# Bi-modal road network design framework using bikeability

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## Short summary

Urban road networks are primarily car-oriented, however, societal challenges necessitate a redesign of these systems. Cycling offers a more sustainable alternative for mobility. Here, we propose a methodological framework to design bimodal road networks for cars and bicycles. This methodology utilizes traffic assignment and mode choice models based on bikeability indicators. The design is conducted using an Inverted Network Growth method. This approach is validated on toy networks before being applied to a case study. Finally, we use this method to propose infrastructure upgrade plans for planners. The results demonstrate that the framework identifies a threshold where additional infrastructure yields diminishing returns for modal shift. Furthermore, the results show that when safety is ensured by separated bike infrastructure, the framework prioritizes aesthetics over distance when selecting roads for infrastructure upgrades. This hierarchical output provides planners with a prioritized sequence for bicycle infrastructure development that balances bikeability with network efficiency.
**Keywords**: Bikeability, Biking, Model-based, Network Design

## 1 Introduction

Cycling has enjoyed a popularity resurgence in recent years, offering a low-cost and sustainable mode of transport. Furthermore, cycling infrastructure is more space-efficient and cost-effective than car-oriented infrastructure. Despite these advantages, cities lack efficient and attractive bicycle networks. While lack of infrastructure availability is often a primary cycling deterrent, high-quality facilities are essential to improve users perceived safety and comfort.

Bike network design problem is a relatively recent field of study, and existing academic literature remains scarce. This problem is approached through three main methods: Bi-level programming using route choice models (lower level) and design models (upper level), Topology-based approaches using network science and graph theory, and Demand-driven models based on GPS or qualitative data.

Early optimization models, such as those proposed in (Gaspar et al., 2015), focused on mathematical feasibility of path placement within a network, considering multi-modal interactions through bi-level optimization method. The lower level represents the network and users behaviour (including different modes). This level includes route choice and traffic assignment models. The upper level consists of network optimization models, it involves link selection to optimizes certain criteria. This methodology has been refined and improved to incorporate several indicators, such as health and social benefits (Doorley et al., 2020).

The second type of design models are topology-based. These methods treat urban road network as mathematical graph. They study network efficiency through structural metrics. Primary focus is on connectivity and directness. Recent advancements in this area have explored synthetically grown networks (Szell et al., 2022) or have focused on graph robust connectivity (Steinacker et al., 2022). While computationally efficient, topological models often ignore important aspects of cycling such as perceived safety or comfort and demand.

Finally, demand-driven approaches prioritize infrastructure placement based on where potential users are already moving or where latent demand is highest. These models utilize GPS traces, census data to provide data-driven decision support tools like BikeNodePlanner (Vybornova et al., 2025). However, these models place infrastructure where current demand exists and fails to expand the network to new user groups or capture demand in underdeveloped areas.

While some researches have been made to solve the bike network design problem, exiting studies often treat traffic flow prediction, network assessment and long term design solution as separate objectives. Perceived safety and comfort are set aside, and the existing methods do not include these criteria inside mode choice or traffic assignment modeling. The goal of this paper is to address these limitations and to propose a bicycle network design framework that bridges this gap by integrating these three dimensions. This framework utilizes a mode choice model and a bimodal traffic assignment model to predict flows across the network. To prioritize the perceived comfort and safety of cyclists, we incorporate a bikeability indicator based on various spatial attributes and the interactions between bikes and motorized vehicles in the traffic assignment. Finally, building on the work of (Steinacker et al., 2025), we employ a Inverted Growth Network design model to improve road networks. The contribution of this article are: the use of mode choice and traffic assignment models to assess bicycle and car flows, the introduction of bikeability to model cyclist perceived comfort and safety and the use of a bikeability aware Inverted Network Growth method.

## 2 Methodology

We propose a framework for developing a long-term plan for progressive improvement of bike network infrastructure. This framework is composed of two levels. The lower level is made of a mode choice model and a bimodal traffic assignment model based on bikeability. The upper level consists of an incremental design model, i.e., the reverse growth network design model, extending the work of (Steinacker et al., 2025) by including mode choice and traffic assignment. With this framework we aim to maximize bikeability and bike modal share, reducing car congestion and overall travel time for all users.

The framework first step utilizes a mode choice model to generate bimodal OD matrix for bicycles and cars. Subsequently, based on updated demand for motor vehicles, we perform traffic assignment, which is elaborately described below. By integrating edge attributes with car flow, we calculate a bikeability coefficient representing perceived comfort and safety of bike infrastructure. We then calculate perceived length of edges, which serves as generalized (dis)utility function for bicycle route choice.
Based on bicycle flows, we rank the network edges and incrementally modify the network by removing the least-utilized bicycle lane. Once all potential bicycle lanes have been removed, the sequence of removal provides an order of priority for infrastructure development on each edge. Resulting output is a road network mapped with improvement priorities, which we use to propose infrastructure development scenarios.

