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Delineating potential DRT operating areas: An origin–destination clustering approach ☆

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ABSTRACT

Investment in Demand-Responsive Transport (DRT) has emerged as a sustainable transport intervention option for areas that are traditionally hard to serve by high frequency public transport. When used as a first- and last-mile feeder, DRT has the potential to reduce car dependency and enhance access to the wider network. However, many DRT schemes fail—often due to overly flexible, poorly targeted service areas that do not align with actual travel patterns, making efficient pooling difficult. While planners may already have a general sense of where DRT might be useful, there is limited guidance on how to identify precise operating zones based on spatiotemporal demand. This paper presents a method for identifying potential DRT service areas using spatial clustering of origin–destination (OD) flows. We apply the method in Leeds, UK, focusing on OD pairs with poor public transport supply and low potential demand. The approach identifies spatial clusters where demand is both underserved and sufficiently concentrated to support DRT operation. By narrowing service areas to zones where pooling is more likely and where DRT complements rather than competes with fixed-route services, the method helps address two key challenges in DRT planning. The results offer a reproducible, data-driven input for delineating preliminary DRT service areas—supporting strategic planning, integration with downstream agent-based models, and further refinement through local knowledge. The method provides a foundation for future work on designing DRT services that complement the public transport network, particularly in low-density urban peripheries.

1. Introduction

Bus networks form the backbone of many public transport systems across the world. They offer affordable mobility (an aspect that is important for social inclusion), mitigate congestion, and reduce emissions associated with car dependence. In many cities, bus services have grown gradually to meet increasing demand from the expanding urban core and peripheries, but the quality of service can suffer from issues such as poor access between neighbourhoods, inefficient network layouts, and poor route synchronisation (Ruiz et al., 2017). Existing research has been conducted on strategic and tactical redesign of bus networks to increase their attractiveness (Ibarra-Rojas et al., 2015; Kepaptsoglou & Karlaftis, 2009; Liu et al., 2021). However, advanced optimisation approaches cannot compensate for the fact that traditional bus services are most suited to dense areas with consistently high demand (Errico et al., 2013) and are inefficient for suburban areas, villages, and low-demand interurban areas (Papanikolaou et al., 2017).

Flexible mobility services, such as Demand Responsive Transport (DRT), have been proposed to serve such areas. We follow Davison et al. (2014) in defining DRT: a service that is (a) available to the general public, (b) provided by low capacity vehicles (relative to buses), (c) responsive to changes in demand, and (d) charged per passenger, not per vehicle. While DRT systems have a higher fixed cost per passenger than traditional fixed bus routes (Currie & Fournier, 2020), they aim to compensate for this by increasing passenger load factors while minimising additional distance through route circuity (Ryley et al., 2014). This balance is difficult to achieve, and even now as technological improvements drive the re-emergence of DRT, failure rates remain high and strongly correlated with operating costs (Currie & Fournier, 2020). When well integrated with high-frequency public transport, DRT may serve as an effective feeder mode—extending the reach of fixed-route services and offering an alternative to private car use in low-density areas.

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Extensive research has been done on DRT planning, but the focus is more on the tactical and operational level and less on the strategic level (Papanikolaou et al., 2017). Strategic-level methods that help identify potential DRT operating zones are important for two main reasons. First, if DRT service areas are based on spatial concentrations of demand, they are more likely to support efficient pooling—one of the main determinants of DRT viability (Enoch et al., 2006). Second, if DRT is to complement fixed-route services—as a feeder mode rather than a competitor—then service areas must be designed to reinforce integration rather than undermine it. While transport planners and operators often have a good understanding of local mobility needs, data-driven methods can complement this knowledge by helping identify specific service areas where travel demand is both concentrated and underserved. Existing approaches define DRT zones based on public transport accessibility gaps (Giuffrida et al., 2021; Räth et al., 2023) or through incremental adjustments to the bus network (Pinto et al., 2020; Zhao et al., 2021), but neither fully captures where DRT could be most effective based on actual travel demand.

In this study, we make both conceptual and methodological contributions to strategic DRT planning. Conceptually, we introduce a demand-driven framework for defining DRT service areas, shifting the focus from supply-based zoning to an approach that accounts for actual travel demand patterns. Methodologically, we apply spatial clustering of origin–destination (OD) flows and integrate it with an assessment of transport supply and demand to identify natural concentrations of travel demand that could be effectively served by DRT. The analysis is repeated across multiple time periods to account for variation in demand throughout the day, ensuring service areas reflect both spatial and temporal concentration. The focus is on identifying feasible service zones for DRT as a feeder to the fixed-route network in low-density areas. This framework ensures that DRT is only proposed in areas where (a) demand is sufficiently concentrated to support pooling, and (b) improved fixed-route bus services are unlikely to be a more appropriate solution. While spatial clustering of flow data is well-studied in spatial data mining, to our knowledge, this is the first paper to apply these methods for strategic DRT planning.

2. Literature review

DRT has become an umbrella term for flexible public transport. Services are classified based on typologies (Enoch et al., 2004) or scheduling and operational characteristics (D'este et al., 1994). Diagrammatic descriptions of these characteristics can be found in Mageean and Nelson (2003) and Pavanini et al. (2023).

The variety of service models and corresponding planning strategies reflects the complexity of DRT implementation. On the one hand, flexibility allows services to be tailored to local demand patterns. However, overly complex services or are prone to failure (Enoch et al., 2006). Inappropriate service selection could lead to poor user experience and unnecessarily high operating costs.

2.1. Planning DRT systems

Public transport planning, particularly for conventional bus services, follows a well-established sequential framework (Ceder & Wilson, 1986; Ibarra-Rojas et al., 2015) emcompassing *strategic*, *tactical*, and *operational* planning. The high failure rate of DRT services has been attributed to the absence of a similarly structured planning methodology (Papanikolaou et al., 2017).

In trying to map DRT research onto the above planning pillars, Papanikolaou et al. (2017) classify studies into two categories. At the strategic level, economic and econometric studies focus on area selection and investment appraisal. This includes research on defining the potential market and operating model of DRT systems (Mulley & Nelson, 2009) as well as cost comparisons between DRT and traditional public transport using analytical models (Nourbakhsh & Ouyang, 2012). At the tactical and operational level, operations research studies explore system typology and operational characteristics (see Vansteenwegen et al., 2022 for a comprehensive review).

While tactical and operational aspects have been extensively studied, identifying suitable areas for DRT remains a research gap (Papanikolaou et al., 2017). This gap has become increasingly relevant as DRT transitions from a niche service catering to specific user groups to an integrated component of public transport, aimed at improving accessibility for entire communities (Nelson et al., 2010).

2.2. Existing approaches to DRT service area delineation

2.2.1. Analytical approaches

Analytical models assess whether an area should be served by fixed-route or flexible (bus or DRT) services. These models often rely on idealised representations at the route level with pre-defined service areas (Li & Quadrifoglio, 2010; Quadrifoglio & Li, 2009; Sivakumaran et al., 2012). Liu and Ouyang (2021) propose a framework that optimises DRT zone size alongside public transport spacing and headways, but its reliance on homogeneous travel demand in a grid network limits real-world applicability. Wang et al. (2018) apply a similar model in a real study area (Calgary, Canada), but their approach also assumes uniform demand distribution and is focused on serving a single hub. While these models offer valuable insights into service feasibility, they rely on simplified demand assumptions and predefined service zones that do not account for actual travel patterns in a real-world context.

2.2.2. Accessibility-based approaches

Accessibility based approaches delineate DRT service areas in real city-level case studies. Some studies restrict DRT to areas with low public transport accessibility to address network gaps (Giuffrida et al., 2021; Räth et al., 2023). Others position DRT as a feeder service, serving buffer zones around rail stations (Oke et al., 2020). DRT investment decisions are then evaluated using measures of social equity (Giuffrida et al., 2021), or agent-based simulations (Oke et al., 2020; Räth et al., 2023), with the latter showing that restricting DRT to specific areas can mitigate mode shift from public transport. However, this approach faces two limitations. First, travel demand is not considered in the initial zoning configuration but is only used later on for network performance evaluation. The variability in mode share results suggests that generic accessibility rules do not generalise well across cities, making demand integration important. Second, public transport networks are treated as fixed constraints, with no reconfiguration being made to accommodate DRT.

2.2.3. Network reconfiguration approaches

Network reconfiguration approaches have also been used to delineate DRT service zones. Giuffrida et al. (2021) propose reallocating buses to improve service frequency on key routes connecting to rail stations, while adding DRT in areas with poor accessibility. While this approach factors in demand conceptually, it does not incorporate a structured approach to delineate zones based on actual demand data. Shen et al. (2018) adopt a similar approach but use demand data and opt to keep the busiest 90% of routes, replacing the remaining 10% with a flexible service.

