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► **To cite this version:**

Manuel Campero Jurado, Carlos Canudas de Wit, Giovanni de Nunzio, Mauro Salazar. On Transport Justice and Safety in Bicycle Network Design Optimization. CDC 2025 - 64th IEEE Conference on Decision and Control, Institute of Electrical and Electronics Engineers, Dec 2025, Rio de Janeiro, Brazil. pp.1-6. <hal-05325750>

HAL Id: hal-05325750

<https://hal.science/hal-05325750v1>

Submitted on 22 Oct 2025

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On Transport Justice and Safety in Bicycle Network Design Optimization

Manuel Campero Jurado¹, Carlos Canudas-de-Wit¹, Giovanni De Nunzio², Mauro Salazar³

Abstract—This paper presents a bi-level optimization framework to decide on urban cycling infrastructure safety upgrades, increasing the degree of separation between bike lanes and motorized traffic, in line with principles of justice. Specifically, we first instantiate the lower level modeling cyclist flows with an all-or-nothing traffic assignment. Second, the upper level allocates upgrades within a fixed budget and in line with two principles of justice: conventional utilitarianism (i.e., the minimization of the overall exposure to traffic *on average*) and sufficientarianism (i.e., ensuring that the highest number of cyclists achieves a sufficient safety level). Third, we propose two heuristic algorithms to efficiently solve the bi-level problem. We showcase our framework for the Grenoble cycling network. Our results reveal that following a sufficientarian paradigm can considerably improve the situation of the most vulnerable users without significantly affecting overall utilitarian safety levels.

Index Terms—Cycling infrastructure, bi-level optimization, safety, transport justice, urban planning.

I. INTRODUCTION

Cycling brings health, environmental, and economic advantages, such as better cardiovascular fitness, lower emissions, and less congestion [1], along with enhanced well-being [2], [3]. Since safety strongly influences ridership, promoting cycling requires investment in infrastructure [4]. Physically separated bike lanes and well-connected networks are shown to increase safety and ridership [5]. Given limited budgets, authorities must choose which lanes to upgrade. Such a decision process calls for the definition of a societal objective as well as frameworks capable of systematically suggesting upgrades in line with it. This paper proposes to leverage transport justice to distribute safety in line with two distinct principles of justice [6]—a *utilitarian* perspective to reduce overall exposure across the network, and a *sufficientarian* perspective aimed at ensuring that as many cyclists as possible reach a minimum acceptable level of safety—and presents a bi-level optimization framework to propose upgrades aligned with such principles accounting for the resulting cycling flows.

Related Work: Our work draws on two primary domains: cycling network optimization and transport justice. The following is an overview of related work in these areas.

We thank Dr. I. New for proofreading this paper. M. Campero Jurado visited Eindhoven University of Technology with the support of an outgoing mobility grant IDEX from the Univ. Grenoble Alpes.

¹Univ. Grenoble Alpes, Inria, CNRS, Grenoble INP, GIPSA-Lab, 38000 Grenoble, France {manuel.campero-jurado@inria.fr, carlos.canudas-de-wit@gipsa-lab.fr}

²IFP Energies nouvelles, Rond-point de l'échangeur de Solaize, BP 3, 69360 Solaize, France, giovanni.de-nunzio@ifpen.fr

³Eindhoven University of Technology, 5600 MB, Eindhoven, The Netherlands m.r.u.salazar@tue.nl

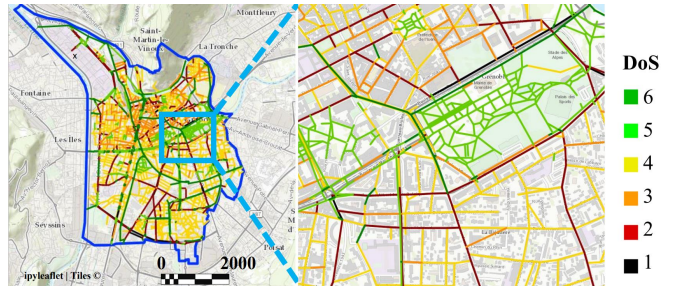


Fig. 1: Cycling network of Grenoble, France. The degree of separation (DoS) score, indicating infrastructure safety, ranges from 1 to 6.

Cycling network optimization uses diverse methodologies, including bi-level frameworks that balance cyclist distance maximization with car travel time reduction [7], while cost-benefit analyses guide phased network expansions [8]. Graph-theoretic approaches prioritize low-cost connectivity [9], and others optimize route efficiency under budget constraints, incorporating terrain and traffic flow predictions [10]. Recent graph-based methods focus exclusively on safety improvements [11], [12], [13]. However, these methods overlook the fair distribution of resources.