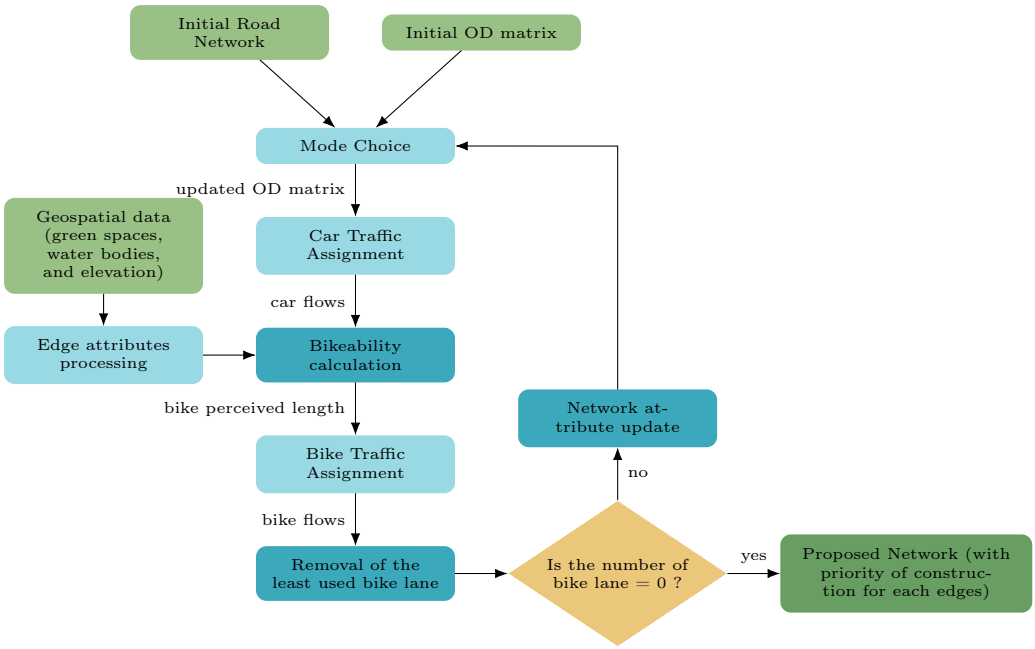



Figure 1: Main framework for bike network design

To execute this model, we utilize the following input data:

- Base road network: set of all edges where construction of bike lane is physically and legally possible.
- Travel Demand: Initial Origin-Destination matrix representing trip demand in the network.
- Geospatial Attributes: Detailed environmental data used to calculate specific edges characteristics such as greenery or topography.

The entire process is illustrated in Figure 1.

***Mode Choice and Traffic assignment***

One of the novelties introduced in this study is the integration of mode choice and bimodal assignment models using bikeability concept. We utilize these models to calculate and evaluate impacts of motor-vehicle traffic on perceived cyclist safety and comfort. Also, these models allow to incorporate the impact of bicycle infrastructure on motor-vehicle traffic flow by considering capacity reduction. The output of these models (key performance indicators such as modal share and travel time and usage prediction) will provide insights to urban planners.

In both mode choice and traffic assignment models, we utilize following cost functions for cars and bicycles: For cars, the cost is defined by Travel Time ($t_{car}$), calculated using the Bureau of Public Roads (BPR) function (Transportation Research Board & National Academies of Sciences, Engineering, and Medicine (2022)). The travel time is defined as:

$$t_{car} = t_0 \left[1 + \alpha \left(\frac{v}{c}\right)^{\beta}\right] \tag{1}$$

where $t_0$ the free flow travel time, $v$ the flow, $c$ the road capacity.

For bicycles, the cost is based on bikeability, which is defined as the convenience for cyclists to travel along a chosen route based on their perceived safety and comfort. A secure and aesthetic environment is consistently preferred by cyclists over high-traffic roads with unprotected bike lanes. Following Grigore et al. (2019), we define a perceived length and a perceived travel time ($t_{bike}$) that depend on subjective aspects.
The relationship between physical length ($l_0$) and perceived length is determined by a bikeability coefficient ($C_{bi}$). In previous research, we categorized bikeability according to four dimensions: infrastructure type, motorized traffic, slope, and aesthetics (Lemoalle et al., 2026). Our findings indicate that bikeability is primarily determined by infrastructure type, specifically, cyclists prioritize safety when a bike lane is not separated from motorized traffic. However, if the bike lane is physically separated, aesthetic factors gain significantly more importance.
The chosen values for $C_{bi}$, presented in Table 1, reflect these findings. Lowest $C_{bi}$ values are assigned to dedicated bike lanes in pleasant environments with flat or negative slopes, while highest values are assigned to high-traffic roads with no dedicated cycling lane. We assume an average speed ($v_{bike}$) for all cyclists, which depends on local urban context. These findings allow us to define bicycle travel time as:

$$t_{bike} = \frac{l_0 C_{bi}}{v_{bike}} \tag{2}$$

where $l_0$ is the physical length, $v_{bike}$ is the speed of cyclists, and $C_{bi}$ is the bikeability coefficient.

