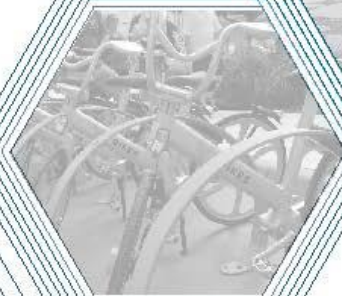

Expanding Mobility Options for All: Optimizing and extending the biking infrastructure to generate complete street networks in Atlanta

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FINAL REPORT

Center for Transportation Equity, Decisions & Dollars

EXPANDING MOBILITY OPTIONS FOR ALL: OPTIMIZING AND EXTENDING THE BIKING INFRASTRUCTURE TO GENERATE COMPLETE STREET NETWORKS IN ATLANTA

FINAL PROJECT REPORT

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16. Abstract
This study investigates the design of complete networks of complete streets by focusing on the bike network as a connective thread. It emphasizes the accessibility of all destinations by various modes of travel and recognizes that not all streets need to be "complete" to provide safe and convenient access to most destinations for all persons, regardless of age and ability.
The objective of this study is to develop, implement, and evaluate an algorithm that would iteratively combine existing fragmented bike lanes, current and future transit hubs, and unmet demand for biking infrastructure into one integrated network which ultimately improves active mobility and public transit ridership. The factors considered to connect the network fragments, and other significant locations mentioned above include transit access, activity location density, proximity to residential and commercial land uses, biking stress, street right-of-way and design, and terrain. The algorithm is implemented for the road network of the City of Atlanta, GA and the resultant network is evaluated in terms of (1) biking stress (based on bike trip route simulations) and (2) traffic flow and biking safety (based on VISSIM traffic simulation model and Surrogate Safety Assessment Model).
The study found that the algorithm-generated network, despite a shorter network length, performed as well as the planned network in reducing biking stress. The simulation on the algorithm-generated network gave a particularly better result for the trips that are accessing transit hubs, which suggests that the algorithm guarantees a network with better multi-modality between active transportation and public transportation. A microscopic simulation model of downtown Atlanta was developed to evaluate the operational and safety effects of this complete network. The network conditions are validated for the afternoon peak hour using travel time on existing key corridors. The network was then modified to create two network designs in addition to the existing network. The first of these designs is called the "Proposed Network," which is based on the algorithm-generated network developed in this research, while the "Alternative Network" is based on the current plan by the city for its bike network. It is worth noting that the proposed and alternative networks have a significant overlap. All three network designs are evaluated on existing demand and 5% and 15% modal shift from automobile mode to bicycle mode. The trajectory data from the simulation model runs were analyzed using the Surrogate Safety Assessment Model (SSAM). The results from trajectory analysis showed that while automobile travel time between key Origin-Destination pairs did not increase, complete networks led to fewer automobile-bicycle conflicts and fewer conflicts between automobiles and bicyclists. The results also showed that if there was a large modal shift from cars to bicycles, and the network remained as it exists today, the automobile-bicyclist conflicts would increase appreciably. Therefore, the infrastructure for bicyclists must be improved since an increase in bike mode share without changes to the network that reduce biking stress would have adverse safety implications.

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Abstract

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The objective of this study is to develop, implement, and evaluate an algorithm that would iteratively combine existing fragmented bike lanes, current and future transit hubs, and unmet demand for biking infrastructure into one integrated network which ultimately improves active mobility and public transit ridership. The factors considered to connect the network fragments, and other significant locations mentioned above include transit access, activity location density, proximity to residential and commercial land uses, biking stress, street right-of-way and design, and terrain.

The algorithm is implemented for the road network of the City of Atlanta, GA, and the resultant network is evaluated by comparing changes in (1) biking stress (based on bike trip route simulations) and (2) traffic flow and biking safety (based on VISSIM traffic simulation model and Surrogate Safety Assessment Model).

The study found that the algorithm-generated network, despite a shorter network length, performed as well as the planned network in reducing biking stress. The simulation on the algorithm-generated network gave a particularly better result for the trips that are accessing transit hubs, which suggests that the algorithm guarantees a network with better multi-modality between active transportation and public transportation.

A microscopic simulation model of downtown Atlanta was developed to evaluate the operational and safety effects of this complete network. The network conditions are validated for the afternoon peak hour using travel time on existing key corridors. The network was then modified to create two network designs in addition to the existing network. The first of these designs is called the "Proposed Network," which is based on the algorithm-generated network developed in this research, while the "Alternative Network" is based on the current plan by the city for its bike network. It is worth noting that the proposed and alternative networks have a significant overlap. All three network designs are evaluated on existing demand and 5% and 15% modal shift from automobile mode to bicycle mode. The trajectory data from the simulation model runs were analyzed using the Surrogate Safety Assessment Model (SSAM). The results from trajectory analysis showed that while automobile travel time between key Origin-Destination pairs did not increase, complete networks led to fewer automobile-bicycle conflicts and fewer conflicts between automobiles and bicyclists. The results also showed that if there was a large modal shift from cars to bicycles, and the network remained as it exists today, the automobile-bicyclist conflicts would increase appreciably. Therefore, the infrastructure for bicyclists must be improved since an increase in bike mode share without changes to the network that reduce biking stress would have adverse safety implications.

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. The "complete streets" policy changes that paradigm by deemphasizing the dominance of the automobile and encouraging multi-modality in transportation. This policy is aimed at transforming street right-of-ways to accommodate multiple modes of travel, including especially the active modes, such as walking and biking. 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 there has been substantial interest in adopting this policy, the progress in meeting all the "complete street" objectives has been limited. In particular, complete street implementation has been focused on street right-of-way design projects and less conscious of the role that a particular street plays in a network of travel modes. As a result, travelers find limited options for accessing destinations outside the limited coverage of complete streets.

This research investigates an important component of the design of complete street networks, which is the inclusion of bike lanes especially in areas that improve transit accessibility. It shifts the focus to the accessibility of all destinations by various modes of travel and recognizes that not all streets need to be "complete" to guarantee safe and convenient trips for everyone regardless of their age and ability. The objective is to find the optimal strategy for connecting isolated complete street segments, potentially with bike lanes, to form complete networks that improve both active mobility and public transit ridership.

In particular, this study focuses on the bike network in the City of Atlanta since: 1) biking 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 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 (*1-6*). Indeed, empirical studies have identified that better bike infrastructure has influenced people's travel behavior and increased the number of bike users (*7-12*). Moreover, a more ubiquitous bike network can provide efficient first-mile and last-mile connectivity, which facilitates transit use.

The objective of this study is to develop, implement, and evaluate an algorithm that would iteratively connect existing bike lanes to create a complete bike network. This network is designed to also connect nearby MARTA subway stations and to reach lower-income households with poor transit access and limited ability to afford private vehicles. The algorithm for creating the complete network prioritizes links that: 1) prioritizes multi-modal trips, 2) connects areas with a high density of points-of-interest (POIs), 3) provides access to areas with high residential and commercial density, 4) serves marginalized neighborhoods, and 5) prioritizes network segments with low traffic volumes (i.e., low biking stress), and 6) gradual slopes.

This study implements the algorithm for the street network of the City of Atlanta and evaluates the performance of the resultant network(s) in terms of 1) biking stress and 2) traffic flow and biking safety. The evaluation of the biking stress is based on two thousand virtual bike trip routes. By comparing with the performance of the bike infrastructure network planned by the local government, this study demonstrates how our algorithm-generated network can help improve the bikeability in the City of Atlanta. In addition, focusing on the Downtown area, this study evaluates how the changes in road infrastructure will affect traffic operations and safety using a microscopic traffic simulation model and a surrogate safety assessment model. Based on these multi-criteria evaluations, this study discusses the overall effectiveness of the bike lane implementation using our network design algorithm.

2. Background

2.1. Complete Streets

Complete streets enable all street users to make safe and convenient trips and encourage active mobility and public transit use. They are expected to provide a wide range of direct and indirect benefits: such as more vibrant and livable communities, lower energy consumption and GHG emissions, and enhanced public fitness and health (*13-17*). In terms of their 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 (*18*). Complete street measures have also improved safety as they help reduce both pedestrian risk and traffic crash risk (*19-20*). Moreover, a walk- and bike-friendly environment fostered by complete streets encourage more physical activities, which ultimately improves public health (*21-23*). Figure 1 shows a rendering of an example complete street project proposed in Atlanta Midtown.

Figure 1. An Example of Complete Street Project (Midtown Alliance, 2022)

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 (*24*). 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 (*25*). 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 (*15*). 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 (*13*). In addition, connections to transit hubs are crucial for expanding bicycling and walking access to multimodal trips for first- and last-mile connectivity (*17*). While no study has focused on the network design of complete streets, there have been numerous studies on the network design of bike lanes. Bicycle Level of Service and connectivity are the most frequently used measures for evaluating and prioritizing bike networks (*26*-*38*). For those studies that focus on bike network optimization, Bicycle Level of Service and budget 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.

2.2. Large-Scale Microscopic Traffic Simulation Model

With the development of new traffic simulation models such as AIMSUN, PARAMICS, and VISSIM, it is now more convenient to simulate increasingly larger networks with complex scenarios that involve intelligent transportation system (ITS) elements, incident scenarios, and highway construction, to name a few. But as the simulation of large networks is like those of smaller ones on the abstract level, it poses some practical (and sometimes theoretical) difficulties concerning the development and calibration of models (*39*). Some difficulties include the high level of uncertainty in modeled systems due to the necessity of a large amount of input data either not being available or observable, making the process of calibration and validation a bit challenging. Bartin et al. (2018) presented the process of building a large-scale traffic simulation model on PARAMICS with the use of multi-source data for its calibration and validation process via the real-world case study (*40*). The case study was done on the reconstruction of one of the bridges located in Newark Bay Hudson County Extension (NBHCE) of New Jersey Turnpike (NJTPK), a tolled highway. The base model of the study area consists of 3,784 links, 2,393 nodes, 133 zones, and 106 traffic signals. Building the model took many years to complete due to the complexity of the network and had been modified multiple times for specific analysis to include various potential alternative routes. The calibration and validation process were performed through an iterative process where each component of calibration is performed, it impacts another component that is already calibrated. By doing this process, higher accuracy would be expected when comparing the simulation model outputs with the observed values. Overall, the paper stated that there are inherent difficulties in building, validating, and calibrating large-scale microscopic traffic simulation models such as constructing the network in the correct scale, inputting the details of link geometry and capacity, adding various traffic control signs and devices, and the details of their turning movement priorities, selecting the number and the location of demand zones and their connections to the traffic network, estimating and converting an origin-destination (O-D) demand matrix, acquiring the necessary data for validation and calibration process and the amount of computational time (*40*).

Another study presented the development and calibration of a microscopic traffic simulation model using MITSIMLab (*39*). The model was done on the entire Des Moines Area and is intended to complement the existing regional planning model, which consists of approximately 200 square miles of various types of roads, including the area freeway, principal arterials, and other major roads. In total, the Des Moines model consists of 1,479 nodes, 3,756 links, 5,479 segments, 10,657 lanes, 1,979 sensors, and traffic signals at about 250 intersections. With this, 400 traffic analysis zones (TAZs) were identified and translated to approximately 150,000 O-D pairs. Parameters and inputs such as parameters of the driving behavior model, route choice model, O-D flow, and habitual travel times were calibrated in this model. Ideally, all parameters would be calibrated together, but due to the large scale of the model, driving behavior was calibrated separately from the others. The calibration process for the remaining parameters was done using an iterative process (*39*). Overall, the article stated that the calibration method and validation results were promising but see the need for further research to improve computational performance.

2.3. Surrogate Safety Assessment Model (SSAM)

The SSAM is a software application developed to automatically identify, classify, and evaluate traffic conflicts in the vehicle trajectory data output from microscopic traffic simulation models (*41*). A conflict is defined as an observable situation in which two or more road users approach each other in time and space in a manner that that creates a risk of collision if their movement remains unchanged (*42*). The safety performance can be examined through analysis of surrogate measures of safety, such as conflicts identified using post-encroachment (PET) or time-to-collision (TTC) (*43*). Surrogate safety parameters can be extracted using the vehicle, bicycle, and/or pedestrian trajectories obtained from microsimulation software using SSAM (*43*). However, in VISSIM, trajectory files are generated for the whole network per selected simulation; there is no option in SSAM to sort conflicts by vehicle type, and post-processing based on the length of the vehicle is required to estimate bicycle-involved conflicts. Overall, SSAM is a promising approach to assessing the safety of new facilities, innovative designs, or traffic regulation schemes (*44*). While the potential 16 conflicts could be reasonably predicted using SSAM (*45*), the accuracy of the safety assessment depends on the microscopic traffic simulation model used to generate vehicle trajectory data (*46*).

3. Network Design

3.1. Design Principles

The design of the bike network to enable complete street development is based on three 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 (*31*,*35*,*38*). 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 considers factors related to transit access, the density of activities and people, biking stress, 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.

Third, this 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 (*47*).

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

Table 1. 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_{pop}^{ij}	Average population density of neighborhoods that inputs i and j belong to
den_{emp}^{ij}	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 (< 100m) 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

Table 2. 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:

$$Gravity_{ij} = \left(l_i * l_j\right) * (den_{pop}^{ij} + den_{emp}^{ij})/\left(d_{ij}\right)^2 \quad (1)$$

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*:

$$score_e = n_{\sum w_k z_k} \quad (2)$$

$$l_e^w = l_e * (1 - score_e) \quad (3)$$

Step 3.2: Choose one optimum route:

$$r_{ij}^{optimum} = \arg\max_{r_{pq}}(\overline{score_e^r} * \varphi_r) \quad (4)$$

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 > 3)
Step 5.4: Calculate a new route on E_{drive} and connect if it is significantly shorter (i.e., Circuity index <1.4)

3.2. What to Connect

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 Table 2 (and the terms used are defined in Table 1). Note that *edge* and *node* indicate road segment (line) and intersection (point) in the network.

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 2). The inputs are compared in pairs using a revised form of the gravity model which takes account of the input pair's length, 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.

3.3. 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 3,000. 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 the PACE cluster, a high-performance computing environment at the Georgia Institute of Technology.

Table 3. 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 population in the block group to which the edge belongs	
Bikeability	Traffic Volume	Annual Average Daily Traffic (AADT)	Georgia DOT
	Slope	Slope of the edge (%)	Google Elevation API

Table 3 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., $score_e = N$) 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 sensitivity analysis where we simulated tens of networks based on different combinations of weights between four categories – multi-modality, potential demand, equity, and bikeability – and chose a set of weight that maximizes the per-mile effects.

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 2). 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. 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 – which is the ratio of network distance to Euclidean distance between a certain O-D pair – is larger 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.

3.4. Generated Network

Figure 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 4.1. 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.

Figures 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 Figure 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 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.

