EVALUATING BICYCLE NETWORKS: VISUALIZING AND MEASURING LOW-STRESS CONNECTIVITY AND ACCESSIBILITY

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ABSTRACT

Bicycling as a means of transportation has several health, economic, and environmental benefits. And yet, mass cycling has not really taken off in the U.S. Lack of safe, connected bicycle networks in most U.S. cities is one of the biggest reasons for this. Cities have been trying to change this and build well-connected bicycle networks and need tools and methods to evaluate their bicycle networks. These methods should be specific to bicycling since bicycle networks with only the low-stress links are often disconnected and circuitous while auto-centric networks usually offer complete connectivity between origins and destinations.

This research builds on the level of traffic stress (LTS) study and introduces improved ways of measuring the effectiveness of bike networks in connecting origins and destinations. Also proposed are ways to visualize accessibility and connectivity on a map. These methods are useful for planners to compare network improvement scenarios, map accessibility and identify barriers in a network. The proposed methods are demonstrated using case studies from Delaware, Greater Boston, and Arlington County, VA.

A case study in Delaware is used to demonstrate the effectiveness of potential bike-to-work trips as a measure in comparing proposed bicycle route alternatives between Newark and Wilmington. This study showed that more direct alignments offer higher connectivity. It showed that constructing multiple alignments have complementing connectivity gains. A study in Greater Boston showed that one-ways have a strong barrier effect on bicycling. Systematic application of contraflow on local streets showed an average increase in percentage jobs accessible from 1.2% to 8.7%. A technique is also proposed to prioritize streets for contraflow application. New methods for associating origin-destination demand from census blocks to street network are also proposed.

An algorithm is developed to identify barriers in a network and draw them on a map. This method successfully overcame the complex structure of low-stress networks and identified barriers in Boston and Arlington, providing a valuable network planning tool for practitioners. A practical guide to bike network analysis was also written to assist future research. Important lessons learned in conducting this research were also documented for facilitating knowledge transfer.
Bicycling as a means of transportation has several health, economic, and environmental benefits to society. Bicycling offers vast health benefits by reducing the risk of cardiovascular disease and cancer (1). A 2016 study (2) found that the health benefits of bike commuting outweigh the adverse effects of being exposed to air pollution. A study from Copenhagen (3) estimated that the cost to society for traveling by car is six times more than that of bicycle. Bicycling is also environmentally friendly by reducing the greenhouse gas emissions and reliance on fossil fuel. Even with all its positive impacts, mass bicycling has not really taken off in the U.S. According to a 2019 INRIX report (4), 48% of all car trips in U.S. metro areas are less than 3 miles, a reasonable distance to ride a bike. Lack of safe, connected bicycle network is one of the biggest deterrents to bicycling (5, 6, 7, 8).

Most U.S. cities do not have a safe, connected bicycle networks as cities have been designed largely for motor vehicles. However, this has been changing and many cities are trying to build better infrastructure for bicycling. Between 2011 and 2018, the number of protected bike lanes in the U.S. have increased from 78 to 550 and this number keeps rising (9). Building isolated segments of bicycle infrastructure is not the same as developing a well-connected network. To fully realize the potential of mass bicycling, cities need to invest in building bicycle networks that connect people to their destinations. For this, cities need tools to evaluate their bicycle networks to better focus their development strategies. This dissertation presents tools and methods to evaluate bicycle networks to assist practitioners in bicycle network development. In addition to quantifying the effectiveness of bicycle networks in connecting origins to destinations, the methods discussed here are also allow visualizing the results on a map, making them more intuitive for a wide range of audience.

The current work builds on the original level of traffic stress (LTS) study (10) and presents improved methods for low-stress connectivity analysis. The first chapter introduces the background for this area of research and provides an overview of different network evaluation measures and their applicability to bicycle networks. The second
chapter proposes a method to measure network connectivity and evaluate improvement scenarios for their potential contribution towards the overall network. The third chapter identifies the importance of roundtrip connectivity. It proposes a framework for measuring the barrier effect of one-way restrictions and quantifying the benefits of contraflow. It also explains different ways to associate demand from census block data to the street network. These demand association methods have a direct effect on visualization and quantifying the analysis results. Chapter 4 proposes an algorithm to identify and draw the gaps that disconnect a network. This algorithm be used by analysts to locate barriers in a network and map them so that plans can be developed to bridge these barriers. The last chapter is a documentation of the practical aspects of coding bike networks and conducting network analysis.

1.1 LOW-STRESS BICYCLE NETWORK ANALYSIS

If one were to define a bicycle network as a collection of streets where bicycles are legally permitted, then this network is usually well connected since bicycling is allowed on almost all roads (except limited access highways). But, many people feel highly stressed by the prospect of riding a bicycle with fast moving automobiles. After all, bicycles and automobiles are highly mismatched in their mass and speed. It is not fair to say that a street network designed for motor vehicles must also be adequate for bicycle traffic. Thus, a low-stress bicycle network should be defined as a network that is limited to the collection of links that the mainstream population is willing to ride on (10). This can be vastly different from a general street network which contains busy streets without adequate accommodation for bicyclists. Geller (11) classified the adult population into four groups based on their willingness to ride in different road and traffic conditions.

1. Strong and fearless – Willing to ride in any conditions.
2. Enthused and confident – Willing to share the road with cars but would prefer operating in their own space.
3. Interested but concerned – Only willing to ride if they have their own protected space or if car traffic is slow and infrequent.
4. No way, no how – No interest in riding a bike under any conditions.
Geller estimated that less than 10% of the population fall in the first two categories and is willing to ride on most conditions. Dill and McNeil (12) verified the proportions for the four groups using surveys and found that Geller’s estimates were reasonably accurate. A vast majority of the population (over 90%), is only willing to bike when they are separated from stress inducing automobile traffic. Thus, to increase mass bicycling in the mainstream population, it is necessary to develop a network of low-stress bicycling routes connecting people to their destinations. The first step in developing a low-stress network is to systematically classify streets according to their stress level.

1.1.1 Rating Streets for Stress

One of the first measures of bicycle stress is the bicycle safety index rating (BSIR), developed by Davis in 1987 (13). This rating method used traffic, pavement, and location factors to calculate a score indicating the segments suitability for bicycling. Building on Davis’ work, other researchers have developed new rating systems. Sorton and Walsh (14) developed the bicycle stress level method in 1994 which gives streets a score ranging from 1 (least stressful) to 5 (very stressful). Their score is based on three variables – traffic volume, speed, and curb lane width. Turner (15) developed the bicycle suitability score (BSS) for Texas state roadways and used five attributes. Harkey et al. (16) developed bicycle compatibility index (BCI) as part of a FHWA sponsored study.

Bicycle level of service (BLOS) (17) is a method published in the Highway Capacity Manual 2010 (HCM), one of the most ubiquitous publications used by transportation professionals in the country. BLOS, like other methods before it, uses roadway geometric and traffic characteristics to calculate a score which corresponds to a letter grade ranging from A to F. Many of these methods use complex equations which generate a score or rating whose value is not very intuitive or easy to understand. These scores are also not very effective in correlating the different type of cyclists to the type of bicycle facilities.

Furth, Mekuria, and Nixon (FMN, 18) introduced the concept of level of traffic stress (LTS), which they defined as the stress induced by traffic on bicyclists on a street segment. They classified each link into one of four LTS values with 1 being the lowest
and 4 being the highest stress. LTS classification is based on traffic and roadway factors such as presence of bike lane, parking and bike lane width, number of lanes, speed limit, bike lane blockage, etc. In addition to the link stress level, they also proposed stress criteria for crossing at intersections. LTS 1 and 2 links, which are considered low-stress, are suitable for the interested but concerned group. These are also the links that meet the Dutch design guidelines for bike facilities (19) LTS 3 is acceptable to the enthused and confident group, while LTS 4 is only acceptable to the strong and fearless group in Geller’s classification. Examples of the four LTS level streets are shown in Figure 1. While LTS is not the first method to systematically rate streets for their bicycle friendliness, it is currently one of the most widely respected and used methods.

Figure 1: LTS 1 due to protected bike lane (top left); LTS 2 (top right) – Bike lane with single lane of traffic; LTS 3 (bottom left) – Single lane without bike lanes; LTS 4 (bottom right) – Multiple lanes with high traffic volume.
Since the introduction of the LTS framework, other researchers have used variants of the LTS method for network analysis. Lowry et al. (20) used a method to determine stress values of stress creating factors and stress reducing factors. Stress creating factors includes variables such as functional classification, speed limit, and traffic variables. Stress reduction factors are based on bicycle accommodations provided like signed bike routes, sharrows, bike lanes, buffered bike lanes, and protected bike lanes. The stress values calculated are then grouped into categories corresponding to LTS values. Bike Network Analysis (BNA) developed by People for Bikes (21) used a slight variation of the LTS criteria to be compatible with the data available through open street map (OSM) to calculate stress.

The choice of criteria for calculating stress can be made by an analyst based on the intent of the study and data availability. The network analysis methods proposed in this study can be applied with the same effect regardless of the choice of stress criteria. However, none of the methods discussed above appear superior to the LTS criteria. For the rest of this study, unless otherwise stated, low-stress implies LTS 1 or 2. The next step in evaluating bike networks is to quantify the effectiveness of a low-stress network in connecting origins and destinations.

1.1.2 Measuring Connectedness

In general road networks, there is almost always a path connecting two points. This is also the case for transit networks within their coverage area. On the other hand, a low-stress bicycle network that is only limited to low-stress links as defined by FMN may not have connected routes between many points, or when there is a low-stress path between points, that path may have a long detour compared to a general road network. This means that many people cannot get to their destination using only the low-stress network. The degree to which a network enables travel between points can be considered at three levels.
1.1.2.1 Point-to-Point

Two points are connected if there is a low-stress path connecting them. The cost of a path is the sum of costs of all the links forming the path. The cost or weight associated with each link is usually the travel time or the length of the link, but an analyst can define a different weight for the link. While a single point-to-point measure is not effective in evaluating the network, it is a basic operation that contributes to the other two levels of connectedness discussed below.

1.1.2.2 One-to-Many

This is an aggregation of the point-to-point connections over one origin and all the possible destinations. Each origin has a value that corresponds to the definition of accessibility proposed by Hansen (22). This measure when used with mapping show the spatial variation of accessibility across a study area. Lowry et al. (23) used this measure to show destination accessibility for origin zones using different colors. A many-to-one measure also serves the same purpose, but for reverse direction of trips. The formulation of one-to-many measure is given below is dependent on the propensity of a path to the destination and the strength of the destination. In this study, we define propensity as a function of distance and/or detour of the low-stress path as explained later in this chapter.

\[ A_i = \sum_j (p_{ij} \times D_j) \]

\[ A_i = \text{Accessibility from origin } i \text{ as a one-to-many measure} \]

\[ p_{ij} = \text{Propensity of the path between } i \text{ and } j \]

\[ D_j = \text{Strength of destination } j \]
1.1.2.3 Many-to-Many

This is a scalar value that represents the aggregation of point-to-point connections from all origins to all destinations for the low-stress network. This single value representing the entire network is the ‘connectivity’ of the network. The connectivity can be formulated as given below.

\[
C = \sum_i \sum_j \left( p_{ij} * O_i * D_j \right)
\]

\( C \) = Connectivity as a many-to-many measure
\( p_{ij} \) = Propensity of the path between \( i \) and \( j \)
\( O_i \) = Strength of origin \( i \)
\( D_j \) = Strength of destination \( j \)

The connectivity as defined above has a different meaning from the way it is used in graph theory, where connectivity is used to denote the number of nodes with direct connections or the ratio of links to nodes. Other measures such as intersection density and street density have been applied to transportation networks which are predominantly designed to serve automobile traffic (24). Dill (25) attempted to apply some auto-oriented network measures for bicycling and walking in Portland, Oregon. These measures are not effective for evaluating low-stress networks where points are often entirely disconnected.

1.1.2.4 Propensity Accounting for Distance and Detour

The connectivity measures used in chapter 2 use a propensity function that takes a value between 0 and 1 to model the effect of distance and/or detour of a low-stress path. For a trip between two points, a propensity value of 1 indicates that the distance and detour are too small to affect the trip and a propensity value of 0 implies a disconnected trip caused by excessive distance or detour. When it comes to utilitarian bicycling, the number of trips tend to decrease as the distance increases (26, 27). In their San Jose LTS study, FMN only counted trips that are within a given distance threshold. If two points are further than their distance threshold, they are not included in their analysis. Similarly, if the low-stress path is significantly longer than the general network path, then the points are determined to be not connected. The propensity function used by FMN is formulated below.
\[ p_{ij} = \begin{cases} 
1 & \text{if } (L_{ij} \leq L_{\text{max}}) \text{ and } (d_{ij} \leq d_{\text{max}}) \\
0 & \text{otherwise} 
\end{cases} \]

\( L_{ij} \) = length of the low-stress path between i and j
\( L_{\text{max}} \) = maximum trip distance allowed
\( d_{ij} \) = detour for the low-stress path between i and j
\( d_{\text{max}} \) = maximum acceptable detour

This all-or-nothing propensity function makes the results extremely sensitive to the distance and detour limits chosen. For example, if the maximum distance chosen is 6 miles, two points which are 5.9 miles apart would be considered fully connected while points that are 6.1 miles will be considered completely disconnected. To reduce the effect of the maximum distance limit, we used a continuous propensity function that decays exponentially beyond a specific distance. Iacono et al (26) estimated simple exponential decay with distance for bicycle trip distribution. A plot of the propensity function accounting for distance is shown in Figure 2.
In addition to distance, the propensity function also accounted for detour. Human beings being shortest path seekers, have an inherent resistance to taking a certain path if a shorter one is available. However, Broach et al. (28) found that cyclists are willing to travel longer to find a lower stress route. But, if the detour is too high, the route becomes less attractive to cyclists. To account for this, we used a propensity function that decays linearly from 1 to 0 as the detour increases from 33% to 100%. Combining the distance and detour effects gives a propensity function that is shown in Figure 3.

Figure 2: Exponentially decaying propensity function accounting for distance. Propensity for cycling halves for every 3 miles beyond a certain critical distance (4 miles in this plot).
In the study discussed in chapter 2, propensity function combining both distance and detour was used to measure connectivity in Delaware. The study was designed to measure the connectivity of network for different trail development alternatives between Newark and Wilmington. The study objective was to measure potential bike-to-work trips under each trail development scenario. Since people’s willingness to use a bicycle goes down with increase in distance and detour, this propensity model made sense.

1.1.2.5 Propensity Based on Just Detour

In the study presented in chapter 3, connectivity measures were defined using a propensity function that uses only detour. The study analyzed Greater Boston area network in which employment is largely concentrated in the downtown area. Using a distance-based propensity would indicate poor accessibility for areas that are far away from downtown, even when there is a good network of low-stress routes connecting them.
to the major employment centers in downtown. For this reason, we used a propensity that accounts for detour alone in this study. The detour-based propensity used in chapter 3 is given below.

\[
p_{ij} = \begin{cases} 
1.25 \times \left(2 - \frac{D_{Low_{ij}}}{D_{High_{ij}}}\right) & \text{if } D_{Low_{ij}} \leq 1.2 \times D_{High_{ij}} \\
0 & \text{if } 2 \times D_{High_{ij}} < D_{Low_{ij}} \leq 2 \times D_{High_{ij}} \\
& \text{if } D_{Low_{ij}} > 2 \times D_{High_{ij}} 
\end{cases}
\]

\(D_{Low_{ij}} = \text{distance of path } i-j-i \text{ on the low stress network} \)

\(D_{High_{ij}} = \text{distance of path } i-j-i \text{ on the entire network (including high stress links)}\)

This formulation of propensity means that propensity drops linearly from one to zero as detour increases from 1.2 to 2. This measure also used the roundtrip distance for propensity while the earlier definition used only a single direction. Chapter 2 connectivity measure used an undirected network in which an outbound trip distance is the same as return trip distance while chapter 3 used a directed network where the trip distances in both directions are not always equal.

1.1.2.6 Travel on High-Stress Links

In this study, low-stress shortest paths are calculated on a network with all the high-stress links removed. This does not allow any travel on high-stress links even if said high-stress links are short. This is different from Lowry’s model (20) which allows travel on high-stress links for short distances by using a constrained shortest path algorithm. In addition to this, Lowry also used both stress and length to define the cost of links. Another study by Lowry (23) used HCM’s BLOS score to calculate cost of the links. This makes the routing algorithm favor lower stress links but does not limit travel on high-stress links entirely. Lowry’s methods allow travel on high stress links when they are short. For example, if there is a route connecting two points which is almost entirely on low-stress links except for one short block that is high stress, Lowry’s routing method still considers the points as connected without too much added cost while our method considers the points as disconnected.
Lowry’s model might be closer to reality as people might be willing to put up with a short high-stress section to be able to use the rest of the low-stress route. For example, they might use the sidewalk, or walk their bike to avoid riding on a high-stress link. Our choice of not allowing any high-stress travel was made partly for policy reasons where we want our analysis to show all gaps in the network, whether they are big or small so that planners can fix them. It is also not entirely clear if people are willing to tolerate a short high-stress section.

1.2 DISSERTATION OUTLINE

This dissertation has five chapters with the current one being the first chapter, which gives a background and basic concepts in low-stress network analysis of the past work done in the area of bicycle networks. The next three chapters propose methods and measures to visualize and calculate network connectivity and accessibility. Chapters 2, 3 and 4 are peer reviewed papers that are published or accepted for publication. The last chapter discusses the practical aspects of coding bike networks and the lessons learned in performing bike network connectivity analysis.

1.2.1 Using Connectivity to Evaluate Bicycle Route Alternatives (Chapter 2)

DelDOT plans to connect Newark and Wilmington, the two biggest cities in the county by building a new path for bicycle use. They identified four different alignments for the path and wished to see how each of these improvements to the network benefits the overall network. In this study, we use network connectivity as a measure to compare the proposed alignments for how effective they are in improving bicycle commute trips. This paper’s contribution to the literature includes updated LTS criteria, a propensity model for both distance and detour, estimating potential new bike-to-work trips, and ways to compare new route development alternatives.

1.2.1.1 LTS 2.0

LTS 2.0, an update to the original LTS criteria were developed using input from the staff at DelDOT and from Arlington County, Virginia where LTS was being used for
another project at the time. Delaware had roads which are more rural and suburbanized than the ones in San Jose which is where the original LTS criteria were developed. This created a need to modify the original criteria and gave us a chance to write them into a more readable format. The changes in LTS 2.0 and the justification for them are explained in detail in chapter 2.

1.2.1.2 New Propensity Model

This paper also introduced a connectivity measure that incorporated a propensity model accounting for distance and detour. The low-stress connectivity study in San Jose used an all-or-nothing approach for detour compared to the high-stress route. If the detour exceeds a specified value, the OD pair was considered as not connected. In this study, the propensity model used a detour penalty that decays linearly from 1 to 0 as detour factor goes up from 1.33 to 2.0. In addition to detour, the model used an exponential decay for distance to factor into the propensity function. Shorter trips are given higher weight than longer trips in the connectivity calculation since the number of people willing to use a bike goes down as the distance of the trip increases. The reasoning behind the distance and detour-based propensity is explained in detail in the next chapter.

1.2.1.3 Evaluating Scenarios Using Connectivity Measures

The analysis used commuting trips to work to evaluate the network. The work started by combining data from multiple sources and data clean up so that each link may be classified based on stress level according to LTS 2.0 criteria. The next steps involved synthesizing the OD data (population-jobs) obtained from census bureau and calculating the connectivity measures. Two connectivity measures were proposed to evaluate the network and proposed improvements.

1. Average number of bike-accessible jobs at a given LTS level
2. Potential bike-to-work trips

Both the proposed measures are scalars for the entire network. The number of bike-accessible jobs are measured as a weighted average of the accessibility for all origins in the study area. This value is first calculated for the base network consisting of
already existing infrastructure. The alignments for each of the improvements are then added to the base network and the connectivity measures were recalculated for each scenario. The increase in the newly calculated connectivity for each scenario when compared to the base network show the net added network connectivity gain. The potential bike-to-work trips that each of the scenarios might add are then estimated using a proportionality factor and the average number of bike-accessible jobs. The increase in the connectivity is compared for all the scenarios at different LTS levels. This project demonstrated how low-stress connectivity can be quantified and used to evaluate alternatives, providing decision makers with a valuable tool for scenario analysis.

