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Sharif Azadeh, Shadi; van der Zee, J.; Wagenvoort, M.

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Choice-driven service network design for an integrated fixed line and demand responsive mobility system

Shadi Sharif Azadeh [a,*], J. van der Zee [b], M. Wagenvoort [b]

[a] Civil Engineering and Geosciences, Department Transport & Planning, Stevinweg 1, 2628 CN Delft, The Netherlands
[b] Econometric Institute, Erasmus University Rotterdam, P.O. Box 1738, 3000 DR, Rotterdam, The Netherlands

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ABSTRACT

Sparsely populated areas tend to be poorly served by Fixed Line and Schedule (FLS) public transport systems as the operation of a regular bus line is not economically viable for such areas. Therefore, introducing a Demand Responsive Transport (DRT) to partially replace FLS can result in increasing mobility service accessibility and inclusion. In this paper, a mixed-integer linear problem (MILP) is proposed to design an integrated FLS and DRT network for a transport operator. Passengers behavior is implicitly incorporated in our proposed approach via a discrete choice model. In addition, a tailored Adaptive Large Neighborhood Search (ALNS) coupled with tabu search and simulated annealing are introduced. We test our algorithm on real instances from a public transport operator in the Netherlands. The proposed algorithm can solve the problem up to 170 times faster than the MILP within 4% to 10% gap. Our proposed resolution approach investigates the temporal and spatial feasibility of deploying these integrated mobility systems based on the service level and provides recommendations to public transport operators.

1. Introduction

With the increase of housing prices in highly populated parts of large cities, more residents are moving towards suburban areas. Uneven spread of population in these areas make the Fixed Line and Schedule (FLS) transport too expensive to operate. In recent years, due to budget cuts to public transport subsidies and the presence of smartphones, public transport operators increasingly consider introducing Demand-Responsive Transport (DRT) mobility services. The objective of a DRT system is to offer flexible mobility options in low demand regions in an effective and efficient way, see, Nelson et al. (2010), Liu and Ceder (2015), and Lyu et al. (2019). Meanwhile, one of the main challenges transport operators face is to analyze spatial and temporal usage patterns to investigate the feasibility of introducing DRT systems or adapting the current fixed-line services, see, Jiateng et al. (2021) and Alonso-González et al. (2018).

To make the usage of DRT services economically viable, the ridership has to increase but if the ridership increases significantly then it makes more sense to keep fixed line public transport in place instead of DRT systems, see, Ryley et al. (2014) and Currie and Fournier (2020). To break this cycle, integrating DRT and FLS services seems to be a logical compromise. These integrated systems are usually costly and in many cases heavily subsidized by governments, see, Davison et al. (2014), Li and Quadrifoglio (2010), Jin et al. (2014), and Yu et al. (2015). FLS services in sparsely populated areas are subsidized due to the obligation of the service provider to ensure accessibility to all villages. Therefore, using smaller DRT buses in low demand areas reduces emissions compared to running a regular FLS service with empty fleet during off-peak hours and offset costs of underperforming FLS system.

* Corresponding author.
E-mail addresses: s.sharifazadeh@tudelft.nl (S. Sharif Azadeh), jessicavdzee@gmail.com (J. van der Zee), wagenvoort@ese.eur.nl (M. Wagenvoort).

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Although a subsidy is assigned to run the integrated system, it still remains economically viable for specific regions with a particular demographic characteristics (i.e., sparsely populated areas with limited accessibility to cities).

In this paper, we tackle a service network design problem that investigates the temporal and spatial feasibility (in terms of the service level) of integrating DRT and FLS networks (in suburban areas) taking passengers' behavior implicitly into account via a choice model. In our case, the DRT service is owned by the same operator as the FLS offering mobility services from *stop to stop* instead of door to door (due to policies imposed by our industrial partner, a Dutch public transport operator).

Even though a single highly complex optimization model may not be the most adequate approach for this highly complex problem, our proposed integrated network benefit from the advantages each service type has to offer depending on the time of the day (and day of the week) as well as the geographical region in which the service is offered. In our case, the aim of this public transport operator is to increase the accessibility of citizens to public transport services in remote areas. These integrated mobility systems especially target passengers with limited mobility capability in order to increase mobility inclusion.

Our proposed Mixed-Integer Linear Problem (MILP) decides which stations should serve the FLS, the DRT or both networks. Passengers' behavior is implicitly included in the proposed mathematical model (via a discrete choice model) and customers' satisfaction is evaluated according to the percentage of served requests as well as the opt-outs. The proposed MILP succeeds to solve small size instances but fails to solve the problem for the whole network. As a result, we propose a tailored Adaptive Large Neighborhood Search (ALNS) algorithm coupled with tabu search and simulated annealing to solve larger instances in reasonable time. The results indicate that the integrated mobility network can significantly improve the service level first during evening hours, then during weekends and public holidays. Also, the results of our sensitivity analysis on the choice parameters show that the sensitivity of passengers against the in-vehicle travel time and travel distance plays the most important role in their decision whether to choose the FLS or DRT system during different time frames.

The remainder of this paper is as follows. Related literature is presented in Section 2 followed by problem description in Section 3. In Section 4, the choice model is introduced. Section 5 presents the mathematical model for the proposed Choice-Driven Inter-modal Service Network Design (CD-ISND) problem. In Section 6, the ALNS algorithm is explained. Computational results are shown in Section 7 followed by conclusion in Section 8.

2. Related literature

The advantage of FLS systems is that they consolidate demand at stations in a network whose lines and timetables are fixed. As mentioned in the previous section, such systems are costly to constantly operate in less populated areas. On the other hand, DRT systems offer flexible mobility services and can tackle the economic and environmental burdens of running FLS in low-demand areas. The question is then in what regions and during what time periods, operators should use such flexible mobility services and whether it is worth integrating these two networks in the first place. There is an extensive body of literature on different aspects of fixed line and schedule transport systems. The readers are referred to Ibarra-Rojas et al. (2015) where the authors provide an extensive review on the subject. In Section 2.1, we first briefly review some of the published articles investigating the potential and the operation of DRT systems. Then in Section 2.2, we present some of the recently published papers that consider DRT and FLS integrated networks. Finally, we highlight the gap in this literature that we aim to address in this paper.

2.1. DRT network

During the last decade, many studies have been conducted to investigate the acceptability and feasibility of introducing DRT systems from passengers' and operators' point of view. A stated preference (SP) survey was introduced by Kim et al. (2017) to assess respondents' preferences regarding DRT introduction in which the willingness to pay for these services was calculated. According to the outcome of this survey, compared to the existing bus (FLS) transport, the value of DRT is considered to be higher in terms of overall usability and convenience. But indeed, these services can improve the service levels for passengers with certain characteristics in particular geographic areas, see also, Ellis and McCollom (2009), Westervelt et al. (2018), Coutinho et al. (2020), Li and Quadrifoglio (2010), Aldaihani et al. (2004).

The tactical and operational planning of the DRT systems in terms of fleet sizing, vehicle routing and line planning have also been studied in the literature. Carotenuto et al. (2012) introduce a simulation framework of a DRT system in a discrete events environment using an insertion heuristic in order to reproduce the movement of the vehicles, the passengers' arrival to the stops and eventually the delays. Winter et al. (2018) examine the potential performance of an Automated Demand Responsive Transport Service (ADRTS) as a replacement for scheduled bus services (FLS) and simulates the effects of demand levels, vehicle capacity, vehicle dwell time and the initial vehicle distribution on system performance in terms of fleet size and system costs. The results suggest that the interaction between vehicle capacity and designed dwell time plays a significant role in defining system performance, see also, Winter et al. (2016) and Qiu et al. (2018). Bruni et al. (2014) study route construction of DRT vehicles upon passengers arrival as well as DRT scheduling problem using stochastic programming. Their results show that the proposed stochastic programming framework allows the construction of routes that are able to absorb late requests without drastic changes in the scheduled routes. In the following section, we introduce several papers that investigate integrated DRT and FLS network which is also the main focus of our paper.

2.2. Integrated FLS and DRT network

In the recent years, there is a growing literature in regards with integrating DRT and FLS systems. Huang et al. (2020) introduce a multi-vehicle routing with pickup and delivery problem for operational decisions related to the demand responsive Customized

Buses (CB). Their approach has two phases: in the dynamic phase, the authors insert passenger requests dynamically. Then, in the static phase, they optimize the service network based on the overall demand. Their proposed MILP model maximizes operator's revenue. The CB passenger's travel behavior is measured by a discrete choice model given the trip plan provided by the operator which is similar to our case in this paper.

Lyu et al. (2019) introduce a CB line planning framework which is applicable to multiple travel data sources. They first present a mode-choice model for estimating the probability of a passenger choosing CB over a set of alternative transport modes, and then formulate the CB line planning problem. In addition, in a similar context, Steiner and Irnich (2020) develop a strategic network planning optimization model that integrates Mobility on Demand (MoD) system into the public transport bus network. They break down the optimization problem by three types of interdependent decisions. They first determine the bus line segments in the future public transport network. Then, they select the MoD zones with their transfer points. Finally, they combine route-assignment and route-choice decision of the passengers.

Even though, the mentioned articles share several characteristics with our proposed framework, none of them investigates the feasibility of such inter-modal networks according to the temporal and spatial demand patterns at strategic level when passengers' behavior is incorporated in the mathematical formulation via a choice model. We call the introduced MILP model a choice-driven inter-modal service network design (CD-ISND). The main challenge is to correctly address the interplay between the DRT and FLS services, as well as approximating DRT costs given that its fleet utilization is a key factor affecting the cost. We solve the proposed CD-ISND for small real case instances. The proposed model is computationally burdensome to solve for large instances. As a result, we introduce a tailored Adaptive Large Neighborhood Search (ALNS) algorithm coupled with tabu search and simulated annealing to solve the problem efficiently.

