

# Assessing the potential of feeder DRT services in urban outskirts

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## 1 Introduction

Demand-Responsive Transport (DRT) can potentially improve public transport offering in urban outskirts, where conventional bus services often struggle to meet dispersed demand efficiently. Despite this promise, many real-world DRT implementations fail—often due to a mismatch between service design and actual travel demand patterns, or an over-reliance on excessive flexibility (Currie and Fournier, 2020). A key determinant of DRT success is its ability to spatially and temporally concentrate demand (Enoch et al., 2006). While extensive research has explored operational characteristics such as pricing, fleet sizing, and vehicle rebalancing, relatively little attention has been paid to the design of DRT service areas. Most studies treat DRT as a standalone mode operating either across the entire study area, and those that consider service design, do so from an operator-centric perspective and suggest zones in high density urban centres (Bischoff et al., 2018; Kaddoura et al., 2020).

In contrast, we explore the use of DRT as a feeder service, constrained to areas with poor public transport coverage but dispersed travel demand. Such areas are typically located on the urban fringe, where the lower travel demand does not facilitate cost-effective fixed-route bus services. This approach to service area design aligns more closely with an environmental perspective, as it aims to assess the potential for feeder DRT to reduce private car use and overall vehicle km on the network by enabling more intermodal journeys.

We examine this concept in the context of Leeds, UK, using an agent-based simulation framework (MAT-Sim) (Axhausen et al., 2016) with a discrete mode choice extension (Hörl et al., 2018; Hörl, 2021). We simulate scenarios where DRT serves as a first- and last-mile connector (Chouaki and Hörl, 2024), and compare mode shift in scenarios where DRT is constrained to service areas delineated through spatial clustering of Origin-Destination (OD) flow data with scenarios where DRT can operate freely across the entire study area.

## 2 Methodology

### 2.1 Candidate DRT zones

Candidate DRT zones are identified using spatial clustering techniques applied to origin-destination (OD) flow data (Tao and Thill, 2016). The process involves: (a) identifying OD pairs where gaps in public transport provision exist, and (b) clustering these pairs to delineate suitable DRT service areas. To extract our DRT zones, a further step is carried out to remove parts of the cluster that overlap with high-frequency

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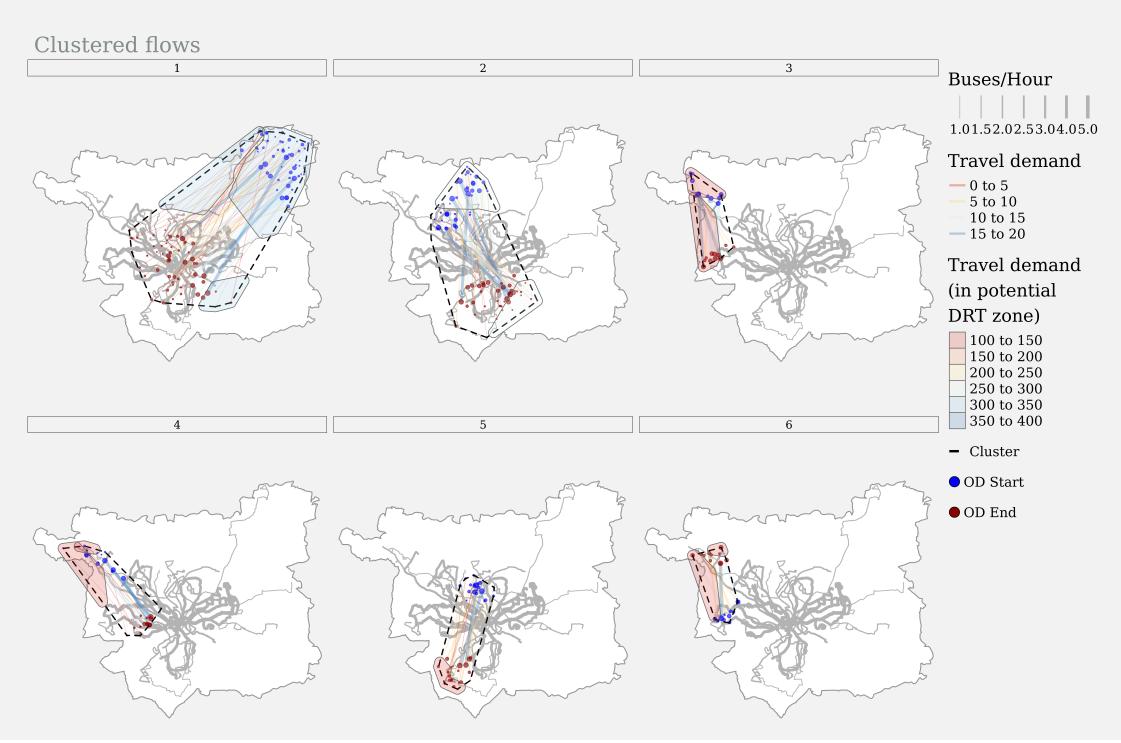


