Road Segment Prioritization for Bicycle Infrastructure

2020-11-07

Abstract

Understanding the motivators and deterrents to cycling is essential for creating infrastructure that is successful in getting more people to adopt cycling as a mode of transport. Therefore, the aim of this study is to develop a methodology that determines where cycling infrastructure should be added by accounting for cyclist preference and UK government policies to create Low Traffic Neighborhoods. Distance decay, routing, and network analysis techniques are used to examine where future cycling demand in a city will come from, how such demand should be routed on the street network, and how to consider fair distribution of cycling infrastructure that is in line with egalitarian principles. The city of Manchester is used as a case study, but the methodology is generic enough to be applicable to any city. For routing, it is found that deviating from shortest paths to avoid high-stress road segments can result in acceptable travel time increases for cyclists. Community detection is used to partition the city and evaluate results from utilitarian to egalitarian algorithms on distributing cycling infrastructure. The results show that the egalitarian algorithm provides comparable city-wide results to the utilitarian one.

Keywords: cycling network, routing, transport equity

1 Ideas and discussion

- Lit Review: I can also organize this thematically and trim down **Planning Cycling Networks** substantially. I would then add some literature in:
  - Calculating Potential Demand
  - Routing
  - Road Segment Prioritization
- Community Detection: Where in the document should this section be?
- Other Cities

2 Introduction

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3 Background

3.1 What Affects the Decision To Cycle

Segregated cycling infrastructure[1] has been shown to increase cycling uptake (Aldred, Croft, and Goodman 2019; Goodman et al. 2014; Marqués et al. 2015), with the separation from motorized vehicles being key (Winters et al. 2011). Revealed preference of cyclists shows that they are willing to deviate from the most efficient routes in order to commute on safer roads (Crane et al. 2017). However, such deviations are only considered if they do not considerably increase route circuitry; behaviour studies have found that the probability of choosing a route

[1] Segregated cycling infrastructure refers to road space that is allocated to cyclists only, with physical separation to protect cyclists from other modes of transport.

decreases in proportion to its length relative to the shortest route (Broach, Gliebe, and Dill 2011; Winters et al. 2010). Another defining feature for cycling infrastructure is how well connected it is. Cyclists prefer cohesive infrastructure, particularly when cycling on arterial roads with high levels of motorized traffic (Stinson and Bhat 2003), and the lack of well-connected cycling infrastructure is one of the main obstacles to increasing cycling uptake (Caulfield, Brick, and McCarthy 2012). While direct and cohesive cycling networks have been shown to positively impact cycling rates, density[2] of the cycling network is also vital (Schoner and Levinson 2014)].

3.2 Planning Cycling Networks

Optimization techniques have been used to propose improvements to cycling networks. Mesbah, Thompson, and Moridpour (2012) propose a bi-level formulation to optimize allocation of cycling lanes to the network without exceeding a set budget. The upper level is the proposed interventions and the lower level is the route choices made by users in reaction to changes in the network. The problem accounts for the effect of cycling lanes on car traffic, and attempts to maximize utilization of said lanes with minimal impact on car travel times. To improve cohesion of the suggested network, a constraint is added so that each link with a bike lane should be connected to at least one destination. Car usage is not considered by Mauttone et al. (2017), who develop an optimization framework that aims to minimize the total user cost of cycling on the network. The aggregate flow on links is obtained by using shortest paths to route existing cycling demand onto the road network, and the solution is a proposed set of links where cycling infrastructure should be added in order to minimize the overall travel cost of cyclists across the network. The cost of traversing a link is given as a function of its length and whether or not it has cycling infrastructure, and a discontinuity penalty is also added to prioritize connected road segments. The problem has also been solved by attempting to find the minimum cost of improving roadway links to meet a desired level of service (LOS) (Duthie and Unnikrishnan 2014). In this formulation, all OD pairs need to be connected by roads that meet the desired LOS, and a directness constraint is added so that paths between OD pairs do not exceed a certain multiple of the shortest path.

These problem formulations do not explicitly solve for continuity, which is dealt with using a either (a) a constraint specifying that each link with a bike lane should be connected to at least one destination (Mesbah, Thompson, and Moridpour 2012), (b) a constraint on deviation from shortest paths (Duthie and Unnikrishnan 2014), or (c) a discontinuity penalty (Mauttone et al. 2017). To solve for continuity, the graph-theoretic concept of *connected components*, has been used. Natera et al. (2019) study the existing cycling network in terms of its disconnected components and introduce two different algorithms to connect these components by their most critical links[3] and, in doing so, measure the size of the growth of the largest connected component as a function of the kilometers of network added. They observe that small investments at strategic points have a large impact on connectivity in most cases. The concept of connected components is also at the core of the methodology proposed by Olmos et al. (2020). After routing the cycling demand onto the network links, they use percolation theory to filter out the links based on the aggregate flow[4] passing through them. They vary the flow threshold for filtering to identify the minimum flow at which the whole city is connected by a giant component. The results show a cycling network that connects the entire city, and subtracting links intersecting with current cycling infrastructure identifies links proposed for intervention.