3. Problem description

We consider an inter-modal mobility system that integrates Demand Responsive Transport (DRT) with a Fixed Line and Schedule (FLS) network of buses. Our goal is to solve a service network design problem where we make a decision about the location of FLS and DRT stations. We are thus interested in evaluating the integration of DRT services in an already existing FLS network from strategical point of view, i.e., deciding which station should serve for DRT services, or FLS service or both. We do not consider the planning of the system. To deal with differences in passenger demand, we use historical data and consider the integration of DRT in an FLS network for different time frames and their corresponding expected demands. We evaluate the system's performance based on the provided service level. For the DRT service, vehicles start and end their journeys at the depot. The routes are not fixed but the stations are. This is an app-based service , which implies that passengers can reserve the trip in advance via an app, that goes from stop to stop. Even though door-to-door transit is more convenient for the passengers, in this case, the public transport operator has decided to provide a stop-to-stop service for the DRT to cover larger service area whose schedule is flexible and it provides an area-based geographical coverage. The FLS network consists of buses that drive fixed routes with their corresponding bus stations at specific times according to a given timetable. In the DRT system, passengers can be directly brought to their destination stop. The aim of the model is to determine the set of bus stations at which DRT should be offered, either by replacing the FLS option at that bus station or by adding this service. Thus, the DRT and FLS network share the same infrastructure.

Ticket prices consist of a fixed price and a variable price based on the distance. These values are predefined by our industrial partner (i.e., public transport operator) and thus are considered to be given parameters in this problem. In the Netherlands, a smart card (called OV-chipcard) is used for all forms of public transport, see, Amsterdam (2015), Alonso-González et al. (2018), Coutinho et al. (2019, 2020). Therefore, all realized trips are registered and known to the operators. We have used the trip data of 2017 resulting in almost 4 million individual trips. Whenever a passenger makes a transfer between modes of transport from the same operator, the OV-chipcard recognizes this as a transfer and hence the full journey is considered to be one trip. This also implies that the fixed price is charged once. In Section 3.1, we present the network followed by Section 3.2 in which we explain the general assumptions of the problem.

3.1. The network

We model the network on a directed graph, $G(V, E, A)$, where the vertices show the stations and arcs/edges show the connections between each pair of stations. Note that *FLS line* and *bus line* are used interchangeably throughout the manuscript. In this paper, the FLS network is already given and in place. We consider integrating DRT and FLS on this already existing bus transport system. The actual network presented in Section 7 includes several bus lines for different regions. However, for the sake of illustration, in this section (i.e., in Figs. 1–3), we show a single line bus network to make a distinction between stations serving DRT, FLS or both services.

For each station on a given bus line, we have to select one of the following options: (i) the station serves as an FLS stop, (ii) a DRT stop (iii) or both. When a station is removed from the bus line, the line can be rerouted that results in reducing its length. Fig. 2 shows the rerouted line in case bus station F is removed from the bus line and added to the DRT network. The bus line then skips bus station F and the length of the bus line reduces, resulting in a shorter travel time for passengers passing stations E and G. In this figure, DRT routes are shown by dashed lines and FLS routes by solid lines.

Fig. 3 shows an example of what the integrated network looks like. Here, bus stations C and D are removed from the route of the bus line and together with bus station A, E and F, they are added to the DRT network which is fully connected. All stations from the original FLS system become a part of either the DRT or FLS or both. Passengers departing from or heading to bus station A, E and F can choose between using FLS or DRT, while from the other stations, the choice is limited to either FLS or DRT services.

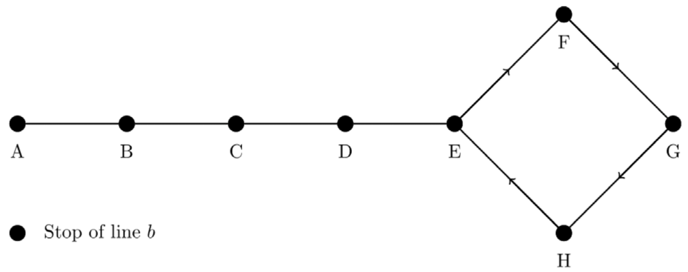


Fig. 1. Single line bus network.

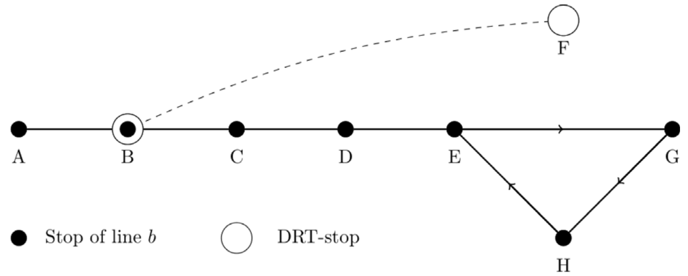


Fig. 2. Rerouted single line bus network integrated with a DRT line.

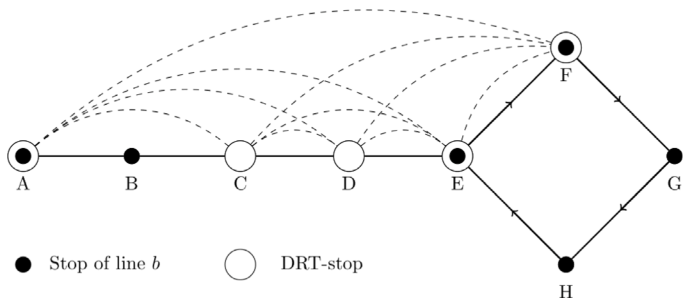


Fig. 3. Illustrative solution of the proposed model in Section 5 and the proposed algorithm in Section 6 for the inter-modal network.

3.2. Problem characteristics

Integrated network consists of heterogeneous fleets. Namely, DRT buses are smaller vehicles and can thus accommodate fewer passengers at the same time with slightly higher price compared to the FLS buses. The FLS fleet size is fixed in the problem. However, the DRT fleet size depends on the number of incoming requests. A vehicle scheduling simulation (provided by the transport operator) is used to predefine the number of DRT vehicles. In this simulation, customer arrivals are stochastic and the fleet size is determined in order to ensure serving at least 90% of the requests. The reason for this assumption is that if 100% service is imposed, the fleet size significantly increases which results in an unrealistically high number of buses. In Section 7, we evaluate the integrated DRT and FLS network for different DRT fleet sizes.

In the model, the origin–destination matrix is given and passenger assignment is done probabilistically according to a choice model explained in Section 4. It is assumed that passengers arrive uniformly over the time period that is considered. Passenger's choice for each trip can be determined from the utility of using FLS and DRT services. This is based on the price, in-vehicle travel time, the number of transfers, and the waiting time outside the vehicle. The waiting time of customers before departure is not considered whereas the waiting time during transfers are considered in the utility function. In the DRT network a booking system is used and in the FLS system a fixed timetable is applied, hence the waiting times before departure are assumed to be equal. For FLS trips these can be directly determined from the network. As detours can be made in the DRT trips when combining the trips of multiple passengers, it is hard to estimate the in-vehicle time for a specific passenger using DRT service. We note that using simulation, a multiplier is determined to indicate the actual distance driven relative to the direct travel distance for DRT vehicles. This multiplier is also used to define the distance driven by vehicles, but not for the price paid by the passenger, for that the direct distance is used, so the passenger does not have to pay for the extra km as a result of a detour.

4. Choice model

In this paper, passengers' individual choices are explicitly incorporated in the mathematical model using discrete choice models originally introduced by McFadden et al. (1973). Given the origin–destination matrix obtained from the OV-chipcard information, utility functions are defined associated to each mode of transport, that is DRT and FLS. These utilities are determined for each transport option and each OD pair. Passengers are not captive in the system and they can choose not to select either of these services defined by utility of the opt-out option. The available options are described as follows:

- DRT: Flexible transport from stop to stop without transfers or fixed timetables. However, a detour can be made to pick-up or drop-off other passengers sharing the vehicle.
- FLS: Transport via fixed routes with or without transfers and according to a fixed timetable.
- Opt-out: Neither DRT nor FLS is chosen and the passenger decides to use an alternative mode.

With the probability that a passenger opts-out or uses one of these services, the expected number of trips can be determined. These probabilities are thus treated as input parameters in the model. We use the same attributes in the utility functions as suggested by Atasoy et al. (2015). The passengers utilities associated with either mobility alternatives are influenced by in-vehicle travel time, fare, type of service, number of transfers and the waiting time outside the vehicle, see also, Robenek et al. (2016).

The utility value associated with a DRT trip from station $o \in S$ to station $d \in S$ depends on the fixed and variable fare (price) of the trip (π^{DRT} and ρ^{DRT}, respectively) and the in-vehicle travel time (IVTT), which consists of the direct traveling time (τ_{od}) plus the added duration of a possible detour that can be made when the ride is shared ($\Delta\tau_{od}$). The utility of an FLS trip from station o to station d depends on the fixed and variable price of the trip (π^{FLS} and ρ^{FLS}, respectively), the total in-vehicle travel time (τ_{od}^{IVTT}), the number of transfers (t_{od}) and the out-of-vehicle time (OVT) in between these rides (τ_{od}^{OVT}). The utility of the reject (or opt-out) option is influenced by the trip length (δ_{od} where $o, d \in S$), presented in Eq. (3).