1.2.2 Effect of One-Ways and Contraflow on Bicycle Networks (Chapter 3)

San Jose study and Delaware study analyzed connectivity using an undirected network, that is, every segment allows travel in both directions. In reality, most one-way streets do not allow bicycles to travel in both directions. In another low-stress connectivity analysis for Seattle, conducted by Lowry et al. (20), the researchers accounted for one-ways. However, they only considered travel in one trip direction, and not the return trip direction. The Bike Network Analysis (BNA) tool developed by People for Bikes (21) is an open source tool used for connectivity analysis. BNA also does not account for roundtrip connectivity. The research presented in chapter 3 explores the barrier effect of one-way restrictions on connectivity and accessibility.

This paper explores the negative effect of one-way direction restrictions on low-stress bike networks. It points out the difference in the connectivity with and without consideration for both directions of trips. Network benefits of contraflow were also quantified and mapped using Greater Boston network case study. The paper also proposes different methods to associated block level demand data to street network. In addition to measuring connectivity, these demand association methods are also useful for mapping accessibility. A prioritizing method is proposed to apply contraflow incrementally for maximizing the marginal gains in connectivity.
1.2.2.1 One-way vs Roundtrip Connectivity

Using Greater Boston area street network, the study demonstrated the stark difference in connectivity and accessibility between one direction and roundtrip. It introduces a framework for incorporating one-way direction restrictions using GIS and measuring roundtrip connectivity. It was observed that roundtrip connectivity is much less than that of either directions connectivity in Greater Boston. The accessibility difference for roundtrip vs one direction was also observed to have a high spatial variability with some locations seeing highly disproportional drop in accessibility when roundtrips are considered.

1.2.2.2 Demand Association Methods

OD data like population and employment is typically obtained in polygon format (census blocks), whereas street networks are in the form of lines. Four different ways of associating the demand data to street network are proposed. The OD demand association methods have a direct bearing on the connectivity analysis. The pros and cons of each of the proposed methods are explained in detail in chapter 3. The effect of these methods on connectivity analysis results are discussed. These new demand association methods also provide an improved way of mapping accessibility.

1.2.2.3 Network Benefits of Contraflow

While contraflow design guidance is provided by both NACTO (29) and AASHTO (30), the number of contraflow applications in the US is very small compared to European countries like Belgium, Netherlands, and France. This study stresses the importance of contraflow to bike network by measuring gains in connectivity when contraflow is systematically applied to all the local streets. The study also considered a dense network proposed by the Boston Cyclists Union called Bikeways for Everybody (BforE). The connectivity gains due to contraflow were significant for both the sparse network (current) and the well-connected network (BforE). This suggests that contraflow is crucial even for a relatively well-connected network.
1.2.2.4 Prioritizing Contraflow

While systematic application of contraflow on local streets is desired, we recognize that cities would be hesitant to adopt it. To provide them with a mechanism to identify key streets for contraflow, a method to prioritize contraflow improvements is proposed based on weighted link centrality. This method enables measuring marginal gains in connectivity as additional contraflow is added to the network. The results from Boston suggest that strategic implementation contraflow on a small number of critical streets can achieve significant gains. This method also highlights the importance of contraflow in designing neighborways (bike boulevards).

1.2.3 Identifying and Visualizing Barriers on a Map (Chapter 4)

The previous two chapters dealt with measuring connectivity and accessibility in low-stress bike networks. This chapter proposes a method to identify and visualize barriers in a network. Our past studies have clearly showed that low-stress bike networks often have gaps (barriers) that disconnect the network or create a large detour that is not acceptable to most riders. There are no methods out there that can systematically identify and draw these barriers. FMN used the idea of connectivity islands in their San Jose study but this way of mapping islands is not effective for certain types of networks. In one of our analyses for Boston, we set about drawing lines that highlight the gaps in the network. These barrier lines were drawn manually, and the results can be seen in Figure 4.
The process of manually drawing barriers was tedious and the results vary based on who is drawing the lines. We developed an algorithmic method that can systematically draw barriers using concepts from GIS, geometric analysis, and graph theory. This algorithm was tested on the low-stress networks of Boston and Arlington County. The results not only successfully identified and highlighted the barriers on a map, we also demonstrated that this can be useful in identifying critical low-stress links that breached what would have been significantly larger barriers. This method for drawing barriers is a valuable tool in network planning. Practitioners can use this method to identify both obvious and not so obvious barriers irrespective of the complexity of the low-stress network.

Figure 4: Manually drawn barriers in the low-stress network. This process is slow, tedious, and the results are not easily replicated.
1.2.4 **Practical Considerations in Evaluating Bicycle Networks (Chapter 5)**

This chapter is essentially a documentation of the bike network coding that was done for the work described in the previous chapters. While several things mentioned in this chapter do not necessarily add to the theoretical knowledge of the field, they are nevertheless important in performing a successful bike network analysis. It explains the basics of GIS as most of the work in this dissertation was heavily dependent on using GIS applications. It assumes a certain level of familiarity from users in working with GIS applications.

It explains the data clean up and preprocessing required for accurate analysis. It also lists some common types of errors expected in the attribute and topology information of GIS data for bicycle networks. Also mentioned in the chapter are systematic fixes and shortcuts that are useful for overcoming some common issues. Chapter 5 also includes an appendix with the data dictionary for all the fields used in LTS calculation and a python code that was used for LTS classification of streets. The intent of this chapter is to assist analysts in performing low-stress network analysis. It can be used by new and experienced researchers to build on current research and advance the field of bicycle network connectivity analysis.
CHAPTER 1 - REFERENCES


   http://peopleforbikes.org/green-lane-project/inventory-protected-bike-lanes/.


2 MEASURING LOW-STRESS CONNECTIVITY IN TERMS OF BIKE-ACCESSIBLE JOBS AND POTENTIAL BIKE-TO-WORK TRIPS: A CASE STUDY EVALUATING ALTERNATIVE BIKE ROUTE ALIGNMENTS IN NORTHERN DELAWARE

ABSTRACT
When road segments with high traffic stress are excluded, the remaining network of low-stress roads and trails can be fragmented, lacking connections between many origin-destination pairs or requiring onerous detour. Low-stress connectivity is a measure of the degree to which origins (for this study, homes) and destinations (jobs) can be connected using only low-stress links and without excessive detour. Revision 2.0 to Level of Traffic Stress criteria is introduced and applied to the road and trail network of northern Delaware. A propensity model is proposed to reflect people’s declining willingness to ride a bike with greater trip length and detour, accounting for the impact to health and other benefits of cycling. New connectivity measures are introduced that can be interpreted as the number of bike-accessible jobs and the potential number of bike-to-work trips, powerful measures for evaluating alternatives. These connectivity measures are applied in a case study evaluating alternative alignments for a bike route between Wilmington and Newark, Delaware’s two largest cities, separated by a distance of about 20 km through a largely suburban landscape. The case study explores the benefits of enhancing alternatives with branches that help connect to population and employment centers. We also find that the connectivity gains from constructing multiple alignments is greater than the sum of connectivity gains from individual alignments, indicating that complementarity between the alternatives, which are spaced roughly 5 km apart, overshadows any competition between them.
2.1 MOTIVATION AND RESEARCH CONTRIBUTION

Like many other transportation agencies, the Delaware Department of Transportation (DelDOT) is actively investing in new bicycling infrastructure, and needs tools for evaluating investments and comparing alternatives. Bicycling facilities can serve both a recreation and a transportation (utilitarian) function, and in urbanized areas, benefits related to transportation use play an especially important role. This paper describes the development of a method for estimating transportation-related benefits of bicycle network improvements in terms of weighted low-stress connectivity:

- “Low stress” means avoiding road segments in which perceived traffic danger is beyond what most people will willingly tolerate. Mekuria, Furth, & Nixon (MFN) (2012) defined four levels of traffic stress (LTS), with levels 1 and 2 considered “low-stress,” i.e., tolerable to the mainstream population. LTS is based on factors such as traffic speed and degree of separation from motor traffic.

- “Low-stress connectivity” is a measure of the degree to which origins and destinations – in this case study, homes and jobs – are connected using low-stress links and without excessive detour (MFN; Furth, Mekuria, Nixon, 2016). Often, when high-stress links are excluded, the remaining bicycling network is fragmented, with many origin-destination (OD) pairs not connected, and others connected only using highly circuitous routes.

- “Weighted low-stress connectivity” recognizes that OD pairs are not all equally valuable. Weights should certainly account for the size of the origin and destination, as in MFN. We introduce here additional weights in the form of a propensity function that reflects people’s limited willingness to use a bicycle for long distances and on routes involving a lot of detour. We show how the appropriate weights can transform the connectivity measure into estimates of number of bike-accessible jobs and the number of potential bicycling trips.

- The new methodology is applied in a case study comparing alternative alignments for a bike route between Wilmington and Newark, Delaware’s two largest cities. Original methodological contributions include refinements to the low-stress criteria, a propensity model for bike travel, and network-wide measures of
number of bike-accessible destinations and potential bike trips. In addition, the case study brings up significant issues related to data and to how alternatives are defined.

2.2 REFINING LEVEL OF TRAFFIC STRESS CRITERIA

Winters et al. (2011) and others have shown that the chief deterrent to riding a bike in North American cities is concerns about the danger or stress from traffic. Several methods have been developed for classifying streets by how comfortable or stressful it is to ride there as a function of traffic characteristics (e.g., traffic speed, volume, number of lanes) and bicycling provisions (e.g., bike lanes), including Bicycle Level of Service (Landis, Vattikuti, & Brannick, 1997) and Bicycle Compatibility Index (Harkey, Reinfurt, & Knuiman, 1998). This study uses the Level of Traffic Stress method (MFN, 2012), which has advantages over previous methods in terms of understandability, data requirements, consistency, and ability to account for intersection effects and protected lane treatments (Furth, Mekuria, and Nixon, 2016). Its four levels of traffic stress are linked to Geller’s popular classification of bicyclists (Geller, 2006; Dill & McNeil, 2013):

- LTS 1: Suitable for children cyclists. Cyclists are either physically separate from traffic, or face a limited volume of low-speed traffic in which they rarely have to deal with more than one vehicle at a time.
- LTS 2: Limits traffic stress to what the mainstream adult population, called “interested but concerned” by Geller, will tolerate. Either cyclists have their own defensible space (i.e., cars reliably stay out of it), or, if in mixed traffic, they have to deal with multiple vehicles at a time only at low speeds and infrequently. They are physically separated from high speed and multilane traffic. The criteria for LTS 2 correspond to a large degree with design criteria for Dutch bicycle route facilities (CROW, 2016).
- LTS 3: A level of traffic stress acceptable to those Geller calls “enthused and confident.” Involves frequent but not severe interaction with moderate speed or multilane traffic.
- LTS 4: A level of stress acceptable only to the “strong and fearless.” Involves being forced to mix with moderate speed traffic or close proximity to high speed traffic.

An updated set of LTS criteria (Furth, 2017), published as Revision 2.0, was used. Updates were made using input from staff at DelDOT and from Arlington County, Virginia, site of another project using LTS. The main impetus for the changes was the need to respond to traffic situations that were not common in San Jose, California, the city for which the original LTS criteria were created, but common in Delaware and/or Arlington – mainly, high traffic 2-lane roads with 25 mph speed limits and rural roads. At the same time, the occasion was used to put the criteria into a more readable format, with LTS in the interior table cells and conditions as row and column heads. The following paragraphs summarize the changes to LTS criteria.

### 2.2.1 Using Average Daily Traffic as an Input for Some Road Types

The biggest change in LTS criteria is that average daily traffic (ADT) has been added as an input for roads in which bikes are in mixed traffic (Table 1). Where ADT is low, cyclists rarely encounter more than one motor vehicle at a time, and passing vehicles tend to grant them ample leeway when passing; however, at higher volumes, cyclists will more frequently experience “triple encounters,” when a bicycle and two opposite direction vehicles meet, creating an uncomfortable situation in which there is a sudden need for the car approaching from behind to slow down, possibly all the way down to the bike’s speed, until it’s clear to pass (Furth, 2008), or else pass with scant clearance. Higher volumes also mean that cyclists will more frequently encounter multiple vehicles driving in a platoon, reducing the visibility and attention that passing motorists give to a cyclist, and creating prolonged intervals in which the cyclist is constrained and threatened (Furth, 2008).

For 1+1 lane roads (that is, 2-lane, 2-way roads with a marked centerline), the critical ADT that triggers LTS 3 on streets with prevailing speeds of 25 or 30 mph is 1500. This threshold was based on input from an Arlington planner that citizens frequently complained of being uncomfortable riding on N. Lexington Street, a 1+1 lane
road with parking on one side and ADT between 1500 and 2000. Unlaned 2-way roads have higher ADT thresholds because on such roads motorists tend to ride down the middle and are accustomed to adjusting their lateral position to make space for other road users they encounter.

The data burden from adding ADT as a factor is limited in several ways. First, ADT is not a factor on roads with bike lanes or bike paths. Second, if the goal is only to distinguish low-stress (LTS 1 or 2) from high, ADT is not a factor on multilane roads. Third, exact values are not needed, but only the range ADT falls in. In cities we have studied, it is safe to assume that streets classified as “local” have a prevailing speed of 25 mph and no centerline; on such streets, the only ADT information needed is whether ADT exceeds 3000 — something rare for a local street, meaning that analysts need only identify exceptions. In a similar study in Arlington, streets classified as local were assumed to have ADT < 1500, and 1+1 lane streets classified as arterials were assumed to have ADT > 3000; that left only two-lane collectors lacking bike lanes as requiring an ADT check. For all of them, it was possible to estimate ADT from the County’s database of turning movement counts, using a standard factor of 10 to expand a peak-hour volume into ADT.
### Table 1: Level of Traffic Stress Criteria for Cycling in Mixed Traffic (Revision 2.0)

<table>
<thead>
<tr>
<th>Through Lanes per Direction</th>
<th>Effective ADT*</th>
<th>≤ 20</th>
<th>25</th>
<th>30</th>
<th>35</th>
<th>40</th>
<th>45</th>
<th>50+</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unlaned 2-way street (no centerline)</td>
<td>0-750</td>
<td>LTS 1</td>
<td>LTS 1</td>
<td>LTS 2</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 3</td>
<td>LTS 3</td>
</tr>
<tr>
<td></td>
<td>751-1500</td>
<td>LTS 1</td>
<td>LTS 1</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td>LTS 4</td>
</tr>
<tr>
<td></td>
<td>1501-3000</td>
<td>LTS 2</td>
<td>LTS 2</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td>LTS 4</td>
<td>LTS 4</td>
</tr>
<tr>
<td></td>
<td>3000+</td>
<td>LTS 2</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td>LTS 4</td>
<td>LTS 4</td>
</tr>
<tr>
<td>1</td>
<td>0-750</td>
<td>LTS 1</td>
<td>LTS 1</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 3</td>
<td>LTS 3</td>
<td>LTS 3</td>
</tr>
<tr>
<td></td>
<td>751-1500</td>
<td>LTS 2</td>
<td>LTS 2</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td>LTS 4</td>
<td>LTS 4</td>
</tr>
<tr>
<td></td>
<td>1501+</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td>LTS 4</td>
<td>LTS 4</td>
<td>LTS 4</td>
</tr>
<tr>
<td>2</td>
<td>0-8000</td>
<td>LTS 3</td>
<td>LTS 3</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td>LTS 4</td>
<td>LTS 4</td>
<td>LTS 4</td>
</tr>
<tr>
<td></td>
<td>8001+</td>
<td>LTS 3</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td>LTS 4</td>
<td>LTS 4</td>
<td>LTS 4</td>
<td>LTS 4</td>
</tr>
<tr>
<td>3+</td>
<td>any ADT</td>
<td>LTS 3</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td>LTS 4</td>
<td>LTS 4</td>
<td>LTS 4</td>
<td>LTS 4</td>
</tr>
</tbody>
</table>

* Effective ADT = ADT for two-way roads; Effective ADT = 1.5*ADT for one-way roads

#### 2.2.2 Other Significant Changes to LTS Criteria

The revised LTS criteria account for a wider range of traffic speeds. 20 mph streets are recognized as having lower LTS than 25 mph streets in many situations, and higher end speed categories have been refined so that rural roads can be better classified.

Revised criteria explicitly provide guidance for how ADT limits apply on one-way streets. On multilane one-way streets, volume thresholds are half those of two-way multilane streets. Essentially one-way multilane roads are treated as if they were half of two-way road with twice the traffic, because on multilane roads, cyclists scarcely interact with opposite direction traffic. However, for single lane one-ways, the same volume thresholds apply as on 1+1 lane streets because in both cases, cyclists face potential stress from all vehicles regardless of direction (recall the triple encounters described earlier).

Revised criteria for riding in bike lanes and shoulders not alongside a parking lane are given in Table 2. As in the original criteria, ADT is not a factor because bikes have
their own space. The main changes are at higher speeds, where bike lane / shoulder width becomes a factor and the speed threshold between LTS 3 and 4 has increased. These changes recognize the popularity among recreational cyclists of high speed rural roads with wide shoulders such as Delaware’s state route 1 between Rehoboth Beach and Bethany Beach.

For all bike lanes, whether alongside a parking lane or not, frequent bike lane blockage is no longer treated as an explicit factor; rather, users are now advised to treat such a situation as one in which bikes are in mixed traffic. Apart from this, no changes were made to criteria for bike lanes alongside a parking lane.

Criteria were also developed for unsignalized intersection approaches with right turn lanes. In Delaware, as a highway approaches a junction with a subdivision entrance, it is common for the shoulder to become an auxiliary right turn lane. This situation will be stressful if cyclists are legally required to merge into the travel lane, or if the turn lane geometry allows vehicles to drive in the turn lane at high speeds (a long turn lane and/or a small turn angle). However, those criteria were not applied in the case study due to an absence of data on where such right turn lanes are located.

**Table 2: LTS Criteria for Cycling in Bike Lanes and Shoulders Not Alongside a Parking Lane (Revision 2.0)**

<table>
<thead>
<tr>
<th>Number of thru lanes per direction</th>
<th>Bike lane width (ft)</th>
<th>Prevailing Speed (mph)</th>
<th>≤ 25</th>
<th>30</th>
<th>35</th>
<th>40</th>
<th>45</th>
<th>50+</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 or unlaned</td>
<td>6+</td>
<td>LTS 1</td>
<td>LTS 1</td>
<td>LTS 2</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 3</td>
<td>LTS 3</td>
</tr>
<tr>
<td></td>
<td>4 or 5</td>
<td>LTS 2</td>
<td>LTS 2</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td>LTS 4</td>
</tr>
<tr>
<td>2</td>
<td>6+</td>
<td>LTS 2</td>
<td>LTS 2</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 3</td>
<td>LTS 3</td>
<td>LTS 3</td>
</tr>
<tr>
<td></td>
<td>4 or 5</td>
<td>LTS 2</td>
<td>LTS 2</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td>LTS 4</td>
<td>LTS 4</td>
</tr>
<tr>
<td>3+</td>
<td>any width</td>
<td>LTS 3</td>
<td>LTS 3</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td>LTS 4</td>
<td>LTS 4</td>
<td>LTS 4</td>
</tr>
</tbody>
</table>
2.3 CONNECTIVITY AND EFFECTS OF DISTANCE AND DETOUR

Transportation networks are typically connected, in the sense that if two points A and B are on the network, then it is possible to travel from A to B. In the U.S. and many other countries, low stress bicycling networks stand out as an exception. Because most local streets are low-stress, the low-stress network is large in terms of number of links. However, because road networks are typically configured to prevent through travel on local streets, those low stress streets tend not to form a coherent network. The low-stress network also includes bicycle paths and streets that have been treated with appropriate bicycling facilities, but those provisions tend to be limited and opportunistic, with the result that the low-stress network is often fragmented.

