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Fixed routing or demand-responsive? Agent-based modelling of autonomous first and last mile services in light-rail systems

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ABSTRACT

This paper examines the potential of autonomous vehicle (AV) technology for enhancing first and last mile services for a light-rail station. We use an event- and agent-based simulation model to compare the performance of fixed and demand-responsive routing services. The routing of on-demand services is based on a matching algorithm in which incoming passenger requests are prioritized and assigned to vehicles under capacity constraints. Our findings indicate that, for a high-frequency light-rail feeder system, fixed routing is the preferred option, even with the assumed reduction in operational costs due to driver-less operations. However, we also observe that demand-responsive services can be as effective as fixed routing in off-peak hours, provided the heuristics for matching passengers to vehicles are effective. This implies that a combination of the two services could be beneficial in certain contexts. In addition, our results demonstrate that urban sprawl has an impact on the performance of the system, with the demand-responsive services becoming relatively better when urban sprawl increases, while the fixed routing remains superior across most key-performance indicators. To assess the performance of the different services, we employ cost–benefit analysis.

1. Introduction

Urbanization and development in many countries have been leading to bigger and denser cities resulting in increasing congestion. Concurrently, we see a massive development in autonomous transport technologies, which in a few years will enable realistic low-cost solutions (Abe, 2019; Becker et al., 2020) for main-line service as well as for first and last mile services. The research and development with respect to autonomous shuttles suited for first and last mile services has led to numerous real-world experiments of semi-automated busses in many cities including Copenhagen and Stockholm (Wodecki, 2021; Linc, 2020; Rizzo, 2021) and it is as relevant as ever to start planning for this technology change in more detail.

From a political perspective, the roll-out of efficient feeder strategies will have an impact on how we design our cities, how we provide transport services to people (Brown et al., 2021), and how services are perceived from equity perspectives (Yan et al., 2021) and traveller perspectives (Thorhauge et al., 2022). New technology gives rise to new opportunities in terms of serving passengers in flexible ways and at lower prices (Bösch et al., 2018) when compared to the current state of play. However, with the rise of these opportunities, it is relevant to consider the degree of service that is offered to individuals at the expense of performance losses for other passengers.

One important issue is determining which systems would benefit from providing demand-responsive services, as opposed to simpler fixed-route services. This is a key question that has been explored by researchers such as Grahn et al. (2021) and Aldaihani

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et al. (2004). Additionally, there is a broader question concerning how to strike a balance between meeting individual needs and maximizing overall system performance, as discussed by Liang et al. (2016). Currie and Fournier (2020) review the performance of numerous demand-responsive systems and suggest that despite years of experience, these services continue to be a high cost, experimental, uncertain and unreliable solution for cities. Their analysis indicates that demand-responsive systems will often fail, and it is relevant as ever to assess if the high rate of failure persists in a context with autonomous busses, and identify the conditions under which, the failure rate is likely to be high.

1.1. Literature review

With the surge in autonomous driving technologies, the prospects of autonomous driving as a means to service first and last mile transport, has changed in recent years. It has gone from being modestly 'interesting' to now becoming a realistic alternative within a foreseen future. These expectations were emphasized in Abe (2019) and Bösch et al. (2018) who suggest that the cost of public transit trips could decrease considerably due to vehicle automation. Zhang et al. (2019) provide further insight by demonstrating that fully autonomous buses have significant potential in reducing operating and waiting costs, despite their high capital cost. The advantages of semi-autonomous buses are shown to be weaker and most relevant for low demand networks.

As stated in Chandra and Quadrifoglio (2013), the general lack of first/last mile connectivity is one of the main challenges faced by public transit today. In this context, it is relevant to consider the different routing services, namely, fixed routing and demand-responsive routing, and how efficient these solutions are in accommodating first and last mile demand in high-frequency light-rail systems. More generally, numerous variants of *demand-responsive* public transit services have been studied in the literature including demand-responsive transit, flexible transit, semi-flexible transit, flex-route services, and hybrid systems (Vansteenwegen et al., 2022). We refer the reader to Errico et al. (2013) and Vansteenwegen et al. (2022) for a detailed taxonomy and characterization of flexible transit services. Within the framework of Vansteenwegen et al. (2022), the demand-responsive service we consider is *fully flexible* in that routes and schedules are determined completely in real-time based on actual demand information. We consider both a *many-to-many* service (users can be picked up and dropped off at any location) and a *many-to-one* service (users can be picked up at any location but are dropped off at a single destination or vice versa). Moreover, we have predefined stop locations, i.e., users are picked up and dropped off at designated locations.

Historically, first and last mile services have been investigated in the operations research (OR) literature (Cordeau and Laporte, 2007) by stating the problem of first and last mile service as variants of travelling salesman problems (Sawik, 2016) and applying mathematical programming as a means to optimize services, fleet sizes and other aspects of the transport service. Within this line of research, early work by Chang and Schonfeld (1991) demonstrated the use of mathematical modelling as a means to minimize total system cost for demand-responsive systems as well as frequency-based systems. They modelled operator and user costs as a function of vehicle size and service zone size. More recently, Wang (2019) determined routes and schedules jointly in a multi-vehicle fleet of delivery vehicles, with the objective of minimizing passenger waiting time and riding time. While an exact mixed-integer programming (MIP) model for last-mile operations is presented, the computational complexity is shown to be large, and a feasible heuristic solution approach is developed by reducing the sight of the planning horizon. Along similar lines, Bongiovanni et al. (2019) developed a Branch-and-Cut algorithm for this specific problem and proposed heuristics as a means to solve the problem in practical applications. Kim and Schonfeld (2014) and Lúcio Martins and Vaz Pato (1998) also investigated fixed and demand-responsive routing on the basis of mathematical programming formulations, which are solved by genetic algorithms and tabu search heuristics. In a recent paper, Gkiotsalitis et al. (2022) considered a simple waiting-time prediction that depends in a deterministic way on the frequencies of shuttles for a given OD pair. This allows a MIP representation of the problem, but with the absence of queuing dynamics in that passengers, who do not fit into the first arriving shuttle, will simply leave the system. Hence, while OR approaches indeed make it possible to describe the first and last mile problem formally, these approaches often fail to address intricate relationships between arrival processes and queuing dynamics.

The difficulty in capturing the intricacies of queuing dynamics and their interactions with demand also extends to the widely used Continuum Approximation (CA) models (Ansari et al., 2018; Badia and Jenelius, 2021). CA models date back several decades and have been used to find approximate solutions to assess the performance of demand-responsive services relative to fixed-feeder systems. Recent applications include the study of flexible transit systems (Nourbakhsh and Ouyang, 2012), and the assessment of demand-responsive services under a variety of operational configurations including non-shared taxis, ridesharing and dial-a-ride services (Daganzo and Ouyang, 2019; Daganzo et al., 2020). CA methods have also been used to compare fixed-route and on-demand services, and determine critical demand-density thresholds beyond which a door-to-door on-demand service is no longer the more efficient solution (Chang and Schonfeld, 1991; Kim and Schonfeld, 2013, 2014; Quadrifoglio and Li, 2009).

The complexity of the different aspects of the problem including arrival processes, queuing dynamics, congestion, and spatio-temporal variations in demand, has given rise to a slightly different approach to the problem, namely the use of micro-simulation and agent-based simulation as a means to analyse true bottom-up effects. For example, Bürstlein et al. (2021) analysed demand-responsive transit systems by using the PTV MaaS Modeller in combination with a mesoscopic simulation. Scheltes and de Almeida Correia (2017) also used an agent-based modelling approach and found that a first and last mile system in the city of Delft is only able to compete with the walking mode. Additional measures are needed to increase the performance of the system in order to be competitive with cycling. Moreover, it was found that pre-bookings lead to a significant reduction in average waiting time, whilst allowing passengers to drive at a higher speed leading to a large reduction in average travel time. Along similar lines, using agent-based simulation of scenarios in Singapore, Oh et al. (2020b) found that a demand-responsive stop-to-stop transit service utilizing larger capacity vehicles can help reduce overall vehicle mileage without a significant decrease in passenger travel and waiting times.

A clear finding that emerges from the literature is that the design of feeder services is largely context specific. As demonstrated in Badia and Jenelius (2021), the efficiency of door-to-door services depends on the demand density in the system. Similar conclusions were reached by Quadrifoglio and Li (2009) and Diana et al. (2009). Furthermore, the design of feeder services depends on the main network and the nature and frequency of this network as demonstrated in Aldaihani et al. (2004) and Grahn et al. (2021). For example, Grahn et al. (2021) demonstrated that total user costs reduce by 18.6% when rides are coordinated with mainline fixed-route transit. Also, as demonstrated in Liang et al. (2016), careful zoning and trip selection for a fleet of automated taxis increases profit.

1.2. Contributions

From the literature, it is evident that while demand-responsive services may be superior from a narrow service perspective, their efficiency is largely dependent on the context they are considered in. Often demand-responsive systems will fail as demonstrated in Currie and Fournier (2020), with the rate of failure depending on: (i) the demand density of the areas, (ii) the degree of urban sprawl, (iii) the nature and frequency of the main-line for which the feeder transport is targeted, (iv) rejection policies for travellers who gain only little from the demand-responsive service, and (v) the 'micro-scopic' behaviour of travellers with respect to destinations, arrival patterns and potential queuing at stations.

Following this, we propose an agent-based model framework for analysing a prototypical high-frequency light-rail autonomous shuttle feeder system. In the paper, we investigate station placements, the number of stations, routing of vehicles, and the size of the vehicle fleet by applying a microscopic simulation framework that allows tracking of agents in the system and the calculation of detailed system KPIs. From a methodological perspective, the paper contributes by allowing for flexible arrival and departure intensities of agents, which is linked to generalized non-parametric queuing models of the G/G/c type (Kendall, 1953). For both routing strategies, we formulate a vehicle routing heuristic inspired by dynamic vehicle routing and dial-a-ride problems. The experiment is based on a typical feeder-station layout for the new Copenhagen light rail. The performance of the different services is measured across several KPI Sections (3.4–3.7) and in a cost–benefit study (Section 3.8) where operational cost and travel- and waiting time savings are measured. While it is indeed difficult to claim generality of our results on the basis of dedicated simulation studies as the one presented here, we believe that the study does provide some interesting insight, especially when combined with the finding of other studies. We find that:

1. Fixed routes perform better than demand-responsive services in all scenarios due to a circular route design and efficient syncing to the light-rail arrivals.
2. Efficient rejection policies for travellers who gain only little from demand-responsive services can almost bring demand-responsive services on par with a frequency-based service.
3. Increased urban sprawl does not undermine the performance of fixed routing when measured on the basis of travel time reductions, but implies a better utilization of buses for demand-responsive services.

The study highlights the fact that demand-responsive services cannot be seen as a universal solution for first and last mile transportation services, as their efficiency is highly dependent on the specific context in which they are used. Therefore, they cannot be considered a 'silver bullet' solution, as emphasized by the study.

2. Methodology

This paper develops a dedicated event-based simulator, which has been specifically designed for a new upcoming urban area in Copenhagen, the Hersted Industrial Park, for which, by 2025, a light-rail station will be in operation. The first and last mile service of the particular area is of relevance for a wide number of planning situations. First, it constitutes a classical service situation where rail passengers need transit between a light-rail station and its hinterland in a system where distances are limited and the light-rail service is frequent. Note that while the current situation explores options only for the one side of the rail corridor (as shown in Fig. 1), it trivially extends to services that consider both sides. Also, due to the agent-based modelling framework, it is straightforward to change the scale of distances in the system. It enables a straightforward investigation of the impacts of increasing urban sprawl simply by increasing distances in the system, as will be considered in Section 3. Moreover, due to a natural circular route design for the area, it provides a proper benchmark between a fixed-route system and a more flexible demand-responsive service. The size of the Hersted Industrial Park is around 1.7 square kilometres (170 hectares).

The OD pattern as well as the temporal arrival pattern of passengers to (and from) stations is based on data from an external traffic model (Fox et al., 2013) and a large-scale trip diary (Christiansen and Baescu, 2020). These data are assumed exogenous for the present design problem and the analysis thereby excludes effects that may result from the change of mode and destination. While such changes might indeed occur, the impact of changes to first and last mile services for the entire trip chain is small as shown in Thorhauge et al. (2022). As a consequence, we will focus on the comparative performance of fixed-route and demand-responsive services conditional on these exogenous inputs.

Due to the heterogeneity in the arrival and departure process of passengers, these processes lend themselves poorly to conventional queuing systems with Markov properties (e.g., M/M/c) and would require the estimation of several arrival regimes.

