

EXPLORING JITTERING AND ROUTING OPTIONS FOR CONVERTING ORIGIN-DESTINATION DATA INTO ROUTE NETWORKS: TOWARDS ACCURATE ESTIMATES OF MOVEMENT AT THE STREET LEVEL

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ABSTRACT:

Origin-Destination (OD) datasets provide vital information on how people travel between areas in many cities, regions and countries worldwide. OD datasets are usually represented geographically with straight lines or routes between zone centroids. For active travel, this geographic representation has substantial limitations, especially when zone origins and centroids are large: only using a single centroid origin/destination for each large zone results in sparse route networks covering only a small fraction of likely walking and cycling routes. This paper implements and explores the use of jittering and different routing options to overcome this limitation, thereby adding value to aggregate OD data to support investment in sustainable transport infrastructure. The route network results — generated from an open dataset representing cycling trips in Lisbon, Portugal — were compared with a ground-truth dataset from 67 count locations distributed throughout the city. This approach enabled exploration of which jittering parameters and routing options lead to the most accurate route network results approximating the real geographic distribution of cycling trips in the study area. We found that jittering and disaggregating OD data, combined with routing using low level of traffic stress (quieter) preferences resulted in the most accurate route networks. We conclude that a combined approach involving 1) jittering with intermediate levels of disaggregation and 2) careful selection of routing options can lead to much more realistic route networks than using established OD processing techniques. The methods can be deployed to support evidence-based investment in strategic cycling and other sustainable transport networks in cities worldwide.

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1. INTRODUCTION

Origin-destination (OD) datasets provide information on aggregate travel patterns between zones and geographic entities, and can be obtained from a wide range of sources making them one of the most commonly used geographic inputs in applied transport planning (Alexander et al., 2015). OD datasets are often ‘implicitly geographic’, containing identification codes of the geographic objects from which trips start and end. Exact coordinates of origins and destinations are provided in this way for good reasons: historically computational resources constrained analysis options, meaning that data reduction (by converting thousands of travel survey responses into a more compact aggregate OD dataset) was important; and privacy considerations prevent the disclosure of exact trip start and end points (Boyce and Williams, 2015).

A common approach to converting OD datasets to geographic entities, for example represented using the simple features standard (Open Geospatial Consortium Inc, 2011) and saved in file formats such as GeoPackage and GeoJSON, is to represent each OD record as a straight line between zone centroids. This approach to representing OD datasets on the map has been since at least the 1950s (Boyce and Williams, 2015) and — despite the development of various methods to add value to OD datasets by

sampling start and end points and ‘connectors’ withing each zone (Lovelace et al., 2022b), discussed below — centroid-based geographic representations of OD data are still dominant (Rae, 2009; Tennekes and Chen, 2021). Before explaining the methods, it is worth defining terms:

- **Origins:** locations of trip departure, typically stored as ID codes linking to zones
- **Destinations:** trip destinations, also stored as ID codes linking to zones
- **Attributes:** the number of trips made between each ‘OD pair’ and additional attributes such as route distance between each OD pair
- **Jittering:** The combined process of ‘splitting’ OD pairs representing many trips into multiple ‘sub OD’ pairs (disaggregation) and assigning origins and destinations to multiple unique points within each zone

Beyond simply visualising aggregate travel patterns, centroid-based geographic desire lines are also used as the basis of many transport modelling processes. The following steps can be used to convert OD datasets into route networks, in a process that can generate nationally scalable results (Morgan and Lovelace, 2020):

- OD data converted into centroid-based geographic desire lines

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- Calculation of routes for each desire line, with start and end points at zone centroids
- Aggregation of routes into route networks, with values on each segment representing the total amount of travel ('flow') on that part of the network, using functions such as `overline()` in the open source R package `stplanr` (Lovelace and Ellison, 2018)

This approach is tried and tested: the OD → desire line → route → route network processing pipeline forms the basis of the route network results in the Propensity to Cycle Tool, an open source and publicly available map-based web application for informing strategic cycle network investment, 'visioning' and prioritisation (Goodman et al., 2019; Lovelace et al., 2017). However, the approach has some key limitations:

- Flows are concentrated on transport network segments leading to zone centroids, creating distortions in the results and preventing the simulation of the diffuse networks that are particularly important for walking and cycling
- The results are highly dependent on the size and shape of geographic zones used to define OD data
- The approach is inflexible, providing few options to people who want to use valuable OD datasets in different ways

To overcome these limitations, methods of 'jittering' OD data have been developed (Lovelace et al., 2022b). While the results from analysis of route networks generated from jittered OD data in that paper were promising, the input datasets were small and technique was not evaluated with reference to ground truth data. This raised the question "Are the jittered results measurably better when compared with counter datasets on the network?" (Lovelace et al., 2022b).

This question was partially addressed during a presentation and subsequent proceedings published as part of the GISRUK conference (Lovelace et al., 2022a). However, the input dataset used for that conference paper was small and overly focussed on Edinburgh. Furthermore, only a single routing option was used, raising the question: what is the relative importance of geographic OD data pre-processing (jittering) and routing options when preparing route networks to support strategic sustainable transport plans? We set out to address this question in this paper.

1.1 Software and reproducibility

In this paper present results generated using the `odjitter` Rust crate. We developed an interface to R in the `odjitter` R package (not on CRAN at the time of writing) that can form the basis of a implementations in other languages that interface with the highly efficient Rust implementation. The results presented in this paper are fully reproducible. See the paper's GitHub repository at <https://github.com/RobinLovelace/foass4g22/> for implementation details and to reproduce the results.

2. APPROACH

2.1 Jittering

Jittering represents a comparatively simple — compared with 'connector' based methods (Jafari et al., 2015) — approach is

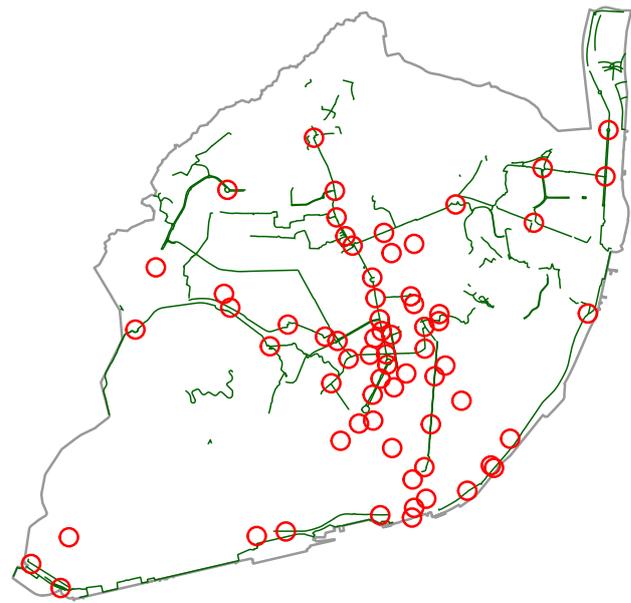


Figure 1. Cycling infrastructure in Lisbon as October 2021 and location of cyclists' counters.

to OD data preprocessing. For each OD pair, the jittering approach consists of the following steps for each OD pair (provided it has required inputs of a disaggregation threshold, a single number greater than one, and sub-points from which origin and destination points are located):

1. Checks if the number of trips (for a given 'disaggregation key', e.g. 'walking') is greater than the disaggregation threshold.
2. If so, the OD pair is disaggregated. This means being divided into as many pieces ('sub-OD pairs') as is needed, with trip counts divided by the number of sub-OD pairs, for the total to be below the disaggregation threshold.
3. For each sub-OD pair (or each original OD pair if no disaggregation took place) origin and destination locations are randomly sampled from sub-points which optionally have weights representing relative probability of trips starting and ending there.

This approach has been implemented efficiently in the Rust crate `odjitter`, the source code of which can be found at <https://github.com/dabreegster/odjitter>.

