

Integrating Low Traffic Neighbourhoods into UK Cycle Network Planning

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Summary

Cycling offers a sustainable and viable mode of transport within cities. However, evidence shows that safe and connected infrastructure is required for mass-adoption, requiring large initial investment costs. In the UK, vast kilometres of safe streets for cycling are provided by Low Traffic Neighbourhoods (LTNs), however they are often not integrated properly into cycle network planning. This study introduces a new algorithm for planning cycle networks, prioritising connections between LTNs and existing infrastructure in order to maximise safe cycling with minimal investment cost. Initial results show the potential to rapidly expand safe cycling networks by closing short gaps between LTNs.

KEYWORDS: Low Traffic Neighbourhoods, Cycle Networks, Transport Planning, Open-source

1 Introduction: Cycle infrastructure and cycle network planning

Cycling is a key alternative for short trips compared with motorised transport (Song et al., 2017; Brand et al., 2022). However, it requires certain conditions to be deemed a viable mode of transport for the general public (Buehler and Dill, 2015). Evidence indicates that cities which invest in protected cycling infrastructure create these conditions, and thus possess higher cycling rates (Figure 1, Pucher and Buehler (2016)).

Reducing motorised traffic on mixed-use streets makes cycling more appealing whilst being more cost-efficient than building dedicated infrastructure (Aldred et al., 2021; Imani et al., 2019; Williams et al., 2024; Savaria et al., 2021; CROW, 2016). Within the UK, these schemes are commonly known as Low Traffic Neighbourhoods (LTNs).

In the UK, cycle network developments have been sporadic, localised and disconnected, resulting

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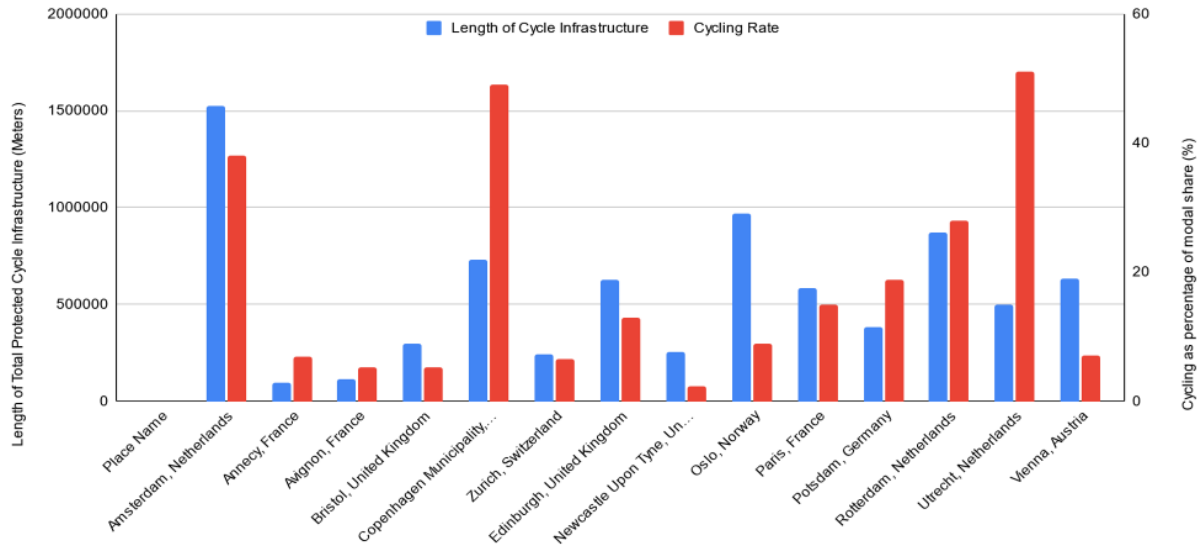


Figure 1: Comparison of cycling levels and level of cycle infrastructure investment. Whilst not uniform, the locations with higher cycling rates are the same locations which have invested in expansive cycle networks. Modal share data is sourced from Eurostat, ONS Census Statistics and The European Cyclists' Federation (European Union, 2023; Office for National Statistics, 2021; European Cyclists' Federation, 2022). Lengths are source from OpenStreetMap (OpenStreetMap contributors, 2024).

in only marginal increases in cycling despite investment and promising potential (Lovelace et al., 2017). Cycling infrastructure must reach a critical threshold before quality indicators trend upwards, highlighting that uncoordinated development is an inefficient use of resources long-term (Szell et al., 2022).

