Cycle Networks — Finding the Missing Links

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March 9, 2021

1 Introduction

Cycling is becoming increasingly more popular as a means of transport around large cities like Bristol [1]. This rise is due to a combination of factors, chiefly, increased environmental awareness, personal health, and the huge amount of road traffic meaning cycling is in some cases faster than driving for short journeys.

The National Travel Survey (NTS) [2] reports that cycling currently makes up 2% of all trips, where a trip is defined as a one-way course of travel with a single main purpose, and that the average length of these trips is 23 minutes. This seems a small proportion given that 38% of people surveyed own a bicycle. The third wave of the National Travel Attitude Survey (NTAS) [3] posed questions as to why people don't like to cycle. Their conclusions found that 60% of people agree that "it is too dangerous for me to cycle on the roads". Research suggests that an increased provision of cycling infrastructure is positively correlated with the proportion of people cycling within that city [4]. The key to increasing cycling rates in Bristol is thus to ensure cyclists feel safe and have segregated paths and lanes to use throughout their journeys.

Currently, when planning road networks, lots of money is spent with engineering consultants to decide where to build new roads [5]. Cycling is much less common as a mode of transport than driving, so planning the cycle network has a significantly lower budget. This means that selecting where new cycle paths are built or lanes are painted is often an arbitrary decision made by the local authority. Therefore, this project aims to develop a mathematical framework to inform these decisions.

There is some previous work in the area of planning cycle networks, and most studies focus on two areas: the effect infrastructure has on the number of cyclists and the evaluation and proposal of cycle schemes based on geographical factors. The first area motivates the need for cycling infrastructure [4]. The second is useful for the evaluation of routes suggested by this project based on urban factors such as the amount of retail or business land area at both origin and destination of the route [6]. The methods presented by Milakis et al. [7] give a comprehensive methodology for evaluating proposed cycle routes. They use a weighted scoring system to assign good scores to origin-destination (OD) pairs attached to important facilities e.g., universities. In the literature little work has been found in the area of assigning new cycle routes automatically using a mathematical approach.

The main concern when automatically proposing roads for new cycling infrastructure is deciding how best to load a road network with cycling demand. Two papers have been identified for their methods in loading street networks with cycling demand. One approach, formulated by Milakis et al. [7], approaches this problem with the use of large demand centres. The study is based in Athens and the idea is to draw centres around areas of large demand. The centres are chosen based on three main criteria: the land use (retail, offices, education or leisure), the OD matrices from the last two travel surveys in Athens, and the network centres detailed in the master plan of Athens. Milakis et al. identify eight such centres and they are used as the OD pairs from which to generate synthetic cycle journeys. This methodology is a good starting point for loading the network with demand, but a set of only eight nodes does not allow for realistic models of commuting in cities such as Bristol, where workers commute from and to a huge number of different locations. This methodology is also not automatic: it requires a survey of cyclists to decide which land use attributes give the largest demand to a centre, and creating and carrying out a comprehensive survey is costly. The survey used in this case is also only considering existing cyclist's behaviour and therefore cannot predict the impact of new infrastructure on cycling demand.

A second paper by Larsen [8] takes a more granular approach. The methodology begins by separating the study area (Montreal) into 300m grid squares; the demand within each of these squares is then derived using both observed cycling trips (OD data from Montreal travel survey) and potential cycling trips (car trips shorter than 2km). These two data sources give OD pairs and then standard shortest path algorithms are used to model the route taken between them. Flow intensity is then given by the proportion of routes passing through a grid square. This analytical methodology is then combined with a survey of cyclists as to which road they think should be prioritised for new infrastructure to yield a prioritisation index.

One part of the Montreal study [8] that could be of particular interest to this project is their study of "Dangling Nodes". These are defined as grid squares in which the cycle infrastructure ends. The study concluded that the presence of a dangling node in itself is not an indicator of a need for new infrastructure. Instead they recommend looking at the amount of infrastructure needed to connect the network and performing a case-by-case assessment. The automatic approach proposed in this project may allow for some dangling nodes to be eliminated from consideration, if connecting them to the rest of the network yields no step change in connectivity.

Research by Mauttone et al. [9] applies formal optimisation techniques to the cycle network in some case study cities. The research proposes optimisation of total user and construction costs where both are proportional to distance and user costs are increased on edges without cycling infrastructure. The paper uses a heuristic approach to optimise for user cost on large scale networks, and compares against exact solutions on smaller artificial network examples. However their algorithm does not naturally penalise disconnections in the resulting network, therefore a methodology for identifying links that join up the cycle network is needed.

One tool that has been recommended to us by sustainable transport planners [10] is the the Cycling Infrastructure Prioritisation Toolkit (CyIPT). This is a combination of smaller tools that aims to provide an interactive map of the UK, detailing areas for proposed new cycling infrastructure. The components of most interest are the propensity to cycle tool (PCT) [11] and the rapid cycleway prioritisation tool (RCPT) [12]. The PCT serves as the CyIPT's demand model, using 2011 census data to provide estimates of OD flows. The PCT also uses geographical factors such as 'hilliness' to reduce the propensity to cycle on any given route. Our key interest in the RCPT is its planned facility to compute cohesive networks, which represent more highly connected cycle networks. However, in the current RCPT documentation there is no formal mathematics presented as to how to find these cohesive networks.

