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Comparing different methods for connecting bike lanes to generate a complete bike network and identify potential complete streets in Atlanta

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A R T I C L E I N F O

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A B S T R A C T

This study compares two different strategies for connecting bike networks – traditional design-based and algorithm-supported – to investigate how their results differ along metrics such as proportion of bike lanes along simulated routes and the resulting cycling stress. The objective is to find optimal strategies for connecting isolated existing cycling infrastructure to form complete networks that improve both active mobility and public transit ridership. By aligning the bike network with transit and activity locations, this research develops an algorithmic framework for generating a skeleton of multimodal networks best suited to become "complete streets." The network generated through an algorithm is compared with a proposed traditionally designed network to determine their relative network performance. The findings suggest that a judicious combination of traditionally designed, and algorithm-supported networks offer better cycling infrastructure than either strategy alone. In addition, algorithms can also be developed to indicate the potential for street segments to be complete streets.

1. Introduction

The transportation system in the U.S. has been, in most parts, designed to promote the mobility of automobiles. This unimodal focus has generated a number of intractable transportation problems, including congestion, pollution, socioeconomic disparities, and inefficiency in the use of scarce resources such as energy and land, among others. Among the various strategies to reduce the dominance of automobiles and promote multimodality in transportation options is the "complete streets" policy, which has been adopted by over 1700 jurisdictions in the U.S. by 2023 (Smart Growth America, n.d.). This policy is aimed at transforming street rights-of-way to accommodate multiple modes of travel, including especially the active modes, such as walking and cycling. The objective is to make streets safe and convenient for all persons, including children, the elderly, and the disabled, who may choose among multiple mobility options.

While complete streets policy is addressed in this article, this study focuses more specifically on bike lanes and their role in complete street designs. It is because 1) cycling and shared micro-mobility are rapidly growing modes of travel in Atlanta and both travel modes benefit from dedicated bike lanes; 2) dedicated bike lanes improve the safety and comfort of all travelers, not just the bicyclists; 3) cycling infrastructure is typically the least well developed among the facilities and services dedicated to various modes of travel (e.g., automobile, transit, and pedestrian); and 4) improved cycling infrastructure encourages more people to ride a bike, which promotes clean energy, better public health, and a cleaner environment (Akar and Clifton, 2009; Aldred and Dales, 2017; Clark et al., 2019; Dill and Voros, 2007; Garrard et al., 2008; Moudon et al., 2005). Indeed, empirical studies have identified that better bike infrastructure has influenced people's travel behavior and increased the number of bike users (Aziz et al., 2018; Buehler and Pucher, 2012; National Association of City Transportation Officials, 2016; Pedroso et al., 2016; Schoner and Levinson, 2014; Zahabi et al., 2016). Moreover, a more ubiquitous bike network can provide efficient first-mile and last-mile connectivity, which facilitates transit use (Hwang & Guhathakurta 2023).

The objective of this study is to develop and implement an algorithm that would iteratively connect existing bike lanes to create a complete bike network. This bike network is designed to align with transit routes and connect to nearby MARTA subway stations, which increases the potential for some network segments to be developed as complete streets. The algorithm for creating the complete network prioritizes links

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that: 1) promote multi-modal trips, 2) connect high density of points-of-interest (POIs), 3) serve areas with high residential and commercial density, 4) connect marginalized neighborhoods, and 5) prioritizes streets with low traffic volumes, and 6) with gradual slopes.

The algorithm is designed to improve bike networks at a local scale by focusing on the local context; in other words, it seeks local optima. Although a globally optimal network 'design' might be an ideal solution, its 'implementation' is inevitably piecewise and takes decades (Szell et al., 2022). A comprehensive city-wide bike network plan is usually not carried out all at once. Local governments generally invest in bike networks in a piecemeal manner as budgets permit. Therefore, the critical decision faced by local governments is the sequence of development of the bike infrastructure. That is, which segments are the most important ones to complete first and which segments can wait for later implementation. Yet, bike network plans that are made by municipalities are often globally optimized and may not offer the information necessary to sequence the implementation. This study will compare the two approaches based on a case study of the City of Atlanta. We also evaluate a network that combines the two approaches to show how our algorithm-generated network can help improve the performance of the network planned by the local government.

This study seeks to introduce a pragmatic and accessible algorithm that aims to streamline the expansion of bike infrastructure, balancing factors like multimodality, equity, and bikeability. We anticipate that this practical approach will not only simplify theoretical models for real-world application but also support the creation of more inclusive and sustainable urban mobility solutions.

2. Prior studies

Complete streets enable all street users to make safe and convenient trips and encourage active mobility and public transit use, which brings a wide range of direct and indirect benefits: such as more vibrant and livable communities, lower energy consumption and GHG emission, and enhanced public fitness and health (Atlanta Regional Commission, 2019; Kingsbury et al., 2011; Litman, 2014; McCann and Rynne, 2010; Sousa and Rosales, 2010). In terms of environmental impact, Shu et al. (2014) reported that the number of pedestrians increased by 37% and the emission-weighted traffic volume decreased by 26% after complete streets treatment. Complete street measures have also improved safety as they help reduce both pedestrian risk and traffic crash risk (King et al., 2003; Pawlovich et al., 2006). Moreover, a walk- and bike-friendly environment encourage more physical activities, which ultimately improves public health (Brown et al., 2015; Brown et al., 2016; Jensen et al., 2017).

Most complete streets have involved designing the rights-of-way to accommodate all street users: pedestrians, bicyclists, transit riders, and motorists. Among them, bike users are most affected by complete street designs according to several studies. Carter et al. (2013) compared the Level of Service (LOS) of each type of street user after a complete street intervention and the results showed that bicycle LOS was improved more than all other modes. A similar analysis by Elias (2011) also shows that designated bike lanes significantly improved bicycle LOS while the LOS of pedestrians, who already had access to sidewalks, was only marginally better by complete street elements. According to Sousa and Rosales (2010), the designated bike lanes not only enhance the bicycling environment but also increase walkability by providing buffer areas to pedestrians. In addition, bike lanes play an essential role in increasing multimodal accessibility.

The connectivity of the transportation network is an important consideration when implementing complete streets and bike lanes. One effective way to encourage active transportation is to ensure the connectivity of pedestrian and bike networks by completing missing network segments (McCann and Rynne, 2010). In addition, connections to transit hubs are crucial for expanding bicycling and walking access to multimodal trips for first- and last-mile connectivity (Atlanta Regional Commission, 2019). While no study has focused on the network design of complete streets, there have been numerous studies on the network design of bike lanes. Table 1 shows the criteria used in various studies to evaluate or optimize bike network design. As can be noted from Table 1, Bicycle Level of Service and connectivity are the most frequently used measures for evaluating and prioritizing bike networks. For those studies that focus on bike network optimization, Bicycle Level of Service, budget, and connectivity are the most commonly used factors. In both categories, only a few studies have considered the impact on car users, multi-modality, and equity. However, since complete streets accommodate not only bike users but also all other street users, criteria should be considered comprehensively to design a "complete" network.