MFN proposed that the essential measure of a bicycling network’s ability to serve transportation needs is its \textit{low-stress connectivity}, meaning the degree to which it is possible to travel between origins and destinations using only low-stress routes and without undue detour. They demonstrated the concept using two sets of origin-destination (OD) pairs: home-work and home-home. Their measure of gross connectivity was the fraction of OD pairs that are connected at a given level of traffic stress, subject to limits on overall distance and detour factor:

\[
G_{C_k} = \sum \sum \delta_{ijk} \ast O_i \ast D_j
\]

\[
\delta_{ijk} = \begin{cases} 1 & \text{if } (L_{ijk} \leq L_{\text{max}}) \text{ and } (d_{ijk} \leq d_{\text{max}}) \\ 0 & \text{otherwise} \end{cases}
\]

where

- \(G_{C_k}\) = gross connectivity at LTS \(k\)
- \(L_{ijk}\) = distance from origin \(i\) to destination \(j\) at LTS \(k\)
- \(L_{\text{max}}\) = distance limit
- \(d_{ijk}\) = detour factor for a trip from \(i\) to \(j\) at LTS \(k\)
- \(d_{\text{max}}\) = maximum detour factor
- \(O_i\) = size of origin \(i\) (e.g., population at \(i\))
- \(D_j\) = size of destination \(j\) (e.g., employment at \(j\))
2.4 A PROPENSITY MODEL TO ACCOUNT FOR DISTANCE AND DETOUR

In equation 1, the behavioral aversion to long trips and large detour are accounted for through an all-or-nothing qualification function $\delta()$ with arbitrary limits $L_{max}$ and $d_{max}$. With this formulation, results can be unduly sensitive to the limits chosen – imagine, for example, a large employment center located 5.5 miles from a large population center, and consider how results could change depending on whether $L_{max}$ was 5 mi or 6 mi. Avoiding an arbitrary distance cutoff was especially important for the case study, since the distance from Wilmington to Newark is roughly 13-20 miles depending on the route alternative. Any distance limit less than 20 miles would appear inconsistent with the project objective of connecting the two cities, and any distance limit between 13 and 20 miles would clearly bias the evaluation in favor of alternatives whose length is below the limit. However, counting OD pairs that are 20 miles apart as equally important as OD pairs that are 5 miles apart clearly runs counter to evidence that people are far less likely to ride the longer distance for transportation trips.

Therefore, instead of a binary qualification function, this study used a propensity function that, beyond specified limits, declines with distance and detour. A constant value for short distances is consistent with bike mode share from the Netherlands (CROW, 2017) which is equally high for the distance bins 0-2.5 km and 2.5-5 km (about 37%) and declines for longer distances. Propensity functions that decline with distance are common in the accessibility literature. For bicycling trips, Iacono, Krizek, and El-Geneidy (2010) estimated simple exponential decay propensity functions for various trip purposes. However, their sample was small, and because it was based on bicycle trip length distribution rather than mode share data, it combines the effects of distance on the general trip length distribution as well as bicycle mode share. Lovelace et al. (2017) used a large dataset from the UK to estimate a propensity function giving bicycle mode share as a function of distance. It has a more complex functional form, rising with distance to a peak at 3 km, presumably due to competition with walking, with generally high values in the range 1-6 km. The decline over the range 6-16 km is very close to an exponential decay which halves propensity every 3.0 mi (4.8 km).

For this study, we used a propensity function that is constant with distance up to 4 mi (6.4 km), and then declines exponentially with parameter 0.231 mi⁻¹, which halves
propensity every 3.0 mi beyond the critical value. This form is consistent with the mode share data reported from the Netherlands and is a reasonable approximation of results from the UK data if competition from walking at very short distances is not considered important from a policy perspective (say, because walking and cycling are both forms of active, non-polluting transportation). Later, we describe a sensitivity test using a critical distance of 2 miles instead of 4 miles.

Intuitively, we find the constant-then-declining model of propensity appealing because of the special properties of bicycle transportation. Bicycle transportation involves not only a time cost, but also physical effort and exposure to outdoors. These latter two factors involve some disutility, but they also confer countervailing benefits. Humans need physical exercise to stay healthy, and being outdoors is pleasurable and contributes to psychological health. However, beyond the time/distance limit at which one’s need for daily exercise and exposure to the outdoors is satisfied, the dominant effect of continued exertion and exposure is negative.

In addition, time spent bicycling for transportation substitutes, at least in part, for time that would have been spent traveling by another mode, usually driving or transit. To the extent that time is substituted, the disutility of time required to travel by bicycle can be heavily discounted. If a person’s 4-mile commute takes 22 minutes by bike and substitutes for a 15-minute commute in a car, that person is getting 22 minutes of exercise and fresh air at a net time cost of only 7 minutes.

Our propensity model was also formulated to account for detour, which we define as the fractional increase in trip length beyond the shortest path. Broach, Dill, and Gliebe (2012) found that cyclists will detour to find a lower stress bike route; on average, they would increase their trip distance by 16% for work commute trips, and 26% for other trips. Because our model limits travel to low-stress routes, the extra distance required to find a low-stress route will be accounted for in a distance-based propensity model. Our propensity model aims to capture two other factors beyond extra distance. One is the substitution effect — the extra distance needed to find a low-stress route does not increase the travel time by competing modes, and so the substitution effect should not apply to detour (that is, travel distance beyond the shortest path) beyond a small level that
people normally associate with bicycling. For this purpose, we used 20% detour as a critical value.

Second, humans are shortest-path seekers, with an innate resistance to paths involving a lot of detour. Often, people won’t look for a route that involves what they consider to be an abnormal level of detour, and therefore won’t be aware of such routes. Even if they become aware of a circuitous low-stress route to reach their destination, emotionally, many will discount the existence of such an alternative if the level of detour involved seems unnatural. To model this effect, we propose a detour-based propensity that falls linearly from 1 to 0 between two values of detour factor, $d_2$ and $d_3$, which for the case study took values of 1.333 and 2, respectively. The idea is that around a detour factor of 1.333, some people will begin to consider the level of detour unnatural, and that once the detour factor reaches 2.0, it will seem sufficiently unnatural that almost nobody will consider making such a trip by bicycle.

Combining the distance-based propensity with detour-based propensity, our proposed propensity model is a function of $L_{ijk}$ and $L_{ij4}$ (the trip length at the specified LTS $k$ and the shortest path distance, which is the distance at LTS 4), which implies the detour factor $d_{ijk} = L_{ijk} / L_{ij4}$. This model has 5 parameters, $L_{crit}$, $d_1$, $d_2$, $d_3$, and $\alpha$, and specifies propensity for four ranges of trip length:

\[
\begin{align*}
\text{if } L_{ijk} &\leq L_1, & p &= 1 \\
\text{if } L_1 &\leq L_{ijk} \leq L_2, & p &= e^{-\alpha(L_{ijk}-L_1)} \\
\text{if } L_2 &\leq L_{ijk} \leq L_3, & p &= e^{-\alpha(L_{ijk}-L_1)} \frac{L_3 - L_{ijk}}{L_3 - L_2} \\
\text{if } L_{ijk} &> L_3, & p &= 0
\end{align*}
\]

where

- $p$ = propensity to use a bicycle
- $L_1 = \min (L_{crit}, L_{ij4} \ast d_1)$
- $L_2 = L_{ij4} \ast d_2$
- $L_3 = L_{ij4} \ast d_3$
Figure 1 illustrates the model for selected values of $L_{ij4}$, the LTS 4 distance from origin to destination. The dotted line is propensity for any value of $L_{ij4}$ when detour factor is less than 1.2.

![Graph](image)

**Figure 1.** Propensity as a function of trip length. Detour factor is implied (i.e., not shown) as the ratio between trip length and $L_{ij4}$. “Simple dist” is the propensity that would apply for any value of $L_{ij4}$ as long as the detour factor $\leq 1.2$.

While the proposed propensity function, like the qualification function used in Mekuria, Furth, and Nixon (2012), still has arbitrarily chosen parameters, its continuous nature ensures that results will not be highly sensitive to chosen parameter values. By allowing long-distance OD pairs to contribute to the benefit measure but with a lower weight, and by allowing that within the population there is range of limits to how much detour a person will accept to follow a low-stress route, the main objections to using an arbitrary distance and detour cutoffs are answered.
2.4.1 Number of Jobs That are Bike-Accessible

The connectivity measure developed by MFN represents the fraction of OD pairs connected at a given LTS level. It is also very sensitive to the limits chosen in the all-or-nothing qualification function $\delta()$. To minimize the strong effect of these distance and detour limits, propensity function as defined above is used to define a new connectivity measure. Replacing the qualification function $\delta()$ in equation 1 with propensity $p()$ and dividing by total population, the gross connectivity measure becomes

$$GC_k = \frac{\sum \sum p(L_{ijk}, L_{ij}) \cdot O_i \cdot D_j}{\sum O_i}$$

(4)

Mathematically, $GC_k$ is a weighted sum of jobs, with each job weighted by (1) the likelihood that the job-holder lives at various origins, with each member of the population equally likely to hold a given job, and (2) the propensity of using a bike to get to that job from that origin. A very interesting interpretation of $GC_k$ is

$$GC_k = \text{number of jobs that are bike-accessible at LTS k}$$

Note that bike accessibility is treated here as a continuous function, so that, for example, 1000 jobs that are 50% accessible are treated as 500 accessible jobs.

2.4.2 Potential Bike-to-Work Trips

Rapidly changing social attitudes toward bicycling as a mode of transportation together with gaps in knowledge about bicycling demand make it difficult to make a reliable prediction of how many people will use an improved bicycle network. However, for project evaluation, it is possible to convert $GC_k$ into a plausible measure of potential bike-to-work trips by taking advantage of the fact that propensity is, by design, roughly proportional to the likelihood of a person choosing to use a bike. A proportionality factor $\tau$ can be defined:

$$\tau = \text{bike modal share under ideal connectivity conditions}$$
where “ideal connectivity conditions” are defined as those for which propensity equals 1—that is, trip length is less than \( L_1 \), and detour factor is less than \( d_2 \). Then, using LTS 2 connectivity (because LTS 2, by design, represents the attitude of the mainstream population), a powerful evaluation measure becomes

\[
\text{potential bike-to-work trips} = \tau \times GC_2 \tag{5}
\]

Clearly, there is a need for future demand modeling research to estimate \( \tau \) from behavioral data and to confirm both the form and the parameters of the proposed propensity model. In the meantime, for project evaluation, a transportation agency can choose a value of \( \tau \) that is reasonable and consistent with agency goals and aspirations. For this case study, we used the value \( \tau = 0.2 \), reflecting a view that in the long run, if the transportation agency creates low-stress, low-detour routes between people’s homes and jobs, 20\% of those with trip length less than \( L_{crit} \) will choose bicycle.

### 2.5 DATA SOURCES, CLEANING, AND INTEGRATION

Network data came mainly from DelDOT’s county-level road inventory file and its E-911 map file. LTS was calculated using the road inventory file whose attributes include number of lanes, presence of a median, and shoulder width, and whose features include roads and paved shared use paths, which are locally called trails.

However, the road inventory file is not “routable,” meaning that roads that appear to intersect may not actually intersect topologically, and therefore cannot be used directly for connectivity analysis. On the other hand, the E-911 file, used for emergency response, is routable. Because there is a one-to-many relationship between the road inventory file and the E-911 file, LTS values calculated in the road inventory file could be pushed to the E-911 file.

Bike lane data, not yet part of DelDOT’s road inventory file, was entered manually. Presence of a bike lane was determined from the county planning agency’s map, while bike lane attributes were determined through observations in the field or using...
Google’s StreetView. Using DelDOT’s sidewalk inventory file, the bike network was augmented with paved paths through parks or campuses, connector paths between shared-use paths and streets, and pedestrian underpasses, overpasses, and median crossings otherwise closed to traffic.

For its pavement management system, DelDOT already had a protocol for assigning ADT measurements made at representative points along a road to the many segments of a road. Segment-level ADT data, held as a separate layer in the road inventory file, was then pushed into the roads layer of the road inventory file. For most roads, this is a simple one-to-one transfer. However, some manipulation was needed for divided roads, which the ADT layer represents as single line features while the road layer represents them as dual features.

The network data required a fair amount of data cleaning. Shoulder width data had frequent errors, especially in more urbanized areas, and was spot checked against Google Maps satellite photos. Roads coded as having 4 lanes were checked systematically because some of them, while wide enough for 4 lanes, are striped for only 2 travel lanes with the remainder allowed for parking. Speed limits were spot checked and corrected, although a systematic review would have been impractical. (DelDOT has a separate ongoing project to document speed limit signs and update coded speed limits.)

Population data, by block, comes from the Census Bureau’s 2010 census. Employment data, also by block, were taken from the U.S. Census Longitudinal Employment Household Dynamics (LEHD) dataset, based on reports that employers make to the IRS, the federal tax bureau. Figure 2 shows the distribution of population and jobs in northern Delaware. There are some weaknesses in the LEHD data. For businesses with multiple locations, all of their employees may be associated with the location of the business headquarters, a practice that tends to undercount employment at branch or retail locations and to over count employees at corporate headquarters. DelDOT is currently developing another dataset of employment locations that should not be subject to that weakness, and it would certainly be worthwhile to repeat this case study when that improved dataset becomes available.

To connect census blocks to the road and trail network, each block’s population and employment was allocated equally over the intersection nodes lying within a 20-
meter buffer of block. An “intersection node” is a node in the street / trail network incident to at least 3 links (i.e., 3 legs). With this model, for a typical rectangular city block, one fourth of its population and employment is allocated to each of the corners.

Figure 2: Population and employment distribution in northern Delaware. Black lines indicate the route alignments studied.
2.6 ALTERNATIVE GREENWAY ALIGNMENTS

A 2014 Trail Study commissioned by DelDOT in association with Delaware State Parks and the Wilmington Area Planning Council (Whitman, Requardt & Associates, 2014) identified links that might be useful as part of a bicycle route connecting Wilmington and Newark. Alignment selection followed a requirement to keep cyclists off-road (a requirement that could be met by sidepaths running alongside roads) and, as much as possible, in a park-like environment in order to make the path attractive for recreational cycling. However, DelDOT recognized that any trail in this well-populated region could also be a vital route for utilitarian travel, and therefore wished to evaluate alignment alternatives in terms of their potential for serving transportation bicycling.

The Trail Study identifies a web of possible route options within which there are four main corridors. We developed a single alignment for each of these corridors, as well as a fifth alternative which enhances the northern alignment by adding branches. The five alternatives are shown in Figure 3.
For the most part, our alignments use segments identified in the Trail Study. However, in several places we added or substituted segments in keeping with the objective of maximizing low-stress connectivity. Substituted segments aim to improve directness by replacing circuitous routings; added segments improve local connectivity by adding small branches that connect alignments to the local street network. All added and substitute segments appear feasible in terms of right of way and available space. However, they were not required to be off-road; thus, they include local streets with low traffic volumes and low speed.
Considering the connectivity objective, it also makes sense to enhance alignments by including longer branches with potential to create a large connectivity increase at low incremental cost. To test this idea, we created an enhancement for the northern alignment called the Greenbank Loop with branches extending to Price’s Corner and Elsmere, areas of population and employment concentration. Because it partially uses existing paths, the connectivity benefit of this enhancement was expected to be high compared to its incremental cost.

Finally, because the alternatives are rather distant from one another from a bicycling perspective, we also created an alternative “Everything but South” that includes all of the routes except the South route, and therefore includes three parallel routes through the study area (North + Greenbank, Central, and Far South). This alternative was included to explore the extent to which the different alignments compete for the same trips.

2.7 RESULTS

Figure 4 shows the number of bike-accessible jobs by level of traffic stress for each of the alternatives. In this analysis the base alternative includes existing paths, paths currently under construction, and local improvements expected to be made in the near future regardless of the alternative chosen, and so it actually represents a considerable improvement from the bicycling network that existed in 2016.
Figure 4: Number of bike-accessible jobs at various LTS levels for different route alternatives between Newark and Wilmington.

First, one can see that at LTS 4, roughly 122,000 jobs are accessible in every alternative, which is 45% of the study area’s 271,000 jobs. This should be understood as 271,000 jobs that are, on average, 45% accessible. At LTS 4, lack of accessibility is not due to lack of connectivity, since at LTS 4 all roads except freeways are deemed bikeable, but rather to the long distance between many jobs and homes that result in low propensity for travel by bike. The LTS 4 accessibility of 122,000 can be viewed as an upper limit for bike accessibility, given distances between homes and jobs in the study area.

Second, it is instructive to see how, for any alternative, number of accessible jobs declines sharply at lower levels of traffic stress. In the Base alternative, for example, there is a 73% dropoff in accessibility from LTS 4 to LTS 3, indicating that in the study area, most home-to-work pairs simply cannot be connected without resorting to LTS 4 roads. At LTS 2 (LTS 1), accessibility is only about 5% (1%) of its LTS 4 level, showing how sparse and disconnected is the low-stress network.

Third, a comparison between alternatives shows that the five primary improvement alternatives all offer modest increases in low-stress connectivity. The
Central Alternative creates the greatest connectivity improvement at LTS 2, while the Far South and North + Greenbank alternatives show the most improvement at LTS 1.

For greater detail in comparing alternatives, Figure 5 shows each alternative’s incremental improvement relative to the base case in terms of potential bike-to-work trips (equation 5). The Central alternative clearly offers the greatest improvement — an addition of 332 potential bike-to-work trips (which is a 25% improvement compared to the base case). The superior performance of the Central alternative can be attributed to its directness and to its connecting important mid-corridor job and population centers.

![Figure 5: Incremental potential bike-to-work trips for the different alternatives.](image)

The worst performing alternative is North, which is considerably less direct and passes through an area with lower population and job density. However, as expected, adding the Greenbank Loop to the North alternative improves connectivity substantially, increasing the number of potential trips added by 33%. This shows the benefit of supplementing a basic alignment with branches that extend to nearby population and job centers, something that should be considered when planning other bike routes.
Finally, we consider the “All but South” alternative. In corridor studies done for other transportation modes, there is typically no thought of providing more than one alignment because they would be competing for the same demand. However, in this study, the distance between alignments is roughly equal to the length of a typical bike trip length, and so the different alignments can be expected to serve distinct populations, removing most of the competition effect.

Indeed, we find that the “All but South” alternative adds 935 potential bike-to-work trips, which is 10% more than what its three constituent alternatives (North + Greenbank, Central, and Far South) would generate. This indicates not only that the competition effect is small, but also that there is a significant and countervailing complementarity effect, meaning that completion of all three alternatives enables connections are not enabled by any of the alternatives separately, such as between Newark’s northern and eastern neighborhoods. Adding additional short branches that would connect the routes mid-corridor would yield a still larger complementarity effect.

While cost estimates for the different alternatives were beyond the scope of this study, Table 3 shows the number of bike-accessible jobs added per mile of new trail, a rough benefit/cost ratio. New trail miles in this analysis do not include local streets that already have LTS 1 or 2, because they need minimal treatment. The Far South alternative looks best, with 242 added accessible jobs per mile of new trail, because while this alternative has the longest path from Wilmington to Newark, it requires the least amount of new trail, only 5.5 miles. Not far behind it is the Central alternative, while the North and South alternatives are far weaker in this metric.
Table 3: Number of bike-accessible jobs added per mile of new trail.

<table>
<thead>
<tr>
<th>Alternative</th>
<th>Added Accessible Jobs</th>
<th>Added Trail (mi)</th>
<th>Added Accessible Jobs per Mile</th>
</tr>
</thead>
<tbody>
<tr>
<td>North</td>
<td>909</td>
<td>9.9</td>
<td>92</td>
</tr>
<tr>
<td>North + Greenbank</td>
<td>1,228</td>
<td>14.4</td>
<td>85</td>
</tr>
<tr>
<td>Central</td>
<td>1,661</td>
<td>8.5</td>
<td>197</td>
</tr>
<tr>
<td>South</td>
<td>1,041</td>
<td>12.6</td>
<td>82</td>
</tr>
<tr>
<td>Far South</td>
<td>1,337</td>
<td>5.5</td>
<td>242</td>
</tr>
<tr>
<td>All but South</td>
<td>4,674</td>
<td>30.1</td>
<td>155</td>
</tr>
</tbody>
</table>

2.8 SENSITIVITY TEST FOR CRITICAL DISTANCE

The model’s sensitivity to the critical distance parameter in the propensity function was tested by repeating the analysis using a critical distance of 2 miles instead of 4. On an absolute basis, the shorter critical distance lowers average propensity, and thus lowers the number of accessible jobs and potential bike-to-work trips by about 30% for all of the alternatives, including the base case. Differences between alternatives are, of course, similarly affected. However, relative accessibility – meaning the ratio of accessible jobs under any given alternative to what it would be if all roads had low traffic stress – is affected very little. For example, when critical distance changes from 4 miles to 2 miles, the gain in relative accessibility at LTS 2 for the “all but south” alternative changes from 4.7% to 4.6%.
2.9 CONCLUSION

Bicycle planners understand the importance of connectivity, and often cite it as a justification for proposed projects; however, until now, they have lacked methods for evaluating the connectivity contribution of a project. This study demonstrates how low-stress connectivity can be quantified and used to evaluate alternatives. A new propensity model solves the problem of arbitrary distance and detour limits that weakened the low-stress connectivity measures previously proposed, and leads to connectivity measures that have intuitive interpretations as number of bike-accessible jobs and potential bike-to-work trips.