For cars and bicycles, we utilize two distinct static traffic assignment methods. The objective is to obtain flows and travel times for large-scale networks.
For cars, we determine flows on each edge while accounting for congestion effects. We employ a Deterministic User Equilibrium (DUE) traffic assignment model based on Wardrop's equilibrium principles, solved using the Biconjugate Frank-Wolfe algorithm (LeBlanc et al., 1975).
For bicycles, congestion effects are considered negligible. However, we recognize that route choice among cyclists can vary depending on individual preferences, a common assumption in existing literature, see for instance (de Freitas et al., 2025). This motivates the use of a stochastic model. This model utilizes a Breadth-First Search on Link Elimination (BFSLE) algorithm, based on (Rieser-Schüssler et al., 2013), to generate choice sets required for stochastic assignment. The

| Bike Infrastructure | Green or traffic attribute | Slope attribute | $C_{bi}$ |
|---|---|---|---|
| Dedicated bike lane | Green $>$ 51% | $\leq$ 2.5% | 0.1 |
| | | 0% | 0.2 |
| | | $>$ 2.5% | 0.3 |
| | Green $\leq$ 50% | $\leq$ 2.5% | 0.3 |
| | | 0% | 0.4 |
| | | $>$ 2.5% | 0.5 |
| No bike infrastructure | Traffic $\leq$ 6000 | $\leq$ 2.5% | 0.7 |
| | | 0% | 0.8 |
| | | $>$ 2.5% | 0.9 |
| | 6000 $<$ Traffic $\leq$ 7500 | $\leq$ 2.5% | 0.9 |
| | | 0% | 1 |
| | | $>$ 2.5% | 1.1 |
| | 7500 $<$ Traffic $\leq$ 8000 | $\leq$ 2.5% | 1.1 |
| | | 0% | 1.2 |
| | | $>$ 2.5% | 1.3 |
| | Traffic $>$ 8000 | $\leq$ 2.5% | 1.3 |
| | | 0% | 1.4 |
| | | $>$ 2.5% | 1.5 |

Table 1: Values of $C_{bi}$ based on different attributes. The values of $C_{bi}$ describe the relationship between the real length and the perceived length depending on comfort and safety. These values are chosen based on Lemoalle et al. (2026).

mode choice model is a Multinomial Logit (MNL) model. The probability of selecting a specific mode for each OD pairs is given by:

$$P_i = \frac{e^{\mu V_i}}{\sum_j e^{\mu V_j}} \tag{3}$$

where $P_i$ is the probability of choosing mode $i$, $V_i$ is the utility of mode $i$, and $\mu$ is a scale parameter. The utility for each mode and each OD pairs is defined as:

$$V_i = ASC_i + \beta_{time} t_i \tag{4}$$

where $ASC_i$ represents the Alternative Specific Constant for mode $i$, $t_i$ is the shortest congested travel time for cars and the shortest perceived travel time for bikes (defined in Equation 1 and 2), and $\beta_{time}$ is the time sensitivity.

***Network Design***

The upper-level problem focuses on modification of the network's physical configuration. Most-utilized edges are prioritized for bicycle lane construction. Once initial bicycle and motor-vehicle flows are assigned, the model identifies bottlenecks or safety deficiencies where existing infrastructure fails to support the predicted demand. To address these gaps, we employ an extended version of the Inverted Network Growth (ING) (Steinacker et al., 2025) method including mode choice, traffic assignment and bikeability calculation. As illustrated in Figure 1, this process is performed incrementally.

The ING method starts with a complete network for cyclists, in which every edge feasible for construction is equipped with separated bike lanes. Following the mode choice and traffic assignment processes, the least-utilized bicycle lane is removed. Once the infrastructure is removed, we update the network characteristics (i.e. space available for motorized-traffic and perceived length for bikes). This process is repeated until there are no bicycle lanes remaining.

Once the iterative process is complete, the specific iteration at which a bike lane is removed determines its construction priority. Effectively, removal order is the inverse of the building priority. For example, a bike lane removed during iteration $n$ (indicating it was the least-utilized segment during that iteration) has lower construction priority than a bike lane removed during iteration

$n + 1$. By recording these removal stages, we can establish hierarchical development plans where the most resilient and highly utilized segments are identified for earliest implementation.

## 3 Case studies and results

***Scenarios***

As proof of concept for this framework, we utilize simplified toy networks. These toy networks allow us to test the framework within reasonable computation times and do not require complex data handling. Furthermore, they serve to illustrate the mechanics of the framework and demonstrate how specific factors influence model's predictions for demonstrative purposes and to provide face validity.

We define four test scenarios (Figure 2), all based on a 3 by 3 $km^2$ grid, with two mixed-traffic lanes on each edge (each lane as a 1500 veh/h capacity i.e. each edge as a 3000 veh/h capacity). Each scenario is modified by specific environmental factors:

- **Scenario A: Grid (Baseline)** – A 3 by 3 $km^2$ grid featuring both a park and a hill. This scenario is the baseline and is illustrated in Figure 3 and 4.
- **Scenario B: H-Network** – An H-shaped network with uniform topography and no greenery. This configuration is used to investigate influence of network bottlenecks on the framework.
- **Scenario C: Tunnel** – An H-shaped network featuring a simulated flat "tunnel" on edge 6-7, steep slopes on edge 10-11, and a park. This scenario possess the same park than scenario A and is presented in Figure 5 and 6.
- **Scenario D: Tunnel-NG (No Green)** – This scenario is identical to Scenario C but excludes the park, allowing for isolated analysis of topographical versus aesthetic influences.