3. Conceptual approach

3.1. The design principles

The design of the bike network to enable complete street development is based on two fundamental principles.

First, the existing bike network is used as the starting point. While most studies on bike network design tend to ignore the existing networks, bike network plans as implemented typically respect the existing conditions to leverage sunk costs (Natera et al., 2019; Guerreiro et al., 2018; Hsu and Lin, 2011). Accordingly, the network design in this study is based on a principle of local optima, rather than global optima. While the global optimization might lead to an ideal design, the implementation is a different story: operationally, the network will be built up in a piecemeal manner as funds become available. Thus, this study hypothesizes that a locally optimized network design, which focuses on addressing local-scale connections from the existing context, can provide greater utilities than a globally optimized network in the process of implementation.

Second, we develop a set of criteria to determine the links that best serve the interest of bikers and adhere to complete street design. These criteria include transit access, the density of activities and people, bikeability, and equity of access to the infrastructure, among other factors. These criteria direct the route-finding algorithm to find the optimum connecting path between a pair of network fragments in a sequence that respects their importance within the network.

3.2. Multi-modality and equity in complete street design

Our study prioritizes multi-modality and equity as key criteria in developing a complete street network. Connecting bike infrastructure to transit hubs advances a critical goal of complete streets, which is to reduce automobile dependency and promote both active mobility and public transit. Thus, one of the goals of this study is to design a network that caters to cyclists who go to or come from transit hubs.

Equity is also one of the essential elements in the complete streets policy. We are particularly focused on ensuring that underserved neighborhoods with a history of disinvestment and a lack of transit options are not left behind in the process of complete street design. Planning for Equity Policy Guide states that people who do not have access to a private vehicle or who are unable to use such a vehicle either due to physical challenges or age-related restrictions need to be supported by multi-modal facilities including complete streets (American Planning Association, 2019).

This study addresses multi-modality and equity aspects in network design in two ways. First, we deliberately address a possible blind spot in connecting the existing network fragments where the neighborhoods with no history of bike facility investments are likely to continue to be isolated during the network build-out process. We identify and include as anchor points those places that have been previously underserved and have a high potential demand for bike travel due to low levels of automobile access. Second, we add subway stations as additional anchor points in order to build a more multimodal network. In addition, the

Table 1
Criteria Used in the Prior Studies for Bike Network Design.

Category	Authors (year)	Criteria							
		Access-ibility	LTS; BLOS	Cost-benefit; Budget	Bike travel demand	Connec-tivity	Impact on car users	Multi-Modality	Equity
Network evaluation & prioritization	McCahill and Garrick (2008)					O			
	Rybarczyk and Wu (2010)		O		O				
	Lowry et al. (2016)	O	O			O			
	Kent and Karner (2018)	O						O	
	Zuo and Wei (2019)		O			O	O		O
Network optimization & allocation	Hsu and Lin (2011)		O						
	Mesbah et al. (2012)		O	O	O	O	O		
	Duthie and Unnikrishnan (2014)		O	O					
	Mauttone et al. (2017)		O	O					
	Guerreiro et al. (2018)		O	O	O				
	Caggiani et al. (2019)			O				O	
	Natera et al. (2019)			O		O			
	Zhu and Zhu (2019)	O	O	O					
	Akhand et al. (2021)		O		O	O	O		
	De Oliveira et al. (2021)	O	O	O		O		O	
	Castiglione et al. (2022)		O		O	O			
	Liu et al. (2022)		O	O	O	O			
	Paulsen and Rich (2023)			O		O			

Table 2
Nomenclature.

E_{all}	Set of all road segments in the network ($E_{all} = E_{bike} \cup E_{drive}$)
E_{bike}	Set of road segments with bike lanes
E_{drive}	Set of road segments that have traffic lanes, but no bike infrastructure (excluding highways)
$P_{transit}$	Set of subway station points
P_{demand}	Set of points from high-demand neighborhoods
P_{equity}	Set of points from underserved neighborhoods
F	Set of bike network fragments (i.e., a set of continuous edges of bike lanes) from E_{bike}
I	Set of inputs —$P_{transit}, P_{demand}, P_{equity}$, and F — to be connected
l_i	Length of an input i ($i \in I$)
d_{ij}	Distance between inputs i and j
den_{ij}^{pop}	Average population density of neighborhoods that inputs i and j belong to
den_{ij}^{emp}	Average employment density of neighborhoods that inputs i and j belong to
w_k	Weight for criteria k, which is based on a sensitivity analysis result
z_k	z-score value (from E_{all}) of criteria k
n_x	The normalized value of x (ranging from 0 to 1)
$score_e$	Composite score of an edge e ($0 \leq score_e \leq 1$)
l_e	Length of an edge e ($e \in E_{all}$)
l_e^w	Weighted length of an edge e ($e \in E_{all}$)
r_{pq}	Weighted-length-minimizing route — generated by A-star algorithm — between node p and q
$r_{ij}^{optimum}$	Optimum route among a set of weighted-length-minimizing routes between inputs i and j
$\overline{score_e^r}$	Route-level (r) average of $score_e$ ($0 \leq \overline{score_e^r} \leq 1$)
φ_r	1.1 if the route r is closer (< 100 m) to another bike network and 1 otherwise
$V_{bike\ end}$	Set of nodes where one edge from E_{bike} and one or more edges from E_{drive} meet
$V_{bike\ divert}$	Set of nodes where two edges from E_{bike} and one or more edges from E_{drive} meet and the edges from E_{bike} are diverted (>240° or <120°) at the nodes

algorithm assigns a higher weight to links that accommodate bus routes to further ensure that multimodality is achieved.

Table 3
The Network Design Algorithm.