Transport justice proposes to design and operate transport systems in line with principles of social justice. Thereby, the seminal work by Martens [6] argues for a sufficientarian perspective on accessibility. Which is further supported in [14] to evaluate transit accessibility levels, and mobilized into a prescriptive optimization framework for intermodal transport planning in [15]. The capabilities approach is applied in [16] and [17] to emphasize minimum standards and guide policy developments which [18] explored through normative planning approaches. Nevertheless, except for [15], most of these papers are aimed at evaluation rather than prescription, and do not focus on cycling safety.

To the best of the authors' knowledge there is no framework to optimize bicycle network safety upgrades in line with principles of justice.

Statement of Contributions: We propose a bi-level optimization framework for planning safer cycling infrastructure under budget constraints, guided by utilitarian and sufficientarian justice principles. Cyclist flows are modeled via all-or-nothing assignment accounting for slope and traffic. We solve the problem using a genetic algorithm and compare results to a connectivity-based method [11]. Applied to Grenoble, our model enhances safety, especially for vulnerable users. In conclusion, we firmly believe that this is the first systematic

DoS	Description	AADT (veh/day)
6	Dedicated bike lanes, fully separated from motor traffic.	14 400
5	Bike lanes shared with pedestrians, separate from cars.	16 000
4	Mixed-traffic roads (30 km/h) without designated bike lanes.	960
3	Shared roads with cycling pictograms.	3 120
2	Roads with painted bike lanes.	6 912
1	Unmarked shared car-bike lanes.	8 448

TABLE I: The degree of separation (DoS) categorizes bike lane infrastructure based on safety levels. The third column presents annual average daily traffic (AADT) on adjacent roads, sourced from the GTLVille platform in Grenoble [19].

application of transport justice principles to optimize cycling infrastructure safety upgrades.

Organization: Section II outlines data, classification, flow modeling, bi-level optimization with utilitarian and sufficientarian perspectives, and algorithms to solve them. Section III details the Grenoble case study. Section IV concludes with findings and future directions.

II. MODEL DESIGN

We first describe the bike lane classification and graph representation, followed by cyclist flow modeling. The utilitarian model minimizes total cyclist exposure, while the sufficientarian model reduces the number of cyclists below safety thresholds. Both NP-hard problems are solved with tailored algorithms.

A. Bike Lane Safety classification and Graph Representation

The DoS classification, adapted from an OSM-based platform, ranks cycling infrastructure by separation from motor traffic. Higher-DoS lanes imply greater safety (Table I) and define arc weights in the network. This upgrade model is detailed in [11], [13], with Fig. 1 illustrating DoS levels in Grenoble.

Let the network be a weighted directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{A}, \mathcal{W})$, where \mathcal{V} is the set of nodes (intersections or endpoints), \mathcal{A} the set of directed arcs (roads), and \mathcal{W} the set of associated weights. For each arc $a = (u, v) \in \mathcal{A}$, with $u, v \in \mathcal{V}$, the weight $w_a \in \mathcal{W}$ indicates the DoS of the link. We assume symmetric weights: $w_{(u,v)} = w_{(v,u)}$. Each arc's geographical length is denoted by d_a . Finally, let $\mathcal{V}_O, \mathcal{V}_D \subseteq \mathcal{V}$ denote the sets of origin and destination nodes for bicycle trips.

B. Cyclist Flows

For $(u, v) \in \mathcal{V}_O \times \mathcal{V}_D$, let $q_{(u,v)}$ represent the cycling demand between node u and v . Following [7], we use an all-or-nothing (AON) traffic assignment model assuming no congestion. We adopt the cyclist distance from [10], which incorporates OpenStreetMap and Cardiff flow data, including infrastructure characteristics. Betweenness centrality then estimates flow distribution. To reflect cyclist-specific routing, we define a modified distance accounting for terrain and traffic. Let $p_{(u,v)} = (a_1, \dots, a_k)$ denote the shortest path

between u and v , where each arc a has length d_a , angular change \angle_a , slope factor s_a (based on slope m_a), and traffic factor f_a . The cyclist distance $b_{(u,v)}$ is:

$$b_{(u,v)} = \sum_{a \in p_{(u,v)}} (d_a \cdot s_a \cdot (f_a)^\rho) + \sum_{a \in p_{(u,v)}} \angle_a \cdot \kappa, \quad (1)$$

with calibration parameters $\rho, \kappa > 0$. The traffic factor f_a is defined as:

$$f_a = \begin{cases} \psi \cdot \exp(x_a^{\text{AADT}}) & \text{if } w_a < 5, \\ \psi \cdot 2.03 & \text{if } w_a = 5, \\ \psi & \text{if } w_a = 6, \end{cases} \quad (2)$$

where, x_a^{AADT} is the adjacent road's average daily traffic (in thousands), w_a is the DoS, and ψ is a scaling factor. As per [20], traffic effects vanish when $w_a \geq 5$, and 2.03 reflects increased crash risks in shared spaces with pedestrians [21]. Let $p_{(u,v)}$ be the shortest path under Eq. (1). The corresponding path-based flow conservation law is:

$$x_{p_{(u,v)}} = q_{(u,v)}. \quad (3)$$

Let $\mathbb{I}_{a \in p_{(u,v)}}$ be a binary variable indicating arc a in $p_{(u,v)}$. The total cyclist flow on arc a is:

$$x_a = \sum_{(u,v) \in \mathcal{V}_O \times \mathcal{V}_D} q_{(u,v)} \cdot \mathbb{I}_{a \in p_{(u,v)}} \geq 0, \quad \forall a \in \mathcal{A}. \quad (4)$$

Finally, for a shortest path $p_{(u,v)}$, cyclist exposure captures the combined effect of traffic-related risk and the distance of cyclist interaction with traffic, and is defined as

$$\mathcal{E} = \sum_{a \in \mathcal{A}} d_a \cdot f_a, \quad (5)$$

Finally, we introduce bi-level optimization models to enhance safety. The lower-level problem uses AON flow assignment incorporating slope and traffic. The upper-level problem selects upgrades to reduce exposure, guided by utilitarian and sufficientarian justice principles. We also present algorithms to solve these NP-hard problems efficiently.

C. Optimization Problem (Utilitarian Perspective)

Given a fixed budget B , we adopt a utilitarian approach to improve cycling infrastructure by upgrading the DoS on selected road segments. The goal is to minimize average cyclist exposure to vehicular traffic, considering flow distribution. Each upgrade has a cost per meter and must respect the budget. We introduce the following notation, where all values are normalized except for the DoS scores:

- $\mathbf{w}_0 = [w_1, \dots, w_{|\mathcal{A}|}]^\top \in \mathbb{N}^{|\mathcal{A}|}$: original arc weights (DoS);
 - $\tilde{\mathbf{w}} = [\tilde{w}_1, \dots, \tilde{w}_{|\mathcal{A}|}]^\top \in \Omega$: optimized candidate weights, where
- $$\Omega = \left\{ \tilde{w} \in \mathbb{N}^{|\mathcal{A}|} : w_a \leq \tilde{w}_a \leq 6, \forall a \in \{1, \dots, |\mathcal{A}|\} \right\}; \quad (6)$$

- $\mathbf{b}(\tilde{\mathbf{w}}) \in \mathbb{R}_{\geq 0}^{|\mathcal{A}|}$: vector of cyclist distances using Eq. (1);
- $\mathbf{x}^*(\tilde{\mathbf{w}}) \in \mathbb{R}_{\geq 0}^{|\mathcal{A}|}$: resulting arc flows from AON assignment by Eq. (3) and Eq. (4);
- $\mathcal{E}(\tilde{\mathbf{w}}) \in \mathbb{R}_{\geq 0}^{|\mathcal{A}|}$: vector of arc cyclist exposure Eq. (5);

- $\pi(w_a, \tilde{w}_a) \in \mathbb{R}_{\geq 0}$: cost per meter of upgrading arc a ;
- $J_{\mathcal{E}} = \mathcal{E}^{\top}(\tilde{\mathbf{w}})\mathbf{x}^*(\tilde{\mathbf{w}})$: total cyclist exposure.

We formulate a bi-level optimization: the upper level selects upgrades, and the lower level estimates cyclist flow. *Upper-Level Problem* (\mathbb{U}): Minimizes total cyclist exposure by selecting DoS upgrades under budget B . It prioritizes upgrades on longer, high-traffic, and high-flow arcs. *Lower-Level Problem* (\mathbb{L}): Computes AON-assigned cyclist flows based on the shortest paths using the updated DoS, as detailed in Section II-B. DoS upgrades impact both perceived distance and flow assignment, nesting the lower-level problem within the upper-level decision process.

