A MINIMALIST ALGORITHM FOR GROWING SAFE CYCLING NETWORKS

Loïc Miara, Polytechnique Montréal
Catherine Morency, Polytechnique Montréal

1. Introduction

Promoting viable alternatives to motorized travel is crucial to reduce car dependency and decrease the number of vehicle-kilometers traveled. Among these alternatives, cycling has proven to be an effective mode of transportation to replace motorized vehicles for certain types of trips, provided that adequate cycling infrastructure is implemented to support this modal shift. However, many protected cycling networks are either too sparse or poorly connected, resulting in unsafe or inefficient routes that deter potential users. Studies on the subject indicate that better-connected networks are associated with higher cyclist ridership (Schön et al., 2024). Budget constraints also limit the number of new infrastructures that can be built to improve existing networks. This study aims to develop a methodology to solve this problem guided by the following research question: given an existing cycling network and a budget constraint, how should we grow a network such that it supports a safe modal shift towards cycling and enhances network performance? Few studies have emerged in recent years to answer this question. Computational methods such as genetic algorithms (Murray, 2024), demand-driven algorithms (Steinacker et al., 2022), and topological methods (Szell et al., 2022) exhibit potential. We propose a stricter, demand-driven approach that only allows door-to-door trips integrally feasible on separated cycling infrastructure. Existing networks are strategically expanded to maximize the number of such trips, to improve overall connectivity and usability. This approach offers a structured method for prioritizing investments in a cycling network, emphasizing user safety, optimizing travel efficiency and reducing motorized trips. Multiple scenarios are considered to showcase how a municipality's priorities would impact the development of a cycling network.

2. Methodology

I. Network data

Because this is an embryonic project, we consider a sub-region of Montreal comprised of four municipal sectors (for ease of testing) as a case study (Outremont, Le-Plateau-Mont-Royal, Villeray-St-Michel-Parc-Extension and Rosemont-la-Petite-Patrie). Network data is downloaded from OpenStreetMap using the Python library OSMnx (Boeing, 2024). We consider two networks: the existing and potential cycling networks. The existing cycling network consists of all existing cycling infrastructure separated from motorized traffic. In the considered subregion, this amounts to 104.3 km of segments, which includes cycleways, off-street cycleways (e.g.: parks) and intersection crossings, that are most often not separated, but we take them to be part of the network. The potential network consists of all links where bicycles are allowed, excluding service roads and alleyways. This amounts to 857.9 km.

II. Demand data

The demand data is extracted from the 2018 Montreal OD survey following a methodology to identify potentially cyclable (latent) trips (Morency et al., 2020). We limit the trips to those whose origin and destination are contained in the polygon defined by the sub-region. This consists of 3982 OD pairs. In the present paper, we consider three demand scenarios: 1) all motorized latent trips (excluding public transport trips) ($N = 2405$); 2) latent trips made by minors ($N = 647$); 3) observed cycling trips (trips done with a bicycle) ($N = 1298$).

III. Algorithm

We base this algorithm on two very strict hypotheses: 1) trips are only realizable if their entire length is travelled on separated cycling infrastructure; 2) cyclists will admit no deviations from the shortest path. In the first phase, all OD pairs are assigned to a start and end node on the network that is geographically closest to it. All routes are then computed using Dijkstra's algorithm. An existing cycling infrastructure is given a cost reduction factor of 0.9, such it is only used if the shortest path goes through the street that runs next to it. The iterative part of the algorithm follows:

i. Compute the "unprotected cyclist-kilometers per invested kilometer": $F = \frac{\sum_i^n L_i f_i}{\sum_i^n L_i}$ for each computed route. Where i is the i^{th} link with no existing cycling infrastructure (unprotected) of a given route comprised of n links, L_i is the length of that link, and f_i is the flow of cyclists (number of trips) on that link.
ii. From routes that use at least one link of the existing network, identify the one that maximizes F and add all its links to the existing network. If no route uses the existing network, choose the route with maximal F from all routes.
iii. Recompute F for OD pairs that are in the top 10% of the ranking of F.
iv. Go back to step *i* until budget is reached.