Algorithm 1: Build a complete street network from the given existing bike network
Step 1: Prepare input data
Step 1.1: Create F from E_{bike} Step 1.2: Identify $P_{transit}, P_{demand}$ and P_{equity}
Step 2: Select a pair to connect
Select a pair from the inputs — $F, P_{transit}, P_{demand}$, and P_{equity} — that maximizes the following gravity value:
$Gravity_{ij} = \ l_i * l_j) * (den_{ij}^{pop} + den_{ij}^{emp})/\ d_{ij})^2$ (1)
Step 3: Generate weighted-length-minimizing routes that connect each possible node pair between the chosen input pair and choose one optimum route among them
Step 3.1: Using the A-star algorithm, find routes that minimize the sum of the weighted length (i.e., l_e^w) for every pair of nodes between input i and j:
$score_e = n_{\sum w_k z_k}$ (2)
$l_e^w = l_e * (1 \quad score_e)$ (3)
Step 3.2: Choose one optimum route:
$r_{ij}^{optimum} = \underset{r_{pq}}{\operatorname{argmax}}(\overline{score_e^r} * \varphi_r)$ [a] (4)
Step 3.3: Merge the pair and its connecting route as one network fragment and switch the edges establishing the connecting route from E_{drive} to E_{bike} **Step 4: Iterate Step 2 to 3 until it becomes an entirely connected network**
Step 5: Improve network connectivity by connecting missing links
Step 5.1: Identify $V_{bike\ end}$ and $V_{bike\ divert}$
Step 5.2: Generate every pair of nodes from $V_{bike\ end}$ and $V_{bike\ divert}$ that are within 0.6 miles (1 km)
Step 5.3: Find the shortest route of those pairs on E_{bike} network and identify the ones whose network distance is too circuitous (i.e., Circuity index[b] > 3)
Step 5.4: Calculate a new route on E_{drive} and connect if it is significantly shorter (i.e., Circuity index <1.4)

Notes: a. If the distance between nodes p and q is shorter than 650 feet (200 m), $r_{ij}^{optimum}$ will be the shortest path between inputs i and j. It is to increase the efficiency of new connecting link between the network fragments when they are very close. b. The circuity index indicates the ratio of the network distance to the Euclidean distance between a certain O-D pair.

4. Data and method

4.1. Study area

The study focuses on Atlanta, Georgia, USA, home to around 500,000 residents. As the principal city of Georgia's most populous metropolitan statistical area, Atlanta plays a vital role in the state's overall dynamics. Atlanta boasts a bus and rail transit system managed by the Metropolitan Atlanta Rapid Transit Authority (MARTA), operating over 500 buses across more than 110 lines and a rail network spanning 38 stations on four lines. The city also features about 120 miles of cycling infrastructure, comprising 65% on-street bike lanes and 35% off-street trails.

Despite these transportation amenities, Atlanta is predominantly oriented towards car usage. Data from the 2021 American Community Survey (ACS) 5-year estimates show that car commuting is preferred by 65% of the population, while transit, walking, and cycling account for 6%, 3%, and 0.4% respectively. This heavy reliance on cars underscores the substantial opportunities for enhancing the city's complete street network to promote more sustainable and diverse modes of transportation.

4.2. Network design algorithm

The design of the algorithm for generating a complete street network by connecting existing bike lanes hinges on two key questions: 1) what to connect? and 2) how to connect? The detail of the algorithm is provided in Tables 2 and 3. Note that edge and node indicate road segment (line) and intersection (point) in the network.

4.3. What to connect

As noted earlier, this study is designed to generate a complete bike network from the current patchwork of bike lanes in an iterative manner. Each bike network fragment, which refers to a set of continuous edges of bike lanes, is used as a connecting thread in the algorithm. These bike lanes are identified using the bike facility inventory data provided by the Atlanta Regional Commission.

Besides the bike lanes, this study includes additional types of entities that the complete street network would connect. These are (1) subway stations and (2) target neighborhoods. Target neighborhoods include two types: (2a) underserved neighborhoods — block groups with low income and a high proportion of minority populations that would benefit most from bike lanes — and (2b) high-demand neighborhoods — block groups that are far from the existing bike network but have a high demand for bike travel. Bike travel demand is measured by the combined value of population density, employment density, and POI density in the block group. The underserved neighborhoods are selected based on poverty rates, and percent racial and ethnic minority populations in the block group. In each of the chosen block groups, non-residential street nodes are selected as candidates for an anchor point to extend the network.

The bike network fragments, the subway stations, and the target neighborhoods make a set of 'inputs' of the algorithm. Both the size of inputs and the distance among them are important factors to consider when prioritizing the connectivity sequence (31). To that end, this study employs a gravity model to prioritize the sequence of inputs to connect (as described in Step 2 in Table 3). The inputs are compared in pairs using a revised form of the gravity model which takes account of the input pair's length,[1] population density, employment density, and the distance between them. Through this process, we generate the sequence of inputs to connect so that we ultimately build out a complete network.

4.4. How to connect

Even after we select one pair of inputs, there can be thousands of pairs of nodes within the input pair which can be used as origin and destination points in the connecting process. For example, if an input pair consists of 50 nodes and the other has 60 nodes, the possible number of node pairs is 3000. Our approach is to test and compare all these possible pairs of nodes using an A-star search algorithm. The algorithm is an advanced version of Dijkstra's algorithm which finds the shortest paths between two nodes in a graph by comparing all the possible paths. While Dijkstra's algorithm searches the whole graph and thereby requires a huge amount of computation, the A-star algorithm includes heuristics to guide its search, making it converge on the optimum path more efficiently. The algorithm heuristically finds the best route that minimizes the cost. Depending on how we define the cost function, it can be used for finding not only the shortest path but also the optimum paths based on user-defined parameters in the network. The A-star algorithm was implemented using the programming language R. The recursive nature of the algorithm requires running the A-star algorithm hundreds of thousands of times, which necessitates the use of cluster computing to manage the runtime of the task. This study heavily utilized a high-performance, cluster computing environment.

Table 4
Criteria used in the A-star Algorithm.

Category	Variables	Description	Source
Multi-modality	Bus Frequency	Number of Buses passing through the edge per day	GTFS
	Transit Hub Proximity	Proximity ($<$ 0.5 miles) to the nearest subway station	-
Potential Demand	POI Counts	Number of POIs within 200 feet from the edge	OpenStreetMap
	Population Density	Population density of the block group to which the edge belongs	American Community Survey
	Employment Density	Employment density of the block group to which the edge belongs	
Equity	Poverty	Ratio of the population whose income is below the poverty level in the block group to which the edge belongs	
	Racial & Ethnic Minority	Ratio of racial & ethnic minority[a] population in the block group to which the edge belongs	
Bikeability	Traffic Volume	Annual Average Daily Traffic (AADT)[b]	Georgia DOT
	Slope	Slope of the edge (%)	Google Elevation API

Notes: a. according to 'Environmental justice policy guidance for federal transit administration recipients' (Federal Transit Administration, 2012), 'Minority persons' include (1) American Indian and Alaska Native, (2) Asian, (3) African American, and (4) Hispanic. b. AADT data counts the traffic volume of all lanes in both directions. Some local roads are omitted in the data. In that case, this study assumes that those local roads have the average AADT of other local roads, which is 450.

Table 4 shows the categories and variables used in finding optimum paths in our complete streets network. Two variables represent multi-modality: bus frequency and proximity to the subway station. Three variables are about potential demand: population and employment density of a block group and the number of POIs near the road segment. As an equity-related variable, we use poverty, racial minority, and ethnic minority in the block groups near the road segments. Two variables — traffic volume and slope — represent bikeability. Note that potential demand and equity may seem duplicated since this study considers those aspects when selecting neighborhoods to connect bike lanes in Section 4.1. However, the geographic scale is different in the two operations. We use the macro neighborhood scale for selecting What to Connect, and the micro road segment scale for determining How to Connect.