These scenarios all uses the same synthetic demand, presented detailed in Figure 7. We tested two design models:

- **Base model** - Construction of a dedicated bicycle lane does not reduce the existing motorized vehicle capacity.
- **Capacity-Aware model** - A "reallocation" approach where a bicycle lane replaces one mixed-traffic lane, reducing motorized capacity to 1500 vehicles/day per edges.

In both design models, all edges are eligible to bicycle lane construction.

The following parameters are employed for traffic assignment models. For motorized vehicles, the BPR function (Equation 1) parameters $\alpha$ and $\beta$ are 0.15 and 4, respectively. For bicycles (Equation 2), speed $v_{bike}$ is set to 15 km/h. Regarding mode choice model (Equation 3), the scale parameter $\mu$ is set to 1. Within the utility function (Equation 4), the alternative-specific constants are $ASC_{car} = 0$ and $ASC_{bike} = -2.15$, while the time sensitivity parameter $\beta_{time}$ is defined as -0.000235 [1]. These values have been validated with a sensitivity analysis displayed on Figure 11.

***Results***

Our initial results, obtained using the base model, show that similar behaviour is observable across all test scenarios, illustrated in Figure 8. Initial construction of bicycle lanes leads to a rapid growth phase in bicycle modal share. During this period, (ranging from 0 to 20 bicycle lanes), construction of bike lanes is prioritized on most-utilized edges connecting high-demand Origin-Destination (OD) pairs, where each new lane significantly improves network-wide bikeability. However, a threshold is reached between 15 and 23 bicycle lanes. Beyond this point, modal share no longer grows rapidly. This reveals a non-linear relationship between number of dedicated bicycle lanes and modal share. There is also a significant drop-off in usage for new infrastructure past the threshold. Further expansion does not yield significant modal shifts because the remaining "missing links" either serve low-demand paths or are redundant to existing high-quality paths. Such a threshold indicates an optimal number of bicycle lanes for maximizing bicycle usage efficiency within the network.

[1] In this model, time is measured in hours [h] and distance in kilometers [km].

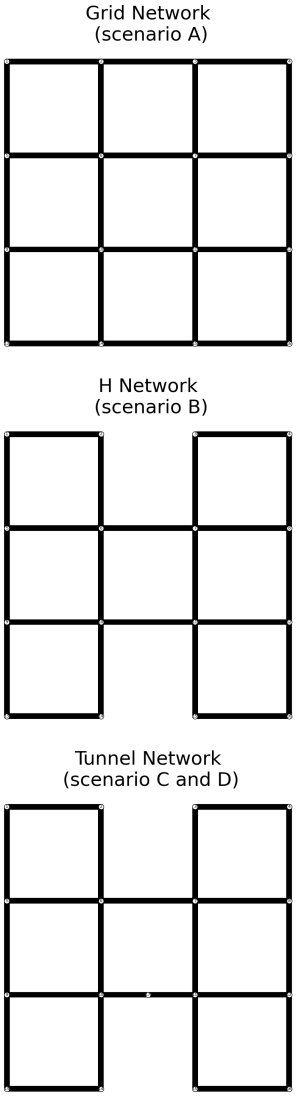



Figure 2: Toys networks

The Capacity-Aware model yields similar results, with comparable thresholds observed for the scenarios B and C. However, for all scenarios expect scenario A, additional thresholds appear, which correspond to the construction of bicycle lanes on bottleneck edges (e.g., edges 6-7 and 10-11). In this model, the number of dedicated bicycle lanes and the bicycle modal share remain closely linked, even beyond the initial threshold and the rapid modal growth phase. Overall, the bicycle modal share is higher in the capacity-aware model than in the base model. This shift is caused by the simultaneous increase in motor-vehicle travel times (due to reduced road capacity) and the improvement in bikeability, even in cases where the newly added bicycle lanes are not utilized. A comparison between the results of both models is provided in Figure 9.

Another significative finding lies in the comparison of scenario C and D. Using the capacity-aware model, we find that the bicycle modal share is higher in scenario C. This result is explained by the phenomena that edge 9-10 possesses a lower bikeability coefficient (a lower coefficient reduces the perceived length of the segment, reflecting the increased perceived safety and comfort) when a bicycle lane is constructed in an aesthetic environment.
Furthermore, we find that the environmental context affects the model as it prioritizes different edges for infrastructure construction. When a park is present, the hill path is prioritized for development. Conversely, when the park is absent, the tunnel path is prioritized instead. These results can be explained by the route choice behaviour of cyclists, who are willing to accept a longer or steeper detour to utilize a more aesthetic path. However, if no superior aesthetic alternative exists, cyclists will naturally default to the shortest and flattest path, in this case, the route through the