The case study showed how using connectivity as an evaluation metric leads to formulating alternatives differently than one might otherwise. This measure rewards alternatives that are more direct, that serve mid-corridor population and employment concentrations, and that include branches that extend a route’s reach to population and destination centers. It also shows that when alternative alignments are as distant from one another as those in this study, there can be a strong complementarity effect that justifies implementing not just one of the alignments, but several, and including links that facilitate connections between those alignments.

The emphasis on “low stress” routes, as opposite to “off-road” routes, allows planners to take advantage of existing low-traffic local streets that can reduce cost and improve directness. The low-stress connectivity metric naturally treats all local streets as extensions of the bicycling network, enabling a true end-to-end analysis of trips.

While this study looked at connecting homes to jobs, one can also consider connectivity between homes and other kinds of destinations including shops, schools, and social activities, as in Lowry et al. (2015). Recognizing these other purposes as well as recreational travel, the number of potential bike-to-work trips calculated in this study represents only a fraction of the network’s potential demand.

2.10 ACKNOWLEDGEMENTS

Delaware DOT funded this study. At this time, no decision has yet been made about which trail options to pursue.
CHAPTER 2 - REFERENCES


3 ONE-WAY STREETS AND BICYCLE CONTRAFLOW: IMPACT ON CONNECTIVITY AND ACCESSIBILITY FOR LOW-STRESS BICYCLING

ABSTRACT

One-way restrictions can create a significant barrier to low-stress cycling by forcing cyclists to use high-stress links. They also force a broader definition of low-stress connectivity that accounts for the need to have a low-stress path to return home. A case study in Greater Boston finds that while low-stress connectivity between homes and jobs would be 12% without one-way restrictions, it is only 1.2% when one-way restrictions are accounted for. Contraflow, a treatment that can undo one-way restrictions on bike travel, is applied sparingly in the US but systematically in Netherland, Belgium, and France. With contraflow on local streets, the case study’s average accessibility rises back to 8.7%. Even with a dense mesh of through bike routes, accessibility is still found to be 16 points lower without contraflow on local streets than with, suggesting that in a city with a lot of one-way streets, having a good bike network isn’t enough; it is also critical to provide contraflow. Moreover, in such a city, contraflow is critical to the development of neighborways (bike boulevards). Methods of associating demand, generally provided in the form of polygons, to the network are particularly important where there are one-way restrictions and irregular street networks because of the assumptions they entail regarding first- and last-segment travel; several segment-based methods are recommended, described, and tested. A method is also proposed for prioritizing contraflow conversion based on weighted centrality.
3.1 INTRODUCTION

One-way streets are common fixtures in urban street networks. By default, direction restrictions on one-ways apply equally to automobiles and bicycles. For autos, these restrictions usually lead to only small increases in distance traveled and never disconnect the network. For bikes, the effect would be the same if cyclists used all the same roads as cars. However, the vast majority of people are willing to ride bikes only on streets with low traffic stress (1). If high-stress roads are eliminated from consideration, the remaining network of low-stress streets and bike paths, compared to the automobile network, tends to be sparser, poorly connected, and possessing less redundancy, making it less resilient (2). In such a network, one-way restrictions can have a serious barrier effect, disconnecting regions of a city and/or substantially increasing travel distance.

Contraflow, which means permitting bicycles to travel in both directions on a one-way street, can eliminate this barrier effect. However, while contraflow is widely practiced in some countries and has long been recognized in the Manual on Uniform Traffic Control Devices (3), its usage is in the US is limited.

Previous studies (2, 4) have shown how roads with high traffic stress, together with natural and man-made barriers such as rivers and freeways, create barriers to cycling, sometimes dividing a city into islands with no connection to each other. However, studies of low-stress bike networks have paid little or no attention to the barrier effect of directional restrictions. While some studies have used network models that account for directionality, they have measured accessibility by considering travel in one direction only, from home to a destination. But if one-way restrictions make it such that there is a low-stress path from A to B but not back to A, can A and B really be considered connected?

This research takes a closer look at how one-way restrictions affect the low-stress bike network. In real bike networks, how big an impact do one-way restrictions have on connectivity and accessibility? How much of this barrier effect could be undone by applying contraflow routinely on local streets, as practiced in some other countries? And is there a way to determine which one-ways would contribute the most to accessibility if treated with contraflow?
3.2 STUDY OBJECTIVE AND PAPER OUTLINE

The objective of this study is to measure the barrier effect of one-way restrictions on low-stress bike accessibility and connectivity, and the effect of easing those restrictions by applying contraflow in different degrees. We expand the definition of low-stress connectivity to account for directional restrictions. We provide a framework for measuring the barrier effect of directional restrictions, and apply it using two bike networks in greater Boston – the current bike network, and a proposed bike network – to get an idea of how big an impact these restrictions have. This analysis framework is used to propose a method for prioritizing streets for implementing contraflow based on incremental gains in low-stress connectivity.

We also discuss geographical information systems (GIS) modelling methods for associating demand (e.g., population, homes, jobs), whose locus is usually blocks or other polygons, to a bike network, which consists of links and nodes. This has important implications to the way first- and last-block access to the bike network is modeled, which is critical where there are one-way restrictions.

The next sections of this paper provide background on one-way streets, contraflow, and low-stress bike network analysis. It then introduces the case study site, and then discusses GIS modeling techniques for associating demand polygons to the bike network. With that background established, it introduces methods for measuring accessibility and connectivity that account for direction restrictions, and applies them to the case study site to measure its average accessibility to jobs. The case study concludes with a proposed method for prioritizing contraflow conversions.

3.3 ONE-WAY STREETS AND CONTRAFLOW

Virtually every one-way street that exists today was originally two-way. Conversion to one-way has generally been for one of three reasons, all related to growth in automobile use beyond the level for which the streets were built. On local streets in older neighborhoods, the main reason for one-way restrictions has been to create more space for parking, leaving a single-lane channel for moving traffic. A second and more recent reason for one-way restrictions on local streets is to divert through traffic away
from neighborhood streets by making it either impossible or difficult to cut through a neighborhood. One-way restrictions intended as traffic diversions have been applied systematically in some places such as Boston’s South End neighborhood and in Brookline (MA), near the Boston University Bridge.

Finally, on arterial streets, one-way restrictions are generally put in place to increase traffic capacity. Because one-way operation eliminates left-turn conflicts with opposing traffic at intersections, it makes traffic flow more efficient.

All of these reasons stem from problems caused by automobiles, not bikes or pedestrians. One-way restrictions never apply to pedestrians, and it is reasonable to ask, why should they be applied to bikes, at least on local streets? A street may be too narrow for autos get by one another, but bikes can almost always get by. One-ways used to divert traffic are intended to protect neighborhood streets from the danger and nuisance of autos, not bikes; ironically, such restrictions are contrary to cyclist safety because they force cyclists to use arterial streets instead of quiet, neighborhood streets which, in general, are far safer.

Contraflow can be provided in one of three ways. The method best known in the US is striped contraflow bike lanes. In Europe, it is far more common for contraflow to be signed but not striped – that is, there is usually no “contraflow lane” per se, but bikes are allowed to ride two-way (just as on most two-way local streets, there are no lanes marked for the two directions). A third way, most commonly applied on one-way arterials, is to provide a two-way separated bike path.

In Netherland and Belgium, most local streets that are one-way allow bicycle contraflow. A briefing by the European Transport Safety Council summarizes safety studies from European cities that show contraflow to be safe, with a very low crash rate and a lower proportion of crashes on contraflow streets involving contraflow cyclists than those riding with-flow (5). Because of this positive safety record, France in 2015 joined Belgium and Netherland in making contraflow the default treatment on local streets in 30 km/h zones (6). This is consistent with a fact sheet published by the European Commission recommending ubiquitous application of contraflow on one-way local streets to improve safety by improving predictability (7).
In the U.S., bikeway design guides published by both NACTO (8) and AASHTO (9) offer guidance for designing contraflow streets, but neither indicate whether contraflow ought to be applied routinely or sparingly. The number of contraflow applications in the US is not known, but is generally understood to be small and non-systematic.

Several reasons have been given for allowing contraflow, including bike safety, reducing the need for extra travel distance (something more important for bikes, which are human-propelled, than for autos), and justice, that is, undoing the harm done to bicycling by one-way restrictions. This study examines a related reason: improving accessibility and connectivity for low-stress bicycling.

3.4 LOW-STRESS BIKE NETWORK ANALYSIS

Furth, Mekuria, and Nixon (2) introduced the concept of low-stress bike network connectivity. They proposed a method for assigning a level of traffic stress to streets, and then measured the connectivity of the network that remains after high-stress links have been removed. This seminal work, which was applied in San Jose, paid no attention to one-way restrictions, treating street segments as undirected links, since San Jose has few one-way streets. Similarly, Furth et al. (10) used undirected links in a low-stress network study in northern Delaware. While Wilmington, a city in that region, has a lot of one-way streets, they nearly always appear in couplets with the same traffic stress (e.g., a couplet of low-stress local streets or a couplet of high-stress arterials), the authors reasoned that permitting two-way travel on every link would barely distort connectivity because cyclists would almost always have a parallel route nearby with the same stress level.

However, our experience analyzing the Boston street network showed that even when one-way streets appear as couplets with identical levels of traffic stress, modeling them as bidirectional can significantly distort a connectivity analysis. Even if a parallel, low-stress street is nearby, it might be impossible to reach it without traveling on a high stress street.

Some studies of low-stress bike networks, including Lowry et al. (11), have used network models with directed (that is, one-way) links, in which two-way streets are represented by
a pair of links while one-way streets are modeled as a single link. However, its analysis of accessibility looked only at travel in one direction, that is, from home to a destination, without considering there is also a low-stress path to get back home.

3.5 **CASE STUDY DESCRIPTION**

Greater Boston, including the municipalities of Boston, Brookline, Cambridge, and Somerville, is used as a case study site. Street network data, including bike paths, is available on MassGIS, published by Massachusetts Department of Transportation. Bike path and bike lane data were also obtained from municipalities directly.

MassGIS street network data contain fields indicating whether a street is one-way and its direction. We found the one-way data to be unreliable – many streets coded as two-way are actually one-way. Therefore, we manually verified each block’s directionality against Google Maps. (Because Google Maps is widely used for navigation, its directionality information was assumed to be correct.) To facilitate the data cleaning process, we created an application in GIS that symbolizes one-way streets with an arrow and allows a person to easily flag and correct streets with incorrect direction data.

Data on bicycle contraflow was likewise manually checked. It is important that contraflow be coded explicitly so that a street’s direction can be identified as two way for bikes and one-way for cars.

In the study area, one-ways constitute over 25% of street mileage (Table 1), excluding freeways. Most of these one-ways are local streets. Only 0.6% of the study area’s one-way streets have contraflow, most of it on local streets. For this purpose, two-way streets with a median were counted as two-way streets, even if they are modeled in GIS as a pair of one-ways.
Table 1: Mileage details of one-Ways in the study area

<table>
<thead>
<tr>
<th></th>
<th>Mileage</th>
<th>Mileage with Contraflow</th>
</tr>
</thead>
<tbody>
<tr>
<td>Local One-way</td>
<td>324.3</td>
<td>1.74 (0.5%)</td>
</tr>
<tr>
<td>Non-Local One-Way</td>
<td>85.6</td>
<td>0.6 (0.7%)</td>
</tr>
<tr>
<td>All One-Way Streets</td>
<td>409.9</td>
<td>2.34 (0.6%)</td>
</tr>
<tr>
<td>All Streets</td>
<td>1,526.6</td>
<td></td>
</tr>
</tbody>
</table>

Both the current street network and a proposed network were analyzed to discern the effect of one-way restrictions. The current street network has rather poor connectivity overall, which might mask the impact of one-way restrictions. Therefore, the case study also examines scenarios using the Bikeways for Everybody (BforE) network proposed by the Boston Cyclists Union, which has a rather dense grid of low-stress bikeways through the study area. The BforE network includes 27 miles of contraflow, including 3 miles on local streets and 24 miles on non-local streets.

Every street in the study area was assigned a level of traffic stress (LTS) based on LTS version 2.0 criteria (12). Figure 1 maps the study area’s one-way streets, its non-local, low-stress streets and paths, and additional low-stress streets that are part of the BforE bike network.
Figure 1: Study area bike network and one-way streets
3.6 ASSOCIATING DEMAND POLYGONS (BLOCKS) TO THE NETWORK

For accessibility studies, demand data such as population and jobs are generally provided in the form of polygons. This section addresses the issue of how to associate polygon-based demand data to the bike network, which consists of links and nodes.

Our study uses population and jobs data from the US Census (jobs data from its Longitudinal Employer-Household Dynamics program). Both are available at the level of Census blocks, which are almost exactly the same as the polygons bounded by the street network. However, as street networks have been edited over the years, block boundaries can differ slightly from the polylines representing streets, and new streets are sometimes added within a block.

Parcel data (smaller than blocks) have been used for bicycle travel (11) and for walk access to transit network (13). Conventional, auto-oriented transportation planning uses traffic analysis zones (TAZs), which are roughly a third of a census tract and are composed of many blocks.

Travel modes other than auto are particularly sensitive to distance and to first- and last-mile access, and so for bicycle travel, the finer the scale of the demand polygons, the better. Polygons larger than blocks can readily be subdivided into blocks, with demand allocated by area, population, or other measure of block size.

In auto-oriented transportation planning, polygon-based demand is typically associated to the network by locating demand at a centroid, with connectors are drawn to the surrounding nodes. (A connector is a link that can be used as only the first or last segment of a trip.) That allows all demand points within a polygon to reach the network via any of the polygon’s surrounding nodes. For low-stress bicycle travel, where some streets are low-stress and others are not, centroid connectors to all the nodes surrounding a block or larger polygon is clearly distorting.

For bicycle travel, it is reasonable to assume that demand points (homes, jobs) must be accessed from a street segment, from an access point which can be considered their address. From that access point, people are expected to travel along the street segment to one end or the other, which will then be a node at which they can access the bike network.
Directly assigning demand to nodes is convenient for network analysis. Most GIS packages have a tool that will divide a study area into Thiessen polygons, also called Voronoi diagrams, which are the subareas closest to each node. Superimposing Thiessen polygons on the layer of blocks, the resulting polygons will be subareas of blocks that share a nearest node. A block’s demand can then be allocated over its subareas in proportion to size.

With a regular grid network and a street network that exactly matches block edges, this method of assignment is completely satisfactory. However, for practical bike network analysis, allocating demand based on proximity to nodes has several drawbacks.

First, in a real street network, the closest node may be completely outside the block. For example, in Figure 2, consider the block (partially shown in the figure) immediately to the left of the highlighted block. For part of that block, the closest node may be the endpoint of the cul de sac in the highlighted block – clearly a wrong association. And if the highlighted block were longer in the north-south direction, the end of that cul de sac would be the closest node to some of the area along the block’s western edge – again, a clearly wrong assignment.

To guard against assigning demand to a foreign node, one might consider finding Thiessen polygons block by block, using only the nodes within or on the perimeter of a block. Besides being time consuming, this procedure is hampered by the fact that because nodes are not always *exactly* on the edge of a block, it is not trivial to find the set of nodes that are on the perimeter of a block. If one puts a small buffer around a block, there is a risk of including foreign nodes, especially when a block is bounded on one or more sides by a divided road represented by a pair of one-way road segments, leading to nodes that are very close to one another.

Rather than assigning demand directly to nodes, the general approach we have come to prefer assigns demand first to segments, and then makes assumptions about how travelers move along their segment to an endpoint (node), where they can access the network.

To assign demand to street segments, we apply the Euclidean Allocation tool found in the ArcMap’s Spatial Analyst toolbox to the study area as a whole, with the only inputs being the study area polygon and the street network. Euclidean Allocation creates
a raster file (a file of pixels) and labels each pixel in the study area by the ID of its nearest street segment. This raster is then converted to a polygon file of segment catchment areas, with each polygon containing the pixels with same ID. These polygons are analogous to Thiessen polygons, except that they partition a plane into regions based on proximity to a set of line segments rather than points.

Segment catchments are then superimposed on the blocks to divide each block into sub-blocks. The demand of each block is then allocated over its sub-blocks in proportion to sub-block area, as given in Equation 1.

\[
W_s = \frac{A_s}{A_b} \cdot W_b
\]

where

\[W_s = \text{demand (weight) allocated to sub-block } s\]
\[A_s = \text{area of sub-block } s\]
\[A_b = \text{area of the parent block}\]
\[W_b = \text{demand (weight) of the parent block}\]

Below, we describe four ways in which the demand allocated to a sub-block – and thus, to a street segment – accesses the street network. Each way implies different protocols for first and last block travel. The demand association techniques are illustrated in Figure 2.

3.6.1 Method A: Access the Network Mid-Block

With this method, the demand associated with each street segment accesses the network at the mid-point of the street segment. All travelers to and from a segment are thereby forced to travel on that segment.

This has two important implications for low-stress accessibility. First, if a street segment is high-stress, the homes and destinations on it will be inaccessible. Second, if a street segment is low-stress but one-way, demand from points along the segment has to leave and return by different paths, and therefore demand points along this segment will be inaccessible unless both the ends of the street segment are connected to the low-stress network. Consider, for example, the homes along a one-way street that is only one block
long, terminating at a low-stress street at one end and at a high-stress street at the other end. With Method A, all of those homes would be inaccessible, because travel either to or from this segment would have to use the adjoining high stress street.

This method of demand association does not consider that a person in such a situation might ride the wrong way on the first or last block, or might ride on the sidewalk (in either direction), or might walk their bike on the sidewalk. In comparison with the other methods, this method of association imposes the most restricting conditions for accessibility.

3.6.2 Method B: Access the Network at Either End of the Street

With this method, the demand from a sub-block can access the network from either end of its associated street segment. It allows travelers to ignore both high traffic stress and one-way restrictions on their first and last segment. It is equivalent to allowing people to walk or ride their bike on the sidewalk, or (on a low-stress, one-way street) to ride in the street in the wrong direction, for any part of their first and last segment.

This method allows people to access the low-stress network even if they live or work on a high stress street as long as one of the two ends of the street segment containing their origin or destination is connected to the low-stress network. It is the most liberal method as regards first- and last-block travel, and will therefore lead to the highest measures of accessibility and connectivity.

Implementing this method involves creating a centroid for each sub-block, with centroid connectors to endpoints of the associated street segment.

3.6.3 Method C: Access the Network at the Nearest Segment Endpoint

This method divides each sub-block into two polygons based on which segment endpoint is closest, and allows access to the network only via the associated endpoint. When a sub-block is divided, its demand is sub-allocated in proportion to area. For a given block, the resulting polygons represents the subareas of the parent block closest to each half-segment of the street network.
Like method B, traffic stress and direction restrictions on the first and last segment of a trip are ignored. On their first and last segment, people are expected to walk or ride on the sidewalk, or ride the wrong way in the street, but for no more than half a block, to reach the closest intersection. While Method A does not tolerate sidewalk use at all and Method B tolerates it completely for first- and last-segment travel, method C tolerates it but with moderation. For the one-way street segment described with Method A, demand points along half of that segment will be accessible (those closest to the intersecting low-stress street), while demand points along the other half will not be accessible.

3.6.4 Method D: Access the Network with a Limited Sidewalk Access Distance.

With this method, off-street access distance – for practical purposes, this means the distance people are expected to walk or ride a bike on the sidewalk, or ride the wrong direction on a one-way segment – is limited to a user-specified distance Z. Each segment is then subdivided into portions, with the segment’s sub-block subdivided correspondingly, as follows:

- **Portions within a distance Z of a particular endpoint but further than Z from the other endpoint:** Demand is associated to the close endpoint. (Such portions will exist only if segment length > Z.)

- **Portions within a distance Z of both endpoints:** Demand is associated via centroid connectors to both endpoints. (Such a portion will exist if segment length < 2Z, and will cover the entire segment is segment length < Z.)

- **Portions that are further than Z from both endpoints:** Demand is associated with an access point in the middle of that portion. Such demand will be required to use the street segment, which could render it inaccessible if the segment is high stress, or is one-way with a low stress connection only at one end. (Such a portion will exist if segment length > 2Z.)

Method D might be appropriate where sidewalk riding is illegal or highly undesirable, in which case the limiting access distance should be based on willingness to walk a bike. We are not aware of any studies of this limit, but 270 ft (60 s walking
distance at 4.5 ft/s) might be a reasonable limit. In upper Manhattan, where many blocks are 260 ft long along avenues and 880 ft long along cross streets, this method would mean that demand points on the avenues could all be accessed from either corner, using the side streets, even if the avenue were high stress. However, along the cross streets, demand points in the middle of the block would only be accessible by riding in the cross street in the legal direction, making it critical that the avenues on either end be part of the low-stress network.