The utility functions U_{od}^{DRT}, U_{od}^{FLS} and U_{od}^{reject} of a trip from station $o \in S$ to station $d \in S$ are calculated as follows,

$$U_{od}^{\text{DRT}} = ASC^{\text{DRT}} - (\pi^{\text{DRT}} + \rho^{\text{DRT}}\delta_{od}) - \beta_{\text{VOT}}^{\text{IVTT}} \times (\tau_{od} + \Delta\tau_{od}), \tag{1}$$

$$\begin{aligned} U_{od}^{\text{FLS}} =& ASC^{\text{FLS}} - (\pi^{\text{FLS}} + \rho^{\text{FLS}}\delta_{od}) \\ &- \beta_{\text{VOT}}^{\text{IVTT}} \times \tau_{od}^{\text{IVTT}} - \beta_{\text{VOT}}^{\text{OVT}} \times \tau_{od}^{\text{OVT}} - \beta_{\text{transfer}} \times t_{od}, \end{aligned} \tag{2}$$

$$U_{od}^{\text{opt-out}} = \beta_{\text{dist}} \times \delta_{od}. \tag{3}$$

The alternative specific constants (i.e., ASC^{DRT} and ASC^{FLS}) project the differences between DRT and FLS in terms of vehicle comfort and service. The coefficients $\beta_{\text{VOT}}^{\text{IVTT}} > 0$ and $\beta_{\text{VOT}}^{\text{OVT}} > 0$ display the monetary value of time (VOT) of the in-vehicle travel time and out-of-vehicle time respectively. Coefficient $\beta_{\text{transfer}} > 0$ is the monetary value associated with a transfer. The opt-out option displays other travel modes than FLS or DRT. As a result, we implicitly take into account the competition between modes of transport. When the travel distance decreases, passengers will be less likely to use public transport (Atasoy et al., 2015). For example, for two different trips of length 2 km and 10 km, the passenger is less likely to use FLS for the trip of 2 km compared to the trip of 10 km. When the travel distance increases, eventually the opt-out option will become more appealing. The coefficient $\beta_{\text{dist}} > 0$ displays the monetary value associated with the traveled distance.

Given the above-mentioned travel alternatives, for an already existing bus network, our proposed model decides whether each station should serve as either an FLS stop, or a DRT stop or both. Transfers are not allowed between modes as well as for the DRT system for a given trip. Three scenarios could potentially happen for a given station:

- $\mathcal{A}^1 = \{DRT\}$, the station serves as a DRT stop. As a result, the only option to travel from this station for a given passenger is DRT.
- $\mathcal{A}^2 = \{FLS\}$, the station serves as an FLS stop. As a result, the only option to travel from this station for a given passenger is FLS.
- $\mathcal{A}^3 = \{DRT, FLS\}$, the station serves as both FLS and DRT stop. Consequently, passengers traveling from this station can choose to travel with either DRT or FLS.

The probability that a given passenger chooses a transport alternative (DRT or FLS) depends on the type of service provided at the origin station. These probabilities are calculated according to a multinomial logit choice model. The probability (p_{od}^{im}) that a passenger chooses transport mode $m \in \mathcal{A}^i$ for the trip from station o to station d when travel option $i \in \{1, 2, 3\}$ is offered, can now be calculated as follows:

$$p_{od}^{im} = \frac{\exp(\beta_{\text{price}} U_{od}^{m})}{\exp(\beta_{\text{price}} U_{od}^{\text{reject}}) + \sum_{j \in \mathcal{A}^i} \exp(\beta_{\text{price}} U_{od}^{j})}. \tag{4}$$

Since the utility functions are normalized in monetary units, they are adjusted by a scale parameter β_{price}. These probabilities are taken as input parameters in our proposed CD-ISND mathematical model to assign passengers to the available travel alternatives.

In Section 5, we present the components of our proposed choice-driven inter-modal service network design problem. The probabilities calculated according to Eq. (4) are used as an input to the model.

Table 1
Variables and parameters in the objective function.

Variable	Explanation
r_{od}	Expected revenue from all trips from origin $o \in \mathcal{S}$ to destination $d \in \mathcal{S}$ (hour)
d^{DRT}	Expected total distance driven with DRT vehicles (km)
d^{FLS}	Expected total distance driven with FLS vehicles (km)
v_{od}^{DRT}	Expected number of trips from station $o \in \mathcal{S}$ to station $d \in \mathcal{S}$ in the DRT network
v_{od}^{FLS}	Expected number of trips from station $o \in \mathcal{S}$ to station $d \in \mathcal{S}$ in the FLS network
Parameter	
α	Drivers salary (hour)
β^{DRT}	Fuel and maintenance price per DRT vehicle (euros/km)
β^{FLS}	Fuel and maintenance costs per FLS vehicle (euros/km)
γ^{DRT}	Write-off cost per DRT vehicle (hour)
γ^{FLS}	Write-off cost per FLS vehicle (hour)
η^{DRT}	Number of DRT vehicles
η^{FLS}	Number of FLS vehicles
ρ^{DRT}	Variable price for DRT tickets
π^{DRT}	Fixed price for DRT tickets
ρ^{FLS}	Variable price for FLS tickets
π^{FLS}	Fixed price for FLS tickets
δ_{od}	Distance of a trip from $o \in \mathcal{S}$ to $d \in \mathcal{S}$ when driving directly (km)

5. Mathematical model

We introduce a mixed integer linear model to formulate the choice-driven service network design problem for this inter-modal transport network. Consider $\mathcal{B}$ to be the set of bus lines in the original FLS network and $\mathcal{S}$ to present the set of bus stations in an already existing bus network. Two decision variables are used: y_{bs} denotes whether station $s \in \mathcal{S}$ serves as an FLS stop in bus line $b \in \mathcal{B}$ and x_s indicates whether bus station $s \in \mathcal{S}$ is assigned to a DRT stop. The organization of this section is as follows: we separately introduce each part of the mathematical model with its associated list of sets, parameters and variables. We first, start with the description of the objective function.

Objective. The aim is to find the optimal service network design for an integrated inter-modal (FLS and DRT) system from both passengers' and operator's perspectives. The problem in fact embeds two objectives: (i) given the inter-modal transport system, the operator aims at designing a cost efficient integrated network, (ii) the service level improvement is captured via the percentage of served passengers as well as the proportion of passengers who drop out. The objective is calculated by subtracting the salary of the drivers, fuel and maintenance costs from the total ticket revenue calculated over all trips. Table 1 presents the list of notations used in the objective function. Eq. (6) shows the revenue function which has two components: the first one shows the expected revenue of each DRT trip and the second term shows the expected revenue of each FLS trip using both variable and fixed price of tickets for each pair of origin $o \in \mathcal{S}$ and destination $d \in \mathcal{S}$. The expected number of trips from station $o \in \mathcal{S}$ to station $d \in \mathcal{S}$ for both DRT and FLS services are calculated via Constraints (13) and (14) using the outcome of the choice model presented in Section 4. v_{od}^{DRT} and v_{od}^{FLS} are applied in order to calculate the expected revenue per origin and destination (r_{od}) in Eq. (6). Finally, expected fuel and maintenance costs, drivers' salaries and write-off costs per DRT and FLS vehicle are presented in the second part of the objective function in Eq. (5).

$$\max \sum_{o\in\mathcal{S}}\sum_{d\in\mathcal{S}} r_{od} - \Big(\alpha\times(\eta^{\mathrm{DRT}}+\eta^{\mathrm{FLS}}) + \beta^{\mathrm{DRT}}\times d^{\mathrm{DRT}} + \beta^{\mathrm{FLS}}\times d^{\mathrm{FLS}} + \gamma^{\mathrm{DRT}}\times\eta^{\mathrm{DRT}} + \gamma^{\mathrm{FLS}}\times\eta^{\mathrm{FLS}}\Big) \tag{5}$$

$$r_{od} = \Big((\rho^{\mathrm{DRT}}\times\delta_{od}+\pi^{\mathrm{DRT}})v_{od}^{\mathrm{DRT}} + (\rho^{\mathrm{FLS}}\times\delta_{od}+\pi^{\mathrm{FLS}})v_{od}^{\mathrm{FLS}}\Big) \quad \forall o,d\in\mathcal{S} \tag{6}$$

In the following, we introduce the set of constraints dedicated to present the connectivity of the network.

Connectivity Constraints. For connectivity of the area, all bus stations should be served by either DRT or FLS or both presented by Constraints (7). We do not consider reconstruction of the network as the station locations are predefined. Therefore, Constraints (8) are imposed to ensure that no bus station is added to a bus line that is not currently in the FLS system (see Table 2).

$$x_s + \sum_{b\in\mathcal{B}} y_{bs} \geq 1 \qquad \forall s\in\mathcal{S} \tag{7}$$

$$y_{bs} \leq \psi_{bs} \qquad \forall s\in\mathcal{S}, b\in\mathcal{B} \tag{8}$$

Service Assignment Constraints at Stations. In this part, we use choice probabilities described in Section 4 as input parameters to decide which station should serve as an FLS stop, DRT stop or both. Table 3 presents the variables and parameters applied in the associated constraints. We assume that there is a limit to the number of DRT trips that can be realized by a given number of

Table 2
Variables and parameters for the connectivity constraints.

Variable	Explanation
y_{bs}	1 if station $s \in \mathcal{S}$ serves as an FLS stop in bus line $b \in \mathcal{B}$, 0 otherwise
x_s	1 if bus station $s \in \mathcal{S}$ is assigned to a DRT stop, 0 otherwise
Parameter	
ψ_{bs}	1 if bus line $b \in \mathcal{B}$ stops at station $s \in \mathcal{S}$ in the original network, 0 otherwise

Table 3
Variables and parameters for the fleet related constraints.

Variable	Explanation
a_{od}	1 if DRT is required for trip (o, d), that is, when at least one of o and d is not part of the FLS network, 0 otherwise
b_{od}	1 when scenario $\mathcal{A}^1 = \{DRT\}$ is offered, that is, when stations o and d are both part of the DRT network and at least one of them is not part of the FLS network, 0 otherwise
d_{od}	1 when scenario $\mathcal{A}^2 = \{FLS\}$ is offered that is, when both station o and d are part of the FLS network but at least one of o and d is not part of the DRT network, 0 otherwise
c_{od}	1 when scenario $\mathcal{A}^3 = \{DRT, FLS\}$ is offered, that is, when both station o and d are part of the DRT and FLS network, 0 otherwise
Parameter	
θ_{od}	Number of passengers who want to travel from origin o to destination d (average per hour)
$p_{od}^{1,\mathrm{DRT}}$	Probability that a customer chooses DRT to travel from station o to station d when scenario $\mathcal{A}^1 = \{DRT\}$ is offered, presented in Section 4
$p_{od}^{2,\mathrm{FLS}}$	Probability that a customer chooses FLS to travel from station o to station d when scenario $\mathcal{A}^2 = \{FLS\}$ is offered, presented in Section 4
$p_{od}^{3,\mathrm{DRT}}$	Probability that a customer chooses DRT to travel from station o to station d when scenario $\mathcal{A}^3 = \{DRT, FLS\}$ is offered, presented in Section 4
$p_{od}^{3,\mathrm{FLS}}$	Probability that a customer chooses FLS to travel from station o to station d when scenario $\mathcal{A}^3 = \{DRT, FLS\}$ is offered, presented in Section 4

vehicles. Four variables, a_{od}, b_{od}, c_{od} and d_{od}, are introduced to determine the number of FLS and DRT trips from station o to d, named v_{od}^{FLS} and v_{od}^{DRT} respectively. We previously mentioned these two variables in the description of the objective function.