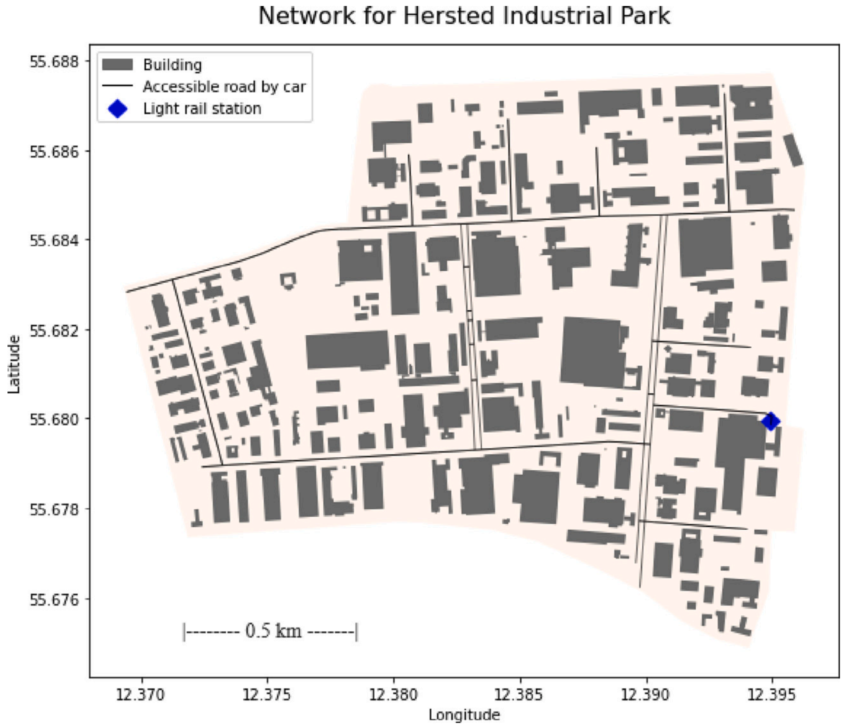


Fig. 1. Network for Hersted Industrial Park including buildings and station.

In the paper, we therefore apply an entirely data-driven queue, which, in the notation of Kendall (1953), is referred to as a G/G/c queuing system. Clearly, this implies that the event-based simulator is a 'black-box' representation of the system and that performance measurement is based on repeated Monte-Carlo simulation experiments. Below, we discuss the placement of stops as well as the agent-based simulation framework for the two competing route design strategies in more detail.

2.1. Placement of stops

The placement of stops is determined on the basis of the locations of buildings in Hersted Industrial Park. To get an overview of the buildings' location, OpenStreetMap (OSM) is used in connection with the Python package OSMNX to connect the road network for the entire area with the buildings' coordinate points. The k-means clustering algorithm (MacQueen et al., 1967) is then used to determine the location of the bus stops by minimizing the overall variation of the distance from the buildings to the stops. By considering different k-values, the optimal number of stops can be estimated using a variant of the elbow method. Here, the number of stops will be determined by choosing the k-value where the decrease in the average distance from a building to a stop no longer changes substantially from iteration to iteration. In doing so, the obtained clusters and stop locations are also visually inspected. The placement of stops for our case study is described in more detail in Section 3.

2.2. Simulation framework and bus routing algorithm

The simulation frameworks for the fixed-route and demand-responsive model are constructed in similar ways. They are both developed as discrete agent- and event-based simulation models and are dependent on the same objects with similar input arguments.

From a strict mathematical point of view, the system can be characterized as a discrete dynamic system for which transitions between states are controlled by transition functions.

Hence, consider $t = t_1, t_2, t_3, \ldots$ where the time steps are event driven and t_i represents the time of event i. The macroscopic state $X(t_i)$ of the system is given by a set of microscopic states of agent $q = 1, \ldots, Q$ at time t_i, which can be stated as

$$X(t_i) = \left(x_q(t_i)\right)_{q=1,\ldots,Q} \tag{1}$$

The state transition for all the agents' internal states yield the transition function for the dynamic system.

$$X(t_{i+1}) = F\left(X(t_i)\right) \tag{2}$$

The transition function F is here a combination of all agents' rules and represents in this context, the tracking of agents in space and time as well as an ordering of how rules are processed. As can be seen in Figs. A.13 to A.18, there are a substantial set of

Table 1
Departure rates from station based on number of buses.

Number of buses	Buses per direction	Departure headway from station
2	1	15 min
4	2	7.5 min
6	3	5 min
8	4	3.75 min
10	5	3 min
12	6	2.5 min

rules that define the different transitions depending on the state of the system. A simplification in the system, however, arises from a decomposition into an arrival stage and a departure state for all agents. Hence, these are considered as different independent stochastic processes. Even so, because every agent is tracked from when he/she arrives to the light-rail station and to the final destination for every trip (and vice-versa), the state space is large and requires a substantial amount of book-keeping to manage the queuing systems and maintain first-come-first-serve principles in the application.

The objects constituting the simulation frameworks are *passengers*, *buses* and *bus stops*. These objects are the physical entities that constitute the simulation environment, and are described by the following set of unique features:

- Passengers
  - *Passenger ID*: Each passenger has a unique ID
  - *Origin*: Where a passenger starts the journey
  - *Destination*: Where a passenger ends the journey
  - *Start time*: When a passenger starts the journey
  - *Allocated bus*: Which bus a passenger is allocated to (unique to the demand-responsive simulation)
- Buses
  - *Bus ID*: Each bus has a unique ID
  - *Bus capacity*: The capacity of the buses
  - *Passenger list*: A list of passengers inside a bus
  - *Route*: The route of each bus (fixed for the fixed-route and dynamic for the demand-responsive model)
- Bus stops
  - *Bus stop ID*: Each bus stop has a unique ID
  - *Passenger queue*: A list of passengers at a bus stop

2.2.1. *Fixed routing model*

In the fixed-route model, it is assumed that the autonomous shuttles will drive under the same conditions as manually operated conventional busses. In order to design the fixed-route service, first, the placement of stops is determined as per Section 2.1 based on solely the building locations in the industrial park. Following this, a TSP problem is solved in order to find the shortest or most efficient manner to traverse these stops such that each stop is visited exactly once. Thus, the TSP is solved just once and the resulting route is fixed across all demand scenarios and fleet sizes.

The shuttles follow a schedule that is based on a fixed arrival rate for the light-rail. This means that a shuttle that has completed a cycle and is ahead of its schedule, will wait for the next train to arrive. The departure headway from the station is set to a maximum of 15 min based on the cycle time of the buses which is 12–13 min with a speed of 21.25 km/h. It implies that a buffer of 2–3 min is added to take account of potential delays. Note that if parameters are adjusted in the simulation model (e.g., distances and speed parameters), it will result in new cycle times and require a recalculation of the departure headways, which are summarized in Table 1.

The departure headway is calculated by dividing the cycle time by buses per direction. It should also be noted that with 6 and 12 busses, there will always be a bus available when the train arrives.

As noted previously, the determination of the route for the fixed-route feeder is formulated as a Travelling Salesman Problem (TSP) (Cordeau and Laporte, 2007), which seeks to determine the shortest route for a collection of stops where all stops must be visited exactly once, and where the route starts and ends at the light rail station. As the TSP formulates a circular route, the final bus route is directed both clockwise and counter-clockwise. The mathematical model for the TSP is based on the Miller-Tucker-Zemlin (MTZ) formulation and is stated below (Sawik, 2016).

The following binary decision variables are first defined:

$$x_{ij} = \begin{cases} 1 & \text{if arc } (i,j) \text{ is used in the solution} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

The objective is to minimize total distance over the set of edges and the corresponding mathematical program is given by:

$$\min Z(\mathbf{x}) = \sum_{i=1}^{n} \sum_{j\neq i, j=1}^{n} c_{ij} \cdot x_{ij} \tag{4}$$

$$\text{s.t.} \quad \sum_{i=1}^{n} x_{ij} = 1 \quad \forall j = 1, \dots, n \tag{5}$$

$$\sum_{j=1}^{n} x_{ij} = 1 \quad \forall i = 1, \dots, n \tag{6}$$

$$u_i - u_j + n \cdot x_{ij} \leq n-1 \quad 2 \leq i \neq j \leq n \tag{7}$$

$$1 \leq u_i \leq n-1 \quad 2 \leq i \leq n \tag{8}$$

$$x_{ij} \in \{0, 1\} \quad i, j = 1, \dots, n \tag{9}$$

$$u_i \in Z \quad i = 2, \dots, \tag{10}$$

where c_{ij} is the distance between stop i and stop j and n is the total number of stops. Constraints (5) and (6) ensure that at each stop, there is an arrival from exactly one other stop, and that from each stop, there is a departure to exactly one other stop during a trip.

The MTZ formulation uses a dummy variable u_i, which is assigned a value for each node (stop) except for the depot (the light-rail station). If a vehicle travels from stop i to stop j, the value of u_j must be greater than the value of u_i. So, each time a new node is visited, the value of u_i increases. Constraints (7) and (8) ensure that there is only a single trip that covers all stops. This can be ensured because the dummy variable u_i indicates the order of the trip. Hence, $u_i < u_j$ indicates that stop i has been visited before stop j. This can be achieved by increasing u_i each time it is visited.

It should be noted that in general, designing a fixed routing service based on a single distance variable is often insufficient. This is particularly important if the system includes several types of vehicles with different acceleration and stopping patterns. However, in this study, in which only a single vehicle type is considered and where the network is extraordinarily simple, we believe this is a reasonable assumption.

2.2.2. Fixed routing and agent-based simulation framework

The framework consists of several events in the simulation. Since the model is event-based, it implies that the state of the system is exclusively changed when a new event takes place. The simulation for the fixed-route model makes use of four different event stages, all of which are described in more detail below. It should be noted that some of these event types are reciprocal, i.e., one event can act as a trigger for another and vice versa.

1. Event 0: Passenger arrives at a stop (passenger starts trip)
2. Event 1: Bus arrives at a stop
3. Event 2: Passenger gets off a bus
4. Event 3: Passenger boards a bus

The first part of the simulation is to generate events for passenger arrivals. All events for passenger arrivals are based on the OD matrix and are generated prior to the processing of the simulation model and stored in a priority queue. This is due to the fact that 'Event 0' is independent of other event types and does not generate new events. When Event 0 occurs, a passenger is drawn from the passenger list and added to one of the passenger queues at that specific stop, based on which direction is fastest for the passenger.

Below, we provide pseudo-code for the different events in the simulation framework. The corresponding notation is provided in Table 2.

The priority queue is a list that contains all events that are to be simulated. The priority queue is a sorted list and every event has a dedicated time-stamp. For each iteration in the simulation framework, the earliest event from the priority queue (that has not yet been processed) is executed. When a new event is generated, it is stored in the priority queue, and the queue is re-ordered to ensure that the events are executed in the correct sequence.

Algorithm 1 Event 0 for fixed route model (Fig. A.13)

```
Passenger p arrives at a bus stop s
if the passenger chooses to travel clockwise then
    Add passenger to CL_s
else
    Add passenger to CC_s
end if
```

In Event 1 (Fig. A.14), there are a number of situations that are checked in the specific order mentioned below. Depending on the situation, these event-functions can generate other events.

Table 2
Notation and description of sets, variables and parameters.

Type	Variable	Description
Sets	P	Set of passengers $p = 1, \dots, P$
	B	Set of buses $b = 1, \dots, B$
	S	Set of bus stops $s = 1, \dots, S$
Variables	$O_p \quad p \in P$	Origin stop of passenger p
	$D_p \quad p \in P$	Destination stop of passenger p
	$R_b \quad b \in B$	Route of bus b
	$T_b \quad b \in B$	Temporary route of bus b
	$PL_b \quad b \in B$	Permutation list for bus b
	$PB_b \quad b \in B$	List of passengers in bus b
	$C_b \quad b \in B$	Number of passengers in bus b
	$PQ_s \quad s \in S$	Passengers at bus stop s
	$CL_s \quad s \in S$	Clockwise queue at bus stop s
	$CC_s \quad s \in S$	Counter clockwise queue at bus stop s
Parameters	k	Number of passengers
	m	Number of buses
	n	Number of bus stops
	c	Capacity of buses

1. When a bus arrives at a stop, the first check is whether there are any passengers in the bus that need to get off. If there are any, Event 2 is generated for those who have to get off. If there are none, nothing happens.
2. The second check is whether the bus has stopped at the light-rail station. If this is the case, the bus will not drive until its next scheduled departure time. Event 1 is thus generated again with a start time corresponding to the next arrival for the light-rail, and the remaining events are skipped.
3. Finally, we check if there are any passengers at the stop. If this is the case, then Event 3 will be generated. If not, the bus will continue on its route.

Algorithm 2 Event 1 for fixed route model (Fig. A.14)

```
Bus b arrives at a bus stop s
Generate and simulate Event 2
if bus stop s is the light rail station then
    Generate Event 1 starting at the bus' scheduled departure time
    (The bus waits until its scheduled departure time)
    Event 1 terminates
else
    if C_b = c then
        Bus b leaves bus stop s and Event 1 is generated for the next stop
    else
        Generate and simulate Event 3
    end if
end if
```

In Event 2 (Fig. A.15), passengers get off the bus. When a passenger leaves the bus, he/she is removed from the bus passenger list.

Algorithm 3 Event 2 for fixed route model (Fig. A.15)

```
Bus b is idle at bus stop s
for each p ∈ PB_b do
    if D_p is bus stop s then
        Passenger p disembarks from bus b
    end if
end for
```

Event 3 deals with whether passengers want to board the bus or not. In this event model, a set of binary decisions is required for the model to be processed:

1. Can the bus leave the stop? First, we check if all passengers at the stop have boarded the bus or whether the bus is full. If

either of these conditions is true, the bus will leave and continue to the next stop on the route. This will cause Event 1 to be generated, where the start time of the event is based on the arrival time of the bus to the next stop.