Figure 2: Methods for associating demand polygons to a street network
Our case study uses Method C, but tests methods A and B as a sensitivity test. Method D was not tested partly to avoid controversy over choosing a limiting access distance and partly because in Massachusetts, riding a bike on a sidewalk is legal except in business districts.

3.7 MEASURING CONNECTIVITY ACCOUNTING FOR ONE-WAY RESTRICTIONS

Generalizing definitions found in (2) to account for one-way restrictions, a pair of points \((i,j)\) is considered to be connected if there is a round trip path \((i-j-i)\) between them on the low-stress network and if the round trip path does not have excessive detour. Detour is measured as the difference in length between the low-stress round trip route and the unrestricted round trip route (that is, the shortest path without regard to traffic stress), expressed as a fraction of the unrestricted route length.

For this study, as in (10), to avoid the all-or-nothing effect of a single limiting amount of detour, we define two thresholds for detour, considering a pair of points fully connected if detour is less than 20%, fully disconnected if detour exceeds 100%, and partially connected in between. Connectivity factor \(c_{ij}\), which ranges from 0 to 1, is given by Equation 2 and expresses the degree to which an OD pair \(i-j\) is connected:

\[
c_{ij} = \begin{cases} 
1 & \text{if } DLow_{ij} \leq 1.2 \times DHigh_{ij} \\
1.25 \times \left(2 - \frac{DLow_{ij}}{DHigh_{ij}}\right) & \text{if } .2 \times DHigh_{ij} < DLow_{ij} \leq 2 \times DHigh_{ij} \\
0 & \text{if } DLow_{ij} > 2 \times DHigh_{ij}
\end{cases}
\]

where

\(DLow_{ij}\) = distance of path \(i-j-i\) on the low stress network
\(DHigh_{ij}\) = distance of path \(i-j-i\) on the entire network (including high stress links)

As discussed earlier, demand actually originates on street segments, not at nodes. However, only distances measured along the network are used. The lengths of the first and last partial segment are ignored.
For a given origin $i$, the total number of jobs that are accessible on the low-stress network is $A_i$, as given in Equation 3, found by summing the number of jobs at all destinations $j (D_j)$ weighted by the connectivity factor $c_{ij}$. Accessibility is a property of a node and of the subblocks that access the network via that node. As such, it can be mapped to indicate which areas of the city have high or low accessibility (many or few accessible jobs). Overall network connectivity $X$, given in Equation 4, is the fraction of OD pairs that are connected; it is also the average accessibility, averaged over all origins, weighted by their size (population), $O_i$.

\[
A_i = \sum_j c_{ij} \cdot D_j \tag{3}
\]

\[
X = \frac{\sum_i A_i \cdot O_i}{\sum_i O_i} \tag{4}
\]

As formulated for this study, these accessibility and connectivity measures do not include a distance-based propensity. It could be applied, as it has in other studies such as (10), by multiplying $c_{ij}$ in Equation 3 by a decreasing function of $DLow_{ij}$ to reflect a declining willingness to use a bike over longer distances. Including a distance-based propensity is probably better for estimating bicycling demand, but for policy analysis, omitting it allows one to isolate the effect of bike network connectivity from the effect of distance, so that poor accessibility in neighborhoods that are distant from job centers is not “blamed” on the bike network.

As a practical matter, to speed data processing and avoid storing a large table of origin-destination results, shortest paths are calculated by looping over origin nodes $i$ and finding the shortest path tree rooted there. To find the return paths from all nodes to $i$, directionality of all links is flipped, and we find a shortest return path tree terminating at $i$. 
3.8 RESULTS

Average accessibility to jobs (i.e., connectivity) for the current network and the proposed Bikeways for Everybody (BforE) network is given in Table 2 for a base case and several alternative scenarios. The base measurement accounts for one-way restrictions and the need for round trip travel, and uses method C for associating demand to the network. In the current network, average accessibility is a little over 1% of jobs, while with BforE, it is roughly 64% of jobs. The lack of accessibility in the current network stems mainly from the lack of through routes, while in the BforE case, it stems mainly from small, scattered pockets that are not connected to the network.

Results are quite sensitive to the method chosen to associate demand with the network. With method A, which imposes the strictest conditions on first- and last-block travel, average accessibility is far lower than with method C (the base case). With method B, accessibility is greater, but the difference compared to method C is not so great.

Table 2: Average accessibility of the current and BforE networks using different demand association methods

<table>
<thead>
<tr>
<th></th>
<th>Current network</th>
<th>Bikeways for Everybody network</th>
</tr>
</thead>
<tbody>
<tr>
<td>With demand association method C (base)</td>
<td>1.2%</td>
<td>64.0%</td>
</tr>
<tr>
<td>With demand association method A</td>
<td>0.7%</td>
<td>46.0%</td>
</tr>
<tr>
<td>With demand association method B</td>
<td>1.4%</td>
<td>72.2%</td>
</tr>
<tr>
<td>One-way connectivity, home to job (method C)</td>
<td>1.8%</td>
<td>71.5%</td>
</tr>
<tr>
<td>One-way connectivity, job to home (method C)</td>
<td>2.3%</td>
<td>72.4%</td>
</tr>
<tr>
<td>With contraflow everywhere (change)</td>
<td>12.1% (+10.9%)</td>
<td>81.9% (+17.9%)</td>
</tr>
<tr>
<td>With contraflow on all local streets (change)</td>
<td>8.7% (+ 7.5%)</td>
<td>80.4% (+16.4%)</td>
</tr>
</tbody>
</table>
The results also confirm the importance of measuring connectivity in terms of round trips rather than one-way. Connectivity appears to be 1.8% when travel in only the home-to-job direction is considered. It would be 2.3% if travel in the opposite direction were considered instead. However, when round trips are considered (base case), as they should be, connectivity is only 1.2%. Because round trip accessibility has a “weakest link” relationship between outbound and inbound connectivity for every OD pair, average round trip accessibility is worse than both average outbound and average inbound accessibility. The distortion from neglecting to consider round trips is not evenly spread across the city, but is concentrated in certain neighborhoods where one-way patterns facilitate low-stress bike travel in one direction but not another, as shown in Figure 3.

Table 2’s results indicate that one-way restrictions have a large barrier effect in the current network, reducing average accessibility from 12.1% to 1.2% – meaning that area residents have 90% fewer jobs accessible via low-stress bicycling because of one-way restrictions. Allowing contraflow on local streets only would undo much of that harm, bringing average accessibility back up to 8.7% – in other words, would give area residents low-stress accessibility to 7 times more jobs than currently. Figure 4 shows the geographic distribution of accessibility gains from implementing local street contraflow. Neighborhoods with a lot of one-way streets such as Dorchester, Roxbury, and much of Somerville would gain low-stress bike access to over 100,000 jobs. Large gains can also be seen in Hyde Park, a neighborhood with few one-way streets, because of new low-stress routes created through adjacent neighborhoods.

Even with the Bikeway for Everybody network, the impact of one-way restrictions is large – removing those restrictions on local streets only would increase average accessibility from 64% to 80%. This result shows that to achieve good bike accessibility, it is not enough to provide a dense mesh of through routes. The barrier of one-way restrictions also has to be removed so that streets and small neighborhoods are not cut off from the low-stress bike network.

Table 2 shows a very small impact of contraflow on non-local streets in the BforE case. This does not indicate any lack of need for contraflow on non-local streets; rather, this result arises only because the Bikeways for Everybody network already includes contraflow on critical non-local streets.
Figure 3: Difference between number of accessible jobs with single direction versus roundtrip connectivity.
Figure 4: Jobs Access gained by adopting local contraflow.
3.9 PRIORITIZING CONTRAFLow APPLICATIONS

Not every one-way street would contribute the same to improving low-stress bike accessibility if contraflow were allowed on it. One can reasonably ask, if a limited application of contraflow is allowed, where would it best applied? Several criteria might be considered, including safety, local attitudes, and the current level of wrong-way riding observed, as suggested by Burkin (14). Another is the degree to which a street, in the context of the city’s bike network, would contribute to improved overall accessibility to jobs or other destinations of interest.

We propose, as an approximate measure of a street’s contribution to overall accessibility – “weighted centrality”. In graph theory, an edge’s or link’s centrality is the number of OD pairs (node pairs) for which the link is part the shortest path. With weighted centrality, each OD pair is weighted by the size of the origin and the destination as shown in Equation 5.

\[ WC(e) = \sum_i \sum_j O_i * D_j * e_{ij} \]  

where
- \( WC(e) \) = weighted centrality of edge (link) \( e \)
- \( O_i \) = Population at origin \( i \)
- \( D_j \) = Jobs at destination \( j \)
- \( e_{ij} = 1 \) if edge \( e \) is on the shortest path from \( i \) to \( j \); 0 otherwise

A link’s weighted centrality will be greater if it is part of more shortest paths between origins and destinations with a large number of population and jobs, respectively. Weighted centrality cannot be seen as an exact measure of incremental contribution because any street’s contribution to accessibility is dependent on which other streets have contraflow. However, in realistic networks, these dependencies have a predictable character, and so we believe that as long as the total number of links that can be changed is more than a few, difference in weighted centrality will be a good measure of contribution in any scheme that reasonably selects links for improvement.

Others, including Lowry (11), have also used weighted centrality to prioritize links for improvement. McDaniel, Lowry, and Dixon (15) also proposed using OD
weighted centrality to estimate bicycle volumes and found that observed bicycle counts correlated well with the proposed centrality metric.

Figure 5 shows the weighted centrality on every link (thicker means more people are expected to use it) if contraflow were allowed on all local streets. Local one-way streets are shown in red color. Thus, heavy red lines indicate streets that would likely see a lot of bicycle use if contraflow were allowed. Segments like this can be found in many study area neighborhoods. [Of interest to the authors is that one of them, Leon Street, is on our university campus, and on which we both ride the wrong way daily.]

One element that increases a link’s centrality is when it helps make a connection with the network’s existing main bike routes such as the Charles River Path and Southwest Corridor Path. This result confirms guidance from Burkin (14) that a connection to an existing path makes contraflow more valuable.
Figure 5: Centrality map of the street network. Thicker lines represent higher centrality.
With local one-way segments sorted based on their centrality score, we applied contraflow in increments of 10 miles to the current network, with the resulting average low-stress accessibility shown in Figure 6. Each 10-mile increment represents about 3% of the study area’s one-way mileage. The figure shows big gains for the first few increments, with generally decreasing returns. Adding contraflow to 10 miles of one-way streets with the greatest change in weighted centrality increases average accessibility to 4.1%, which is nearly 40% of the gain that would be realized by adopting contraflow on all local streets. This shows that a substantial fraction of the benefit of local contraflow could be realized at relatively little cost.

![Average Accessibility (X) vs Miles of Local Contraflow](image)

**Figure 6: Incremental benefits of local contraflow.**

### 3.9.1 Contraflow and Neighborways (Bike Boulevards)

Many cities use bike boulevards, also called neighborhood greenways or neighborways, as a low-cost and effective way of creating key low-stress routes. A neighborway is a route of substantial length following low volume local streets that is suitable as a through route for bikes, but not for autos. In cities like Boston and its neighboring communities in which a lot of their local streets are one-way, the ability to create neighborway routes depends heavily on contraflow. For example, in Somerville, a new neighborway was recently been created by applying contraflow to Hancock Street.
(14), where opposing one-way restrictions prevent through auto traffic. It is noteworthy that while Boston’s bike network plan since 2013 has recommended the development of neighborways, the city has developed none as yet, and probably will not be able to develop any without using contraflow.

3.10 CONCLUSION

One-way restrictions can create a significant barrier to low-stress cycling. In the Greater Boston area, these one-ways reduce low-stress network connectivity by 90%. Allowing contraflow on all local one-way streets – a practice followed in several European countries restores most of the connectivity lost due to one-ways. Applying contraflow to only 3% of local streets can achieve 40% of the total gain possible, if streets are chosen based on change in weighted centrality.

Creating a dense network of through routes does not obviate the need for contraflow, without which many streets and small neighborhoods can still be inaccessible to the low-stress bike network. At the same time, in cities with many one-way streets, contraflow can be an indispensable tool for developing neighborways (bike boulevards).

Methodologically, where there are one-way restrictions, measures of accessibility and connectivity will be distorted unless roundtrip connectivity is accounted for. The method by which demand data, which generally comes in polygons, is associated to the street network, can be critical for analysis involving one-way streets, because it determines what kind of first- and last-block travel is permissible.
CHAPTER 3 - REFERENCES


4 A METHOD TO IDENTIFY AND VISUALIZE BARRIERS IN A LOW-STRESS BIKE NETWORK

ABSTRACT

Low-stress bike networks are often disconnected, with gaps or barriers that make travel between two points impossible without riding on high stress roads. Barriers can also force long detours that people are not willing to make. While existing methods of low-stress bike network analysis have been used to point out some barriers, a method is needed to systematically identify and draw barriers to assist in network planning. Such a method is developed, taking only the low-stress network as an input, and yielding a set of polylines that indicate barriers to bicycling. Applications in Arlington, Virginia and Boston show how it detects what might otherwise have been hidden barriers. The method also successfully highlights critical low stress links that breach what would otherwise have been a far longer barrier.
4.1 INTRODUCTION

Most urban street networks are dense and offer motor vehicle users redundancy in connecting origins to destinations. The same cannot be said for bicycle networks, if the bicycling network is limited to segments with low traffic stress. In many cities, the low-stress bicycling network is disconnected, with gaps that may completely cut off an origin from many destinations, or require a circuitous path. When a gap extends wider than a level of detour most cyclists will accept, it becomes a barrier to the connectivity the bike network. Generally speaking, well connected bike networks have smaller barriers to connectivity.

Most bicycle planners understand that a critical task in network is to break connectivity barriers. To help with this task, they need methods to identify and visualize barriers, both for their own analysis and design and for communicating with the public and other stakeholders. This study’s objective is to develop a method for identifying and displaying barriers in low-stress bike networks, a method that we hope can be a valuable tool in the qualitative assessment of a network’s deficiencies.

4.2 LOW-STRESS CONNECTIVITY

Krizek and Roland (1) analyzed the effect of discontinuities in on-street bicycle facilities on cyclist comfort and safety by surveying participants who bicycled through different kinds of breaks in the network. This work focused on microscopic scale where discontinuities exist for a short section. It shows the effect of different types of discontinuities in the on-street bike facility on a cyclist’s perception of safety and comfort.

Birk and Geller (2) found strong correlations between bicycle use and the improvements made to the bicycle facilities at four key bridges that connect across the Willamette River in Portland, Oregon. Until those bridges were improved for cycling, the river was a major barrier between Portland’s downtown and its largest residential areas. The large ridership gains that accompanied these improvements highlight the importance of breaching barriers as a main emphasis in bicycle network development.
Furth, Mekuria, and Nixon (3) introduced the concept of a low-stress bike network, pointing out that when reasonable criteria are used to classify streets as high- or low-stress, and the high stress segments that most people are unwilling to ride on are removed, the resulting network is often disconnected. They developed criteria for assigning four levels of traffic streets to street segments and crossings; however, the concept of low-stress connectivity can be applied with other classification methods as well. They defined a system-level measure of network connectivity, the number of origin-destination pairs that are connected without undue detour.

Furth et al. (3) also explored the concept of barriers within the low-stress network. By plotting sets of connected segments, called “islands of connectivity”, in different colors, they were able to point out some barriers in a case study of San Jose. However, our experience with other cities has shown that visualizing gaps using connectivity islands works well only when the islands are neither too big nor too small. Large islands, in particular, can mask long barriers within them. For example, Figure 1 shows the connectivity islands for Arlington County, Virginia. There is a large connectivity island covering much of the county, which might suggest excellent connectivity; however, there are significant barriers within that island (shown later in this paper in Figure 10).
Lowry and Hadden-Loh (4) developed a method of measuring low-stress connectivity following the logic of geographic accessibility, measured as the number of desirable destinations that can be reached within a given distance of an origin. Because this measure is origin-based, it can be mapped to show regions of high and low accessibility. However, with such a measure it isn’t clear whether low accessibility is due to network barriers or to a lack of nearby destinations such as shops and restaurants.

Lowry, Furth, and Hadden-Loh (5) developed the concept of centrality as a measure of a link’s importance; it is the number of origin-destination (O-D) pairs whose shortest path includes that link. Comparing an ideal (future) bicycle network map with an existing map of low-stress bike routes, they used the before-after difference in a link’s centrality as a means of prioritizing links. Links that breached an important barrier scored high by this metric.
The Dutch Design Manual for Bicycle Traffic (6) lists safety, comfort, attractiveness, cohesiveness, and directness as the key requirements for an effective bicycle network. The first three requirements can be seen as an elaboration of “low-stress,” and the last two as “connectivity.” With respect to cohesion, the key measure used in the Dutch guide is grid size or mesh size, which can be seen as the distance between parallel links in a network. They recommend a mesh size of 500 m for main bike routes in urban areas, and 1000 to 1500 m in rural areas. By their criteria, then, gaps in an urban bike network significantly wider than 500 m represent barriers on which network development should focus. They measure directness as the ratio of actual trip length to the Euclidean distance for the same O-D pair.

Where the bike network does not have a well-defined grid, mesh size is not a practical measure. Compared to an ideal, dense grid, a city’s low-stress network might have hundreds of gaps that exceed an ideal mesh size; which of them are the most important? If the bike network is fragmented, directness loses its meaning since the bike network might not even connect many trips. These issues point again to barriers, which directly affect a network’s cohesiveness and directness as a key concept for analyzing the deficiencies of a bike network.

4.3 BARRIERS AS NEGATIVE OF THE LOW-STRESS NETWORK

While some barriers in a low-stress bicycling network are easy to identify, many are not as obvious. Furth et al. (3) point out the variety of barriers types that can affect a low-stress bike network. They include natural barriers such as rivers and impassible hills; manmade linear barriers such as freeways, high-speed arterials, and railroads; large land parcels such as cemeteries, private developments, and even large parks that lack bike access; and discontinuities in the street network that may be artifacts of urban development.

The negative of the low-stress network is the “no-bicycling” space, and is a collection of polygons. A polygon that’s part of the no-bicycling space can be considered a barrier if it spans a distance greater than a specified length. In our case studies, we used 600 meters. A longer threshold is suitable for rural areas.
There will be many polygons in the no-bicycling space that do not meet the minimum span threshold, such as common city blocks; these smaller polygons are not significant barriers to bicycling. When they are deleted from the no-bicycling space, the remaining, larger polygons form the barrier space. Figure 2 shows one such barrier polygon in Arlington, Virginia whose span, from its extreme north point to its extreme south point, is 2 miles. That makes it a significant barrier to east-west travel. For example, in Figure 2, the straight-line distance between points A and B is only 0.5 mi, but any low-stress route between these points must go around the barrier polygon. In this example, the shortest low-stress route from A to B is 3.5 miles, representing a level of detour that most cyclists will not accept.

FIGURE 2: Polygon and polyline representation of a barrier in Arlington, Virginia

While a barrier polygon that is long, straight, and thin constitutes an obvious barrier to travel along one axis, polygons with more complex shapes can represent multiple barriers, making it challenging to visualize effectively. For example, the barrier in Figure 2 has a shape that can be summarized roughly as an “I”: a central north-south
barrier that inhibits east-west travel, and a pair of east-west barriers roughly a mile apart that inhibit north-south travel. The lines drawn in Figure 2 represent those barriers, and were generated using the methodology proposed in the next section.

We believe that for analysis and planning, barriers represented as lines are easier to understand than barrier polygons with complex shapes. Our objective, then, is to find a method to reduce barrier polygons to barrier lines, as shown in Figure 2. This task involves finding a balance between too many and too few lines. Having too many barrier lines will clutter the map with near-duplicates, and not having enough barrier lines may result in some important barriers not being represented.

4.4 METHODOLOGY

This algorithm uses a geographical boundary (polygon) and the low-stress bike network (lines) for the study area as inputs. The low-stress bike network is not limited to streets with separated bike infrastructure but can also include mixed riding conditions that are low-stress due to low traffic volume and speed. In the case studies presented here, the stress classification was done using a local adaptation of the criteria given in Furth et al. (3). The proposed algorithm will generate a set of lines that represent the spatial barriers to the bike network.