Optimisation algorithms have also been developed to determine where to adjust public transport routes and introduce DRT. Pinto et al. (2020) formulate an optimisation problem that minimises passenger wait time by modifying route frequencies, removing routes, and adjusting DRT fleet sizes. While this approach uses travel demand to inform where to add DRT stops, it does not limit service areas, allowing DRT fleets to operate across an entire area. This is not ideal as simulation results have shown that competition with public transport, as well as increases in congestion and system-wide total VMT are likely when services are not constrained (Kagho et al., 2021; Oke et al., 2020; Räth et al., 2023). Zhao et al. (2021) formulate a similar optimisation problem that aims to minimise both travel time and fleet size of public transport and DRT by shortening bus routes and adjusting DRT service areas, but their work is applied to a model network with 5 bus lines.

These models focus on incremental adjustments to existing public transport networks rather than designing integrated public transport and DRT systems from scratch. While this reflects practical constraints—major bus network overhauls are rare—it also means that DRT zones tend to be confined to network edges (Zhao et al., 2021). However, DRT services could provide more flexible connectivity beyond these edges, linking passengers to multiple points along bus routes rather than just at terminals.

2.2.4. Advancing DRT service area delineation

While a number of studies have looked at strategic level DRT planning, existing methods do not fully integrate travel demand patterns into the initial zoning process. Analytical models rely on simplified demand assumptions and predefined zones, making them difficult to apply to real-world networks. Accessibility-based approaches identify DRT zones based on public transport accessibility gaps, but they do not assess whether demand is sufficiently concentrated to make services viable. Meanwhile, optimisation-based methods reconfigure bus networks based on demand, but they confine DRT to the ends of existing bus routes, potentially overlooking other areas where demand is high enough to support flexible services.

To ensure DRT service areas are optimally located, it is important to base them on observed spatial and temporal demand patterns (Kagho et al., 2021), rather than constrain them to the ends of existing bus routes. A method to delineate service areas based on spatial concentrations of travel demand could be useful in two ways: (a) as a simpler alternative to current optimisation-based approaches, addressing root causes of high DRT failure rates identified in the literature, or (b) as a way to generate preliminary DRT zones that serve as inputs for optimisation models. Starting with DRT zones informed by actual demand may lead to more effective network configurations compared to models that begin without predefined DRT zones.

The following section examines clustering techniques for identifying these demand concentrations directly from OD data, offering a data-driven foundation for DRT zone delineation.

2.3. Clustering techniques for identifying demand concentrations in travel patterns

By analysing OD flow data, clustering reveals travel demand concentrations, enabling a demand-driven definition of DRT service areas. We focus on clustering as standard methods for visualising OD data struggle to capture spatial and temporal variations in demand due to the volume of data being represented (Guo, 2009). Alternative methods like community detection (Guo, 2009) and edge bundling (Selassie et al., 2011) help reduce visual clutter and salience bias but compromise spatial information—community detection lowers spatial granularity, while edge bundling obscures distinct OD patterns. Since both are crucial for our analysis, we use clustering methods to identify patterns directly from raw OD data without altering its spatial characteristics.

Clustering methods can be broadly categorised into two groups (Song et al., 2019):

1. Spatial statistics-based methods, which identify anomalies in spatial homogeneity using measures such as Moran's I, Getis–Ord G, and Ripley's K. While effective for detecting presence of clusters at different spatial scales, these methods do not group data into clusters.
2. Hierarchical and density-based clustering methods, which group OD flows based on distance measures, offering more actionable insights for DRT planning.

Density-based clustering is particularly effective for identifying spatial clusters. Algorithms such as DBSCAN (*Density-based spatial clustering of applications with noise)* (Ester et al., 1996), HDBSCAN (Hierarchical DBSCAN) (Campello et al., 2013), and OPTICS (*Ordering Points To Identify the Clustering Structure*) (Ankerst et al., 1999) are widely used.

These algorithms rely on distance calculations, which are straightforward for points but less so for multilocation geometries like lines. Tao and Thill (2016a) developed methods to measure distances between lines, enabling their use in flow data (Fang et al., 2021; Tao & Thill, 2016b.; Tao et al., 2017). Other approaches incorporate a temporal dimension into cluster detection (Yao et al., 2018).

The ability of these algorithms to cluster OD 'flow' data without loss of spatial information is invaluable for understanding the spatial concentrations of demand that exist in a network. This research incorporates density-based clustering as part of a larger approach to identify travel demand concentrations in travel demand that could be served by DRT.

3. Methods

DRT services are most effective when aligned with actual travel demand (DfT, 2020). However, there is no standardised method for identifying demand gaps suitable for DRT in a way that ensures seamless integration with existing public transport networks. This section presents a novel approach to address this gap by identifying areas of unmet demand and clustering them to inform potential DRT operating zones.

Our method involves two key steps: (1) identifying demand gaps through a supply–demand analysis, and (2) clustering travel demand within these gaps to delineate DRT service areas. First, we define and measure public transport supply (Section 3.3.1) and potential demand (Section 3.3.2) to identify areas with inadequate service. Next, we introduce a clustering approach (Section 3.4) to reveal spatial concentrations of travel demand. This clustering is applied to two datasets prepared using the methods in Section 3.2: (1) OD pairs with poor public transport supply, and (2) OD pairs with both poor public transport supply and low potential demand.

The overall workflow is illustrated in Fig. 1. Our approach is applied to a case study city, Leeds (Section 3.1), to demonstrate its practical utility.

3.1. Case study

This research uses Leeds, UK, as a case study. As one of the largest European cities without rapid transit, Leeds relies heavily on buses (Fig. 2). The regional transport authority, West Yorkshire Combined Authority (WYCA), has set a net-zero target for 2038, requiring a 52% increase in bus mode share (WYCA, 2021a) —an ambitious goal given the 15% decline in annual bus trips from 2009 to 2019 (WYCA, 2021b).

Under the Bus Services Act (UK-Parliament, 2017), WYCA's Bus Service Improvement Plan aims to enhance bus services and better integrate multimodal transport (WYCA, 2021b). DRT is considered a means to improve access in low-density areas, and a pilot service (Flexibus) was trialled in East Leeds. However, during its 18-month pilot phase, it struggled with low ridership, covering only 5% of operating costs (WYCA, 2022). Its average of 1.38 passengers per trip reflected a service design that failed to effectively pool demand. Services that are informed by spatial concentrations in travel demand could improve DRT viability.

3.2. Demand data

The origin–destination matrices used in this analysis are derived from the GB Trip Database (GBTD),[1] a national dataset produced by

[1] https://cp.catapult.org.uk/project/great-britain-trip-database-portal/

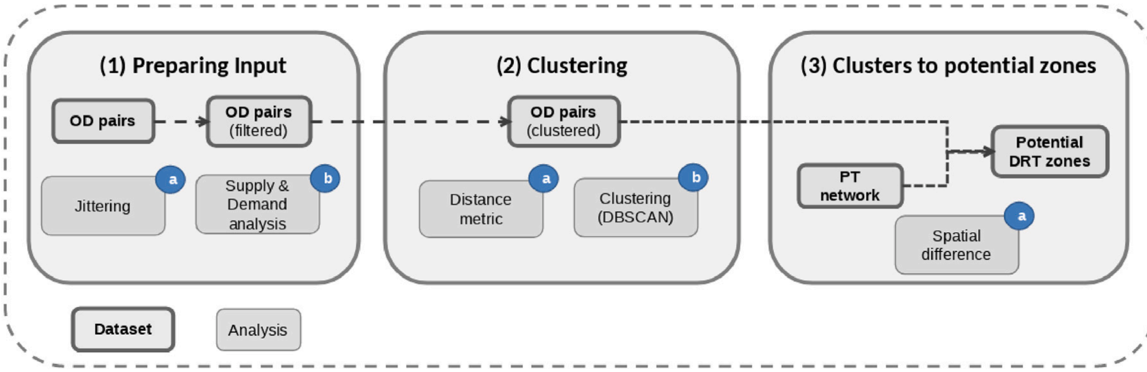


Fig. 1. Workflow for generating potential DRT zones. The workflow is split into 3 separate steps, and the analysis components of each step are given alphabetical labels to show the order they are carried out in.

