'best case' scenario comparisons of fixed versus demand-responsive operational policies. Both the generation and characterization of comparable feeder network structures and demand patterns, as well as optimal stop placement dependent on this, are thus interesting avenues of future work.

Finally, it is worth emphasizing that both operational and capital cost changes induced by the automation of public transit is still highly uncertain. Furthermore, the uncertainty of changes in traffic dynamics, operational speeds, and passenger behavior with AVs and their influence on estimated performance are not negligible. While this limits the external validity of inferences one can make from the presented results, the simulation framework and study of this paper contribute in isolating important performance indicators and allowing the analysis of different specifications and design alternatives of fixed and on-demand transit systems.

CRediT authorship contribution statement

David Leffler: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Data curation, Visualization, Project administration. **Wilco Burghout:** Conceptualization, Methodology, Software, Investigation, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Erik Jenelius:** Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Oded Cats:** Conceptualization, Methodology, Software, Writing – review & editing, Supervision, Project administration.

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