Summary of studies

Study	Methodology
Athens [7]	Select centres throughout the city based on their land use e.g., university. The land uses have a cycling priority index based on an OD survey. Then load demand between centres.
Montreal [8]	Split city into 300m grid squares. Then load underlying road network using OD survey data. Prioritise grid squares based on OD demand and a cyclist survey.
Network Optimisation [9]	OD matrix derived from a 2009 household survey in Montevideo (Uruguay). The algorithm presented then tries to optimise for user cost given the length of edges in the road network.
CyIPT [11], [13]	Demand matrix comes from the PCT lower-level tool which uses 2011 census data for OD pairs along with geographical measures such as incline. These are used to assign a value to each edge as to how likely people are to cycle on it. The CyIPT then takes this demand and proposes schemes with high upside whist minimising estimated construction cost.

2 Methods and Results

2.1 Data and Demand

Any form of transport modelling requires a demand structure

Data

To create the network needed for the analysis proposed in this project, OpenStreetMaps (OSM) has been identified as the primary data source. A python package OSMnx [14] has been used for easy conversion of OSM data to a network topology. To obtain the data from OSM we must query the OSM overpass API. OSMnx streamlines the query process, although in the case of this project a custom query is built to obtain all the data required to build the cycle network. The fist step is to convert the OSM map of Bristol, our selected bounding geography, to a network. This yields a set of 'ways' (all roads and paths) that can be cycled on within the bounding geography, hence excluding motorways etc. This can then be used to create a graph G whose edge set E represents the set of all ways and whose vertex set V represents junctions between ways and points at which ways gain or lose cycling infrastructure. The number of vertices in G will typically be much less than the number in the OSM data as it is not necessary to describe the curvature of each way in our study.

Prescribing the weights of edges

The first step in the analysis of Bristol's road network is to identify the edges corresponding to existing cyclepaths. The OSM tags of interest are 'Highway', 'Cycleway' and 'Bicycle', although not all of these are present for every way in the network. Our conditions for a way to be identified in the cycle network are: (a) its 'Highway' tag takes the value 'cycleway'; or (b) its tag set includes 'Cycleway'; or finally (c) its tag set includes 'bicycle' which takes the value 'designated'.

These criteria give rise to a binary indicator variable $\chi_{i,j}$ for the edge connecting nodes i and j which takes values,

$$\chi_{i,j} = \begin{cases} 1, & \text{if } (i,j) \text{ is a cycle path,} \\ 0, & \text{otherwise.} \end{cases}$$

The network with edges taking value $\chi_{i,j} = 1$ highlighted can be seen in Figure 1 with a zoomed in section showing the fine detail.

The edges (i,j) of G are weighted to represent the cycled length $l_{i,j}$ of the edge and a parameter $p_{i,j}$ which represents the impedance to cycling. The value of $p_{i,j}$ can in principle take into account lots of real world factors such as: hills, speed limit of roads etc. The analysis presented here will take a very simplified approach by setting

$$p_{i,j} = 1 - \chi_{i,j}.$$

Each putative cyclist k should also have a personal parameter ω_k which describes their propensity to cycle on ways without cycling infrastructure.

From this the effective length of the edges in the graph G can be modelled as

$$\hat{l}_{i,j} = l_{i,j}(1 + \omega_k p_{i,j}), \tag{1}$$

meaning that an edge without cycling infrastructure has a larger perceived length than its true length according to the cyclists disposition. The idea then is that if a given cyclist tries to minimise the effective length of their route, they will prioritise routes that follow cycling infrastructure, provided the detour is not too large.

The way the road networks are converted into a network structure for python removes some of the physical meaning for the parameter ω_k. The streets in Bristol's road network are made up of multiple edges in the python network. This means are larger than expected ω_k is needed to yield the desired effect on roads whose python representation is in many very short edges.