This lack of cohesive planning extends beyond just protected infrastructure. Whilst LTNs create quiet and relatively safe cycling when implemented properly into a city, a lack of connection between LTNs leads these zones to act as isolated islands of safety. When cyclists cannot reach destinations outside of LTNs without using high stress streets, the benefits of a LTN for cycling are diminished (Yang et al., 2022).

Currently, many cities globally have neglected cycling in transportation planning (Szell et al., 2022). Several academic works have looked to solve this problem, either from a bespoke localised approach (Folco et al., 2023; Olmos et al., 2020; Paulsen and Rich, 2023; Rybarczyk and Wu, 2010; Akbarzadeh et al., 2018) or through generalised methods (Vybornova et al., 2022; Szell et al., 2022; Orozco et al., 2020).

Whilst these approaches effectively plan street networks from scratch, most do not consider the existing infrastructure which could be exploited to minimise the requirement to build new facilities. More specifically, none of the studies consider the 'soft' infrastructure of LTNs in their network

planning, which overlooks vast kilometres of safe cycling.

Here, we develop an algorithm to generate bicycle network plans, prioritising connections between LTNs. Our contribution is to add consideration of existing infrastructure to network planning, in order to connect up cities with minimal investment. We also create a connection between generalisable and localised approaches, by localising agnostic methods to be suited to the street networks of the UK.

2 Methods: An algorithm to connect LTNs and cycling infrastructure

This section describes the materials and processing methods employed to generate a generalised bicycle network which connects LTNs. We apply these methods to Newcastle Upon Tyne, United Kingdom to demonstrate.

2.1 Input Data

Street networks are accessed from OpenStreetMap (OSM), using OSMNx (Boeing, 2017; OpenStreetMap contributors, 2024). We consider two network types: roads and segregated cycling networks. A combined cycleable network is also created as a combination of the road network and the segregated network.

Our other integral dataset consists of polygons representing LTNs. In this study, these polygons are derived from an automated analysis of Local Authority District areas discussed in Larkin et al. (2024). Whilst the outputs of these methods provides scores along a sliding scale of LTN plausibility, for this study a binary cut-off score of 55 is set manually to obtain a discrete number of LTN areas. This cut-off is used during this exploratory stage of research and is set by authors' knowledge of LTNs within the study area. This is required as the study area does not produce a map or dataset of LTN zones, however if a local authority does publish this, those zones would be favourable as an input dataset.

2.2 Network Preparation

The segregated cycling network used in this study is comprised only of infrastructure which separates cyclists from vehicular traffic, with the sole exception of streets within LTNs, which are deemed cycleable given the very low traffic volume and speed restrictions of 20 mph, in line with the safety literature on bicycle separation (CROW, 2016; Teschke et al., 2012; Buehler and Dill, 2015).

Not all streets are equally suited to cycling on, regardless of level of separation from traffic. We consider this when routing our network (Section 2.4). To better represent the route choices preferred by cyclists, we adjust edge weights based on OpenStreetMap tags, which we use to estimate level of stress for any given street (Table 2).

2.3 Seed Points

In order to determine where the cycle network should connect to and from, we extend the methods outlined by Szell et al. (2022) to generate a set of seed points. An initial set of seed points is generated

Table 1: Level of Stress Calculation

Cycle facility type from OSM	Level of Stress Classification
(Cycle) Path	1
Cycleway	1
Track	1
Bridleway	1
Living Street	2
Residential	2
Unclassified	3
Tertiary	3
Secondary	4
Primary	4
Trunk	4
Motorway	4

Table 2: Level of Stress values assigned to OpenStreetMap Highway tags. This system of ranking follows the work of Wasserman et al. (2019).