The problem formulations outlined above look at the network as a whole when attempting to improve it. An alternative approach is to identify the different sub-networks that exist within the larger network, and work on improving each separately. Trip patterns in a city are not uniformly distributed geographically, and *community finding* methods have been used to partition study areas into localized areas that experience a disproportionate number of trips within them. Akbarzadeh, Mohri, and Yazdian (2018) use a modularity maximization approach (Blondel et al. 2008) on taxi trip data to identify 7 different communities in the city of Isfahan, Iran. An optimization problem is then formulated to connect nodes within each community with cycling infrastructure. The emphasis is on connectivity within the communities, not between them. Bao et al. (2017) adopt a similar methodology, but use hierarchical clustering to specify the desired number of clusters. They use a greedy network expansion algorithm, where the link with the highest benefit/cost ratio in each cluster is selected, and the network is grown by adding

[2]making an area's bicycle network denser means adding more cycling routes in the area and thereby giving cyclists more route options

[3]*link* refers to a road segment throughout this research

[4]*flow* is used throughout this research to refer to the cycling demand when it is routed onto the road network. The flow on any road segment is the cumulative demand on it, resulting from cyclists commuting between various OD pairs

neighboring links to the solution until a budget limit is met. The benefit is the flow on the link, and each link is assigned a cost based on current road conditions.

3.3 Underlying Ethical Principles

The methodologies in Section 3.2 are underpinned by different ethical principles, even though these principles are not explicitly acknowledged by the authors. This is important since different ethical principles constitute different problem formulations and targets. Broadly speaking, transport appraisal can be based on either utilitarian or egalitarian principles. The former seeks to maximize the overall benefit, while the latter is concerned with a fair distribution of benefits (Jafino, Kwakkel, and Verbraeck 2020). Nahmias-Biran, Martens, and Shiftan (2017) criticize the utilitarian approach that has been historically popular in the evaluation of transport investments, explaining how the maximization of overall benefit fails to account for the distribution of that benefit among communities or individuals. Lucas, Van Wee, and Maat (2016) explain how transport studies have traditionally looked at the bigger picture without studying the distribution of investments on the different parts of the study area, and go on to propose an egalitarian approach that ensures the dis-aggregation of transport policy benefits across the study area. Pereira, Schwanen, and Banister (2017) also emphasize the need for a more egalitarian approach to transport planning. They highlight accessibility as a cornerstone of distributive justice, and contend that policies should aim to distribute investments in a way that minimizes spatial variations in accessibility. This research attempts to provide a methodology that is grounded in egalitarian principles. **Write some more here**

4 Data and Geographical Scale of Analysis

The analysis is heavily dependant on Origin-Destination census data (commuter data). Commuter data in the UK is publicly available at the Middle layer Super Output Area (MSOA) level; the average MSOA has a population of 8209 (ONS 2018). Iacono, Krizek, and El-Geneidy (2010) note that such large travel zones are not ideal for understanding route choice behaviour of cyclists and pedestrians. They also give rise to an 'ecological fallacy' whereby average characteristics are assumed to apply to all residents of the aggregated geographical area. Given that more granular data is not publicly available, the study uses MSOA-level commuter data. The methodology is however applicable to more granular commuter data should it become available.

5 Calculating Potential Cycling Demand

Using existing cycling demand to inform decisions on where cycling infrastructure should be added reinforces existing cycling patterns and ignores potential cycling demand that could be satisfied by a connected network. To avoid this issue, Duthie and Unnikrishnan (2014) choose to ignore demand completely, and focus on creating a network that connects the entire study area. Olmos et al. (2020) obtain the distance distribution of cyclists using a smartphone-based bicycle GPS data. They then use a rejection-sampling algorithm on the OD data of the study area to match the potential demand distribution to the distribution obtained from GPS data.

For our purposes, we use a logistic regression model to calculate potential cycling demand. The model is adopted directly from the Propensity to Cycle Tool (PCT) (Lovelace et al. 2017). The PCT estimates the proportion of cyclists ($\boldsymbol{C_p}$) for each MSOA pair should the government achieve its target of doubling cycling by 2025. The logistic regression model used to calculate $\boldsymbol{C_p}$ has the following parameters:

$$\begin{aligned} logit(C_p) = &- 4.018 - 0.6369d + 1.988\sqrt{d} + 0.008775d^2 \\ &- 0.2555s + 0.00206ds - 0.1234\sqrt{d}s \end{aligned} \tag{1}$$

where **d** and **s** are the distance and slope respectively for the OD pair. The authors use square and square-root distance terms "to capture the non-linear impact of distance on the likelihood of cycling", and interaction terms to capture the combined effect of slope and distance (Lovelace et al. 2017).

The potential demand calculations show that the current and potential number of cyclists both follow a bell-shaped distribution, with the number of trips peaking around the 3-5km commuting distance and then going back down for longer distances (see Figure 1).