2.2 Case study

Lisbon, Portugal, is a city with about half million residents. By 2018, when a mobility survey was carried on, and only about 0.5% of trips were made by bicycle. However, the investments in cycling infrastructure, reaching 150 km of cycling network in 2021, and the implementation of a dock-based bike-sharing system had a major impact on cycling levels (Félix et al., 2020).

Cyclists' counts are performed yearly from 2017 to 2021 at more than 65 locations in Lisbon during morning and afternoon peak hours (8-10 am and 5-7 pm). In 2021, these were carried out in October. The 67 locations, shown in Figure 1, were chosen considering to the existent and planned cycling infrastructure, and places where there was no cycling infrastructure, but had already some presence of cyclists.

2.3 Methods

We use data from a mobility survey (Instituto Nacional de Estatística, 2018) at district level (Lisbon has 24 districts), including 4955 daily bicycle trips, represented by 122 desire lines. Cycling count data includes 26464 passings in the total of the 67 locations (one trip may pass at more than one location).

Routes were computed using *CycleStreets*, which relies on 2022 road network from OpenStreetMap, using the *r5* engine (Pereira et al., 2021), and using *Google Maps* service, for routing comparison. Routes were calculated using reproducible code available in the GitHub repo associated with this paper thanks to the *stp1anr*, *r5r* and *cyclestreets* R packages that provide interfaces to these routing engines.

Regarding the routing options, *CycleStreets* provides 3 options of cycling routes: “fastest”, “balanced” and “quietest”, while *r5r* uses the Level of Traffic Stress (LTS), ranging from 1 — less bicycle friendly, to 4 — more bicycle friendly (Mekuria et al., 2012). *Google Maps* does not provide such profile options for bicycle routing. In this research we compared *CycleStreets*’ “quietest” and “fastest” modes, and LTS 2 and 4 (Desjardins et al., 2022; Mekuria et al., 2012).

This was an iterative process, and not all options were tested due to the computational requirements. We started by generating routes with *CycleStreets* for the 3 routing profiles and for unjittered, jittered with no disaggregation, and jittered with disaggregation level of 500 trips. Then we compared the results with routes generated by *r5r*, for 2 levels of traffic stress (2 and 4), and with routes generated by *Google*. Other jittering disaggregation level of 200 trips was also compared with the previous results, for routes generated with *CycleStreets* (“quietest” profile) and for routes generated with *r5r* (LTS 2).

Results were then assessed. Count data was compared with the resulting route networks (with information on bike trips at each segment level, from the mobility survey data) by taking the value of the nearest segment, and using a R^2 correlation fit.

3. RESULTS

We generated route networks based on a range of different jittering parameters and routing options. The results presented in this section not only report estimates of model-counter fit but also provide indication of the type of networks generated, through route network maps. Figures 2, 3 and 4 show the difference between desire lines with centroids approach and the jittering approach, for bike trips in Lisbon.

Figures 5, 6, 7 and 8 show examples of route networks from unjittered OD pairs, and jittered OD pairs with disaggregation level of 500 trips, for different routing providers, and the counters location.

When comparing the route network with unjittered desire lines (Figure 5) with the jittered ones (Figures 6, 7 and 8), we may find that the route networks from jittered desire lines are more diffuse, and not concentrated in a few routes. For cycling and walking, this brings more realistic routes for this transport modes. Nevertheless, we are aware that routing options “quiet”, and LTS 2 (quieter than LTS4), have a higher weight in using the existing cycling network infrastructure, and then the resulting route network can be similar to the cycling network silhouette (see Figure 1). In fact, cyclists tend to opt for a cycling