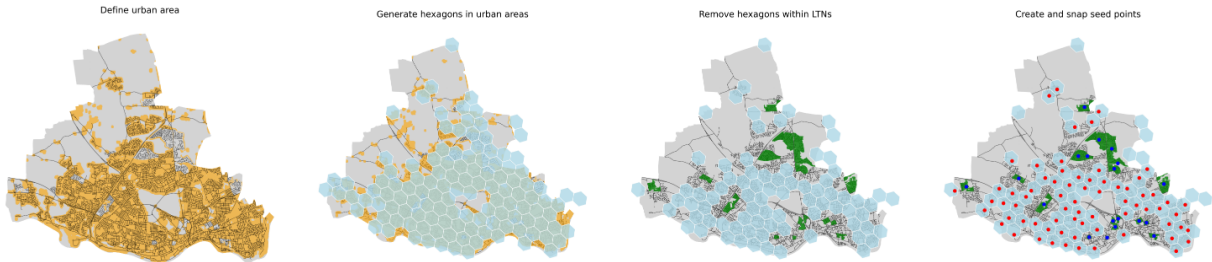


Figure 2: Seed point generation workflow. Steps move from left to right. Blue points represent seed points within LTNs, red points represent seed points from the hexagonal tessellation.

from each LTN zone, snapped to the nearest street. For areas not in LTNs, a second set of seed points is generated using TessPy’s (Saki et al., 2022) hexagonal tessellation, with cell diameters of approximately 1 km. In order to best represent the geography of the area, the tessellation is constrained to urban areas by using the Global Urban Footprint dataset from DLR (Esch et al., 2018) as a bounding polygon (Figure 2).

From the tessellation, a seed point is snapped to the nearest section of the protected cycle network within the cell. For cells without protected cycle infrastructure, the centroid is snapped to the street with the highest stroke value within the cell. The stroke value refers to the street with the highest continuous linearity, as calculated by Tripathy et al. (2020) and implemented in momepy (Fleischmann, 2019). This is used to ensure any future cycle infrastructure follows the logical path through a given area, as humans generally follow continuous streets in route finding (Manley et al., 2015).

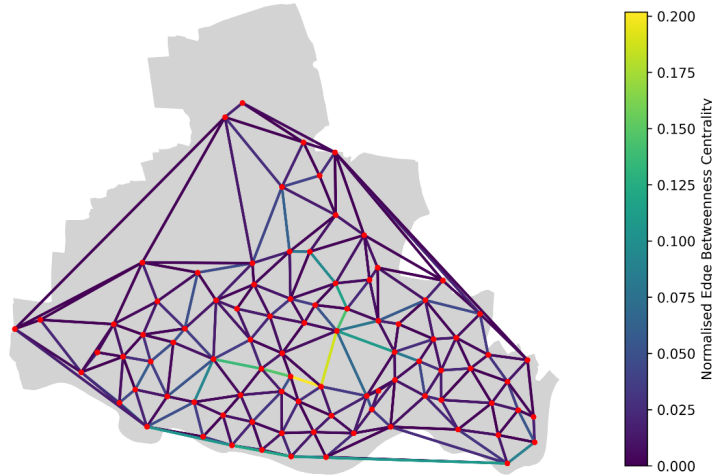


Figure 3: Edge betweenness on a fully connected greedy triangulation, using all seed points. Betweenness is calculated using the "on the ground" routed distance between seed point as the edge weighting to reflect the distance a cyclist would travel between any given pair of points.

2.4 Greedy Triangulation

With seed points set, greedy triangulation is employed to provide the connections (Szell et al., 2022; Folco et al., 2023). Greedy triangulation is first applied to LTN seed points, in order to find each LTN's respective neighbour. A second greedy triangulation is then calculated to order all pairs of nodes, LTNs and Tessellation-based (Figure 3).

To determine the order of connections, the betweenness centrality of this greedy triangulation is calculated as a proxy for demand across the city Szell et al. (2022); Vybornova et al. (2022). Connections are ranked by betweenness. The LTN seed points are moved in this ranking to always come prior to any Tessellation-based points. This is done to ensure that connections between LTNs are made as the first priority, as this rapidly unlocks many kilometres of safe cycling, with minimal cost. Links between seed points are added to the solution under a budget of 500m per investment, capped at the size of a completely connected network where all seed points have been joined.