Problem 1 (Utilitarian Network-Upgrade):

$$\mathbb{U}: \quad \mathbf{w}^* = \arg \min_{\tilde{\mathbf{w}} \in \Omega} J_{\mathcal{E}}(\tilde{\mathbf{w}}) = \mathcal{E}^{\top}(\tilde{\mathbf{w}})\mathbf{x}^*(\tilde{\mathbf{w}}) \quad (7)$$

$$\text{s.t.} \quad \sum_{a=1}^{|\mathcal{A}|} d_a \cdot \pi(w_a, \tilde{w}_a) \leq B \quad (8)$$

$$\mathbb{L}: \quad \mathbf{x}^*(\tilde{\mathbf{w}}) = \arg \min_{\mathbf{x} \in \mathbb{R}_{\geq 0}^{|\mathcal{A}|}} \mathbf{b}(\tilde{\mathbf{w}})^{\top} \mathbf{x} \quad (9)$$

$$\text{s.t.} \quad x_a = \sum q \cdot \mathbb{I}_{a \in p} \geq 0 \quad \forall a \in \{1, \dots, |\mathcal{A}|\} \quad (10)$$

as in (4).

Problem 1 is NP-hard due to the combinatorial selection of arc upgrades under a fixed budget, akin to the 0-1 knapsack problem. While \mathbb{U} is non-convex and non-linear, \mathbb{L} is linear and convex. The main complexity lies in balancing upgrade costs with safety benefits.

D. Optimization Problem (Sufficientarian Perspective)

We now extend Problem 1 with a sufficientarian perspective, aiming to ensure that as many cyclists as possible achieve a minimum safety level. Using the path exposure $\mathcal{E}_{p(u,v)}$ from (5), we define the path safety score as $s_{p(u,v)} = \frac{1}{\mathcal{E}_{p(u,v)} + \epsilon}$, where $\epsilon > 0$ prevents division by zero and caps safety values. This score is a simplification of the route choice model in [22], using cyclist exposure as a proxy for perceived safety. To define a sufficiency threshold, we compute the global average safety:

$$s_{\mathcal{G}} = \frac{1}{|\mathcal{V}|} \sum_{u \in \mathcal{V}} s_{p(u,v)} \quad \forall v \in \mathcal{V}. \quad (11)$$

We then define a relative safety threshold s_{thr} as a proportion of the average safety level $s_{\mathcal{G}}$, using a parameter λ that takes values from the set $\{10\%, 20\%, 30\%, 40\%, 50\%\}$, that is,

$$s_{\text{thr}} = \lambda s_{\mathcal{G}}. \quad (12)$$

This method follows the standard practice proposed by Martens in the context of transport justice [6], [23], where sufficiency thresholds are defined as a proportion of an average (or median) accessibility level. Paths with safety scores below s_{thr} are considered insufficiently protected. Following a similar approach to [15], we define the path-level safety insufficiency as

$$\mathcal{I}_{p(u,v)} = \max \left\{ 0, \frac{s_{\text{thr}} - s_{p(u,v)}}{s_{\text{thr}}} \right\}, \quad (u, v) \in \mathcal{V}_{\mathcal{O}} \times \mathcal{V}_{\mathcal{D}}. \quad (13)$$

We divide the network into regions $\mathcal{R} = \{1, \dots, R\}$, with $\mathcal{V}^r \subseteq \mathcal{V}$ as nodes in region $r \in \mathcal{R}$ and in $\mathcal{V}_{\mathcal{O}}$. The regional safety insufficiency is the demand-weighted average:

$$\mathcal{I}_r = \frac{\sum_{u \in \mathcal{V}^r} \mathcal{I}_{p(u,v)} \cdot q(u,v)}{\sum_{u \in \mathcal{V}^r} q(u,v)} \quad \forall v \in \mathcal{V}_{\mathcal{D}}, \quad (14)$$

and the total population-weighted network-level insufficiency is:

$$J_{\mathcal{I}} = \frac{\sum_{r \in \mathcal{R}} n_r \cdot \mathcal{I}_r}{\sum_{r \in \mathcal{R}} n_r}, \quad (15)$$

where n_r is the number of cyclists in region r . Finally, we define the sufficientarian bi-level optimization problem, where \mathbb{U}_{thr} ensures that as many cyclists as possible meet the minimum relative safety threshold while minimizing cyclist exposure, and as before, \mathbb{L} models the resulting flow distribution.