The values of the four variables are aggregated into a composite score (i.e., $score_e = N_{\sum w_k z_k}$) in the algorithm so that it can proxy as a composite cost function (i.e., weighted length; $l_e^w = l_e * (1 - score_e)$) in the path-finding algorithm. When aggregating the values, each category is weighted in a way that corresponds to its importance in enhancing the performance of the resultant network. The weights were identified by a

[1] When it comes to point inputs, we assigned 650 feet (200 m) of length so that we can handle them in the algorithm as if those are network fragments.

sensitivity analysis.[2]

Based on the composite score and length of each road segment, the A-star algorithm finds the weighted-length-minimizing routes connecting all the possible node pairs (Step 3.1 in Table 3). The suggested routes are then compared by their average score value. The route with the maximum average score will be chosen as the optimum route.[3] If the optimum route is closer to another existing input network fragment, the route is assigned extra points in the form of a 10% addition to the average score, which is intended to enhance the overall efficiency of the network connection process.

The network connecting process—Steps 2 and 3—are iterated until the existing network fragments are fully connected. Although it becomes one connected bike network after the process, there may still be many opportunities to make the bike network less circuitous. We look for such links that improve network connectivity and add them to the network. Candidate nodes for these links are usually located where the bike network ends or turns. From the chosen candidate nodes, all pairs that meet the following three conditions are potential links that improve connectivity: (1) not far from each other (less than 0.6 miles), (2) the route using the bike network is too circuitous (Circuity index is bigger than 3), and (3) the route on the traffic network is significantly shorter (Circuity index is smaller than 1.4). The chosen missing link pairs are connected using the same algorithm in step 3. Fig. 1 shows the identified links that meet the criteria above and their new connections.

4.5. Evaluation

To evaluate whether the resultant network performs as we designed, this study simulates two thousand virtual bike trips. The simulation-based evaluation again employs the A-star routing algorithm, but in this case, the goal of optimization is to minimize the stress or disutility of the trip from a bike user's perspective, which is referred to as cycling stress in this study. We hypothesize that the cycling stress during a bike trip is induced by (1) cycling distance, (2) traffic conditions, (3) slope, and (4) bike lane accommodation. To combine these stress factors into a single index, it is important to numerically identify the trade-off between them. This study borrowed insights from previous literature (Broach et al., 2012; Hood et al., 2011; Lowry et al., 2016) which quantified the factors affecting cycling stress based on the marginal rate of substitution (MRS). MRS is defined as the amount of one good (e.g., cycling distance) that provides the same amount of (dis)satisfaction as another good (e.g., traffic condition) – in the context of this study, MRS can indicate the distance by which bike travelers are willing to substitute the stress from the given traffic conditions. For example, a route with 130% cycling stress in terms of MRS indicates that an average bike traveler is willing to take a detour that is 30% longer but has lower traffic stress (such as trails).

The MRS values for each factor are as follows. Firstly, the number of lanes and speed limit are stress-inducing factors. Table 5 below details how these two factors affect cycling stress in terms of MRS, as reported by Lowry et al. (2016). Additionally, the steepness of the route, or slope, is another factor that increases stress. Broach et al. (2012) determined that the stress resulting from the slope is measured at 37% in MRS for slopes between 2–4%, 120% for slopes of 4–6%, and 320% for slopes greater than 6%. Conversely, bike lanes contribute to a decrease in cycling stress: striped bike lanes lower stress by 50%, buffered lanes by 65%, and protected lanes by 75% (Lowry et al., 2016). In the evaluation process, this study assumes that all the proposed networks will accommodate protected bike lanes.

The simulation is conducted using two types of trip samples: (1) between-TAZ trip sample (n = 1000) and (2) station-access trip sample (n = 1000). The station-access trip sample represents first/last mile trips and is employed to evaluate the impact of the network on improving multi-modality. The average Euclidean distance of the between-TAZ trip sample is 2.6 miles, and that of the station-access trip sample is 0.6 miles. The sampling method is detailed in Appendix A.

This study evaluates the proposed network improvement using three criteria: (1) the proportion of bike lanes in the route, (2) the proportion of either bike lanes or residential streets in the route, and (3) the average cycling stress. The first criterion is to see how well bike routes are covered by bike lanes (in length). Similarly, the second criterion checks how much proportion of bike routes are covered by either bike lanes or residential streets because residential streets are normally safe to bike and thus not a target of bike lane investment.

It is important to note that the two criteria used in the evaluation phase are different from the criteria used in the design phase. The separation of criteria between the two phases was a strategic decision rooted in the desire to provide a holistic assessment of the network. While the design phase focused on theoretical and strategic aspects to build an optimal network, the evaluation phase aimed to test its practicality and user-centric performance. This dual approach allowed us to ensure that the network is not only well-designed on paper but also functional and beneficial in real-world scenarios. By employing different sets of criteria in the design and evaluation phases, we aim to capture a comprehensive view of the network's effectiveness.

The simulation result is then compared to future bike network plans made by multiple local entities,[4] assuming that those networks will also be protected bike lanes. The comparative data shows how well the locally optimized network proposed in this study performs compared to the existing plans which are globally optimized. Furthermore, this study simulates the sample bike trips on the network that combines both the algorithm-generated network and the planned network to demonstrate the efficacy of the algorithm in improving the performance of municipality-led plans.

5. Results

5.1. Network design result

Fig. 2 shows the initial inputs for the network design. It shows the current bike infrastructure (i.e., dedicated lanes) as well as the locations of transit stations and target neighborhoods as noted in Section 4.3. Among the target neighborhoods, the underserved neighborhoods are mostly in the Southwestern part of the city, while the high-demand neighborhoods are in the East close to Midtown.

Fig. 3 shows the network generated by the algorithm: it created a fully connected network based on the given inputs: the existing bike lane fragments, subway stations, and target neighborhoods (i.e., underserved neighborhoods and high-demand neighborhoods). Compared to the network planned by local entities in Fig. 4, the algorithm-generated network looks less dense and more winding, which does not seem very ideal. However, note that the point of the algorithm is not to come up with a completely developed network that serves every corner of the city; it is rather to build a skeletal network

[2] To decide the set of weights, this study simulated tens of networks based on different combinations of weights between four categories: multi-modality, potential demand, equity, and bikeability. The simulated networks were then compared in terms of per-mile effects of the network improvement. A set of weight that provides the highest per-mile effects was chosen, which is '3–1-3–3′ in the order of multi-modality, potential demand, equity, and bikeability.

[3] If an input pair is too close to each other (i.e., the distance between the closest node pair is less than 650 feet or 200 m), the shortest route between the input pair is chosen as the optimum route to avoid generating a circuitous network.