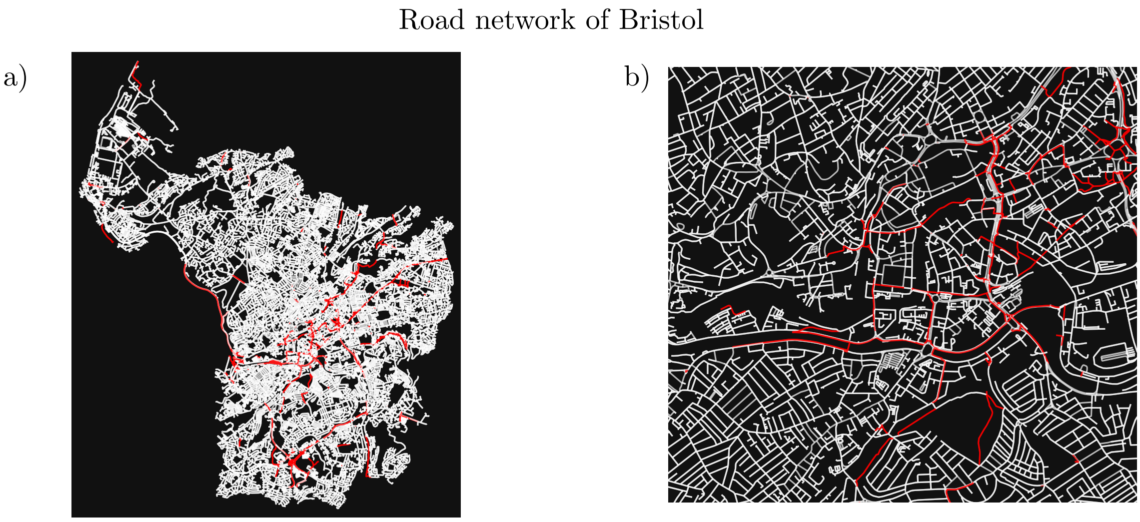


Figure 1: Road network of Bristol with edges (i, j) whose $\chi_{i,j} = 1$ highlighted in red. A section in the centre of a) is seen zoomed in b) to show the finer detail of the network.

Uniformly random OD pairs

Naturally the simplest way of loading the network with cycling demand is to sample OD pairs randomly from the set of all nodes within the network. The next step is to compute the shortest route between each OD pair. At this stage we suppose that $\omega_k = 0$ to model the case where cyclists have equal propensity to cycle on roads with or without cycling infrastructure. We compute 500 such shortest routes and the percentage of time spent on cycle infrastructure is found for each one, see the distribution in Figure 2.

Ignoring the huge peak at 0% the proportion of route length spent within the cycle network seems to decay exponentially, with the vast majority of routes spending less than 15% of their length on cycle infrastructure. This result makes sense given the unconnected nature of Bristol's cycle network, which does not allow for whole routes to use cycling infrastructure. The peak around 0% is due to the random selection of OD pairs giving rise to extremely short routes in areas of Bristol with no cycling infrastructure, so it is impossible for the shortest route to contain cycle lanes. In this computation the mean number of edges used in shortest paths is 120 which, when the network contains $56,000$ edges, is conducive to a large number of short routes. Another explanation for this peak is simply that the cycle network in Bristol is so sparse that most shortest routes cannot use cycling infrastructure. Some users may be able to increase their percentage of time on cycling infrastructure by allowing for not strictly shortest routes.

Promote use of cycle paths

The literature suggests that the majority of cyclists prefer to cycle on designated cycling infrastructure [4]. This means that ω_k should be strictly positive. The larger the value given to ω_k, the larger the penalisation of routes with no cycling infrastructure. A learner cyclist k' should have a large value for $\omega_{k'}$, as it is highly unlikely that a learner would want to cycle without dedicated infrastructure. Furthermore a second bounding geography Amsterdam is also presented in order to compare model results on a more highly connected cycle network. In order to control

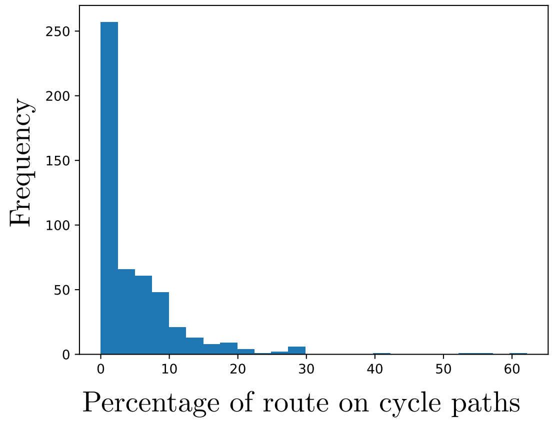


Figure 2: Histogram showing the percentage of routes taken on cycle lanes within shortest routes using uniform random OD selection, with parameter $\omega_k = 0$ so that streets with no cycling infrastructure are not penalised.