Adding entire routes to the existing cycling network ensures that the OD pair associated with it is completely linked by dedicated infrastructures. Adding the route that maximizes F prioritizes links that benefit to many cyclists or short additions that enable the completion of routes according to the strict criteria defined above. Furthermore, adding links that are part of routes that use at least one link from the existing network ensures that the added links are connected. Iteratively improving the network in this manner does however imply that routes that are not integrally cyclable on dedicated infrastructure do weigh in through f_i. Realistically, many cyclists will still complete trips using a cocktail of separated and shared bicycle infrastructure. Hence, we believe that it is motivated that these routes influence the choices of the algorithm, albeit to a lesser extent. This approach also has the benefit of being computationally inexpensive, as the routes only need to be computed once. This is due to strict hypothesis 2), as the links used for a route will not change if no deviations from the shortest path are allowed. Instead, we only need to change the label of each added link and recompute the F metric. Recomputing F for the uppermost 10% also assumes that the route with maximal F after an intervention is part of this 10%. This is done to speed up computation and is a wide enough range such that no ideal solutions are missed.

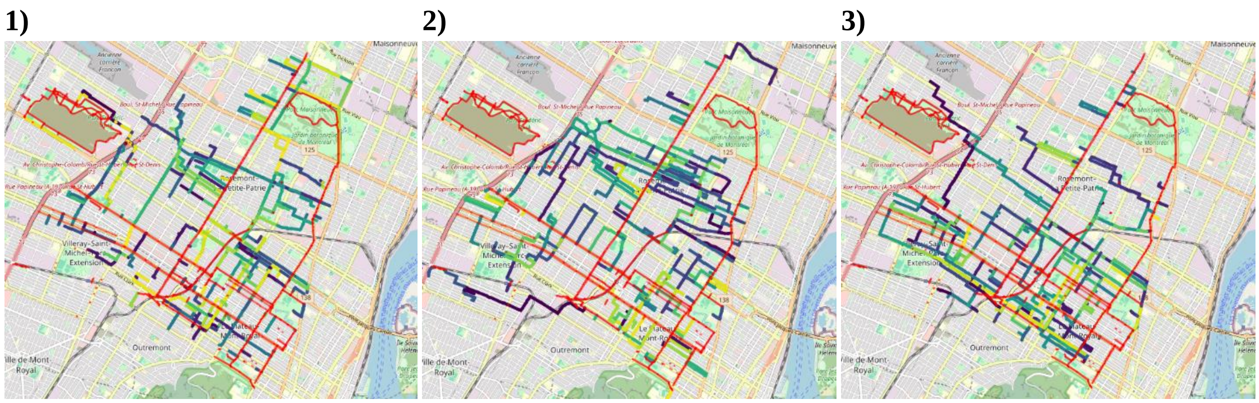
3. Results

We run the algorithm with a budget of 105 km, which roughly corresponds to a doubling of the length of currently built separated cycling infrastructure in the examined region. This is done for each demand scenario.

I. Generated networks

Figure 1 displays the network produced by the algorithm for each demand scenario. Scenario 1 notably generates long East to West connections to the initial network in early iterations, such as on Jean-Talon and Masson streets, or St-Joseph boulevard. This is somewhat consistent with the municipality's endeavors, as a cycleway was built on Jean-Talon Street recently (roughly corresponding to the improvement on iteration 41 of the algorithm), though it is not yet uploaded to OSM. Scenario 2 is mainly connecting schools to residential areas, as home-school trips are the most frequent for minors. Scenario 3 interestingly prioritizes the same link as scenario 1 on its first iteration, namely connecting the two existing major North-South cycleways of the region on Jean-Talon Street, though further West than the newly built cycleway abovementioned. However, it differentiates itself from scenario 1 on later iterations, where North-South links appear more critical on average, though several East-West links are also added in early iterations.

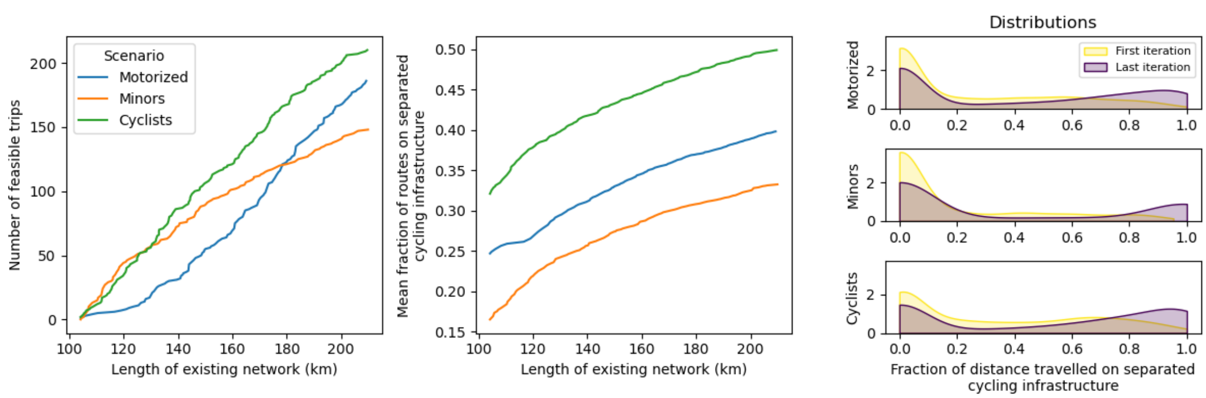
Figure 1: Generated networks for each demand scenario and a fixed budget of 105 km: 1) all motorized latent trips; 2) latent trips made by minors; 3) observed cycling demand. In red is the currently built separated cycling network. The color scale from yellow to purple indicates the iteration at which it was added to the network, where purple corresponds to 121,110 and 161 iterations, respectively.