Figure 1: Results from clustering OD flow data

bus routes (so that the DRT feeds, and does not compete with, these routes). Clustering results can be seen in Figure 1.

## 2.2 Simulation setup

Our candidate zones are tested in a MATSim simulation. As input to the simulation, a synthetic population with activity plans is generated using a custom pipeline<sup>1</sup>. The pipeline enriches an existing synthetic population (Salat et al., 2023) through activity scheduling and location assignment, and includes calibration parameters and validation checks.

For our simulation, we use the discrete mode choice extension (Hörl, 2021) with a multinomial logit model for Leeds (Tsoleridis et al., 2022). DRT utilities are obtained from public transport (as done in Räth et al. (2023)). The feeder extension (Chouaki and Hörl, 2024) is used to allow users to choose one of (a) the existing modes, (b) a standalone DRT service, or (c) a PT trip with a feeder DRT connection.

## 3 Results and Conclusion

The simulation results demonstrate how the spatial configuration of DRT service areas influences travel behaviour, particularly the role of DRT as a feeder service. A city-wide DRT service produce the highest overall shift from public transport to DRT, but largely in the form of standalone DRT trips (Table 1). In contrast, zone-based services—focusing on peripheral areas with limited public transport—encourage greater use of DRT as part of a multimodal journey, particularly as a feeder to public transport. This suggests that geographically constrained services may be more effective at reinforcing, rather than replacing, the existing

<sup>1</sup><https://github.com/Urban-Analytics-Technology-Platform/acbm>

Table 1: Which modes are DRT trips coming from?

For each mode, we show: Number of Trips shifted to DRT (% of mode total that shifted to DRT). The service area column distinguishes between a city-wide service (drt), a service in the Zone-based service in the North East (drtNE) and a zone-based service in the North West (drtNW). Alone refers to a standalone DRT trip for a whole journey, while feeder refers to a DRT trip for part of a PT journey