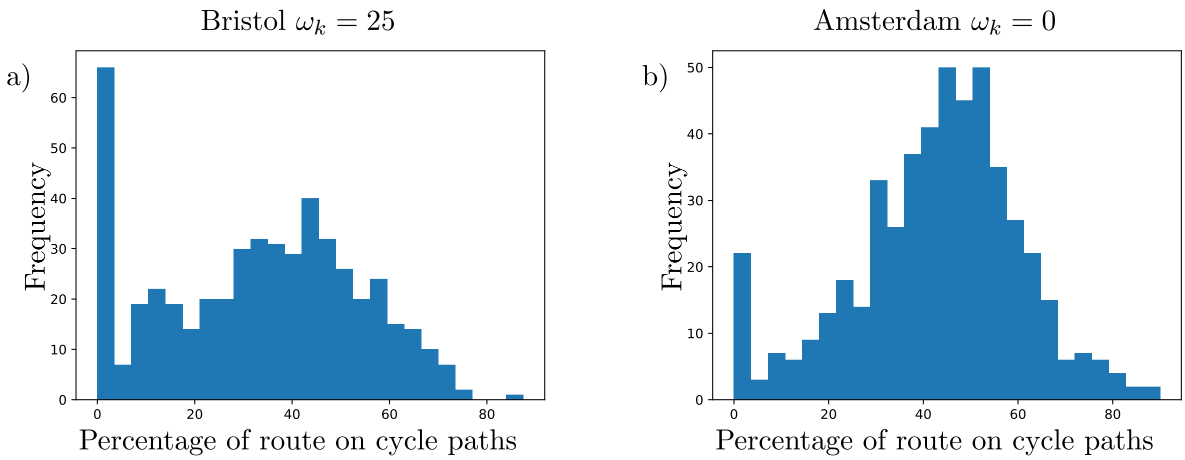


Figure 3: Histograms showing that both increasing ω_k in Bristol a) and the more connected city of Amsterdam (with $\omega_k = 0$) b) have a similar percentage of routes on cycle infrastructure.

changes to the model, ω_k is left as 0 in the case of Amsterdam, to see whether connectivity or propensity to cycle on roads has a larger impact on the model result. Amsterdam is selected as a bounding geography not just for its much more comprehensive cycle network but also for its higher quality OSM data. Amsterdam's higher degree of connectivity should yield a higher percentage of time spent on cycle paths within shortest routes.

Figure 3 shows that by decreasing a cyclist's propensity to cycle on roads without infrastructure, we do in fact increase the percentage of length routes spend on cycle paths. However, this effect is small in comparison to using a different bounding geography with a more highly connected cycle network. It is the case that in Amsterdam routes use more cycling infrastructure than Bristol even with $\omega_k = 0$. The issue with the outlier peak at 0% is still somewhat present, but in the case of Amsterdam almost certainly due to a small amount of very short routes that cannot feasibly use cycling infrastructure. Further computations (not presented here) have shown that as ω_k is increased for cyclists in Amsterdam, most routes are nearly 100% on cycle paths.

After restricting the model to choose shortest paths with at least 50 edges, the results obtained from the Amsterdam network with an $\omega_k = 0$ yield the same result but without a large peak at 0%. This confirms that this peak is caused by very short routes that simply cannot use cycling infrastructure. The problem is much larger in the Bristol network due to its low degree of connectivity, meaning paths would have to use almost the entire network to guarantee the use of cycling infrastructure.

Census Demand

Until now all the cycling demand had been modelled using uniformly randomly assigned OD pairs. This is not a good representation of true journeys within a city like Bristol. The next step in creating a realistic demand model for this project is to look at empirical data. Bristol, like any large city, owes most of its traffic flow to commuters, if we can simulate commuter journeys and assume they can be made by bicycle we will get a more realistic model for the flows of cyclists through Bristol. This means that census commuting data can be used to predict cycle flows. Unfortunately the most recent census data available is from 2011 and therefore, is not entirely accurate to today's commuting trends. The data being used is at LSOA level as this gives 263 zones in Bristol for flows to be generated between. Trip generation is then as follows:

1. Select at random an origin LSOA.
2. Using the commuting row corresponding to the origin LSOA calculate a probability vector for flows to other LSOAs
3. Sample a destination using the probability vector found above.
4. Map LSOA centroids onto the network
5. Find the shortest path between the centroids with penalty applied.

This method provides a more realistic representation of cycling demand in Bristol if people consider switching their commute to bicycle. One of the key drawbacks of this method is that with enough journeys demand will be very large near centroids and distributed more evenly away form them.

2.2 Upgrading the Network

Once a demand model is set, in this case the commute data demand model in Bristol, we can decide which parts of the road network are most in need of cycling infrastructure. The goal is to solve an optimal network design problem. That is, for a given budget can we maximise the percentage of the length of cycle trips that is on cycling infrastructure given our chosen demand model. Naturally to solve this completely is extremely difficult bordering on impossible for networks of the same size as Bristol's road network. This chapter defines a heuristic approach to the optimal network design problem.