II. Performance metrics

To assess the performance of the network, we evaluate the number of trips from the demand scenario that are feasible, and the mean distance travelled on separated cycling infrastructure at each iteration. Even if the methodology relies on providing completely separated itineraries for cyclists, it is meaningful to look at the second indicator, as it provides a sense of improvement of the network. The results are presented in Figure 2.

Figure 2: Evolution of performance indicators during the growth of the networks. The rightmost panel gives the entire distribution of the fraction of routes on cycling facilities.



It is interesting to note that the of the number of feasible trips is not strictly linear with respect to the length of the existing network (left panel) and varies from one demand scenario to another. This is in part because of the variable distance between routes, but also because some iterations result in more than one new feasible trip. We notice that in both curves of scenario 1, there is a distinct change of behaviour around the 120 km mark. This is because the first routes with the maximum F are long ones that also have high usages. It then takes longer for these improvements to reach all the potential beneficiaries. In demand scenario 2, when reaching a longer network, rate of growth of the number of feasible trips declines. This is due to data limitations, as for fewer observations, there are less links that are crucial for many OD pairs. If no two routes go through the same link, $F \to 1$ for all routes such that a random route is added, benefiting to 1 OD pair at a time. The second panel of Figure 2 reveals that there is a clear difference between each demand scenario in initial proportion of the shortest OD path that is travelled on separated cycling infrastructure. Current cyclists are comfortably in front with (32%), followed by motorists (25%) and minors (17%). The increase in this metric is however similar across scenarios.

4. Discussion

This approach offers a quick way to generate new, productive cycling networks. The methodology is very flexible, such that different hypotheses can be input in the model. This work is the first phase of a more comprehensive approach. Future improvements will namely need to include the consideration of road gradients, separation of bidirectional links, or different infrastructure types particularly those not strictly limited to on-street network, such as cyclable bridges and tunnels. Hypothesis 2 is also far from realistic and will need to be relaxed in future works. Detours are an inherent part of transportation networks and need to be considered. This comes at the cost of recomputing routes at each iteration, which is computationally more expensive. Methods to limit the number of recomputed routes will need to be implemented. Limitations from this method also lie in the consideration of the demand data. Because OD surveys rely on population samples with varying response rates, respondents are attributed variable weights to allow for statistical inference. However, this micro-aggregation translates to OD pairs that are attributed to multiple individuals. Results in this paper are not weighted and serve as a proof of concept of the methodology. Making use of a disaggregation model to represent the demand would be more realistic. However, the method presented in this work only makes use of OD pairs, which can represent any type of demand, if properly devised.

References

Boeing, G. (2024). *Modeling and Analyzing Urban Networks and Amenities with OSMnx*. https://geoffboeing.com/publications/osmnx-paper/

Morency, C., Verreault, H., & Frappier, A. (2020). Estimating latent cycling and walking trips in Montreal. *International Journal of Sustainable Transportation*, *14*(5), 349-360. https://doi.org/10.1080/15568318.2018.1558467

Murray, D. (2024). *Algorithme de conception de réseaux cyclables* [Masters, Polytechnique Montréal]. https://publications.polymtl.ca/57731/

Schön, P., Heinen, E., & Manum, B. (2024). A scoping review on cycling network connectivity and its effects on cycling. *Transport Reviews*, *44*(4), 912-936. https://doi.org/10.1080/01441647.2024.2337880

Steinacker, C., Storch, D.-M., Timme, M., & Schröder, M. (2022). Demand-driven design of bicycle infrastructure networks for improved urban bikeability. *Nature Computational Science*, *2*(10), 655-664. https://doi.org/10.1038/s43588-022-00318-w

Szell, M., Mimar, S., Perlman, T., Ghoshal, G., & Sinatra, R. (2022). Growing urban bicycle networks. *Scientific Reports*, *12*(1), 6765. https://doi.org/10.1038/s41598-022-10783-y