2. Should passengers walk or wait? If it turns out that the bus leaves a stop because there is no more room for passengers, the passengers at the stop will be forced to make a choice between waiting for the next bus or walking. The choice is based on which alternative has the shortest total travel time (journey time).
3. Should passengers take the bus or walk? If, the bus is not full, the passengers at the stop will have to make a choice whether to take the bus or walk. This choice is again based on the alternative with the shortest travel time (journey time).

Algorithm 4 Event 3 for fixed route model (Fig. A.16)

```
Bus b is idle at bus stop s
if the bus travels clockwise then
    Q = CL_s
else
    Q = CC_s
end if
for each p ∈ Q do
    if C_b = c or Q is empty then
        Bus leaves bus stop. Event 1 is generated for the next stop
        break
    else
        if it is faster for passenger p to walk then
            Passenger p walks
        else
            Passenger p boards bus b
        end if
    end if
end for
if Q is empty then
    Event 3 terminates
else
    for each p ∈ Q do
        if it is more time efficient for passenger p to walk then
            Passenger p walks
        else
            Passenger p waits for the next bus
        end if
    end for
end if
```

2.2.3. Demand-responsive model

In the simulation model, the procedure for the demand-responsive service is also event-driven as illustrated in the flow chart in Fig. A.16. The demand-responsive model involves a heuristic procedure (described in more detail in the next section) that approximately solves a Dial-A-Ride Problem (DARP), a well known variant of the Dynamic Vehicle Routing Problem. Vehicles that operate with a demand-responsive service pick up and drop off passengers in locations according to their needs. In simple terms, passengers request a bus at a given time and a specific bus will then be allocated to them based on certain criteria. Routes are dynamic and updated whenever a passenger is allocated to the bus. This means that routes can vary by travel length and travel patterns, which can result in passengers having a final travel time that differs from the initial (expected) travel time. Note that the demand-responsive vehicles, when idle, wait curbside at the point of drop-off of the last passenger. In other words the vehicles are not rebalanced. This will introduce a waiting period upon request if no vehicles are located at the origin of the requested trip. We also assume that the service is stop-based (rather than door-to-door), namely, passenger pick-ups and drop-offs happen at the same bus stops used in the fixed-route model.

2.2.4. Heuristic for demand-responsive model

The DARP is known to be NP-hard and only small sized problem instances can typically be solved to optimality, often at a large computational cost (Ho et al., 2018). Consequently, the algorithm we apply for matching passengers to buses is a type of insertion heuristic that is commonly used to approximately solve such DARPs. Insertion heuristics have been widely applied (Ho et al., 2018;

Häme, 2011; Van Engelen et al., 2018) and have been shown to yield good near-optimal, efficient solutions (Häme, 2011), which are often good enough in practice and suffice for the comparisons in our context (see also Oh et al., 2020b; Atasoy et al., 2015; Koh et al., 2018; Oh et al., 2020a). More importantly, our intention is to provide a realistic comparison of the fixed-route and demand-responsive systems. In reality, demand is not known in advance and is uncertain and hence, we deem it reasonable to use a matching heuristic that can be applied online with no advance information about bookings.

The heuristic involves the following steps.

1. A passenger requests a bus when registered in the system.
2. Before allocating the passenger to a bus, it excludes buses that have reached maximum capacity. The heuristic prioritizes allocation based on the buses' distance to the passenger.
3. The heuristic will allocate the passenger to the nearest available bus (a bus is deemed unavailable if the bus has reached full capacity, or if none of the possible new bus routes are available).
   (a) If there are no other available buses, the heuristic terminates and the passenger walks.
   (b) if there are available buses, the heuristic moves on to Step 4
4. Check whether the bus is empty or not:
   (a) If the bus is empty, the heuristic checks whether the passenger request is satisfied (based on the expected total journey time relative to walking, details in Section 2.2.5). In this case, the passenger is allocated to the bus and the heuristic terminates. If the passenger is not satisfied, the bus is deemed unavailable, and the heuristic goes back to Step 3.
   (b) If the bus is not empty, the heuristic moves on to Step 5
5. The passenger's origin and destination is added to the existing bus route list, where the goal is to find the shortest available route.
6. A list with all possible route permutations for the bus is created. If the origin and/or destination already exists on the route, duplicate routes and adjacent stops are removed. Hereafter, every possible route of the bus is checked for feasibility in the order of the shortest to the longest path.
   (a) If none of the permuted routes are feasible, the heuristic goes back to Step 3 (a route is deemed infeasible if one or more bus passengers are dissatisfied).
   (b) If the heuristic finds a feasible route, the bus adopts this new route, the passenger request is allocated to the bus and the heuristic terminates.

2.2.5. *Demand-responsive routing simulation framework*

The main part of the event-handling in the algorithm is addressed in Event 1. As it can be seen in Algorithm 5, Event 2 is only generated when the bus is empty, i.e., when the bus is idle at a bus stop and waiting for requests. In the processing, Event 1 will generate Event 2 when the bus is empty and hereby indicate that the bus is "active". However, if a passenger is allocated to an already "active" bus, Event 1 will not generate Event 2. Instead, Event 2 handles this by generating another instance of itself every time it has to drive to a new bus stop. If Event 2 stops generating itself, it means that the bus has no more passengers to serve, and becomes "inactive" at its current bus stop.

As mentioned, a passenger will only be allocated to a bus if every affected passenger in the bus is satisfied. Passengers are satisfied when the sum of their waiting time, travel time with bus, walking time to stop/building and service threshold is below the walking time on foot. The service threshold is set to 60 s (this a critical parameter in the insertion heuristic and sensitivity tests are performed on it in Section 3), which means that travel time reductions should be at least 60 s, before he/she considers taking the bus. There are three types of passengers that are considered, during the satisfaction check:

1. Passenger request
2. Passengers in bus
3. Allocated passengers (former "requests" that have been allocated but are yet to board a bus)

Event 2 handles the arrival of a bus at a stop. Essentially, this event has two objectives: (i) To cause a bus to drive to its next stop, and (ii) To make passengers board or alight from the bus. While the bus drives to its next stop, the last stop will be removed from the route list, as the event is repeatedly generated until there are no longer any stops left in the bus route. Note that Event 2 is

Algorithm 5 Event 1 for demand-responsive model (Fig. A.17)

```
Passenger p requests a bus
Sort B according to which bus b is closest to the passenger request
for each b ∈ B do
    if C_b = c then
        continue
    else if C_b = 0 then
        Add O_p and D_p to T_b
        if the passenger is satisfied then
            R_b = T_b
            Make T_b empty
            Allocate passenger to the bus
            Generate Event 2
            break
        end if
    else
        Create every possible permutation and add it to PL
        Sort PL according to the length of the routes
        for each r ∈ PL do
            if all passengers related to b are satisfied with route r then
                R_b = r
                Allocate passenger to the bus
                break
            end if
        end for
    end if
end for
```

dependent on Event 1. While Event 1 populates the route list with origins and destinations, Event 2 has the objective of removing these.

Algorithm 6 Event 2 for demand-responsive model (Fig. A.18)

```
Bus b arrives at a bus stop s
Bus stop s is removed from R_b
for each p ∈ PB_b do
    if D_p is bus stop s then
        passenger p is removed from PB_b
    else
        continue
    end if
end for
for each p ∈ PQ_s do
    if O_p is bus stop s then
        passenger p is added to PB_b
    else
        continue
    end if
end for
Generate Event 2 with start time equal to the arrival time at the next bus stop
```

3. Application and case study

3.1. Number and placement of bus stops

As described in Section 2.1, the first step in the design of the fixed-route feeder service is the determination of the number of bus stops and their placement. In order do so, we apply the k-means clustering algorithm (MacQueen et al., 1967) to the co-ordinates (locations) of the 220 buildings in the Hersted Industrial Park, each of which contains several workplaces. A similar approach has been used in Nadinta et al. (2019), Sarubbi et al. (2016) in the clustering of bus-stops. The algorithm takes as an input the number

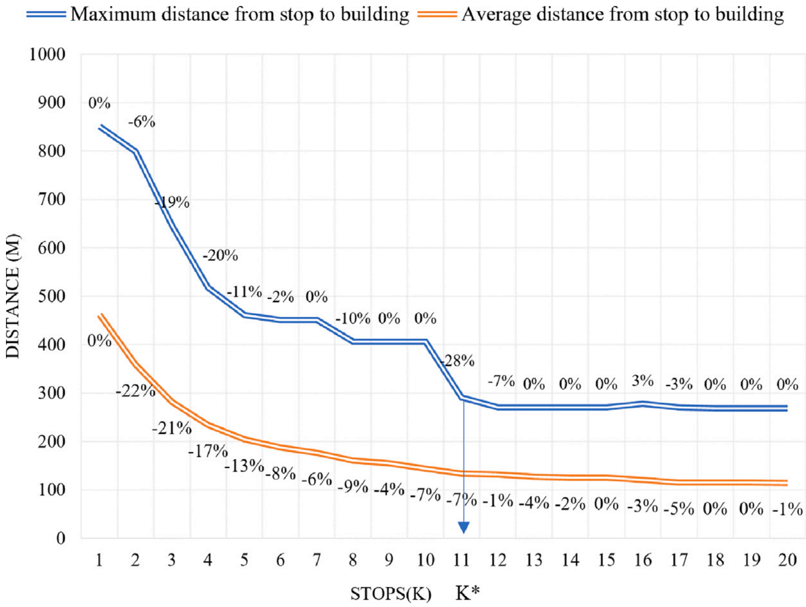
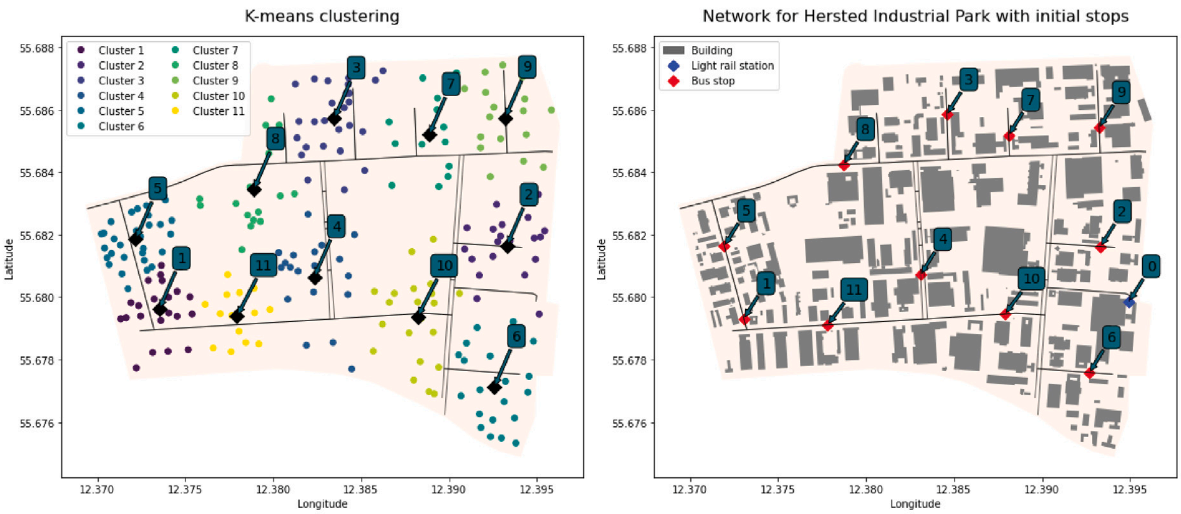


Fig. 2. Variation of maximum and average distance with number of stops.



(a) Derived centroids

(b) Initial stops after assigning centroids to nearest nodes

Fig. 3. Result of k-means clustering.

of clusters k, assigns each individual building to one of the k clusters and determines the location of the centroid of each cluster. The network links closest to the centroid of each cluster are classified as the k bus stops of the fixed-route feeder service.

Note that the number of clusters k is an exogenous input to the k-means clustering algorithm. A specific configuration of clusters and bus stops can be assessed in terms of; (i) the average distance between buildings and their respective cluster centroid (bus stop), and (ii) the maximum distance between any building to its respective cluster centroid or bus stop. In order to determine a suitable k or number of bus stops, we examine the variation of these two metrics as a function of k, which is shown in Fig. 2 (this is a variant of the commonly used *elbow* method to determine a suitable value for k). Clearly, the average and maximum distances between buildings and bus stops does not change significantly beyond a value of $k = 11$. The corresponding cluster configuration and centroids for $k = 11$ are shown in Fig. 3(a) (left), and the resulting bus stop locations on the network are shown in Fig. 3(b) (right).