The methodology can be divided into three main steps – 1) Extract barrier polygons, 2) Identify prominent points to serve as barrier line endpoints and 3) Draw barrier lines. Figure 3 gives an overview of the methodology. The methodology described in the following text is demonstrated using the low-stress bike networks in Boston, MA and Arlington, VA. All of the analysis and implementation of the suggested algorithm was done using ArcGIS and python scripting.
4.4.1 Extract Barrier Polygons

In a network, streets are drawn as lines which typically represent their centerlines even though streets are actually polygons with a narrow width. Consequently, streets that are incident to the same intersection might not be represented as such. To avoid this potential misrepresentation, a small buffer can be drawn around the low-stress bike network. Considering that local Boston streets tend to be 20ft wide, we used a 20ft buffer – large enough to bridge most inadvertent intersection gaps, but not so large as to obliterate real gaps.

The buffered bike network then becomes a set of polygons representing space that can be used for bicycling. Clipping or subtracting the buffered bike network from the boundary polygon results in the negative of the bicycling space or the “no-bicycling” zone, which is a collection of polygons, each of which is bounded by low stress streets and/or the study area boundary. Polygons that do not meet the minimum span threshold discussed earlier are discarded. The remaining polygons collectively form the barrier space, and represent true barriers to connectivity. Figure 4 shows the set of polygons that constitute the barrier space for the low-stress bike network of Arlington County, Virginia.
The low stress streets are in white; the smaller polygons in the no-bicycling space that are not considered barriers are gray; and the barrier polygons are shown in bold color.

FIGURE 4: Barrier space in Arlington County, VA, consisting of multiple (colored) polygons.

4.4.2 Identify Prominent Points to Serve as Barrier Line Endpoints

The next step is to select from each polygon’s boundary a set of points (P) that will form the ends of the barrier lines to be drawn. In order to get the longest possible barriers, the selected endpoints should be points that are “prominent” in the sense that they are far from the interior of the polygon compared to other nearby points on the boundary. In order to avoid parallel duplicate barrier lines, prominent points should be
separated by a distance greater than a minimum separation distance \( \text{min}_S \) chosen by the analyst. A longer \( \text{min}_S \) is desirable to avoid redundant barriers; however, with small polygons, a large value of \( \text{min}_S \) can result in missing meaningful barriers. To balance those concerns, in our case studies, we used a 1600 m separation distance for large polygons, while for smaller polygons \( \text{min}_S \) is proportional to the polygon span, down to a minimum of 400 m (see equation 1):

\[
\text{min}_S = \min(1600, \max(0.4 \times \text{span}, 400))
\]  

(1)

where \( \text{min}_S \) = minimum separation distance (m) and \( \text{span} \) = polygon span.

4.4.2.1 Polygon Smoothing

Since prominent points must be on the polygon perimeter, they form a subset of the polygon’s vertices. Due to the complex shape of each polygon, the number of vertices on the perimeter can be large. This is especially true for polygons that have a lot of streets cutting into the perimeter, creating multiple ‘fingers’ whose width is twice the street buffer size (and thus 40 ft in our case studies). We reduce the number of vertices by filling in narrow fingers, thus smoothing the polygon boundary. This is accomplished by drawing a buffer around the perimeter that is slightly bigger than that of the streets (21 feet), and then removing the outermost 21 feet of the buffered polygon in order to conserve most of the original polygon boundary. The vertex set (V) from the perimeter of the smoothed polygon is smaller than that of the original polygon. Figure 5 shows the result of polygon smoothing compared to the original polygon for a barrier containing Arlington National Cemetery.

It is important to note that the smoothed polygon is only used to obtain the prominent points, which serve as barrier endpoints. The original polygon is used as input for drawing the barrier lines.
4.4.2.2 Prominent Points and the Convex Hull

A starting point for selecting the set of prominent points is the set of extreme points of the polygon. For a two-dimensional polygon, extreme points are points that cannot be expressed as a convex combination of any two other distinct points in the polygon, and thus tend to be farthest from the interior of the polygon. The extreme points of a polygon represent the vertex set of its convex hull. If one were to stretch a large rubber band to surround all the points in the geometry and release it, the resulting shape when the rubber band becomes taut is the convex hull. Figure 6 shows the convex hull of the smoothed polygon.
FIGURE 2 Smoothed polygon and its Convex Hull.

If any side of the smoothed polygon is longer than $2\times\text{min}_S$, it is diced into segments of equal length and whose length is between $\text{min}_S$ and $2\times\text{min}_S$. This dicing adds vertices to smoothed polygon boundary, and avoids the possibility of a gap greater than $2\times\text{min}_S$ between barrier endpoints.

To find a set of prominent points suitable to drawing boundaries, the set of extreme points has to be both reduced by eliminating points that lack the minimum separation distance from a neighboring point and augmented by adding points where extreme points are too far apart.

If the shortest side of the convex hull is longer than the minimum separation, all the vertices of the hull will be chosen as prominent points. Otherwise, the following procedure was used to select the extreme points to be included in the set of prominent points. First, the span points (the two most distant extreme points) are selected. Extreme points within minimum separation distance from the span points are then eliminated and the convex hull redrawn.

Next, the shortest side of the convex hull is selected. If it is shorter than minimum separation, at least one of its vertices cannot be selected. We eliminate the vertex with the smaller “deflection sum,” which is one-half the sum of deflections of the point’s incident
edges, as shown in Figure 7. In that figure, consider point B, with incident edges AB and BC. Line A′C′ is drawn through point B bisecting the deflection angle between segments AB and BC. Segment CC′ is half the deflection involved in the turn from segment AB to BC, and segment AA′ is half the deflection involved in the turn from BC to AB. The deflection sum is the sum of the lengths of AA′ and CC′, and is given by

\[
DeflectionSum_B = (AB + BC) \times \sin\left(\frac{\pi - \theta_B}{2}\right) \tag{2}
\]

where

DeflectionSum\_B is the deflection sum for point B, points A and C are its neighboring points, AB and BC are the lengths of segments AB and BC, and \(\theta_B\) is the interior angle at B.

**FIGURE 7: Illustration of deflection sum for a vertex**

Once the vertex with the smaller deflection sum is eliminated, the hull polygon is redrawn with the remaining vertices. The new shortest side is compared against the minimum separation and the process of eliminating vertices is repeated until the smallest side of the residual hull polygon is bigger than the minimum separation. The vertices left in the residual hull polygon are added to the prominent point set (P).

Next, if all the vertices of the smoothed polygon (V) are within a distance \(\text{min}_S\) of any prominent point, no more vertices will be added to the set of prominent points. Otherwise, additional prominent points are chosen using geoprocessing techniques explained in the following paragraphs.
4.4.2.3 Prominent Points from Peninsulas

If the smoothed perimeter of the polygon is thought of as the coastline of an island, the area between the perimeter and the convex hull can be viewed as bays. The convex hull of a given bay will overlap with part of the island; this overlap can be viewed as one or more peninsulas, which are essentially the parts of the islands that extend into the bays. Figure 8 shows the island, bays and peninsulas for a polygon. Every vertex of the island belongs to the vertex set of a peninsula or the convex hull of the island.

![Diagram of an island, bays, and peninsulas](image)

**FIGURE 8: Bays, peninsula and peninsula bases of an island**

Each peninsula is connected to the rest of the island by a distinct line which can be called the peninsula base. For a vertex of a peninsula, the distance from the vertex to the peninsula base is a good measure of how far the point is from the interior of the island. For every point in V that is farther than min_S from all points in P, the distance to its corresponding peninsula base is calculated. The point that is farthest from its peninsula base is added to P. We then remove all points in V that are within a distance min_S of the newly added point. This process is repeated until there are no more points left in the set V.

The points in P form the final set of prominent points and will be used as the terminal points for drawing barrier lines. The prominent points selected for a polygon in Arlington using this method can be seen in Figure 8.
In our experience with applying this algorithm, the points generated adequately represent the vertices of the original polygon that are “prominent” in the general sense of being further from the interior of the polygon than any nearby point. However, if a large barrier polygon has a long “inlet” of bicycling space with a narrow mouth (e.g., a low stress street penetrating deep into the polygon), exterior points on both sides of the inlet may be prominent in a general sense, but points on both sides may not selected by the algorithm because of how the smoothing process closes narrow inlets. In such cases, which can happen only with a large polygon, an analyst can add a point manually.

4.4.3 Draw Barrier Lines

The next step is to draw paths between all pairs of prominent points to represent barrier lines. A barrier line by definition should not intersect with any low-stress bike link, which means that it should remain within the barrier polygon, whose internal space is not solid but can contain many voids that represent bicycling space. Because of those voids as well as a polygon’s irregular edges, the barrier lines often have to be curves or polylines, but for purposes of effective visualization should be as smooth as the geometry allows. Highly irregular voids and polygon edges make it such that a line-drawing heuristic that follows a direct line between endpoints until meeting a void or edge and then seeks a path around the obstruction can result in a convoluted path that is not at all smooth to the eye.

Therefore, the approach we follow is to draw shortest paths on a pixel grid. Hexagonal pixels are used for this as nearest neighbor interaction is less ambiguous in a hex grid compared to a square grid. Birch, Oom, and Beecham (7) suggests that hex grids are more suitable than square grids in connectivity and movement path applications. While a square grid has the advantage of being described by two axes, a hex grid can also be described by two axes using axis transformation.

The barrier space is tessellated with equal sized regular hexagon pixels such that none of the pixels are completely outside the barrier space and the entirety of the barrier space is covered by pixels. Pixel size should small enough that no two adjacent pixels can bridge the buffer created by a low-stress street. Equation 3 shows the upper limit of pixel
spacing \( p \) for a given street buffer \( b \), based on the geometry of similar hexagons that share an edge.

\[
p < \sqrt{\frac{12}{13}} * b
\]

(1)

For a 20 foot street buffer, \( p \) should not exceed 19.21 feet. While a smaller pixel size could be used, that is computationally costly, and so we used this upper limit as our pixel spacing.

4.4.3.1 Pixel Grid as a Graph

The hex pixel grid for a barrier polygon can be modeled as a graph with the pixel centroids as nodes and with each node having links to neighboring pixel centroids. For each prominent point in \( P \), the pixel containing that point is the starting point. A breadth-first search of the graph generates the shortest paths on the pixel network to the all other points in \( P \). This is repeated for all the points in \( P \) to get the pixel-based shortest paths between all pairs of prominent points.

4.4.3.2 Reducing the Pixel Paths

When overlaid on a map, the pixel-based shortest paths between prominent point pairs can be visually cluttered due to the irregular shape of the polygon’s interior and exterior boundaries. Eliminating links from the shortest path network can reduce this clutter; however, it should be done in such a way that the resulting set of links still include visually “reasonable” paths between prominent points.

The common cases which contribute to clutter are close parallel lines and dense lines that form small polygons. To reduce this clutter, we first model the shortest paths map as a planar graph, with nodes at the prominent points and wherever shortest paths intersect.

For an edge in the planar graph, if there is an alternative path between its endpoints whose length is either less than 100 m longer than the edge or less than 1.5
times the edge length, then the edge is removed from the planar graph because its connecting function can adequately be replaced the alternative path. If this elimination creates any 2-degree node, it is eliminated by joining its incident edges. We iterate over all the edges of the planar graph in this manner, removing all the close parallels. Figure 9 shows both the original and reduced version of the pixel paths which represent the barrier lines.

**FIGURE 9: Pixel paths before and after reduction**

### 4.5 IMPLEMENTATION ON REAL NETWORKS

The algorithm is illustrated in two case study applications, Arlington County, Virginia and Boston, whose low-stress bike networks were available to us from previous studies. Results may not reflect current conditions, because the network data do not reflect recent improvements.

#### 4.5.1 Arlington County, Virginia

Figure 10 shows the barrier lines for Arlington ranked by size to highlight the larger barriers. The largest 8 barriers are shown in distinct colors; smaller barriers are all
shown in the same washed-out color. (Because small barriers can be very close to one another – e.g., having endpoints on opposite sides of a low-stress street – they can appear to merge and thus be a long barrier; that is only an artifact of the figure’s resolution.) The largest barrier includes Arlington National Cemetery, the Pentagon, Interstate 395, and US Route 1, and spans 3.6 miles. The second biggest barrier is the Potomac River between Key Bridge and Chain Bridge, spanning 3.3 miles.

Recall the connectivity island shown in Figure 1 – while it spans most of the county, it still contains many significant barriers which our method discovered, including a 1.9-mile barrier (from 17th Street N just west of Glebe Road to 35th St N near Gulf Branch), a 1.3-mile barrier (from U.S. 50 north to 11th St N), and 0.9 mile east-west barrier along Lee Highway (Edison St. to Nottingham St.). While barriers that lie within a connectivity island do not disconnect a bike network completely, they can force long detours and thus break the network’s functional connectivity.
4.5.2 Boston

The study area for Boston also includes the town of Brookline, which is bordered by Boston on three out of four sides, and excludes East Boston, which is cut off from the rest of the city by Boston Harbor.

The eight biggest barriers for Boston are shown in Figure 11. Many of the barrier lines formed closed loops; surrounded areas like that are cut off from the rest of the street network. These loops are connectivity islands, yet many of them have barriers within them, which our algorithm has mapped successfully.
Wherever barriers come close to one another, it represents a “breach” in what would otherwise have been a far longer barrier. Such breaches can be very important links in a bike network. For example, the breaches between the biggest barrier (blue) and the second and third biggest barriers (orange and red) are the Southwest Corridor bike path and South Bay Harbor Trail. The breach can also be a quiet neighborhood street such as Sherrin Street and Bourneside Street, which might serve as a base for new local street bikeway.

FIGURE 11: Barriers to low-stress bike network in Boston
4.6 APPLICABILITY AND LIMITATIONS

The method presented here can be applied to rural, suburban, and urban bike networks. However, it important that analysts select distance thresholds that are appropriate to the local density of the road network, so that detours that would be considered common or normal do not get classified as barriers.

For very sparse low-stress networks where nearly all space is a barrier, this method will be of little value. However, it can be of value even in places with a well-developed bike network, identifying barriers that may not be obvious.

Because the barrier lines drawn by our method follow a hex grid, they can have small, unnatural angles and irregularities. For public presentations, it may be worthwhile to smooth the lines further. Another weakness of the method is that the barriers it draws may not coincide exactly with features such as rivers, lakes, or freeways that are obvious barriers. The next generation model should incorporate a way to use known barrier lines or polygons supplied externally.

4.7 CONCLUSION

Being able to visualize barriers in a low-stress bicycling network is valuable for network planning. While some barriers are obvious, others are not. Previous research identified the concept of connectivity islands; however, within the general area of a connectivity island, there can sometimes be long, significant barriers. We have developed a method that identifies and draws linear barriers in low-stress networks, dealing successfully with the complexities of street and low-stress network patterns. This method successfully finds a balance between drawing too many and too few barrier lines, yielding maps that are intuitive and that clearly show gaps in the bicycling network that need to be addressed.

A visualization of the barriers in a low-stress network reveals points where barriers come very close to one another; they represent breaches in what would otherwise be a much longer barrier, and as such could be valuable for bike network planning as the anchor of new routes to be developed.
CHAPTER 4 - REFERENCES


5 PRACTICAL CONSIDERATIONS IN EVALUATING BICYCLE NETWORKS

The previous chapters discussed methods and results from different types of low-stress bike network analysis. While the previous chapters discussed the merits, drawbacks and applicability of various analysis, they do not go into the nuts and bolts of performing such analysis. Street network data are often far from perfect. Fixing errors and inadequacies in street data is one of the most time taking part of performing low-stress connectivity analysis. It also involves thoroughly understanding the principles behind any software and programming tools used for the analysis. We have learned many lessons, developed shortcuts and tricks to aid us in doing bike network analysis. This chapter documents and explains the lessons we learned over the course of doing this research.

The first part gives an overview and basics of working with GIS applications as they are relevant to the present research. It also mentions some things that increased the efficiency and quality of research. The second part of the chapter documents the steps involved in tackling data challenges and coding bike networks. The documentation of coding bike networks is presented with a focus on Greater Boston bike network which includes the cities of Boston, Brookline, Cambridge, and Somerville. Some of the other area street networks we worked with (Oakland, Arlington and Delaware) presented similar challenges and some of these ideas can be applied to other networks as well. This chapter is intended to act as a guide for anyone analyzing bike network connectivity and continuing this research.

5.1 GIS BASICS

Manipulating and analyzing bike networks using requires working with GIS data. While there are many GIS applications out there, ArcGIS is one of the most widely used applications. It has a robust documentation and support for users of all levels. It has a vast array of tools capable of powerful spatial and data analysis. Most of the methods mentioned in this chapter are explained and illustrated using ArcGIS tools. The
comprehensive explanation of the tools mentioned in this chapter can be found on the website for ArcGIS Desktop (1). Other GIS applications are also capable of performing the tasks mentioned here. This section explains general GIS basics and commonly used functions that I found useful in performing bike network connectivity analysis.

5.1.1 Raster and Vector Data

In GIS, spatial data are commonly represented using two types of data – raster and vector (Figure 1). Raster data are commonly represented by a grid of pixels. Each pixel can have different color or value associated with it and is typically stores as image files with varying formats. Raster format is better suited to display continuous data like satellite images and aerial photos. Raster format is dependent on resolution, meaning the display/print quality changes based on the scale of viewing. Raster resolution is represented by pixels per inch (PPI) or dots per inch (DPI) which is an indication of the size of the pixel in a given file. While raster files are useful for viewing and printing maps, most spatial and network analysis uses vector data.

Vector data are represented as points, polylines, and polygons. Points are represented by XY coordinates. Polylines are represented as paths connecting an ordered series of points (vertices). Polygons are formed by connecting vertices as a closed path. Vector data is not dependent on the resolution and can be scaled up or down for viewing and printing maps of different sizes. Vectors can be converted to raster and vice versa but most of the analytical methods and tasks described in this chapter use vector data as they can be represented mathematically.
5.1.2 Vector Data Formats

One of the most popular formats for representing vector data is shapefile (2). A shapefile is a collection of files with the same name but with a different file extension. A valid shapefile has three mandatory files with extensions .shp, .shx, and .dbf. Another file which is highly recommended and required for some analysis is the .prj file, which stores the projection information. All the individual files associated with a shapefile must have the same name and be in the same directory. The sizes of the .shp and .dbf files cannot exceed 2 GB. This is usually not an issue unless the shapefile has an extremely large number of vertices or fields in the attribute table. A shapefile also limits the field name to ten characters and it also does not allow NULL values in numeric fields. If a field value is NULL, a shapefile will use 0 as a default. Shapefiles can be opened by a wide variety of GIS software and for this reason it still one of the most commonly used spatial data formats.

Another popular format is a file geodatabase (GDB) which is more recent than shapefile (3). The GDB has a much higher storage limit (1 TB) than that of a shapefile. It also allows longer field names and NULL values in numeric fields. While converting data from shapefiles and GDB or vice versa, it is important to remember that the name of the fields and attribute tables and values may not transfer exactly as they were in the source file. ArcGIS also supports many other vector data formats including but not limited to
Excel, GPS, KML, JSON etc. Conversion from any of the supported formats to a shapefile or GDB is done using the ‘Conversion Tools’ toolbox.

5.1.3 Coordinate Systems

The spatial information associated with GIS datasets is represented as a latitude-longitude or XY coordinates with a linear unit of measure. Most GIS software automatically integrate multiple datasets with a well-defined spatial reference. It projects the data for mapping even if the datasets have different coordinate systems. If a dataset does not have a spatial reference, it might be difficult integrating it into the current map. In such cases, a projection information can be created using the ‘Define Projection’ tool found under ‘Data Management Tools > Projection and Transformations’.

In some cases, while combining multiple datasets, it might make sense to change the projection for the sake of uniformity. This is especially important when looking at the datasets with different units of measure. This can be done using the ‘Project’ tool found under ‘Data Management Tools > Projection and Transformations’.

5.1.4 Attribute Table and Fields

Attribute table contains information associated with a feature class. Each row in the attribute table represents a geometric object or a feature. Each column represents a field that stores the value of a specific attribute. A unique identifier links the attribute information to its corresponding feature. This unique identifier value is a system-managed value called ‘ObjectID’ which is a mandatory field in the attribute table. Depending on the format of the data, the name of the unique identifying field may be different. For example, shapefiles use the field name ‘FID’ while GDBs use the name ‘OBJECTID’. Another mandatory field named ‘SHAPE’ indicates the type the geometry. The most common geometries are point, polyline and polygons. ObjectID and Geometry fields are system generated.