Binary variable a_{od} takes value 1 when DRT is necessary for the trip from station o to station d, i.e. when neither of these stations is part of the FLS network. If we consider bus station o, then we know that if $\sum_{b\in\mathcal{B}} y_{bo} \geq 1$ it is visited by at least one FLS line. If either of $\sum_{b\in\mathcal{B}} y_{bo}$ or $\sum_{b\in\mathcal{B}} y_{bd}$ equals to 0, then a DRT service is required for a trip from o to d. a_{od} is equal to 1 if either one of these takes a value of 0 denoted by Constraints (9).

$$a_{od} = 1 - \min\left\{1, \sum_{b\in\mathcal{B}} y_{bo}, \sum_{b\in\mathcal{B}} y_{bd}\right\} \qquad \forall o, d \in \mathcal{S} \tag{9}$$

Therefore, a_{od} shows whether a DRT service is required in order to travel from o to d. If both stations are in the DRT network and at least one of them is not in the FLS network, scenario $\mathcal{A}^1 = \{DRT\}$ is offered, presented in Section 4. Consequently, binary variable b_{od} takes value 1, Constraints (10).

$$b_{od} = \min\{x_o, x_d, a_{od}\} \qquad \forall o, d \in \mathcal{S} \tag{10}$$

Note that when $a_{od} - b_{od} = 1$, it means that DRT is required for trip o to d but at least one of them does not provide DRT stop. In addition, when both stations are parts of DRT and FLS networks, then c_{od} takes value 1, shown by Constraint (11).

$$c_{od} = \min\{x_o, x_d, 1 - a_{od}\} \qquad \forall o, d \in \mathcal{S} \tag{11}$$

Finally, when both stations serve as FLS stops but at least one of them is not part of the DRT network, FLS is the only travel option at that station. As a result, d_{od} equals to 1, Constraint (12).

$$d_{od} = 1 - \max\{a_{od}, c_{od}\} \qquad \forall o, d \in \mathcal{S} \tag{12}$$

Note that some of these constraints are non-linear. The linearized constraints are given in the Appendix. Given these binary variables, the expected number of DRT and FLS trips can be determined using the output of the choice model in Section 4, presented by

Table 4
Parameters for the DRT constraints.

Parameter	Explanation
ϵ	Coverage multiplier for a DRT trip to estimate the travel distance of the vehicle for a trip
λ	The maximum number of DRT trips that can be served

Table 5
Variables and parameters of the FLS constraints.

Variable	Explanation
n^b_{ij}	Binary variable takes value 1 if bus line b stops at station σ^b_j directly after station σ^b_i, 0 otherwise
ℓ_b	Length of bus line b
z_{bs}	1 if station s is a transfer station of bus line b, 0 otherwise
Parameter	
σ^b_i	Order of bus line b in the FLS timetable, $\sigma^b_i = s$ if station s is the ith station of bus line b
μ^b_{od}	1 if station d needs to be part of bus line b when station o is part of bus line b, 0 otherwise
ω_b	Frequency of bus line b

Constraints (13) and (14).

$$v^{\text{DRT}}_{od} = \theta_{od}\left(p^{1,\text{DRT}}_{od} \times b_{od} + p^{2,\text{FLS}}_{od}(a_{od} - b_{od}) + p^{3,\text{DRT}}_{od} \times c_{od}\right) \qquad \forall o, d \in \mathcal{S} \tag{13}$$

$$v^{\text{FLS}}_{od} = \theta_{od}\left(p^{2,\text{FLS}} \times d_{od} + p^{3,\text{FLS}}_{od} \times c_{od}\right) \qquad \forall o, d \in \mathcal{S} \tag{14}$$

DRT Constraints. The number of DRT trips that can be served depends on the number of available DRT vehicles, Constraints (15). The distance traveled by these vehicles can be computed using a multiplier factor caused by possible detours, Constraints (16) (see Table 4).

$$\sum_{o,d \in \mathcal{S}} v^{\text{DRT}}_{od} \le \lambda \tag{15}$$

$$d^{\text{DRT}} = \epsilon \sum_{o \in \mathcal{S}} \sum_{d \in \mathcal{S}} \delta_{od} \times v^{\text{DRT}}_{od} \tag{16}$$

FLS Constraints. The length of the FLS trips are determined based on whether bus stations assigned to FLS stops are visited directly after each other or not (see n^b_{ij} in Table 5). This is particularly useful to calculate the total traveled distance by the FLS fleet in order to calculate the total cost. Thus, n^b_{ij} takes value 1 if the ith and jth bus stations are in the FLS line, and none of the bus stations between the ith and jth are visited, Constraints (17).

$$n^b_{ij} = \max\left\{0, \min\left\{y_{b,\sigma^b_i},\ y_{b,\sigma^b_j},\ 1 - \sum_{s=i+1}^{j-1} y_{b,\sigma^b_s}\right\}\right\} \quad \forall i, j \in \{0, \dots, |\sigma^b|\}, b \in \mathcal{B} \tag{17}$$

This variable is used to determine the length of the FLS line in Constraints (18). The linearization of these constraints are presented in the Appendix. Finally, the total distance traveled can be determined by using the length of each FLS line and their frequency, Constraint (24).

To allow for connectivity of the network, it is imposed that all FLS lines should at least have one transfer bus station. This is a bus station that is visited by at least two FLS lines. This is modeled by Constraints (19), (20), (21) and (22). Constraints (23) impose that a station from a set of bus stations $\mathcal{S}^* \subset \mathcal{S}$ is either visited by all or by none of the FLS lines. These constraints are imposed by the public transport operator for all stations that are originally visited by exactly two bus lines.

$$\ell_b = \sum_{i=0}^{|\sigma^b|} \sum_{j=0}^{|\sigma^b|} \delta_{\sigma^b_i, \sigma^b_j} \times n^b_{ij} \qquad \forall b \in \mathcal{B} \tag{18}$$

$$y_{bd} \ge \mu^b_{od} \times y_{bo} \qquad \forall o, d \in \mathcal{S}, b \in \mathcal{B} \tag{19}$$

$$\sum_{s \in \mathcal{S}} z_{bs} \ge 1 \qquad \forall b \in \mathcal{B} \tag{20}$$

$$y_{bs} \ge z_{bs} \qquad \forall s \in \mathcal{S}, b \in \mathcal{B} \tag{21}$$

$$\sum_{x \in \mathcal{B} \setminus \{b\}} y_{xs} \ge z_{bs} \qquad \forall s \in \mathcal{S}, b \in \mathcal{B} \tag{22}$$

$$\psi_{b_1 s} \times \psi_{b_2 s}\left(y_{b_1 s} - y_{b_2 s}\right) = 0 \qquad \forall s \in \mathcal{S}^*,\ b_1, b_2 \in \mathcal{B} \tag{23}$$

$$d^{\mathrm{FLS}} = \sum_{b \in \mathcal{B}} \omega_b \times \ell_b \tag{24}$$

In the results, we show that we manage to solve the above mathematical model (CD-ISND), (5)–(24), for small size real instances. However, this proposed model is computationally difficult to solve for larger size instances. Therefore, to find a high quality solution in a computationally efficient way, we propose a tailored Adaptive Large Neighborhood Search (ALNS) algorithm in the next section. In Section 7.1, we compare the computational results of the CD-ISND with the results of our proposed ALNS algorithm.

6. Adaptive large neighborhood search

An Adaptive Large Neighborhood Search (ALNS) is an extension of the Large Neighborhood Search (LNS) introduced by Ropke and Pisinger (2006) to solve the pick-up and delivery problem. In the LNS method, a solution is destroyed and consequently repaired using operators, Gendreau and Potvin (2010). ALNS method, however, considers multiple destroy and repair operators chosen at random based on their weights. The weights of the destroy and repair operators are adjusted according to their performance in the objective value. In this paper, to avoid being trapped in a local optima, simulated annealing and tabu search are incorporated in the ALNS framework to change the search neighborhood. In the remainder of this section, we first explain the ALNS algorithm, then, we present the parameter settings in Section 6.1. Algorithm 1 summarizes an overview of our proposed ALNS resolution approach.

Algorithm 1 Adaptive Large Neighborhood Search

Input: a feasible solution h, the number of iterations n_{max}
Output: the best solution found h^*

Set $n = 1$ and $h^* = h$
while $n < n_{max}$
  Select a destroy operator and a repair operator
  Find h' using the operators taking into account the tabu list
  if $f(h') > f(h^*)$
    Set $h^* = h'$ and $h = h'$
  else if h' is accepted by simulated annealing
    Set $h = h'$
  end
  Update the scores for the operators
  if n mod $n_{update} == 0$
    Update the weights
  end if
end while
return h^*

Here, an initial feasible solution h is given as an input as well as the number of iterations for which the ALNS is executed. Based on the weight of each operator i, $weight_i$, a destroy and a repair operator are selected at random. Initially, all operators have the same weight. Every n_{update} iterations, the weights of the operators are updated, where n_{update} is a predefined value. An operator i is rewarded by points, $points_i$, if it finds a new global best solution, that is, a new solution with a better objective value than the current solution or a new solution with a worse objective value than the current solution but accepted according to simulated annealing or a new solution that has never occurred before. The total number of points obtained over the n_{update} iterations is divided by the number of times this operator is used, n_i, as otherwise good performing operators that are chosen few times are not rewarded according to their relative performance. Using a parameter ζ between 0 and 1, the weight of operator i is updated as follows, $weight_i = \zeta(\frac{points_i}{n_i}) + (1-\zeta) weight_i$, see, Ropke and Pisinger (2006).