Based on the determined order, links are routed onto the OpenStreetMap network. The routing uses the length of a given edge, multiplied by the level of stress assigned in Section 2.2 in order to route realistically. For the case of routing connections involving LTN zones we connect to an "exit point" of a neighbourhood, since streets within LTNs are already deemed to be cycleable. Both the underlying greedy triangulation network and the routed network are stored per iteration to generate performance metrics.

3 Initial Results and Discussion

All results at this stage are preliminary and will be subject to future revisions.

LTNs are dispersed across the city region and variable in size, varying from 0.05km^2 to 1.03km^2 . Several neighbourhoods border one another, requiring only a short connection to unlock increased numbers of streets for safe cycling. Tessellation based points constitute 79.5% of the seed points, with 18 LTN zones.

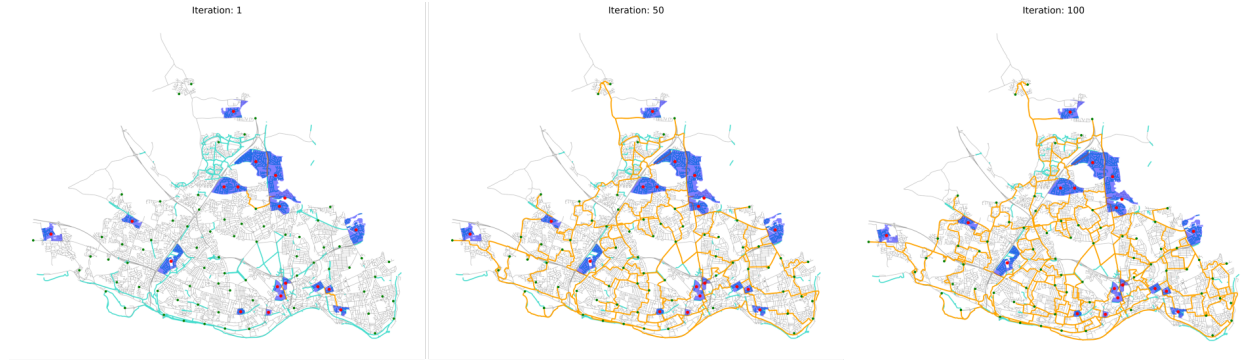


Figure 4: Three stages of network growth. The new investments (orange) connect the LTN zones (dark blue) across the existing street (grey) and cycling (light blue) networks. LTN centroids are shown in red and tessellation based seed points are shown in green.

The growth phase applied to Newcastle is shown in Figure 4. Within the first 50 iterations, all 18 LTNs are covered by the network and connected to all other LTNs, although not via the most direct route. Whilst the full connection between all LTNs has not been completed yet, six of the tessellation based points are already connected to as they are on existing cycle infrastructure used by the grown connections (Figure 5). Further, when considering a 500 m buffer around the network, an additional 10 seed points are covered by the 50th iteration (Figure 6).

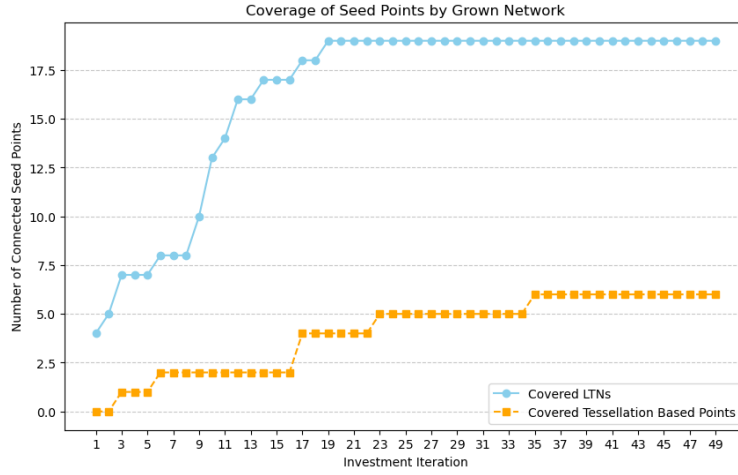


Figure 5: Seed Points connected by growth stage.