Ranking the edges

To begin to upgrade the network we need some notion of priority so that we know which edges to upgrade first, a scoring system is proposed to rank the edges for upgrade. Each edge is given

Road network of Bristol before and after upgrade algorithm is applied

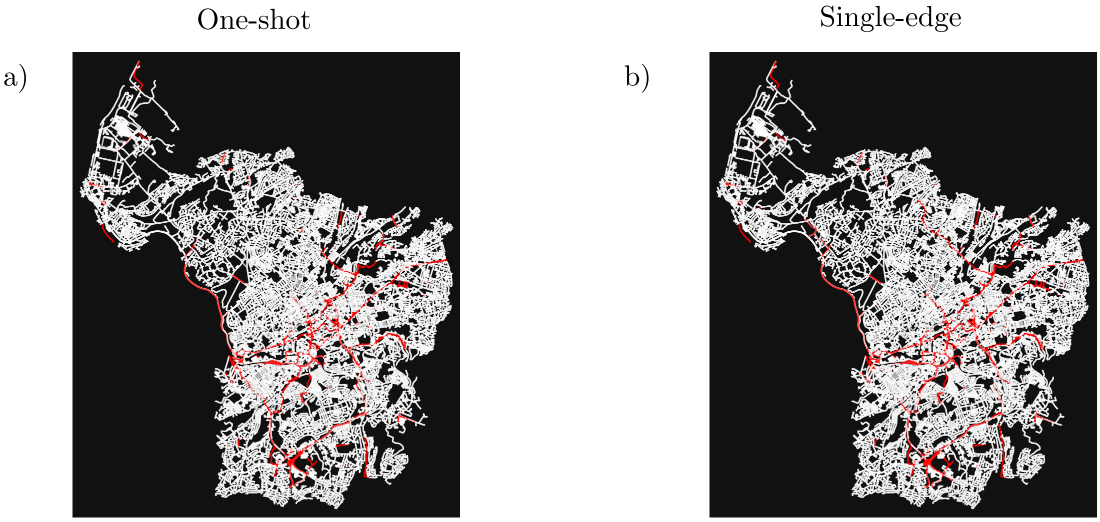


Figure 4: Road network of Bristol with edges (i, j) whose $\chi_{i,j} = 1$ highlighted in red. a) shows the network after a one-shot process has been applied to upgrade $N_e = 500$ edges and b) shows the result of a single-edge scheme upgrading $N_e = 500$ edges also.

a betweenness centrality like score to rank their priority for upgrade. This is done by simulating a set of N_t cycle trips on the network using a penalty factor ω_k as described earlier. Each edge is then assigned a score $\phi_{i,j}$ as to how many times it is used through all the simulated trips naturally this score $\phi_{i,j} \in [0, N_t]$. One factor that needs to be explored is the use of the LSOA centroid demand model as this will, with large N_t, lead to higher than average $\phi_{i,j}$ on edges connected to the centroids.

Upgrading the edges

After ranking the edges, the question is now how to most effectively implement an upgrade process on the network. Two extreme options are identified 'one-shot' and 'single-edge'. One-shot is that once all edge scores have been computed with a trip simulation of size N_t, a certain budget of non-cycle edges N_e are then upgraded and the resulting network is returned as the upgrade scheme. Single-edge on the other hand, upgrades the network incrementally. We compute all edge scores for a given trip simulation and then only upgrade the highest ranking non-cycle edge. The two methods have very different computational implications. The one-shot method is extremely fast but in theory fails to capture the 'attractiveness' of longer continuous cycle paths. However, single-edge will theoretically encourage growth of connected networks by prioritising flow on the new generated paths batch by batch, but will be significantly more computationally intensive with a new trip simulation being computed for each edge upgrade.

Figure 4 shows the two output networks for a) one-shot and b) single-edge schemes. The key are of focus is in the top right of the figures, there are multiple LSOA centroids in this are and therefore trips exist between there and the city centre. Only the single-edge scheme has grown a cycle network spoke into this area. This suggests that there is probably sampling error in the one shot approach. To combat this we would need to simulate a much larger amount of trips however, as discussed previously this will lead to unwanted trip density around the centroids. Even though the single-edge approach is more computationally expensive it did generate a spoke into the top right area and therefore is more representative of a network designed for better user experience.

A compromise needs to be found between these two approaches, so a batch upgrade process is proposed to save on computational complexity whilst also incentivising connected networks. The process is as follows:

- Simulate N_t trips on the network using a demand model of your choice (in this case LSOA census demand) and $\omega_k = \omega_d$.
- Compute edge scores $\phi_{i,j}$ and rank the edges.
- Upgrade N_b edges to cycle infrastructure by editing their 'highway' tag to be 'cycleway'.
- Return the new network and simulate a new batch of N_t trips.
- Repeat until B batches have been complete and a total of N_e edges have been upgraded.

Key parameters	
Parameter	Definition
N_t	The number of simulated cycling trips in a batch. This value should be large enough to avoid sampling bias but not too large as to focus demand on the centroids.
ω_d	The propensity to cycle factor for a 'design' cyclist. This is unique for the upgrade and need not be the same value in test cases.
N_b	The number of edges upgrade in a batch. This value need to balance computational intensity and the ability for the algorithm to find connected networks.
B	The number of batches required to reach the edge budget with the current N_b.

Using a batch process with the parameters $N_t = 500$, $N_b = 100$, $B = 20$, and $\omega_d = 25$. The upgraded network in Figure 5 is found.

The batch process is much less computationally intensive and, as seen in Figure 5 still yields connected cycle paths. Key areas of note are the connected paths extending from existing infrastructure in the centre of the map up towards the top where previously very little existed. This suggests that a batch process is the best system moving forward.