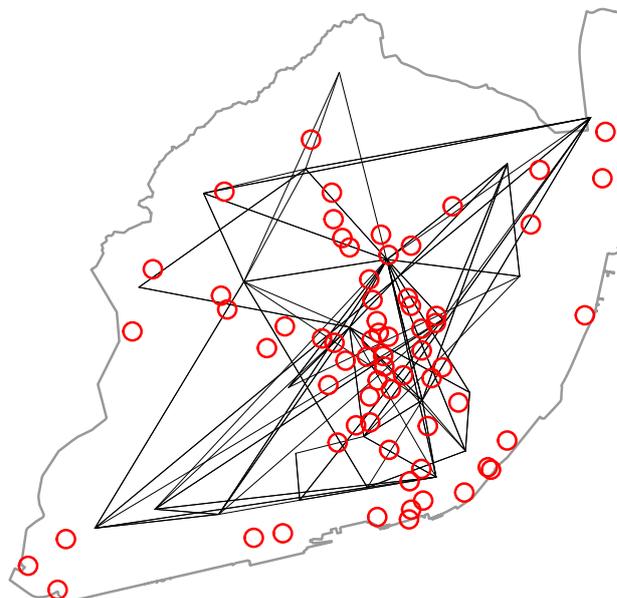


Figure 2. Trips represented with desire lines from centroids of 24 areas. The red circles represent the counters locations.

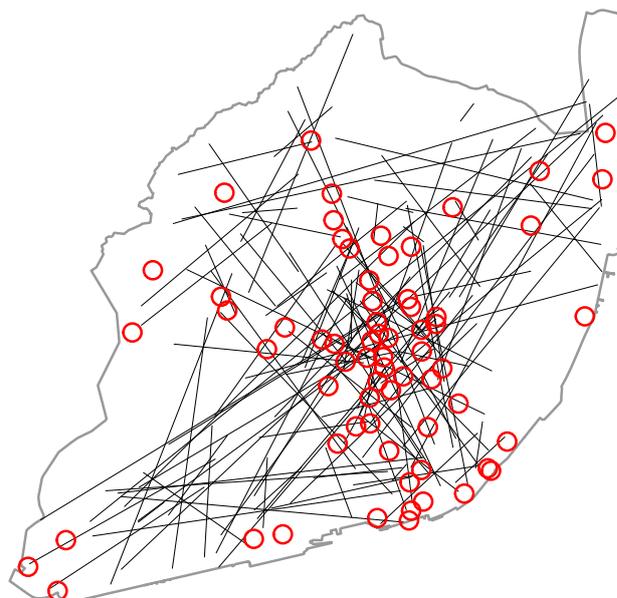


Figure 3. Trips represented with jittered desire lines, with no disaggregation.

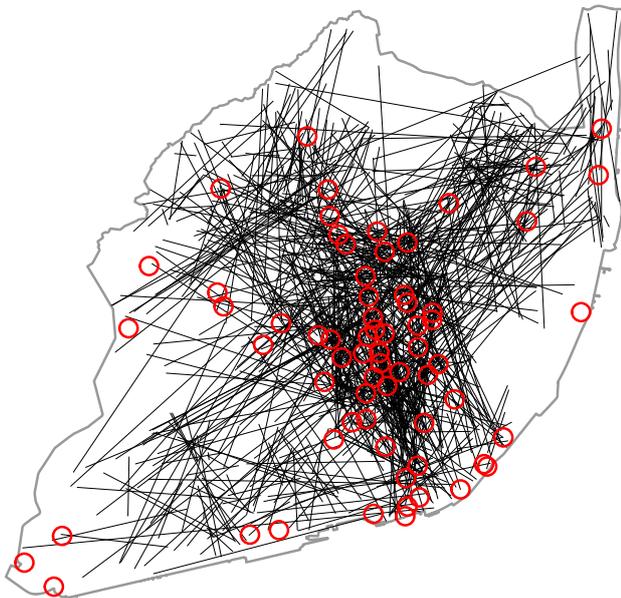


Figure 4. Trips represented with jittered desire lines, with disaggregation of 500 trips.