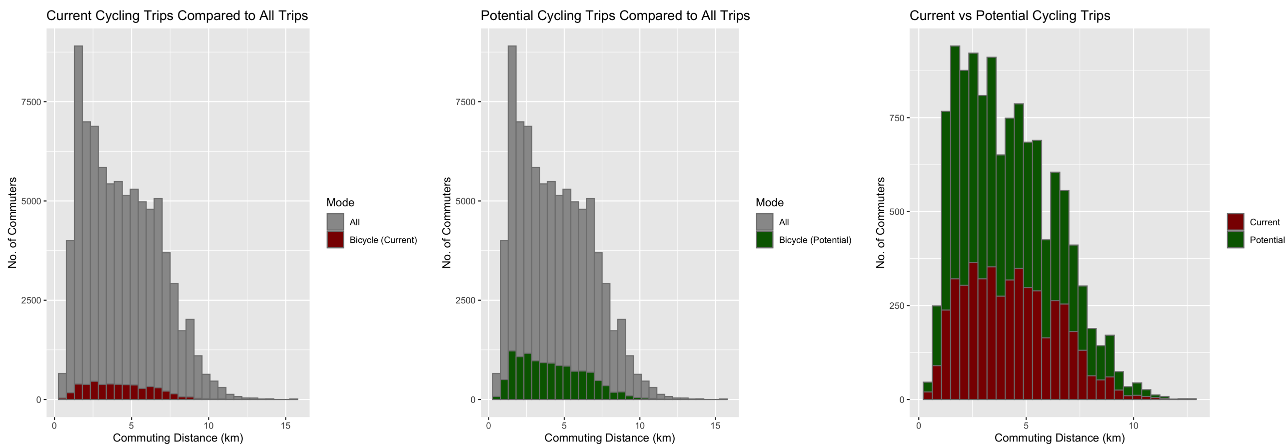

Figure 1: Distribution of Potential Cycling Demand

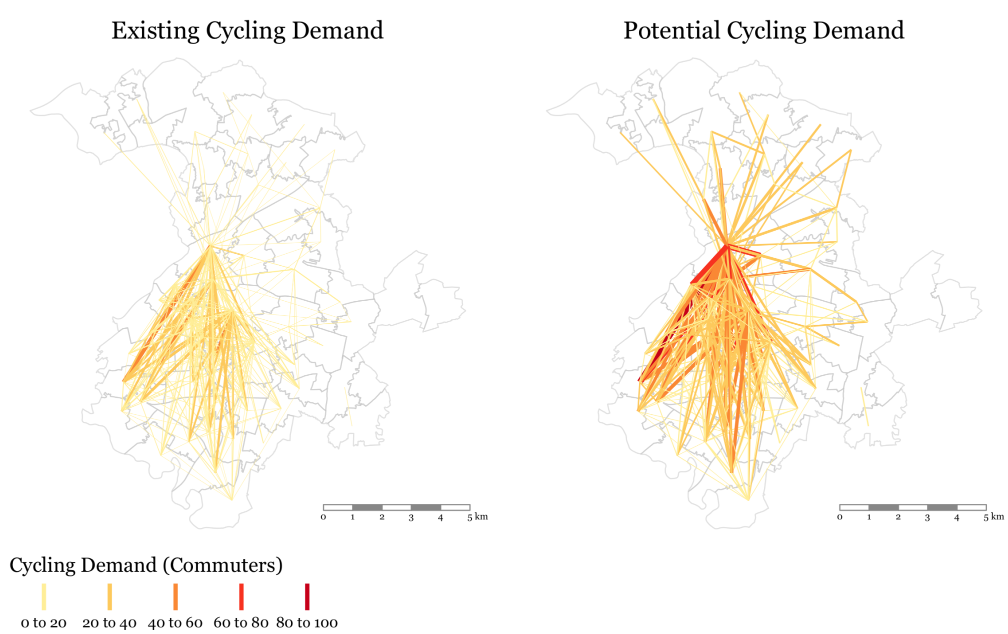

Figure 2: Current and Potential Cycling Demand

It should be noted that the calculations assume a future that is constrained by physical geography; i.e. we consider cycling in the traditional sense. Recently there have been various micro-mobility solutions, including e-bikes, that allow commuters to traverse longer distances and hillier roads with less effort than traditional bicycles. While these modes would probably be associated with less geographical impedance, it is beyond the scope of this work to integrate that into the analysis. Doing so is partially restricted by the lack of data on the proliferation of these modes, which raises the point that perhaps the census data category of 'Bicycle' is too vague, and should be further dis-aggregated to distinguish between traditional bicycles and other forms of micro-mobility.

6 Routing

The next step is to route the potential cycling demand ($\boldsymbol{C_p}$) between all OD pairs onto the road network.

ADD TABLE

To conduct routing, the following is considered:

1. **Cyclist Preference**: Work done by Dill and McNeil (2013) on examining cyclist typologies determined that around 60% of Portland residents fit under the *interested but concerned* category. These were people that enjoyed cycling but avoided it due safety concerns. The key to encouraging this group was to create a low-stress cycling network, not only though segregated infrastructure but also by planning routes that passed through residential streets.
2. **Low-Traffic Neighborhoods**: The UK Department for Transport is allocating funding to local authorities to invest in Active Transport, partially through the creation of LTNs (DfT 2020b). This includes closing off residential streets to motorized traffic
3. **Existing Cycling Infrastructure**: Utilizing existing cycling infrastructure makes economic sense, as small investments may lead to large connectivity gains as the disconnected cycling infrastructure gets joined together.

The weighting profiles are therefore adjusted to favor less-stressful streets (based on information from Table **REFERENCE THE TABLE**), and roads with existing cycling infrastructure. This is also in line with the creation of LTNs, as residential streets are those where motorized traffic is most likely to be banned in the creation of LTNs.

ADD TABLE

A weighted distance $\boldsymbol{d_w}$ for each road segment is calculated as following:[5]

$$d_w = d_{unw} \; / \; W \tag{2}$$

where $\boldsymbol{d_{unw}}$ is the unweighted distance and $\boldsymbol{W}$ is the weight from Table **??**.

All weights are between 0 and 1, and the values in the *Weighted* profile are chosen so as to be inversely proportional to the stress level experienced by cyclists on them. The *Unweighted* weighting profile is used to compare increases in route length resulting from two different approaches:

1. **Weighted**: Relatively high impedance on Primary and Trunk roads (to minimize cycling on them).
2. **Weighted_2**: Avoiding Primary and Trunk Roads completely.

Comparing the cycling demand routed on the weighted and unweighted road network allows us to get a better understanding of the importance of different road types. In the case of Manchester, trunk roads bisect the city and are a major part of unweighted shortest paths (Figure 3). On the other hand, cycleways are not part of unweighted shortest paths, and so very little of the cycling demand is routed through them. In the weighted network, cycleways are much better utilized, and the majority of the cycling demand passes through tertiary roads, as expected.