Observe that there exists a trade off between the number of bus stops and travel times experienced by passengers. Thus, although the value of $k = 11$ is ideal with regard to the aforementioned distance metrics, it may result in increased travel times. Hence, we

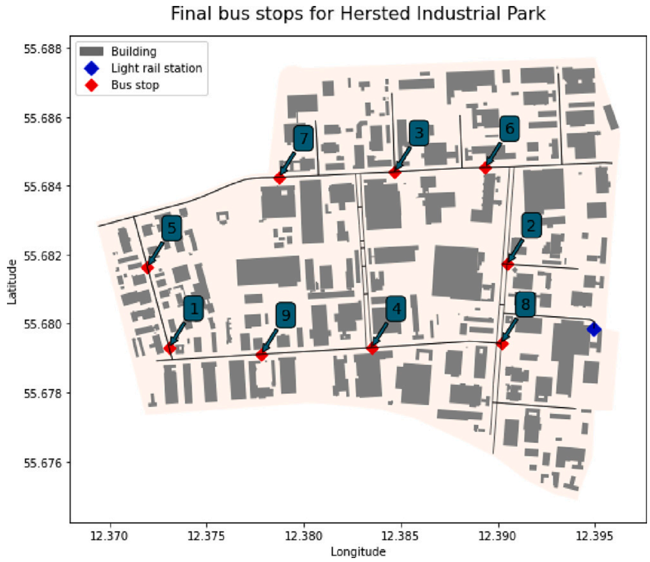


Fig. 4. Selected stop placement for the simulation scenarios.

next compare the cluster assignments for $k = 8$ to $k = 11$ by running simulations of the fixed feeder service for these four sets of stop locations. The results indicate that there is a significant deterioration in travel times between $k = 8$ and $k = 11$ whereas the differences between $k = 8$ and $k = 10$ are minimal. Based on these results and those in Fig. 2, we choose a value of $k = 8$, and the resulting set of bus stop locations is shown in Fig. 4.

3.2. Passenger data

The spatio-temporal distributions of travel demand in the study region are a key input for the simulation model. Specifically, in our context, we require (a) time-dependent distributions of arrivals and departures at the light rail station, and (b) the specific trip destination and origin within the industrial park of each passenger that passes through the station and travels to and from buildings in the area. The approach for determining each of these is described next in turn.

The temporal distributions of passenger arrivals and departures are determined using two different data sources. First, the total number of passengers boarding and disembarking for a single day at the Hested Industrial Park station (in 2032) are obtained from forecasts of the Metroselskabet (Metro corporation of the Copenhagen region). In the data, for year 2032, a total of 1027 disembarking and 1084 daily boarding passengers is estimated for the station. The corresponding temporal distribution of this total demand is estimated using data from the Danish Transport Habits Survey (TU). The TU survey contains detailed trip diaries of a sample of individuals in the Capital region of Denmark, from which we extract trips to and from the Albertslund Municipality (region containing the Hersted Industrial park).

Given that the temporal distribution of the disembarking and boarding passengers is likely to depend on the land-use of the area, separate temporal passenger distributions are estimated as:

1. *Travellers from the light rail station to work places (disembarking passengers)*
   Passengers who have destinations within Albertslund or a nearby municipality as their final destination. The arrival time at their final destination is applied as a representative arrival profile for passengers in the study area.
2. *Travellers from work places to the light rail station (boarding passengers)*
   This includes passengers who have origins within Albertslund or a nearby municipality as their trip origin. The departure time from their origin is applied as a representative departure profile for passengers in the study area.

With these definitions, the passenger distributions from the TU data are plotted in Fig. 5 below, which describe the temporal pattern of passengers' arrivals and departures over the day.

In this paper, we only consider the temporal distribution of demand between 6.00 to 20.00, which, from the TU data for the Albertslund region, comprises around 93%–94% of total demand for the 24 h period. The demand over the rest of the day (20.00 to 6.00) is too low to justify operations of autonomous buses from a cost perspective. Thus, based on the total arrivals and departures at the light rail station and the temporal distribution from the TU data (Fig. 5), we limit the analysis to the passenger arrivals and departures summarized in Table 3. This includes a total of 956 disembarking and 1018 boarding passengers in this time interval in 2032 (corresponding to a total of 1974 passengers in the entire system for Hersted Industrial Park).

In addition to the temporal distribution of arrivals and departures described previously, specific locations (buildings) need to be assigned within the industrial park for each trip to and from the region. For this, we assume that trips are uniformly distributed

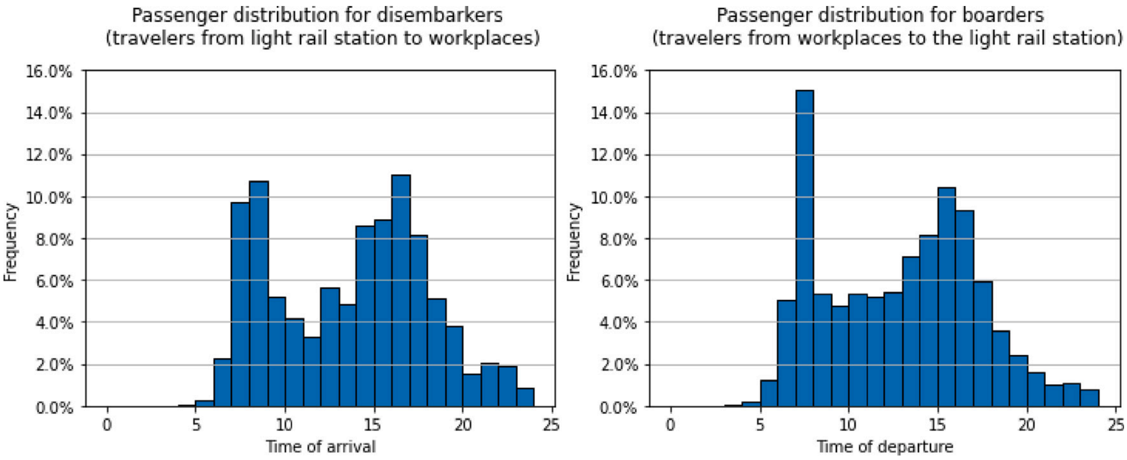


Fig. 5. Passenger distribution for Hersted Industrial Park for disembarksers and boarders, respectively.

Table 3
Derived passenger distributions between 6.00 to 20.00 on a given day in 2032.

Time interval	Density		Frequency		
	Disembark	Board	Disembark	Board	Total
6.00–7.00	2.3%	5.1%	23	55	78
7.00–8.00	9.9%	15.2%	101	165	266
8.00–9.00	11.0%	5.4%	113	58	171
9.00–10.00	5.3%	4.8%	55	52	107
10.00–11.00	4.3%	5.4%	44	59	103
11.00–12.00	3.3%	5.3%	34	57	91
12.00–13.00	5.8%	5.5%	59	59	118
13.00–14.00	5.0%	7.1%	51	77	128
14.00–15.00	8.7%	8.2%	90	89	179
15.00–16.00	9.1%	10.5%	93	114	207
16.00–17.00	11.2%	9.4%	115	102	217
17.00–18.00	8.3%	6.0%	85	65	150
18.00–19.00	5.2%	3.6%	53	39	92
19.00–20.00	3.9%	2.5%	40	27	67
Passengers kept	93.3%	94%	956	1018	**1974**
Passengers left out	6.7%	6%	71	66	137
Total	**100%**	**100%**	**1027**	**1084**	**2101**

across the 220 buildings in the industrial park (i.e., all buildings have equal probability of being selected for a given trip). In the scenarios where demand between buildings is also considered, both the origin and destination building are generated randomly in a similar manner, with the constraint that both the origin and destination building are not associated with the same bus stop (in which case, walk would be preferable by design).

A uniform random allocation of arrivals and departures may result in a less spatially concentrated arrival and departure pattern. While it is unlikely that it would change the routing structure for this particular system, it could affect the locations of stops and also potentially alter the comparative performance between systems slightly.

3.3. Overview of assumptions and scenarios

This section describes additional assumptions underlying the simulations and the design of scenarios. Details of the geography of the study region, Hersted Industrial Park, are described in Section 2. For the simulation of movements of vehicles and travellers, two types of networks are considered; the road network and the network for pedestrians, respectively. The road network (Fig. 1) consists of 180 nodes and 333 edges and the pedestrian network (Fig. 6) consist of 442 nodes and 921 edges. These networks will be used throughout the analysis to calculate distances between stops, stations and buildings, and to track pedestrians and buses in the simulation on the respective networks.

The baseline assumptions for both the fixed-route and demand-responsive model are as follows:

- The simulation period is from 6.00 to 20.00 with the temporal arrival and departure distributions described in Section 3.2
- The bus speed is constant at 21.25 km/h
- Passenger walking speed is constant at 5 km/h
- The fleet size of operating buses varies between 2 to 12, with increments of 2

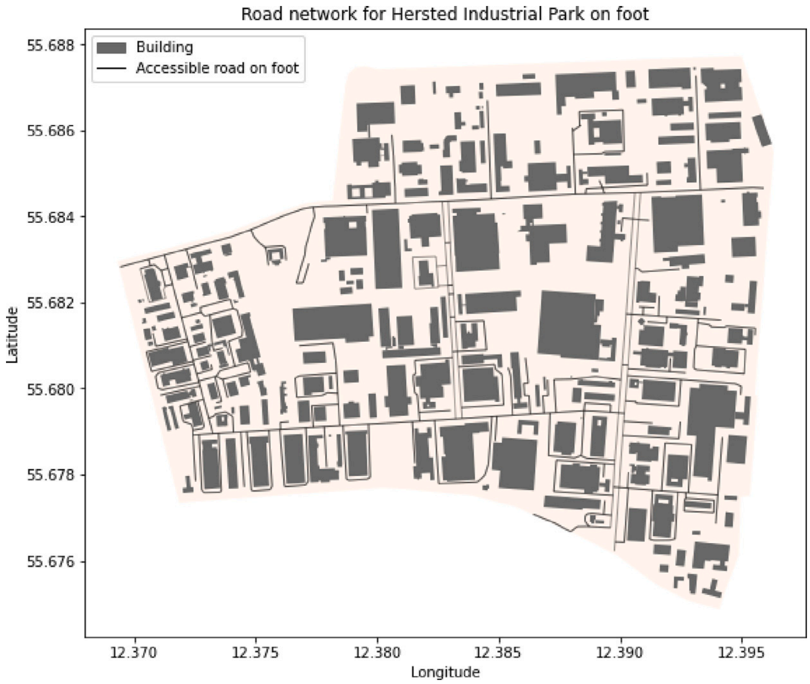


Fig. 6. Network for Hersted Industrial Park by foot.

- The bus capacity is 12 passengers
- Number of stops, buildings and passengers are fixed (except in Scenario 3)
- The boarding and disembarking passengers are based on a *free flow* and *first come, first serve principle*
- The boarding and disembarking time is 1 s per passenger
- It takes 3 s for the buses to open and close the doors, respectively
- The light rail train arrives at the station every 5 min in the time period between 6.00 to 19.00 and every 10 min in the time period between 19.00 and 20.00.

The comparison of the fixed-route and demand-responsive feeder service is performed in four distinct scenarios. In Scenario 1, all trips pass through the light rail station to stops in the areas (and vice versa) as described in Section 3.2. In Scenario 2, it is assumed that trips connect all pairs of bus stops within the industrial park (not just originating or terminating at the light rail station). This is a hypothetical scenario wherein only a small percentage of total trips originate and terminate at the light rail station, while a large proportion of trips consists of internal trips within the park. Scenario 3 combines Scenario 1 and 2 in that we apply the demand distribution of Scenario 1 but with a 20% addition of trips between stops within the industrial park (internal trips). This scenario is likely to best represent travel demand given the projected land-use patterns for 2040. Finally, in Scenario 4, we consider a similar demand pattern as in Scenario 1 but with a 100% increase of travel distances. This scenario thereby represents a simple investigation of how ‘urban sprawl’ (Harvey and Clark, 1965) may affect operations. When distances are increased while arrivals and departures are maintained, it allows us to examine a system with reduced population density. In fact, as the area increases with distances raised to the power of two, the population density reduces by a factor of four.

To evaluate these different scenarios, a number of Key Performance Indicators are considered. Many of these KPIs are self-explanatory although some need further elaboration.

- % Demand served
  - Expresses the percentage of travellers who use the bus relative to the total number of travellers
- Occupancy rate
  - Percentage of the average number of travellers per stop with respect to the bus maximum capacity (e.g., served demand compared to maximum capacity)
- Service level
  - Service level has different definitions with respect to the fixed-route and demand-responsive model

- Fixed-route: fraction of travellers that board a bus (calculated as the number of travellers who board the bus divided by total number of travellers who wish to board the bus). Hence, the service level is a measure of how often a passenger is rejected due to the lack of capacity (in case maximum capacity is reached)
- Demand-responsive: fraction of travellers whose trip requests are accepted.
  Requests can be rejected even when the requesting passenger is satisfied, if one or more passengers, either in the bus or allocated to the bus, are unsatisfied.

• Bus idle time

- The time a bus is on hold compared to the total driving time (applies only to the demand-responsive service). The idle time is considered as the time where empty buses do not move or are inactive (e.g. a bus that is at stand still while picking/dropping off passengers is not considered idle).

• Reduction in travel time

- Difference in total travel time with respect to the baseline where all travellers walk.

3.4. Scenario 1: Trips from only Station to Stops (StS) and vice versa

The first scenario includes only trips that pass through the light rail station to stops or from stops back to the station. Hence, it is assumed that passengers use the light rail as the primary mode of transport to the area and either use walk or one of the two routing services (fixed-routing or demand responsive routing). In this scenario we omit trips between the different stops within the area. Fig. 7 summarizes the various performance measures for both the fixed-route feeder and the demand-responsive feeder for Scenario 1. In general, increasing the fleet size of buses for both services has the following impact as anticipated:

- The % of demand served, service level and bus idle time (for the demand-responsive service) increase due to more vehicles being available. In contrast, the average occupancy rate decreases since the increase in seat availability (capacity) is higher than the increase in number of trips served.
- The total travel time decreases, mainly due to lower waiting and in-vehicle travel times for bus passengers. The walking time for bus passengers is more or less constant, which is intuitive as they walk to and from the same stops regardless of the number of buses. However, the average walking time for all passengers as a whole decreases since more passengers make use of the buses (reflected in the increasing % of served demand).