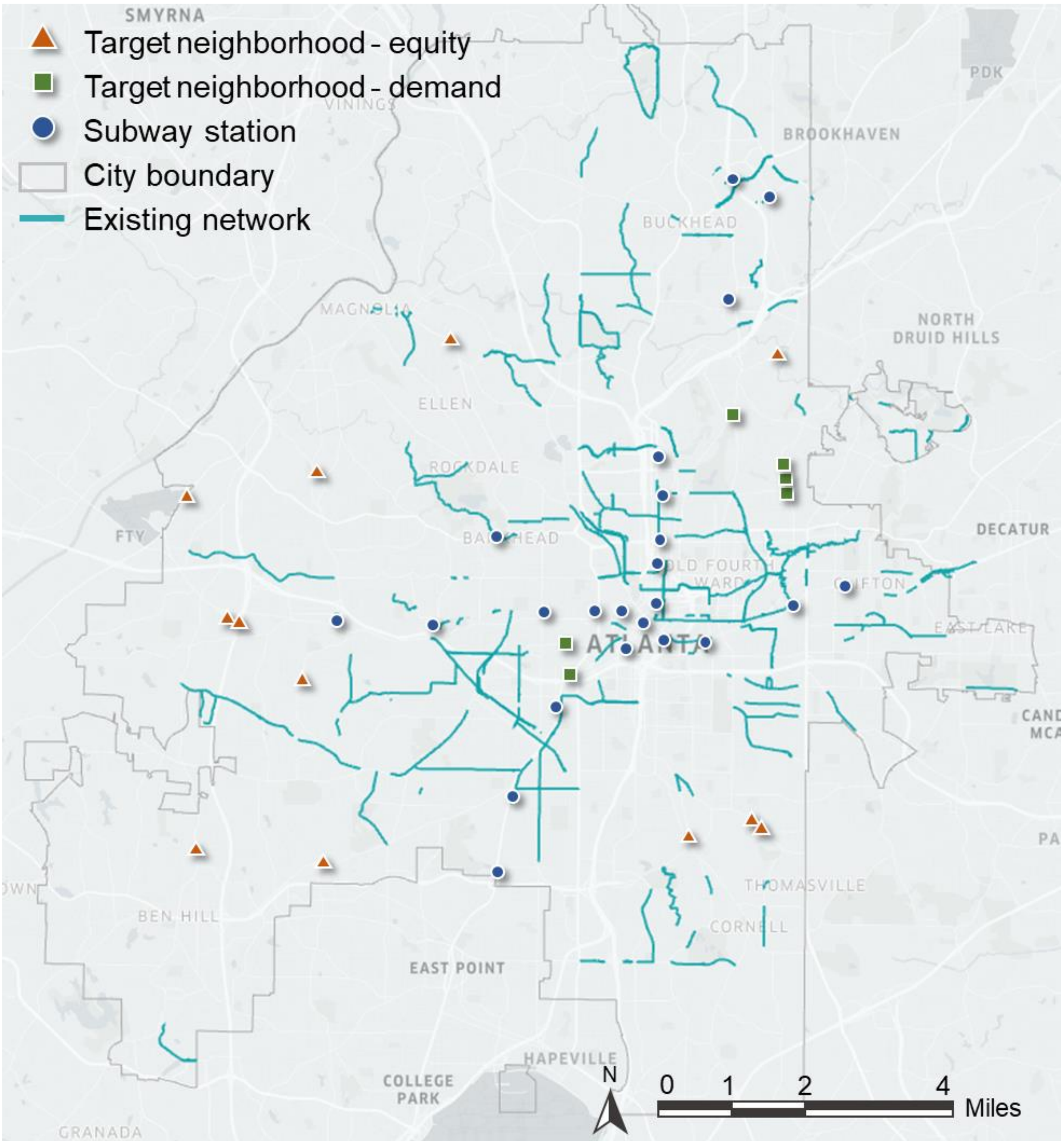


Figure 2. Algorithm Input

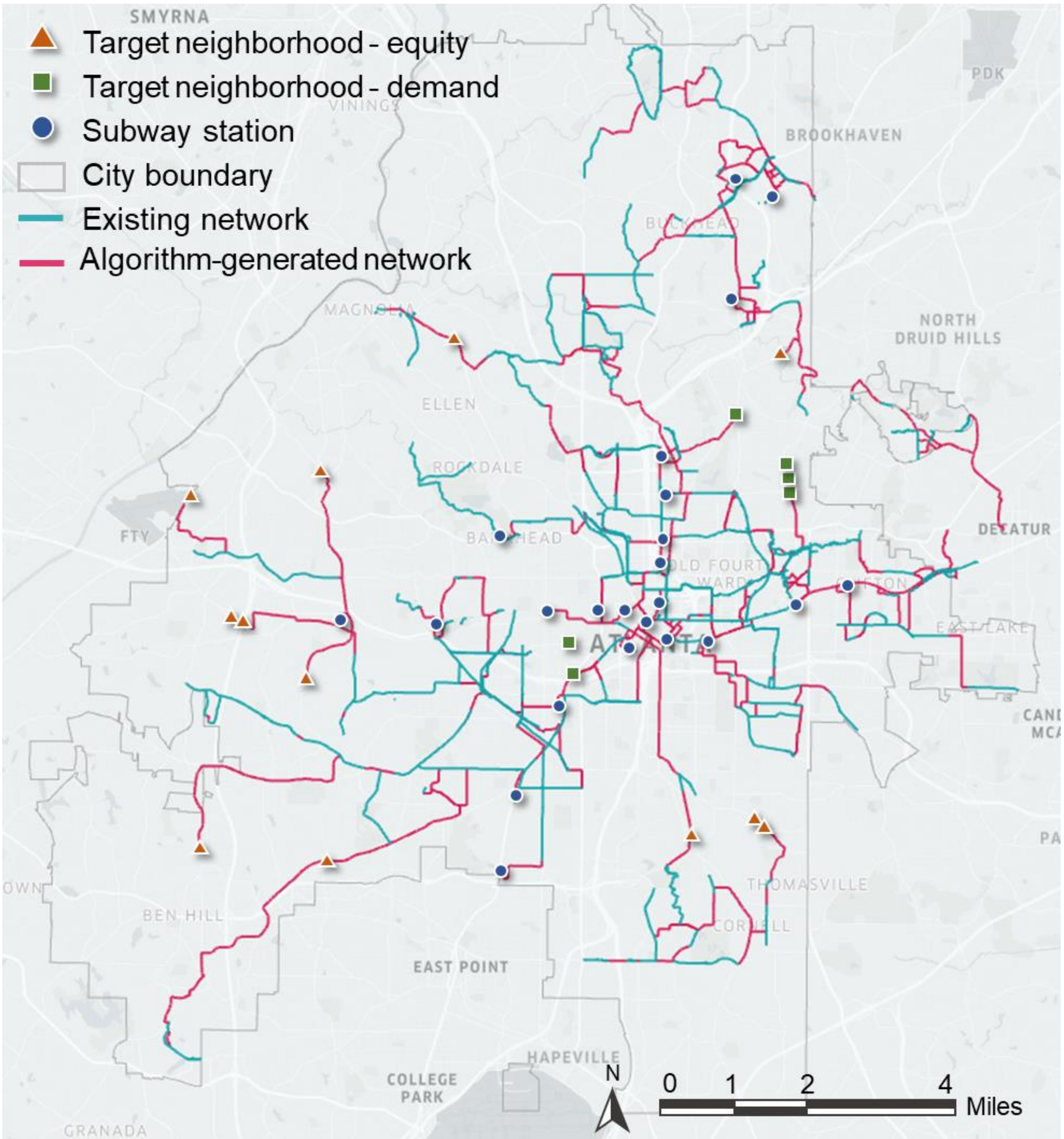


Figure 3. Algorithm-generated Network

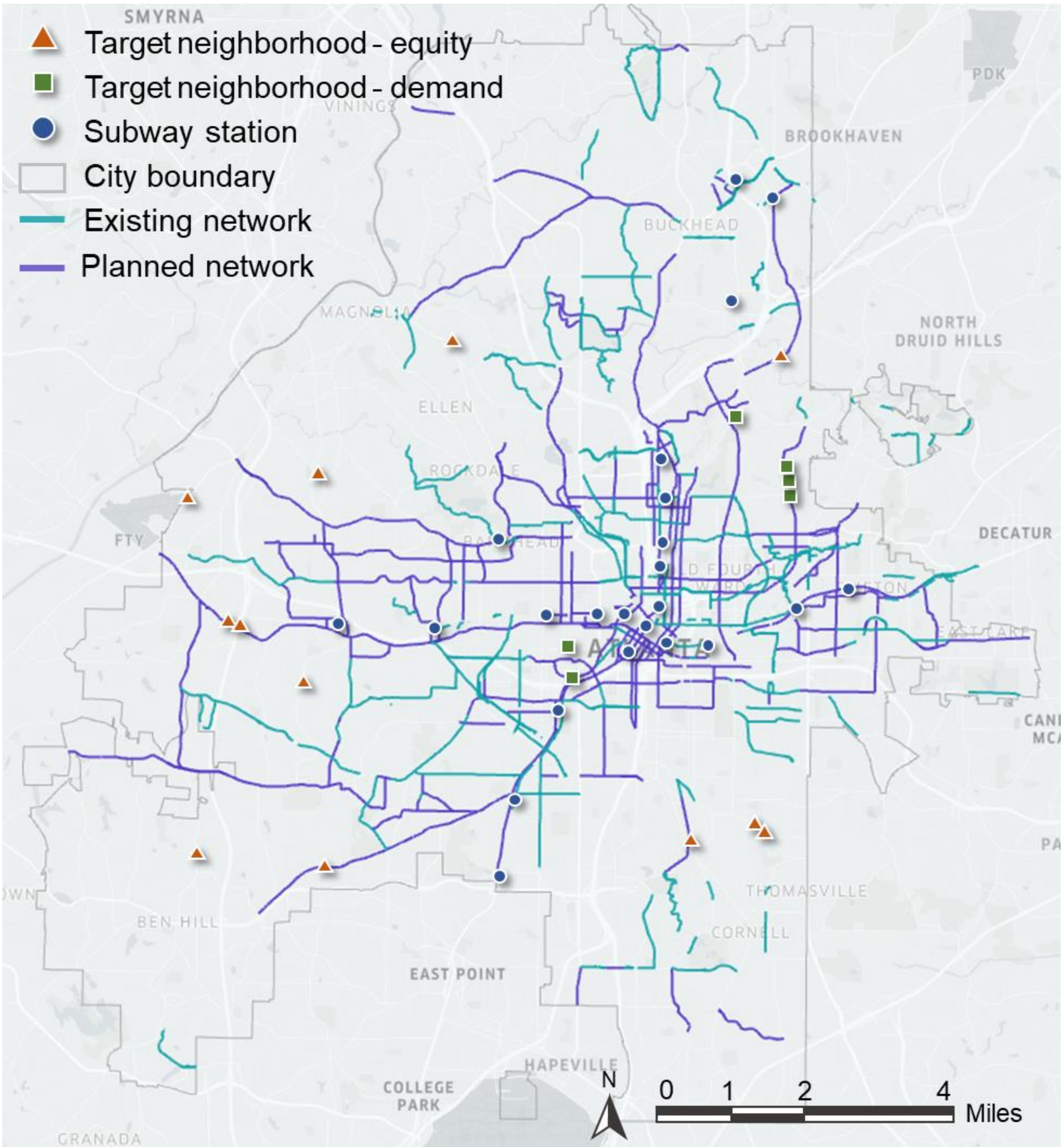


Figure 4. Planned Network

4. Biking Stress Evaluation

4.1. Simulation-based Evaluation

To test the biking stress, 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 user's perspective. This study hypothesizes that the stress during a bike trip is induced by (1) biking distance and (2) traffic conditions. To combine the two stress factors into a single index, it is important to numerically identify the trade-off between the stress from the prolonged biking distance and the stress from traffic conditions. This study borrowed insights from previous literature (*29, 48, 49*) which quantified the factors affecting biking stress based on the marginal rate of substitution (MRS). MRS is defined as the amount of one good (e.g., biking 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% biking 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). Many factors induce/reduce traffic stress; this study calculates the stress using vehicular lanes, vehicle speed limit, slope, and most importantly, availability of bike lanes, which is based on the previous study (*29*). Also, we assume that all the proposed networks will accommodate protected bike lanes.

4.2. Simulation Samples and Criteria

The evaluation is based on two types of samples (as shown in Figures 5 & 6): (1) between-TAZ trip sample and (2) station-access trip sample. First, the between-TAZ trip sample is to evaluate the biking environment between TAZs within six miles which is considered a strong threshold of the bicycle mode choice (50-*51*). 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 Equation 5, *i* and *j* indicate TAZs.

$$Travel\ Demand_{ij} = (Pop_i + Emp_i) * \left(Pop_j + Emp_j\right) \ /\ Distance_{ij} \tag{5}$$

Second, the station-access trip sample is generated by connecting TAZs to their nearest subway station. The station-access trip sample represents first/last mile trips and is employed to evaluate the impact of the network on improving multi-modality. To be consistent with past studies (*51-52*), 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. 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.

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 biking 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.

The simulation result is then compared to available future bike network plans made by multiple local entities (*53*), assuming that those networks will also be protected bike lanes on streets with heavy traffic. 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.

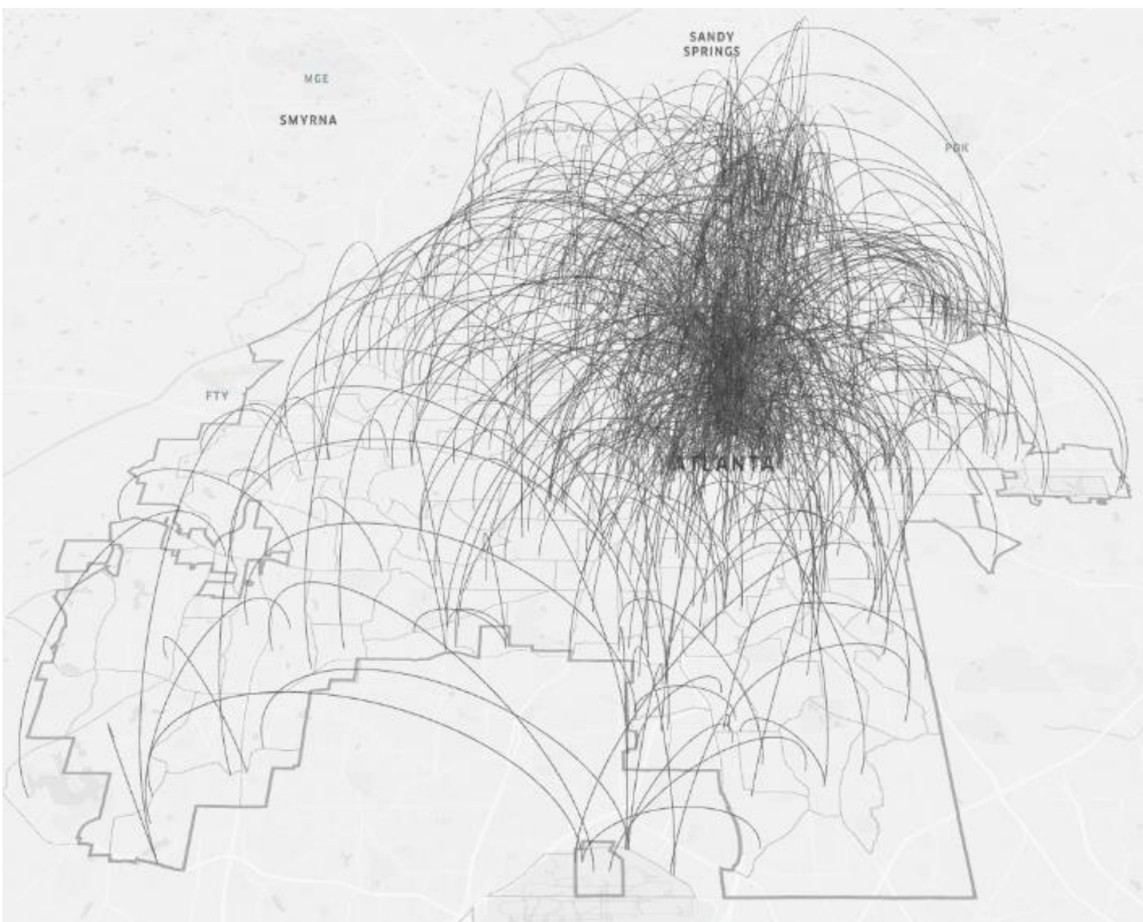


Figure 5. Between-TAZ Trip Sample

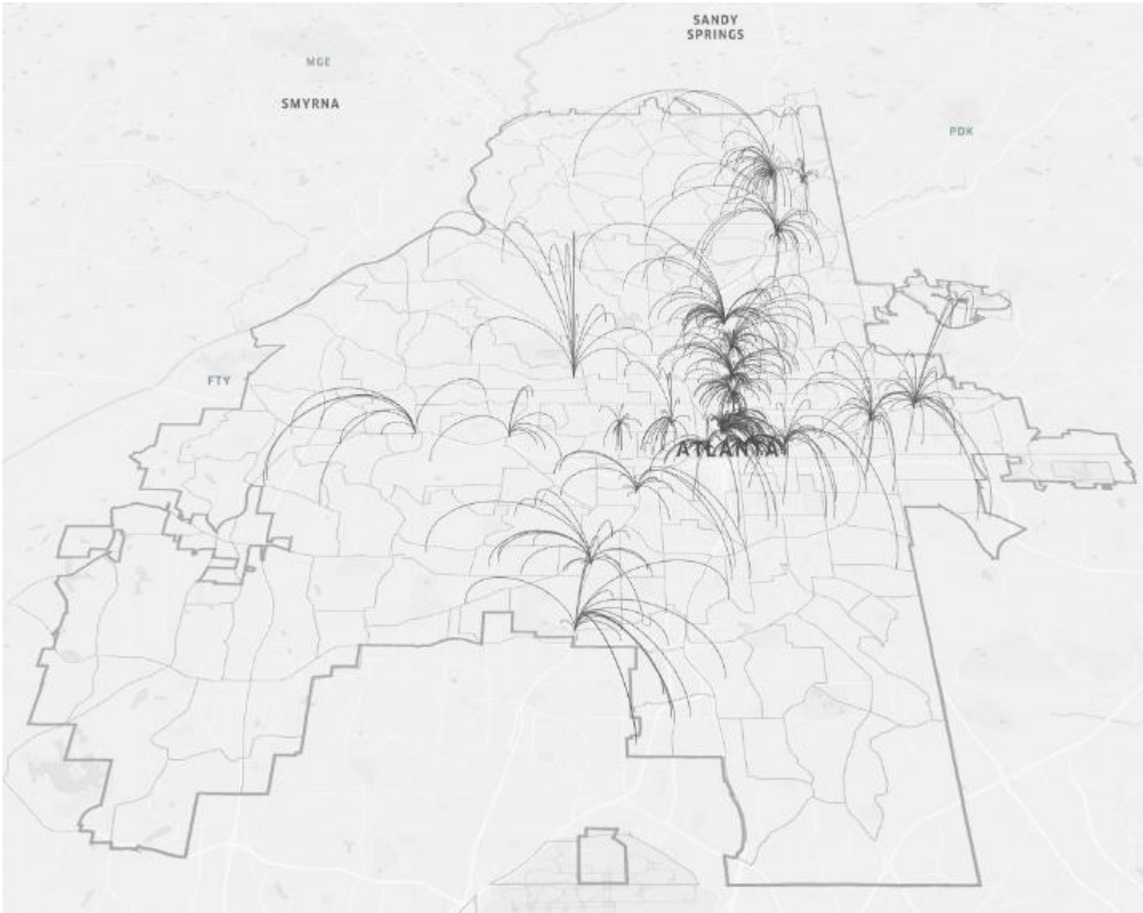


Figure 6. Station-access Trip Sample

In the next chapter, we describe the development of microscopic simulation models that are used to evaluate the operational and safety impacts of bicycle infrastructure provided according to the network design principles described in this chapter.

4.3. Biking Stress Simulation Result

Table 4 shows the simulation-based evaluation result of (1) the existing bike network, (2) the network planned by multiple local entities, and (3) 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 biking stress is, on average, 151.6% in the between-TAZ trips and 153.5% in the station-access trips.

Table 4. Simulation-based Evaluation Results

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

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 biking stress considerably decreases compared to the current network.

The algorithm-proposed network shows performance similar to 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 biking 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. These results suggest that the algorithm can refine the performance of the planned network and ensure a safer biking environment.

5. Traffic Operation Evaluation

5.1. Microsimulation Modeling of Existing Network

The research team worked with project stakeholders to obtain the base network of Midtown and Downton Atlanta. Shapefiles and other data sets were collected to build a base map on ArcMap. The study area, which was modeled in VISSIM, covered all signalized intersection locations in Downtown Atlanta and most of Midtown. Signal timing and traffic volumes were provided by the city staff and included in the Synchro network provided to the research team. To accurately replicate the most congested period for the network, weekday PM peak hour traffic was modeled. This section explains the network modeling procedure, calibration, and validation. Figure 7 is a visualization of all signalized intersections within the study. Note that the region shown in Figure 7 is larger than the Midtown and Downtown modeled in VISSIM.