The results of routing potential cycling demand on the weighted and unweighted networks are understandably quite different. From Figure 3 we can see that trunk and primary roads are the most efficient means of traversing the road network of Manchester. Both of these road types are classified as Primary A roads according to the UK Department for Transport's road classification (**Reference the table**), and are therefore part of the Primary Route Network

[5]The **dodgr** r package (Padgham 2019) is used to route cycling demand onto the road network. The package uses the OpenStreetMaps (OSM) road network and allows the user to assign weights to roads based on their type. The routing is done based on weighted shortest paths, with the distance along each road segment being divided by a factor to obtain the weighted distance for routing. It is more intuitive to multiply when weighting a network, but the dodgr package divides by numbers between 0 and 1, which achieves the same result. For the sake of reproducibility, we stick to the convention used in the package.

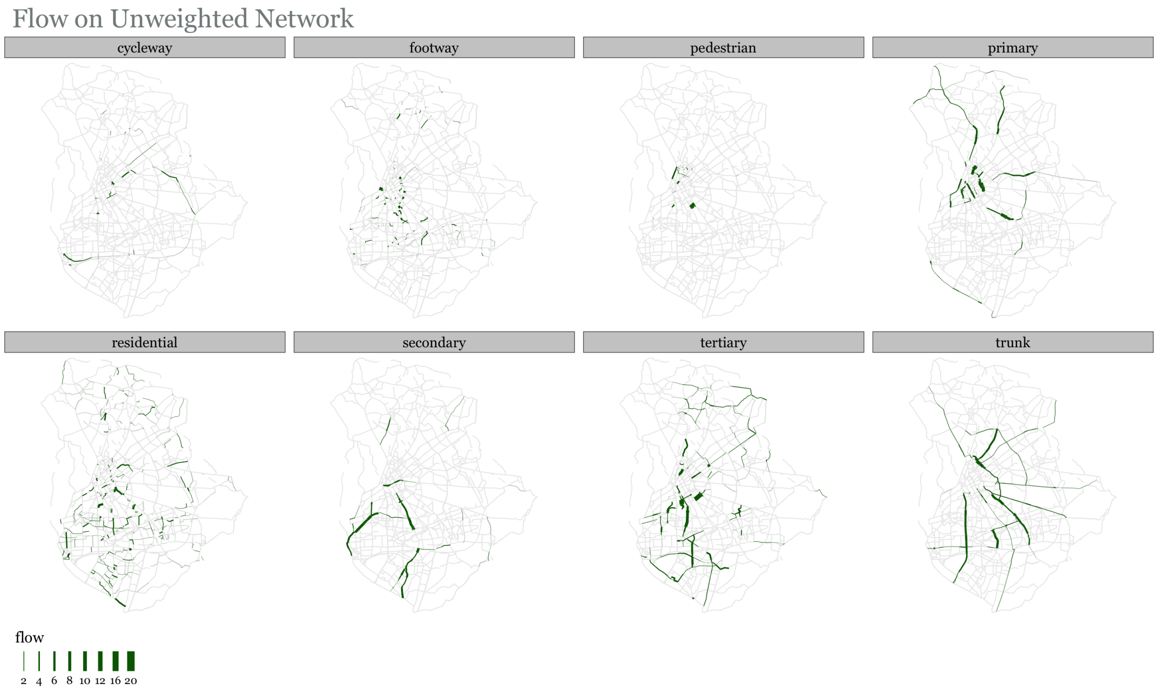

Figure 3: Flow Results Based on **Unweighted** Shortest Paths (Manchester)

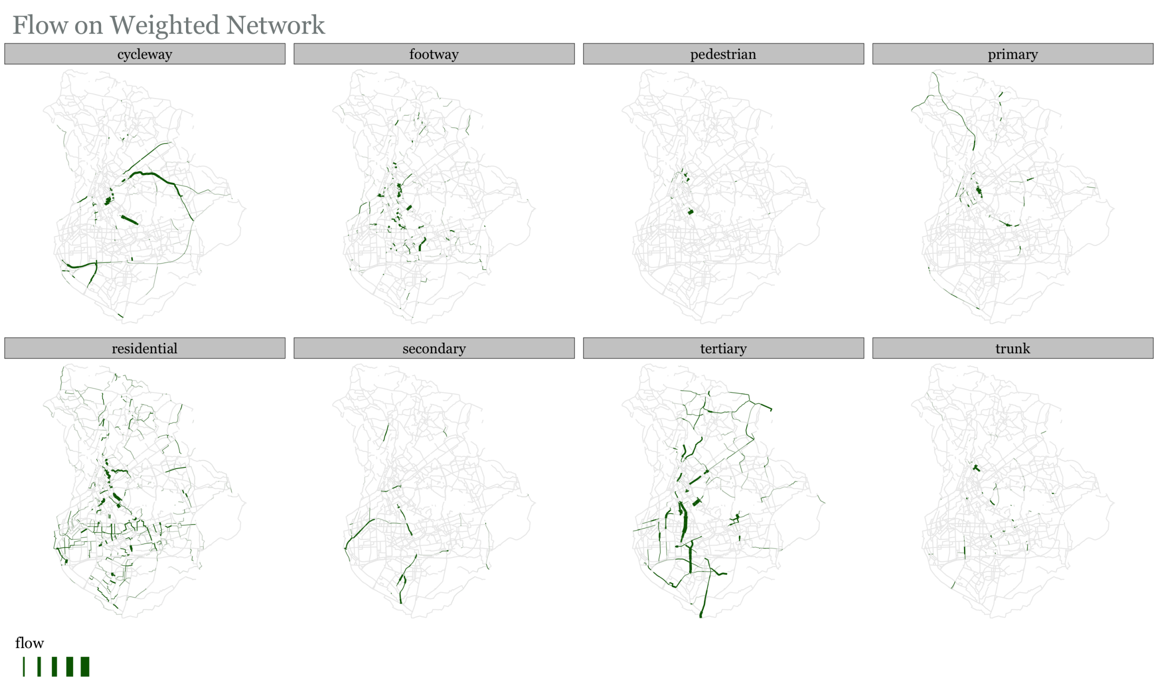

Figure 4: Flow Results Based on **Weighted** Shortest Paths (Manchester)

(PRN) (DfT 2012). The PRN has the widest, most direct roads on the network, and carries most of the through traffic. This includes freight, with all roads in the PRN being required by law to provide unrestricted access to trucks up to 40 tonnes (DfT 2012).