[4] According to Annual Bicycle Report by City of Atlanta (City of Atlanta Department of City Planning, 2018), the planned network includes all bike lane projects listed in Cycle Atlanta 1.0, Cycle Atlanta 2.0, Renew Atlanta (TSPLOST), and Atlanta Transportation Plan.

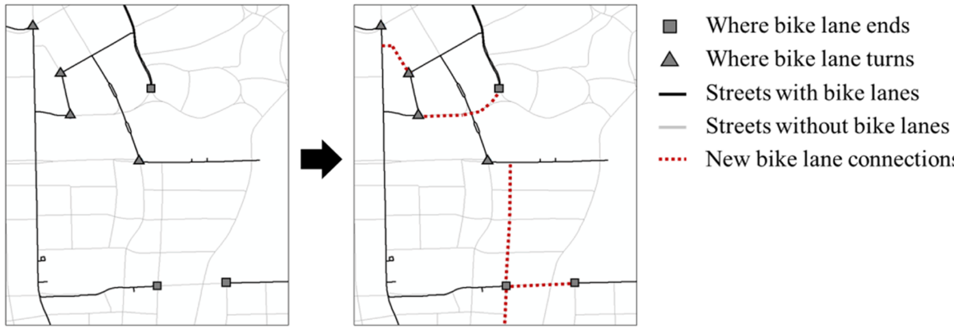

Fig. 1. Illustration of Identifying Missing Links and Making New Connections.

Table 5
Cycling stress in terms of the marginal rate of substitution (Lowry et al., 2016).

Number of Lanes	2	2	2-3	4-5	2-3	6 +	4-5	6 +	2-3	4-5	6 +
Speed Limit	25	30	25	25	30	25	30	30	35 +	35 +	35 +
Cycling Stress (in MRS)	10%	15%	20%	35%	40%	67%	70%	80%	100%	120%	140%

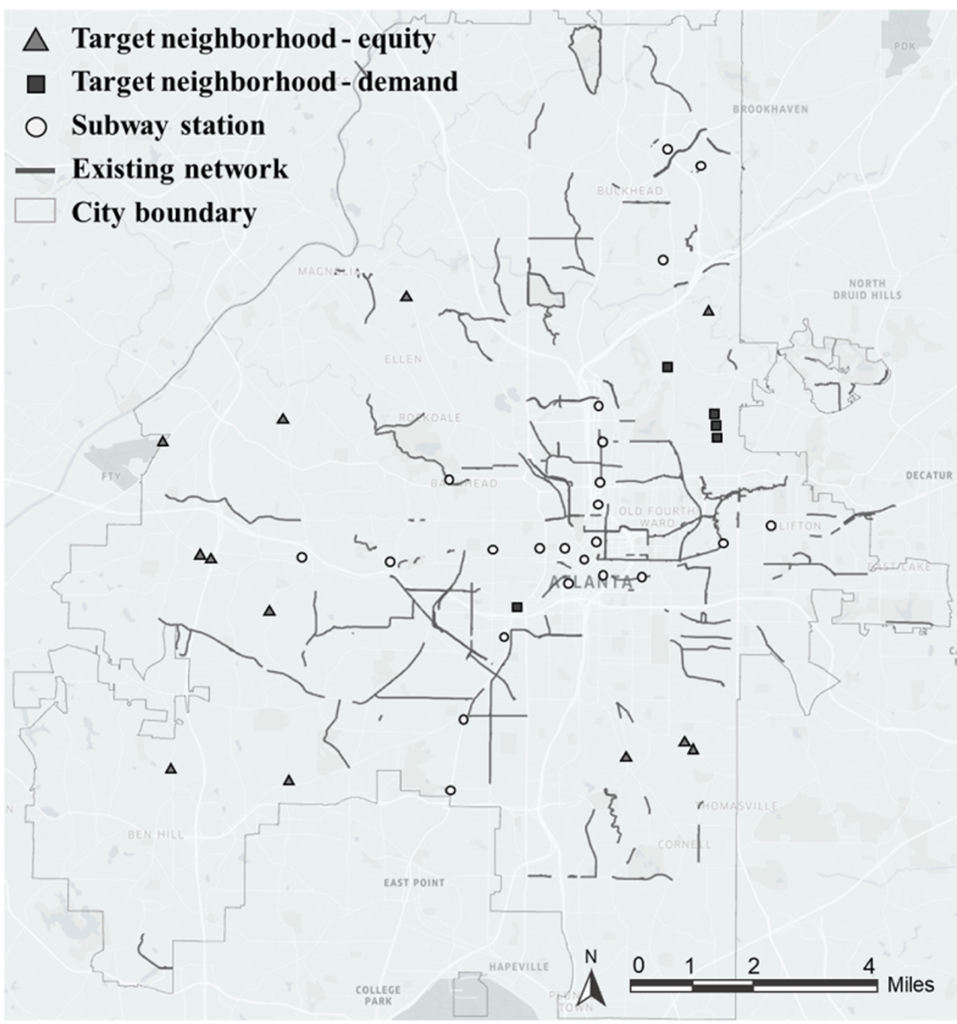

Fig. 2. Algorithm Inputs.