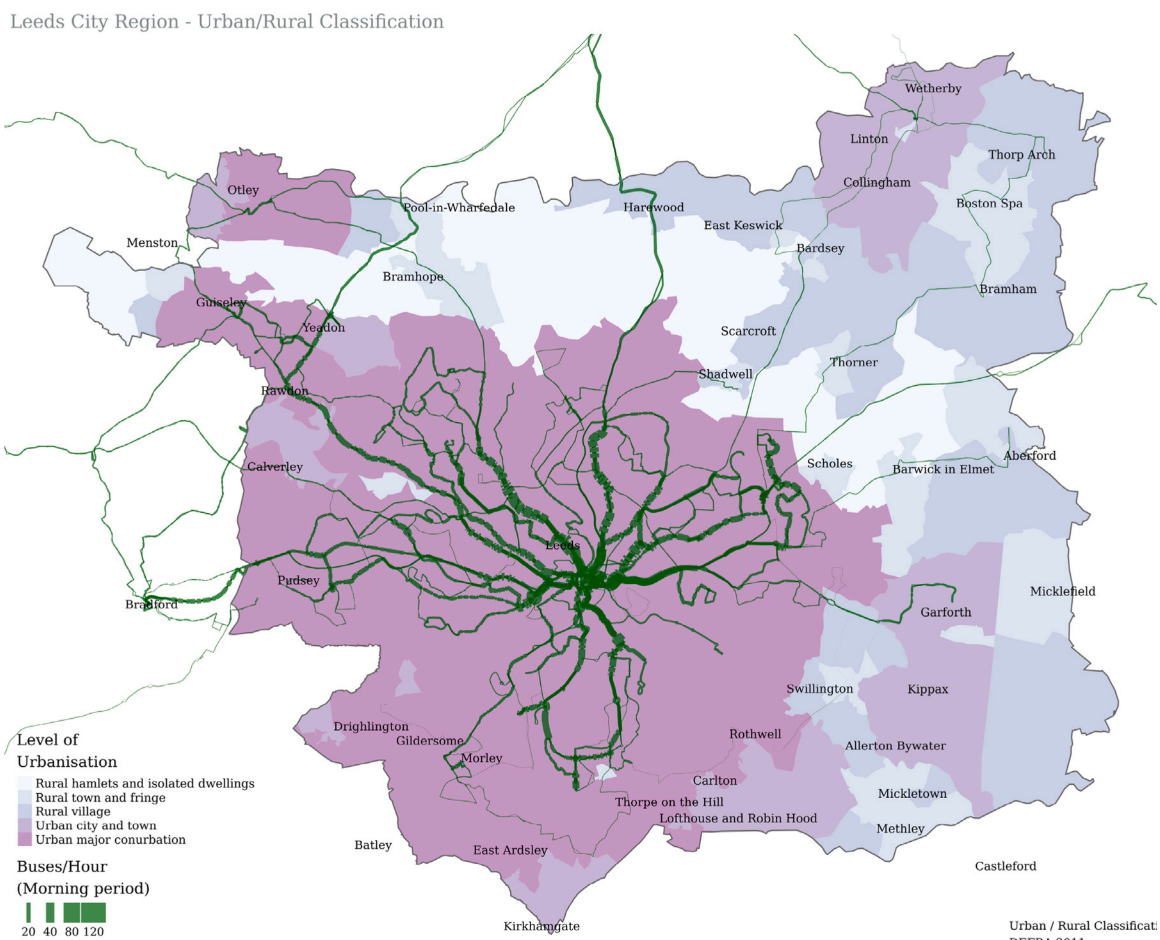


Fig. 2. Urban Rural Classification: Explained in the 2011 Rural–Urban Classification User Guide.

Telefónica (O2) in partnership with the UK Department for Transport. The data are based on anonymised mobile phone events, filtered to include only users with consistent daily activity over a 16-day window, and expanded to represent the wider population using area-level weighting factors. These factors are calculated at the Middle Layer Super Output Area (MSOA) level using comparisons with census commuting flows and travel survey data, helping to correct for demographic and spatial bias.

Trips are inferred from sequences of handover events (signal transfers between mobile cells) and dwell periods (extended time spent in one location). Trips are assigned to origin and destination zones based on users' repeated activity patterns. While no mobile dataset is error-free, the GBTD methodology offers a robust foundation for our OD analysis, and has been used in a study to generate activity patterns for an agent-based simulation (Franco et al., 2020).

For this study, we requested OD data for 2019 from Connected Places Catapult, covering all motorised road and rail trips in Great Britain. The request specified a date range and a zoning system based on MSOA boundaries. The resulting dataset provides the average number of trips between each zone pair, disaggregated by hour of day and weekday/weekend. To simplify the analysis, we aggregate the data into five broad time periods: 5–8am, 8–11am, 11am-–2 pm, 2–5 pm,

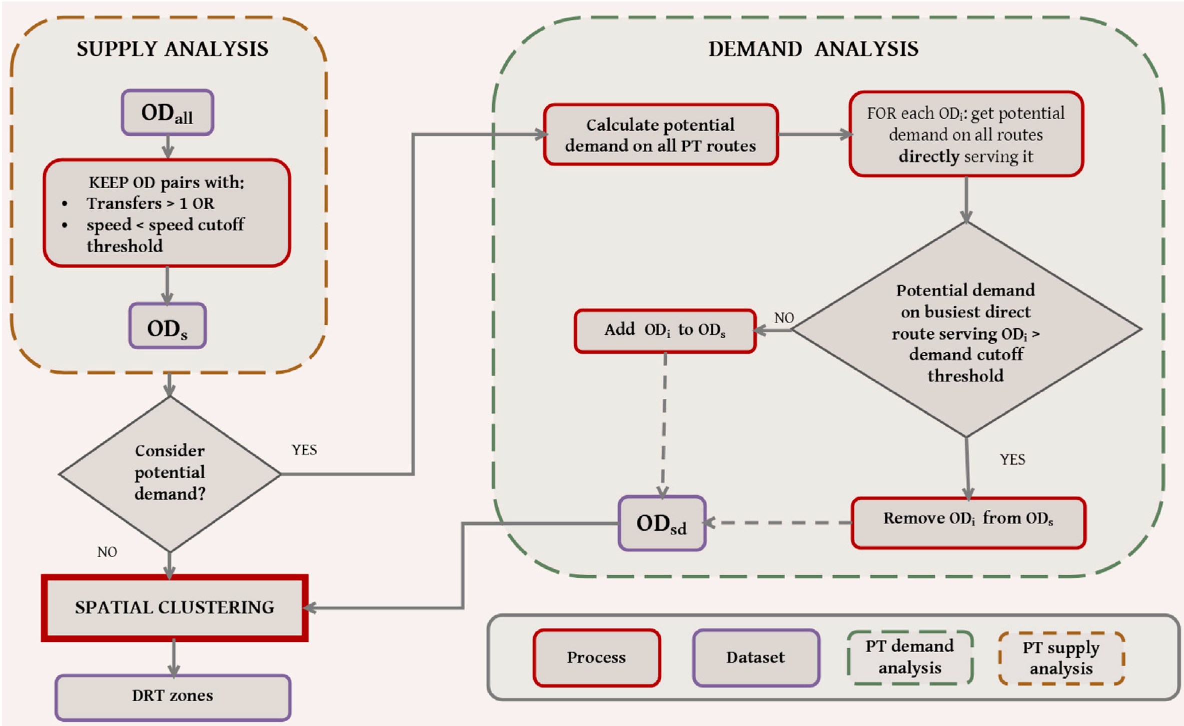


Fig. 3. Flowchart for determining input to clustering algorithm.

and 5–8 pm. However, the clustering method is compatible with other temporal resolutions and could be applied at finer levels where needed.

3.2.1. Disaggregating OD data

Our OD data is aggregated at the Middle Super Output Area (MSOA) level, a geographical unit defined by the Office for National Statistics (ONS) that represents areas with populations of 5000–15,000 people. Our study area, Leeds, is divided into 107 MSOAs. However, this aggregation level is too coarse for our clustering analysis. To address this, we apply jittering (Lovelace et al., 2022) to disaggregate OD pairs with high traveller counts into multiple smaller OD pairs. The start and end points of the new ODs are constrained to their original MSOAs, but are snapped probabilistically to subzones of 100 m^2 based on the population density distribution within each MSOA. A disaggregation threshold ensures no OD pair exceeds 100 people.

3.3. Preparing input data for clustering

After disaggregating the OD trip data, we need to decide which OD pairs to use for clustering. If we were to pass all OD pairs to the algorithm, then our clusters may include noise from OD pairs that are well served by public transport. We would also generate DRT zones that serve all demand, whereas our objective is to propose DRT zones that complement bus routes and fill the gaps in the bus network, as explained in Section 2.2. We identify gaps in public transport service provision by trying two different inputs: (1) OD pairs with poor public transport supply (OD_s), and (2) OD pairs with poor public transport supply and low potential demand (OD_{sd}).

OD_s is meant to suggest DRT zones that complement the existing bus network by only including the OD demand that is not well served by said network, as explained in Section 3.3.1. OD_{sd} is similar, but also excludes OD pairs that could be served by a better bus service. This exclusion is based on criteria explained in Section 3.3.2. The workflow for the supply and demand analysis is shown in Fig. 3. The number of OD pairs in each approach is shown in Table 1.