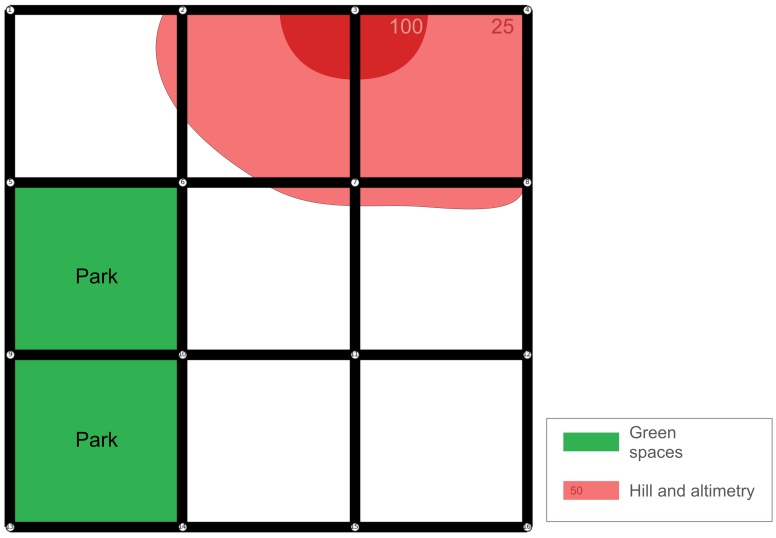



Figure 3: Scenario A - Grid toy network with green space and altimetry

tunnel. These results are presented in Figure 10.

Overall, these results demonstrate that our proposed design framework successfully captures the subtle specificity of bicycle travel choices. This is achieved through a network design approach involving a survey-validated bikeability calculation method, a mode choice model, and a bimodal traffic assignment model. To the best of our knowledge, this study is the first to utilize these combined concepts to propose a comprehensive bicycle network design model.