We choose to avoid routing the potential cycling demand on Primary A Roads for the following 2 reasons:

1. **Logistical Difficulty**: Changes on these roads need to be agreed upon by all affected authorities (DfT 2012), which may prove to be difficult.
2. **Low Traffic Neighborhoods (LTNs)**: The UK government is aiming to restrict access to motorized vehicles on residential roads to create LTNs (DfT 2020b). This is part of a policy to prevent automobile rat-running and make streets more accessible to cyclists and pedestrians. Under such a policy, Primary A roads would become even more essential for motorized traffic and it would be more difficult to reallocate road space on these roads to cyclists.

Routing potential cycling demand on a weighted network is more in line with government policy to create LTNs. Figure 4 shows that routing on the weighted network significantly reduces flow on the trunk and primary roads, but does not eliminate it completely. This is intentional, as the impedance on these roads is only slightly higher than remaining road types (See Table **Reference the table**). Potential cycling demand is only routed on these roads if there are no routes through other roads that offer comparable directness.

Banning cycling flow completely on trunk and primary roads may result in excessively circuitous paths, as seen in Figure 5. When routing using the weighting profile in Table **Reference Table**, we see that shortest paths increase by less than 5% on average from unweighted shortest paths, with the largest increases still below 30%. When routing on primary and trunk roads is banned, the average increase relative to unweighted shortest paths rises to 10%, with certain locations experiencing more significant negative effects on accessibility.

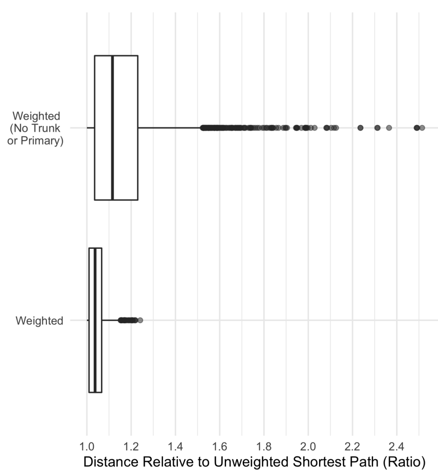

Figure 5: Effect of Banning Cyclists from Trunk and Primary Roads for all OD Pairs (Manchester)

Given that cyclists will only deviate from shortest paths by a certain amount to access better cycling infrastructure (as explained in Section 3.1, allowing flow on some stretches of trunk and primary roads is necessary to insure cycling uptake and equitable access to cycling infrastructure. In its new vision for walking and cycling, the Department for Transport acknowledges that minimal segregated stretches of bicycle lanes on main roads will be necessary to avoid circuitous cycling networks (DfT 2020b).

Weighting the road network also allows us to better utilize existing cycling infrastructure, as can be seen by the higher flow on cycleways in Figure 4. Again, the small differences in impedance between cycleways and other road types mean that cycleways that require significant deviation are not routed on.

It should be reiterated that the weighting profile used for routing has been developed for the purposes of this study. It creates a hierarchy of road preference that is grounded in cyclist preference and government plans to create LTNs. Sensitivity analysis should be done to determine an optimal weighting profile, but given the variation in city road networks , , these would probably require calibration to the specific city. More accurate routing could be carried out given the availability of road-level data. In such cases we would add additional impedance to specific roads, giving more useful routing results than the current methodology which considers all roads of the same type to be equivalent.

One use-case of such granular data would be to identify roads that serve schools. The Department of Transport notes that the number of school children being driven to school has trebled over the past 40 years (DfT 2020b), and so having cycling infrastructure serving schools is key to achieving the government target of getting more children to cycle. This would not be difficult, as over 75% of children in the UK live within a 15 minute cycle from their school (DfT 2020a). Goodman et al. (2019) show that if dutch levels of cycling were achieved in the UK, the % of children cycling to school could increase from 1.8% to 41%.

In their typology of cyclists, Dill and McNeil (2013) found that a majority of people who say they would never cycle had never cycled to school, whereas confident cyclists were those most likely to have cycled to school. Getting people to cycle from a young age is therefore key to achieving societal change in commuting habits.

7 Community Detection

One of the main aims of this research is to incorporate egalitarian principles by fairly distributing investments in cycling infrastructure. One way of quantifying this is to split up the city into smaller geospatial areas and target equal investment in each of those areas. Community detection offers us a way to delineate such a split; cyclists are limited in their commuting distance (see Figure 6), and so trip attractors are more likely to have a local catchment area of cyclists.