3.3.1. Supply analysis

A supply analysis is carried out to determine the OD pairs that are included in OD_s. The main components of transport supply are the road network, and the public transport timetables for buses and rail. We get the updated road network from OpenStreetMap. Bus timetable data is obtained in GTFS format from the Bus Open Data Service (BODS)[2] and rail data is obtained from the Rail Delivery Group.[3]

The OSM road network and timetable data are fed into a multimodal routing engine (Pereira et al., 2021) to calculate travel time between zones. Euclidean distance between an OD pair is used to calculate travel speed. OD pairs with speed below a defined speed cutoff threshold or that require more than one transfer to be reached by public transport are considered to have poor supply. We use the 50th percentile of OD speeds as our threshold, but the distribution of OD speeds is shown in Appendix A.1.

3.3.2. Demand analysis

Our transport demand analysis is meant to identify bus routes that warrant an increase in route frequency. We calculate potential demand on all routes, and identify routes that have sufficient potential demand to warrant said increase in frequency. Potential demand is defined here as the demand along a bus route that could theoretically be served by the route (i.e. the route directly connects between the origin and destination zones). We only look at existing travel patterns and do not consider induced demand that could result from a better bus service.

To calculate potential demand on each public transport route, we followed a three-step process. First, we identified which routes directly serve each OD pair—defined as routes that pass through both the origin and destination zones. An OD pair may be served by multiple common lines. Second, we assigned demand from each OD pair to its corresponding routes. As our flow data contains total trip volumes for all MSOA pairs, we distributed demand equally across all common lines serving each OD (see Dios Ortúzar and Willumsen (2024) for overview

[2] https://data.bus-data.dft.gov.uk/
[3] https://data.atoc.org/

Table 1
Number of OD pairs in after each step.

Name	No. of OD pairs	Description
OD_{all}	50,301 (100%)	All OD pairs in the study area that have people travelling between them
OD_s	40,183 (80%)	OD pairs with poor public transport supply (see Fig. 3)
OD_{sd}	34,837 (68%)	OD pairs with poor public transport supply and low potential demand (see Fig. 3)

of methods). Although frequency-based assignment[4] may better reflect current conditions, we opted for equal assignment to represent demand potential under improved frequencies. Finally, we calculated the total potential demand on each route by summing the contributions from all relevant OD pairs.

We then excluded OD pairs from our target set OD_{sd} if the potential demand on the busiest direct route serving them exceeded our route demand threshold (see Fig. 3). OD pairs with high potential demand are not included in OD_{sd} as there is sufficient demand to justify a high frequency bus route, even if one does not currently exist. The heuristic for calculating potential demand allows us to avoid serving areas with DRT just because there is poor public transport supply; there must also be insufficient demand to warrant a high frequency bus route.

We set a threshold of $p75$ which implies that service on the top 25% of routes in terms of potential demand is sufficient to warrant higher-frequency routes and should not be part of our DRT analysis. In reality, this % could be edited based on the budget available for additional buses or operator figures on the demand necessary to provide a service with a certain headway. Appendix A.1 shows the number of OD pairs retained for different supply and demand thresholds.

3.4. Clustering flow data

After filtering the OD trip data in the supply and demand analysis, we apply a spatial clustering approach to identify spatial concentrations in travel demand. Spatial statistics methods for cluster detection — such as DBSCAN (Ester et al., 1996) — have mainly been developed for point data. Recently custom distance metrics that account for the multilocation nature of line data have allowed these methods to extend to flow data (Tao & Thill, 2016a).

We use the DBSCAN algorithm which takes two parameters: epsilon (the search radius to look for clusters) and minimum points (or minpts — the minimum number of points required to be inside the specified radius from a given point for a cluster to form around it). The distances between OD flows are the values that are compared to epsilon. It is calculated using the custom distance metric introduced by Tao and Thill (2016a): let the flow process F_i with origin $O_i(x_i, y_i)$ and $D_i(u_i, v_i)$ be modelled as a vector point with 4 coordinates $F_i(x_i, y_i, u_i, v_i)$. The calculation for flow dissimilarity (FDS_{ij}) between F_i and F_j is shown in Eq. (1).

$$FDS_{ij} = \sqrt{\frac{\alpha[(x_i - x_j)^2 + (y_i - y_j)^2] + \beta[(u_i - u_j)^2 + (v_i - v_j)^2]}{L_i L_j}} \tag{1}$$

where α and β control the relative importance of the origins/destinations: higher α means we focus more on origins and vice-versa ($\alpha > 0$; $\beta > 0$; $\alpha + \beta = 2$). Dividing by the geometric mean of the flow lengths (L_i and L_j) implies that, all else being equal, flow pairs of longer length are considered closer than shorter ones. A parameter sweep is done to determine feasible DBSCAN parameter combinations. A sensitivity analysis is then carried out to determine if minor changes to the parameters affect the clustering results.

[4] Demand is distributed between the common lines (routes) in proportion to the frequency of each route.

3.5. Clusters to potential DRT zones

Our clustering algorithm may return clusters that cover large geographical areas. These areas may, in turn, be partly served by high frequency bus services. Having DRT cover the entirety of such areas may not be optimal as it (a) may provide competition to these bus services, and (b) may necessitate complex operations that make the service more prone to failure (as mentioned in Section 2).

We therefore propose a subsequent step to extract potential DRT zones from the obtained clusters. We get the spatial difference between each cluster and the high frequency bus routes in the study area (routes with at least 1 bus per hour), leaving us with polygons that extend to but do not overlap with said routes. This is in line with a DRT service that acts as a complimentary first/last mile connector.

4. Results

This section presents clustering results for the morning peak period. As noted in Section 3.2, the analysis was conducted for all time periods, but we use the morning peak to illustrate results in detail.

Section 4.1 focuses on clustering based solely on transport supply. Section 4.2 extends this analysis by integrating transport demand, allowing for a more targeted identification of underserved OD flows. This section also includes a more detailed examination of individual cluster composition, analysing trip homogeneity in terms of length and directionality (see Section 4.2.1).

Finally, as part of the transport demand analysis, Section 4.2.2 presents a temporal extension of the clustering results, showing how aggregate spatial patterns vary across different times of the day.

4.1. Clustering based on transport supply only

Fig. 4 and Fig. 5 present the clustering results based on OD_s and OD_{sd} respectively. Each facet in the plots represents a cluster, with the following components:

(a) OD pairs: Represented as straight lines, with colour indicating trip volume. Endpoints are shown, scaled by the number of trips.

(b) Cluster areas: Defined by a concave hull around OD pairs, shown with a black dotted border.

(c) Bus routes: High-frequency services ($\geqslant$ 1 bus/hour during the morning peak) are overlaid for reference (Section 3.3.1).

(d) Potential DRT zones: Areas within each cluster not covered by high-frequency bus routes, visualised using the spatial difference between cluster areas and bus routes (see Section 3.5). Colours indicate the total trip volume of OD pairs making up the cluster.

The spatial clusters identified (based on OD_s) in the analysis reveal several distinct patterns of travel demand, both on the outskirts and closer to the urban core Fig. 4. In the south and south-west, Clusters 8 and 10 capture trips from areas such as Batley and Kirkhamgate to the city centre, where high-frequency public transport is largely absent. Cluster 6 connects the south to locations just north of the urban core, but public transport routes in this area are limited. Even where services exist, they primarily connect to the city centre, and travellers