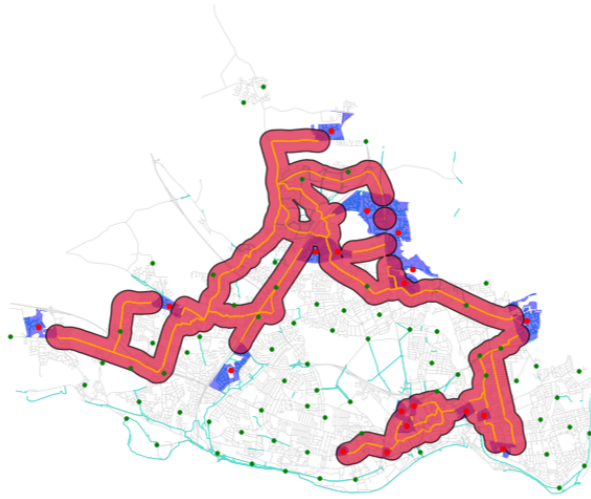
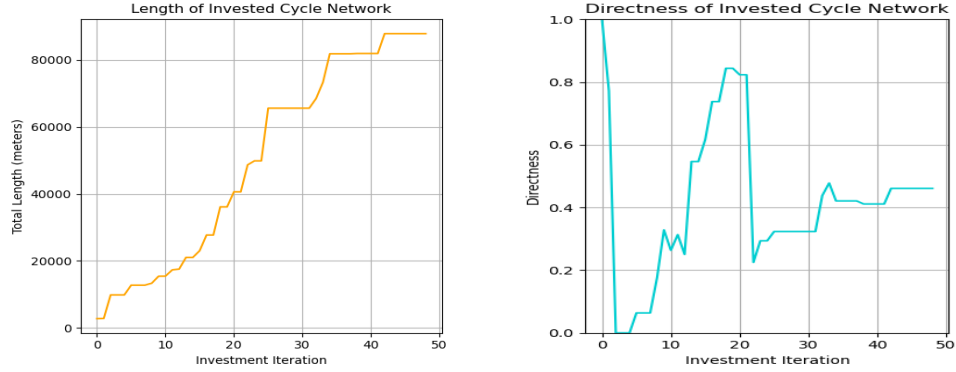


Figure 6: A 500m buffer around the network at 25km of investment. A 500m buffer is used as it represents an acceptable distance for people to cycle to infrastructure from. Whilst separation is preferred, the bicycle is flexible to street type at the start and end of trips.

The rate of growth is not uniform, despite the regular investment intervals because the shorter, more central gaps in infrastructure are closed first (Figure 7a). Larger jumps in investment size are required to connect neighbourhoods which are isolated and towards extremities of the network.

As seen in Figure 4 and 6, not all grown segments provide direct connections between LTNs at this stage of investment. This is reflected in the directness of the network shown in Figure 7b (measured as the euclidean distance divided by network distance). Directness is unstable at this stage of investment, however as further segments are implemented the directness is expected improve as

more direct routes between all seed points are created.



(a) The length of the cycle network does not increase linearly across iterations. (b) Directness of grown cycle network across iterations.

Figure 7: Network growth metrics

Broadly, these results highlight that LTNs can be integrated into cycle network planning to create larger, more connected networks. Initial gains make fast improvements to the whole city by closing short and high demand gaps. Planners can utilise this to identify priority connections to make, within an overall aim of creating a full city-wide network.

However, the methods are not without limitations. Betweenness centrality can be effective as a proxy for cycle demand, however real world origin-destination data could provide differing results, particularly in changing the order of investment. We are also limited by the assumption that the cost per meter of cycling infrastructure investment is equal across all roads, and that all roads could have cycle infrastructure built upon them.

4 Conclusion

This study presents the development of a novel approach to integrating LTNs into cycle network planning in the UK, aiming to maximise safe cycling with minimal investment cost. We use open-source data and tools to create plausibly realistic links between LTNs, using existing cycle infrastructure where possible. Preliminary results show potential for use in transport planning applications in locations without cohesive cycle networks. Further work includes analysis of overlap, coverage and introduction of further variables such as elevation.

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6 Biography

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Michael Szell is an Associate Professor at NERDS (ITU Copenhagen) researching sustainable mobility and bicycle networks through network analysis, data science, and data visualization.

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