Problem 2 (Sufficientarian Network-Upgrade):

$$\mathbb{U}_{\text{thr}}: \quad \mathbf{w}^* = \arg \min_{\tilde{\mathbf{w}} \in \Omega} (J_{\mathcal{I}}(\tilde{\mathbf{w}}) + \eta \cdot J_{\mathcal{E}}(\tilde{\mathbf{w}})) \quad (16)$$

$$\text{s.t.} \quad \sum_{a=1}^{|\mathcal{A}|} d_a \cdot \pi(w_a, \tilde{w}_a) \leq B,$$

$$\mathbb{L}: \quad \mathbf{x}^*(\tilde{\mathbf{w}}) = \arg \min_{\mathbf{x} \in \mathbb{R}_{\geq 0}^{|\mathcal{A}|}} \mathbf{b}(\tilde{\mathbf{w}})^{\top} \mathbf{x} \quad (17)$$

$$\text{s.t.} \quad x_a = \sum q \cdot \mathbb{I}_{a \in p} \geq 0 \quad \forall a \in \{1, \dots, |\mathcal{A}|\} \quad (18)$$

as in (4).

where η is the regularization weight. The problem \mathbb{U}_{thr} is non-convex and non-linear, analogous to its respective counterpart \mathbb{U} .

E. Solution Algorithms

To manage the complexity of Problems 1 and 2, we propose two heuristic algorithms: a genetic algorithm (GA) with efficient budget use, and the maximize largest connected component algorithm (MLCC) from [11]. GA is implemented in two variants: GA-U (utilitarian) and GA-S (sufficientarian), differing only in their objective functions.

1) *Genetic Algorithm with Efficient Budget Spending (GA)*: Both GA-U and GA-S search for feasible upgrade plans under budget constraints using a genetic heuristic. Starting from an initial population, solutions are iteratively recombined (crossover) and modified (mutation). If budget remains, low-DoS arcs are greedily upgraded. This approach ensures efficient budget allocation, though it may yield local optima. GA-U minimizes total exposure (Problem 1), while GA-S maximizes the number of cyclists reaching safety thresholds (Problem 2). The pseudocode is shared for both variants, differing only in the objective function.

- \tilde{B} : Remaining budget after the initial solution $\tilde{\mathbf{w}}$ has been evaluated.
- Δ_a : Cost to upgrade arc a to DoS = 6, i.e., $\pi(\tilde{w}_a, 6)$.

Algorithm 1 *GA Algorithm (used for GA-U and GA-S)*

1: **Input:** Remaining budget \tilde{B} , candidate weights $\tilde{\mathbf{w}}$
2: **Output:** Updated weights \tilde{w}_a , remaining budget \tilde{B}
3: **for** $a \in \mathcal{A}$ sorted by $\text{DoS}(w_a)$ **do**
4: Compute upgrade cost: $\Delta_a = \pi(\tilde{w}_a, 6)$
5: **if** $\tilde{B} \geq \Delta_a$ **then**
6: Upgrade \tilde{w}_a to $\text{DoS} = 6$
7: Update budget: $\tilde{B} \leftarrow \tilde{B} - \Delta_a$
8: **end if**
9: **if** $\tilde{B} \leq 0$ **then Exit**
10: **end if**
11: **end for**
12: **Return:** \tilde{w}_a, \tilde{B}

2) *Maximize Largest Connected Component Algorithm (MLCC):* The MLCC algorithm [11] aims to expand high-DoS subnetworks ($\text{DoS} = 6$) to enhance connectivity. It starts by identifying the largest connected component (CC) with $\text{DoS} = 6$, then links other high-DoS CCs to it using shortest paths, prioritizing arcs with higher existing DoS. Upgrades are applied iteratively until the budget is used. This method indirectly improves cyclist flow by increasing network-level high-safety connectivity. Key notation:

- \mathcal{C} : Largest connected sub-network with $\text{DoS} = 6$.
- \mathcal{C}_γ : CC with DoS level $\gamma \leq 6$.

Algorithm 2 *MLCC Algorithm*

1: **Input:** Budget B , graph \mathcal{G}
2: **Output:** Upgraded DoS levels for arcs \mathcal{A}
3: **while** $B > 0$ and \exists connected component \mathcal{C}_γ with $\text{DoS} \gamma \leq 6$ **do**
4: Find shortest path between \mathcal{C} and \mathcal{C}_γ
5: Upgrade arcs along path to $\text{DoS} = 6$ and update B
6: Upgrade arcs in \mathcal{C}_γ to $\text{DoS} = 6$ and extend \mathcal{C}
7: **end while**
8: **Return:** Final DoS levels for all arcs in \mathcal{A}

III. GRENOBLE CYCLING NETWORK CASE STUDY

This section presents the AON flow assignment parameters, a budget sensitivity analysis, and a case study in Grenoble, France. It also compares the performance of the MLCC, GA-U, and GA-S algorithms against the original scenario.