Given the destroy and repair operators, the current solution h is destroyed by removing (bus line–bus station) pairs from the network and consequently repaired that results in a candidate solution h'. Note that the tabu pairs are taken into account. That is, when a (bus line–bus station) pair is removed, this pair is tabu, i.e. it is forbidden to remove this pair again by one of the destroy operators and remains tabu for a predefined number of iterations, (Gendreau, 2003). This method avoids the solution from cycling between the same set of solutions.

If the candidate solution achieves a better objective value, $f(h')$, compared to the value obtained from the current global best solution h^*, the candidate solution is accepted as the new optimal solution. If the solution is not a new global best solution, simulated annealing is used to determine whether the solution should be accepted or not. Simulated annealing allows for accepting a candidate solution h' with a worse objective value compared to the current solution h, according to probability $e^{-(f(h')-f(h))/T}$ where value of $T > 0$ is the temperature, see Ropke and Pisinger (2006). This method helps to escape from a local optima. The starting temperature is set such that a solution that has a given percentage ($w\%$) worse objective value compared to the initial solution is accepted with 50% probability. The temperature decreases over time by using a cooling rate. This implies that the probability of accepting a solution with a worse objective value decreases over time.

As mentioned in Section 3, there is a maximum on the number of DRT trips, λ. Therefore, if a solution exceeds the number of possible DRT trips, a penalty is imposed. The number of DRT trips in the initial solution can already exceed λ, therefore, solutions

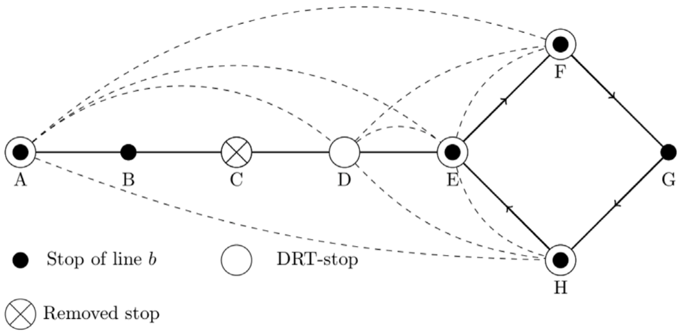


Fig. 4. Example of a network after executing a destroy operator.

where the number of DRT trips is closer to λ should be perceived better compared to solutions where the excess number of trips is larger. The penalization of going beyond λ is proportional to the deviation. Thus, the extra number of trips is penalized in the objective value at a high cost, namely the fixed price of a DRT trip plus the variable price of a DRT trip multiplied by the maximum distance between stations in the network.

In this algorithm, we start with the solution in which all bus stations operate on the bus lines and can be used as a DRT stop. Then, using a destroy operator, a set of bus stations are removed from (part of) the FLS and/or DRT networks and consequently we decide for each station whether it is served by FLS and/or DRT using a repair operator. Fig. 4 shows an example of what the destroyed initial solution could look like. Bus station B is removed from the DRT network, bus station D from the bus line, and bus station C from both the bus line and the DRT network. Note that this example considers one bus line and it could be that bus station C and D are parts of another bus line in the FLS network.

All (bus line–bus station) pairs that are part of the destroy set are considered to be repaired. There are four options in the repair operator: (i) adding the station to the bus line, (ii) adding the station to the DRT network, (iii) adding the station to both the bus line and the DRT network, or (iv) making no changes. Depending on the current state, some of these options might be infeasible, therefore, they cannot be executed. For bus station B in Fig. 4, the bus station can be added to the DRT network, or no change is made, but adding B to FLS or adding it to both FLS and DRT is infeasible. For bus station D, the bus station can be added to the bus line, or no change can be made. For bus station C, the bus station can either be added to the bus line, or to the DRT network or both.

Different destroy operators are used to diversify and intensify the solution:

Random Pair Removal. A bus line and its corresponding bus station are selected at random. If the bus station is solely in the bus line or in the DRT network, it is removed from either of them. If the bus station is shared between the DRT and FLS networks, it is decided at random with equal probabilities whether it should be removed from the bus line, from the DRT network, or both. The number of (bus line–bus station) pairs that should be removed is chosen at random. There are some bus stations that are part of a pair that should be either in or out of the bus line, as presented by Constraint (19). Therefore, if one of these bus stations is removed from the bus line, the other bus station is removed too.

Bus Station Removal. Offering DRT service at a bus station affects the decision for the FLS network for all bus lines visiting that bus station and vice versa. In the Bus Station Removal operator, a bus station is chosen at random. For each bus line that contains this bus station in its network, the bus station is removed from the bus line and/or the DRT network. As long as the number of removed (bus station–bus line) pairs is smaller than the predetermined number of removal pairs, another bus station is chosen. This operator is similar to the Random Pair Removal operator. However, here a set of bus stations is selected and all bus lines that cover these stations are in the destroy set unlike the Random Pair Removal operator in which a set of (bus line–bus station) pairs are removed.

Worst Removal. In the Worst Removal operator, stations that have the highest demand either as origin or destination of the trips, are removed from the DRT network, and stations that have the lowest demand, are removed from the FLS network. The intuition behind this operator is that if there are many passengers, it is worthwhile for an FLS bus to stop at that bus station compared to stopping at a bus station with low expected number of passengers. Similarly, the reverse holds for the DRT vehicles. For each origin–destination pair, the expected number of FLS and DRT trips is used to find the bus stations with the lowest number of FLS trips and highest number of DRT trips. From the predefined number of pairs that should be removed, half are removed from the FLS stations with the lowest demand, and half from the DRT stations with the highest demand. Below, list of repair operators are presented:

Greedy Repair. In the Greedy Repair operator, the change in the objective value for all options are determined for each bus line and bus station pair that were removed from the solution. There are four options for each pair, (i) making no changes, (ii) adding the bus station to the bus line, (iii) adding the bus station to the DRT network, or (iv) adding the bus station to both the FLS and the DRT networks. Depending on the current solution, one or more of these options are infeasible. For example, when the bus stop is in neither the FLS network nor the DRT network, the decision to make no changes is infeasible. The change of any infeasible option is set to negative infinity. The option that yields the highest change in objective value, or lowest decrease, is selected. After executing this change to the networks, the deviation in the objective value is recomputed for all remaining (bus line–bus station) pairs that were removed.

Historical Repair. This operator repairs the solution based on the historical performance, namely the set of $|H^*|$ best solutions. For the set of best solutions, the frequency of the FLS, DRT and FLS+DRT options are stored for each bus line and its corresponding stations. Then, for each bus station the option with the highest frequency among these best $|H^*|$ solutions is selected.

6.1. Parameter settings

An ALNS algorithm consists of several parameters whose values could affect the performance of the algorithm. Therefore, we tune these values by performing experiments for different combinations of these parameters' discretizations. We shortly discuss the parameter settings below.

Weight Updates. Initially all destroy and repair operators have the same probability of being selected. Rewards are given in three situations: (i) when a new best solution is found, (ii) when a new solution is found that does not improve the global best solution, and (iii) when a new unique solution is found. We set ζ, defined in Section 6, to 0.1, see Ropke and Pisinger (2006).

Simulated annealing: The start temperature is set such that a solution that is $w\%$ worse compared to the initial solution is accepted. This temperature is decreased using a cooling rate in every iteration. Various combinations of these parameters were tested among which the best is selected.

Tabu Search: When a (bus stop–bus line) pair becomes tabu, we have to determine for how long this pair cannot be removed from the solution. After implementing a sensitivity analysis using multiple values for the tabu length, we have chosen ten iterations.

Other ALNS Parameters: The ALNS is run for 100 iterations where the best 25 solutions are stored and the weights are updated after 25 solutions. Using more iterations results in a longer running time, however the improvement in the objective value was relatively low. Also, $|H^*|$ is set to 25.

The Choice Simulation Model: To determine the expected number of trips, a choice model is used to compute the utilities for different trips and transportation modes mentioned in Section 4. Running surveys and estimating the choice parameters for our case study region is out of the scope of this paper. The reason is that the focus of this research is on the strategic decisions (by the public transport operator) on the network design, given demand and travel decisions by the passengers. Therefore, we borrow the choice parameters from the most relevant literature in order to estimate the travel behavior. We use the following values corresponding to the model presented in Section 4: $\beta_{\text{DRT}} = 8.25$, $\beta_{\text{FLS}} = 7$, $\beta^{\text{IVTT}} = 0.0032$, $\beta^{\text{OVT}} = 1.7$, $\beta_{dist} = 0.002$, (Atasoy et al., 2015) and $\beta_{transfer} = 600$ (i.e. 10 min) (de Keizer et al., 2012). Here, β_{DRT} and β_{FLS} are constants. A parameter β_{price} is used to normalize the utility function and is set to 0.4, see Koppelman and Bhat (2006).

7. Computational results

In this section, we present the computational results and evaluate the performance of an integrated DRT and FLS network on real case instances provided by a public transport service supplier in the Netherlands. We first introduce the characteristics of this network. Then, in Section 7.1, we solve our proposed choice-driven inter-modal service network design (CD-ISND) model for a small size instance and compare its performance with the outcomes of the proposed ALNS algorithm. We show that the mathematical model is only capable of solving the small instances to optimality which shows the need for introducing an efficient algorithm to solve larger cases. Our proposed ALNS method can solve the problem efficiently within a small gap.