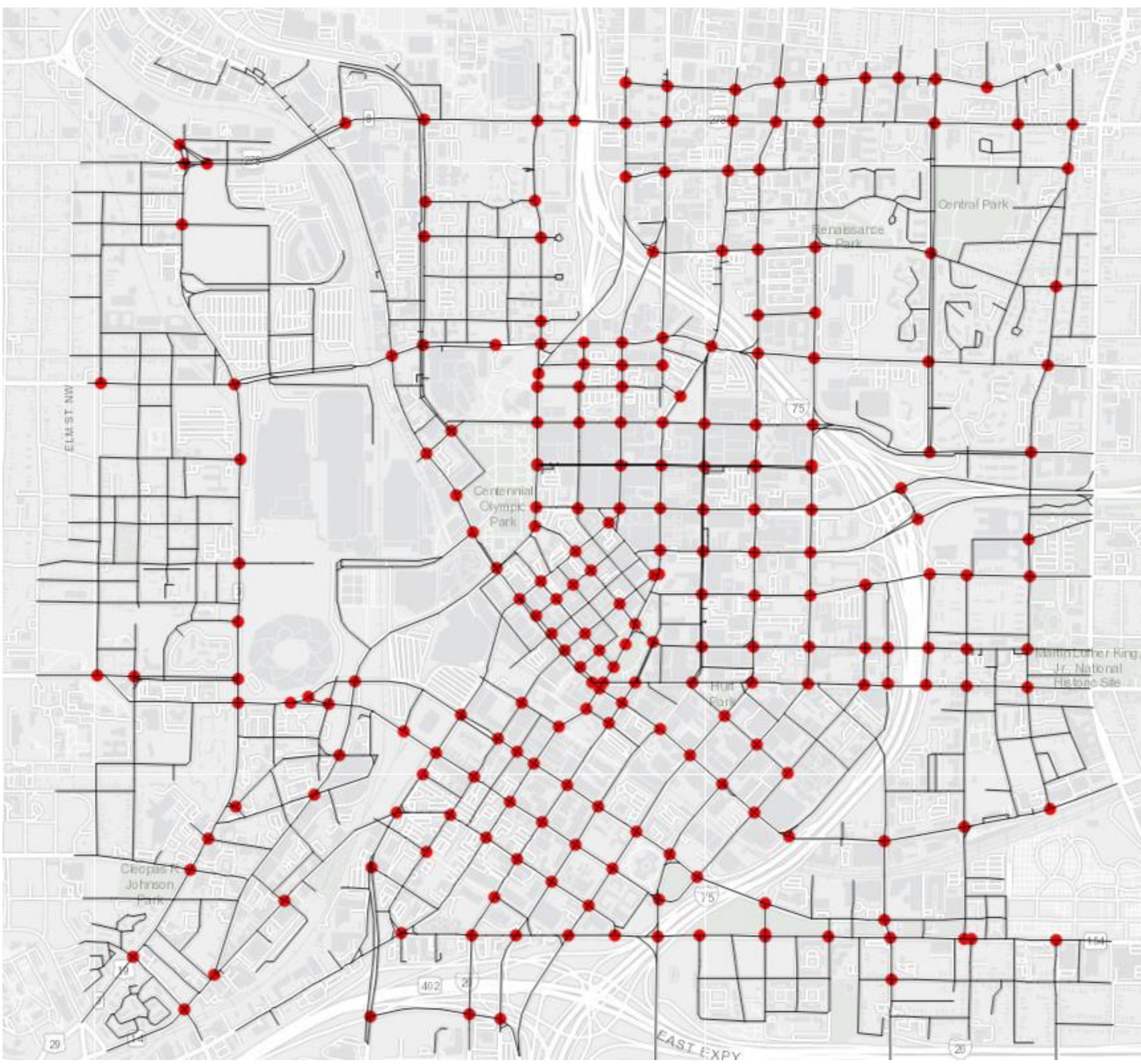


Figure 7. Signalized Intersections Within Study Area

5.1.1. Network Creation

Road Network. The City of Atlanta worked with Kimley-Horn to provide us with the base network modeled using Synchro and Simtraffic. Within the network, signal timing, lane geometry, speed limits, and traffic counts were embedded within the base network. The general lane geometrics included existing automobiles and bike lanes, but there was no clear differentiation between vehicle and bike counts. The network provided consisted of 214 intersections and 3,700 links resulting in a total length of 757,361 feet (143.5 miles) in the network shown in Figure 8. Out of the 214 intersections in the study area, approximately 207 of the intersections operated on a pre-timed basis during PM peak hour, 5 intersections were all-way stop, and 2 were two-way stop intersections. To enable surrogate safety assessment, this model was imported into PTV VISSIM. As the model's primary focus is to evaluate biking infrastructure expansion and improvements within Downtown and Midtown, freeway mainline segments with no bicycle traffic were not included in the model. In addition to parking lots, off-ramps and on-ramps to the regional freeways that are connected to downtown served as origins and destinations in the VISSIM model.

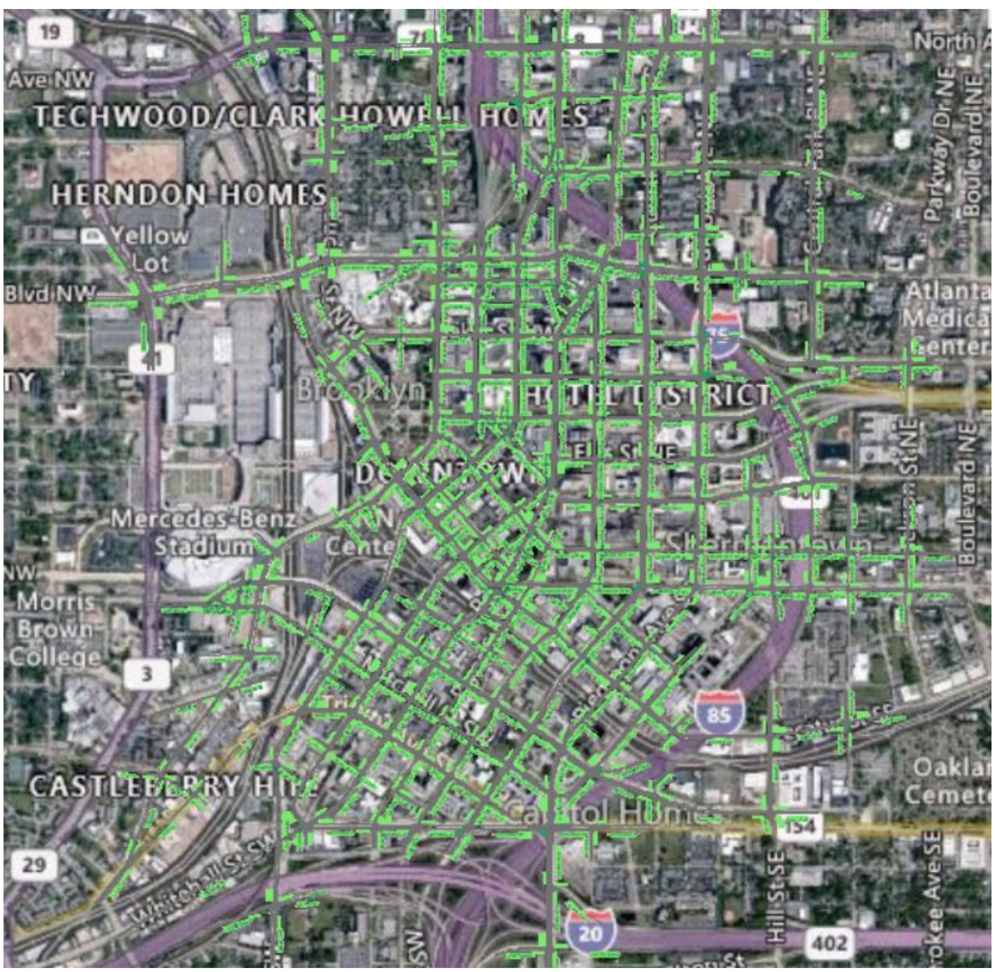


Figure 8. Synchro 11 Model for Downtown and Midtown

Importing Synchro Network into VISSIM. As the Synchro network included basic properties for the network, speed, lane geometry, vehicle volume data, and signal timing, the most efficient way to accurately bring in all data and parameters was to import the whole Synchro network over to VISSIM. As a result, importing the network saved multiple steps of a preliminary setup, including estimating vehicle data and composition, vehicle speed data, and signal timing data. However, the Synchro network that was transferred over to VISSIM only had automobile data, so any parameters relating to the bikes had to be manually inputted or adjusted; this includes any bike lanes, speed, vehicle compositions, and conflict areas. Figure 9 shows a visualization of the imported network in VISSIM.

Figure 9. VISSIM Model for Downtown and Midtown

Existing Bike Infrastructure. Existing bike lane infrastructure that falls within the study area is listed in Table 5. Existing bike classifications are listed according to what is currently in Google Maps. A visualization of the existing bike infrastructure on ArcGIS ArcMap 10.8 is shown in Figure 10.

Table 5. List of Existing Bike Infrastructure Within the Study Area

Street Name	From	To	Direction	Type
Marietta St	North Ave	Ivan Allen Jr Blvd	NB/SB	Class II
Luckie St	North Ave	Baker St	NB/SB	Class III
Peachtree Center Ave	Pine St	Edgewood Ave	NB/SB	Class II
Jackson St	Highland Ave	Irwin St	NB/SB	Class II
Jackson St	Irwin St	Auburn Ave	NB/SB	Class III
Jackson St	Auburn Ave	Edgewood Ave	NB/SB	Class II
Park Pl	Auburn Ave	Edgewood Ave	NB/SB	Class IV
Piedmont Ave	Baker St	Harris St	NB/SB	Class II
Peters St	Walker St	Spring St	EB/WB	Class II
Mitchell St	Mangum St	Spring St	EB/WB	Class II
Ivan Allen Jr Blvd	Northside Dr	Spring St	EB/WB	Class II
Ralph McGill Blvd	William St	West Peachtree St	EB/WB	Class II
Highland Ave	Piedmont Ave	Jackson St	EB/WB	Class IV
Harris St	Techwood Ave	Piedmont Ave	EB/WB	Class II
Edgewood Ave	Park Pl	Boulevard	EB/WB	Class II
Decatur St	Jesse Hill Dr	Jackson St	EB/WB	Class II

Data Collection. As bike lanes were drawn into the model in VISSIM, the following strategies were used to closely replicate each level of bike lane classification in the simulation model:

- For Class II bike lanes, bike lanes were drawn along the relevant road. To depict the driving behavior along the routes with Class II bike lanes, bicycle volumes were put into the bike route and along the main road. The vehicle composition for these road segments includes bicycle percentage. The reason for this is to describe the behavior of some bike users who bike outside the painted bike lanes along the road.
- For Class III, the road segment volumes include bike volumes and relative mode share. There are no separate bike lanes along this roadway.
- For Class IV, a separate bike lane was put along the relevant roadway segments. Bike volumes and composition are only put into the Class IV bike lanes; no bike volume is put into the main road to depict the separate bikeways.

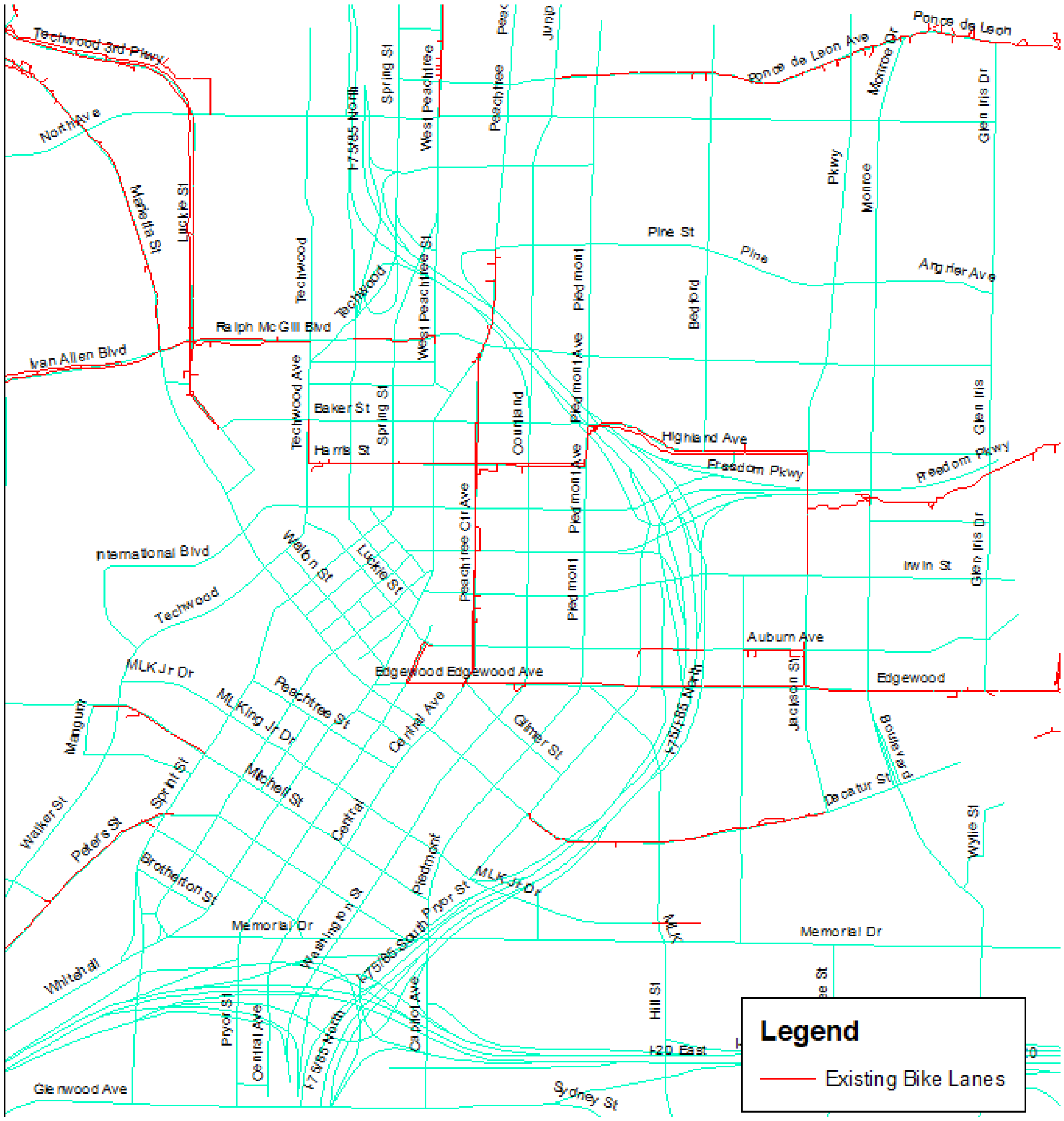


Figure 10. Existing Bike Lanes Within Study Area

Conflict Areas. Conflict areas within the network are areas that have overlapped links and connectors. To prevent vehicles, bicyclists, and pedestrians from appearing to be colliding or moving over each other in the simulation, conflict areas assign the priority of movement. Movement priorities were assigned at merge points for vehicles at intersections for left and right turn movements yielding to the through traffic.

Speed Data. Speed distributions are required to be defined for all vehicle classes. As most speed distributions have been set when the network was imported from Synchro, the only speed distribution manually assigned in VISSIM was the bike speed distribution. The speed distribution used for VISSIM was set to be 8 mph for the minimum and 25 mph for the maximum. Speeds were determined according to the average speeds of bike riding comfort level found in *Guide for Development of Bicycle Facilities* written by AASHTO (*55*). Figure 11 shows the input for bicycle speed profile in VISSIM.

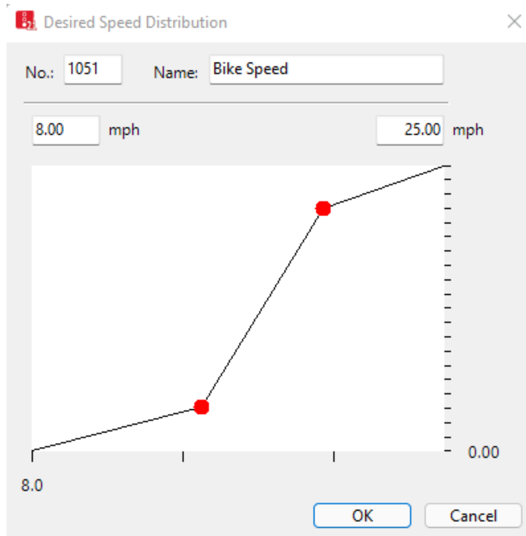


Figure 11. Bike Speed Distribution in VISSIM

Signal Timing Data. No changes were made to the traffic signals within the network, as all signal timing, sequences, and cycles were embedded in the Synchro network. Figure 12 shows an example of a standard signal timing template and entry that was carried over from the Synchro file. All signals were modeled as a Ring Barrier Controller (RBC) in VISSIM, which modeled actuated signal timing patterns as well as coordination. Each signal head and signal controller were assigned to each other through the RBC interface of VISSIM, which fulfills our needs of protecting left turns and vehicle detectors.

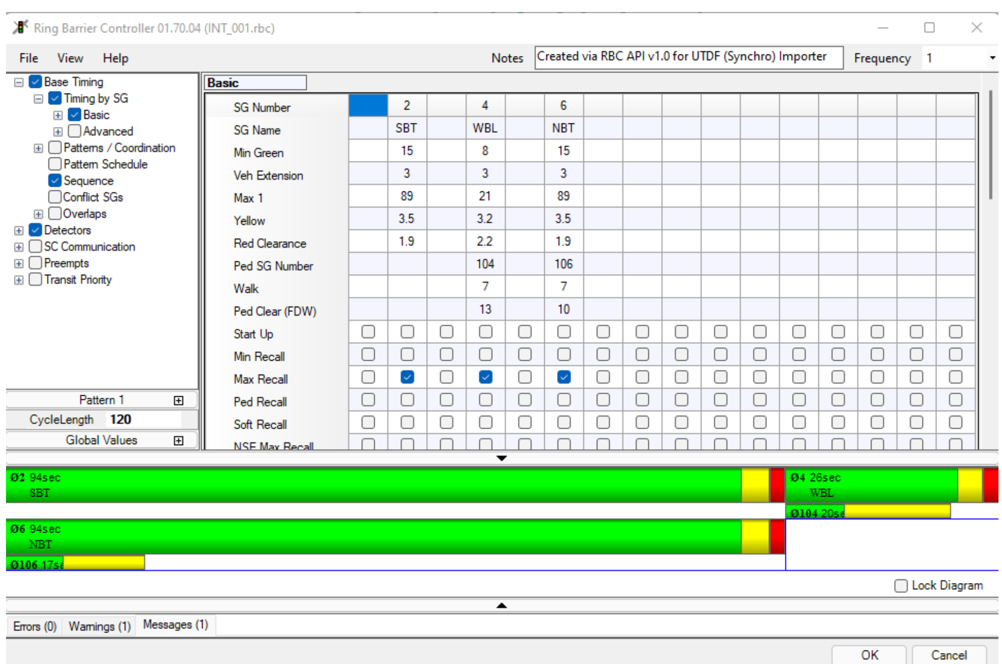


Figure 12. Ring Barrier Controller Timing in VISSIM

Bicyclists. Bicyclists were coded in VISSIM as their vehicle class and routed through corridors. These corridors were identified based on the Current City Bike Infrastructure

Map found in the City of Atlanta 2018 Annual Bicycle Report, found in Appendix A of this report. An estimate of 5 bicyclists per hour in each corridor was coded into the network. The average hourly count of cyclists was based on the bike counts provided by the Annual Bicycle Report.

5.1.2. Calibration

Calibration and validation are necessary steps to ensure the model's accuracy and reliability. Azevedo et al. recommended the calibration of microsimulation models considering key uncertainty sources such as data input, the methodology of calibration, the model structure, and its parameters (*56*). The network is calibrated using automobile driving behavior and parameters.

Simulation Parameters. A well-calibrated model is essential to the system that is being modeled as it increases the reliability of the predicted traffic patterns and scenarios. The simulation period is set to be 3600 seconds (one hour) with a 15-minute start time. This means that VISSIM will start analyzing the vehicles and travel time after 15 minutes into the run time. It ensures that analysis excludes the initial simulation period when the network elements (automobiles, bicycles, pedestrians etc.) are still being populated into the network. Figure 13 shows the simulation parameter setup for the simulation model.