Furthermore, the results show that the fixed-route feeder is far superior to the demand-responsive feeder across almost every KPI in this scenario:

- The average travel time is much lower compared to the demand-responsive service, which can be attributed to the low waiting time and to some degree also the bus travel time (refer Table A.6 for the 10th and 90th percentiles of the user metrics). The spatial distribution of demand (trips to and from the light rail station) appears to clearly favour the fixed-route feeder service, which is also better synchronized with the light-rail service. Observe also that in case of the fixed-feeder the reduction in overall travel time is not monotonic. This is due to the fact that when the number of buses is 6 (or 12), there is always a bus available exactly when the train arrives at the station (as the departure rate from the station is every 5 min). This result in low waiting times at the station (1.11 min). This also explains why the reduction in overall travel time for 6 buses is higher compared to 8 buses.
- % Demand served and service level increases with the number of buses for both services as described previously with the fixed-route yielding higher percentages of served demand and service levels at all fleet sizes. However, when the number of buses reaches 6 or more, the demand-responsive model appears to deploy the buses more efficiently in terms of occupancy rate. However, this finding should be interpreted with caution since in-vehicle travel times for the demand-responsive service are higher, which in itself could cause an increase in occupancy rates.

In case of the fixed-feeder service, it is apparent that an ideal fleet size is six, since increasing the fleet size further does not improve either travel times or the % of served demand significantly. Similarly, in case of the demand-responsive feeder, the increase in idle times suggest that a fleet size of six is ideal given the marginal improvements in travel times and waiting times beyond six buses.

The variation in the total mileage travelled as a function of the fleet size is shown in Fig. 8. As expected, mileage in the fixed-route feeder increases linearly with fleet size. In case of the demand-responsive service, the produced mileage is linear up to a fleet size of six, after which the produced mileage tapers off and is significantly lower than for the fixed-route feeder. This obviously is the result of a more 'surgical operation' of busses when demand is present. It suggests that if demand levels were higher and a larger fleet was required to satisfy demand, the demand-responsive service would operate at lower costs due to a lower produced mileage.

In order to further assess the demand responsive service, we examine the variation of the KPIs with time of day. The results, summarized in Fig. 9, indicate that the demand-responsive feeder performs notably better (lower total travel times) in the off-peak periods (when demand is relatively lower), compared to the peak period (this complies with Calabrò et al., 2021). This underscores the fact that in some contexts, it may be beneficial to combine fixed-route with demand responsive services. Observe also in Fig. 9, that the percentage of users taking the bus is lower in the peak period. This is the result of a higher proportion of rejected requests during the peak period due to the constraints on waiting time and travel time in the matching heuristic. Nevertheless, as expected, the total number of users served by the demand-responsive service is significantly higher in the peak period.

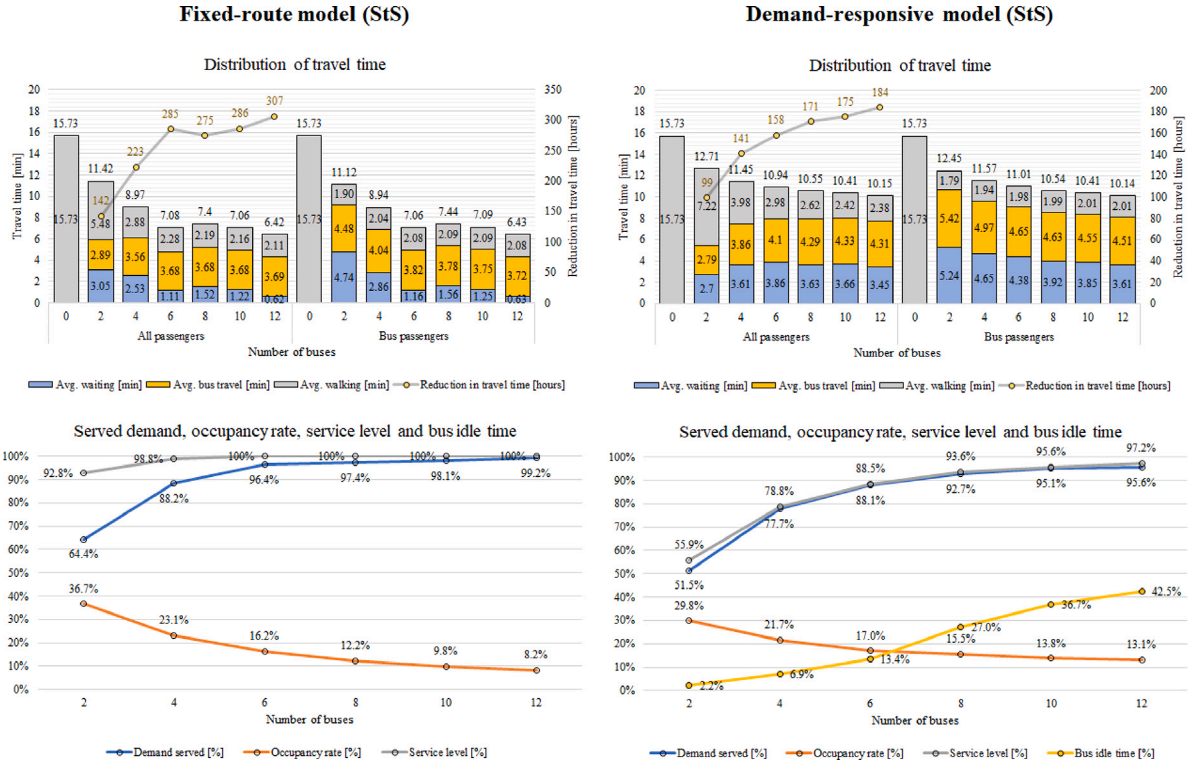


Fig. 7. Results for Scenario 1 for year 2032: Demand is formed from station to stop.

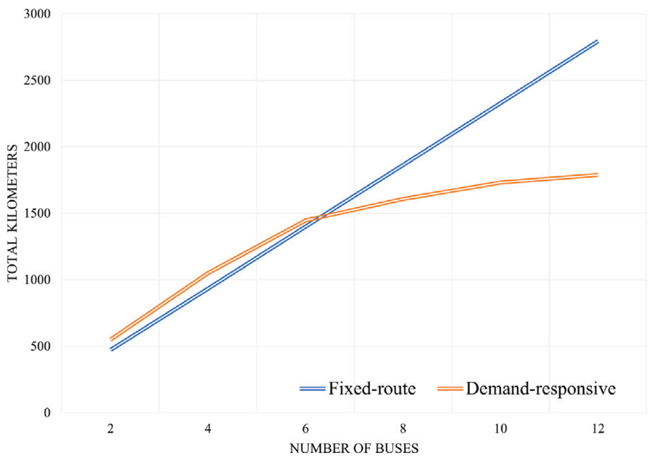


Fig. 8. Total bus kilometers for fixed-route and demand-responsive model.

3.5. Case 2: Travelling Between all Stops (BS)

This scenario differs from Scenario 1 in that passengers now travel between all stops in the system. This means that trips are now shorter, and it is therefore expected that travel times are lower compared to Scenario 1.

The results in Fig. 10 show that the performance of the fixed-route service once again is superior to the demand-responsive service in terms of waiting and travel times (refer Table A.7 for the 10th and 90th percentiles of the user metrics). However, the difference between the two services is markedly smaller than in the case of Scenario 1, where demand patterns (to and from the light rail station) favour a fixed-route service. In contrast with the passenger metrics, it can be seen that the demand-responsive service yields a higher percentage of served demand than the fixed-route feeder, which is not surprising given that the design of the fixed-route service is tailored to the demand pattern in Scenario 1.

Fig. 9. KPI development over time periods for the demand-responsive model.

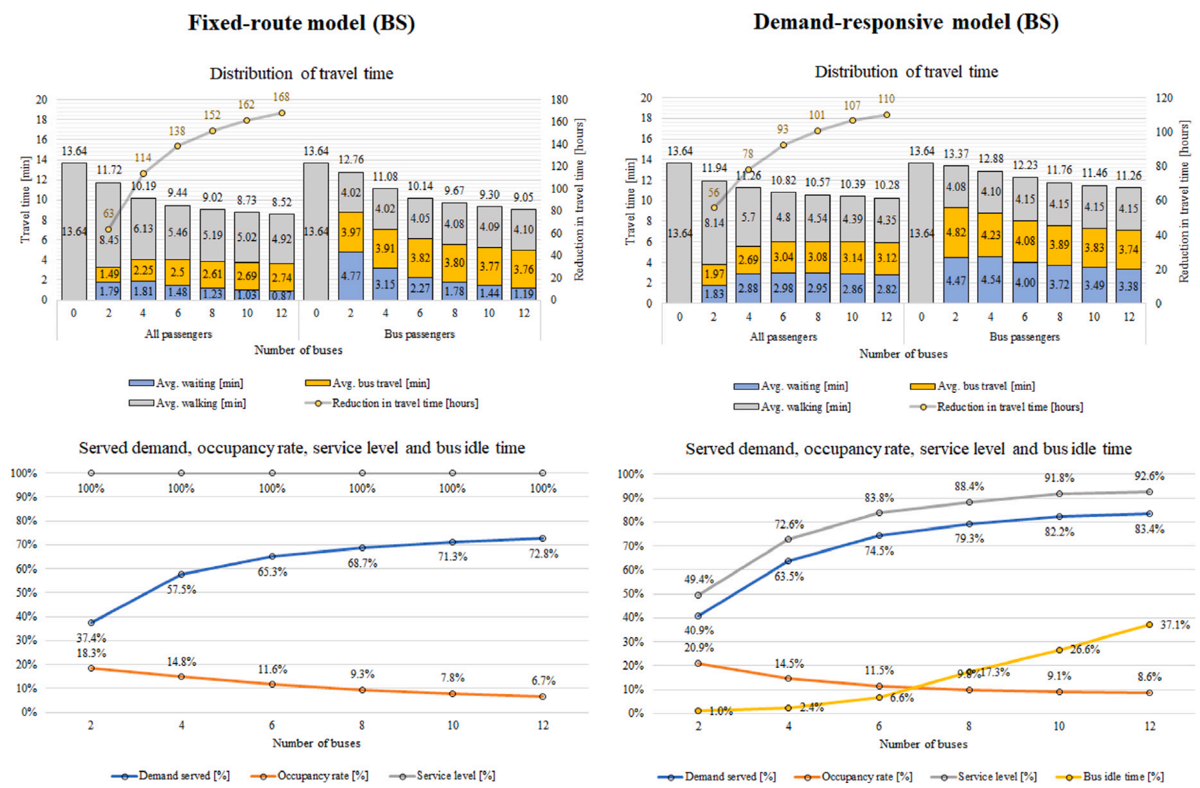


Fig. 10. Results for Scenario 2 for year 2032: Demand is formed between stops.