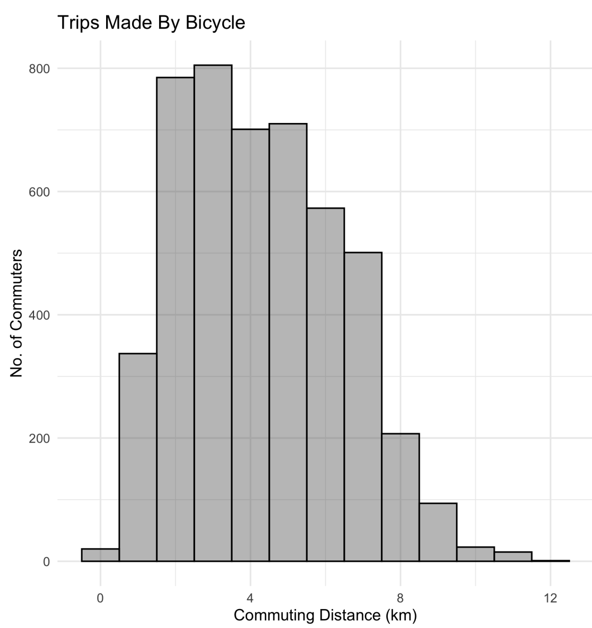

Figure 6: Cycling Commuting Distance - Manchester (2011 Census Data)

In our case, the network is the city; the nodes are the population-weighted MSOA centroids and the links connecting each MSOA pair are weighted by the potential cycling demand between them. The Louvian method (Blondel et al. 2008) is used to separate MSOAs into communities. Potential cycling demand is used since we assume that this is what the cycling demand will be once the cycling infrastructure is added. To assign road links to communities, the following steps are carried out:

1. Create links between MSOA centroids and weigh these links by potential cycling demand between them.
2. Use Louvian method to determine optimal number of communities and assign each MSOA centroid to a community.
3. Assign each road link to the same community as the closest MSOA centroid to it.

The results show that Manchester can be split into four large communities and one small one (Figure 7).

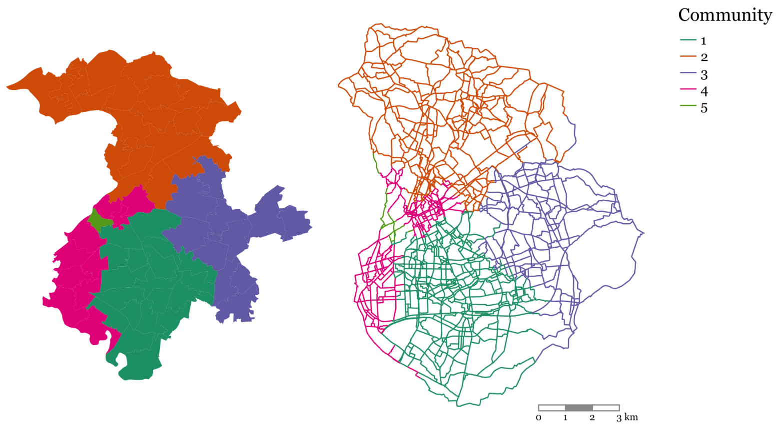

Figure 7: Communities Based on Potential Cycling Demand (Manchester)

8 Road Segment Prioritization

After routing the potential cycling demand onto the road network using weighted shortest paths, we have estimates for the cumulative potential cycling demand passing through all road segments. This cumulative demand (referred to as *flow* is then used as a basis for determining where best to invest in segregated cycling infrastructure. In doing so, we must account for the motivations and deterrents for cycling identified in Section 3.1, namely direct and well connected routes.

For this purpose, two algorithms are proposed. Both utilize existing infrastructure from the beginning and allow us to compare a solution that focuses on utilitarianism to one that focuses on egalitarianism. In both algorithms, links[6] are selected iteratively and the iteration at which each link is added to the solution is recorded. Investments in cycling infrastructure can be limited by budget constraints, so it can be useful to see where best to allocate a defined length of segregated infrastructure.

8.1 Algorithm 1: Utilitarian Growth

1. Identify all links that have segregated cycling infrastructure and add them to the initial solution
2. Identify all links that neighbor links in the current solution
3. Select neighboring link with highest flow and add it to the solution
4. Repeat steps 2 & 3 until all flow is satisfied or investment threshold is met

This algorithm ensures that the resulting network is connected. It also satisfies the directness criteria, since links on the weighted shortest paths are those that have the highest flow passing through them (this is a result of the routing in Section 3.1.

8.2 Algorithm 2: Egalitarian Growth (Focus on Fair Distribution of Resources)

The first algorithm focuses on connectivity and directness, but not on fairly distributing investment. The latter is not a requirement for increasing cycling uptake, but it is fundamental for spatial equity, as explained in Section 3.3. This algorithm incorporates the ideal of fair distribution by using community detection to partition the road network.

The algorithm uses the following logic to ensure fair distribution between communities:

1. Identify all links that have segregated cycling infrastructure and add them to the initial solution
2. Identify all links that neighbor links in the current solution
3. Select *from each community* one neighboring link with highest flow and add it to the solution
4. If there are no more neighboring links in a community, select the link with the highest flow in that community, regardless of connectivity, and add it to the solution

[6] *link* refers to a road segment

Table 1: Total Person-Km in Different Communities (Manchester)

Community	Person-Km (Total)	Person-Km (%)
1	284458	44.4
2	163877	25.6
3	79218	12.4
4	109635	17.1
5	3317	0.5

5. Repeat steps 2, 3 & 4 until all flow is satisfied or investment threshold is met

Even though we may end up with a more disconnected network, we will have separate connected networks in each community. Given that communities are defined by having more internal flow than external flow, this is a satisfactory solution.

The results of the community detection are used to evaluate the algorithms. This is done by looking at the *person-km satisfied* as cycling infrastructure is added. Person-km is a measure of the total km cycled on a road segment, so it is the product of the number of potential commuters cycling on that road segment ($flow$) and the length of the segment in km (l). For each road segment, the person-km is equal to $flow * l$. In the case of Manchester, Table (**Reference the table**) shows that almost half of the person-km is in community 1 , while only 0.5% of total person-km on the network is in community 5.