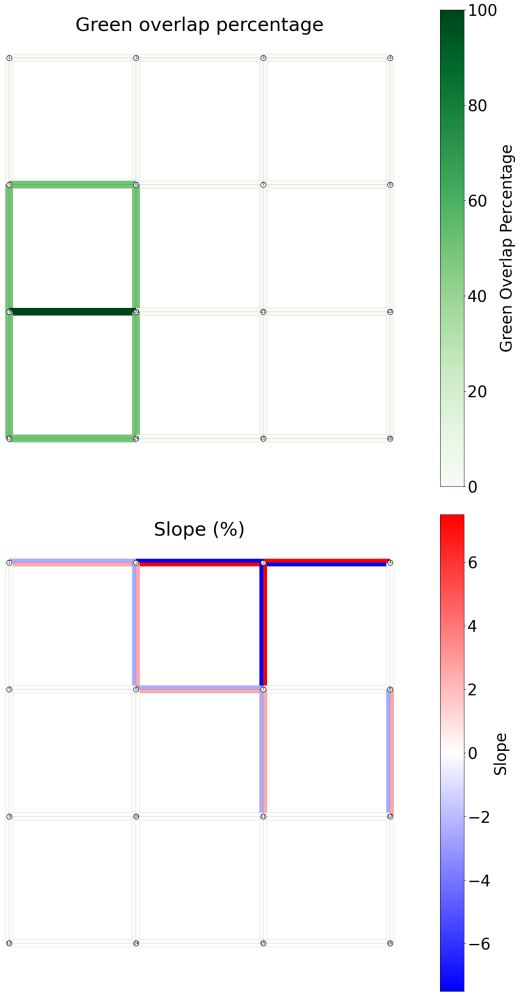



Figure 4: Scenario A - Grid toy network with green coverage and slopes

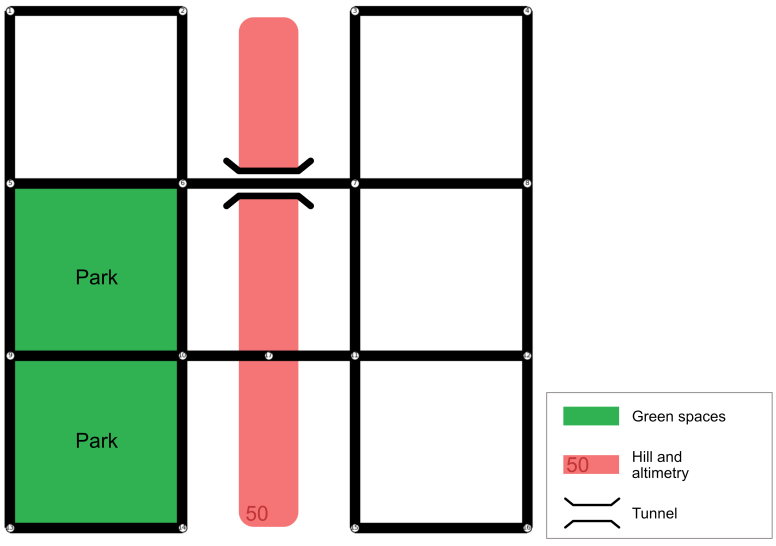



Figure 5: Scenario C - Tunnel toy network with green space and altimetry

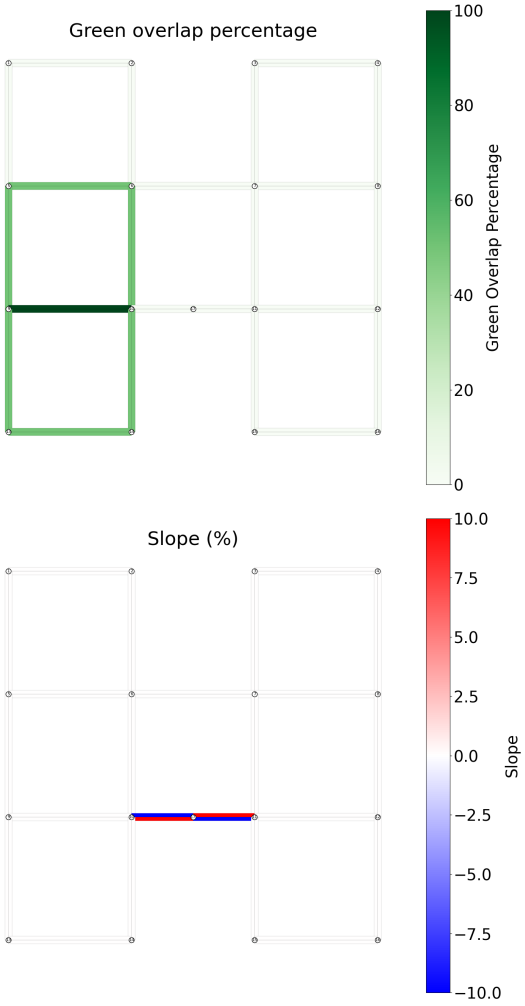



Figure 6: Scenario C - Tunnel toy network with green coverage and slopes

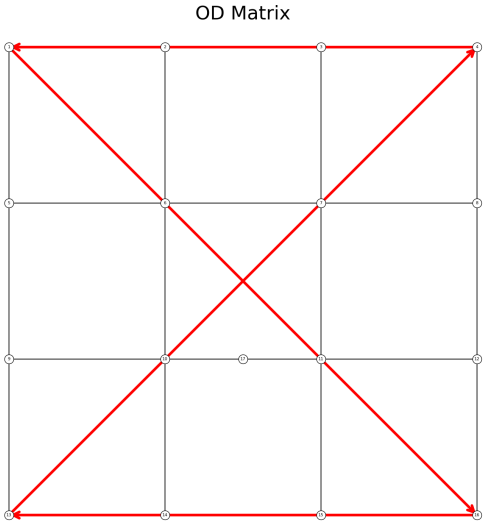



Figure 7: Synthetic demand for toy network

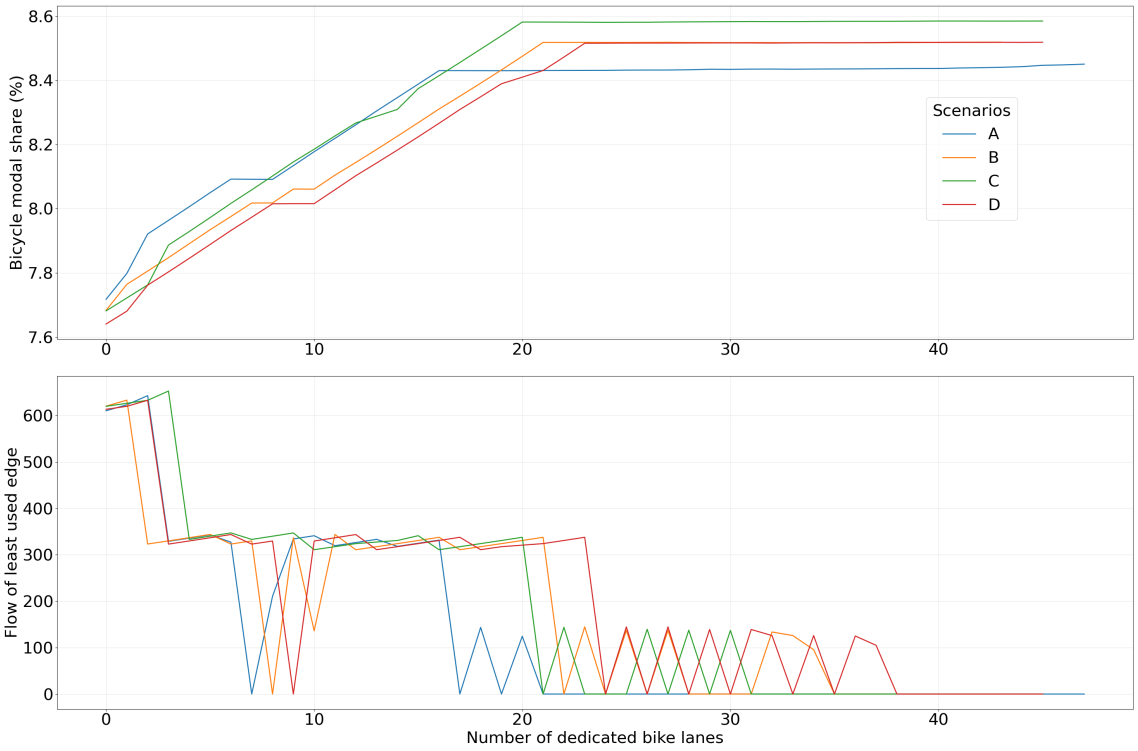



Figure 8: Bicycle modal share and bicycle flow of the least used bicycle lane, compared to the number of dedicated lanes constructed for different test scenarios.