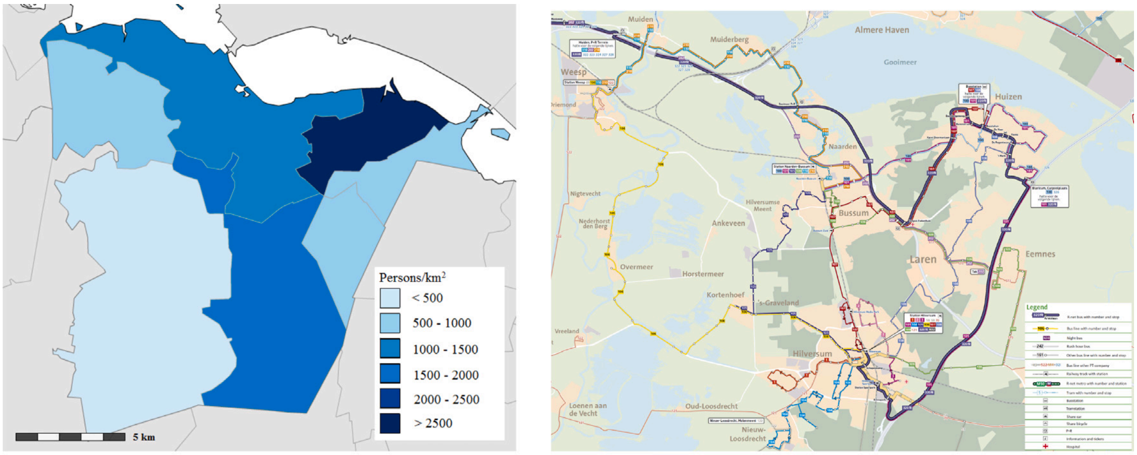
In Section 7.2, we test the performance of the integrated FLS and DRT network. The results suggest that during off-peak hours and non-working days these inter-modal mobility services could improve the service level (measured by the percentage of opted-out passengers). We provide statistical tests to show the significance of their impact. Finally, in Section 7.3, we present the results of a sensitivity analysis implemented on the choice parameters and their associated effects on passenger dropout percentage (i.e., service level). Based on the outcomes, passengers are mostly sensitive against "in-vehicle travel time" and "traveled distance".

The case instances are provided by a public transport company that offers mobility services in Gooi en Vechstreek region in North Holland province in the Netherlands. Gooi en Vechstreek is a demographically diverse district consisting of the city of Hilversum, a few villages, and rural areas with varying population densities shown in Fig. 5(a). The bus network in Gooi en Vechtstreek presented in Fig. 5(b) contains nineteen bus lines nine of which operate within the city of Hilversum. The other 10 bus lines connect the villages with each other and to Hilversum as well as connecting Hilversum to Amsterdam. For the FLS network, timetable is fixed operating in three different time frames: (i) TF0: Monday–Saturday during the day, (ii) TF1: Evenings and, (iii) TF2: Sundays and Public Holidays during the day. The timetable, historical travel data, and parameters regarding the price of the tickets, driver salary, travel distances, fuel and maintenance costs, and vehicle write-off costs are provided by the public transport operator.

In this network, the fixed price of a DRT service is set to 2.5 euros and the variable price for the ticket of 0.5 euro per kilometer, see, Studio (2017), voor de Statistiek (2017). Table 6 shows the instances used to test the performance of the proposed solution methods for the available data. The instances are defined based on the number of bus lines and DRT fleet size. In Section 7.1, we evaluate the performance of the mathematical model and the ALNS algorithm for these instances.

7.1. Performance of CD-ISND versus ALNS

The proposed mathematical model and the ALNS algorithm were coded in Java and solved by CPLEX 12.8. All experiments were carried out on a computer with 1.8 GHz CPU and 8 GB of RAM. We first solve the CD-ISND model for IS1 and IS2 presented in



(a) Population density   (b) Bus network

Fig. 5. Network characteristics and demographics in Gooi en Vechtstreek.

Table 6
Characteristics of the instances.

Instance Name	# Bus line	# DRT fleet	Region
IS1	2	6	Hilversum
IS2	2	9	Hilversum
IL1	9	6	Hilversum
IL2	19	9	Gooi en Vechtstreek

Table 7
Performance of the MIP and the ALNS for IS1 and IS2 instances.

Instance	Time frame	CD-ISND			ALNS		Gap (%)
		obj.	Time (min)	#Nodes	obj.	Time (min)	
IS1	TF0	−200.66	73.15	79988	−220.86	2.02	10.07
	TF1	−303.39	3.47	1049	−322.18	2.09	6.19
	TF2	−240.43	401.21	118604	−257.49	1.26	7.10
IS2	TF0	−154.26	17.11	22358	−166.40	5.76	7.87
	TF1	−252.29	359.57	168788	−263.51	2.67	4.44
	TF2	−192.32	59.12	30438	−205.97	6.71	7.10

Table 6 consisting of two bus lines in Hilversum. Then, we compare its performance with the ALNS algorithm. Table 7 summarizes the computational results associated with the performance of both the ALNS algorithm as well as the CD-ISND model. For two different DRT fleet size scenarios (obtained from a vehicle scheduling simulation provided by our partner company) and three time frames (i.e., TF0, TF1 and TF2), the value of the objective function, computational time (in minutes) and the size of the problem (in terms of the number of generated nodes) are reported. As can be seen, even for small size instances, the mathematical model takes a long time to solve. In fact, our proposed CD-ISND model fails to solve larger instances within a reasonable period of time.

The results in Table 7 imply that the high computational time calls for a tailored heuristic algorithm to solve the problem more efficiently. In the second part of this table, the results associated with the ALNS algorithm are presented. As the performance of the ALNS can be affected by the choice of the initial seed, we present the results over ten different instances having separate initial seeds and report the average computational time. As shown in the table, the gap between the solution of the ALNS and the optimal solution obtained from solving the mathematical model is between 4.5% and 10% compared to the optimal solution, however the computational time of ALNS is from 1.3 to over 170 times less than the CD-ISND model.

Table 8 presents the performance of the ALNS for larger instances (i.e., IL1 and IL2 shown in Table 6). As previously mentioned, Hilversum contains nine bus lines (with 6 DRT vehicles) and the larger network in Gooi en Vechstreek includes nineteen bus lines (with 9 DRT vehicles). Using the proposed CD-ISND model to solve these instances takes several hours, whereas the tailored ALNS algorithm manages to solve them in less than an hour except for the IL2, TF0 instance for which the feasible solution in terms of number of DRT trips was not found within a reasonable time interval.

Table 8
Performance of the ALNS for IL1 and IL2 instances.

Time frames	IL1		IL2	
	obj.	Time (min)	obj.	Time (min)
TF0	498.02	24.68	–	–
TF1	−21.32	25.46	−187.55	45.87
TF2	341.12	25.99	466.42	39.70

Table 9
Service level comparison between only FLS and inter-modal network generated by the ALNS algorithm.

Instance	Time frame	Hour	Only FLS (%)		Best Integrated[a] (%)			Average Integrated[b] (%)			T-statistic (p-value)		
			FLS	Dropouts	DRT	FLS	Dropouts	DRT	FLS	Dropouts	DRT	FLS	Dropouts
IL1	TF0	All	95.47	4.53	2.65	92.87	4.48	2.26	93.34	4.4	8.77 (0.0000)	−8.74 (0.0000)	−4.85 (0.0005)
		9–14	95.62	4.38	5.70	89.94	4.36	3.19	92.45	4.36	3.62 (0.0028)	−3.62 (0.0028)	−3.27 (0.0048)
		9–11	94.71	5.29	3.60	91.72	4.67	2.61	92.43	4.96	4.57 (0.0007)	−4.56 (0.0007)	−3.83 (0.0020)
	TF1	All	95.60	4.40	12.98	82.62	4.40	10.08	85.71	4.21	5.97 (0.0001)	−5.94 (0.0001)	−0.98 (0.1766)
		22–24	95.84	4.16	18.69	77.16	4.16	18.93	77.81	3.25	47.42 (0.0000)	−51.51 (0.0000)	−2.66 (0.0130)
	TF2	All	95.21	4.79	4.30	91.49	4.21	2.45	93.04	4.51	3.66 (0.0026)	−3.66 (0.0026)	−3.31 (0.0046)
		9–11	94.53	5.47	6.03	89.27	4.69	4.57	90.30	5.14	5.93 (0.0001)	−5.94 (0.0001)	−3.76 (0.0023)
IL2	TF0	9–14	93.71	6.29	5.11	88.76	6.13	1.47	92.29	6.24	1.96 (0.0407)	−1.96 (0.0408)	−1.92 (0.0433)
		9–11	93.32	6.68	5.78	87.99	6.23	0.58	92.79	6.63	1.00 (0.1717)	−1.00 (0.1717)	−1.00 (0.1717)
	TF1	All	94.11	5.89	18.25	78.70	3.05	17.47	79.18	3.35	84.16 (0.0000)	−76.65 (0.0000)	−28.19 (0.0000)
		22–24	93.71	6.29	27.44	71.90	0.66	27.24	71.97	0.79	309.28 (0.0000)	−164.57 (0.0000)	−52.13 (0.0000)
	TF2	All	93.77	6.23	5.48	89.44	5.09	1.57	92.47	5.96	1.96 (0.0407)	−1.96 (0.0408)	−1.77 (0.0554)
		9–11	92.67	7.33	8.46	86.76	4.79	0.85	92.08	7.07	1.00 (0.1717)	−1.00 (0.1717)	−1.00 (0.1717)

[a]Percentages according to the solutions associated with the best objective value.
[b]Average percentages averaged over ten solutions. If a solution is infeasible in terms of the number of DRT passengers, they are replaced by the FLS results.

7.2. Transportation outcomes

In this section, we aim at evaluating the impact of integrating DRT services inside fixed lines and schedule mobility system over different regions and for different time frames. Although the objective is to maximize the profit for the operator, we refrain from comparing the profit for the FLS scenario with the profit from the integrated network, since, we have incomplete information on all costs and parameters such as the required number of buses to operate an FLS system. This lack of information prevents us from making a fair comparison between the profit of the two networks, because the costs of the DRT vehicles should be considered when integrated in the FLS network. Consequently, we make the comparison scheme focused on the changes in the service level quantified by the average travel time, travel distance, waiting time, and number of transfers for passengers from solely FLS network to the integrated case. Table 10 summarizes these comparisons.