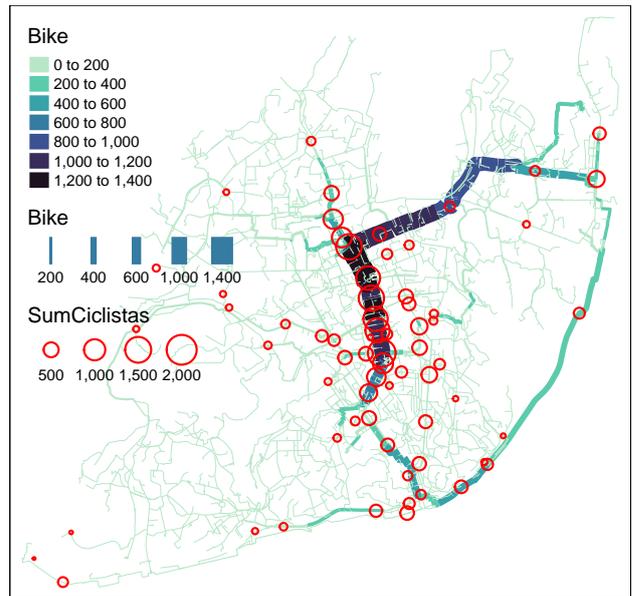


Figure 6. Route network from jittered desire lines with disaggregation of 500 trips, with routes from CycleStreets, in quietest routing option.

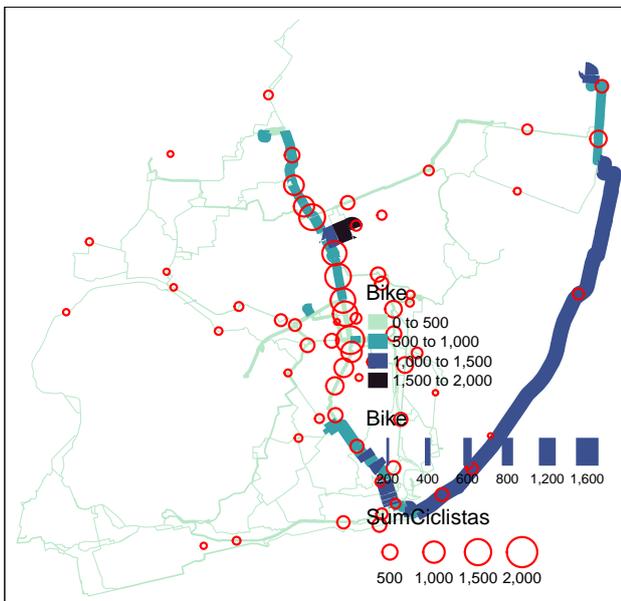


Figure 5. Route network from unjittered desire lines, with routes from CycleStreets, in quietest routing option.

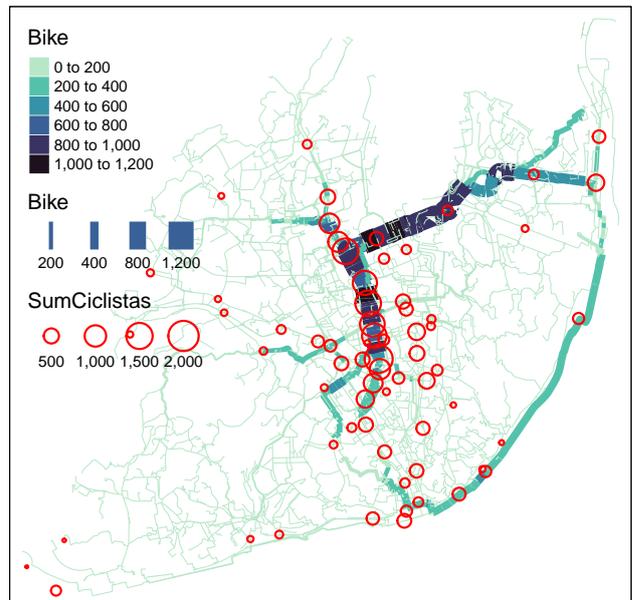


Figure 7. Route network from jittered desire lines with disaggregation of 500 trips, with routes from r5r, level of traffic stress 2 (quiet) routing option.