A. Parameters and Algorithm Comparisons

To compute cyclist flows via the AON assignment (Section II-B), we adopt parameter values from [10], setting $\rho = 0.04$, $\kappa = 0.14$, and $\psi = 0.84$ for the distance and traffic factors. The slope factor s_a is specified in Table II, with downhill values computed as the reciprocal of their uphill counterparts.

Slope (m_a) %	Uphill Factor (s_a)	Downhill Factor (s_a)
$m_a < 2$	1.0	1.0
$2 \leq m_a < 4$	1.371	$1/1.371 \approx 0.729$
$4 \leq m_a < 6$	2.203	$1/2.203 \approx 0.454$
$m_a \geq 6$	4.239	$1/4.239 \approx 0.236$

TABLE II: Slope factors for cycling distance calculation.

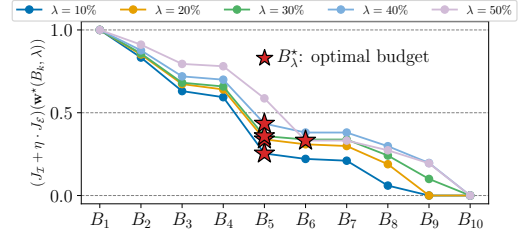


Fig. 2: Normalized marginal cyclist exposure reduction relative to budget increments to solve Eq. (20).

B. Sensitivity Analysis for Budget

We optimize cycling network upgrades using a logarithmic budget sampling approach. Let B_{\max} denote the full network upgrade cost to $\text{DoS} = 6$. The budget range is constrained to $[\frac{B_{\max}}{100}, \frac{B_{\max}}{2}]$ with logarithmic sampling:

$$B_k = B_{\min} + \left(\frac{B_{\max}}{2} - B_{\min} \right) \cdot \frac{\log(k)}{\log(10)}, \quad k \in \{1, \dots, 10\} \quad (19)$$

For each $\lambda \in \{10\%, 20\%, 30\%, 40\%, 50\%\}$, we solve the optimization problem for all B_k to obtain solutions $\mathbf{w}^*(B_k, \lambda)$. The most cost-effective budget B_λ^* is selected by minimizing the marginal cyclist exposure per cost:

$$B_\lambda^* = \arg \min_{B_k} \left(\frac{\Delta \mathbf{w}^*(B_k, \lambda)}{B_k - B_{k-1}} \right) \quad (20)$$

where $\Delta \mathbf{w}^*(B_k, \lambda) = \mathbf{w}^*(B_k, \lambda) - \mathbf{w}^*(B_{k-1}, \lambda)$ represents the marginal cyclist exposure reduction. This approach identifies budgets yielding the highest gains per monetary unit invested.

C. Grenoble Case Study

Our case study focuses on the Grenoble cycling network. Fig. 2 shows the optimal budget B_λ^* for each threshold λ . For $\lambda \in \{10\%, 20\%, 30\%, 40\%\}$, the maximum marginal gain occurs at $B_\lambda^* \approx 0.056 \cdot B_{\max}$, and for $\lambda = 50\%$, at $0.087 \cdot B_{\max}$. Higher thresholds thus require larger budgets to reach cost-effective improvements. We use these values for further analysis. Fig. 3 compares the original network with the results of MLCC, GA-U, and GA-S for $\lambda = 40\%$. MLCC focuses on connecting high-DoS components, while GA-U spreads upgrades more evenly. GA-S, however, achieves the lowest regional safety insufficiency, especially in vulnerable zones (Fig. 3 e–h). Fig. 4 shows that while MLCC gives the most cyclists the safest possible routes, GA-S ensures more cyclists meet the threshold. Fig. 5 confirms that GA-S consistently reduces the proportion of cyclists below each safety threshold, even as λ increases.

Fig. 6 presents the results of the sufficientarian approach in Problem 2, specifically to calculate the upper level \mathbb{U}_{thr} for the different candidate solutions and threshold values given by λ . We observe that when λ is small, safety insufficiency remains low. However, as λ increases, insufficiency also rises. Despite this, GA-S repeatedly achieves the greatest reduction in safety insufficiency. To better interpret the results, we compare them with a baseline scenario (Problem 1)