Measuring upgrade success

To measure the effect of a given upgrade scheme we consider once again the percentage of trips length on cycling infrastructure. This shows how connected the cycle network is for cyclist travelling common routes between the network LSOA centroids. To calculate this summary statistic, a large number of new trips are simulated on the upgraded network. These trips are

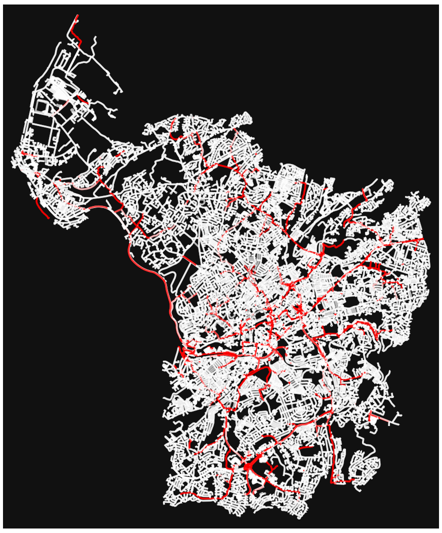


Figure 5: The upgraded Bristol network using parameters $N_t = 500$, $N_b = 100$, $B = 20$, and $\omega_d = 25$ for a batch process.

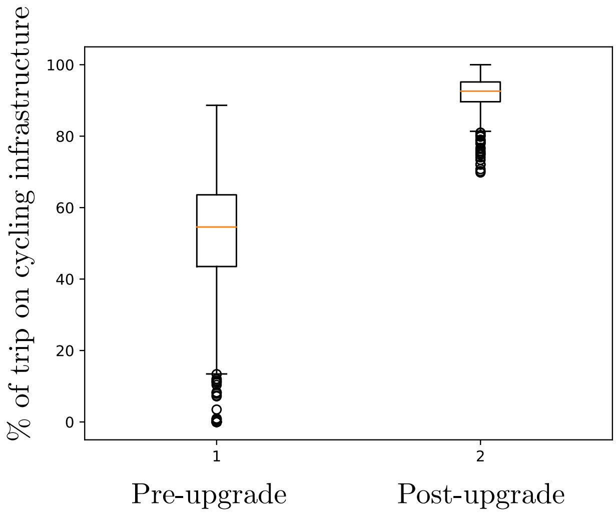


Figure 6: Box plot comparing the percentage of trips on cycling infrastructure before and after applying the upgrade algorithm. The cyclist considered for trip evaluation is given the same ω value as design $\omega_t = 25$.

considered for a cyclist with propensity ω_t which can be distinct from ω_d of the design cyclist for the upgraded network. For each of these trips a score is calculated as

$$P_{O,D} = \frac{l_{cyc}}{L} \times 100, \tag{2}$$

where l_{cyc} is the total length of used cycle edges and L is the total length of the trip. The distribution of these scores can then be compare with that of the true Bristol network to see the effect of the upgrade scheme.

Figure 6 shows a clear increase in the average percentage of cycle trips that fall on existing or

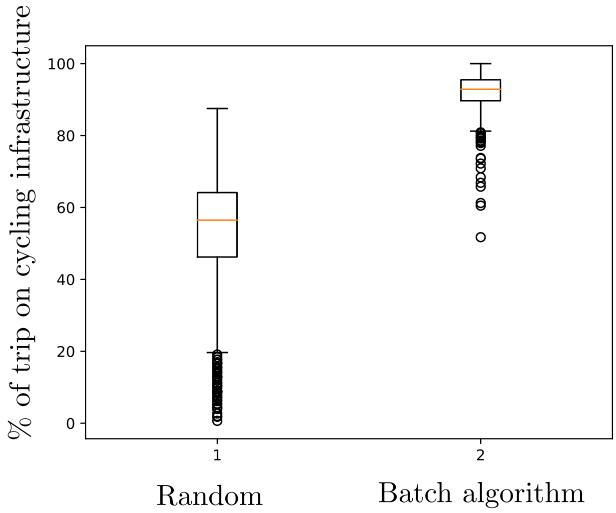


Figure 7: This box plot shows that the increase in the percentage of trip length on cycle paths seen in Figure 6 is not simply due to an increase in the amount of cycle paths. The algorithm does encourage connected infrastructure which leads to a better user experience.

suggested infrastructure. The upgrade algorithm has suggested a few long infrastructure 'spokes' from the centre of the network, meaning that for most cyclists it is only a short hop from their initial position at a centroid onto one of these spokes and the rest of the now connected cycle network. If the cyclist also only has a small hop off to their destination this means that a huge percentage of their route is on cycling infrastructure. It is worth noting that with the relatively large penalty parameter $\omega_k = 25$ cyclists will be highly incentivised to stay on the cycle network once they are on it.