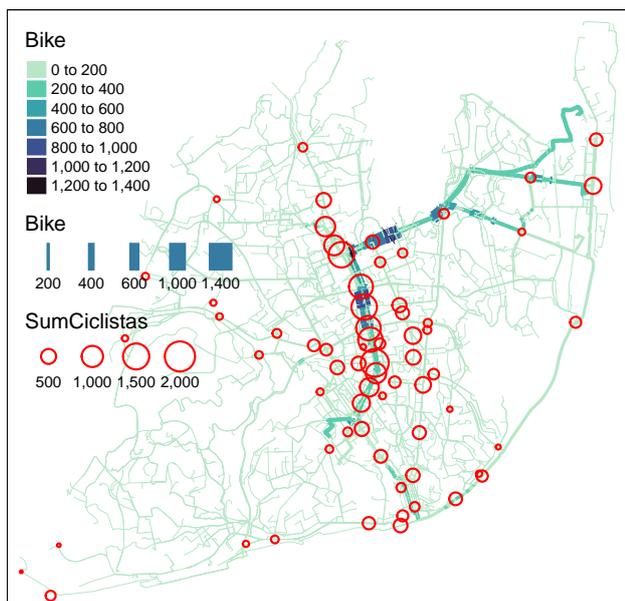


Figure 8. Route network from jittered desire lines with disaggregation of 500 trips, with routes from Google.

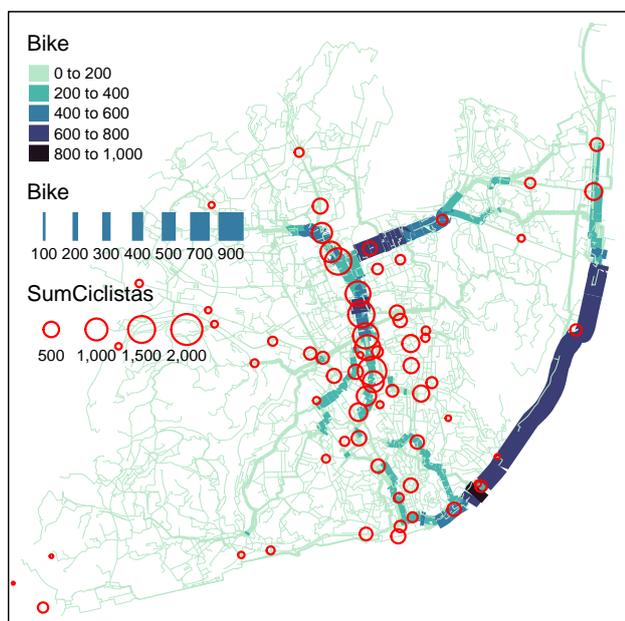


Figure 9. Route network from jittered desire lines with disaggregation of 200 trips, with routes from r5r, level of traffic stress 2 (quiet) routing option.

Table 1. Results showing counter/model fit for route networks generated from different routing and jittering parameters

Jittering	Routing	Nrow	R-Squared
Unjittered	quietest	122	0.23
Unjittered	balanced	122	0.22
Unjittered	fastest	122	0.10
Unjittered	LTS2	122	0.35
Unjittered	LTS4	122	0.04
Jittered, no disaggregation	quietest	122	0.26
Jittered, no disaggregation	balanced	122	0.11
Jittered, no disaggregation	fastest	122	0.00
Jittered, 500 disaggregation	quietest	799	0.50
Jittered, 500 disaggregation	balanced	799	0.42
Jittered, 500 disaggregation	fastest	799	0.08
Jittered, 500 disaggregation	LTS2	799	0.54
Jittered, 500 disaggregation	LTS4	799	0.14
Jittered, 500 disaggregation	Google	799	0.25
Jittered, 200 disaggregation	quietest	1895	0.54
Jittered, 200 disaggregation	LTS2	1895	0.54

infrastructure when it is available, even if it compromises the directness of their trips (Broach et al., 2012). It is also noticed that “Fastest” and LTS4 routing option does not have a good fit with the counting data, when compared with the “Quietest” and LTS2.

Regarding the different disaggregation levels, a route network build from a jittering disaggregation of 200 trips is shown in Figure 9, with a more diffuse network.