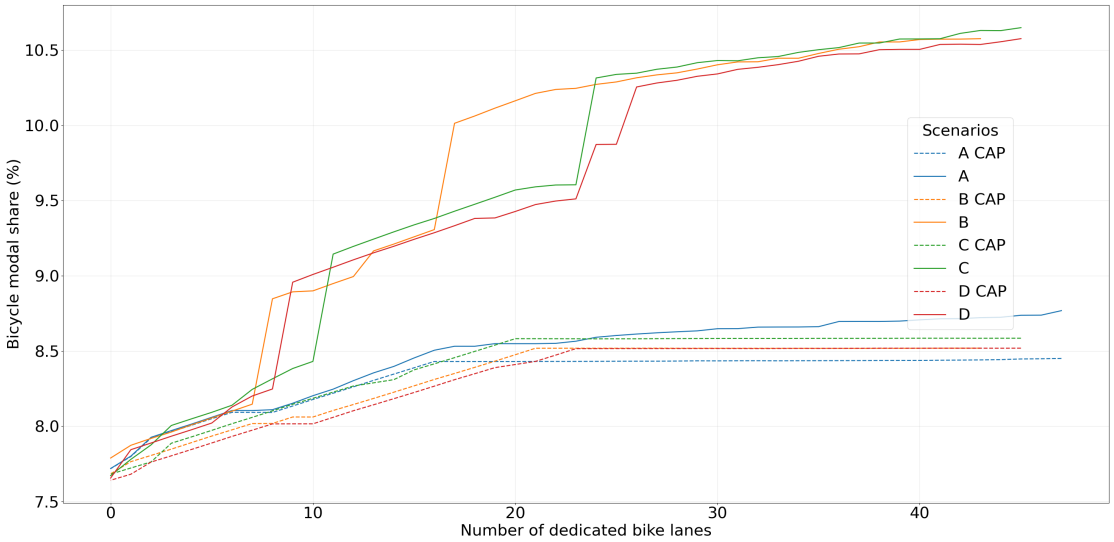



Figure 9: Comparison between base model and capacity aware (CAP) model. Bicycle modal share compared to the number of dedicated lanes constructed for different test scenarios.