Fleet Size	Service Area	Car		Public Transport		Bike		Walk		Taxi	
		Alone	Feeder	Alone	Feeder	Alone	Feeder	Alone	Feeder	Alone	Feeder
100	drt	157 (0.03)	27 (0) (1.79)	1979 (0.21)	229 (2.75)	78 (NA)	NA (NA)	1301 (1.29)	46 (0.05)	1332 (4.35)	50 (0.16)
	drtNE	33 (0.01)	160 (0.03)	148 (0.13)	652 (0.59)	38 (1.34)	7 (0.25)	207 (0.21)	21 (0.02)	133 (0.43)	186 (0.61)
	drtNW	177 (0.03)	202 (0.04)	405 (0.37)	1024 (0.93)	21 (0.74)	6 (0.21)	546 (0.54)	68 (0.07)	202 (0.66)	236 (0.77)
200	drt	299 (0.05)	99 (0.02)	3484 (3.15)	587 (0.53)	115 (4.06)	3 (0.11)	2387 (2.37)	80 (0.08)	2256 (7.37)	116 (0.38)
	drtNE	33 (0.01)	168 (0.03)	152 (0.14)	666 (0.60)	38 (1.34)	7 (0.25)	208 (0.21)	21 (0.02)	136 (0.44)	188 (0.61)
	drtNW	176 (0.03)	212 (0.04)	407 (0.37)	1040 (0.94)	21 (0.74)	6 (0.21)	547 (0.54)	70 (0.07)	202 (0.66)	242 (0.79)
500	drt	511 (0.09)	187 (0.03)	5361 (4.84)	1300 (1.17)	183 (6.46)	7 (0.25)	4006 (3.98)	208 (0.21)	3358 (10.98)	238 (0.78)
	drtNE	33 (0.01)	171 (0.03)	155 (0.14)	675 (0.61)	39 (1.38)	7 (0.25)	206 (0.20)	21 (0.02)	136 (0.44)	189 (0.62)
	drtNW	175 (0.03)	209 (0.04)	405 (0.37)	1041 (0.94)	21 (0.74)	6 (0.21)	549 (0.55)	69 (0.07)	202 (0.66)	243 (0.79)
1000	drt	549 (0.10)	261 (0.05)	5918 (5.35)	1627 (1.47)	209 (7.37)	9 (0.32)	4425 (4.40)	261 (0.26)	3738 (12.22)	324 (1.06)
	drtNE	34 (0.01)	176 (0.03)	153 (0.14)	674 (0.61)	39 (1.38)	7 (0.25)	208 (0.21)	21 (0.02)	136 (0.44)	190 (0.62)
	drtNW	179 (0.03)	209 (0.04)	408 (0.37)	1045 (0.94)	21 (0.74)	6 (0.21)	549 (0.55)	67 (0.07)	202 (0.66)	243 (0.79)

How to read: 150 (0.03) = 150 trips shifted to DRT (0.03% of mode total shifted to DRT).

public transport network by pooling dispersed demand to a limited number of bus routes. For example, under a zone-based configuration, a higher proportion of users switch from private car or taxi to a combination of DRT and public transport. In these scenarios, feeder DRT trips represent a much higher % of total DRT trips and distance travelled (Table 2). Interestingly, they also allow a higher concentration of feeder trips per unique bus route (Figure 2). The addition of ridership on bus routes could lead to positive knock-on effects, such as improvements in route progress, which in turn could increase the appeal of intermodal DRT + PT trips.

The results provide insights into how targeted service areas and intermodal strategies impact DRT performance, offering guidance for optimising DRT deployment in car-dependent urban fringe areas. By identifying configurations that encourage the use of DRT as a feeder mode, we can mitigate potential unintended consequences, such as the shift of passengers from public transport and walking. At the same time, these configurations can improve the operational efficiency of both DRT and the bus routes they feed by pooling demand more effectively. Future work will focus on the temporal aspects of DRT service design, including spatiotemporal demand clustering and fleet size variations throughout the day. Further research is also needed to develop a more accurate utility estimator for trips that include a feeder DRT leg, as well as to model scenarios that further incentivise the use of DRT as a feeder service.