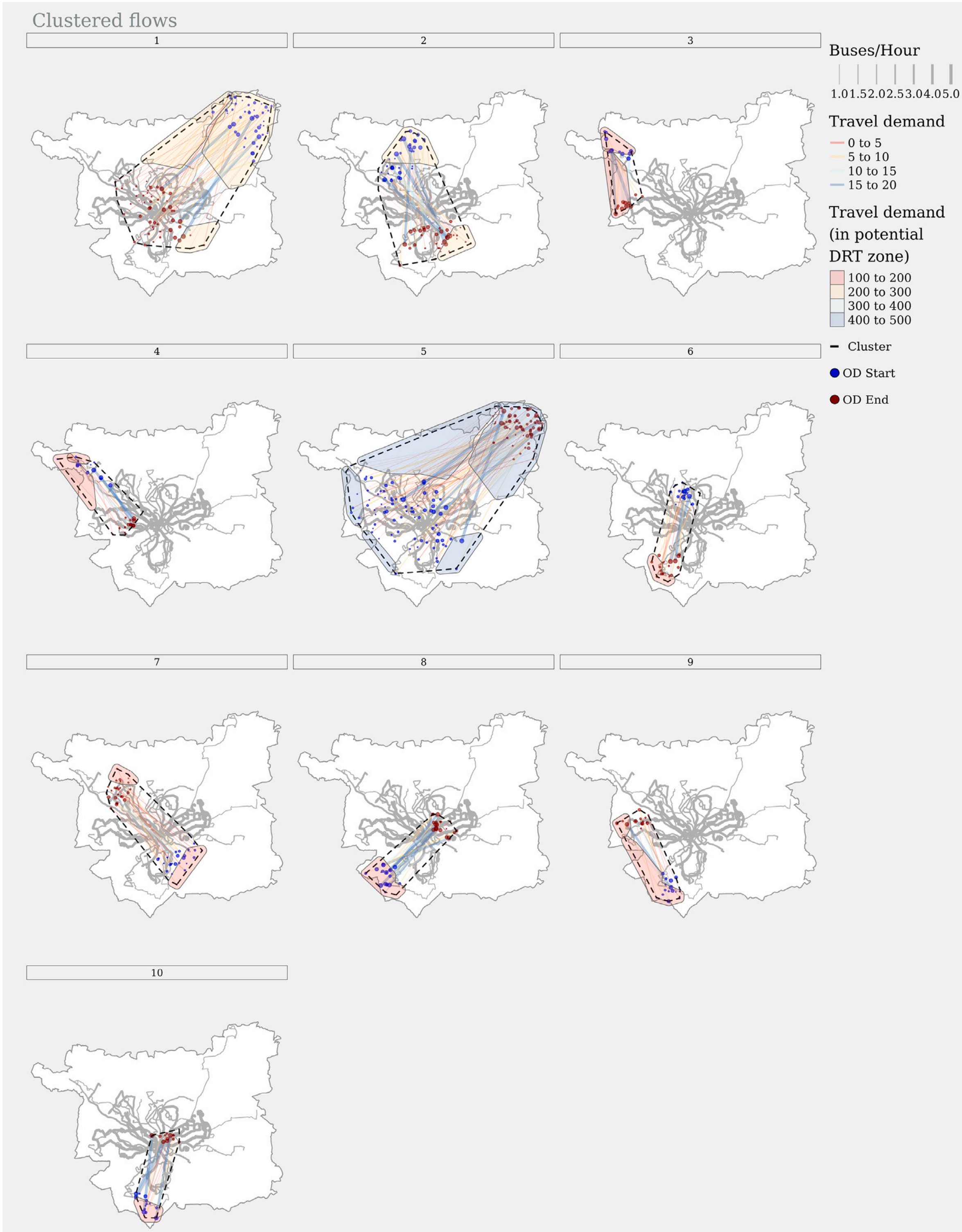


Fig. 4. Clustering results — OD pairs with poor PT supply (OD_s). Desire lines represent OD pairs making up each cluster, dashed black lines represent convex hull around desire lines, coloured polygons represent part of cluster that does not overlap with existing high frequency bus routes (see Section 3.5).

are often subject to long transfer times at central interchanges. In the west, Clusters 3 and 9 show vertical demand between Guiseley and Yeadon in the north and Morley in the south, with destinations concentrated around Pudsey. These trips are not well served by existing public transport, as north–south routes are largely absent and users are often forced to detour via the centre. The north-east (Clusters 1 and 5) shows scattered demand from rural areas to the urban core. Only one high-frequency bus route serves this region, meaning most trips would require either a first-/last-mile drop-off, a transfer in the city centre, or both. Cluster 2 similarly includes dispersed origins in the north with very limited bus service, and most destinations lie just south of the urban core. Finally, Cluster 7 shows a clear travel pattern from the

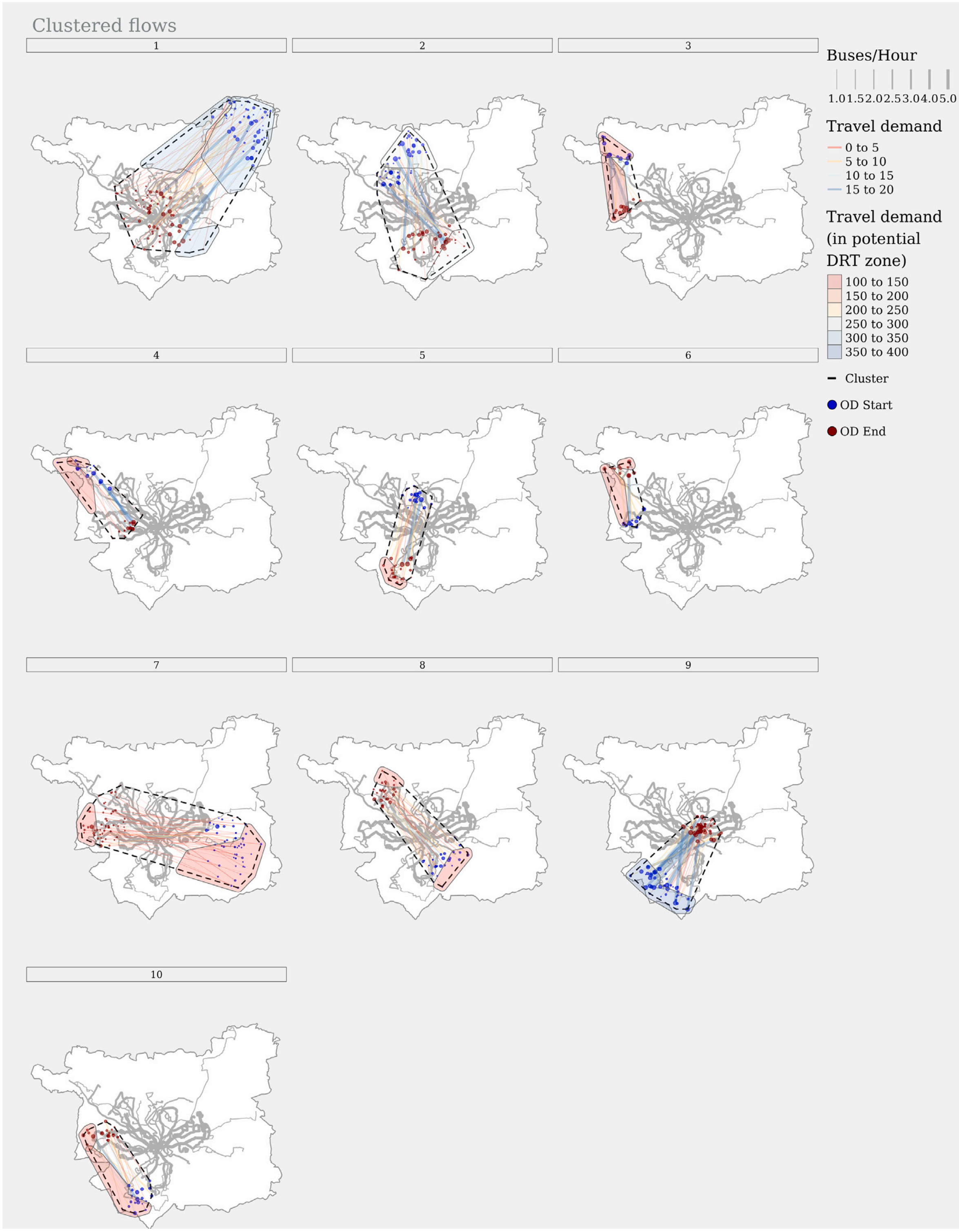


Fig. 5. Clustering results — OD pairs with poor PT supply and low potential demand (OD_{sd}) - Desire lines represent OD pairs making up each cluster, dashed black lines represent convex hull around desire lines, coloured polygons represent part of cluster that does not overlap with existing high frequency bus routes (see Section 3.5).

south-east to Horsforth and nearby towns in the north-west, originating in locations where there are no bus services.