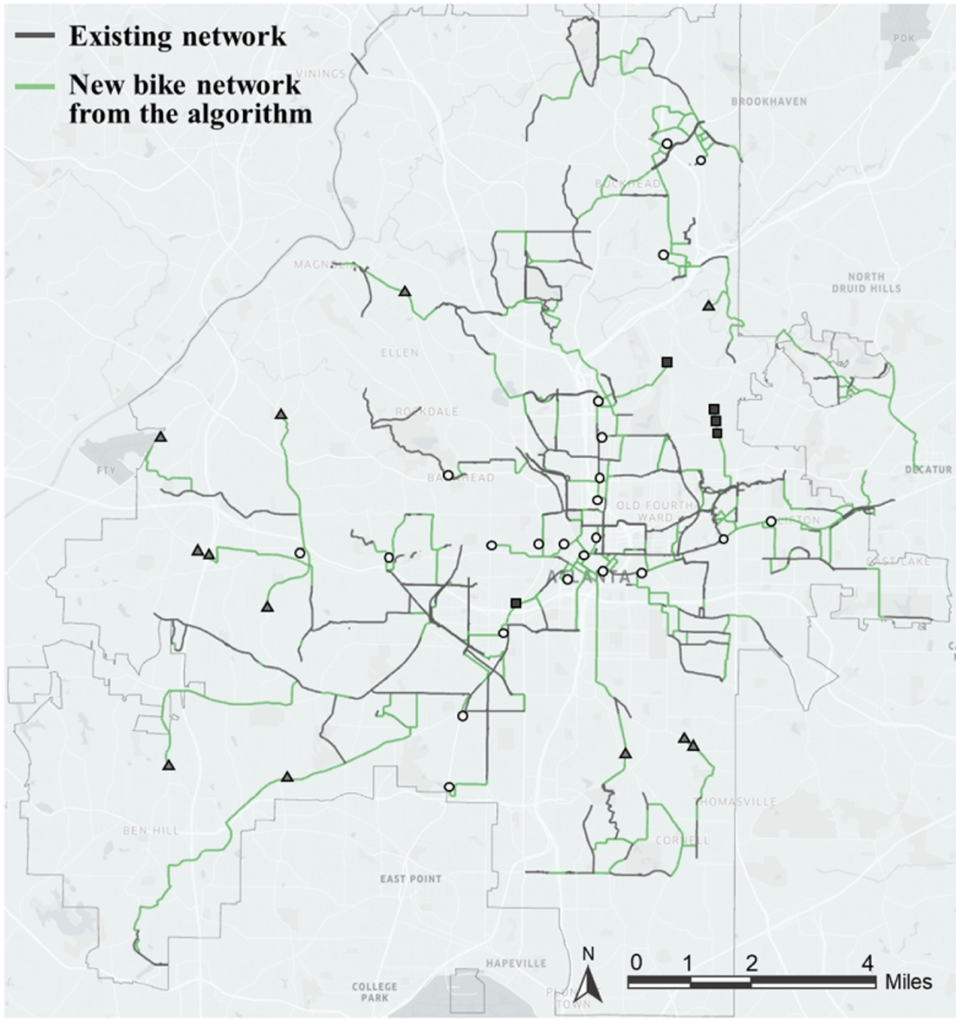

Fig. 3. Algorithm-generated Network.

that focuses on connecting crucial missing links from the existing context, which serves as a skeletal network to build out further based on future plans. On this point, combining the algorithm-generated network with the planned network would let us get a glimpse of the network that the authors are envisioning. Fig. 5 shows the algorithm-generated network overlaid on top of the planned network. The figure illustrates that about 30% of segments (i.e., red-colored streets) in the algorithm-generated network are overlapped with segments in the planned network. The rest 70% (i.e., green-colored streets) are unique segments of the algorithm-generated network, and they are mostly in the periphery of the city.

5.2. Evaluation result

Table 6 shows the simulation-based evaluation result of (1) the existing bike network, (2) the network planned by multiple local entities, (3) the network generated by the algorithm, and (4) the combined network between the planned network and the network generated by the algorithm.

On the existing network, only 23.6% of the routes of the between-TAZ trips and 21.4% of the routes of the station-access trips are covered by bike lanes on average. If we count not only bike lanes but also residential streets in the routes, the proportion goes up to 58.2% in the between-TAZ trips and 50.1% in the station-access trips; the 50.1% means, when a person rides a bike to the nearest subway station, about a half of the total length of the route is expected to be covered by either bike lane or residential street. The average cycling stress is, on average, 151.6% in the between-TAZ trips and 153.5% in the station-access trips.

On the planned network, which is twice as long as the current network, the evaluation results are expectedly much better. The proportion of bike lanes is 53.4% in the between-TAZ trips and 55.0% in the station-access trips. The proportion of either bike lanes or residential streets is much higher: 76.5% and 79.3% respectively. Accordingly, the average cycling stress considerably decreases compared to the current network.

The algorithm-proposed network shows similar performance as the planned network even though its total length is much shorter (259.2 miles) than that of the planned network (310.6 miles). The average proportion of bike lanes is 45.0% in the between-TAZ trips and 57.3% in the station-access trips, which displays that the algorithm does its job in improving the quality of first/last mile bike trips to transit stations. The proportion of either bike lanes or residential streets is 73.0% in the between-TAZ trips and 77.7% in the station-access trips; both are a few percentage points lower than the values of the planned network. The average cycling stress in the between-TAZ trips is about 5% lower (in terms of the MRS) than the existing network and about 10% lower in the station-access trips.

Finally, the performance of the network that merges the two is

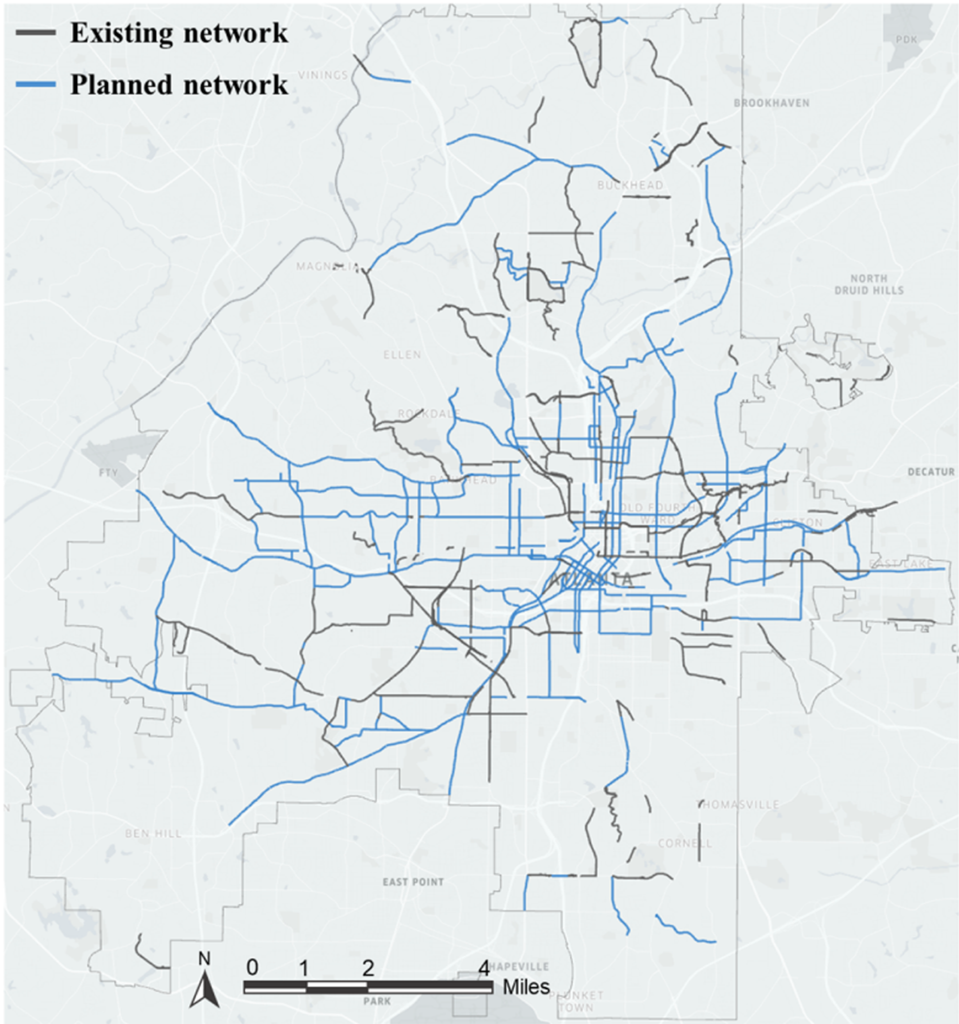

Fig. 4. Planned Network.

remarkable. The proportion of bike lanes in the between-TAZ trips is 62.7% which is a 9.3% increase from the result of the planned network. The proportion of bike lanes in the station-access trips is 71.4% which is a 16.4% increase. Again, it shows that the algorithm is particularly effective in enhancing the accessibility to the transit network. The proportion of either bike lanes or residential streets is 86% in the between-TAZ trips and 90% in the station-access trips, which indicates that only less than 10% of the routes will be non-residential streets that do not have bike lanes. The average cycling stress in the between-TAZ trips is 7.4% lower than the existing network and 13.3% lower in the station-access trips. These results suggest that the algorithm can refine the performance of the planned network and assure a safer cycling environment.