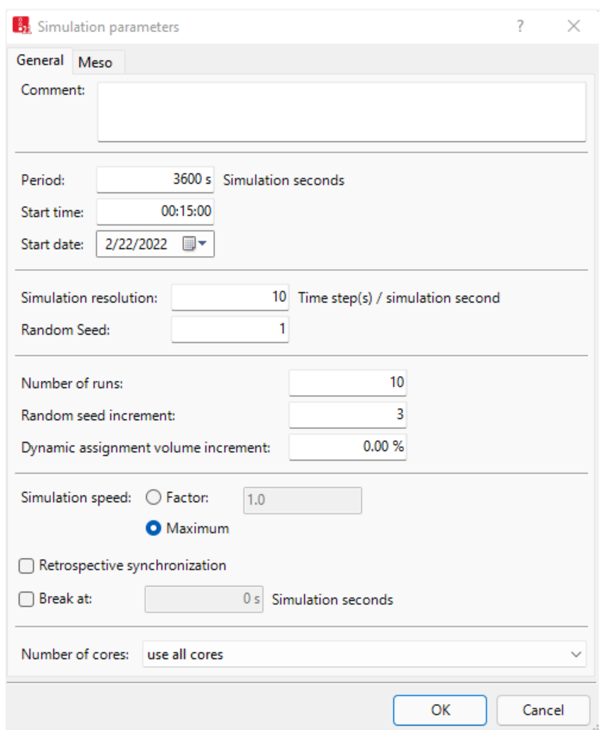


Figure 13. Simulation Parameters for the Model

Seed Numbers. Validation of the model requires a series of runs of the simulation model at different seed numbers. Random seed numbers were put into VISSIM, which would affect the start values of random generators used internally in the model. This means that having random seeds would influence the arrival times of the vehicles within the network and the variability of the driving behaviors. Due to the stochastic nature of the simulation, random fluctuations occur in the results of the individual simulation runs (*57*) based on the seed, and it captures random variations in users' travel and driving/biking/walking behavior. This allows for the comparison of the changes in traffic patterns within the same location. If the same seed number was used for each simulation run, the output data, such as the volumes, speeds, and travel times, would be identical for each run. According to the user manual, a more reliable output is obtained by averaging the results of a sufficient number of simulation runs with different random seeds. Therefore, the validation of each network is based on an average of 10 simulation runs. Fries et al. have suggested that models evaluating system-wide metrics such as average vehicle speeds or vehicle hours traveled need at least 5 runs and models measuring arterial travel times or total delay require 10 or more runs (*58*). According to MDOT's simulation modeling guidelines, a minimum of 5 simulation runs must be completed before the average outputs of all runs can be used for analysis (*59*).

Vehicle Volume Input. To ensure reliability of the model output, the model's traffic volumes were compared with the real-world data from the City of Atlanta and Georgia DOT. Real-world speed and travel times for the network were estimated using Google Maps during the afternoon peak period (between 4:00 PM – 5:00 PM) and were used to appropriately calibrate the model.

User Behavior Parameters. Driver behavior parameters were adjusted to include urban bike behavior to make sure that the model's data closely resembled the actual data. Figure 14 shows an example of the urban bike behavior parameters used in VISSIM.

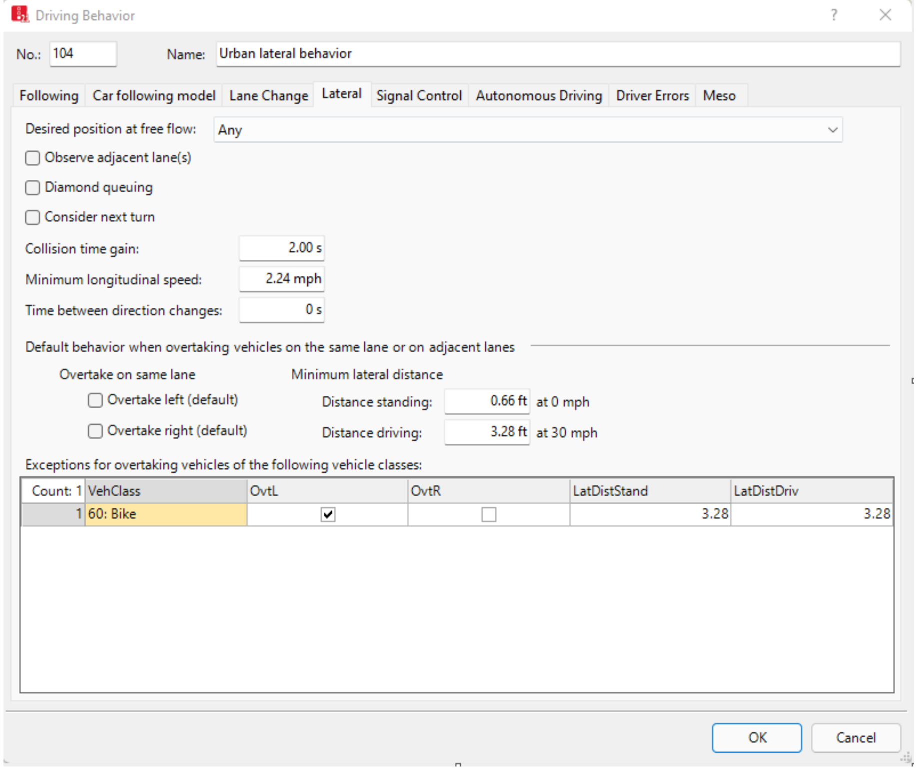


Figure 14. Urban Bike Behavior Parameters

5.1.3. Validation

The validation process involved running multiple runs of the calibrated network and comparing the output data to the real world for accuracy. Below are the measures used to validate the microsimulation model in VISSIM. (Azevedo, Ciuffo, Cardoso, & Ben-Akiva, 2015). The network is calibrated using automobile driving behavior and parameters.

Vehicle Record Data. The first validation step was based on the traffic output data from the VISSIM model using the elements of travel time measurements and vehicle network performance. Travel times were measured as the average travel time for vehicles to cross the origin and destination specified for the travel time measurement places on key corridors. Delay measurements were obtained for any selected segment where travel time is measured. The average delay is calculated from all vehicles observed on a single link or several linked sections. Appendix B summarizes all corridors/locations where travel times were measured.

Speed Validation. Key corridors were selected within the network to perform speed validation. The following segments were selected as they either have existing biking infrastructure along the route or intersect with other biking infrastructure. Real-life estimated average speed range and time were collected on a Friday from 4:00 PM – 5:00 PM from Google Maps. This information was compared and matched with spot speed data from VISSIM to ensure the replication of the drivers' behavior. The average speed along the corridor recorded by VISSIM must fall within the range of speed calculated by Google Maps. Table 6 summarizes the average speed data from the ten runs of the existing network compared to the corridor average speed range from Google Maps, which provides a range based on historical data from real-world conditions. All key corridors had the average speed within the distribution range of historical data other than Peachtree Street, which was just outside the range.

Table 6. Existing Baseline Speed Summary

Street Name	Length (mi)	Existing Baseline VISSIM model travel time (min)	Model Average Speed (mph)	Google Estimated Speed Range (mph)	Posted Speed Limit (mph)
North Ave (WB)	1.4	5.85	14.44	7-21	30
Ivan Allen Jr Blvd to Ralph McGill Blvd (EB)	1.7	9.91	10.29	6-18	30
Marietta St to Decatur St (EB)	2	12.05	9.95	7-20	30
Piedmont Ave to Capitol Ave (NB)	2.2	10.07	13.11	6-19	30
Juniper St to Washington St (SB)	1.9	15.22	7.49	10-23	25
Peachtree St (SB)	1.3	4.24	18.41	6-16	25

Travel Time Validation. The following key corridors were selected for travel time validation. Travel times of each route were recorded within VISSIM and compared to travel times obtained from Google Maps during Friday PM peak hour. Estimated real-life travel time ranges were collected from Google Maps since no real-time travel data was available. 83% of the travel times of the selected key corridors fall within Google Maps' estimated travel time range. Table 7 summarizes the travel time outputs from VISSIM compared to Google Maps. Travel time for each run can be found in Appendix C.

Table 7. Existing Baseline Travel Time Summary

Street Name	Length (mi)	Existing Baseline (min)	Google Range (min)
North Ave (WB)	1.4	5.85	4-12
Ivan Allen Jr Blvd to Ralph McGill Blvd (EB)	1.7	9.91	6-16
Marietta St to Decatur St (EB)	2.0	12.05	6-18
Piedmont Ave to Capitol Ave (NB)	2.2	10.07	7-20
Juniper St to Washington St (SB)	1.9	15.22	5-12
Peachtree St (SB)	1.3	4.24	5-14

In this chapter, the process of network creation, calibration, and validation was discussed. Calibration consisted of updating and adding any missing parameters and validation was done on the existing condition Scenario 0 (exiting travel demand conditions) by comparing the model's average speed and travel time data to real-world data. As a result of the calibration and validation process, the existing condition model is sufficient to be used to assist the other alternative conditions. The next chapter discusses alternative bike infrastructure designs and modal demand adjustments to evaluate the effectiveness of the bike network improvement and extension.

5.2. Simulation Analysis of Alternatives

This chapter describes the two alternative conditions for the network in terms of bicycle infrastructure. These alternative conditions are evaluated on three different travel demand scenarios, including the existing levels of automobile/bicycle demands.

5.2.1. Travel Demand Adjustments

The initial plan is to test the existing condition and each alternative with the existing traffic volumes and then with adjustments in the traffic volumes. The existing demand is referred to as Scenario 0 in this report. The first scenario, labeled as Scenario 1 for the rest of the report, is the 5% adjustment in the vehicle and bicycle volumes. In this scenario, existing demand is altered by substituting 5% of the vehicular volume with a 5% increase in bicycle volume. The second scenario, referred to as Scenario 2, involves a similar adjustment of 15%. The reason for these scenarios is to estimate the impacts on network MOEs and conflicts resulting from the modal shifts towards bicycles with or without the infrastructure changes. These demand scenarios were evaluated to reflect past findings from the literature that found that higher levels of street connectivity for bicyclists are associated with more cycling for utilitarian trips (*4*). While estimating the precise modal shift is beyond the scope of this work, the demand scenarios evaluated here can provide the network MOEs for possible mode shifts ranging from no shift (existing demand), moderate shift (5%), and high shift (15%).

The bicycle network based on the algorithm developed in this study is referred as the Proposed Network Condition. The proposed conditions are essentially the ideal bike networks through midtown and downtown Atlanta that enable the most equitable connectivity of destinations. The City has also proposed its bike lane implementation and extension plans, which is referred to as the Alternative Network Condition in this report. While there are some differences in the network, several bike lane connections are common between the Proposed and Alternative networks. Each alternative was modeled in VISSIM and evaluated at the three different demand scenarios mentioned in the previous paragraph. Hence, a total of 3 travel demand scenarios (including Scenario 0, which is the base case) were analyzed for each network condition (Existing, Proposed, and Alternative). Each alternative and scenario are described along with the network metrics collected using VISSIM in the subsequent subsections of this section.

5.2.2. Existing Condition Demand Scenarios 1 And 2

As the existing condition at the existing demand scenario (scenario 0) were summarized in the previous chapter, this section describes the results of Scenarios 1 and 2 with the existing network conditions. As mentioned previously, 5% modal demand adjustment was done in Scenario 1 and 15% was done in Scenario 2.

Analysis and Network Measures of Effectiveness (MOEs). Table 8 shows the network measures of effectiveness for Existing Conditions at demand scenarios 1 and 2 compared to the baseline (Scenario 0). A full summary of Network MOEs for this scenario can be found in Appendix C.

Table 8. Existing Condition at Demand Scenarios 1 and 2 Network MOEs

	Existing Baseline (Scenario 0)	5% Modal Demand Adjustment (Scenario 1)	15% Modal Demand Adjustment (Scenario 2)
Average Speed (mph)	7.57	7.77	8.18
Average Delay (s)	252.16	243.12	213.96
Average Number of Stops	7.62	7.43	6.42
Average Stop Delay (s)	190.34	183.04	162.33

Results from Table 8 show a decrease in average delay and stop delay and the average number of stops which results in higher average speed in Scenarios 1 and 2 compared to the baseline demand scenario. This shows how fewer automobiles on the road and more bicycle riders will positively impact travel time for all users. The reason for the decrease in the total and average delay is most likely due to fewer vehicles on the road, which leads to a smaller number of stops, as shown in Table 8. Average speed during peak hour increased as a result of the demand adjustment, which is expected when there are fewer cars on the road during peak hours.

5.2.3. Proposed Condition at Demand Scenario 0

The proposed condition includes the addition of proposed bike lanes based on the algorithm developed in this research (See Chapter 3). Bike routes were updated to connect and include the proposed bike lanes. All bike lanes are modeled to depict Class II bike lanes unless specifically specified. The list of proposed bike infrastructure is provided in Table 9. Figure 15 is a visualization of the proposed bike lanes in ArcGIS ArcMap 10.8.

Table 9. List of Proposed Bike Infrastructure Within the Study Area

Street Name	**From**	**To**	**Direction**
North Ave	Techwood Pkwy	Peachtree St	EB/WB
Ralph McGill Blvd	Techwood Ave	Peachtree St	EB/WB
Baker St	Luckie St	Techwood Ave	EB/WB
Pine St	West Peachtree St	Peachtree St	EB/WB
Harris St	Techwood Ave	Piedmont Ave	EB/WB
Ellis St	Peachtree St	Peachtree Center Ave	EB/WB
Edgewood Ave	Peachtree St	Peachtree Center Ave	EB/WB
MLK Jr Dr	Forsyth St	Piedmont Ave	EB/WB
Mitchell St	Spring St	Capitol Ave	EB/WB
Brotherton St	Spring St	Peachtree St	EB/WB
Mitchell St	Northside Dr	Mangum St	EB/WB
Decatur Ave	Jackson St	Boulevard	EB/WB

Marietta St	Techwood Ave	Peachtree St	EB/WB
Peachtree St	Ponce de Leon Ave	Pine St	NB/SB
West Peachtree St	North Ave	Pine St	NB/SB
Peachtree Center Ave	West Peachtree St	Harris St	NB/SB
Peachtree St	Harris St	MLK Jr Dr	NB/SB
Jackson St	Highland Ave	Decatur At	NB/SB
Techwood Ave/Spring St	Ralph McGill Blvd	MLK Jr Dr	NB/SB
Peters St	Fair St	McDaniel St	NB/SB
Spring St	Mitchell St	Brotherton St	NB/SB
Forsyth St	Edgewood Ave	Trinity Ave	NB/SB
Piedmont Ave	Edgewood Ave	MLK Jr Dr	NB/SB
Central Ave	MLK Jr Dr	Memorial Dr	NB/SB

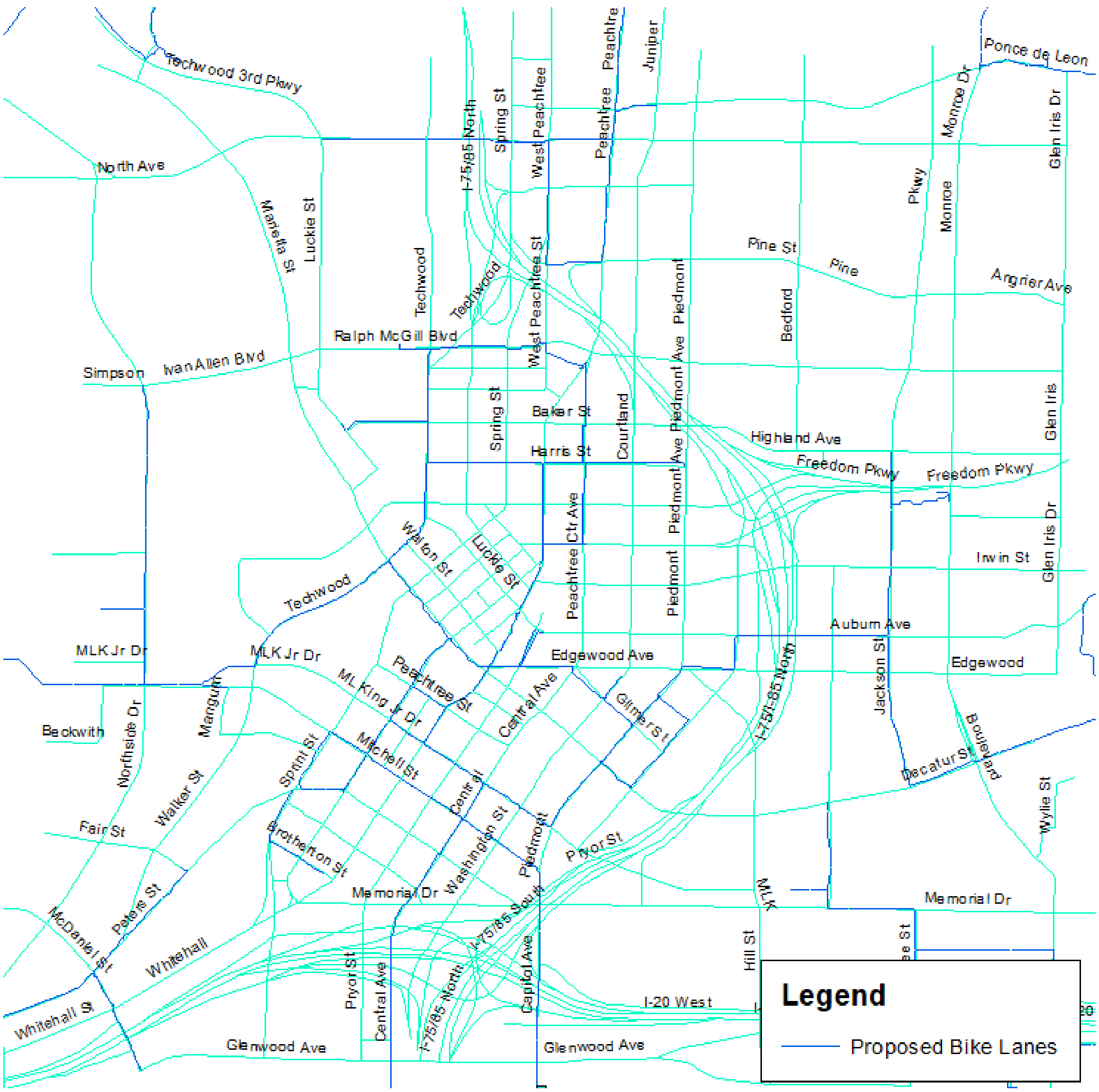


Figure 15. Proposed Bike Lane within Study Area

Analysis and Network Measures of Effectiveness (MOEs). Proposed Condition Scenario 0 models the proposed bike network with existing traffic volumes (i.e., travel demand). Table 10 shows the network measures of effectiveness for the Proposed baseline condition compared to Scenario 0 of the existing condition.