Looking at the person-km satisfied (Figure 8), we see that the incremental addition of cycling infrastructure is better distributed between communities using Algorithm 2; equal distribution of investment results in the gain in % of person km satisfied in each community being inversely correlated with the size of the community. In addition, we find that the restrictions imposed by Algorithm 2 on the network growth do not seem to have a noticeable effect on the city-wide % of person-km satisfied. Comparing both algorithms, we can see that Algorithm 1 provides only marginally quicker city-wide gains than Algorithm 2.

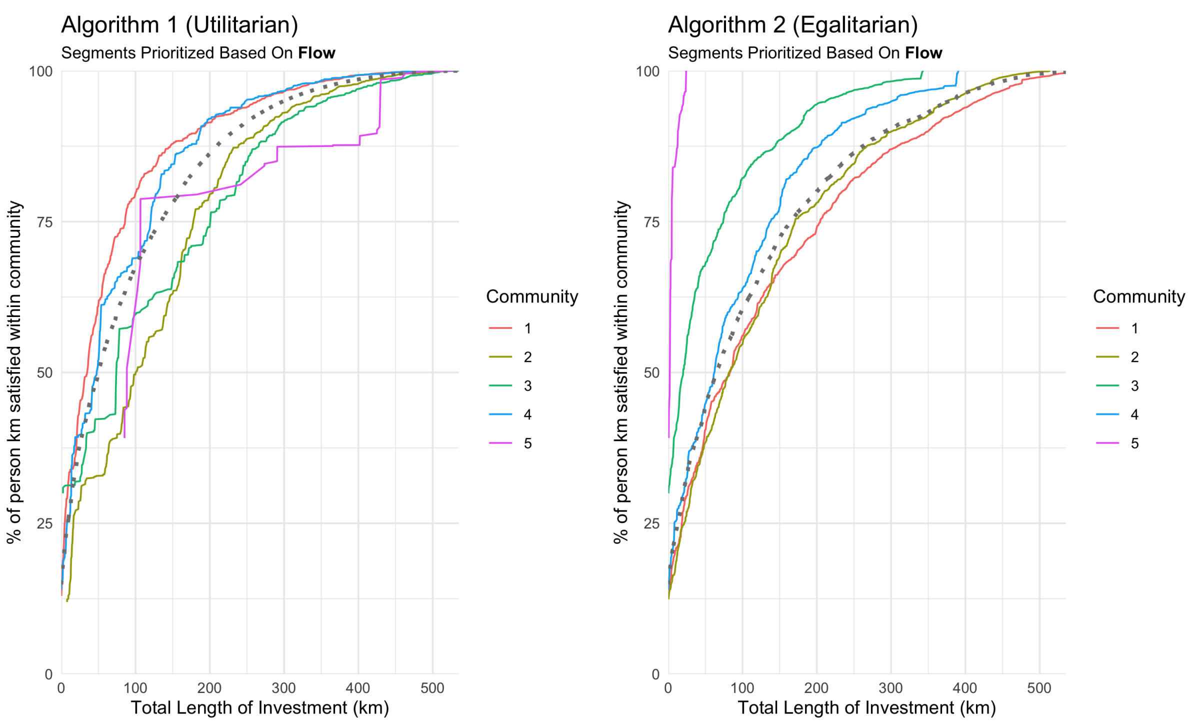

Figure 8: Comparing Overall (Dashed) and Community Level Person-Km Satisfied (Manchester)

Figure 9 gives us a geographic representation of the results from Algorithm 2; it shows when each link was added to the solution (first 100km, second 100km, etc). We can see that, generally, road segments around cycling infrastructure are prioritized, except for those neighboring cycling infrastructure on the very periphery. The first 100km is also spatially distributed across the city, with no apparent bias towards a particular area.

It is also important to understand how the different highway types contribute to the proposed network. Figure 9 shows that most of the flow will be on residential and tertiary roads, as expected from the weighting profile defined in Table **reference the table**.