These patterns reveal four major challenges for the current public transport network: insufficient coverage in peripheral areas, lack of north–south connectivity, poor accessibility in rural zones, and long transfer times for cross-city trips. In the south-west and south-east (Clusters 6, 7, 8, and 10), bus routes often terminate before reaching areas of demand. In the west, Clusters 3 and 9 reflect unmet demand for cross-city travel (between Morley, Pudsey, and Guiseley/Yeadon) not aligned with radial service patterns. In the rural north and north-east (Clusters 1, 2, and 5), low-density development makes fixed-route provision impractical. Finally, several clusters suf-

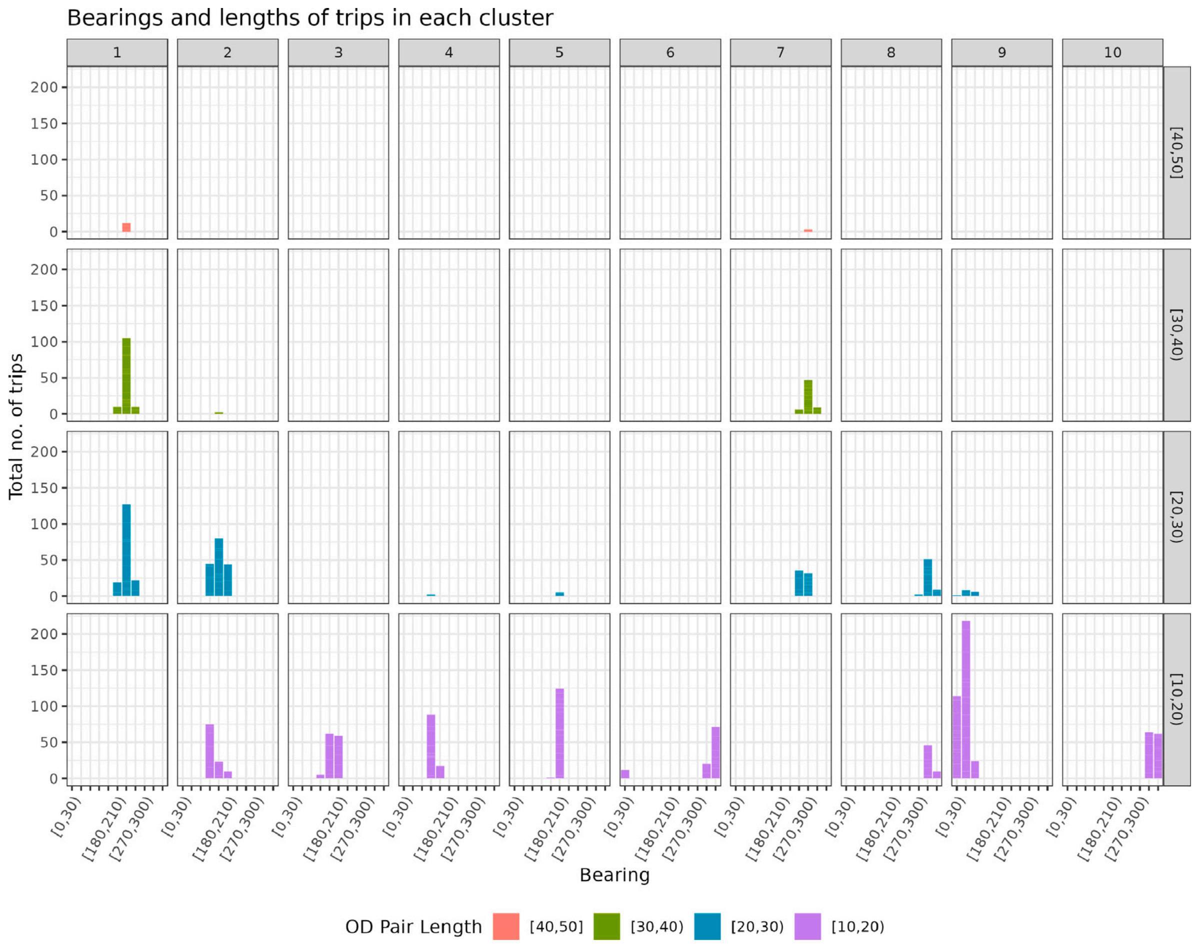


Fig. 6. Distribution of trips (weighted OD pairs) in each cluster. Each column shows the bearing and length composition of a cluster. This includes histograms of the number of trips (weighted OD pairs) in each (30 degree) bearing range (x-axis). The trips are also faceted by length ranges (10 km each).

fer from long transfer times, particularly those requiring city-centre interchanges.

In these contexts, DRT services could help fill network gaps by complementing existing bus services. In some cases, such as along the Guiseley–Pudsey or Morley–Pudsey axes (Clusters 3 and 9), standalone DRT services could address entire trips. In others, especially low-density rural areas (Clusters 1, 2, and 5), DRT could provide first-/last-mile access to frequent bus routes. For clusters that rely on city-centre transfers (e.g. Clusters 2 and 6), a combination of DRT and improved transfer coordination may be needed. Here, DRT alone may not suffice—schedule synchronisation would be necessary to improve the overall passenger experience.

4.2. Clustering based on transport supply and demand

This section presents the results of clustering the remaining OD pairs after conducting both the supply and demand analysis (OD_{sd}) (See Fig. 3). We compare these results to those of OD_s (Section 4.1) to assess the impact of incorporating potential demand. Section 4.2.1 examines cluster composition, and Section 4.2.2 presents aggregated results across different time points.

The clustering results are similar to those in Section 4.1, with some key differences. Cluster 9 in Fig. 5 is a combination of cluster 8 and 10 in Fig. 4. OD_{sd} has fewer OD pairs (Table 1) as we exclude those with sufficient demand for a bus service (see Section 3.3.2). The clustering algorithm, which is based on a minimum threshold of OD flows, requires a larger spatial coverage to reach the threshold given fewer OD pairs.

Another important distinction is that cluster 5 from Fig. 4 does not appear here. The high demand from the urban core to the North East led the demand analysis (Section 3.3.2) to exclude many of the OD pairs that were in that cluster, as they could be served by improved headways on existing public transport routes. The remaining OD pairs, which lack sufficient concentrated demand, do not form a separate cluster.

4.2.1. Examination of cluster homogeneity

To better interpret the clustering results, we examine the internal homogeneity of OD flows within each cluster, focusing on trip direction and length (Fig. 6). Greater homogeneity suggests that a DRT service could pool passengers more effectively, as trips follow similar spatial patterns.

Several clusters, such as 4 and 5, show strong directional alignment and low variation in trip length. These clusters are made up of short OD flows with consistent bearings, indicating tightly grouped demand likely to support more direct services. In contrast, clusters with longer OD flows—such as 1, 2, and 7—exhibit greater directional variance, partly due to the normalisation in the flow distance metric (Eq. (1)), which can group dissimilar long-distance flows together.

This analysis offers a way to assess the operational potential of each cluster based on the consistency of travel patterns they contain. Clusters with more homogeneous OD flows may be better suited to pooled DRT operations, whereas those with more internal variation will

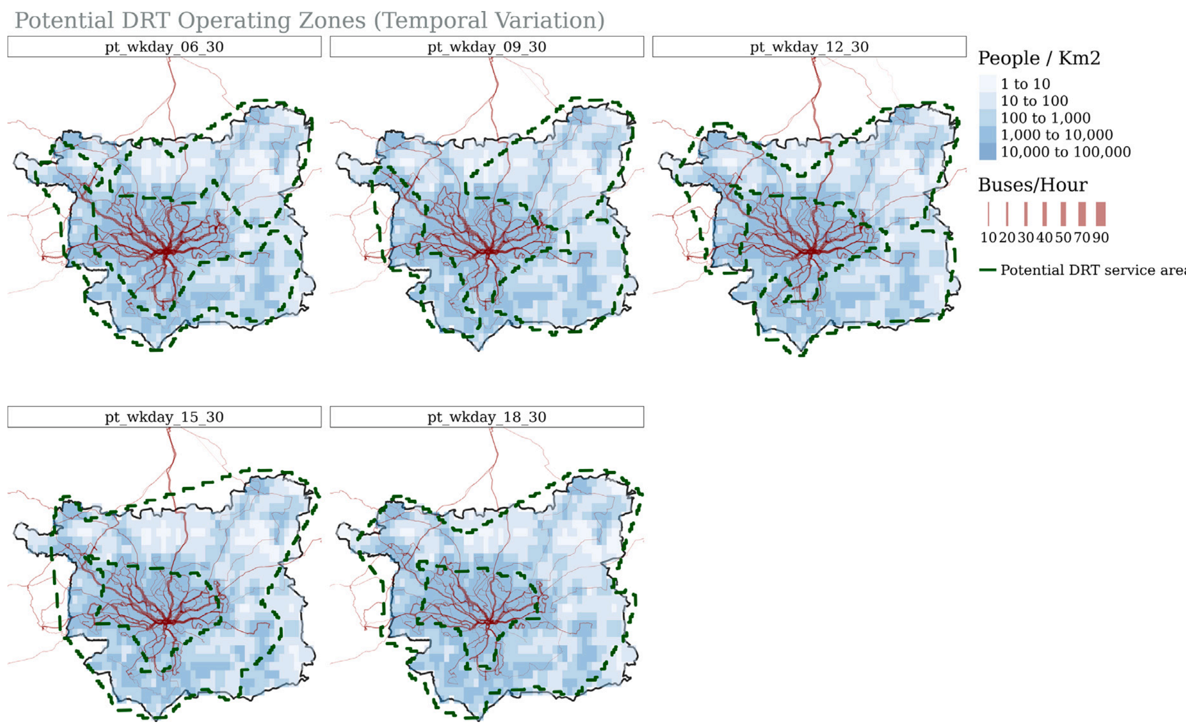


Fig. 7. Aggregate DRT zones generated by combining individual DRT zones. Each facet shows the result for a different time of day. Analysis is based on weekday supply and demand data.

require greater operating flexibility and may struggle to pool demand as efficiently.