Table 10. Proposed Condition Scenario 0 MOEs

	Per Vehicle	
	Existing Baseline	Proposed Baseline
Average Speed (mph)	7.57	8.21
Average Delay (s)	252.16	222.31
Average Number of Stops	7.62	7.12
Average Stop Delay (s)	190.34	164.46

The results indicate that traffic network MOEs may be positively impacted as more bike infrastructure is implemented or extended within Downtown and Midtown Atlanta. Table 10 shows that the proposed network slightly reduced delays and average travel time even at existing demand levels. This likely results from the separation of bike traffic and reduction in interactions between slower bicycles and relatively faster automobiles. Furthermore, it also reflects that the automobile demand for the network is high enough that the present network already leads to slow movement during peak hours.

5.2.4. Proposed Condition at Demand Scenarios 1 And 2

For the proposed network condition, the 5% modal demand adjustment was done on the first scenario and 15% adjustment in the second scenario. Bike routes remained the same as the Proposed Condition Scenario 0.

Analysis and Network Measures of Effectiveness (MOEs). Table 11 shows the network measures of effectiveness for the Proposed Network Condition for each of the three demand scenarios.

Table 11. Proposed Condition Scenarios 1 and 2 MOEs

	Per Vehicle		
	Proposed Baseline	5% Modal Demand Adjustment	15% Modal Demand Adjustment
Average Speed (mph)	8.21	8.49	9.06
Average Delay (s)	222.31	212.52	193.82
Average Number of Stops	7.12	6.93	6.35
Average Stop Delay (s)	164.46	156.83	142.40

Comparing the results for the three demand scenarios, there was a significant drop in the total delay, which shows the positive impact of the modal shift in demand. With the shift of 15% of vehicular volume to bike volume, the average delay dropped ~15% from the baseline condition. The average speed also increased due to the decreased delay and the average number of stops. This means that traffic is flowing much more smoothly than at the base demand scenario indicating the benefits of modal shift. Full network MOEs for each seed can be found in Appendix C.

5.2.5. Alternative Condition Scenario 0

The alternative condition includes alternative bike lanes connectivity currently planned by the City. This network condition was analyzed based on feedback from the project stakeholders. This model excludes the bike lanes from the proposed condition. Compared to the proposed bike network, most of the planned alternative bike lanes run in the northbound/southbound direction, connecting the north part of the city to the south. Bike routes were updated to model these alternative network conditions. All bike lanes are modeled to depict Class II bike lanes unless otherwise specified. The list of proposed bike infrastructure is in Table 12. Figure 16 is a visualization of the proposed bike lanes in ArcGIS ArcMap 10.8.

Table 12. List of Alternative Bike Infrastructure Within the Study Area

Street Name	From	To	Direction
Ralph McGill Blvd	West Peachtree St	Boulevard	EB/WB
Highland Ave	Jackson St	Boulevard	EB/WB
West Peachtree Pl	West Peachtree St	Peachtree St	EB/WB
Baker St	Luckie St	Piedmont Ave	EB/WB
International Blvd	--	Marietta St	EB/WB
Walton St	Techwood Ave	Peachtree St	EB/WB
MLK Jr Dr	Techwood Ave	Grant St	EB/WB
Mitchell St	Northside Dr	Jesse Hill Jr Dr	EB/WB
Whitehall St	McDaniel St	Spring St	EB/WB
Memorial Dr	Peachtree St	Martin St	EB/WB
Piedmont Ave	Ponce de Leon Ave	Mitchell St	NB/SB
Capitol Ave	Mitchell St	Fulton St	NB/SB
Courtland Ave	Ponce de Leon Ave	Edgewood Ave	NB/SB
Washington St	Edgewood Ave	Memorial Dr	NB/SB
Peachtree St	West Peachtree St	Harris St	NB/SB
West Peachtree St	West Peachtree Pl	West Peachtree St	NB/SB
Peachtree St	Walton St	Memorial Dr	NB/SB
Spring St	Ponce de Leon Ave	North Ave	NB/SB
Techwood Ave	North Ave	Highland Ave	NB/SB
Techwood Ave	Harris St	Mitchell St	NB/SB
Walker St	Mitchell St	Peters St	NB/SB

Peters St	Walker St	McDaniel St	NB/SB
Forsyth St	Carnegie Way	Memorial Dr	NB/SB
Pryor St	MLK Jr Dr	Memorial Dr	NB/SB
Central Ave	MLK Jr Dr	Memorial Dr	NB/SB

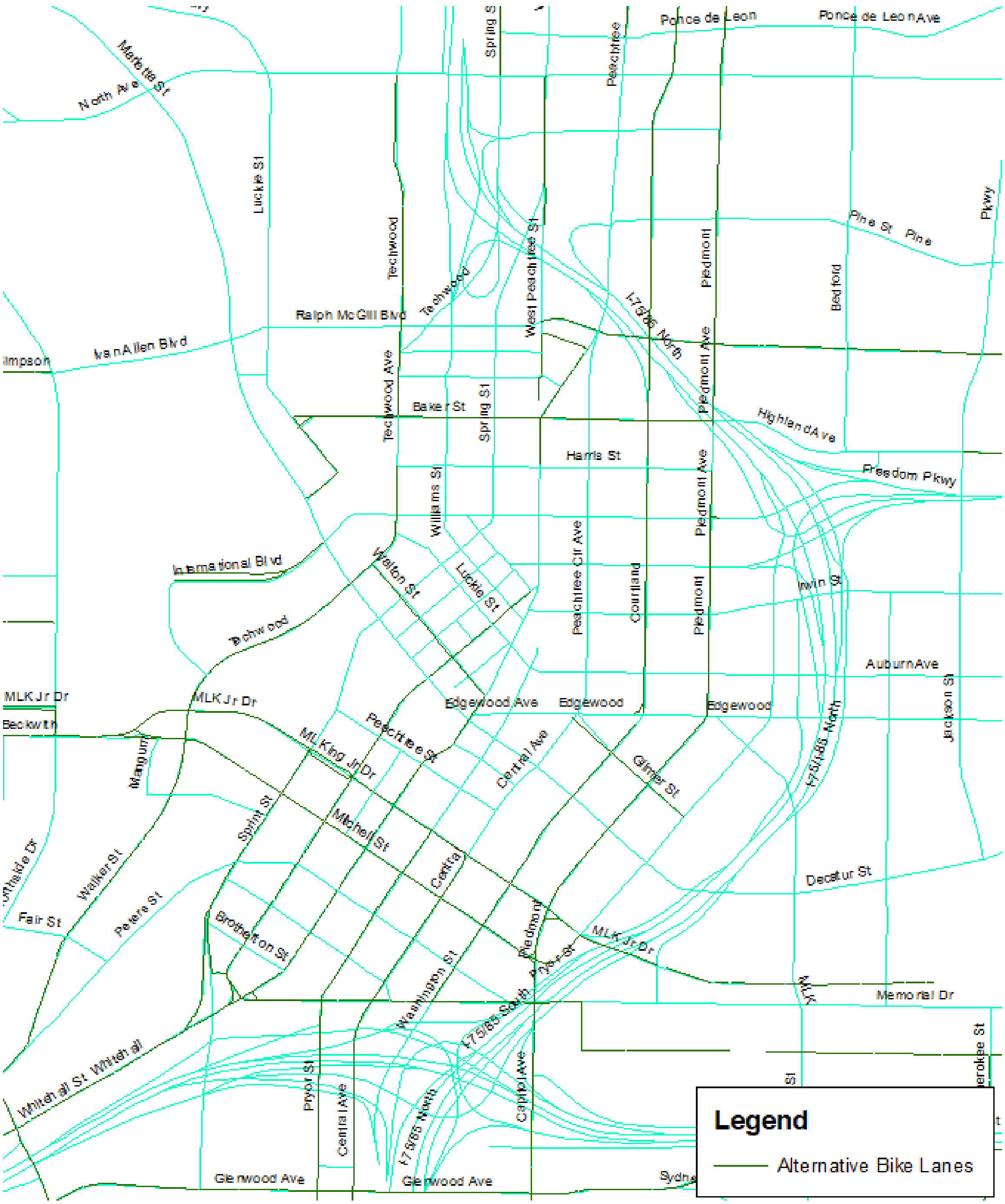


Figure 16. Alternative Bike Lane within Study Area

Analysis and Network Measures of Effectiveness (MOEs). Table 13 shows the network measures of effectiveness for the baseline scenario for the alternative condition compared to the existing condition baseline scenario. Full network MOEs for each seed can be found in Appendix C. Addition of bicycle infrastructure based on this network condition also reduced the delay slightly, similar to the proposed conditions described in the previous section. Furthermore, the numbers are quite similar since there is a significant overlap between Proposed and Alternative Network Conditions.

Table 13. Alternative Condition Scenario 0 MOEs

Per Vehicle		
	Existing Baseline	Alternative Baseline
Average Speed (mph)	7.57	8.22
Average Delay (s)	252.16	222.18
Average Number of Stops	7.62	7.12
Average Stop Delay (s)	190.34	164.21

5.2.6. Alternative Condition Scenarios 1 And 2

Modal demand adjustments of 5% and 15% were applied for this alternative network condition to model Scenarios 1 and 2, respectively. Bike routes remained the same from Alternative Condition Scenario 0.

Analysis and Network Measures of Effectiveness (MOEs). Table 14 shows the MOEs for two alternative scenarios, network measure of effectiveness compared to Scenario 0. Note that 5% and 15% modal adjustment for this network condition would lead to reduced delay and higher average speeds, with more considerable improvements resulting from a 15% mode shift. In other words, consistent improvement in MOEs results from the modal shift for this alternative network condition.

Table 14. Alternative Condition Scenario 1 and 2 MOEs

Per Vehicle			
	Alternative Baseline	5% Modal Demand Adjustment	15% Modal Demand Adjustment
Average Speed (mph)	8.22	8.48	9.07
Average Delay (s)	222.18	212.32	193.57
Average Number of Stops	7.12	6.94	6.34
Average Stop Delay (s)	164.21	156.80	142.20

Figure 17 summarizes the results for comparison of all network conditions and corresponding demand scenarios.

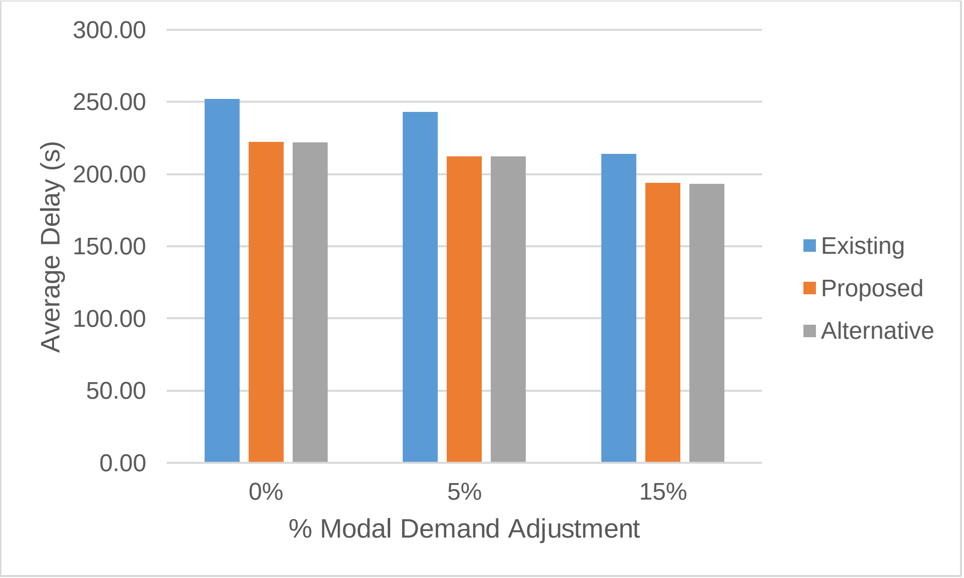


Figure 17. Average Delay Comparison of all Conditions and Scenarios

From the figure, the average delays for the proposed and alternative conditions were very similar in each demand scenario. The alternative condition delays were very slightly lower than the proposed condition delays. However, a more meaningful result of this analysis is that completing the network for bicycles leads to smaller delay(s) during peak hour with or without any modal shift (see results for 0% modal adjustment).

6. Safety Evaluation

6.1. Safety Evaluation based on Trajectory Data

Surrogate Safety Assessment Model (SSAM) Version 3.0 was used to estimate the number of potential conflicts within the VISSIM network. SSAM analyzes the frequency of narrowly missed vehicle collisions in microscopic traffic simulation software like VISSIM to assess safety (*60*). The trajectory of each vehicle is analyzed for every tenth of a second. The literature has established that the expected number of crashes in the long-term are proportional and represented by the simulated number of conflicts at each study intersection. Trajectory files for this project were generated from the simulation runs in VISSIM. Note that these runs were also used to obtain the operational MOEs shown in the previous chapter(s). Each trajectory file is then inputted into SSAM to estimate the number of conflicts within the whole network. There are three categories of conflicts that are based on the type of crashes, i) crossing collisions, ii) rear-end collisions, and iii) lane-change collisions.

The time to collision (TTC) and post encroachment time (PET) values were set to default in SSAM for the conflict analysis. TTC represents the number of a second required for overlapping trajectories to be considered a conflict (*60*). PET has defined as the time between the moment that the first road user leaves the path of the second and the moment that the second reaches the path of the first (*61*). The range for TTC is set at a minimum of zero seconds and a maximum of 1.5 seconds, and the range for PET is set to zero as the minimum and 5 seconds as the maximum.

Trajectory data from microscopic traffic simulation software, such as VISSIM, may underestimate the number of conflicts at intersections. In a study done by Wu et al., it was observed that VISSIM models underestimate the number of pedestrian-vehicle conflicts at intersections under specific circumstances such as involving illegal pedestrian behavior such as pedestrian signal violation (*62*). It was eventually concluded that it was hard to cross-check illegal biking behaviors or signal violations as real-world trajectory data of vehicles/bicycles and related observations at or near the study intersection were not available (*60*). Even considering this limitation, the SSAM can provide a relative assessment of safety for the scenarios.

6.2. Safety Evaluation of The Existing Condition

For safety evaluation, SSAM-estimated conflicts were normalized by the total simulated number of vehicles within the entire network. It provides the average number of conflicts experienced per vehicle. Table 15 summarizes the number of conflicts per vehicle type from each scenario. A complete summary list of SSAM results can be found in Appendix D.

Table 15. Existing Condition SSAM Results

Average Number of Conflicts Per Vehicle by Type			
	Exiting Baseline	5% Modal Demand Adjustment	15% Modal Demand Adjustment
Crossing	0.17	0.16	0.09
Rear-End	0.54	0.53	0.45
Lane-Change	0.14	0.13	0.12
Total	0.85	0.83	0.67

With the 5% and 15% modal demand adjustments to the vehicles and bike volumes, the model experiences a decrease in each type of conflict and the total conflicts. From the existing baseline (with no demand adjustments) to the 15% shift in modal demand, there was a 21% decrease in total conflicts and a 47% decrease in crossing conflicts. With the adjustment to the traffic volumes, it can be expected that there would be fewer interactions between automobiles and between automobiles and bicyclists, resulting in a larger reduction in crossing conflicts.

6.3. Safety Evaluation of The Proposed Condition

Table 16 compares the number of conflicts per vehicle for the proposed network at each of the three demand scenarios. A complete list of SSAM results can be found in Appendix D.

Table 16. Proposed Condition SSAM Results

Average Number of Conflicts Per Vehicle by Type			
	Proposed Baseline	5% Modal Demand Adjustment	15% Modal Demand Adjustment
Crossing	0.15	0.14	0.12
Rear-End	0.50	0.49	0.47
Lane-Change	0.13	0.13	0.12
Total	0.78	0.76	0.71

For the proposed network baseline, results show (See Table 16) that the number of conflicts per vehicle is lower than the existing network baseline (See Table 15). The decrease in conflicts at baseline demand for the Proposed Network conditions likely results from a more connected bike network and the separation of vehicles traveling at different speeds. Similar to the existing condition scenarios, the biggest change lies within the crossing and total conflicts. Comparing the proposed baseline scenario and the 15% modal demand adjustment scenario, crossing conflicts decreased by 20%, while the total conflicts decreased by 8%.

6.4. Safety Effect on The Alternative Condition

Table 17 compares the number of conflicts per vehicle for the alternative network at each of the three demand scenarios. A complete list of SSAM results can be found in Appendix D.

Table 17. Alternative Condition SSAM Results

Average Number of Conflicts Per Vehicle by Type			
	Alternative Baseline	5% Modal Demand Adjustment	15% Modal Demand Adjustment
Crossing	0.15	0.14	0.12
Rear-End	0.50	0.49	0.47
Lane-Change	0.13	0.13	0.12
Total	0.78	0.75	0.71

Like the proposed condition scenarios, the biggest change occurs for crossing conflicts. Comparing the alternative baseline scenario and the 15% modal demand adjustment scenario, crossing conflicts decreased by 20%, while the total conflicts decreased by 8%. With a more connected bike network, bicyclists have separated from vehicular traffic; therefore, a greater reduction in crossing conflicts shows the combined influence of a more connected bike network and modal demand shift.

Figure 18 visually compares the total conflicts/vehicle between all conditions and scenarios. It shows that the lower rate of total conflicts in the existing network at 15% modal shift (compared to proposed/alternative conditions) is noteworthy. It is caused primarily by a reduction in automobile-automobile conflicts with significantly fewer automobiles on the roads (due to modal shift) sharing the existing infrastructure (that still has higher automobile capacity). A more complete infrastructure (in alternative and proposed network conditions) leads to capacity reduction for automobiles leading to slightly more automobile-automobile conflicts. Note that this does not mean that a 15% demand adjustment with existing infrastructure is preferred. In fact, as demonstrated in Figure 19, bicycle-automobile conflict increases by 28% in such a scenario which more than offsets this marginal lowering of all conflicts compared to alternative/proposed conditions.