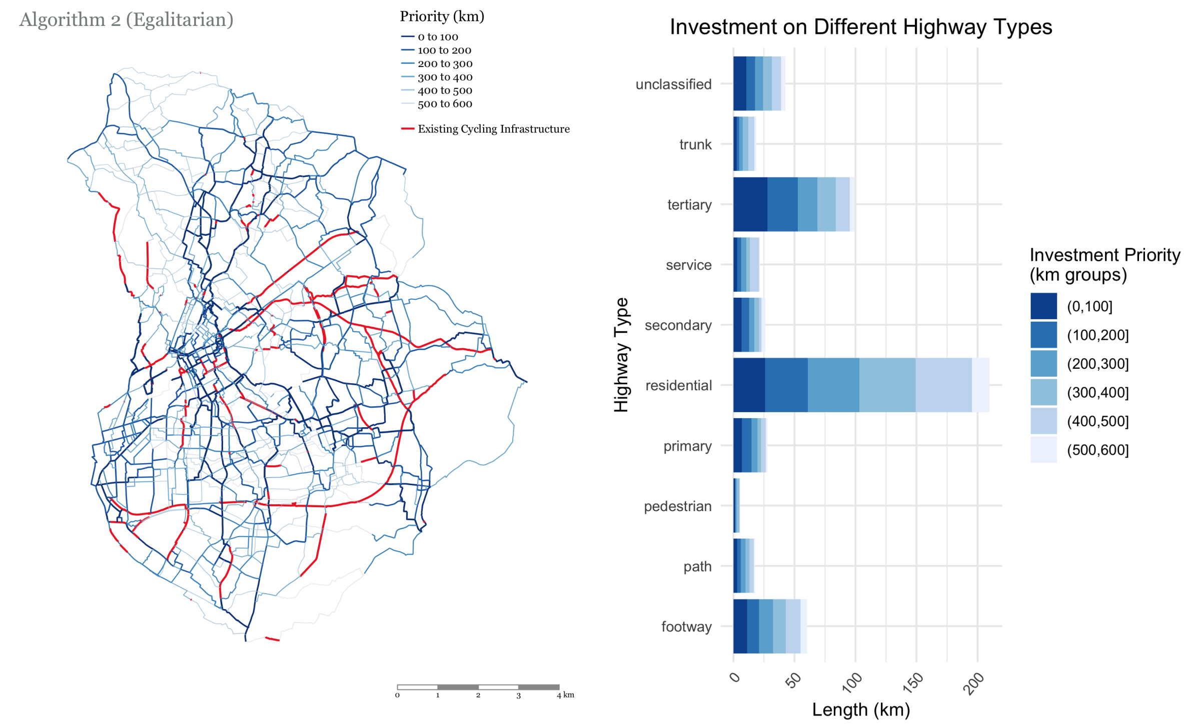

Figure 9: Results of Alg. 2 (Manchester)

8.3 Connectivity

Existing cycling infrastructure is made up of many disconnected components. Both Algorithm 1 and 2 start with all existing segregated cycling infrastructure and aim to create an efficient, connected network. Figure 10 shows that both algorithms gradually reduce the number of components as more infrastructure is added, but Algorithm 2 is able to provide better connectivity with less investment.

Consistent growth can also be seen for the size of the Largest Connected Component in the proposed bicycle network (Figure 10). Here however, we find that there is little difference between both Algorithms.

9 Overarching Policies

While segregated, connected, and direct cycling infrastructure is key to achieving high levels of cycling, research has shown that it cannot exist in a vacuum. Wardman, Tight, and Page (2007) developed a mode choice model for the UK and their results showed that improved cycling infrastructure on its own only had modest impacts on mode shift, and even the unlikely scenario of all urban routes being serviced by segregated bike lanes was forecast to increase cycling mode share by only 3%. However, cities that invest in more comprehensive cycling projects show a more significant increase in the number of cyclists as well as the cycling mode share (Pucher, Dill, and Handy 2010). These cities do not just focus on infrastructure, but on general policies as well as restricting car use. Evaluation of policies in Denmark and Germany and the Netherlands has shown that their high cycling mode share is down to a broader set of policies that also include traffic calming, cycling rights of way, bike parking, integration with the public transport network, and making driving cars both expensive and inconvenient (Pucher and Buehler 2008). While these policies are outside the scope of this research, it is important to recognize their key role in bringing about an increase in levels of cycling.

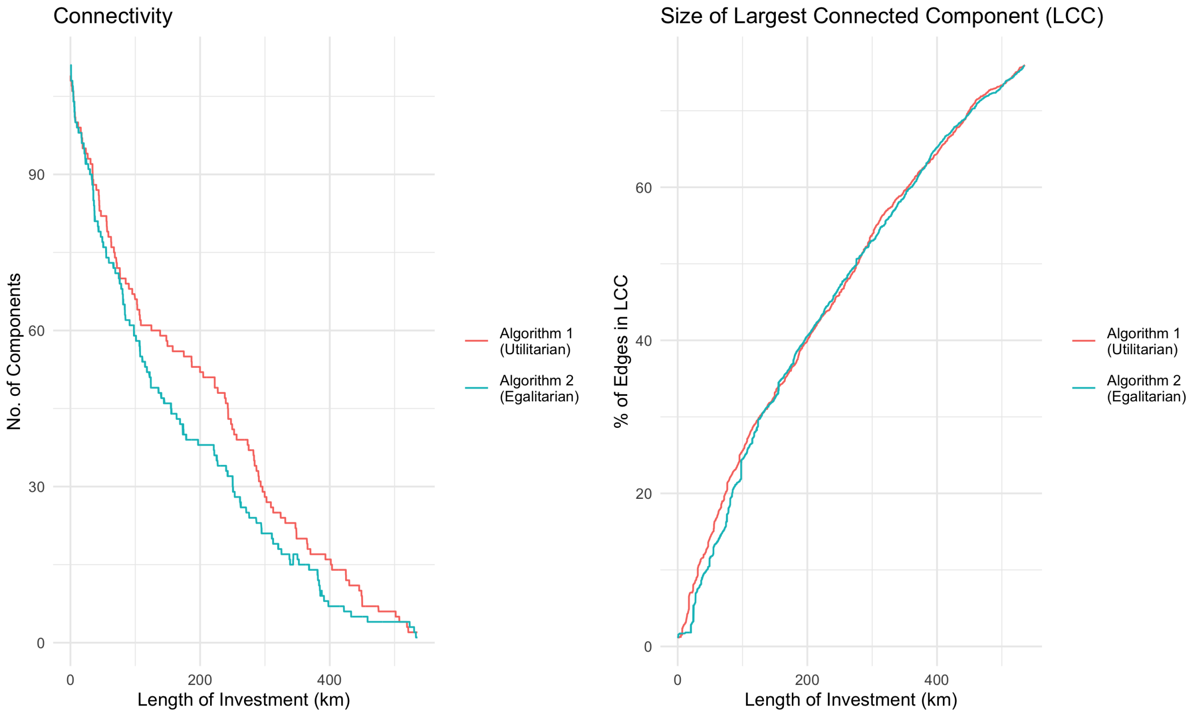

Figure 10: Network Characteristics

10 Conclusions

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