Attribute tables also have non-system generated fields of which the most common types are numerical, text and date. The numerical fields are further divided into types based on their range and precision. When creating a new field, it is useful to select the
type with the least memory that is acceptable for the purpose. A user can manipulate and modify these values in different ways. The most common way is to use the ‘Calculate Field’ tool which can be found in the ‘Data Management Tools > Fields’ toolbox. Field calculator expressions can be written in VBScript or Python. Of the two, Python gives more functionality and supports calculations that are more complex. Simple calculations can be done using the dialog box that can be accessed by right clicking a field in the attribute table. More complex calculations can be done using code block which enables the user to write a python function and executing the function with the proper parameters. Attribute tables also enable users to add or delete fields and select and highlight features based on a query of the field values.

5.1.5 Z Values and Elevation Information

Z values represent the elevation properties of a feature. Some graph theory modules in python may not work as well when reading a shapefile with Z values. If this happens, the Z values can be removed by creating a copy of the dataset and disabling the Z value in the environment settings. If elevation values are needed, they can be obtained using a Digital Elevation Model (DEM). This elevation information can be used in calculating the slope of streets.

A DEM is a 3D representation of the terrain and is represented as a raster or as a vector in the form of a triangulated irregular network (TIN). In a TIN, a continuous surface is partitioned into triangles with each vertex having information about its x, y, and z coordinates. These vertices are created from the spot measurements of elevations. Raster DEM on the other hand are computed to create a grid of equal sized squares (pixels). The vertical and horizontal resolution of the DEM has a large bearing on slope calculations of the streets. For example, a resolution for a pixel size of 100 meters is useless on a street segment shorter than 100m.

5.1.6 Edit Features Mode

The geometry and topology of features can be modified in edit mode. Edit mode allows users to create new features and modify the vertices of existing features as well.
Any changes made in edit mode will have to be saved before exiting the edit session. It is recommended to save the changes periodically if the user is making a large number of geometry changes so as not to lose any progress. This is true for changes made to the attribute table as well and these changes will not reflect in the data unless saved specifically. There is also an ‘Editing Tools’ toolbox with tools that enables more automated editing tasks. One must exercise caution when using editing tools as the results are often permanent and difficult to reverse.

5.1.7 Definition Queries and Selections

While displaying a dataset as a layer in ArcGIS, sometimes it might be desirable to only draw some of the features. Definition query enables filtering a layer for the feature that only meet the criteria set by a query expression. Selection on the other hand highlights features meeting the criteria set by a query expression. Selection can also be done based on location in relation to other layers on the map. Most tools and operations in ArcGIS are only run on features specified in the definition query and are selected (if a selection is made).

5.1.8 Multipart vs Singlepart

Some GIS datasets contain multipart features, which means that a feature can have multiple geometries at different locations and not necessarily touching. All these geometries share the same ObjectID and attributes. Singlepart datasets have a single geometry (point, polyline or polygon). Figure 2 shows examples of multipart and singlepart datasets. Network analysis involving nodes and links can only be performed on singlepart datasets. Multipart features can be useful in several preprocessing operations like finding imperfections in the geometries and joining topology of features. Some attribute and topology information can be lost while converting singlepart to multipart, but it is an essential operation for some topological modifications.
5.1.9 Cursors

Cursors are data access objects that enable users to iterate and manipulate tables. There are three main types of functions for cursors – Search Cursor, Update Cursor and Insert Cursor. While field calculator can calculate a given column based on the values of other columns in the same row, they are not suitable to calculate a field value based on other rows in the same attribute table or based on the attribute table from other feature classes. Cursors are efficient in reading/writing information between tables when used in conjunction with python dictionaries. Python dictionaries are a data type containing a collection of key-value pairs with each key being unique. Keys and values can be of any object type making dictionaries extremely versatile. Table joins can also be used in connecting different tables together, but cursors are much more powerful and customizable. There are three types of cursors – SearchCursor, UpdateCursor, and InsertCursor. SearchCursor is the read-only function that enables accessing any value in the attribute table using the column name and row ID. UpdateCursor is the write function that can edit any value in the attribute table. InsertCursor creates new rows in the attribute table. Adding rows to the table does not add a geometric feature to the map unless the geometry information is added to the row.

Figure 3: Multipart and singlepart features. (Source: ArcGIS website)
5.2 BIKE NETWORK ANALYSIS

Network analysis for low-stress bike networks can be divided broadly into three steps.

1. LTS classification of streets
2. Integrating origin-destination (OD) information with street network
3. Shortest path analysis

LTS classification of streets involves calculating LTS of each link using the characteristics of streets as specified in the version 2.0 of LTS tables (4, Appendix A). The LTS calculation was done using a python script (Appendix C) that reads the attributes from the GIS data set and updates the value of an LTS field in the attribute table. The most time-consuming part of this step is ensuring data accuracy and completeness. Some of the shortcuts and workarounds for ensuring accurate data are described in the later part of this section. Integrating OD information with street network involves calculating how many trips start and end in each location of the street network. The OD information is usually in the form of polygons or points while the street network consists of lines. The challenge here is to figure out how to associate OD demand from polygons/points to polylines. The final step of the analysis is to run a shortest path algorithm between all possible origin and destination points on the street network which can result in several million operations. The shortest path algorithms require modelling street network as a graph and the practical challenges involved are explained in the later part of this section.

5.2.1 Attribute Coding for LTS Calculation

LTS calculation requires information about certain characteristics of the street network. This information is stored in the attribute table of a GIS file. Depending on where the GIS data originated, the fields in attribute table can have different names. Some GIS sources publish a data dictionary that explains the information stored under different fields names. Greater Boston’s data dictionary is attached in Appendix B. If a street network does not have a data dictionary, building one from scratch is recommended.
LTS tables show the specific attribute information required for LTS calculation. From experience, we have found that not all the fields in the attribute table are accurate or reliable. The rest of this section explains the data limitations in the attribute table and methods to overcome these limitations.

5.2.1.1 Attributes by Direction

In some street network files, the left and right side of the streets have separate fields in the attribute table. This is the case for the Oakland street dataset. This is useful for when the road is two way and it is asymmetric. In such cases, it is essential to check that the correct side of the street is matched with the attribute corresponding to that direction. This will aid in doing an analysis using a directed network accounting for direction restrictions. If the direction does not match the attribute, the line direction needs to be reversed as explained later in this chapter. For Boston, attributes are not given by direction. Instead, they are given as a combination of both directions (for two-ways).

5.2.1.2 Asymmetric Treatments

If the street network does not have two sets of attributes for each side of the streets, one needs to account for the asymmetric roads by applying the worst-case scenario that LTS classification uses. For example, if one side has a bike lane and the other does not, then the whole segment should be treated as not having a bike lane. This is only relevant when each feature does not have attributes for each direction separately. While not having two sets of attributes might be less accurate when it comes to directional analysis, it also uses less memory.

5.2.1.3 Speed

Speed limit in the street data is a poor indicator of the prevailing speeds. The default speed limit (25 mph for Boston city streets) applies to streets unless a different speed limit is specified. We observed that the speed limit value in the attribute table is not reliable. In many cases, the speed limit field value was missing or set to zero by default. In Boston, on most local streets, prevailing speed is between 20 and 25 mph, while on
multilane roads with no parking, it tends to be 35 to 40 mph, even though all have the
same speed limit. In order to assign an accurate prevailing speed to streets, a temporary
speed is assigned based on the street type, and this value is then modified based on a set
of speed rules which are coded under the field ‘Speed_Rule’. For local streets, the
temporary speed of 25 was assigned. For non-local streets, a temporary default speed was
set to the speed limit field value if it is non-zero and 30 mph otherwise. These temporary
values are then modified using the Speed_Rule field with the format explained in Table
1.

**Table 1: Format and explanation of speed_rule field.**

<table>
<thead>
<tr>
<th>Speed_Rule format</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABS_xx_abcd</td>
<td>xx – Numerical value that is equal to the prevailing speed in mph.</td>
</tr>
<tr>
<td></td>
<td>abcd – Reason for assigning a speed of ‘xx’ mph.</td>
</tr>
<tr>
<td></td>
<td>Examples:</td>
</tr>
<tr>
<td></td>
<td>ABS_20_Calm: 20 mph speed because of traffic calming.</td>
</tr>
<tr>
<td></td>
<td>ABS_20_Short: 20 mph speed because of short blocks.</td>
</tr>
<tr>
<td>ADD_xx_abcd</td>
<td>xx – Numerical value to be added to the default speed in mph.</td>
</tr>
<tr>
<td></td>
<td>abcd – Reason for adding ‘xx’ mph to the speed.</td>
</tr>
<tr>
<td></td>
<td>Examples:</td>
</tr>
<tr>
<td></td>
<td>ADD_10_LongBridge: Add 10 mph on long uninterrupted bridges.</td>
</tr>
<tr>
<td></td>
<td>ADD_10_Parkway: Add 5 mph on a parkway with higher speed.</td>
</tr>
</tbody>
</table>

The Speed_Rule field is coded based on expert knowledge from people familiar
with the area. Traffic calming, short blocks with close stop signs, and roundabouts are
some of the more common reasons for lower speeds on the streets. Long bridges,
parkways without parking, longer intersection spacing, and multilane roads usually had
higher speeds. The above-mentioned factors affecting speeds can be easily identified and
highlighted on a map. This enables easily and systematically modifying the Speed_Rule
field and error checking for the speed.
5.2.1.4 Functional Classification Codes

FHWA classifies streets and roads into groups based on their primary function. There are seven functional classes for streets ranging from interstates to local streets (Table 2). The street data file for Boston has a field ‘FEDERALFUN’, which stores this classification code. The values 1 and 2 indicated limited access highways and the value 7 indicates local streets. We found that these values to be reliable across the entire dataset. There boundaries between the rest of the classes of roads are very fuzzy. Only the values 1, 2, and 7 are relevant for LTS calculations. Streets with functional classification 1 or 2 are not included in the analysis since bicycles are not allowed on limited access highways.

<table>
<thead>
<tr>
<th>Functional Classification Code</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Interstate</td>
</tr>
<tr>
<td>2</td>
<td>Other Freeways and Expressways</td>
</tr>
<tr>
<td>3</td>
<td>Other Principal Arterial</td>
</tr>
<tr>
<td>4</td>
<td>Minor Arterial</td>
</tr>
<tr>
<td>5</td>
<td>Major Collector</td>
</tr>
<tr>
<td>6</td>
<td>Minor Collector</td>
</tr>
<tr>
<td>7</td>
<td>Local</td>
</tr>
</tbody>
</table>

When we added Cambridge and Somerville streets to the Boston and Brookline dataset, they did not have a functional class attribute. Instead, they had a different code under the field ‘CLASS’ which uses a scale of 1-6. A visual inspection of the map with different CLASS values highlighted showed that the local streets had CLASS value of 5 or 6 while the interstates and limited access highways had a value of 1. This enabled easy calculation of the functional classification code for the newly added data.
5.2.1.5 Centerline

Most street data do not contain information on whether a street has a centerline or not. Most local streets do not have a centerline in Boston and most non-local streets have a centerline. However, this assumption does not always hold true. There are local streets with a centerline and non-local streets without a centerline. Instead of checking every street and coding a centerline field, we use two exception fields called ‘No_CL’ and ‘Has_CL’. For local streets, we assume no centerline unless the Has_CL value is 1. For non-local streets, we assume a centerline unless the No_CL value is 1. Since we are only coding exceptions to the norm in both the cases, it is much less labor intensive and local expert knowledge are used to identify these exceptions.

5.2.1.6 Number of Lanes

LTS data requires information on a street’s number of lanes per direction or if it is an unlaned two-way street. The number of lanes field in the Boston street data was found to be reliable only for two-way undivided streets with a centerline. For many of the rest of the streets, it a value of two lanes was used, which appears to have been the default from when the GIS data was created. This is clearly not the case for streets without a centerline, one-way streets, and divided streets. Two-way streets with no centerline are identified based on the centerline assumptions explained earlier and these are assumed to have zero lanes (unlaned two-ways).

The number of lanes on one-way streets are coded in a field ‘Lanes_OW’. This Lanes_OW field is an exception field and is only coded when there are two or more lanes on a one-way. Most one-way streets in Boston have only one lane and the exceptions to this are easily identified and coded in the Lanes_OW field. For two-way streets with an odd number of total lanes, the side of the street with a higher number of lanes governs the LTS value. For example, if a two-way has 3 lanes total, then the number of lanes in one direction is assumed to be 2.
5.2.1.7 Divided Streets

Street data typically have a field that indicates the presence of a median on a street. Even if this field is missing or not accurate, many datasets represent median divided streets using a set of parallel lines, one for each side of the median. This way of drawing divided streets makes them easy to identify by visual inspection of a map. It is important to check if the attribute table values correspond to just one side of the street or the combined value for both directions.

If a divided street is shown as a single line, it is essential to check the accuracy of the attributes. If the attribute table does not have fields based on direction, check to see if the field value follows a specific rule based on the values corresponding to each side. For example, the number of lanes for the segment could be the sum of the two sides or the average of the two sides. This will help in interpreting the attribute data accurately.

5.2.1.8 Traffic Volume

Volume of traffic is one of the most important factors effecting LTS for mixed traffic riding conditions. Unfortunately, most cities, like Boston, lack comprehensive volume data for all their streets. The LTS tables for mixed conditions have critical values of ADT at which a street’s stress level changes. These critical values depend on the type of street and number of lanes of travel on these. We infer default ADT values for streets based on a set of rules. Like the centerline field, we assume defaults and code exceptions. The defaults and exceptions for estimating ADT are given in Table 3. For two-ways, ADT includes traffic moving in both direction and for one-ways, it only considers traffic moving in one direction. To account for this, the LTS tables uses Effective ADT = 1.5*ADT for one-way streets. This is based on a 66% directional split assumption for the peak direction. Local streets typically have low volumes unless vehicles use them as cut through streets to avoid the busier roads. Experts with knowledge of local street conditions coded all the exception fields for traffic volumes.
Table 3: Defaults and exceptions for ADT

<table>
<thead>
<tr>
<th>Street type</th>
<th>Default Effective ADT</th>
<th>Exception Field Value and Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-way local streets</td>
<td>1500 or less</td>
<td>GT30L = 1 if $ADT &gt; 3000$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>GT15L = 1 if $1500 &lt; ADT \leq 3000$</td>
</tr>
<tr>
<td>1-way local streets</td>
<td>1500 or less</td>
<td>GT20LO = 1 if $ADT &gt; 2000$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>GT10LO = 1 if $1000 &lt; ADT \leq 2000$</td>
</tr>
<tr>
<td>2-way with 1 lane per direction</td>
<td>3001+</td>
<td>LT15 = 1 if $ADT \leq 1500$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LT30 = 1 if $1500 &lt; ADT \leq 3000$</td>
</tr>
<tr>
<td>Non-local 1-way with 1 lane</td>
<td>3001+</td>
<td>LT10NO1 = 1 if $ADT \leq 1000$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LT20NO1 = 1 if $1000 &lt; ADT \leq 2000$</td>
</tr>
<tr>
<td>2-way with 2+ lanes per direction</td>
<td>8001+</td>
<td>LT802P2 = 1 if $ADT \leq 8000$</td>
</tr>
<tr>
<td>1-way with 2+ lanes</td>
<td>8001+</td>
<td>LT56O2 = 1 if $ADT \leq 5333$</td>
</tr>
</tbody>
</table>

5.2.1.9 Protected Bike Facilities

Boston area has number of off-road bike trails and paths that form the backbone of the low-stress bike network. In addition to these off-road paths, some on-street protected bike lanes were also built in the recent years. Some of these were coded in MassDOT’s GIS layers under the field ‘bike_type’. This is a text field and has information on whether a street has a cycletrack or if it is an off-road path. We created a field ‘qProtected’ to combine the different type of protected bike facilities and populated this field based on bike_type field. There are additional segments of street and trail that were not coded as protected facilities under bike_type field. These were identified with the help of local knowledge and google maps and coded accordingly in the qProtected field. More recently developed protected bike facilities were added periodically and the data contains all the protected bike facilities in the Boston area built until May 2019.
5.2.1.10 Bike Lane Width

Bike_type field also contained information on which streets have bike lanes. Even though this information got progressively out of date as new bike lanes were added to streets, it gave us a starting point for coding the bike lane width under the field ‘BL_WIDTH’. Streets with bike lanes were verified against google maps for their width and coded accordingly. In Boston, most of the bike lanes without any buffer are 5 feet wide.

5.2.1.11 Bike Lane Reach

When a bike lane is next to parking, the total combined width of the parking lane and bike lane affects the stress level. This total width is called bike lane reach. There is a field called ‘PARKALONG’ which indicates whether there is a parking along a street with bike lane. While we did not have information on the parking lane width for all the streets, most of the parking lanes are 8 feet wide. If PARKALONG = 1, then the bike lane reach (BL_REACH) field is set equal to 8 + BL_WIDTH. If there is any buffer in the parking lane or the bike lane, that had to be included in the BL_REACH calculation.

5.2.1.12 Illegal Parking

It is not uncommon for bike lanes to be blocked by parked cars in the Boston area. This is especially frequent in commercial areas. For streets in commercial zones, the value of a field ‘ILLPARKING’ was set to 1. If a street has BL_WIDTH ≥ 4 feet and ‘ILLPARKING’ = 1, then it is assumed that the bike lane is blocked frequently enough that the bicyclists are forced to ride in mixed traffic and LTS criteria for mixed traffic apply. Protected bike lanes have a vertical separation which makes it difficult for drivers to park in them and block them.

5.2.1.13 Excluded Links

In addition to the streets and trails, the GIS files have many other features that are not part of the network. These include features like driveways, parking lots, cemetery paths, walking paths that do not allow bicycling, and some proposed routes that are
currently not in existence. These links were flagged using an attribute ‘qExclude’ and excluded from analysis. Some of these links are easy to identify for someone with knowledge of the area while some are not as obvious. Over the years, we have regularly identified more of these links and excluded them. Occasionally, we still find some links that need to be excluded. Sometimes these links only become apparent when we inspect accessibility maps and find unexpected anomalies.

5.2.1.14 Freeways and Ramps

While interstates and limited access highways are easily identified using their functional classification, some of the ramps and connectors may not have the same functional classification. Luckily, most of these have a specific way they are named under the ‘STREETNAME’ field which makes the easy to identify. For example, querying the STREETNAME field for rows containing the works ‘RAMP’ or ‘INTERSTATE’ identifies some of the links where bicycling is not allowed. These links are also not included in the network analysis.

5.2.2 OD Demand Association with Street Network

Origin and Destination data usually comes as points or polygons. OD demand needs to be associated with street network differently based on the demand type and the purpose of analysis. OD data that come as points can be associated with the nearest intersection on the street network or to any intersection within a specified distance from the point. This can be done by using the ‘Spatial Join’ tool found in ‘Analysis > Overlay’ toolbox. Alternatively, a demand point can be associated with intersections manually. This is a slow process, but it might be essential to accurately reflect how the demand accesses the network. We did this for a supermarket analysis by drawing the driveways to the street network. This ensured that each supermarket is accessed from the streets in the exact same way that people get to supermarkets. For another analysis done in Oakland that involves mapping the service areas of BART stations, we used the nearest intersection method. When the OD data come as polygons as is the case for population
and employment data at block level, there are different ways of associating demand with the street network. These methods are discussed in detail in chapter 2.

5.2.3 Shortest Path Analysis

Once the streets are classified based on their LTS value and OD demand is associated with intersections on the street network, the next step is to calculate shortest paths between all the possible origin and destination combinations on the network. This is done by modelling the GIS street data as a graph with nodes and edges. While ArcMap has a ‘Network Analyst’ toolset, it is more suited towards running a small number of routing operations. For a large street network, say Greater Boston, there are over 15,000 origins and destinations which results in a total of over 225,000,000 shortest path operations which is not practical in Network Analyst. Instead we create a graph using the street layer in a python library called networkx which has a wide array of inbuilt and efficient functions that can run routing and shortest path algorithms. The process of creating a graph involves reading the topology of the street layer to establish the relationship between links and intersections. Unfortunately, there are some data challenges when it comes to reading the topology that needed to be addressed before running a shortest path analysis for an accurate result.