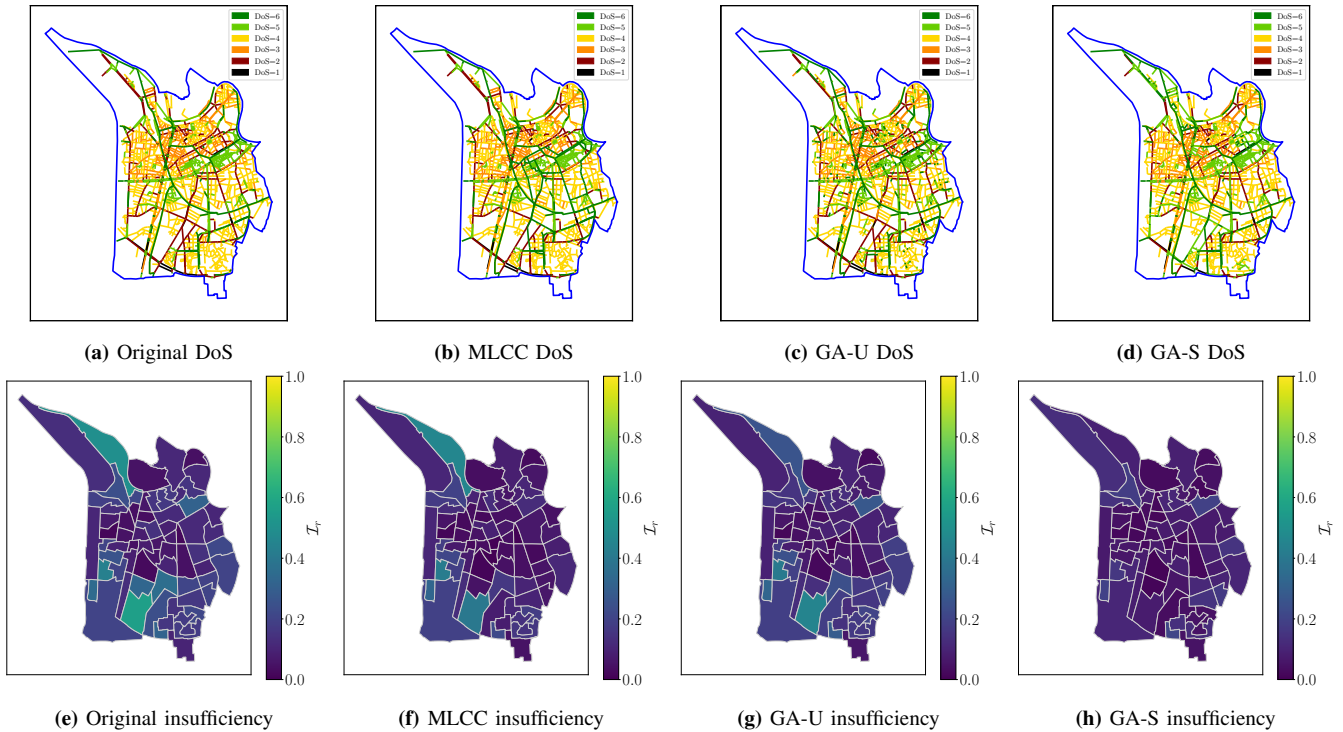


Fig. 3: The top section displays the DoS configuration, while the bottom illustrates regional safety insufficiency. The optimization algorithms are applied with $\lambda = 40\%$ and a budget of $B_\lambda^* \approx 0.056 \cdot B_{\max}$.

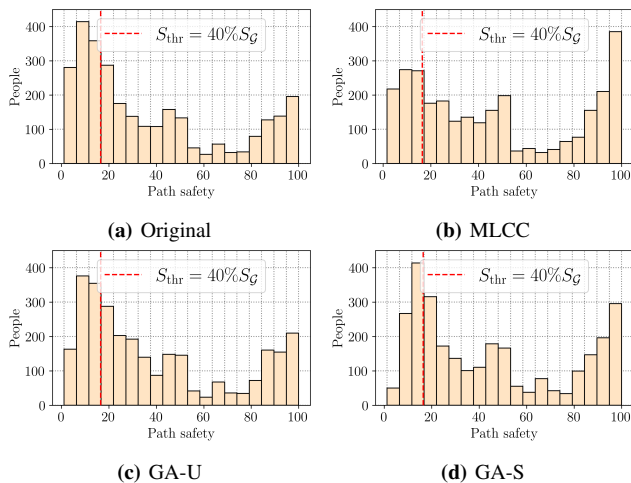


Fig. 4: Path safety versus the number of individuals above and below the threshold $\lambda = 40\%$ and a budget of $B_\lambda^* \approx 0.056 \cdot B_{\max}$.

that minimizes cyclist exposure without explicitly addressing safety insufficiency. As shown in Fig. 7, GA-U achieves the largest reduction in exposure. However, GA-S performs similarly across all thresholds, despite also accounting for safety insufficiency. This suggests that incorporating insufficiency can improve safety without significantly compromising exposure reduction. To evaluate the robustness of GA-S at $\lambda = 10\%$ and its optimal budget B_λ^* , we ran 10 Monte Carlo simulations using a population size of 30 over 100 generations. The algorithm consistently produced similar

results, with a mean objective value of 0.02168 (standard deviation 0.00050) and an average runtime of 4.16 hours (± 230.53 seconds), confirming its stability under random initialization (see Fig. 8) and reducing the likelihood that results are driven by convergence to poor local optima.