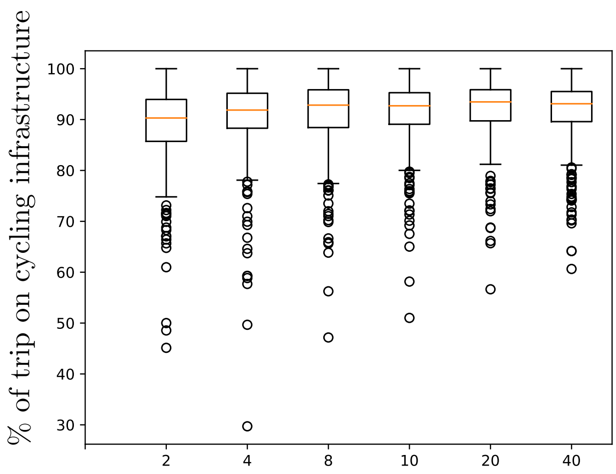
This increase in the percentage of length of trips on cycling infrastructure can be explained in two ways. First that simply the increased amount of cycling infrastructure means that more trips will use more of the cycle lanes, or secondly, the new network is more connected so there is little need for cycling outside of the cycle network. To test that thee former is true it is enough to compare the batch upgrade network to a randomly assigned upgrade process with the same edge budget $N_e = 2000$.

Figure 7 shows that in fact simply upgrading a random set of streets does not improve a given cyclists experience under an LSOA demand model. The improvement therefore must be due to the connectivity of suggested upgrade schemes from the proposed algorithm rather than simply the length of cycle infrastructure on the road network in Bristol.

Batch sizing

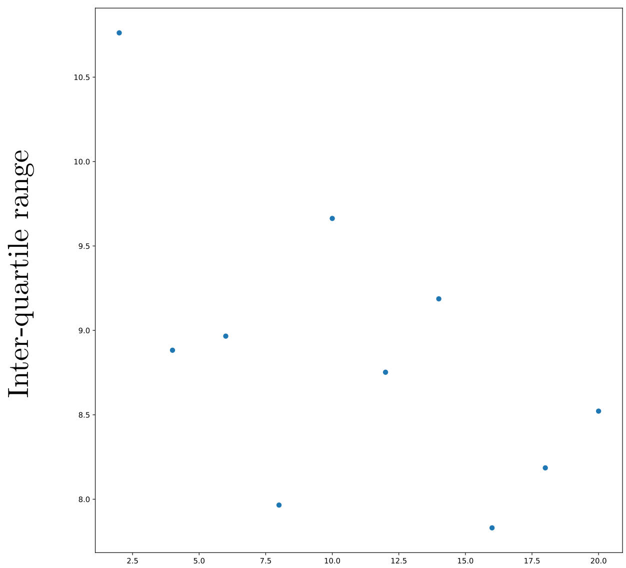
If we take an edge budget $N_e = 2000$ we would like to find the fastest running parameter set that yields a significant improvement in the distribution of trip $P_{O,D}$ scores.

Figure 8 details the impact on batch sizing on the scoring of the output network. While all batch sizes yield a marked improvement over a random assignment, again demonstrating the effectiveness of the proposed upgrade scheme, the is some improvement in having more smaller batches. The plot shows a small increase in the average percentage of trip length on cycle paths but not enough to justify the computational cost of smaller batch sizes. However, the decrease



No. of Batches (batchsize adjusted for $N_e = 2000$)

Figure 8: The difference batch size has on the resulting upgraded network scores for an edge budget $N_e = 2000$.



No. of Batches (batchsize adjusted for $N_e = 2000$)

Figure 9: The difference batch size has on the resulting upgraded network's spread of $P_{O,D}$.

in the spread of these scores as batch size is decreased is indicative of a better overall user experience with most if not all cyclists being able to spend the majority of their journey on cycling infrastructure. There does seem to be a sweet spot at $N_b = 20$ as the next increment $N_b = 40$ yields no improvement to spread yet takes twice the computational effort.

The relationship between this spread and the batch size is seen in Figure

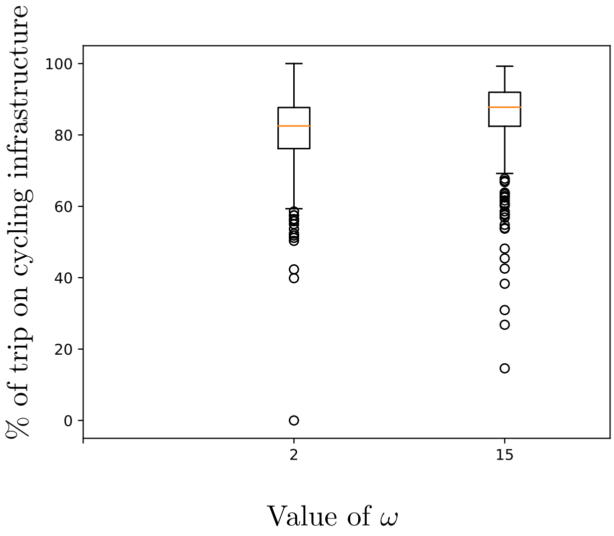


Figure 10: The differnce in scores for two types of design cyclist a confident low penalty and a nervous high penalty one. The networks are tested for a given nervous cyclist.