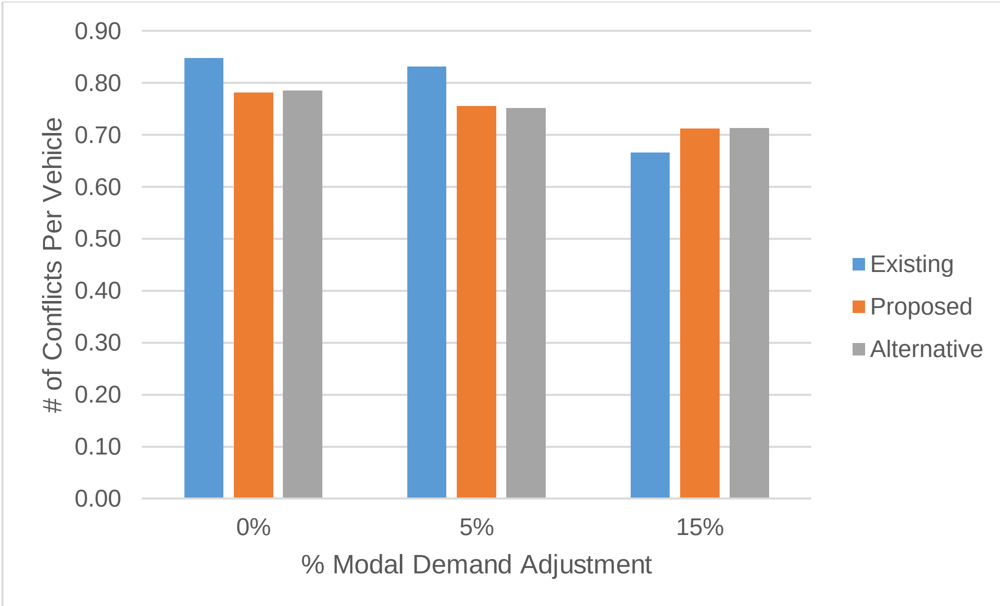


Figure 18. Total Conflicts Comparison Between al Conditions

The next step of analysis involved estimating the conflicts specifically involving bicycles in the network. The estimated number of total conflicts involving bicyclists are shown in Figure 19. These estimates are based on filtering only the conflicts involving vehicles less than 10 ft in length in SSAM 3.0. It may be observed that the complete networks (either the proposed or the alternative) lead to fewer bicycle conflicts than the existing network conditions, regardless of the demand scenario analyzed. However, a critical result from this analysis is based on the demand scenario that involves 15% demand shift from automobiles to bicycles. In such a large demand shift scenario, the existing network will see conflict increase by about 28% (the number of conflicts involving bicycles increases from 908 to 1187). Hence, not only is the modal shift to bicycles unlikely without infrastructure changes based on past research; our research shows such a shift would be undesirable since it would increase bicycle-involved conflicts and present a safety issue.

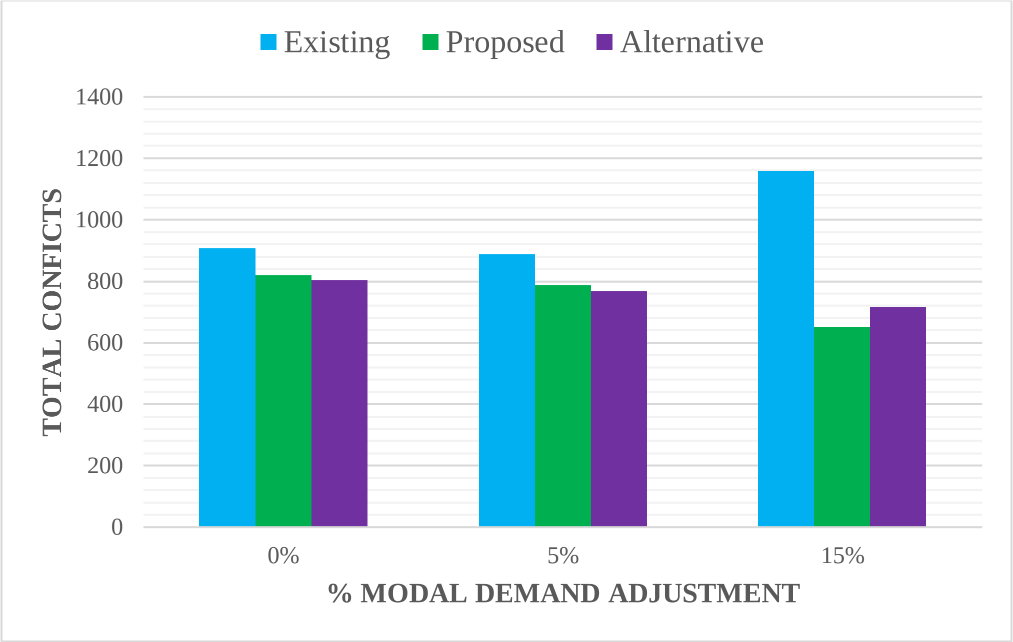


Figure 19: Number of conflicts involving bicyclists

When comparing SSAM results of all conditions and the demand scenarios, a more connected network always resulted in fewer conflicts per vehicle. This may be a result of the more complete bike networks leading to fewer streets working as 'sharrows.' Reduction in sharrows means reduced interaction(s) between relatively faster automobiles and slower bicycles. The complete network conditions (both the Proposed and Alterative) also reduced the number of conflicts involving bicycles. The results also show that if the modal shift of as large as 15% were to occur without accompanying infrastructure changes, it would lead to an increase in bicycle-involved conflicts making such a shift undesirable.

7. 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 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 in terms of biking stress, we ran two thousand trip simulations from the perspective of bike users seeking to minimize biking stress. The simulations were conducted on four types of networks: (1) existing network, (2) planned network, and (3) algorithm-generated 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. Furthermore, the safety performance of the complete network is improved as measured by the number of conflicts. The simulation provides evidence of no meaningful increase in automobile delays during peak hours for the two network conditions with more segregated bicycle infrastructure.

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.

References

1. Akar, G., & Clifton, K. J. (2009). Influence of individual perceptions and bicycle infrastructure on decision to bike. *Transportation research record*, *2140*(1), 165-172.

2. Aldred, R., & Dales, J. (2017). Diversifying and normalising cycling in London, UK: An exploratory study on the influence of infrastructure. *Journal of Transport & Health*, *4*, 348-362.

3. Clark, C., Mokhtarian, P., Circella, G., & Watkins, K. (2019). User preferences for bicycle infrastructure in communities with emerging cycling cultures. *Transportation research record*, *2673*(12), 89-102.

4. Dill, J., & Voros, K. (2007). Factors affecting bicycling demand: initial survey findings from the Portland, Oregon, region. *Transportation Research Record*, *2031*(1), 9-17.

5. Garrard, J., Rose, G., & Lo, S. K. (2008). Promoting transportation cycling for women: the role of bicycle infrastructure. *Preventive medicine*, *46*(1), 55-59.

6. Moudon, A. V., Lee, C., Cheadle, A. D., Collier, C. W., Johnson, D., Schmid, T. L., & Weather, R. D. (2005). Cycling and the built environment, a US perspective. *Transportation Research Part D: Transport and Environment*, *10*(3), 245-261.

7. Aziz, H. A., Nagle, N. N., Morton, A. M., Hilliard, M. R., White, D. A., & Stewart, R. N. (2018). Exploring the impact of walk–bike infrastructure, safety perception, and built-environment on active transportation mode choice: a random parameter model using New York City commuter data. *Transportation*, *45*(5), 1207-1229.

8. Buehler, R., & Pucher, J. (2012). Cycling to work in 90 large American cities: new evidence on the role of bike paths and lanes. Transportation, 39(2), 409-432.

9. National Association of City Transportation Officials. (2016). *Equitable Bike Share Means Building Better Places for People to Ride* (Nacto Bike Share Equity Practitioners' Paper #3). https://nacto.org/wp-content/uploads/2016/07/NACTO_Equitable_Bikeshare_Means_Bike_Lanes.pdf

10. Pedroso, F. E., Angriman, F., Bellows, A. L., & Taylor, K. (2016). Bicycle use and cyclist safety following Boston's bicycle infrastructure expansion, 2009–2012. *American journal of public health*, *106*(12), 2171-2177.

11. Schoner, J. E., & Levinson, D. M. (2014). The missing link: Bicycle infrastructure networks and ridership in 74 US cities. *Transportation*, *41*(6), 1187-1204.

12. Zahabi, S. A. H., Chang, A., Miranda-Moreno, L. F., & Patterson, Z. (2016). Exploring the link between the neighborhood typologies, bicycle infrastructure and commuting cycling over time and the potential impact on commuter GHG emissions. *Transportation research part D: transport and environment*, *47*, 89-103.

13. McCann, B. & Rynne, S. (2010). *Complete streets: best policy and implementation practices*. American Planning Association.

14. Kingsbury, K. T., Lowry, M. B., & Dixon, M. P. (2011). What makes a "complete street" complete? A robust definition, given context and public input. *Transportation research record*, *2245*(1), 103-110.

15. Sousa, L. R., & Rosales, J. (2010). Contextually complete streets. In *Green Streets and Highways 2010: An Interactive Conference on the State of the Art and How to Achieve Sustainable Outcomes* (pp. 94-106).

16. Litman, T. (2014). *Evaluating complete streets: The value of designing roads for diverse modes, users and activities*. Victoria Transport Policy Institute.

17. Atlanta Regional Commission. (2019). *Regional workbook for complete streets*. https://cdn.atlantaregional.org/wp-content/uploads/arc-complete-streets-workbook-webview.pdf

18. Shu, S., Quiros, D. C., Wang, R., & Zhu, Y. (2014). Changes of street use and on-road air quality before and after complete street retrofit: An exploratory case study in Santa Monica, California. *Transportation Research Part D: Transport and Environment*, *32*, 387-396.

19. King, M. R., Carnegie, J. A., & Ewing, R. (2003). Pedestrian safety through a raised median and redesigned intersections. *Transportation research record*, *1828*(1), 56-66.

20. Pawlovich, M. D., Li, W., Carriquiry, A., & Welch, T. (2006). Iowa's experience with road diet measures: use of Bayesian approach to assess impacts on crash frequencies and crash rates. *Transportation research record*, *1953*(1), 163-171.

21. Brown, B. B., Werner, C. M., Tribby, C. P., Miller, H. J., & Smith, K. R. (2015). Transit use, physical activity, and body mass index changes: objective measures associated with complete street light-rail construction. *American journal of public health*, *105*(7), 1468-1474.

22. Brown, B. B., Smith, K. R., Tharp, D., Werner, C. M., Tribby, C. P., Miller, H. J., & Jensen, W. (2016). A complete street intervention for walking to transit, nontransit walking, and bicycling: a quasi-experimental demonstration of increased use. *Journal of physical activity and health*, *13*(11), 1210-1219.

23. Jensen, W. A., Brown, B. B., Smith, K. R., Brewer, S. C., Amburgey, J. W., & McIff, B. (2017). Active transportation on a complete street: perceived and audited walkability correlates. *International journal of environmental research and public health*, *14*(9), 1014.

24. Carter, P., Martin, F., Núñez, M., Peters, S., Raykin, L., Salinas, J., & Milam, R. (2013). Complete enough for Complete Streets? Sensitivity testing of multimodal level of service in the highway capacity manual. *Transportation research record*, *2395*(1), 31-40.

25. Elias, A. (2011). Automobile-oriented or complete street? Pedestrian and bicycle level of service in the new multimodal paradigm. *Transportation research record*, *2257*(1), 80-86.

26. Rybarczyk, G., & Wu, C. (2010). Bicycle facility planning using GIS and multi-criteria decision analysis. *Applied Geography*, *30*(2), 282-293.

27. McCahill, C., & Garrick, N. W. (2008). The applicability of space syntax to bicycle facility planning. *Transportation Research Record*, *2074*(1), 46-51.

28. Zuo, T., & Wei, H. (2019). Bikeway prioritization to increase bicycle network connectivity and bicycle-transit connection: A multi-criteria decision analysis approach. *Transportation research part A: policy and practice*, *129*, 52-71.

29. Lowry, M. B., Furth, P., & Hadden-Loh, T. (2016). Prioritizing new bicycle facilities to improve low-stress network connectivity. *Transportation Research Part A: Policy and Practice*, *86*, 124-140.

30. Kent, M., & Karner, A. (2018). *Prioritizing Low-Stress and Equitable Bicycle Infrastructure Using a Novel Accessibility Measure* (No. 18-01492).

31. Natera, L., Battiston, F., Iñiguez, G., & Szell, M. (2019). Data-driven strategies for optimal bicycle network growth. *arXiv preprint arXiv:1907.07080*.

32. Hsu, T. P., & Lin, Y. T. (2011). A model for planning a bicycle network with multi-criteria suitability evaluation using GIS. *WIT Transactions on Ecology and the Environment*, *148*, 243-252.

33. Guerreiro, T. D. C. M., Kirner Providelo, J., Pitombo, C. S., Antonio Rodrigues Ramos, R., & Rodrigues da Silva, A. N. (2018). Data-mining, GIS and multicriteria analysis in a comprehensive method for bicycle network planning and design. *International journal of sustainable transportation*, *12*(3), 179-191.

34. Mauttone, A., Mercadante, G., Rabaza, M., & Toledo, F. (2017). Bicycle network design: model and solution algorithm. *Transportation research procedia*, *27*, 969-976.

35. Zhu, S., & Zhu, F. (2019). Multi-objective bike-way network design problem with space–time accessibility constraint. *Transportation*, 1-25.

36. Duthie, J., & Unnikrishnan, A. (2014). Optimization framework for bicycle network design. *Journal of Transportation engineering*, *140*(7), 04014028.

37. Mesbah, M., Thompson, R., & Moridpour, S. (2012). Bilevel optimization approach to design of network of bike lanes. *Transportation research record*, *2284*(1), 21-28.

38. Caggiani, L., Camporeale, R., Binetti, M., & Ottomanelli, M. (2019). An urban bikeway network design model for inclusive and equitable transport policies. *Transportation research procedia*, *37*, 59-66.

39. Jha, M., Gopalan, G., Garms, A., Mahanti, B. P., Toledo, T., & Ben-Akiva, M. E. (2004). Development and calibration of a large-scale microscopic traffic simulation model. *Transportation Research Record*, 1876(1), 121-131.

40. Bartin, B., Ozbay, K., Gao, J., & Kurkcu, A. (2018). Calibration and validation of large-scale traffic simulation networks: a case study. *Procedia computer science*, 130, 844-849.

41. U.S. Department of Transportation Federal Highway Administration. (2022, December 16). *Surrogate Safety Assessment Model Overview*. https://highways.dot.gov/research/safety/ssam/surrogate-safety-assessment-model-overview

42. Gettman, D., & Head, L. (2003). Surrogate safety measures from traffic simulation models. *Transportation Research Record*, *1840*(1), 104-115.

43. Lemcke, D., Riffle, K., Russo, B. J., & Smaglik, E. J. (2021). *Examining the Use of Microsimulation Modeling to Assess Bicycle-Vehicle Conflicts at Intersections: A Case Study Incorporating Field-Observed Conflict Data* (No. TRBAM-21-03286).

44. Preston, A., & Pulugurtha, S. S. (2021). Simulating and assessing the effect of a protected intersection design for bicyclists on traffic operational performance and safety. *Transportation research interdisciplinary perspectives*, *9*, 100329.

45. Muley, D., Ghanim, M., & Kharbeche, M. (2018). Prediction of traffic conflicts at signalized intersections using SSAM. *Procedia computer science*, *130*, 255-262.

46. Vasconcelos, L., Neto, L., Seco, Á. M., & Silva, A. B. (2014). Validation of the surrogate safety assessment model for assessment of intersection safety. *Transportation Research Record*, *2432*(1), 1-9.

47. American planning association. (2019). *Planning for Equity Policy Guide*. https://planning-org-uploaded-media.s3.amazonaws.com/publication/download_pdf/Planning-for-Equity-Policy-Guide-rev.pdf

48. Hood, J., Sall, E., Charlton, B., 2011. A GPS-based bicycle route choice model for San Francisco, California. Transportation letters, 3(1), 63-75.

49. Broach, J., Dill, J., Gliebe, J., 2012. Where do cyclists ride? A route choice model developed with revealed preference GPS data. Transportation Research Part A: Policy and Practice, 46(10), 1730-1740.

50. Winters, M., Davidson, G., Kao, D., & Teschke, K. (2011). Motivators and deterrents of bicycling: comparing influences on decisions to ride. *Transportation*, *38*(1), 153-168.

51. Bearn, C., Mingus, C., & Watkins, K. (2018). An adaption of the level of traffic stress based on evidence from the literature and widely available data. *Research in Transportation Business & Management*, *29*, 50-62.

52. Martens, K. (2004). The bicycle as a feedering mode: experiences from three European countries. *Transportation Research Part D: Transport and Environment*, *9*(4), 281-294.

53. City of Atlanta Department of City Planning. (2018). *City of Atlanta 2018 Annual Bicycle Report.*

54. Midtown Alliance. (2022 December 16). *5th Street Complete Street*. https://www.midtownatl.com/project/5th-street-complete-street

55. AASHTO. (2012). Guide for Development of Bicycles Facilities 4th Edition.

56. Azevedo, C. L., Ciuffo, B., Cardoso, J. L., & Ben-Akiva, M. E. (2015). Dealing with uncertainty in detailed calibration of traffic simulation models for safety assessment. *Transportation research part C: emerging technologies*, 58, 395-412.

57. VISSIM 2021 User Manual. (2021). PTV Group.

58. Fries, R., Qi, Y., & Leight, S. (2017). How many times should I run the Model? Performance Measure Specific Findings from VISSIM models in Missouri (No. 17-00470).