Table 9 reports the expected percentage of passengers who are served by either FLS, or DRT, as well as the expected percentage of the passengers who decide to opt-out for each instance scenario. As previously mentioned, the ALNS algorithm is implemented for ten different seeds. As a result, we report both the average percentages over these ten solutions as well as the percentages corresponding to the solution with the best objective value. The number of DRT trips is limited, therefore, when the expected number of these trips exceed the limit, the solution becomes infeasible. To compute the average over the ten ALNS solutions when one or multiple seeds result in infeasible solutions, we use the results from the case where only FLS is applied to calculate the average. The first three columns in Table 9 report the characteristics of instances based on the information presented in Table 6, time frames during the week and discretized time slots during the day.

The columns underneath “Only FLS” show the usage percentage of the public transport system during different time frames and over different hours of the day. The columns under “Best Integrated” present the shares of FLS and DRT modes as well as the percentages of dropouts associated with the solutions having the best objective value for the integrated transport network. The three

Table 10
Service level comparison between only FLS and inter-modal network generated by the ALNS algorithm based on the average travel time, travel distance, waiting time, and number of transfers of passengers.

Instance	Time frame	Hour	Average improvement network				T-statistic (p-value)			
			Travel time (s)	Distance (m)	Waiting time (s)	Number of Transfers	Travel time (s)	Distance (m)	Waiting time (s)	Number of Transfers
IL1	TF0	All	528.27	3234.75	105.21	0.17	2.93 (0.0168)	6.42 (0.0001)	3.16 (0.0116)	4.24 (0.0017)
		9–14	−75.58	1197.37	80.38	−0.31	−0.99 (0.3480)	2.72 (0.0236)	3.50 (0.0067)	−2.49 (0.0344)
		9–11	333.39	1171.71	31.36	−0.19	2.16 (0.0591)	2.77 (0.0218)	2.75 (0.0225)	−0.85 (0.4174)
	TF1	All	−249.29	999.83	94.85	0.07	−2.32 (0.0455)	1.37 (0.2039)	4.41 (0.0017)	0.81 (0.4388)
		22–24	−452.14	287.00	156.80	0.29	−3.95 (0.0034)	0.45 (0.6634)	6.84 (0.0001)	6.79 (0.0001)
	TF2	All	−116.28	3503.23	156.98	0.06	−2.40 (0.0399)	3.43 (0.0075)	2.92 (0.0170)	0.30 (0.7710)
		9–11	179.69	910.32	57.20	0.09	2.37 (0.0419)	2.59 (0.0292)	2.99 (0.0152)	2.71 (0.0240)
IL2	TF0	9–14	40.87	530.38	18.03	−0.05	1.21 (0.2571)	1.77 (0.1105)	1.95 (0.0830)	−1.90 (0.0899)
		9–11	64.62	170.67	1.01	0.01	1.00 (0.3434)	1.00 (0.3434)	1.00 (0.3434)	1.00 (0.3434)
	TF1	All	114.14	2756.81	175.12	0.16	4.16 (0.0024)	18.32 (0.0000)	45.27 (0.0000)	2.77 (0.0218)
		22–24	937.73	295.60	163.12	−0.13	62.81 (0.0000)	2.99 (0.0152)	63.59 (0.0000)	−1.74 (0.1159)
	TF2	All	78.25	482.61	23.22	0.01	1.74 (0.1159)	1.49 (0.1704)	1.96 (0.0816)	0.81 (0.4388)
		9–11	336.65	−455.14	0	−0.02	1.00 (0.3434)	−1.00 (0.3434)	NA (1.000)	−1.00 (0.3434)

columns under “Average Integrated” depict the average percentages of FLS, DRT and dropouts over ten solutions for each instance scenario. Based on the results, we observe that for both regions, during late evening hours and off-peak days, the share of DRT is high that results in reduction of passengers drop-out percentage (i.e., improved service level). Therefore, we evaluate the effect of integrating DRT into the FLS network using statistical tests shown in the last part of the table under “T-statistic”. We use the sample of ten ALNS solutions for each instance scenario to perform the statistical tests.

We aim at testing whether using an integrated mobility network during specific hours result in significant usage of DRT trips (i.e., the expected number of FLS trips and passengers drop-outs is reduced significantly). Let μ_{FLS} and $\mu_{\text{opt-out}}$ show respectively, the expected percentage of passengers using FLS and the expected percentage of opt-outs in the case where only FLS is offered. And, let μ'_{FLS}, μ'_{DRT} and $\mu'_{\text{opt-out}}$ be the average expected percentages of passengers who use either FLS or DRT or decide to opt-out in the integrated network. Then, we use the following one-sided T-tests. For the expected percentage of FLS passengers, we test $H_0 : \mu_{\text{FLS}} \leq \mu'_{\text{FLS}}$ against $H_1 : \mu_{\text{FLS}} > \mu'_{\text{FLS}}$. For the expected percentage of DRT passengers, we test $H_0 : \mu'_{\text{DRT}} = 0$ against $H_1 : \mu'_{\text{DRT}} > 0$. Finally, for the expected percentage of passengers who opt-out, we test $H_0 : \mu_{\text{opt-out}} \leq \mu'_{\text{opt-out}}$ against $H_1 : \mu_{\text{opt-out}} > \mu'_{\text{opt-out}}$.

From the results in Table 9, we see that in most cases the null hypothesis is rejected at 5% significance level. There are a couple of time frames for which we cannot reject the null hypothesis at this significance level, namely in Gooi en Vechstreek at TF0 from 9–11 and at TF2 up until 11 o’clock. The reason is that the ALNS could not find a feasible solution for some of the instances. We have tested the sensitivity of the results of the statistical tests against the number of runs. Our findings show that if a significance conclusion is achieved for the average value based on the sample of 10 solutions, it is already significant for a sample with a smaller number of solutions. Based on our experiment, the p-values are not monotonically decreasing in the number of runs.

To evaluate the service level, we consider multiple performance measures, namely the travel time, travel distance, waiting time, and number of transfers. We compute these values for both scenarios (i.e., only FLS network and integrated inter-modal network) and we calculate the difference. A positive value indicates an improvement (for the associated performance measure) in the integrated inter-modal network. We evaluate whether the average improvement over all passengers is significantly different from zero by using a t-test. The average improvement with their corresponding t-tests and p-values are given in Table 10. The table shows that not all changes in the performance measures are significantly different from zero. For example, for the full region Gooi en Vechtstreek (IL2) during workdays, there is no significant improvement in any of the performance measures. Furthermore, for the cases where the improvement is significant, it does not necessarily imply the universality of this outcome over all indicators. For example, in Hilversum (IL1) during workdays (TF0) between 9–14, a significant improvement is observed for travel distance and waiting time at the cost of a significant increase for the number of transfers (i.e., improvement is negative). There are indeed cases with significant

Table 11
Results of the two-sample test when varying β_{dist} with +/- 5%.

Instance	Time frame	$\beta_{dist} - 5\%$			$\beta_{dist} + 5\%$		
		Average % Dropouts	Degrees of freedom	T-statistic (p-value)	Average % Dropouts	Degrees of freedom	T-statistic (p-value)
IL1	TF0	4.1047	17.9246	91.1317 (<0.0001)	4.7542	14.2291	−57.0111 (<0.0001)
	TF1	3.9701	17.7873	1.4010 (0.0892)	4.5076	16.8012	−2.5156 (0.0112)
	TF2	4.1685	17.9999	12.1472 (<0.0001)	4.7985	17.9917	−9.9352 (<0.0001)
IL2	TF1	3.2605	17.9613	2.7772 (0.006223)	3.6500	12.8515	−3.4033 (0.0024)
	TF2	5.4766	17.0077	6.4118 (<0.0001)	6.1315	17.7460	−2.0755 (0.0264)

Table 12
Results of the two-sample test when varying $\beta_{\mathrm{VOT}}^{\mathrm{IVTT}}$ with +/- 5%.

Instance	Time frame	$\beta_{\mathrm{VOT}}^{\mathrm{IVTT}} - 5\%$			$\beta_{\mathrm{VOT}}^{\mathrm{IVTT}} + 5\%$		
		Average % Dropouts	Degrees of freedom	T-statistic (p-value)	Average % Dropouts	Degrees of freedom	T-statistic (p-value)
IL1	TF0	4.1104	17.9215	101.8917 (<0.0001)	4.7293	16.8106	−80.2135 (<0.0001)
	TF1	4.1712	9.0029	0.4829 (0.3203)	4.6523	9.0054	−5.8856 (0.0001)
	TF2	4.1483	17.4564	15.1693 (<0.0001)	4.8207	17.7585	−9.6629 (<0.0001)
IL2	TF1	3.0360	12.7950	3.4509 (0.0022)	3.4528	16.8845	−2.4032 (0.0140)
	TF2	5.4124	17.0468	7.2358 (<0.0001)	6.1906	17.9989	−2.5053 (0.0110)

positive improvements across all indicators. For instance, the performance measures of IL1-TF2 and IL2-TF1 are positively improved. These instances correspond to the evening hours, Sundays and public holidays, which are periods with low demand.

Overall, the results suggest when DRT is integrated into the FLS network, the expected number of drop-outs significantly decrease. They also imply that integrating FLS and DRT services to introduce an inter-modal mobility network can lead to an improved service level for most cases. In this paper, we do not take into account scenarios in which some passengers change their start and end stops in response to sudden changes in the network. In the following section, we evaluate the sensitivity of the outcomes based on the parameters of the choice model.