Note also that the performance of the demand-responsive service is highly dependent on the parameters (specifically, the service threshold described in Section 2.2.5) of the matching heuristic. Thus, increasing this threshold places a stricter requirement in terms

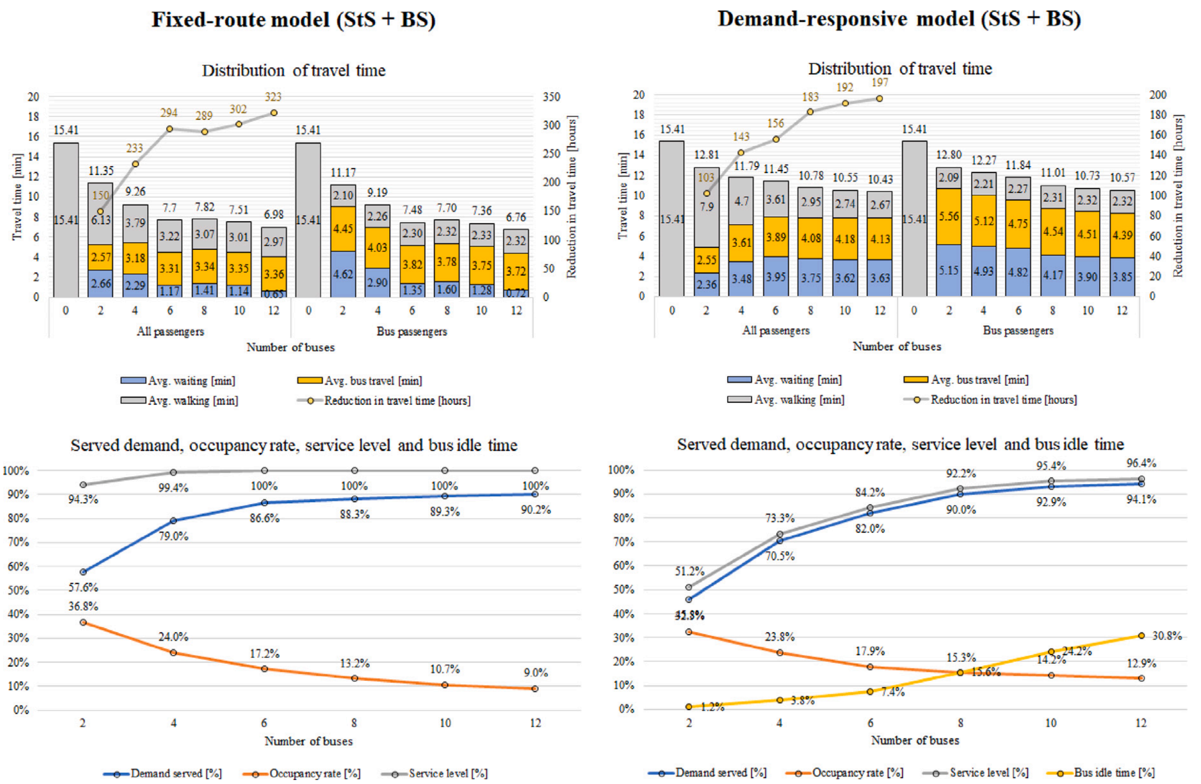


Fig. 11. Results for Scenario 3 for year 2032: Combined station-to-stop and stop-to-stop demand where stop-to-stop demand is formed from an added 20% increase in demand which is distributed uniformly between stops.

of the travel time improvement relative to walking needed for a passenger request to be accepted. In several tests, the threshold was increased in order to examine the effect of more firm rejection policies. An experiment applied a six minute threshold in the matching heuristic and it was observed that such a rejection policy significantly improved the travel time. More specifically, a threshold of six minutes results in:

- Lower waiting and bus travel time, which effectively results in a higher reduced travel time. This is positive from a business case perspective, as an eventual cost–benefit analysis will yield higher benefits (and lower costs), as the benefits are typically related to how much the travel time can be reduced.
- Lower % of served demand, occupancy rate and service level. From a service operator perspective, this can be deemed as negative because all KPI's related to service and usage are worsened.

It is relevant to consider in more details the effect of increasing the service threshold. First of all, it will now be harder for a request to get accepted in a bus that has passengers on board. This means that empty buses will be more likely to accept a request and it is therefore anticipated that passengers will be more evenly distributed across buses when the threshold is set to 360 s compared to 60 s. This also means that the occupancy of buses will also be more evenly distributed as seen in Fig. A.19. Furthermore, passengers with only modest reductions in travel times (compared to walking) are simply excluded or not considered at all, which effectively means that passengers with a higher reduction in travel times will be prioritized.

3.6. Case 3: Travelling from Station to Stops + 20% Between all Stops (StS + BS)

This scenario combines Scenario 1 and 2 in the sense that there are now passengers travelling from both station to stops and between stops.

The results (Fig. 11) show that overall, the fixed-route feeder once again is superior to the demand-responsive model for both passenger and operator metrics. It is noteworthy that the difference in total travel times (for instance 7.7 min vs 11.45 min for a fleet size of 6) is the largest amongst Scenarios 1–3 (refer Table A.8 for the 10th and 90th percentiles of the user metrics). Thus, the performance of the two systems (in terms of user metrics) differs the most when the demand is a combination of trips to and from a major hub (in this case the light rail station) and trips between stops. Note also that this demand scenario is likely to most realistically represent demand patterns in a future context.

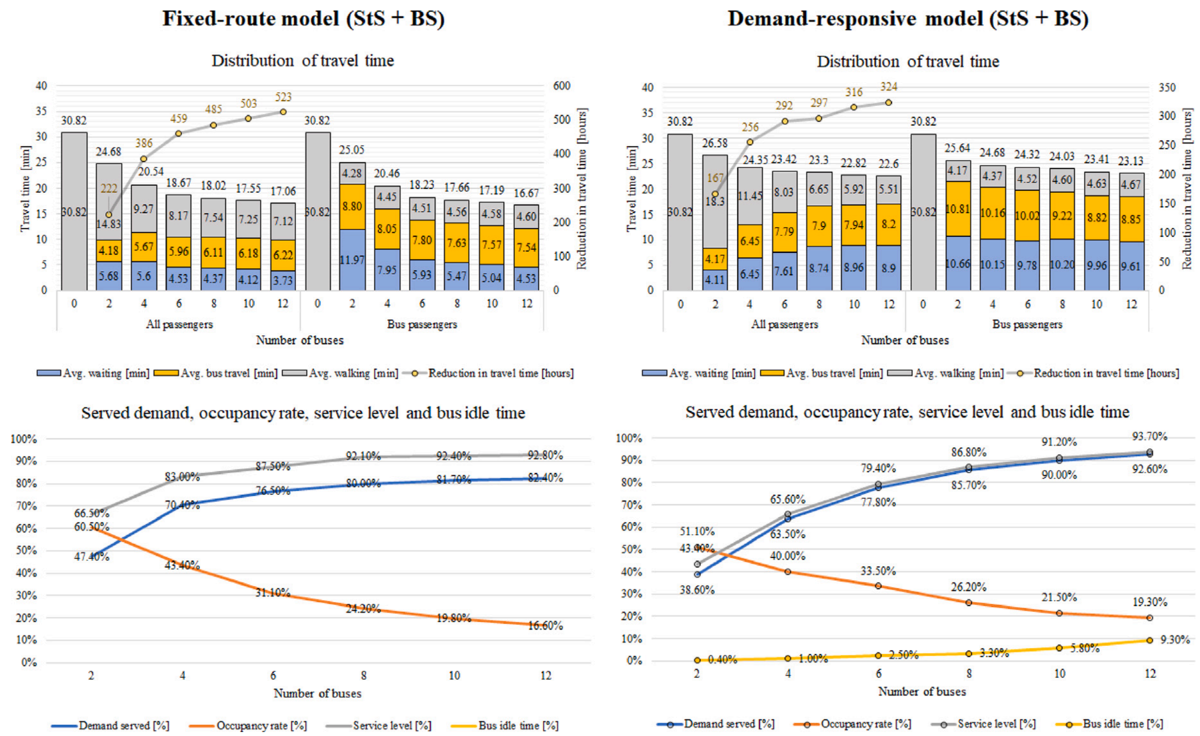


Fig. 12. Results for Scenario 4 for year 2032: Distances are increased by 100% in a scenario with combined station-to-stop and stop-to-stop demand (stop-to-stop demand is formed from an added 20% increase in demand which is distributed uniformly between stops).

3.7. Case 4: Distances increased by 100%

So far, it has been established that the fixed-route service performs notably better than the demand-responsive service in a dense urban context. However, it is also interesting to examine how the services perform when operated in a larger and less dense area. In this scenario, which is a continuation of Scenario 3, distances are increased by 100% between stops, buildings and between stops and buildings. The results for the scenario is illustrated in Fig. 12.

Compared to Scenario 3, % demand served and service levels are lower. This is a result of buses being unavailable for longer periods of time, which is explained by the higher occupancy rates and much lower bus idle time compared to Scenario 3.

Furthermore, the % demand served in the demand-responsive model exceeds the fixed-route model for a fleet of six buses, after which the difference gets larger and larger. This result may seem counter-intuitive, as it is generally established that demand-responsive models rarely perform well in larger areas (Badia and Jenelius, 2021). However, it is its flexibility that allows it to get such high percentages of served demand, because the buses are only driving to the stops that actually have demand, and in a scenario where distances are increased, more passengers are inclined to take the bus rather than walk. The same cannot be said for the fixed-route, because every stop has to be visited in a circulation, so walking in some instances will be more preferable. Since distances are now 100% longer, some of the fixed route's weaknesses become more apparent compared to the other scenarios. However, it should be noted that the fixed-route is in general still performing well and still superior when the objective is to reduce travel times.

A final point to note is that the operation of the demand-responsive service is stop-based, i.e., passengers board and alight the buses at the same bus stops used for the fixed-route service. In Scenarios 1–3, this allows for more effective operations (compared to a door-to-door service) through the aggregation of pick-ups and drop-offs. The small size of the service area and relatively large capacity of the buses make a stop-based service a more viable alternative. However, in Scenario 4, when the size of the area increases, it is conceivable that the overall performance of the demand-responsive service can be improved by increasing the number of designated locations for pick-ups and drop-offs. Although an important element in the design of the stop-based service, we defer this to future research.

3.8. Cost–benefit analysis of scenarios

In this section, the performance of the different scenarios is evaluated in a cost–benefit analysis (CBA). While such an analysis is difficult to carry out and is based on a number of uncertain inputs, the aim is to include both monetary and non-monetary societal gains and costs across the different scenarios. In this study, we define the baseline (i.e., the do-nothing scenario) as the solution

Table 4
Key input parameters for the cost–benefit analysis.

Factor	Unit	Year		
		2020	2025	2035
Discounting factor		1	1.09	1.25
Travel time savings	DKK/h	91.49	100.03	114.12
Waiting time savings	DKK/h	182.99	200.07	228.25
Bus operating costs	DKK/km	5.9	6.45	7.36
Health effects of walking	DKK/km	7.38	8.07	9.21

Table 5
Cost–benefit ratios for different scenarios and different number of busses.

Scenario's			# Busses					
	Routing	Health effects incl.	2	4	6	8	10	12
1:StS	Fixed	Yes	0.347	0.494	0.686	0.555	0.542	0.569
		No	0.561	0.826	1.248	0.894	0.844	0.874
	Demand-responsive	Yes	0.283	0.276	0.270	0.289	0.287	0.305
		No	0.417	0.398	0.381	0.409	0.404	0.432
2:BS	Fixed	Yes	0.235	0.329	0.362	0.363	0.353	0.336
		No	0.373	0.509	0.547	0.529	0.497	0.459
	Demand-responsive	Yes	0.219	0.187	0.190	0.192	0.197	0.202
		No	0.307	0.250	0.249	0.250	0.255	0.261
3:StS + BS	Fixed	Yes	0.343	0.478	0.645	0.547	0.540	0.564
		No	0.571	0.817	1.187	0.909	0.867	0.894
	Demand-responsive	Yes	0.279	0.252	0.232	0.260	0.266	0.266
		No	0.414	0.361	0.321	0.362	0.368	0.367
4:StS + BS + Dist	Fixed	Yes	0.270	0.414	0.504	0.507	0.508	0.516
		No	0.442	0.706	0.894	0.878	0.863	0.866
	Demand-responsive	Yes	0.284	0.270	0.253	0.224	0.224	0.223
		No	0.430	0.401	0.369	0.315	0.311	0.309

where self-driving buses are not implemented and people can only walk to and from the station. Hence, only changes in gains and costs compared to the baseline are included in the analysis.

The components that are considered are; (i) the reduced journey times and the increased waiting times, (ii) the direct costs related to the operation of busses including costs for insurance, energy, and maintenance. Indirect costs in the form of health effects of travellers walking less after the implementation of buses are also considered.

The value of travel time savings and health effects for pedestrians are based on official unit prices (DTU, 2022). These prices are projected from 2020 to 2025 and 2032 with the discounting factor. The operation costs for buses are due to Bösch et al. (2018). The cost of operating an electric, autonomous minibus with space for 20 passengers is estimated at 0.98 CHF, whereas the cost for an electric, autonomous van with space for 8 passengers is estimated at 0.74 CHF. As Nobina's autonomous buses studies here are a hybrid of these vehicles with space for 12 passengers, the average of the two estimates is used. Hence, the final estimate of operation costs is CHF 0.86 or DKK 5.9 per km.

Note that these costs cover all costs. This includes fixed costs per vehicle per day (acquisition, interest, insurance, tax, parking, fees) and variable costs per vehicle per day (charging, depreciation, maintenance, cleaning, etc.)

The cost–benefit calculation below expresses the trade-off between a number of different components. First, the monetized travel time savings, second, the bus operation costs resulting from multiplying the km per vehicle with the unit cost per km, third, the monetized waiting time savings (or cost), fourth, the total walking kilometers minus total walking kilometers for the baseline, which is used to calculate the costs of the reduction in the health benefits.

The cost–benefit analysis in Table 5 provides interesting insight. Firstly, it is clearly demonstrated that in every scenario, the fixed-route service is superior to demand-responsive service. Of course, this does not consider additional benefits that could result from a demand-responsive service but only considers the components shown in Table 4. It is also shown that accounting for the loss in health benefits of increased bus travel significantly reduces the benefit–cost ratio. This illustrates a paradigm in first and last mile transport, which has not been debated much in the literature. Namely, that it is sometimes better for society to reduce the level of service in order to harvest health benefits. Another finding is that from an operational perspective, most of the fixed routing scenarios are best served by six busses. For demand-responsive services, all scenarios perform so poorly that it is best to have only 2 busses (or essentially none as the BC is below unity). A final takeaway is that, for urban areas with a higher degree of urban sprawl, performance for fixed routing declines whereas the opposite is true for demand-responsive services.