4.2.2. Aggregate result and temporal dimension

Fig. 7 shows how the potential DRT zones could look like if combined together. This includes merging all the cluster areas after step 3 in Fig. 1. This visualisation is presented for five different times of day (as described in Section 3.2) to capture temporal variations in transport supply and travel demand.

The resulting DRT zones form a doughnut-shape around the periphery of the study area, with the city centre excluded due to the concentration of high-frequency bus routes. The shape is more pronounced and continuous outside of the morning peak (12:30, 15:30, 18:30), which aligns with the reduction in bus services during those periods (visible as fewer and thinner red lines).

Aggregating the clusters into a single map highlights that potential DRT zones are primarily located in the outskirts where population densities are low.

5. Discussion

In this paper, we propose a method for delineating DRT operating zones, responding to the need for strategic-level approaches that can guide the design of DRT services. Despite growing interest in DRT, there remains no well-defined methodology for identifying service areas that effectively complement fixed-route public transport. Our method is intended to support early-stage planning by identifying spatial concentrations of unmet demand. We see this as a tool to assist, rather than replace, the work of transport planners and local stakeholders, whose knowledge of context-specific travel needs is essential for refining and validating potential service areas.

As DRT evolves into a service that aims to improve accessibility for all, its integration with existing public transport systems becomes increasingly important for offering multimodal alternatives to private car use (Nelson et al., 2010). The success of DRT schemes is conditional on such integration and on their ability to serve spatial concentrations of travel demand (Enoch et al., 2006). Using a density-based clustering algorithm, our analysis identified groups of OD flows with sufficiently similar patterns. This cluster identification can be used to design distinct DRT fleets based on the needs of each cluster (or group of similar clusters). Research has shown that assigning specific fleets to serve defined routes, rather than operating across the entire study area, improves system performance and fleet utilisation (Inturri et al., 2019). This approach avoids the operational complexity that has historically undermined many DRT services (Enoch et al., 2006).

Our clustering results help highlight the different DRT services that could operate across our study area, Leeds. In areas such as the North-South axes in the West, DRT could serve as a standalone mode, providing direct trips where fixed-route public transport is unavailable. In sparsely populated rural areas in the periphery, DRT is better suited as a first/last-mile feeder service, connecting dispersed travellers to high-frequency public transport routes and thereby improving the accessibility and usability of the public transport system. Previous research has highlighted the potential of DRT feeders that extend bus services to rural areas (Schlüter et al., 2021; Sörensen et al., 2021). However, DRT on its own is insufficient to improve the public transport offering in some cases. Clusters that traverse the city centre are made up of trips that may require a bus transfer, and the attractiveness of such trips largely depends on improvements in public transport headways and schedule synchronisation.

The representation of the aggregated results at different times of day (Section 4.2.2) demonstrates conceptually that a temporal dimension can be added to the analysis, and that temporal variations do exist. It is important to note that while there may be little temporal variation in these aggregated zones, this does not mean that the exact same services are required throughout the day. The disaggregate results (Fig. 4 and Fig. 5) are essential for understanding the variation in the specific clusters that make up each temporal snapshot. Such variation should inform the number of services and the operational characteristics of each service.

While we have used Leeds as a case study, the approach is generalisable to any city or region with an existing public transport network. The main requirements are public transport supply data and travel demand matrices. We provide the code in a public repository[5] to facilitate reproducibility and extension of the work.

5.1. Implications for strategic planning of DRT

The composition and spatial extent of our clusters inform the design and operation of DRT services. Clusters vary in terms of the number and characteristics of OD pairs they encompass, supporting the evidence that DRT solutions need to be tailored to the area they are serving. Clusters with a high concentration of trips in a small area may require more direct services to one or two stops, while clusters with dispersed demand patterns may benefit from flexible, many-to-many DRT services. Simulation frameworks that incorporate disaggregate travel patterns and DRT routing—such as that of Melo et al. (2024) —can be used to test operational feasibility within each zone under different strategies.

Essential to our analysis is the use of DRT as part of an intermodal transport offering. It is clear that our clusters often overlap with high-frequency bus routes (Fig. 5), highlighting the potential for DRT to act as a feeder service. By limiting DRT coverage to areas that are not covered by a high-frequency bus routes (step 3 in Fig. 1), we aim to minimise unnecessary mode shift (e.g. public transport to DRT) and enhance the efficiency of public transport systems. Intermodal routing has only recently become possible in agent-based transport simulations (Haslebacher, 2018), with the integration of DRT into this intermodal framework being a subsequent development (Chouaki, 2023). Such a framework should be used to test the feasibility of our DRT zones in facilitating intermodal trips, but it should be noted that the success of such integration is dependent on other factors besides operating zones, such as seamless transfers and fare structures that do not penalise the use of multiple modes.

The candidate zones identified by the method vary in size, and a follow up exercise would be necessary to validate them. Analytical models mentioned in Section 2.1 could be used to determine more precise service areas. They could identify whether the critical demand density for a DRT service is met (Quadrifoglio & Li, 2009), look at schedule coordination with bus network (Sivakumaran et al., 2012), and predict DRT performance based on the street network layout in the different zones (Chandra & Quadrifoglio, 2013). Future work could also explore optimisation approaches — such as extensions to the Transit Network Design and Frequency Setting Problem (TNDFSP) — that can output both a bus network and DRT service areas. Future work could also assess the financial viability of different DRT service models. A cost–benefit analysis—considering fares, vehicle costs, pooling efficiency, expected mode share (based on mode choice modelling), and potential subsidies—would offer further insight into which service configurations are most appropriate in each zone. While beyond the scope of this study, such analysis is important for evaluating the economic sustainability of DRT deployments.

5.2. Comparison with alternative methods

Alternative methods have been used to identify DRT operating areas. One approach is to focus on the supply side, and allow DRT to operate in areas of poor public transport accessibility (Giuffrida et al., 2021; Räth et al., 2023). While such extensive service provision is important from a transport equity perspective, the lack of focus on demand could lead to DRT services with low passenger load factors (Creutzig et al., 2024). Areas with poor accessibility are also normally spread out across a study area, and it is important to go beyond just identifying these areas to seeing how they can be grouped into similar demand patterns so as not to operate overly complex DRT services that cannot pool travel demand (Enoch et al., 2006).

Optimisation models typically start with an existing public transport network and focus on incremental adjustments, such as modifying route frequencies, removing or trimming routes, or adjusting DRT fleet sizes (Pinto et al., 2020; Zhao et al., 2021). While valuable for fine-tuning service operations, these models either allow DRT to operate across the entire network, or limit service areas to the edges of existing bus routes. Our flexible approach to service area delineation, informed by demand patterns, could serve as either a simpler alternative to complex optimisation models or as a way to define initial DRT service areas for further refinement through optimisation.

5.3. Limitations and future work

5.3.1. Input data and demand analysis

In the approach outlined in this paper, we conduct a supply and demand analysis to ensure that we focus only on OD flows that are not, or do not have the necessary demand to be, served by a high frequency bus route. Our demand analysis is based on splitting OD demand equally between its common lines. While this is justified by our need to represent route demand given hypothetical improvements in headway, more robust methods can be used for scenario modelling of such improvements. Our results can be used as input for optimisation frameworks that adjust route headways and DRT fleet sizes, given pre-defined DRT service areas (Pinto et al., 2020). They could also be used as an initial solution for optimisation frameworks that simultaneously modify public transport routes and DRT service areas (Zhao et al., 2021). Since the core novelty of our approach is the identification of spatial concentrations in travel demand, we deliberately avoid adding further layers of complexity. This allows the results to be useful as an output in themselves, or as input to optimisation and agent-based simulation frameworks for further refinements.

Moreover, our current method is based on trip matrices at MSOA level with little information besides number of people. Datasets that have complete travel patterns of a population, such as activity-based models (Rasouli & Timmermans, 2014) would give us a more representative picture of travel demand and trip chains throughout the day. They would also enable linking travel patterns to sociodemographic characteristics and analysing for which categories of people and trip purposes DRT can improve accessibility.

5.3.2. Refinements to clustering algorithm

The clustering algorithm used (DBSCAN) requires the input of two parameters: epsilon (the search radius) and minpts (the minimum number of points inside the radius necessary for a cluster to form). In the absence of established theoretical framework for this approach, we adopt an iterative and exploratory method to parameter setting. Future work could explore algorithms that simultaneously identify clusters at different scales (Fang et al., 2021; Tao et al., 2017) to avoid having results based on one fixed radius.