5.3. Limitations

This study has a few limitations. Firstly, this study does not include a detailed cost-benefit analysis, which is crucial for understanding the financial feasibility of implementing the proposed bike network. Future research could explore the economic implications, weighing construction and maintenance costs against potential benefits like reduced congestion and environmental improvements. Secondly, the methodology assumes a static demand for bike lanes, not accounting for demand fluctuations due to factors like seasonal changes or urban development. This could affect the network's long-term effectiveness and utilization, indicating a need for an adaptive approach in future designs. Lastly, this study does not extensively address the practical challenges of implementing the proposed bike network, such as navigating existing urban infrastructure, property rights issues, and potential resistance from various stakeholders. The actual process of transforming the existing urban fabric to accommodate a new bike network can be complex and may encounter unforeseen obstacles.

6. Conclusion

Implementing complete streets should be viewed and evaluated from the network standpoint. As an approach to propose the complete streets network, this study focused on the dedicated bike lane networks since the connectivity and accessibility of bike infrastructure are crucial not only for bike users but also for pedestrians and transit users.

This study developed an algorithm that combines the fragmented bike networks and expands the network to the subway stations as well as

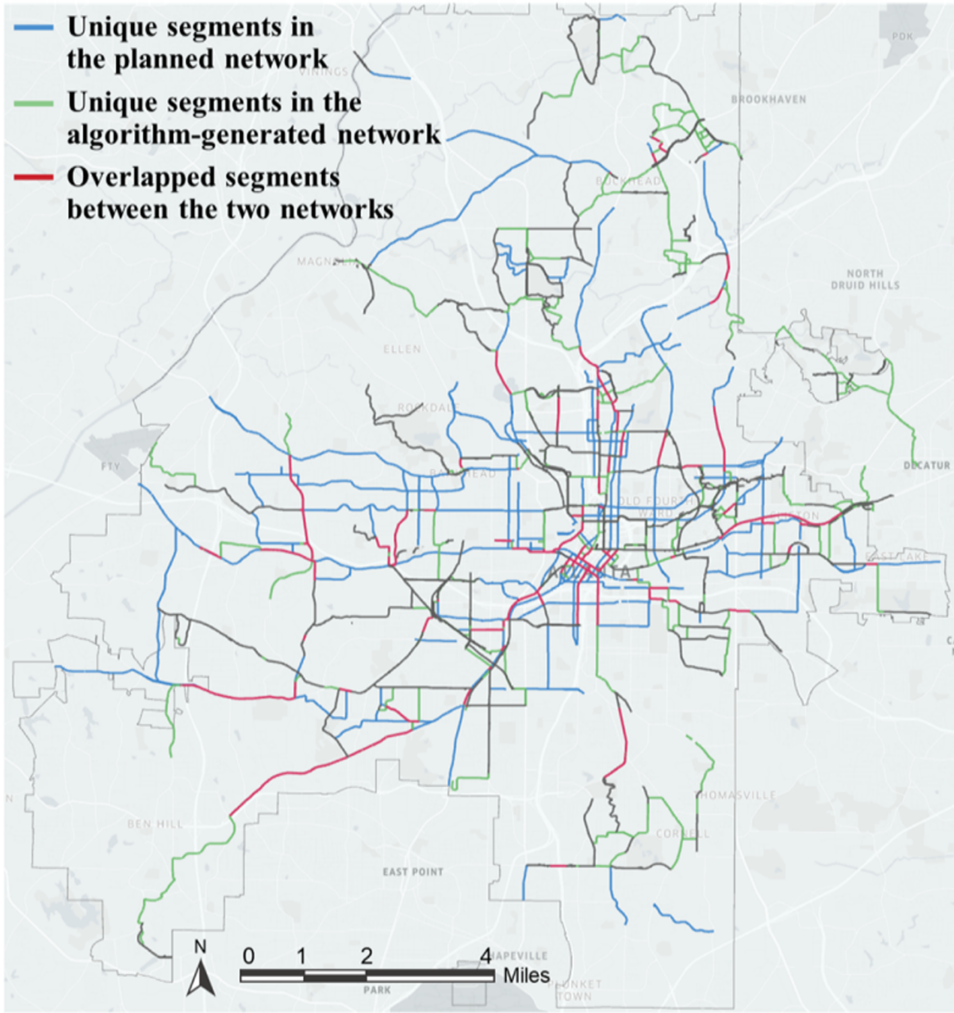

Fig. 5. Planned + Algorithm-generated Network.

Table 6
Simulation-based Evaluation Results.

Category		Existing Network	Planned Network	Algorithm-generated network	Algorithm-generated + planned network
Between-TAZ trip sample	Proportion of bike lanes	23.6%	53.4%	45.0%	62.7%
	Proportion of either bike lanes or residential streets	58.2%	76.5%	73.0%	86.0%
	Average cycling stress	151.6%	145.6%	147.0%	144.2%
Station-access trip sample	Proportion of bike lanes	21.4%	55.0%	57.3%	71.4%
	Proportion of either bike lanes or residential streets	50.1%	79.3%	77.7%	90.0%
	Average cycling stress	153.5%	145.0%	144.0%	140.2%
Length of the network (unit: mile)		155.8	310.6	259.2	378.8

neighborhoods that are underserved and/or in high demand. The algorithm picks up a pair of network fragments and iteratively connects them until it forms one integrated network. We employed the gravity model to choose the pair which is then connected based on the A-star path-finding algorithm. The algorithm accounted for multi-modality, potential demand, equity, and bikeability to find the optimum route for complete street networks. The algorithm generated an integrated network that looks significantly different from the network planned by the local entities: the algorithm-proposed network is much shorter and more evenly distributed throughout the city. This is a reasonable outcome since the algorithm-generated network is designed to work as an artery network that connects existing networks and important destinations and can be further developed into a fuller network.