4. Discussion

Although demand-responsive transit services have been around for several decades in the form of dial-a-bus services and paratransit (refer to Currie and Fournier (2020) for a detailed taxonomy), they have received renewed attention in the recent past largely due to technological developments (automation, telecommunications, smartphones) and the emergence of new business models within the broader context of the sharing economy and two-sided markets. Despite the promise of lower costs (Bösch et al., 2018; Becker et al., 2020) and a more efficient utilization of supply, evidence indicates that almost 50% of DRT systems over the past 40 years have failed (Currie and Fournier, 2020) due to a multitude of reasons (largely due to high costs per passenger, which continue to grow). Other papers, such as Calabrò et al. (2022) illustrate that the relative performance of demand-responsive and fixed routing services indeed depend on context. However, presentation of cost–benefit assessments as in Section 3.8, with the inclusion of losses in health costs, is something we rarely see in the literature. In view of these considerations, it is instructive to examine the performance of such automated demand-responsive services relative to conventional fixed-route services.

The experiments in this study (Section 3) perform such a comparison of fixed-route and demand-responsive services within a specific study area (the Hersted Industrial Park) in the Capital region of Denmark. The use of an agent-based modelling approach allows us to incorporate a generalized queuing model and accurately capture the topology of a real-world network and spatio-temporal patterns of travel demand. While the literature on agent-based simulation models often refrains from descriptions of the internal logic of the models, this paper includes a detailed description of these parts and provides pseudo-code and event-graphs. The event-trajectories and the decision rules correspond to the intrinsic parts of a mathematical program aimed at solving the first and last mile problem. Hence, leaving details out leads to an incomplete representation of the non-parametric system we are simulating. It is our hope that the detailing of the simulation system can be an inspiration for how to describe the growing number of agent-based models within this research area.

Our findings indicate that the cost–benefit performance for fixed route is consistently superior for three distinct demand patterns wherein first, trips are solely to and from a major hub in the area, second, trips are spatially uniformly distributed between locations in the area, and third, a combination of the previous two scenarios. In the first and third scenarios, the fixed-feeder service yields lower travel times due to the circular nature of the route and the absence of detours. Further, it allows for a better synchronization with the light rail system, thus contributing to lower waiting times and better cost–benefit performance. Nevertheless, it should be pointed out that even in situations where the spatial pattern of demand involves trips to and from a major hub, the geography and topology of the network do play a role. For instance, Koh et al. (2018) find that a demand-responsive dynamic bus service outperforms a fixed-route service (under a demand pattern similar to our Scenario 1) largely because their study region involves isolated regions that entail longer walk legs and multiple transfers to access the transfer hub (train station) via the fixed-feeder. In contrast, the placement of bus stops in our region is designed to ensure a high degree of accessibility to and from the buildings and in such a setting, the fixed-route system is clearly preferable. In summary, careful consideration should be given to the topology and geography of the underlying region when assessing the viability of demand-responsive transit services.

In terms of the percentage of travellers served by the bus service, the fixed-route feeder is superior in scenarios where the demand largely involves trips to and from a major hub (Scenarios 1 and 3). In contrast, the demand-responsive service yields superior percentages of demand served (albeit at higher total travel times) when the demand is more spatially distributed and when the area of the region is larger. The latter finding accords with those in the literature which show that demand responsive services are generally more cost effective at lower demand densities (Badia and Jenelius, 2021; Sharif Azadeh et al., 2022). Further, the performance of the demand responsive service is significantly better in off-peak periods (in terms of both fleet metrics and traveller metrics) than in peak-periods, suggesting that a combination of fixed route services and demand responsive services may be the most appropriate configuration for the system as a whole (similar conclusions are reached in Calabrò et al. (2021, 2023) who propose adapting between fixed-route and demand responsive services based on demand density and the time-of-day).

Other metrics from the fleet operator's perspective also do not make a case for the demand-responsive service, particularly when the topology of the region lends itself to simple fixed-route designs. This is also reflected in the cost–benefit analysis. Moreover, the vehicle mileage of the demand-responsive services is significantly smaller than that of the fixed-route service only at large fleet sizes. This indicates that at higher demand levels, the demand-responsive service could potentially operate at lower costs as also seen from the cost–benefit analysis. Occupancy rates for the demand-responsive service are also not significantly higher than that of fixed-route services to the extent that they would enable a smaller fleet and hence, cost savings. All in all, the cost effectiveness of the demand-responsive service is critical and a large majority of failures occur due to high operational costs (Currie and Fournier, 2020).

Although the simulations are performed on a specific network and region, broader implications may be drawn, since the findings can be expected to generalize to regions with land-use patterns that generate similar spatial and temporal distributions of demand. For example, population-dense residential districts – within large metropolitan regions – that are linked to critical transport nodes (either rail stations or trunk bus lines) by feeder services. However, as noted previously, caution should be exercised in doing so, particularly when multiple transfers are required, stops are not uniformly accessible and parts of the network are isolated.

A final observation is that external health benefits could play a role in the design of feeder transport systems. The paradigm presented here, is that by serving trips that would otherwise had been walking trips, a welfare loss is incurred resulting from people being less active. Hence, there is a sweetspot between providing services and attracting travellers to such services, and the opportunity cost of health dis-benefits.

5. Conclusions and future work

The investigation of first and last mile feeder services is a challenging mathematical problem that involves models for passenger demand in space–time, bus route and stop design, the integration of capacity limitations and bus routing algorithms. In this paper, we take on this challenge by framing the problem as an agent-based simulation model in which data driven queuing systems interplay with the routing of the busses. The intricate logic of the model is carefully described in a series of event-based graphs and pseudo-code that describe the transitions between different event stages. It is our hope, that the exposition of an event-based simulation model in this context can be an inspiration for others.

Several findings are provided in the paper. First, it is demonstrated that fixed-routing performs better than the demand-responsive model in all scenarios when evaluated in a cost–benefit framework and with respect to other level-of-service metrics. The fixed-routing is generally more robust and can handle sorts of variations, which makes it much more consistent. A main reason for this is that the optimal route design is circular and is easily synchronized to the light-rail frequency. Similar results can be expected for the large number of similar urban station hinterlands. It is shown however, that increasing the acceptance threshold for entering busses in the demand-responsive model can improve travel times, though at the expense of a lower service level as more and more passengers will get rejected. In a scenario where passengers can travel between all stops, demand-responsive services perform relatively better if the threshold is increased. The implied prioritization of passengers leads to a more effective utilization of buses although the latent cost of unserved demand increases. It is also established that the demand-responsive model performs better during off-peak periods. In a system with periods of low passenger arrivals and departures, the usage of a demand-responsive model can be a better choice. Subsequently, a combination of a fixed-route and demand-responsive model can be a viable solution for the entire system, in which buses are adhering to a fixed-route service in peak periods and a demand-responsive service in off-peak periods.

The effect of increased urban sprawl is also examined by increasing all distances in the system. While the fixed-routing is still superior in a scenario where distances are doubled, the demand-responsive model has better percentages of served demand when the fleet of busses is increased. Hence, while it is generally established that demand-responsive models rarely perform well in sparsely populated areas (Badia and Jenelius, 2021) it appears that such findings depend on the context.

5.1. Future research

There are many parameters and assumptions that can be modified in the demand-responsive model that can improve results in each scenario by designing a tailor-made solution for each.

A natural extension of the application in this paper is to consider multiple stations with a proximity that allows collaborative routing along the rail corridor. This would give access to a larger fleet, which could be dynamically assigned to stations on a need basis. By sharing resources across stations it should be possible to reduce the fleet-size for the system. The complexity of such system fit well with an agent-based simulation approach as introduced here. Another related challenge is the battery charging constraint and the avoidance of unnecessary battery degradation across the fleet. The avoidance of Depth of Discharge (DoD) incidences require a careful planning of the battery management. This management may further restrict the modus operandi of the buses and a cross-station collaboration could be a natural way of partly overcoming such restrictions.

Based on the literature and the findings in the present paper, we emphasize that first and last mile solutions are indeed context specific. It is therefore relevant that future studies investigate first and last mile services in a multitude of urban and non-urban contexts and propose a generic representation of failure and success criterion's beyond demand density measures. Our research suggest that it is important to also look at network topology features.

While the effect of wheelchairs were not included as part of this study, it would be relevant to study this in the future. Generally speaking, it would increase on-loading and off-loading times in certain situations and somewhat increase the uncertainty and heterogeneity in the system. It would reduce the average waiting time performance somewhat, but is not expected to change results unless the proportions of wheelchairs differed significantly in arrivals and departure time patterns and in the type of service demanded by such users.

Finally, we urge researchers to look into the balance between services that attract travellers in the context of first and last mile transport and the opportunity cost of health dis-benefits.

CRediT authorship contribution statement

Jeppe Rich: Conceptualization, Methodology, Supervision, Writing. **Ravi Seshadri:** Conceptualization, Methodology, Supervision, Writing. **Ali Jamal Jomeh:** Visualization, Writing of first draft, Programming, Software. **Sofus Rasmus Clausen:** Visualization, Writing of first draft, Programming, Software.

Data availability

Data will be made available on request.

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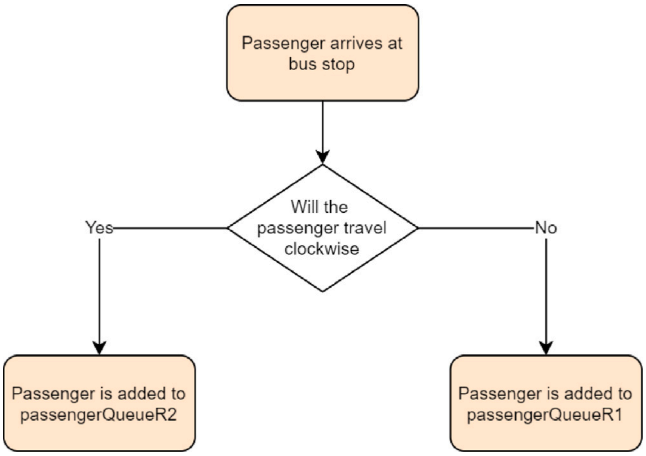

Fig. A.13. Flow chart for **Event 0** in the fixed-route simulation model.

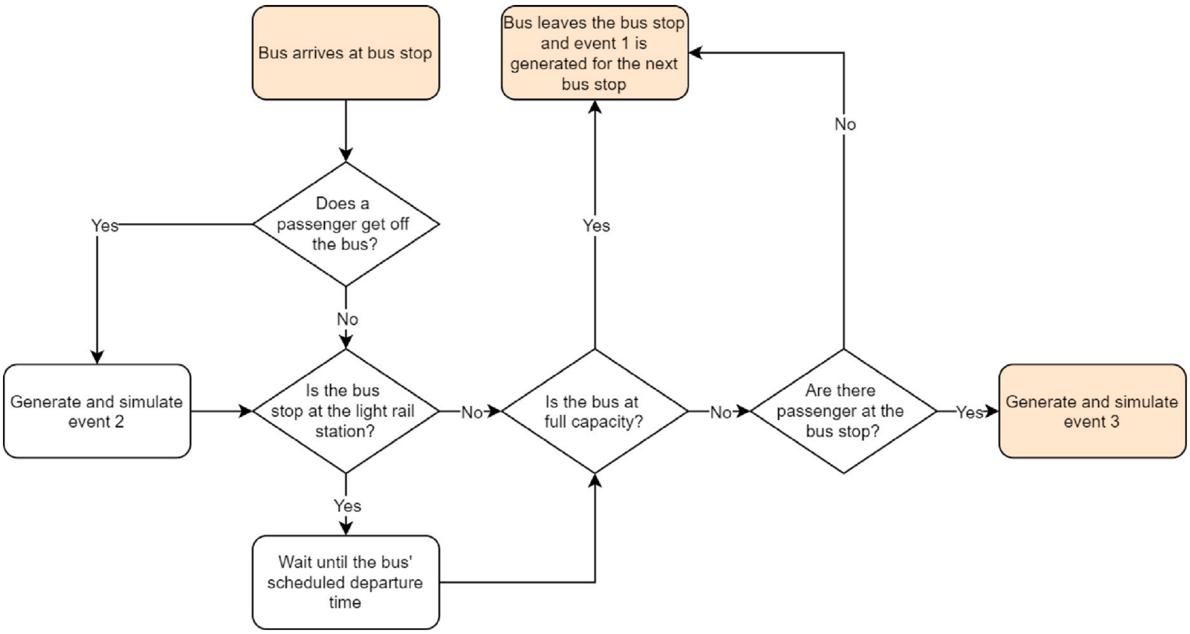

Fig. A.14. Flow chart for **Event 1** in the fixed-route simulation model.

Appendix. Illustration of event logic

See Figs. Fig. A.13–Fig. A.19 and Tables A.6–A.8.

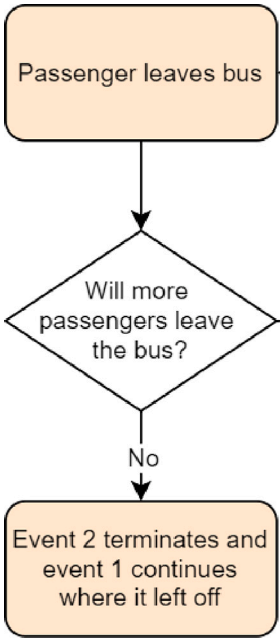

Fig. A.15. Flow chart for **Event 2** in the fixed-route simulation model.