7.3. Behavioral sensitivity analysis

In Section 6.1, we presented the parameter settings used to calculate the utility of different alternatives in Eqs. (1), (2) and (3). We aim at testing the impact of changes in the choice parameters on the service level (quantified by percentage of drop-outs). We evaluate how much the percentage of drop-outs would change while changing the value of each parameter by plus or minus 5%. We use a two-sample T-test to test whether the changes are significant. Table 11 presents the average percentage of passengers who opt-out when β_{dist} decreases or increases by 5%. When β_{dist} decreases, the utility of opting-out is reduced relative to the utility of using DRT or FLS and hence we expect the percentage of passengers who opt-out to decrease, see, Eqs. (1) and (2). We use a one-sided two-sample T-test where we test $H_0 : \mu_{\mathrm{opt-out}} \geq \mu_{\mathrm{opt-out}}^{-5\%}$ versus $H_1 : \mu_{\mathrm{opt-out}} < \mu_{\mathrm{opt-out}}^{-5\%}$ in which $\mu_{\mathrm{opt-out}}^{-5\%}$ shows the expected percentage of passengers who opt-out when β_{dist} decreases by 5% and $H_0 : \mu_{\mathrm{opt-out}} \leq \mu_{\mathrm{opt-out}}^{+5\%}$ versus $H_1 : \mu_{\mathrm{opt-out}} > \mu_{\mathrm{opt-out}}^{+5\%}$ in which $\mu_{\mathrm{opt-out}}^{+5\%}$ presents the expected percentage of passengers who opt-out when β_{dist} increases by 5%. The results show that changes in the sensitivity of passengers against traveled distance has a significant impact on the expected percentage of passengers who opt-out. Thus, when β_{dist} decreases by 5%, the number of passengers who opt-out decreases significantly.

Table 12 presents the average percentage of passengers who opt-out when $\beta_{\mathrm{VOT}}^{\mathrm{IVTT}}$ changes by plus or minus 5%. When $\beta_{\mathrm{VOT}}^{\mathrm{IVTT}}$ decreases, using the integrated mobility service becomes more attractive relative to opting-out from the network. As a result, we expect the number of passengers who choose none of these services to decrease (see, Eqs. (1) and (2)). In order to test the significance of this impact, we use a one-sided two-sample T-test with $H_0 : \mu_{\mathrm{opt-out}} \geq \mu_{\mathrm{opt-out}}^{-5\%}$ versus $H_1 : \mu_{\mathrm{opt-out}} < \mu_{\mathrm{opt-out}}^{-5\%}$ when $\mu_{\mathrm{opt-out}}^{-5\%}$ shows the expected percentage of passengers who opt-out when $\beta_{\mathrm{VOT}}^{\mathrm{IVTT}}$ decreases by 5% and $H_0 : \mu_{\mathrm{opt-out}} \leq \mu_{\mathrm{opt-out}}^{+5\%}$ versus $H_1 : \mu_{\mathrm{opt-out}} > \mu_{\mathrm{opt-out}}^{+5\%}$ when $\mu_{\mathrm{opt-out}}^{+5\%}$ presents the expected percentage of passengers who opt-out when $\beta_{\mathrm{VOT}}^{\mathrm{IVTT}}$ increases by 5%. The results indicate there is a significant effect on opt-out percentage when $\beta_{\mathrm{VOT}}^{\mathrm{IVTT}}$ decreases by 5%. Tables 11 and 12 summarize the results.

Although changing β_{dist} and $\beta^{\text{IVTT}}_{\text{VOT}}$ by 5% have a significant effect on the percentages of drop-outs, changing values of $\beta_{transfer}$ or $\beta^{\text{OVT}}_{\text{VOT}}$ has no significant impact on the expected percentage of passengers who opt-out. A possible explanation for this is that the number of trips with transfers is very limited, and therefore the relative utilities only change for a limited number of passengers.

The results show that changes to the parameters in the utility function affect the output of the model. Therefore, the effect of integrating DRT into an FLS network on the number of passengers that are served will be dependent on the relative preferences of the passengers. Therefore, integrating DRT in an FLS network can be effective in one region, but ineffective in another. Before the investment in purchasing DRT vehicles and altering the network, it is therefore worthwhile to analyze the behavior and preferences of the potential users of these systems.

8. Conclusion and future work

In this paper, we introduce an inter-modal public transport by integrating Demand Responsive Transport (DRT) services into an existing Fixed Line and Schedule (FLS) network. In this problem, the FLS network is taken as given where bus lines are predefined and fixed whereas for the DRT services the pick-up and drop-off locations are fixed while routes are flexible. For each bus station, we decide whether it should belong to the DRT, or the FLS or both networks. We introduce a mathematical model called choice-driven inter-modal service network design that we can solve to optimality for small instances. Due to its high computational time for larger instances, we introduce a tailored Adaptive Large Neighborhood Search (ALNS) algorithm to solve this problem efficiently.

Integrating DRT and FLS networks can improve the service level of the public transport system by increasing accessibility and mobility inclusion. This integration especially works well in off-peak hours during non-working days (and holidays) when the number of passengers traveling in the network is low. Implicitly incorporating passengers' behavior via a discrete choice model results in more realistic passenger assignment to each mode of transport and helps to better understand and evaluate the advantages of introducing such hybrid mobility services given already existing infrastructure. Our sensitivity analysis on choice parameters indicates that passengers are mostly sensitive against the "in-vehicle travel time" as well as the "traveled distance" when it comes to using this integrated public transport system. Our proposed framework can be easily adapted to other multimodal mobility services. **Impact of findings on policy:** Based on the results found in this study, it would thus be beneficial to use an integrated network with both DRT and FLS in low demand areas, especially during off-peak hours. Furthermore, using such an integrated network could work as a mid-way solution for expanding areas. This makes the area more attractive due to the high connectivity and therefore could increase the demand for public transport. This result is especially important when it comes to efficient public spatial usage in under development areas. If shared mobility is facilitated and encouraged this way by making them accessible and convenient, more private cars could be removed from the roads whose space can be dedicated to greener areas and public places.

For the extension of this research, we aim at capturing the dynamic aspect of demand when real-time changes in the decisions of passengers can be taken into account. In addition, fleet sizing of the DRT system can be included as a decision variable instead of being an input to the proposed mathematical model.

CRediT authorship contribution statement

Shadi Sharif Azadeh: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Data curation. **J. van der Zee:** Conceptualization, Methodology, Writing – original draft. **M. Wagenvoort:** Methodology, Writing – original draft, Writing – review & editing, Investigation, Conceptualization, Validation.

Appendix. Linearized constraints

Some of the constraints given in Section 5 are non-linear. They can be linearized as presented below. The first non-linear constraint in Section 5 is Constraint (9). This constraint sets a_{od} such that it is equal to one whenever DRT is necessary for a trip from bus station $o \in S$ to bus station $d \in S$. This can be linearized by considering the following constraints:

$$a_{od} \geq 1 - \sum_{b \in \mathcal{B}} y_{bo} \qquad \forall o, d \in \mathcal{S} \tag{25}$$

$$a_{od} \geq 1 - \sum_{b \in \mathcal{B}} y_{bd} \qquad \forall o, d \in \mathcal{S} \tag{26}$$

$$a_{od} \leq 1 - \frac{1}{|\mathcal{B}|} \sum_{b \in \mathcal{B}} y_{bo} + \mathcal{I}_{od} M \qquad \forall o, d \in \mathcal{S} \tag{27}$$

$$a_{od} \leq 1 - \frac{1}{|\mathcal{B}|} \sum_{b \in \mathcal{B}} y_{bd} + (1 - \mathcal{I}_{od}) M \qquad \forall o, d \in \mathcal{S} \tag{28}$$

Afterwards, the other two constraints that are required to be linearized are Constraints (10) and (11). These variables represent whether scenarios $\{DRT\}$ and $\{DRT, FLS\}$ are offered for a trip from bus station $o \in S$ to bus station $d \in S$, respectively. These variables can both be determined by using a minimization constraint and hence can be linearized as follows:

$$b_{od} \leq x_o \qquad \forall o, d \in \mathcal{S} \tag{29}$$

$$b_{od} \leq x_d \qquad \forall o, d \in \mathcal{S} \tag{30}$$

$$b_{od} \leq a_{od} \qquad \forall o, d \in \mathcal{S} \tag{31}$$

$$b_{od} \geq -2 + x_o + x_d + a_{od} \qquad \forall o, d \in \mathcal{S} \tag{32}$$

$$c_{od} \leq x_o \qquad \forall o, d \in \mathcal{S} \tag{33}$$

$$c_{od} \leq x_d \qquad \forall o, d \in \mathcal{S} \tag{34}$$

$$c_{od} \leq 1 - a_{od} \qquad \forall o, d \in \mathcal{S} \tag{35}$$

$$c_{od} \geq -1 + x_o + x_d - a_{od} \qquad \forall o, d \in \mathcal{S} \tag{36}$$

To determine whether scenario of only $\{FLS\}$ is offered, Constraint (12) is used. This is a maximization constraint that can be formulated as:

$$d_{od} \leq 1 - a_{od} \qquad \forall o, d \in \mathcal{S} \tag{37}$$

$$d_{od} \leq 1 - c_{od} \qquad \forall o, d \in \mathcal{S} \tag{38}$$

$$d_{od} \geq 1 - a_{od} - c_{od} \qquad \forall o, d \in \mathcal{S} \tag{39}$$

Finally, n^b_{ij} denotes whether bus line b stops at stop σ^b_j directly after stop σ^b_i or not. This constraint can be linearized as follows:

$$n^b_{ij} \leq y_{b\ \sigma^b_i} \qquad \forall i, j \in \{0, \dots, |\sigma|\}, b \in \mathcal{B} \tag{40}$$

$$n^b_{ij} \leq y_{b\ \sigma^b_j} \qquad \forall i, j \in \{0, \dots, |\sigma|\}, b \in \mathcal{B} \tag{41}$$

$$n^b_{ij} \leq 1 - \frac{1}{|\sigma^b|} \sum_{s=i+1}^{j-1} y_{b\ \sigma^b_s} \qquad \forall i, j \in \{0, \dots, |\sigma|\}, b \in \mathcal{B} \tag{42}$$

$$n^b_{ij} \geq -1 + y_{b\ \sigma^b_i} + y_{b\ \sigma^b_j} - \sum_{s=i+1}^{j-1} y_{b\ \sigma^b_s} \qquad \forall i, j \in \{0, \dots, |\sigma|\}, b \in \mathcal{B} \tag{43}$$

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