Table 2: DRT feeder statistics

Distinguishing between standalone and feeder DRT trips

Fleet Size	Service Area	Distance travelled (km)			Waiting times (s)		No. of trips			PT connections		
		Alone	Feeder	Feeder %	Alone	Feeder	Alone	Feeder	Feeder %	Feeder trips per bus route	Top 5 routes	
100	drt	51373	281	1	392	220	14343	2689	16	4	12	
	drtNE	5525	1934	26	191	140	575	1102	66	42	148	
	drtNW	9572	1480	13	186	138	1363	1626	54	42	166	
200	drt	87797	709	1	361	213	14713	2856	16	9	29	
	drtNE	5734	2114	27	172	137	577	1101	66	43	148	
	drtNW	9621	1517	14	162	120	1362	1638	55	43	167	
500	drt	133031	1587	1	274	178	15191	3115	17	19	67	
	drtNE	5740	2224	28	154	118	577	1107	66	43	150	
	drtNW	9535	1496	14	147	101	1361	1631	55	43	167	
1000	drt	147962	2096	1	209	141	15354	3276	18	25	84	
	drtNE	5638	2196	28	136	106	578	1109	66	43	151	
	drtNW	9586	1491	13	134	89	1368	1629	54	42	166	

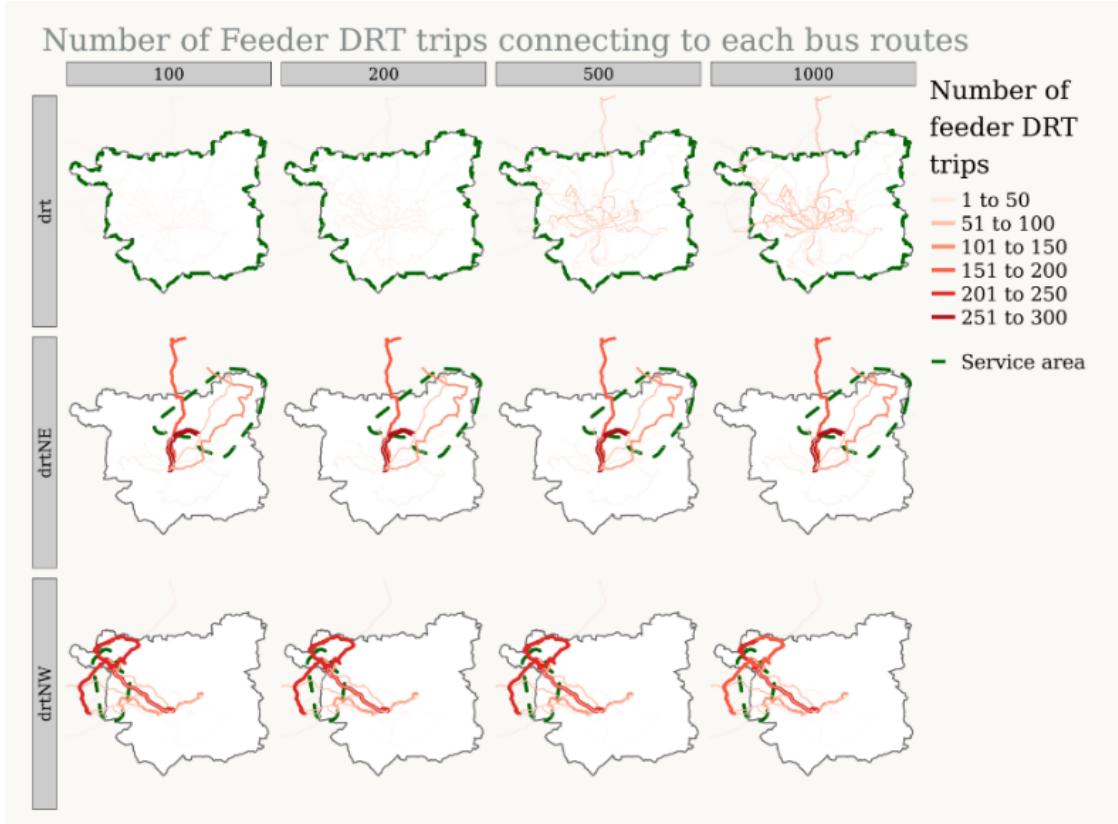


Figure 2: Number of feeder DRT trips connecting to each unique bus route. Lines represent unique bus routes, with line color representing the number of feeder trips that connect to the route

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