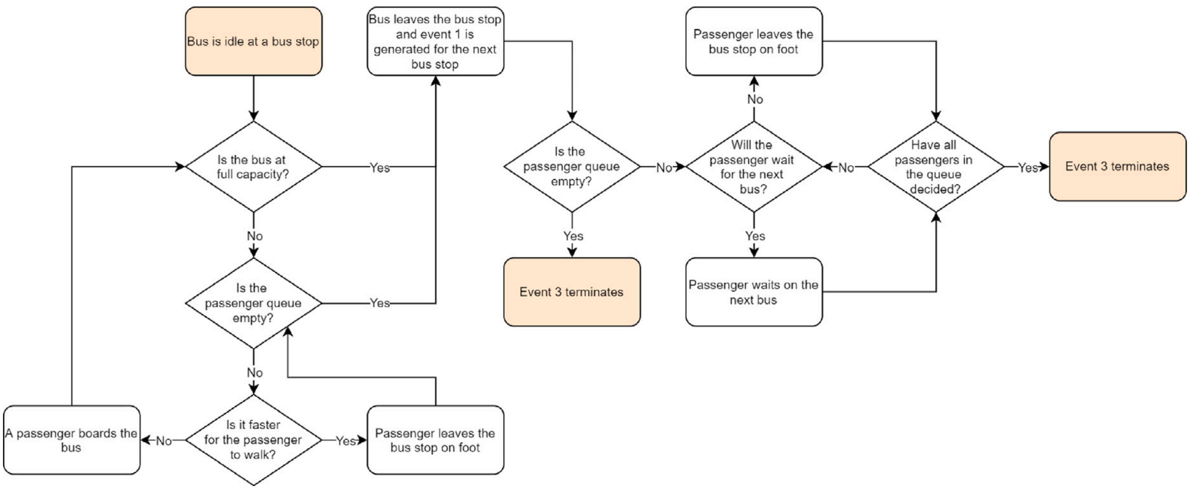

Fig. A.16. Flow chart for **Event 3** in the fixed-route simulation model.

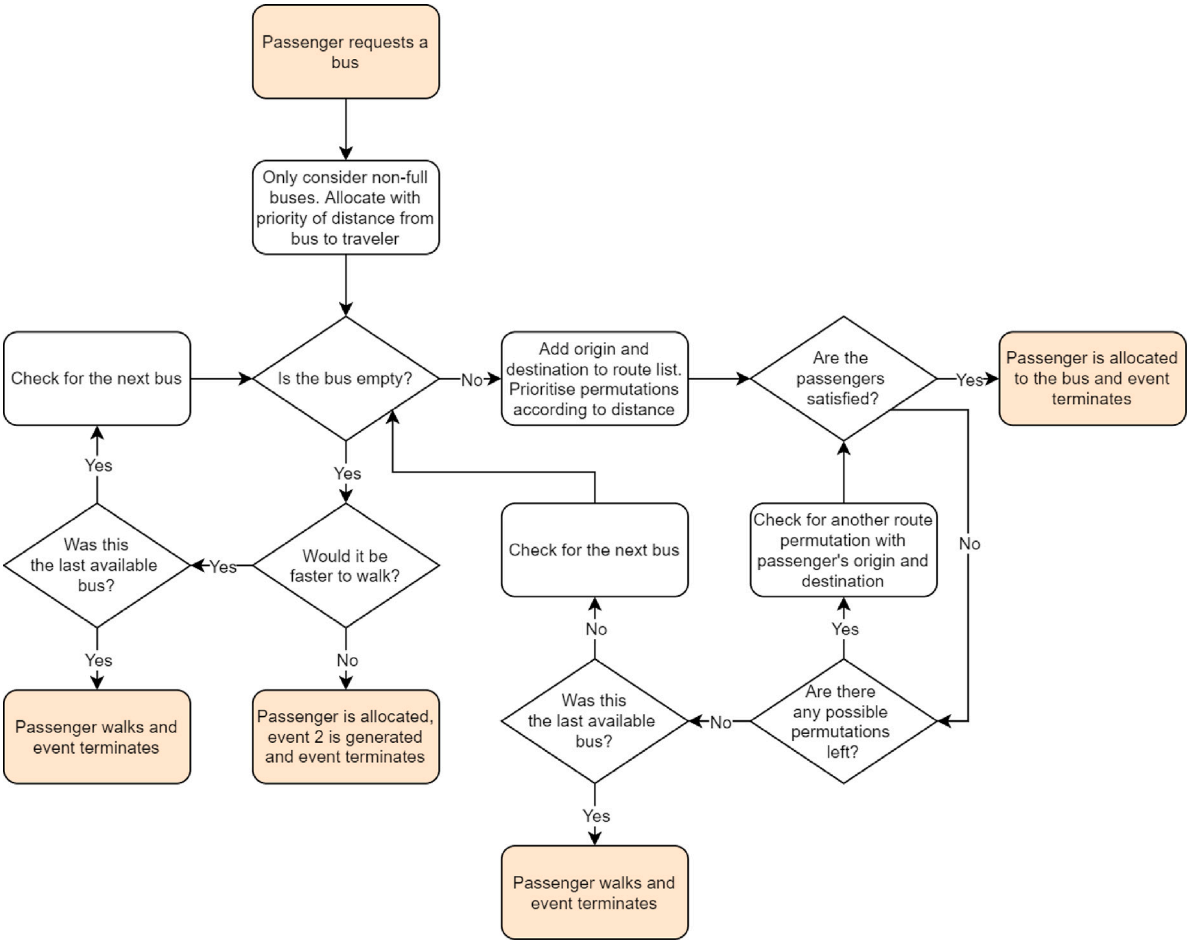

Fig. A.17. Flow chart for **Event 1** in the demand-responsive simulation model.

Table A.6
10th and 90th percentile for travel times in fixed-route and demand-responsive model (StS).

Number of buses	2	4	6	8	10	12
Fixed-route						
Waiting time (10th)	0	0	0	0	0	0
Waiting time (90th)	10	5.62	3.77	2.97	2.42	1.96
Bus travel time (10th)	2.23	1.82	1.67	1.65	1.65	1.65
Bus travel time (90th)	5.97	5.72	5.58	5.55	5.5	5.45
Walking time (10th)	0.78	0.8	0.82	0.82	0.82	0.82
Walking time (90th)	3.23	3.5	3.57	3.57	3.57	3.57
Total travel time (10th)	5.38	5.4	4.07	5	4.675	3.93
Total travel time (90th)	17.42	12.43	10.22	9.75	9.18	8.51
Demand-responsive						
Waiting time (10th)	0.74	0.23	0.00	0.00	0.00	0.00
Waiting time (90th)	10.29	9.94	9.98	9.17	9.30	9.00
Bus travel time (10th)	2.50	1.68	1.58	1.58	1.57	1.57
Bus travel time (90th)	8.35	7.93	7.60	7.68	7.56	7.55
Walking time (10th)	0.67	0.78	0.80	0.80	0.80	0.80
Walking time (90th)	3.15	3.34	3.38	3.42	3.45	3.45
Total travel time (10th)	6.78	5.73	4.98	4.78	4.35	4.32
Total travel time (90th)	18.11	17.70	17.58	16.82	17.02	16.63

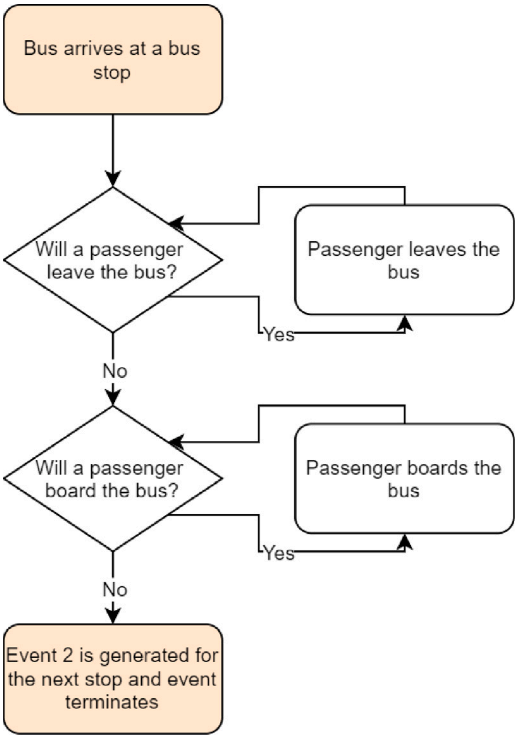

Fig. A.18. Flow chart for **Event 2** in the demand-responsive simulation model.

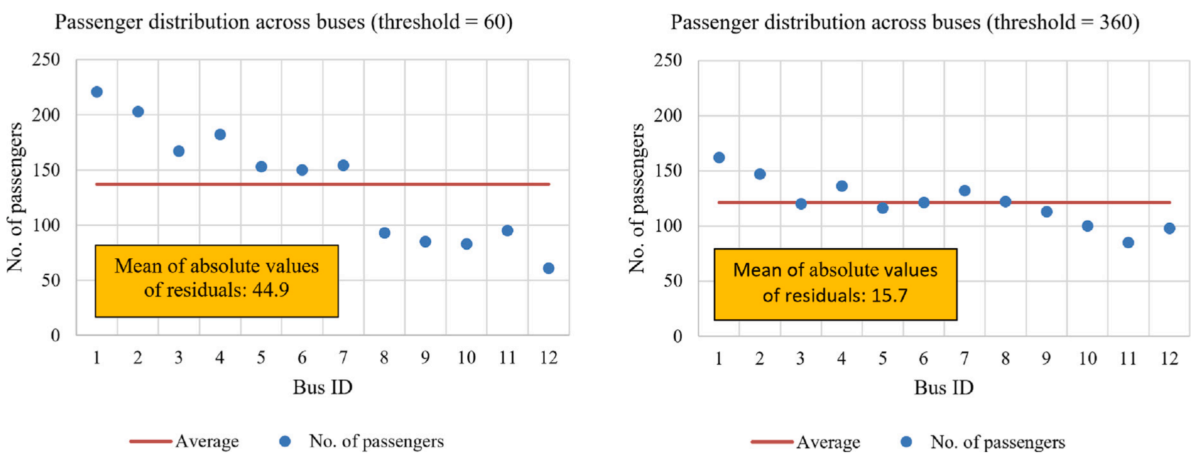

Fig. A.19. No. of passengers across all buses when threshold is set to 60 and 360 s, respectively.

Table A.7
10th and 90th percentile for travel times in fixed-route and demand-responsive model (BS).

Number of buses	2	4	6	8	10	12
Fixed-route						
Waiting time (10th)	0.716	0.52	0.37	0.32	0.262	0.18
Waiting time (90th)	9.98	6.22	4.33	3.3	2.62	2.22
Bus travel time (10th)	1.42	1.56	1.33	1.33	1.32	1.3
Bus travel time (90th)	6.284	6.22	6.13	6.12	6.07	6.08
Walking time (10th)	2.19	2.20	2.22	2.26	2.27	2.24
Walking time (90th)	5.99	6.00	6.04	6.08	6.09	6.14
Total travel time (10th)	7.51	7.06	6.51	6.41	6.09	5.91
Total travel time (90th)	18.77	15.13	13.70	13.02	12.57	12.24
Demand-responsive						
Waiting time (10th)	0.77	0.77	0.58	0.43	0.35	0.33
Waiting time (90th)	9.31	9.07	8.22	7.76	7.40	7.20
Bus travel time (10th)	1.98	1.80	1.28	1.28	1.27	1.27
Bus travel time (90th)	8.11	7.26	7.28	6.82	6.78	6.63
Walking time (10th)	2.33	2.27	2.30	2.27	2.27	2.27
Walking time (90th)	6.05	6.08	6.18	6.24	6.25	6.25
Total travel time (10th)	8.45	7.62	7.20	6.54	6.53	6.26
Total travel time (90th)	18.61	18.75	17.77	16.98	16.92	16.71

Table A.8
10th and 90th percentile for travel times in fixed-route and demand-responsive model (StS + BS).

Number of buses	2	4	6	8	10	12
Fixed-route						
Waiting time (10th)	0	0	0	0	0	0
Waiting time (90th)	10	5.72	3.97	3.08	2.52	2.03
Bus travel time (10th)	2.07	1.77	1.65	1.63	1.63	1.62
Bus travel time (90th)	6.08	5.78	5.67	5.62	5.58	5.57
Walking time (10th)	0.8	0.85	0.89	0.89	0.89	0.89
Walking time (90th)	3.63	3.93	4.05	4.08	4.14	4.11
Total travel time (10th)	5.44	5.45	4.26	4.97	4.68	4.1
Total travel time (90th)	17.5	12.76	10.92	10.22	9.59	9.11
Demand-responsive						
Waiting time (10th)	0.58	0.35	0.32	0.05	0.00	0.00
Waiting time (90th)	10.65	10.35	10.38	9.55	9.30	9.22
Bus travel time (10th)	2.60	1.98	1.62	1.58	1.57	1.55
Bus travel time (90th)	8.77	8.42	7.80	7.70	7.70	7.53
Walking time (10th)	0.78	0.80	0.82	0.83	0.83	0.83
Walking time (90th)	3.76	3.92	3.97	4.02	4.03	4.03
Total travel time (10th)	6.93	6.28	5.83	5.05	4.98	4.78
Total travel time (90th)	18.77	18.48	18.25	17.23	17.00	16.95

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