IV. CONCLUSIONS AND FUTURE WORK

This work introduced a bi-level optimization framework that incorporates transport justice principles into cycling infrastructure planning. We balanced overall safety improvements with sufficientarian goals to ensure that most cyclists reach a minimum safety threshold. Our results show that, compared to a conventional utilitarian approach, it is possible to significantly reduce safety insufficiency whilst still achieving similar overall safety improvements. These findings highlight the value of integrating transport justice principles into infrastructure design.

Future work will extend this framework to a dynamic setting, analyzing how incremental infrastructure development influences safety, cyclist behavior, and car travel times [7], supporting more equitable and adaptive transport planning.

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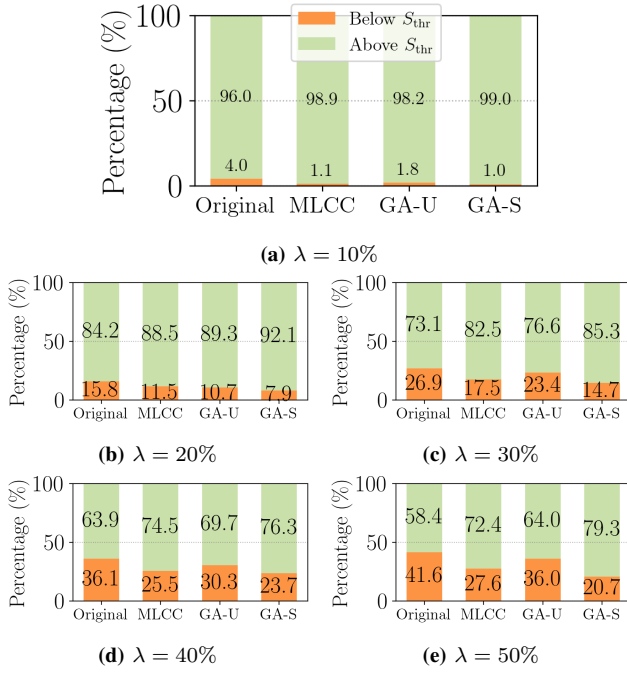


Fig. 5: Percentage of people above and below the threshold for different λ and solutions.

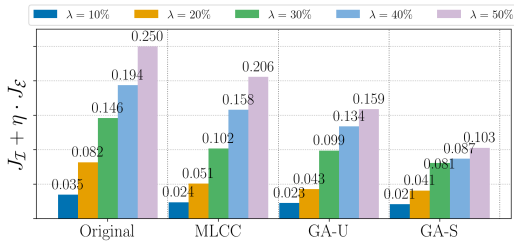


Fig. 6: Safety insufficiency comparison of upper level U_{thr} of Problem 2, $\eta = 0.5$, and the color legend indicates the λ threshold.

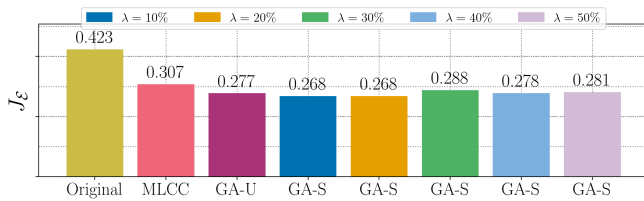


Fig. 7: Cyclist exposure comparison of upper level U of Problem 1, where for GA-S the percentage indicates the λ value for the threshold.

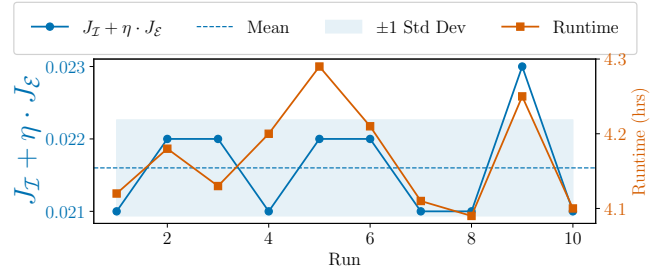


Fig. 8: Monte Carlo simulation for safety insufficiency perspective with $\lambda = 10\%$ at its optimal budget B_x^* .

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