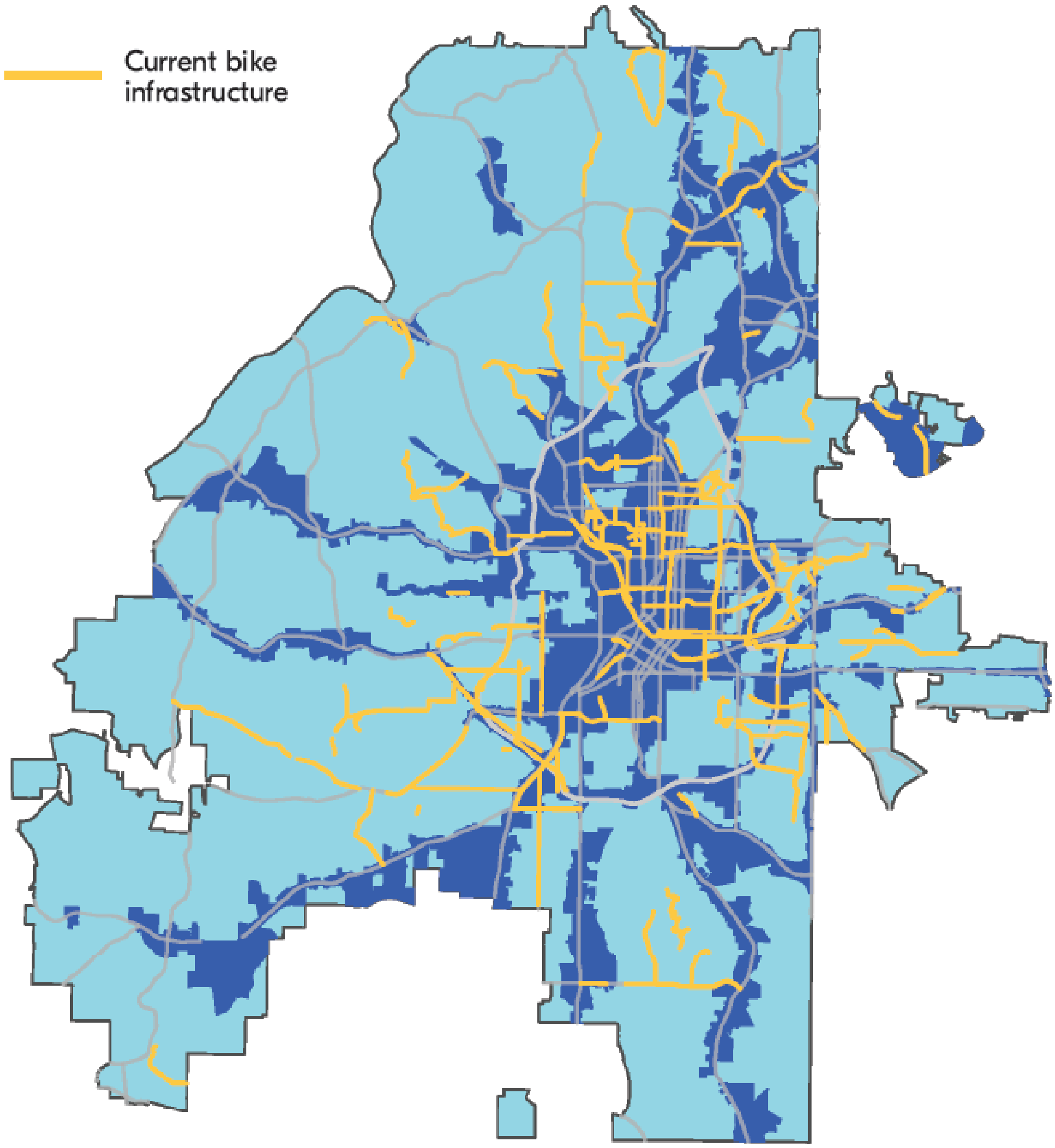
59. MDOT. (2017). *VISSIM Modeling Guidance.*

60. Preston, A., & Pulugurtha, S. S. (2021). Simulating and assessing the effect of a protected intersection design for bicyclists on traffic operational performance and safety. *Transportation research interdisciplinary perspectives*, 9, 100329.

61. Allen, B. L., Shin, B. T., & Cooper, P. J. (1978). Analysis of traffic conflicts and collisions (No. HS-025 846).

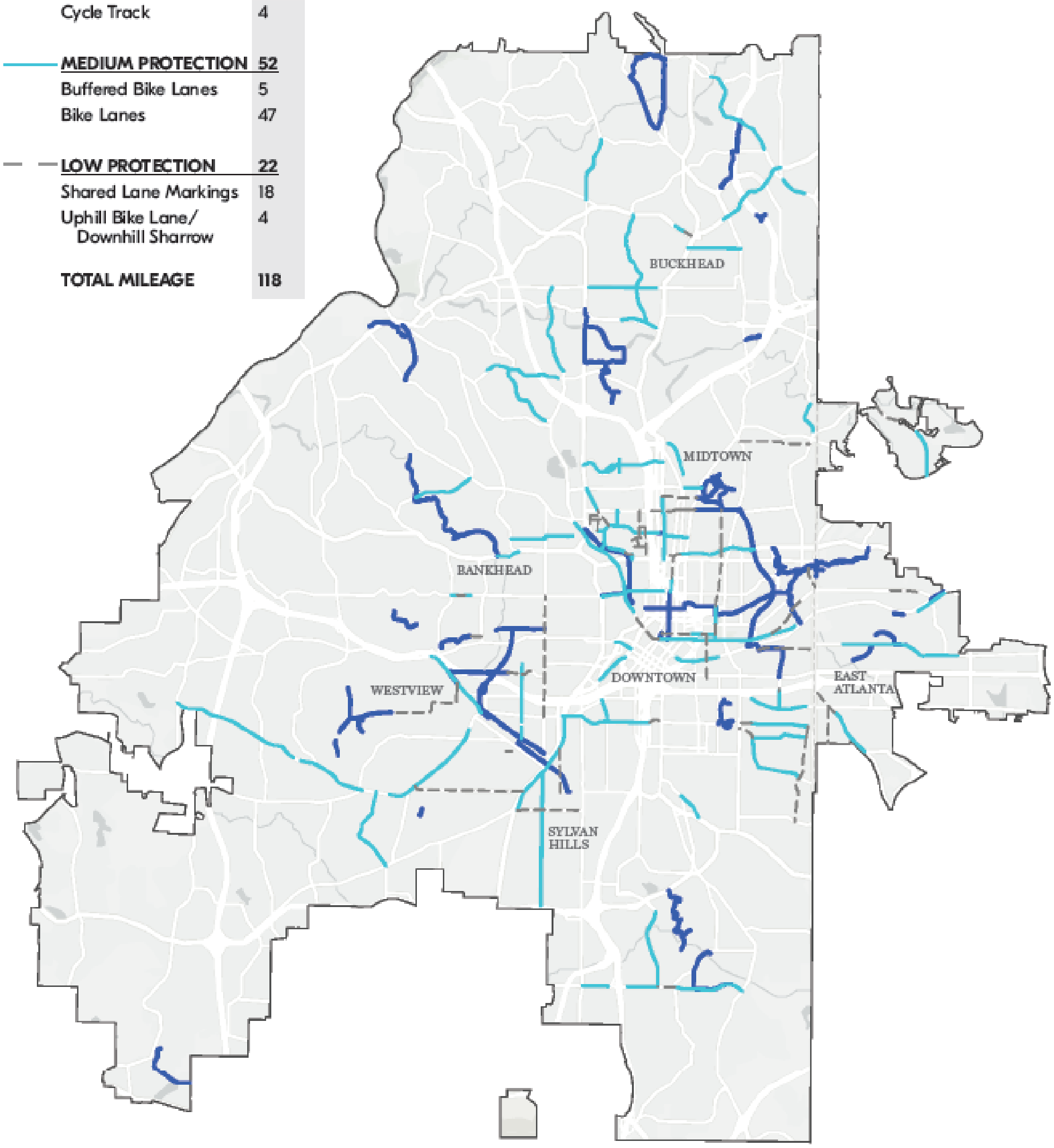
62. Wu, J., Radwan, E., & Abou-Senna, H. (2018). Determination if VISSIM and SSAM could estimate pedestrian-vehicle conflicts at signalized intersections. *Journal of Transportation Safety & Security*, 10(6), 572-585.

Appendix A: Current City Bike Network



Current City Bike Infrastructure Map

HIGH PROTECTION	**44**
Multi-Use Path	40
Cycle Track	4
MEDIUM PROTECTION	**52**
Buffered Bike Lanes	5
Bike Lanes	47
LOW PROTECTION	**22**
Shared Lane Markings	18
Uphill Bike Lane/ Downhill Sharrow	4
TOTAL MILEAGE	**118**



Appendix B: Locations for Travel and Delay Time Measurements

Street Name	From	To	Direction
North Ave	Marietta St	Nutting St	EB/WB
Linden Ave	William St	Willow St	EB/WB
Marrietta Ave	Luckie St	William St	EB/WB
Pine St	Luckie St	COP Dr	EB/WB
Pine St	Spring St	Felton Dr	EB/WB
Currier St	Courtland St	Piedmont Ave	EB/WB
Joseph E Boone Blvd/ Ralph McGill Blvd	Maple St	Felton Dr	EB/WB
West Peachtree Pl	COP Dr	Peachtree St	EB/WB
Simpson St	COP Dr	Peachtree St	EB/WB
Baker St	Marietta St	COP Dr	EB/WB
Baker St/Highland Ave	Piedmont Ave	Jackson St	EB/WB
Baker St	Piedmont Ave	COP Dr	WB
JBP/Harris St	COP Dr	Piedmont Ave	EB/WB
AYI Blvd	COP Dr	William St	EB/WB
AYI Blvd	John Lewis Freedom Pkwy	William St	WB
Ellis St	Carnegie Way	Peachtree St	EB/WB
Ellis St	Peachtree St	John Lewis Freedom Pwky	EB
JWD Ave/Irwin St	Park Pl	Hillard St	EB/WB
Luckie St/Auburn Ave	COP Dr	Boulevard NE	EB/WB
Edgewood Dr	Peachtree St	Boulevard NE	EB/WB
Decatur St	Edgewood Sr	Jackson St	EB/WB
Mitchell St/Capitol Square	Jondelle Johnson Dr	Capitol Ave	EB/WB
Jesse Hill Dr	Capitol Ave	Gilmer St	NB/SB
Gilmer St	Peachtree Center Ave	Jesse Hill Dr	EB/WB
Mitchell St/MLK Jr Dr	Jondelle Johnson Dr	Fort St	EB/WB
Memorial Dr	Ted Turner Dr	Martin St	EB/WB
Marietta St	Ivan Allen Jr Blvd	Edgewood Dr	NB/SB
Peters St	Walker St	Ted Turner Dr	NB/SB
Walker St/COP Dr	Peters St	Marietta St	NB/SB
COP Dr	West Peachtree Pl	Marietta St	SB
COP Dr	West Peachtree Pl	North Ave	NB/SB
Whitehall St	McDaniel St	Forsyth St	NB/SB
Windsor St/Ted Turner Dr	Eugenia St	MLK Jr Dr	NB/SB

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Ted Turner Dr	MLK Jr Dr	Ivan Allen Jr Blvd	NB
Spring St	Ivan Allen Jr Blvd	West Peachtree St	NB
West Peachtree St	Pine St	Ponce de Leon Ave	NB
West Peachtree St	Pine St	Peachtree St	NB/SB
Peachtree St	Ponce de Leon Ave	Memorial Dr	NB/SB
Forsyth St	Carnegie Way	Memorial Dr	NB/SB
Park Pl/Pryor St	Auburn Ave	Memorial Dr	SB
Central Ave/Peachtree Center	Memorial Dr	Peachtree St	NB
Juniper St/Courtland St/Washington St	Ponce de Leon Ave	Memorial Dr	SB
Argonne Ave/Central Park Pl	Ponce de Leon Ave	Baker St	NB/SB
Tech Pkwy/Luckie St	North Ave	Marietta St	NB/SB
Northside Dr	John St	Thurmond St	NB/SB

Appendix C: Network Evaluation Performance Measure

Existing Network; Baseline; Network Level

	Number of Vehicles	Total Travel Time (h)	Total Distance (mi)	Total Delay (h)
Existing Baseline	1,992	12,727	215,772	6,855,910
Seed 1	2,144	14,723	236,571	7,016,752
Seed 4	1,953	12,364	203,526	6,483,034
Seed 7	2,044	12,872	223,283	6,894,441
Seed 10	2,001	11,201	189,768	6,710,521
Seed 13	1,943	13,257	226,326	6,554,902
Seed 16	1,964	12,945	217,911	7,269,951
Seed 19	2,030	13,643	233,863	6,615,969
Seed 22	2,018	13,507	227,076	6,873,162
Seed 25	1,887	10,733	190,511	7,291,700
Seed 28	1,936	12,020	208,883	6,848,669

Existing Network; Baseline; Per Vehicle Level

	Number of Vehicles	Total Travel Time (h)	Total Distance (mi)	Total Delay (h)
Existing Baseline	7.57	252.16	7.62	190.34
Seed 1	7.41	257.28	7.44	195.55
Seed 4	7.86	241.18	7.53	180.36
Seed 7	7.57	253.1	7.73	191
Seed 10	7.66	249.44	7.56	188.91
Seed 13	7.83	241.42	7.36	180.95
Seed 16	7.26	264.19	7.77	201.45
Seed 19	7.75	244.85	7.67	182.92
Seed 22	7.53	252.52	7.56	191.08
Seed 25	7.26	266.05	8.1	200.56
Seed 28	7.54	251.57	7.52	190.61

Existing Network; 5% More Demand; Network Level

	Number of Vehicles	Total Travel Time (h)	Total Distance (mi)	Total Delay (h)
Existing plus 5% Demand	1,931	12,597	217,803	6,418,012
Seed 1	2,078	12,150	208,134	6,278,391
Seed 4	1,904	13,482	223,932	6,133,142
Seed 7	1,958	11,430	206,912	6,379,163
Seed 10	1,924	11,742	197,844	6,367,296
Seed 13	1,879	12,798	218,050	6,514,110
Seed 16	1,924	12,398	209,534	6,694,622
Seed 19	1,957	14,170	240,456	6,243,830
Seed 22	1,948	11,881	209,414	6,437,267
Seed 25	1,823	11,750	206,903	6,675,764
Seed 28	1,915	14,174	256,845	6,456,533

Existing Network; 5% More Demand; Per Vehicle Level

	Number of Vehicles	Total Travel Time (h)	Total Distance (mi)	Total Delay (h)
Existing plus 5% Demand	7.77	243.12	7.43	183.04
Seed 1	7.88	237.31	7.18	178.13
Seed 4	8.02	234.12	7.07	175.05
Seed 7	7.86	241.96	7.6	182.41
Seed 10	7.81	243.05	7.53	182.96
Seed 13	7.67	247.74	7.58	187.29
Seed 16	7.59	249.95	7.81	187.2
Seed 19	7.87	237.97	7.13	179.28
Seed 22	7.75	243.38	7.34	183.5
Seed 25	7.56	251.18	7.85	189.07
Seed 28	7.69	244.58	7.26	185.5

Existing Network; 15% More Demand; Network Level

	Number of Vehicles	**Total Travel Time (h)**	**Total Distance (mi)**	**Total Delay (h)**
Existing plus 15% Demand	1,641	11,138	193,689	4,772,467
Seed 1	1,702	11,236	196,093	4,886,889
Seed 4	1,622	11,211	197,481	4,571,953
Seed 7	1,638	12,359	218,744	4,815,702
Seed 10	1,659	9,309	154,332	4,795,964
Seed 13	1,612	11,186	198,517	4,636,513
Seed 16	1,635	12,191	207,216	4,768,492
Seed 19	1,659	9,926	178,875	4,618,455
Seed 22	1,659	11,104	193,517	4,877,266
Seed 25	1,601	11,437	199,878	4,804,318
Seed 28	1,621	11,414	192,228	4,949,115

Existing Network; 15% More Demand; Per Vehicle Level

	Number of Vehicles	**Total Travel Time (h)**	**Total Distance (mi)**	**Total Delay (h)**
Existing plus 15% Demand	8.18	213.96	6.42	162.33
Seed 1	8.02	218.28	6.31	166.08
Seed 4	8.36	206.38	6.2	156.93
Seed 7	8.18	214.5	6.67	161.75
Seed 10	8.11	217.27	6.61	164.8
Seed 13	8.31	209.29	6.23	159.25
Seed 16	8.25	212.21	6.6	159.88
Seed 19	8.28	208.5	6.27	158.58
Seed 22	8.07	218.66	6.42	166.59
Seed 25	8.18	214.01	6.35	161.94
Seed 28	8.06	220.46	6.54	167.45

Proposed Network; Baseline; Network Level

	Number of Vehicles	Total Travel Time (h)	Total Distance (mi)	Total Delay (h)
Proposed Baseline	2,837	9,434	189,980	6,160,418
Seed 1	2,839	10,179	180,324	6,094,603
Seed 4	2,793	8,884	188,233	5,831,004
Seed 7	2,927	8,714	179,040	6,222,147
Seed 10	2,860	8,640	175,632	6,179,009
Seed 13	2,855	10,076	204,503	6,082,195
Seed 16	2,818	9,919	196,296	6,482,002
Seed 19	2,984	9,707	200,698	5,918,743
Seed 22	2,810	9,397	207,232	6,132,458
Seed 25	2,760	9,023	191,097	6,537,847
Seed 28	2,722	9,803	176,750	6,124,169

Proposed Network; Baseline; Per Vehicle Level

	Number of Vehicles	Total Travel Time (h)	Total Distance (mi)	Total Delay (h)
Proposed Baseline	8.21	222.31	7.12	164.46
Seed 1	8.25	219.85	7.15	162.27
Seed 4	8.51	212.81	6.91	156.43
Seed 7	8.16	225.11	7.15	168.13
Seed 10	8.15	225.02	7.1	168.53
Seed 13	8.31	219.32	7.15	161.58
Seed 16	7.95	230.65	7.28	170.88
Seed 19	8.42	214.8	6.87	157.85
Seed 22	8.26	220.57	7.01	163.34
Seed 25	7.9	234.12	7.43	173
Seed 28	8.22	220.88	7.12	162.62

Proposed Network; 5% More Demand; Network Level

	Number of Vehicles	Total Travel Time (h)	Total Distance (mi)	Total Delay (h)
Proposed plus 5% Demand	2,731	9,324	169,493	5,694,698
Seed 1	2,754	8,757	162,683	5,672,318
Seed 4	2,698	9,159	168,485	5,400,164
Seed 7	2,794	9,432	173,822	5,688,011
Seed 10	2,743	8,972	156,144	5,902,166
Seed 13	2,721	9,265	168,892	5,552,144
Seed 16	2,729	9,361	165,883	5,785,518
Seed 19	2,861	9,724	174,002	5,575,665
Seed 22	2,680	9,505	174,205	5,751,568
Seed 25	2,684	9,009	164,033	5,833,527
Seed 28	2,639	10,051	186,772	5,785,902

Proposed Network; 5% More Demand; Per Vehicle Level

	Number of Vehicles	Total Travel Time (h)	Total Distance (mi)	Total Delay (h)
Proposed plus 5% Demand	8.49	212.52	6.93	156.83
Seed 1	8.48	210.84	6.58	156.79
Seed 4	8.82	203.29	6.66	148.53
Seed 7	8.49	213.22	7.11	158.04
Seed 10	8.24	222.45	6.86	167.28
Seed 13	8.66	207.2	6.92	151.39
Seed 16	8.45	213.56	7.31	156.31
Seed 19	8.56	209.49	6.98	154.02
Seed 22	8.45	213.65	6.76	157.92
Seed 25	8.36	216.24	7.33	158.34
Seed 28	8.34	215.25	6.76	159.69

Proposed Network; 15% More Demand; Network Level

	Number of Vehicles	**Total Travel Time (h)**	**Total Distance (mi)**	**Total Delay (h)**
Proposed plus 15% Demand	2,485	8,926	167,002	4,802,775
Seed 1	2,508	9,453	175,801	4,847,984
Seed 4	2,454	8,978	163,597	4,511,795
Seed 7	2,508	8,619	167,440	5,037,585
Seed 10	2,518	8,349	158,689	4,814,587
Seed 13	2,497	9,393	174,955	4,923,724
Seed 16	2,507	9,233	167,582	4,790,394
Seed 19	2,597	9,027	165,808	4,701,937
Seed 22	2,486	8,895	169,202	4,720,494
Seed 25	2,419	8,368	155,609	4,862,493
Seed 28	2,356	8,950	171,336	4,816,756