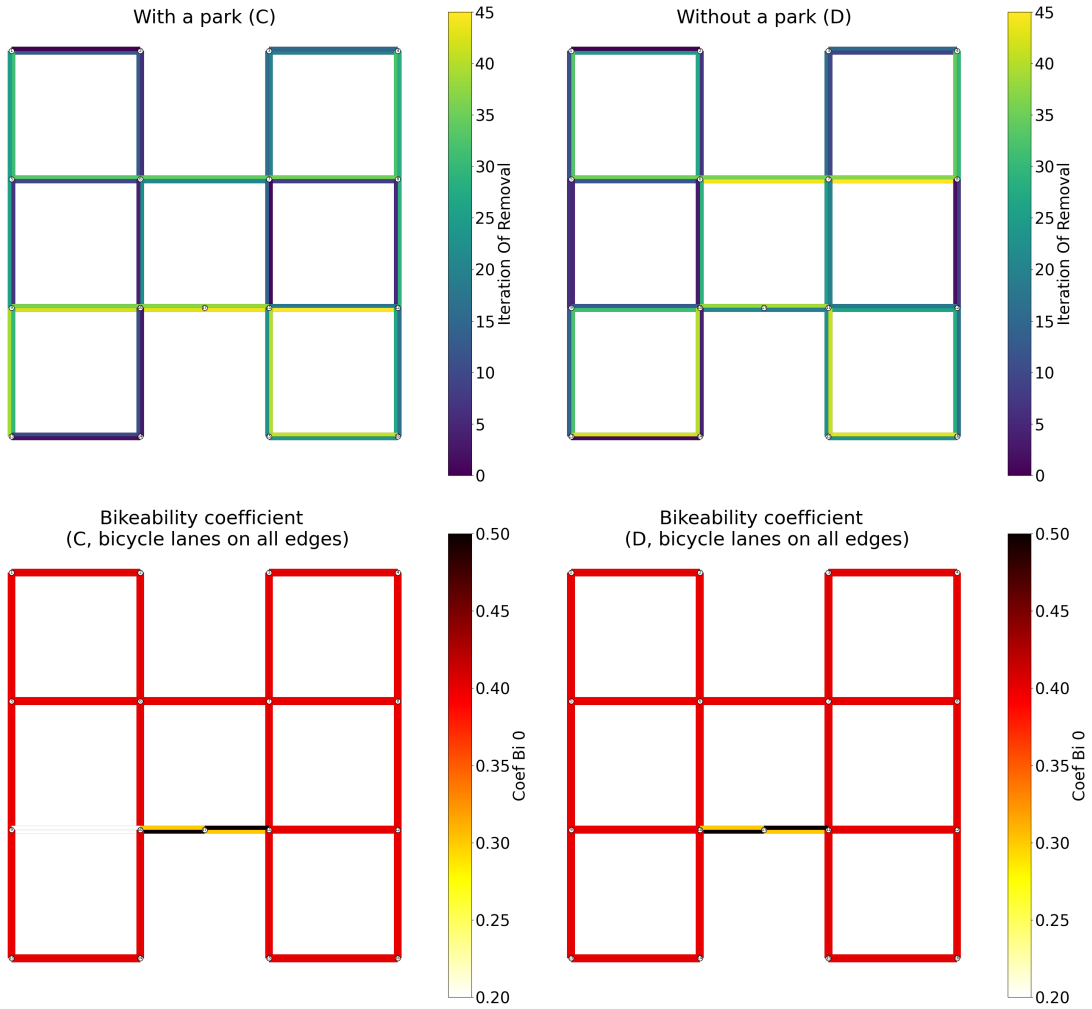



Figure 10: Comparison of design model results scenarios C and D. First row represents the iteration of removal of each edge. This can be interpreted as the prioritization of bicycle construction. Second row represent bikeability coefficient with a bicycle lane on all edges.

## 4 Conclusions

This study presents a novel bimodal road network design framework that integrates mode choice, traffic assignment, and bikeability and propose long term development strategies. The framework is designed to provide data-driven guidance for bicycle infrastructure planning. By combining a Deterministic User Equilibrium (DUE) model for motorized vehicles with a stochastic model, incorporating a bikeability coefficient, for cyclists, our framework successfully captures the complex trade-offs between traffic congestion for cars and the perceived safety and comfort of cyclists.
The application of this methodology to diverse scenarios yields three primary findings. In all scenarios, we identify a threshold in the number of dedicated bicycle lanes built on a network to improve the bicycle modal share. This suggests that for any specific network configuration, there is a threshold beyond which additional lanes only provide marginal improvements. With scenarios C and D, our results highlight the critical role of aesthetic and topographical factors in cyclist route choice, when safety is ensured by separation from motorized traffic. The model demonstrates that infrastructure requirements and prioritization differ based on the environmental context of a given edge, as cyclists often favour high-quality, scenic routes when safety is provided by separated infrastructure, even when they require a detour. Finally, the use of a capacity-aware model reveals that reallocating a mixed-traffic lane to a dedicated bicycle lane simultaneously improves bikeability and reduces the utility of motorized travel. We also see impact on cyclist route choice. This dual effect significantly enhances the bicycle modal share compared to base models.
While these results are based on toy networks, they lay the groundwork for more realistic models and provide a robust proof of concept, but they do not generalize to large-scale urban systems. Also, the IGN methods used here can provide disconnected networks. Future work will focus on scaling this framework to real-world networks, which will be facilitated by implementing realistic budget constraints for bicycle infrastructure. Other potential improvements lie in the consideration of heterogeneous user preferences, multi-class route choice model, more realistic variable cycling speed and different criteria of edge ranking.
Ultimately, this framework provides urban planners with a data-driven, model-based approach to long term development strategies. This transition strategy is essential for transforming car-centric cities into resilient, liveable urban environments.

*The conference paper is eligible for the Reproducible Research Prize. The code and data associated with this work are available at* `https://github.com/tim-lemm/BMND`. *The repository is prepared at SRL 5.*

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## A Sensitivity Analysis

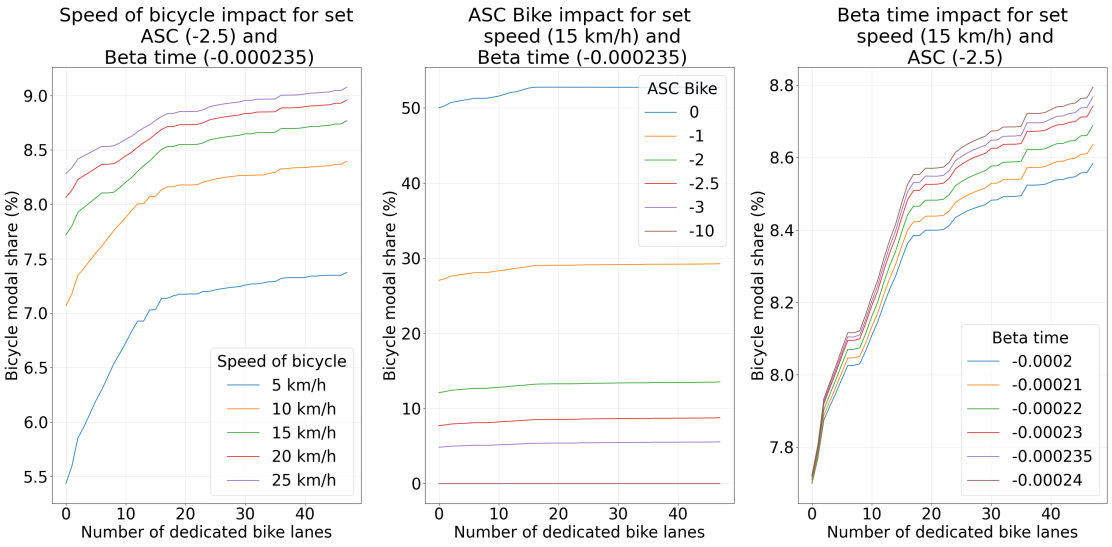



Figure 11: Design model sensitivity analysis parameters.