To evaluate the resultant network, we ran two thousand trip simulations from the perspective of bike users seeking to minimize cycling stress. The simulations were conducted on four types of networks: (1) existing network, (2) planned network, (3) algorithm-generated network, and (4) algorithm-generated + planned network. The algorithm-generated network, despite a shorter network length, performed as well as the planned network. On the algorithm-generated network, compared to the existing network, the proportion of bike lanes in the routes was increased by 21.4% (from 23.6% to 45.0%) in the between-TAZ trips and 36% (from 21.4% to 57.3%) in the station-access trips. The simulation on the algorithm-generated network gave a particularly better result in the station-access trips, which suggests that the algorithm guarantees a network with a better multi-modality between active mobility and public transportation. This result is likely because not only the subway stations are included as inputs to connect but also because the algorithm considers multi-modality as one of the criteria for network design. The evaluation proved that the algorithm generates a skeletal network that guarantees performance for the criteria emphasized in the design process to generate complete street networks.

The algorithm-generated + planned network, compared to the planned network, showed clear improvements. The proportion of bike lanes in the routes was increased by 9.7% in the between-TAZ trips and 16.4% in the station-access trips. The proportion of either bike lanes or residential streets was 86% and 90% respectively, which means most street segments of the routes would be safe and comfortable to bike. The evaluation results demonstrate that the algorithm-generated network works as it is designed to – it not only performs well as a stand-alone network but also makes the bike network plan made by local entities more complete.

This study provides an algorithmic framework for network design that has three distinctive aspects: local optima, equity, and multi-modality. First, the algorithm addresses local-scale connections and improves the overall accessibility of the existing network which is often fragmented. Based on the evaluation, we demonstrated that the locally optimal network has the potential of benefitting the municipality-led network plans. Second, this study incorporated equity and multi-modality as core values in designing the network. The algorithm is designed to cater to a more inclusive range of neighborhoods and populations including underserved ones and public transit hubs, which is often unheeded in previous studies.

Our approach to designing a bike network can go a long way in achieving the goal of developing a complete street network that accommodates all modes and users. Bike lanes benefit more than just bike users, it benefits micro-mobility users and pedestrians by physically separating pedestrian infrastructure and bike lanes. In addition, our design deliberately connects with public transit hubs and routes to offer first/ last mile connectivity. Thus, designing a bike lane network that ensures comfortable access to destinations, and to public transit, offers an effective approach to attain a complete street network.

The algorithm in this study has the flexibility of being adapted to other criteria and objectives – local governments can customize the model by adding other aspects that are not considered in this study such as safety, aesthetics of streetscape, or inputs guided by public outreach. While this study focused on the Atlanta metropolitan region, we believe this approach can offer a pathway for generating optimal bike networks and complete street networks in other places as well.

This study contributes to the literature by introducing a practical, user-friendly algorithm for local optimization of bike network development. Unlike more complex models, the algorithm in this study simplifies the expansion of bike infrastructure, focusing on local government needs and constraints. It efficiently prioritizes network segments based on criteria like multimodality, equity, and bikeability, bridging the gap between theoretical models and real-world application. This approach is particularly valuable for its practicality in integrating bike lanes within existing urban landscapes, ensuring equitable access and enhancing urban mobility. In essence, this research provides an accessible, effective tool for urban planners and municipalities to improve sustainable transportation infrastructure.

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CRediT authorship contribution statement

Van Hentenryck Pascal: Project administration, Investigation, Funding acquisition, Conceptualization. **Hwang Uijeong:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kim Ilsu:** Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Guhathakurta Subhrajit:** Writing – review & editing, Writing – original draft, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Pascal Van Hentenryck reports financial support was provided by National Science Foundation.

Data availability

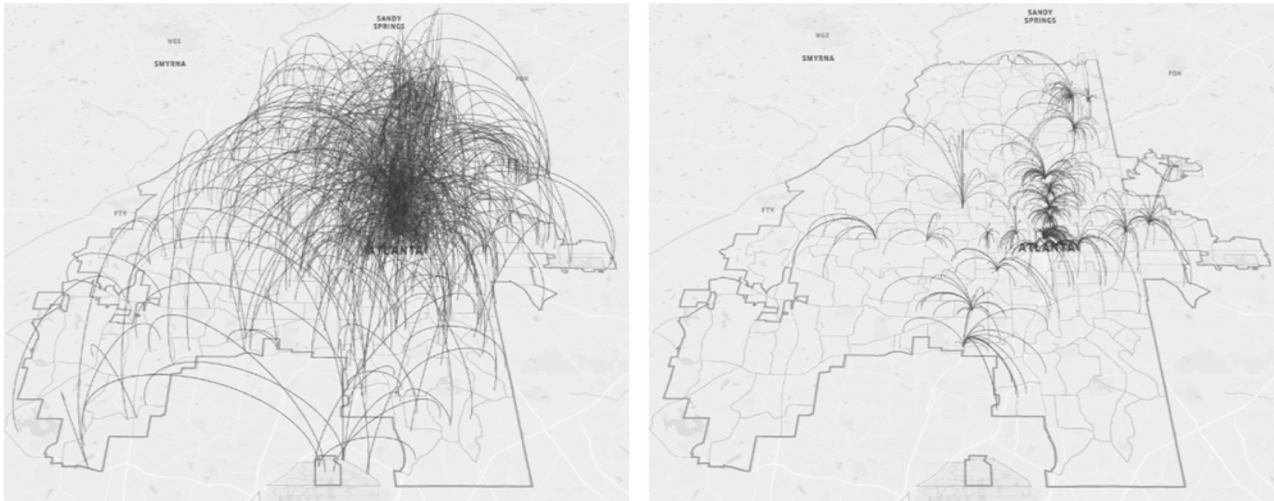
Data will be made available on request.

Appendix A

The evaluation is based on two types of samples shown in Figure A1: (1) between-TAZ trip sample and (2) station-access trip sample. First, the between-TAZ trip sample is to evaluate the cycling environment between TAZs within six miles which is considered a strong threshold of the bicycle mode choice (Bearn et al., 2018; Winters et al., 2011). The between-TAZ trips were chosen based on travel demand: out of 17,664 possible TAZ pairs within 6 miles in the city of Atlanta, 1000 pairs are sampled using a weighted random sampling method considering their travel demand. The travel demand between two TAZs is defined by their population and employment size, and distance. In Eq. (5), i and j indicate TAZs.

$$Travel \quad emand_{ij} = (Pop_i + Emp_i) * \quad Pop_j + Emp_j\big) \big/ \quad istance_{ij} \tag{5}$$

Second, the station-access trip sample is generated by connecting TAZs to their nearest subway station. To be consistent with past studies (Bearn et al., 2018; Martens, 2004), we defined the catchment area of public transit as three miles. 1000 pairs between TAZs and stations that are less than three miles are sampled using a similar method as above: in this case, we use the frequency of transit service of the station instead of population and employment.



(a) Between-TAZ Trip Sample (b) Station-access Trip Sample

Fig. A1. Two Types of Samples for the Simulation-based Evaluation.

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