Another component of the clustering algorithm worth exploring further is the metric used to calculate distance between flows. Our clustering algorithm relies on distances between OD flows when creating clusters. Given the large study area, and the variation in trip distances, we use a distance metric (Tao & Thill, 2016a) that normalises distances so that the values cover a smaller range. This is useful for DBSCAN, which takes one value for the search radius. If we do not normalise the flows, our distance metric will have a wider range, but we would not be able to choose a search radius that accommodates all the flows (a smaller radius would produce better results for shorter flows, and a larger search radius would produce distorted clusters that group the

[5] The code is in: github.com/Hussein-Mahfouz/drt-potential. In addition, we have developed an R package, `flowcluster` (Mahfouz & Lovelace, 2025) which implements the core clustering algorithm used in this study, enabling its straightforward reuse in other contexts.

shorter flows with the longer ones). However, this normalisation is not perfect, as can be seen in Fig. 6 where some clusters have OD flows of various lengths.

To address the challenges of clustering OD flows of varying lengths, several research directions could be pursued. One approach is to improve the current distance metric by applying transformations that reduce the influence of OD length—such as log transformations to the denominator of the similarity function. Incorporating a parameter that explicitly represents OD flow bearing could also help minimise circular variance within clusters. An alternative direction is to use different distance metrics altogether. For example, the Fréchet distance (Eiter & Mannila, 1994) could be applied, as it measures the similarity between curves by identifying the minimum "leash" length required to traverse them simultaneously. Another strategy is to explore clustering at different scales, rather than modifying the distance metric itself. This could involve partitioning the data by OD length and running DBSCAN separately for each group. Alternatively, algorithms such as HDBSCAN (Tao et al., 2017) or OPTICS (Fang et al., 2021) may be better suited to this task. These methods are capable of detecting clusters at multiple scales and can extract clusters of different lengths without requiring manual distance normalisation.

6. Conclusion

The need to decarbonise the transport sector, improvements in real-time routing technology, and the proliferation of app-based services have all contributed to a surge in DRT research and real-world schemes (Castellanos et al., 2022). However DRT services continue to suffer from the lack of robust strategic level planning, and many fail to capture sufficient passenger demand to make them economically viable (Creutzig et al., 2024; Enoch et al., 2006). The OD clustering approach presented in this paper seeks to address this challenge by identifying potential DRT operating zones that align with spatial concentrations of unmet travel demand. While we do not claim that these delineated zones will, on their own, guarantee high ridership, they provide a data-driven foundation for more targeted and effective service design. In particular, the method can support planning for DRT as a feeder to public transport where appropriate, while also accommodating the possibility of standalone services in areas with limited transit access. This framing reflects a broader environmental objective: to reduce car dependency and support more sustainable, integrated mobility systems.

Strategic planning of DRT that accounts for its integration with more traditional public transport systems presents a promising avenue for improved mobility in areas with pockets of concentrated travel demand that are difficult to serve cost-effectively by fixed-route public transport. The approach presented in this paper offers both conceptual and methodological contributions that can help realise this promise. Conceptually, we borrow methods from spatial data mining and argue that they are well suited to filling gaps in the current approaches for strategic planning of DRT services. We build on this concept methodologically by embedding a clustering algorithm into a larger transport planning pipeline with more traditional supply and demand components. Our findings show that spatial clustering of OD flow data can contribute to delineating operating zones in strategic DRT planning, but that more research should be done on improving distance metrics that are core to clustering and on refining the supply and demand analysis used to extract the OD flows to be clustered.

The approach can be adopted by practitioners in early stage strategic planning of DRT, and the outputs can be tested in agent-based simulations to understand how a service could perform in one of the suggested zones, the operational characteristics required, and the associated mode shift and VMT on the network under different scenarios.

CRediT authorship contribution statement

Hussein Mahfouz: Visualization, Methodology, Conceptualization, Writing – original draft, Formal analysis, Software, Data curation. **Malcolm Morgan:** Writing – review & editing, Conceptualization, Supervision. **Eva Heinen:** Supervision, Writing – review & editing, Conceptualization. **Robin Lovelace:** Supervision, Conceptualization, Writing – review & editing.

Declaration of competing interest

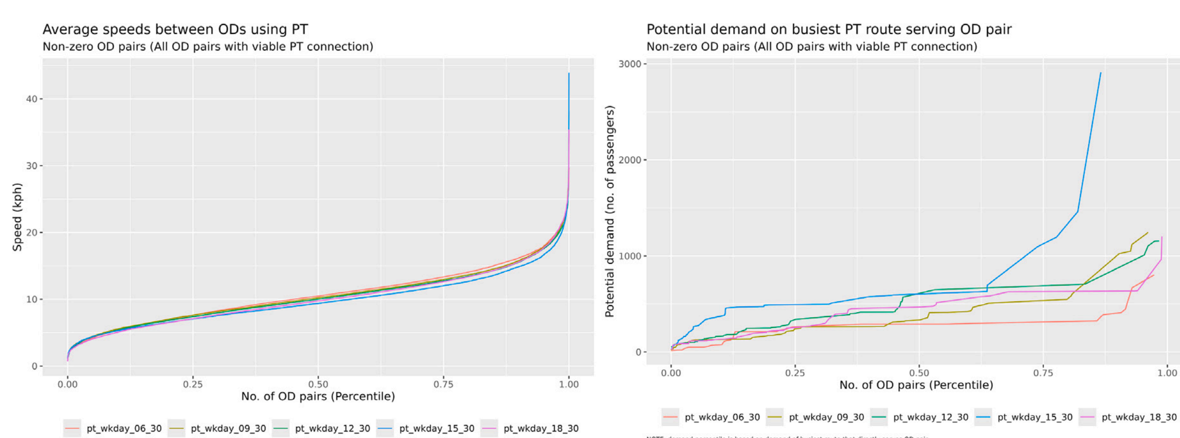
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

A.1. Sensitivity analysis for speed and demand thresholds

In Section 3.3, we filter ODs based on supply and demand thresholds. Below we show the distribution plots and sensitivity analysis that are used to inform these thresholds. For the speed and demand distributions (Fig. A.1(a) and Fig. A.1(b)), we do not include OD pairs with 0 values (OD pairs with no PT connection) as these dominate the distribution and skew the percentile results.

The sensitivity analysis (Fig. A.2) shows the number of OD pairs retained at different speed and demand thresholds. We can see that 60%



(a) Distribution of speed values (b) Distribution of potential demand values

Fig. A.1. Speed and demand distributions of OD pairs.

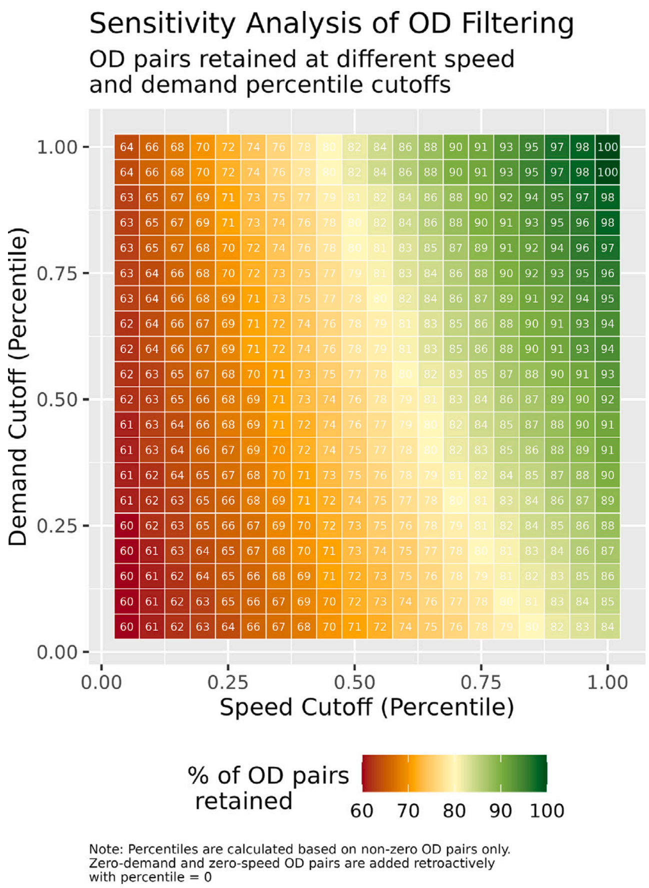


Fig. A.2. Sensitivity analysis showing the number of OD pairs retained at different speed and demand thresholds.

of OD pairs are retained no matter how low our threshold is set. These OD pairs have no direct PT connection and so their values for speed and demand are 0. The number of OD pairs retained is more sensitive to the speed cutoff threshold than the demand cutoff threshold.

Data availability

Data sources used throughout this paper are publicly available and can be found as referenced in the text, with the exception of the OD demand data which requires requesting access from Connected Places Catapult. The code used for this work can be found at: https://github.com/Hussein-Mahfouz/drt-potential.

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