Although useful for visualizing the complex and spatially diffuse reality of travel patterns, we found that the most valuable use of jittering is as a pre-processing stage before routing and route network generation. Route networks generated from jittered desire lines are more diffuse, and potentially more realistic, than centroid-based desire lines.

We also found that the approach, implemented in Rust and with bindings to R and Python (in progress), is fast. Benchmarks show that the approach can ‘jitter’ desire lines representing millions of trips in a major city in less than a minute on consumer hardware.

We also found that the results of jittering depend on the geographic input datasets representing start points and trip attractors, and the use of weights.

Table 1 shows the counter data vs modeled route network fit, with different routing and jittering parameters. We can observe that jittered OD pairs provide a better fit result, with disaggregation.

A higher jittered disaggregation level (200 trips) does not bring a better fit against a lower disaggregation level of 500 trips. This might be explained but the routing profile used in the routing engines, and the location of the cycling counters — most of them at the existing cycling infrastructure. Although a more diffuse route network is expected in active transportation modes, the available data and computed routes are usually closer to where cycling infrastructure exists. Other data should be used to validate this hypothesis, such as a more diffuse cyclists’ counters location, or/and the actual cyclist’s routes — for example, bike sharing trips routes, despite their access is not usually guaranteed for research purposed.

The results from our analysis suggest that investment in cycle infrastructure is particularly important in a few key locations

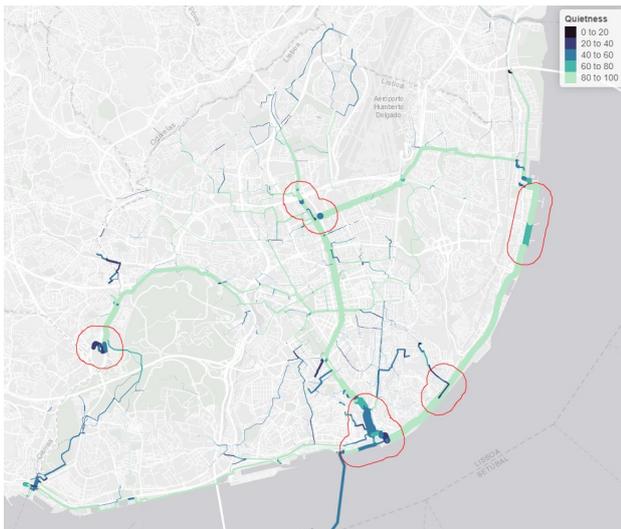


Figure 10. Segments on the transport network of Lisbon where investment in new cycling infrastructure should be prioritised according to the route networks generated using methods presented in this paper, alongside local knowledge.

where cycling potential is high yet provision is poor. These locations are highlighted in Figure 10, which was generated using information from three key sources:

- Estimates of cycling potential, generated using the jittering → routing → route network methods presented in this paper.
- Estimates of quietness of links on the network, computed with the open source `cyclestreets` R package (Desjardins et al., 2022).
- Local knowledge, which was used to visually inspect the resulting networks and identify key ‘severance’ points in the network (Mindell and Ancaes, 2020).

Figure 10 highlights the policy relevant nature of this research. A key finding is that, combined with local knowledge and detailed data on existing transport infrastructure, which can be used to generate metrics such as Level of Traffic Stress (LTS) (Wang et al., 2016) and Cycling Level of Service (CLOs) (Deegan, 2015), route networks generated from jittered, disaggregated, and appropriated routed OD data can help prioritise investment where it is most needed. Results were presented to stakeholders working in the local area who said that these new results would support their investment plans.

The overall result was the finding that OD jittering methods first developed by Lovelace et al. (2022b) are not enough on their own to generate accurate route networks. Jittering leads to more spatially diffuse route networks than networks generated from the common approach of routing from and to zone centroids. However, the results presented in this section show that careful consideration of routing options is needed in addition to evidence-based selection of jittering parameters.