Proposed Network; 15% More Demand; Per Vehicle Level

	Number of Vehicles	**Total Travel Time (h)**	**Total Distance (mi)**	**Total Delay (h)**
Proposed plus 15% Demand	9.06	193.82	6.35	142.4
Seed 1	8.97	195.66	6.28	144.31
Seed 4	9.42	183.69	6.08	133.21
Seed 7	8.8	204.29	6.69	152.19
Seed 10	9.04	195.06	6.19	144.42
Seed 13	8.93	197.94	6.14	146.53
Seed 16	9.11	191.68	6.36	139.63
Seed 19	9.15	190.41	6.24	140.29
Seed 22	9.17	189.87	6.32	138.75
Seed 25	9.03	195.44	6.62	142.32
Seed 28	9.01	194.22	6.53	142.38

Alternative Network; Baseline; Network Level

	Number of Vehicles	Total Travel Time (h)	Total Distance (mi)	Total Delay (h)
Alternative Baseline	2,835	9,317	217,965	6,154,968
Seed 1	2,839	10,179	236,571	6,107,839
Seed 4	2,791	8,877	206,267	5,897,642
Seed 7	2,927	8,714	226,024	6,153,857
Seed 10	2,851	9,397	192,509	6,118,717
Seed 13	2,852	8,417	226,326	6,130,245
Seed 16	2,816	9,993	220,652	6,474,060
Seed 19	2,984	9,921	236,604	5,914,109
Seed 22	2,805	9,705	229,818	6,141,208
Seed 25	2,764	9,022	193,252	6,511,867
Seed 28	2,720	9,805	211,624	6,100,133

Alternative Network; Baseline; Per Vehicle Level

	Number of Vehicles	Total Travel Time (h)	Total Distance (mi)	Total Delay (h)
Alternative Baseline	8.22	222.18	7.12	164.21
Seed 1	8.21	220.37	6.94	163.21
Seed 4	8.44	215.27	6.97	158.42
Seed 7	8.23	223.05	7.05	166.07
Seed 10	8.22	222.93	7.13	165.95
Seed 13	8.24	221.61	7.04	163.42
Seed 16	7.97	230.08	7.36	170.32
Seed 19	8.43	214.18	7.06	157.29
Seed 22	8.26	220.84	7.04	163.35
Seed 25	7.93	233.08	7.41	172.08
Seed 28	8.24	220.37	7.22	162.01

Alternative Network; 5% More Demand; Network Level

	Number of Vehicles	Total Travel Time (h)	Total Distance (mi)	Total Delay (h)
Alternative plus 5% Demand	2,729	9,307	169,225	5,687,640
Seed 1	2,754	8,713	161,896	5,634,624
Seed 4	2,698	9,150	168,485	5,415,839
Seed 7	2,794	9,432	173,822	5,687,721
Seed 10	2,741	8,974	156,144	5,900,812
Seed 13	2,717	9,154	167,013	5,561,549
Seed 16	2,727	9,362	165,883	5,812,901
Seed 19	2,861	9,724	174,002	5,583,397
Seed 22	2,671	9,509	174,205	5,668,849
Seed 25	2,686	9,003	164,033	5,833,394
Seed 28	2,638	10,047	186,772	5,777,318

Alternative Network; 5% More Demand; Per Vehicle Level

	Number of Vehicles	Total Travel Time (h)	Total Distance (mi)	Total Delay (h)
Alternative plus 5% Demand	8.48	212.32	6.94	156.8
Seed 1	8.52	209.54	6.62	155.15
Seed 4	8.78	203.81	6.61	149.18
Seed 7	8.49	213.29	7.1	158.11
Seed 10	8.24	222.09	7	166.92
Seed 13	8.64	207.48	6.91	151.99
Seed 16	8.39	214.36	7.15	157.98
Seed 19	8.53	210.15	7.05	154.8
Seed 22	8.53	211.02	6.86	155.51
Seed 25	8.36	216.16	7.33	158.29
Seed 28	8.33	215.3	6.8	160.11

Alternative Network; 15% More Demand; Network Level

	Number of Vehicles	**Total Travel Time (h)**	**Total Distance (mi)**	**Total Delay (h)**
Alternative plus 15% Demand	2,486	8,926	167,002	4,800,348
Seed 1	2,508	9,453	175,801	4,851,905
Seed 4	2,454	8,978	163,597	4,493,245
Seed 7	2,508	8,619	167,440	5,037,520
Seed 10	2,518	8,349	158,689	4,814,579
Seed 13	2,497	9,393	174,955	4,923,869
Seed 16	2,507	9,233	167,582	4,790,410
Seed 19	2,597	9,027	165,808	4,702,068
Seed 22	2,486	8,895	169,202	4,710,415
Seed 25	2,425	8,367	155,609	4,862,650
Seed 28	2,356	8,950	171,336	4,816,824

Alternative Network; 15% More Demand; Per Vehicle Level

	Number of Vehicles	**Total Travel Time (h)**	**Total Distance (mi)**	**Total Delay (h)**
Alternative plus 15% Demand	9.07	193.57	6.34	142.2
Seed 1	8.96	195.7	6.24	144.23
Seed 4	9.45	182.98	6.11	132.7
Seed 7	8.8	204.14	6.69	152.08
Seed 10	9.04	194.92	6.18	144.32
Seed 13	8.93	197.76	6.14	146.4
Seed 16	9.12	191.53	6.36	139.52
Seed 19	9.15	190.22	6.24	140.15
Seed 22	9.2	189.2	6.27	138.17
Seed 25	9.03	195.25	6.61	142.18
Seed 28	9.02	194.02	6.52	142.23

Appendix D: Surrogate Safety Assessment Model

Raw Data; Existing Network

		Crossing	Rear-End	Lane-Change	Average	Total
Existing Baseline	Seed 1	4,962	14,448	3,743	7,718	23,153
	Seed 4	4,316	14,173	3,520	7,336	22,009
	Seed 7	4,345	14,548	3,715	7,536	22,608
	Seed 10	4,501	13,804	3,600	7,302	21,905
	Seed 13	4,371	14,034	3,646	7,350	22,051
	Seed 16	4,796	15,188	3,978	7,987	23,962
	Seed 19	4,459	14,410	3,881	7,583	22,750
	Seed 22	4,450	14,638	3,734	7,607	22,822
	Seed 25	4,700	15,237	4,123	8,020	24,060
	Seed 28	4,567	14,287	3,830	7,561	22,684
Existing plus 5% Demand	Seed 1	4,413	13,286	3,532	7,077	21,231
	Seed 4	3,820	13,427	3,205	6,817	20,452
	Seed 7	4,091	13,888	3,378	7,119	21,357
	Seed 10	4,279	13,251	3,476	7,002	21,006
	Seed 13	3,969	13,627	3,267	6,954	20,863
	Seed 16	4,223	14,393	3,584	7,400	22,200
	Seed 19	4,329	13,496	3,453	7,093	21,278
	Seed 22	4,084	13,642	3,641	7,122	21,367
	Seed 25	4,185	14,217	3,590	7,331	21,992
	Seed 28	4,227	13,402	3,383	7,004	21,012
Existing plus 15% Demand	Seed 1	2,310	10,428	2,819	5,186	15,557
	Seed 4	2,014	9,619	2,606	4,746	14,239
	Seed 7	2,254	10,405	2,788	5,149	15,447
	Seed 10	1,994	10,234	2,884	5,037	15,112
	Seed 13	1,952	9,760	2,410	4,707	14,122
	Seed 16	2,093	10,539	2,834	5,155	15,466
	Seed 19	1,806	9,745	2,567	4,706	14,118
	Seed 22	1,811	10,249	2,834	4,965	14,894
	Seed 25	2,071	10,386	2,867	5,108	15,324
	Seed 28	2,045	10,654	2,875	5,191	15,574

Average Number of Conflicts Per Vehicle by Type; Existing Network

		Crossing	Rear-End	Lane-Change	Average	Total
Existing Baseline	Seed 1	0.18	0.54	0.14	0.29	0.86
	Seed 4	0.16	0.53	0.13	0.27	0.82
	Seed 7	0.16	0.54	0.14	0.28	0.84
	Seed 10	0.17	0.51	0.13	0.27	0.81
	Seed 13	0.16	0.52	0.14	0.27	0.82
	Seed 16	0.18	0.56	0.15	0.3	0.89
	Seed 19	0.17	0.54	0.14	0.28	0.85
	Seed 22	0.17	0.54	0.14	0.28	0.85
	Seed 25	0.17	0.57	0.15	0.3	0.89
	Seed 28	0.17	0.53	0.14	0.28	0.84
Existing plus 5% Demand	Seed 1	0.17	0.52	0.14	0.28	0.83
	Seed 4	0.15	0.52	0.13	0.27	0.8
	Seed 7	0.16	0.54	0.13	0.28	0.83
	Seed 10	0.17	0.52	0.14	0.27	0.82
	Seed 13	0.15	0.53	0.13	0.27	0.81
	Seed 16	0.16	0.56	0.14	0.29	0.87
	Seed 19	0.17	0.53	0.13	0.28	0.83
	Seed 22	0.16	0.53	0.14	0.28	0.83
	Seed 25	0.16	0.56	0.14	0.29	0.86
	Seed 28	0.17	0.52	0.13	0.27	0.82
Existing plus 15% Demand	Seed 1	0.1	0.46	0.13	0.23	0.69
	Seed 4	0.09	0.43	0.12	0.21	0.63
	Seed 7	0.1	0.46	0.12	0.23	0.69
	Seed 10	0.09	0.45	0.13	0.22	0.67
	Seed 13	0.09	0.43	0.11	0.21	0.63
	Seed 16	0.09	0.47	0.13	0.23	0.69
	Seed 19	0.08	0.43	0.11	0.21	0.63
	Seed 22	0.08	0.46	0.13	0.22	0.66
	Seed 25	0.09	0.46	0.13	0.23	0.68
	Seed 28	0.09	0.47	0.13	0.23	0.69

Raw Data; Proposed Network

		Crossing	Rear-End	Lane-Change	Average	Total
Proposed Baseline	Seed 1	4,255	13,360	3,429	7,015	21,044
	Seed 4	3,609	13,111	3,232	6,651	19,952
	Seed 7	3,842	13,451	3,564	6,952	20,857
	Seed 10	4,325	12,829	3,399	6,851	20,553
	Seed 13	3,736	13,249	3,378	6,788	20,363
	Seed 16	4,192	14,336	3,727	7,418	22,255
	Seed 19	3,642	13,430	3,356	6,809	20,428
	Seed 22	3,907	13,282	3,623	6,937	20,812
	Seed 25	4,052	14,514	4,193	7,586	22,759
	Seed 28	3,851	13,449	3,787	7,029	21,087
Proposed plus 5% Demand	Seed 1	3,668	12,415	3,279	6,454	19,362
	Seed 4	3,129	12,237	3,074	6,147	18,440
	Seed 7	3,436	12,264	3,460	6,387	19,160
	Seed 10	3,678	12,293	3,023	6,331	18,994
	Seed 13	3,355	12,818	3,113	6,429	19,286
	Seed 16	3,689	12,900	3,434	6,674	20,023
	Seed 19	3,391	12,393	3,282	6,355	19,066
	Seed 22	3,496	12,757	3,638	6,630	19,891
	Seed 25	3,682	12,864	3,272	6,606	19,818
	Seed 28	3,564	12,510	3,356	6,477	19,430
Proposed plus 15% Demand	Seed 1	2,973	10,709	2,661	5,448	16,343
	Seed 4	2,460	10,393	2,271	5,041	15,124
	Seed 7	2,720	10,637	2,927	5,428	16,284
	Seed 10	2,759	10,519	2,649	5,309	15,927
	Seed 13	2,382	10,457	2,501	5,113	15,340
	Seed 16	2,881	10,695	2,585	5,387	16,161
	Seed 19	2,580	10,483	2,596	5,220	15,659
	Seed 22	2,737	10,542	2,763	5,347	16,042
	Seed 25	2,826	11,031	2,807	5,555	16,664
	Seed 28	2,789	10,809	2,907	5,502	16,505

Average Number of Conflicts Per Vehicle by Type; Proposed Network

		Crossing	Rear-End	Lane-Change	Average	Total
Proposed Baseline	Seed 1	0.16	0.5	0.13	0.26	0.78
	Seed 4	0.13	0.49	0.12	0.25	0.74
	Seed 7	0.14	0.5	0.13	0.26	0.77
	Seed 10	0.16	0.48	0.13	0.25	0.76
	Seed 13	0.14	0.49	0.13	0.25	0.76
	Seed 16	0.16	0.53	0.14	0.28	0.83
	Seed 19	0.14	0.5	0.12	0.25	0.76
	Seed 22	0.15	0.49	0.13	0.26	0.77
	Seed 25	0.15	0.54	0.16	0.28	0.85
	Seed 28	0.14	0.5	0.14	0.26	0.78
Proposed plus 5% Demand	Seed 1	0.14	0.48	0.13	0.25	0.76
	Seed 4	0.12	0.48	0.12	0.24	0.72
	Seed 7	0.13	0.48	0.14	0.25	0.75
	Seed 10	0.14	0.48	0.12	0.25	0.74
	Seed 13	0.13	0.5	0.12	0.25	0.75
	Seed 16	0.14	0.5	0.13	0.26	0.78
	Seed 19	0.13	0.48	0.13	0.25	0.74
	Seed 22	0.14	0.5	0.14	0.26	0.78
	Seed 25	0.14	0.5	0.13	0.26	0.77
	Seed 28	0.14	0.49	0.13	0.25	0.76
Proposed plus 15% Demand	Seed 1	0.13	0.48	0.12	0.24	0.73
	Seed 4	0.11	0.46	0.1	0.22	0.67
	Seed 7	0.12	0.47	0.13	0.24	0.72
	Seed 10	0.12	0.47	0.12	0.24	0.71
	Seed 13	0.11	0.46	0.11	0.23	0.68
	Seed 16	0.13	0.48	0.11	0.24	0.72
	Seed 19	0.11	0.47	0.12	0.23	0.7
	Seed 22	0.12	0.47	0.12	0.24	0.71
	Seed 25	0.13	0.49	0.12	0.25	0.74
	Seed 28	0.12	0.48	0.13	0.24	0.73

Raw Data; Alternative Network

		Crossing	Rear-End	Lane-Change	Average	Total
Alternative Baseline	Seed 1	4,068	13,562	3,534	7,055	21,164
	Seed 4	3,674	13,390	3,364	6,809	20,428
	Seed 7	3,871	13,400	3,816	7,029	21,087
	Seed 10	4,371	12,830	3,409	6,870	20,610
	Seed 13	3,746	13,518	3,364	6,876	20,628
	Seed 16	4,210	14,208	3,863	7,427	22,281
	Seed 19	3,671	13,430	3,364	6,822	20,465
	Seed 22	3,906	13,429	3,545	6,960	20,880
	Seed 25	4,075	14,515	4,198	7,596	22,788
	Seed 28	4,028	13,298	3,586	6,971	20,912
Alternative plus 5% Demand	Seed 1	3,746	12,322	3,286	6,451	19,354
	Seed 4	3,189	12,262	3,093	6,181	18,544
	Seed 7	3,444	12,278	3,452	6,391	19,174
	Seed 10	3,650	12,320	3,130	6,367	19,100
	Seed 13	3,365	12,879	3,013	6,419	19,257
	Seed 16	3,724	12,657	3,327	6,569	19,708
	Seed 19	3,288	12,324	3,334	6,315	18,946
	Seed 22	3,504	12,390	3,199	6,364	19,093
	Seed 25	3,689	12,860	3,274	6,608	19,823
	Seed 28	3,528	12,418	3,296	6,414	19,242
Alternative plus 15% Demand	Seed 1	3,004	10,710	2,687	5,467	16,401
	Seed 4	2,427	10,384	2,117	4,976	14,928
	Seed 7	2,756	10,644	2,927	5,442	16,327
	Seed 10	2,804	10,522	2,657	5,328	15,983
	Seed 13	2,438	10,455	2,506	5,133	15,399
	Seed 16	2,936	10,698	2,595	5,410	16,229
	Seed 19	2,619	10,483	2,599	5,234	15,701
	Seed 22	2,815	10,504	2,753	5,357	16,072
	Seed 25	2,871	11,032	2,817	5,573	16,720
	Seed 28	2,853	10,811	2,911	5,525	16,575

Average Number of Conflicts Per Vehicle by Type; Alternative Network

		Crossing	Rear-End	Lane-Change	Average	Total
Alternative Baseline	Seed 1	0.15	0.5	0.13	0.26	0.79
	Seed 4	0.14	0.5	0.12	0.25	0.76
	Seed 7	0.14	0.5	0.14	0.26	0.78
	Seed 10	0.16	0.48	0.13	0.26	0.77
	Seed 13	0.14	0.5	0.12	0.26	0.77
	Seed 16	0.16	0.53	0.14	0.28	0.83
	Seed 19	0.14	0.5	0.12	0.25	0.76
	Seed 22	0.15	0.5	0.13	0.26	0.78
	Seed 25	0.15	0.54	0.16	0.28	0.85
	Seed 28	0.15	0.49	0.13	0.26	0.78
Alternative plus 5% Demand	Seed 1	0.15	0.48	0.13	0.25	0.76
	Seed 4	0.12	0.48	0.12	0.24	0.72
	Seed 7	0.13	0.48	0.13	0.25	0.75
	Seed 10	0.14	0.48	0.12	0.25	0.75
	Seed 13	0.13	0.5	0.12	0.25	0.75
	Seed 16	0.15	0.49	0.13	0.26	0.77
	Seed 19	0.13	0.48	0.13	0.25	0.74
	Seed 22	0.14	0.48	0.12	0.25	0.75
	Seed 25	0.14	0.5	0.13	0.26	0.77
	Seed 28	0.14	0.48	0.13	0.25	0.75
Alternative plus 15% Demand	Seed 1	0.13	0.48	0.12	0.24	0.73
	Seed 4	0.11	0.46	0.09	0.22	0.66
	Seed 7	0.12	0.47	0.13	0.24	0.73
	Seed 10	0.12	0.47	0.12	0.24	0.71
	Seed 13	0.11	0.46	0.11	0.23	0.68
	Seed 16	0.13	0.48	0.12	0.24	0.72
	Seed 19	0.12	0.47	0.12	0.23	0.7
	Seed 22	0.13	0.47	0.12	0.24	0.71
	Seed 25	0.13	0.49	0.13	0.25	0.74
	Seed 28	0.13	0.48	0.13	0.25	0.74

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