Design vs Tesing ω

So far the value of ω has been fixed between upgrading and testing the network, that is to say $\omega_d = \omega_t$. However, it is worth exploring the impact that designing a network for a cyclist with a given propensity ω_d has on the resulting networks fitness for a cyclist with a different propensity ω_t. For example, if we design a network with cyclists who don't have much preference between cycling on and off designated infrastructure will this have an impact on the experience of a cyclist with a much higher penalty factor in the testing stage. Conversely, if a cyclist has a low penalty factor in the test stage will they prefer routes that are off the cycling infrastructure as they are more direct than the continuous cycle paths desired by more cautious riders.

If we design a network with a low penalty factor say $\omega = 2$, representing a cyclist who is only slightly less likely to cycle on roads without cycling infrastructure and design another to the same edge budget using a higher penalty factor $\omega = 15$ for a cyclist who is nervous and therefore highly prioritises cycling on designated infrastructure. When we then test these networks we test with the nervous cyclist as they benefit more from new cycle paths.

Figure 10 shows that for a nervous test cyclist $\omega = 15$ the updated network performs better when designed with a cyclist of the same propensity to cycle. The two are however very similar

Physical meaning of batches

The batches in the proposed upgrade algorithm are until now just a synthetic time-step to encourage connected networks.However, there is a very nice parallel between batches and individual cycle schemes. In reality the council, or anyone else building new infrastructure, want to stagger the implementation of new cycle schemes to gauge the true impact that new infrastructure has on cycle demand. In this model it is appropriate to view the batches as these implementations. The characteristic of growing connected cycle paths then follows naturally. If there is new infrastructure naturally simulated cyclists with high penalty factor ω_d will want to use the new infrastructure to service their journeys. This would in reality then lead to higher flows on roads at the end of this new infrastructure, so long as it doesn't terminate in an LSOA centroid. Therefore the upgrade algorithm should and does prioritise these edges for upgrade in the next batch.

Therefore is it worth exploring the improvement batch on batch for these incremental cycle schemes. It is in the councils best interest to minimise their cost whilst maximising user experience. Hence, if there is a huge improvement to the $P_{O,D}$ scores in the first couple of batches and only very small improvements after, it may not be worth investing in further improvement.

2.3 Optimal Networks

References

[1] C. Allan. Cycling UK's cycling statistics. `https://www.cyclinguk.org/statistics`. Accessed 2020-12-02.

[2] Conclusions from the National Travel Survey 2019. `https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/905887/national-travel-attitudes-study-wave-3.pdf`. Accessed 2020-11-09.

[3] Conclusions from the National Travel Attitude Survey wave 3 2019. `https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/905887/national-travel-attitudes-study-wave-3.pdf`. Accessed 2020-11-09.

[4] J. Dill and T. Carr. Bicycle commuting and facilities in major US cities: if you build them, commuters will use them. *Transp. Res. Rec.*, 1828(1):116–123, 2003.

[5] G. Topham. Chancellor announces £27bn for roadbuilding in budget. `https://www.theguardian.com/uk-news/2020/mar/11/chancellor-announces-27bn-for-roadbuilding-in-budget`. Accessed 2020-11-29.

[6] R. Cervero and M. Duncan. Walking, bicycling, and urban landscapes: evidence from the San Francisco bay area. *Am. J. Public Health*, 93(9):1478–1483, 2003.

[7] D. Milakis and K. Athanasopoulos. What about people in cycle network planning? Applying participative multicriteria GIS analysis in the case of the Athens metropolitan cycle network. *J. Transp. Geogr.*, 35:120–129, 2014.

[8] J. Larsen, Z. Patterson, and A. El-Geneidy. Build it. But where? The use of geographic information systems in identifying locations for new cycling infrastructure. *Int. J. Sustain. Transp.*, 7(4):299–317, 2013.

[9] A. Mauttone, G. Mercadante, M. Rabaza, and F. Toledo. Bicycle network design: model and solution algorithm. *Transp. Res. Rec.*, 27:969–976, 2017.

[10] P. Freestone. Personal communication. October 2020.

[11] R. Lovelace, A. Goodman, R. Aldred, N. Berkoff, A. Abbas, and J. Woodcock. The propensity to cycle tool: An open source online system for sustainable transport planning. *J. Transp. Land Use*, 10(1):505–528, 2017.

[12] R. Lovelace and J. Talbot. Rapid cycleway prioritisation tool: Technical specification. `https://www.cyipt.bike/rapid/`. Accessed 2020-12-08.

[13] DFT. The cycling infrastructure prioritisation toolkit. `https://www.cyipt.bike/report1/`, 2018.

[14] G. Boeing. Osmnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. *Comput. Environ. Urban*, 65:126 – 139, 2017.