4. CONCLUSION

Building on previous work (Lovelace et al., 2022b), we have explored the relative importance of jittering and routing options for generating accurate route network level estimates of movement, down to the street level. In corroboration with previous

research, we found that jittering leads to more spatially diverse geographic representations of travel between zones and estimates of flow down to the link level (Lovelace et al., 2022a). A new finding was that jittering alone cannot be guaranteed to generate accurate route network level results: appropriate routing options should be tested and identified.

The results were generated only for a single city and we did not explore the full parameter space (alternative subpoint weighting parameters in the jittering process are discussed below). For these reasons, we cannot draw specific and universally applicable conclusions about the optimal settings for accurate route network generation in other cities: it should be remembered that route networks and cycling preferences vary from city to city (Buehler and Dill, 2016). However, although our findings were based on a single case study, Lisbon, Portugal, the findings have implications for future work using OD data to support evidence-based investment in sustainable transport infrastructure (e.g. Vybornova et al., 2022). The main conclusion is that both careful translation of OD data to geographic start and end locations and disaggregation and careful selection of routing options are needed *in combination* to ensure that route networks derived from OD data are diffuse and accurate.

Accurate route network representations of transport systems are needed to support investment in a variety of transport interventions (Morgan and Lovelace, 2020). We have focused in this study on cycleway network because a complete cycle network represents one of the most cost-effective ways to reduce car dependence and associated environmental, economic, social and health costs (Wałdykowski et al., 2022). Cycleway networks, rather than simply isolated routes or other geographically sparse interventions, are vital for successful active travel investment (Buehler and Dill, 2016). Our results are therefore highly policy relevant, adding value to established methods of adding value to OD data to support sustainable transport planning (Larsen et al., 2013; Lovelace et al., 2017; Mohammed and Oke, 2022).

The research presented in this paper is not without limitations. We did not explore the full range of jittering and routing options available due to time and computational resource constraints. Specifically, varying the type and weights of origin and destination subpoints, as advocated in Lovelace et al. (2022b), could lead to improved fit. This would require filtering the subpoints used to include only certain types of nodes on the road network (all vertices on the road network were used as the basis for both origin subpoints and destination subpoints in this study, see documentation in the `odjitter` Rust crate for details). Future work could explore the use of including only residential roads, or increasing the weight associated with residential roads, in the origin subpoints, for example. Likewise, destination subpoints and associated weights could be altered to prioritise key trip attractors such as schools and commercial centres. Another limitation is the simplistic measure of accuracy used in this study. Accuracy was inferred from goodness-of-fit between aggregated flow values at 67 counter locations and modeled flow on nearest segment on the network. Future work could use alternative measures of fit such as root-mean-square error (RMSE) and more sophisticated ways of comparing observed counter values to modeled networked values, e.g. using inverse distance weighted measures associated with links in close proximity to each counter, with empirically derived bandwidths.

More broadly, the quality of the underlying route network data is imperfect. Efforts to improve the underlying OpenStreetMap

data will continue to overcome this limitation, not just in Lisbon but worldwide (Barrington-Leigh and Millard-Ball, 2017). This will improve the results over time because all routing engines used in this study, except for Google's routing service, use OSM data. Furthermore, alternative data sources and methods could be used to generate more accurate road networks (e.g. Leninisha and Vani, 2015). Future work should seek to test a wider range of jittering parameters in multiple case study areas with larger ground truth datasets. Other fit measures, such as GEH or SQV statistics, may also be used to compare count data with simulated traffic volumes.

Despite these limitations, and the need for future academic work, the results are already useful. Imperfect data-driven evidence is better than no systematic evidence, especially when practitioners are aware of the mechanisms underlying route network level estimates of travel behavior such as those presented in this paper. A benefit of the approach is that it based on open source software and reproducible code, allowing others to build on the methods (Lovelace et al., 2020). Indeed, a next step building on directly on the research presented in this paper is to use the results to support strategic cycle network planning in Lisbon and the wider area. In parallel to efforts to improve route network representations of transport systems we therefore advocate for the use of the approach presented in this paper, and related methods (e.g. Cooper, 2018; Vybornova et al., 2022), to be implemented in support of more evidence-based investment in sustainable transport infrastructure at city, regional and national scales worldwide.

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