5.2.3.1 Effect of One-ways

In the beginning of our connectivity analysis, we used an undirected street network which assumes that all the streets are two-ways. This is not a problem if the study area does not have many one-ways or if most of the one-ways have a parallel reverse street which is also has the same stress level. This is because if there is a low stress path in one direction, a reverse direction low-stress path will most likely exist using the return parallel street. If the parallel return street has a higher stress, one can presume that there is likely no low-stress path for the return trip. To account for this, one-way streets were paired with a nearby parallel reverse streets and the stress level of the streets takes on the higher of the two values. This pairing was done manually and is heavily dependent on the analyst.
In many cities, one-ways do not always have an obvious parallel return street. In such cases, the pairing method is not appropriate, and the end results can be heavily distorted. The only proper way to account for direction is to ensure that the directions are accurate. Every line feature in GIS has a default direction in which it is drawn. This digitized direction can be seen by symbolizing the feature using an arrow. A direction field in the attribute table is used to show if a given line is two-way or one-way. If it is a one-way the same field can also indicate the direction for one-way streets. One common convention for the direction field is to use the values FT (from-to) and TF (to-from) whether travel is permitted in the digitized direction or against it. In our analysis, we used a field ‘StOperNEU’ which takes numerical values indicating whether a street is one-way (1), divided (11), two-way (0, 2), or contraflow (21).

We have found that the street network data that we have for the Boston area was not reliable for the direction of the streets. The most efficient way to fix the direction information is to check if there is pattern to the errors in direction and use a systematic fix to exploit the pattern. If there is no pattern as was the case in Boston, each street had to be manually verified for direction accuracy. Any incorrectly drawn features are flagged and flipped using the ‘Flip Line’ tool in the ‘Editing Tools’ toolbox. One needs to be extra careful when using any tool in the editing toolbox as the changes are extremely hard to reverse. This process is tedious and time consuming, but it only needs to be done once to be useful for all future analysis. We split the work among multiple people with each person working on a specific location to make the process quicker. They were then combined to get a complete network with the direction information. Care should be taken to not change any other field values accidentally or not overwriting changes unintentionally while combining the datasets.

5.2.3.2 Imperfect Intersection Locations

It is not uncommon for many datasets to have streets coincident to the same intersection not meeting at the exact same spot. This is especially true for features that were drawn without snapping them to nearby features. This is not something that is easy to identify just by looking at the map even at a highly zoomed in view. For the purposes of simply mapping streets, topology may not have an adverse effect. Figure 3 gives an
example of such an intersection at two levels of zoom. Juniper Terrace meets Juniper Street just a little distance away from where Juniper Street breaks. This makes it impossible for a shortest path to be routed from Juniper Terrace onto Juniper Street and vice versa.

Figure 3: Juniper Terrace and Juniper Street intersection at two zoom levels.

It is almost impossible to identify these imperfect intersections just by visual inspection. For this reason, one might want to have a method to systematically identify the locations of the potential problem intersections. A method that we used for identifying the imperfect intersection is explained in the steps given below.

1. Use the Feature Vertices to Points tool found in Data Management/Features toolbox on the street network feature class. This will create two points for a street feature, one each for start and end. This will create duplicates when two streets intersect at a point.

2. Use the Dissolve tool found in Data Management/Generalization toolbox on these points to remove duplicates and create a multipart feature.

3. Draw a buffer polygon around the dissolved points using the Buffer tool in Analysis Tools/Proximity toolbox. Specify a buffer size of to be equal to the snapping distance (say $r$) discussed before.

4. Convert the buffers to single part. These buffer polygons will be circles with an area $\pi r^2$ when any two start/end points are farther than twice the snapping
distance. If they are closer than that, the buffer polygon will not be a perfect circle with an area greater than $\pi r^2$. These imperfect circles are the area locations of the potential areas of topology errors.

Figure 4 shows the result of the above-mentioned steps on the Juniper terrace and Juniper Street intersection. The circles around the intersections can be seen in pale lilac color. The left most of the buffers is not a perfect circle. Every buffer in the picture has an area of 3.14 square meters except for the buffer near the intersection of Juniper Terrace and Juniper Street. Once these locations are identified, they can then be flagged for systematic fix across the entire network. Snap tool found in the Editing Toolbox can be used to fix these topology errors systematically. The tool enables snapping the vertices of a feature class to a different feature class with in a user specified snapping distance. If the snapping distance is too short, it will not fix all the locations and if it is too long some erroneous connections are created. Usually, there is not one good snapping distance that fixes everything with the topology of a street network. It is a good idea to start with a very small value for the snapping distance. The use of snap tool might move vertices and affect topology in ways that are hard to track and this in many cases is an irreversible operation.
5.2.3.3 Missing Intersections

The other topology problem we observed in several street networks is the problem of missing intersection where there is one. This comes from drawing street lines without breaking them every time they meet another street or trail. This is especially common when new street lines are added to existing data. There is a tool in ArcGIS that can easily break a street every time it crosses another street, but this tool does not consider bridges and underpasses which are grade separated and hence do not form a real intersection. This can be fixed by identifying the locations of all the bridges and underpasses and only breaking the streets at crossings that are not bridges or underpasses. This method will fail if there is a real intersection right underneath/above a bridge/underpass. This is a very uncommon occurrence and can be fixed manually if one encounters such a situation.
5.2.3.4 Duplicate Links

Some links in the street networks have duplicates, especially for the off-road paths and trails. We suspect that this happened as trails and links were added to an existing dataset that already has these links. Some of these duplicates may occasionally be identified by visual inspection if they deviate from each other enough, but we have observed that this is not very common. These duplicates add unnecessary computational effort to the analysis. They also create confusion when editing the attribute tables for the features with duplicates. For these reasons, it is recommended that these duplicates be cleaned up before any analysis. These duplicates can be located by iterating over each link in the network and checking if there is another shortest path between the two ends of a link with a comparable length. This graph required for this analysis should allow for more than one link between a pair of nodes. This method also may not work all the time since the duplicate links may be broken in different places than the original links.

5.2.3.5 False Intersections (2-degree intersections)

In addition to missing and imperfect intersections, some street links have breaks mid-block in the GIS data. This does not affect the accuracy of shortest path analysis in any way, but it increases the number of links and nodes in the graph. Sometimes, these mid-block break in the links is for reasons like changes in attributes such as street name, lanes, and bike facilities. In other cases, they might be broken for no apparent reason. These false intersections can significantly increase the computational time of the analysis if they are coded as origins or destinations. They can be filtered out by modeling the street network as a graph and querying for nodes with a degree of 2. In addition to the 2-degree nodes, there can also be some false intersections when an undivided street splits into two lines when it becomes divided. They are not necessarily real intersections where trips can start or end. These can also be filtered by querying for a slightly modified definition of a node degree called ‘name_degree’. Name_degree is the total number of unique street names that the intersection is incident to. Calculating name_degree requires the data to have an attribute table with a field for street name.
5.2.3.6  Short Links on a Divided Street

While looking at the accessibility maps, we observed that there are areas near low-stress routes that had poor accessibility which was not what was expected. Upon closer examination, we noticed that this break in accessibility was caused by the high stress on short links that connect the two sides of a divided street (Figure 5). These short links are more of a crossing links across a divided street where there is a cut in the median. The attributes of these short links are mostly blank or take on a value of zero if it is a numerical field. Based on these attributes, our code assumes that it is a two-way non-local street with a centerline with no bike facilities. This gives it an LTS value of 3. Even if the streets on either side of this are low stress, they are not connected by a low stress crossing link. In some cases, these crossings were missing entirely even if a break in the median exists. These can only be high stress if the crossing stress is high and if there are no traffic signals to facilitate crossing. In Boston, most if not all the high stress crossings are signalized, eliminating the need to apply crossing stress to the links. Because the links were next to divided streets, they are easy to visually inspect and code as low stress. The missing crossing links on the other hand had to be drawn manually after verifying with google maps if there is a break in the median. This was a slow and tedious process, but we could not find a systematic way to speed this up.
Figure 5: Short links across Massachusetts Avenue.

5.2.3.7 Python and Networkx

GIS applications are powerful tools for manipulating spatial data and most transportation agencies store street network data in formats usually supported by GIS software. They are also very capable in mapping and displaying the results of spatial analysis. They are not efficient in large scale network analysis tasks. For this reason, we run the shortest path and routing algorithms using ‘networkx’, a python library called. Networkx has several inbuilt functions for network analysis. It has a function ‘read_shp’ that enables reading shapefiles as graphs. The networkx graphs created by this function have the nodes as a coordinate tuple of the form (x, y). We used this method for a few years, but this method also means that if the precision of the x or y values were to be affected, it would cause the same problem as having imperfect intersections. Instead, we now use unique integer IDs for all the intersections in preprocessing and then create a networkx graph. This method is faster for querying through links and nodes that are
represented by (x, y) coordinates. Using integer labeled nodes also makes it easier to troubleshoot and debug the code.

While it is tempting to store the shortest paths and distance between all pairs of nodes in a matrix, we found that most computers run out of RAM, which triggers a memory error in the program. Instead, we can store 4 shortest paths trees and any given time – two for the low-stress network (outbound + inbound) and two for the entire network including the high-stress links. The high-stress network shortest paths are necessary for when using the detour limits as suggested in earlier chapters. For calculating the paths to return to a given origin, a new graph is created whose links have the opposite direction of the original graph. Running a shortest path algorithm returns a shortest path tree in which all the paths lead back to the origin.

Python is the programming language of choice for scripting geoprocessing tasks in ArcGIS. Python also has a vast collection of libraries that are designed to perform tasks with relative ease. ArcGIS has its own python module called ‘Arcpy’ that comes with the installation of the application. Most ArcGIS tasks and tools can be implemented using Arcpy module and writing a few lines of code without the need for using the graphical user interface (GUI) for the tools. Due to the seamless integration of python with ArcGIS, it is also possible to combine the functionality of external libraries with Arcpy and create custom tools tailored to the user’s needs. Most of the network analysis from the previous chapters was done by building custom tools in ArcGIS. Other users with ArcGIS installation can also use these tools with little to no knowledge of python or programming.
CHAPTER 5 - REFERENCES


2. Environmental Systems Research Institute. *ArcGIS Desktop: Shapefiles*


REFERENCES


## APPENDIX A: LTS 2.0 TABLES

### Mixed traffic criteria

<table>
<thead>
<tr>
<th>Number of lanes</th>
<th>Effective ADT*</th>
<th>≤ 20 mph</th>
<th>25 mph</th>
<th>30 mph</th>
<th>35 mph</th>
<th>40 mph</th>
<th>45 mph</th>
<th>50+ mph</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unlaned 2-way street (no centerline)</td>
<td>0-750</td>
<td>LTS 1</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>751-1500</td>
<td>LTS 1</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1501-3000</td>
<td>LTS 2</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3000+</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td>LTS 4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 thru lane per direction (1-way, 1-lane street or 2-way street with centerline)</td>
<td>0-750</td>
<td>LTS 1</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>751-1500</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1501-3000</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3000+</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 thru lanes per direction</td>
<td>0-8000</td>
<td>LTS 3</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>8001+</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3+ thru lanes per direction</td>
<td>any ADT</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Effective ADT = ADT for two-way roads; Effective ADT = 1.5*ADT for one-way roads

### Bike lanes and shoulders not adjacent to a parking lane

<table>
<thead>
<tr>
<th>Number of lanes</th>
<th>Bike lane width</th>
<th>≤ 25 mph</th>
<th>30 mph</th>
<th>35 mph</th>
<th>40 mph</th>
<th>45 mph</th>
<th>50+ mph</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 thru lane per direction, or unlaned</td>
<td>5+ ft</td>
<td>LTS 1</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4 or 5 ft</td>
<td>LTS 2</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 thru lanes per direction</td>
<td>6+ ft</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4 or 5 ft</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3+ lanes per direction</td>
<td>any width</td>
<td>LTS 3</td>
<td>LTS 4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Notes**
1. If bike lane / shoulder is frequently blocked, use mixed traffic criteria.
2. Qualifying bike lane / shoulder should extend at least 4 ft from a curb and at least 3.5 ft from a pavement edge or discontinuous gutter pan seam.
3. Bike lane width includes any marked buffer next to the bike lane.

### Bike lanes alongside a parking lane

<table>
<thead>
<tr>
<th>Number of lanes</th>
<th>Bike lane width = Bike + Pkgr lane width</th>
<th>≤ 25 mph</th>
<th>30 mph</th>
<th>35 mph</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 lane per direction</td>
<td>15+ ft</td>
<td>LTS 1</td>
<td>LTS 2</td>
<td>LTS 3</td>
</tr>
<tr>
<td></td>
<td>12-14 ft</td>
<td>LTS 2</td>
<td>LTS 2</td>
<td>LTS 3</td>
</tr>
<tr>
<td>2 lanes per direction (2-way)</td>
<td>15+ ft</td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 3</td>
</tr>
<tr>
<td>2-3 lanes per direction (1-way)</td>
<td></td>
<td>LTS 2</td>
<td>LTS 3</td>
<td>LTS 3</td>
</tr>
<tr>
<td>other multilane</td>
<td></td>
<td>LTS 3</td>
<td>LTS 3</td>
<td>LTS 3</td>
</tr>
</tbody>
</table>

**Notes**
1. If bike lane is frequently blocked, use mixed traffic criteria.
2. Qualifying bike lane must have reach (bike lane width + parking lane width) ≥ 12 ft.
3. Bike lane width includes any marked buffer next to the bike lane.
# APPENDIX B: DATA DICTIONARY FOR BOSTON GIS DATA

<table>
<thead>
<tr>
<th>Field Name</th>
<th>Source</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADT_Infer</td>
<td>Derived</td>
<td>Effective ADT values calculated using the fields StOperNEU, qDirLanes, FEDERALFUN. Volume exception fields (GTnnXX, LTnnXX). For one-ways, effective ADT = 1.5*ADT. Only relevant when there is no bike lane.</td>
</tr>
<tr>
<td>ADTNEED</td>
<td>Derived</td>
<td>Indicates a category of street based on its default ADT range and need for exception. Applies only to roads for which FEDERALFUN &gt; 2 and that have no bike lane or cycle track. Used to identify the road segments that might need ADT exceptions. LTW: local without centerline and 2-way. NLNCL: non-local without centerline and 2-way. LOW: local, one-way, 1 lane. 1P1: 1+1 lane road without bike lane. NLOW1: non-local one-way with 1 lane, no bike lane. 2P2: 2+2 (or more) lanes, no bike lane. OW2: one way, 2+ lanes, no bike lane.</td>
</tr>
<tr>
<td>bike_type</td>
<td>MassDOT Bike Layer</td>
<td>Indicates type of bike facility. Values used in Boston LTS analysis – Cycle track: (qProtected = 1). Off-Road Path: (qProtected =1). Other values not used in Boston LTS analysis – Bike Lane: Not used because in Boston LTS analysis,</td>
</tr>
<tr>
<td>Field</td>
<td>Type</td>
<td>Description</td>
</tr>
<tr>
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</tr>
<tr>
<td>BL_REACH</td>
<td>Manual</td>
<td>Sum of the width of the bike lane, adjacent parking lane and buffer (if there is one), in feet. This field is only filled in for bike lanes which are adjacent to a parking lane.</td>
</tr>
<tr>
<td>BL_WIDTH</td>
<td>Manual</td>
<td>Width of the bike lane including any buffers, in feet. 0 or NULL: There is no bike lane.</td>
</tr>
<tr>
<td>FEDERALFUN</td>
<td>MassDOT</td>
<td>It is the road classification as defined by MassDOT. 1: Interstate. 2: Principal Arterial – Other Freeways and Expressways. 3: Principal Arterial – Other. 4: Minor Arterial. 5: Major Collector. 6: Minor Collector (not used in Boston LTS analysis). 7: Local.</td>
</tr>
<tr>
<td>GTnnXX, LTnnXX</td>
<td>Manual</td>
<td></td>
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<tr>
<td>----------------</td>
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<tr>
<td>Exception dummies (0,1) for ADT ranges; no value if there’s a bike lane. GT10LO: local 1-way (ADTNEED = LOW) has ADT 1001-2000. GT20LO: local 1-way (ADTNEED = LOW) has ADT &gt; 2000. GT15L: local 2-way (ADTNEED = LTW) has ADT 1501-3000. GT30L: local 2-way (ADTNEED = LTW) has ADT &gt; 3000. LT30: non-local 2-way (ADTNEED = 1P1 or NLNCL) has 1501-3000 ADT. LT15: non-local 2-way (ADTNEED = 1P1 or NLNCL) has ADT 1500 or less, and is assumed to have ADT of at least 751. LT20NO1: non-local 1-way, 1 lane (ADTNEED = NLOW1) has ADT 1001-2000. LT10NO1: non-local 1-way, 1 lane (ADTNEED = NLOW1) has ADT 501-1000. (Assume that none has ADT &lt; 500). LT802P2: 2+2 or more lane (ADTNEED = 2P2), ADT&lt;8000. LT56O2: 2+ lane one-way (ADTNEED = OW2), ADT &lt;5667.</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Has_CL</th>
<th>Manual</th>
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</thead>
<tbody>
<tr>
<td>Centerline exception. 1 if a two-way, local street (i.e., street for which FEDERALFUN = 7) has a centerline.</td>
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</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>ILLPARKING</th>
<th>Manual</th>
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</thead>
<tbody>
<tr>
<td>Indicates streets where motor vehicles tend to illegally park, drive or stop within the bike lane. Input manually by local experts.</td>
<td></td>
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<tr>
<td>Field</td>
<td>Source</td>
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<tr>
<td>Lanes_OW</td>
<td>Manual</td>
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<tr>
<td>LTS_2018</td>
<td>Derived</td>
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<tr>
<td>MEDIAN</td>
<td>MassDOT with manual corrections</td>
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<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>No_CL</td>
<td>Manual</td>
</tr>
<tr>
<td>Field</td>
<td>Type</td>
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<tr>
<td>------------</td>
<td>------------</td>
</tr>
<tr>
<td>NUMLANE</td>
<td>MassDOT with manual corrections</td>
</tr>
<tr>
<td>PARKALONG</td>
<td>Manual</td>
</tr>
<tr>
<td>qDirLanes</td>
<td>Derived</td>
</tr>
<tr>
<td>qExclude</td>
<td>Manual</td>
</tr>
<tr>
<td>Field</td>
<td>Description</td>
</tr>
<tr>
<td>-------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
</tbody>
</table>
| qNoAccess   | Derived with manual corrections 1: Roads that do not permit bicycle travel  
|             | Freeways (FEDERALFUN is 1 or 2) Ramps                                       |
| qProtected  | Manual 1: Cycle tracks and off-road bike paths/trails                      |
| SPD_MDOT    | MassDOT Speed limit as received from MassDOT, in mph.                       |
| SPEED       | Derived Prevailing speed in mph. Calculated using the fields FEDERALFUN     
|             | StOperNEU SPD_MDOT Speed_Rule                                              |
| Speed_Rule  | Manual Speed rules to be applied to default speeds                          
|             | ABS_nn_xxxx: Prevailing speed = nn.                                         
|             | ADD_nn_xxxx: Add nn mph to the default speed                                |
| StOperNEU   | Derived with manual corrections 1: One-way street that isn’t part of a     
|             | divided street. 0 or 2: If it is a two-way street.                          
|             | 11: One-way street that is part of a divided street                         
|             | 21: Contraflow. Two-way for bikes, one-way for cars.                        |
import arcpy
intable = "All Streets"

### Calculate lanes per direction. Need this for LTS calculation

```python
# Define the function to calculate lanes

def get_dir_lanes(st_oper_neu, lanes_ow, num_lanes, fed_fun, no_cl, has_cl):
    if st_oper_neu in (1, 11):
        if lanes_ow > 0:
            return lanes_ow
        else:
            return 1
    elif fed_fun == 7:
        if has_cl == 1:
            return (0.1 + max(num_lanes, 2))/2
        else:
            return 0
    elif no_cl == 1:
        return 0
    else:
        return (0.1 + max(num_lanes, 2))/2
```

arcpy.CalculateField_management(intable, dir_lanes_field, lanes_expression, "PYTHON_9.3", lanes_codeblock)

### Calculate speed based on speed rules

speed_field = 'SPEED'
spd_expression =
'getSPD(!Speed_Rule!,!SPD_MDOT!,!FEDERALFUN!,!StOperNEU!,!qDirLanes!,
!Has_CL!, !No_CL!)
'spd_codeblock = """def getSPD(spd_rule, spd_mdot, fed_fun, st_oper_neu,
ln_oneway, has_cl, no_cl):
    if (fed_fun == 7 and has_cl == 0) or (fed_fun < 7 and no_cl == 1):
        spd = 25
    elif spd_mdot > 0:
        spd = spd_mdot
    else:
        spd = 30

    if spd_rule[:3] == "ABS":
        spd = int(spd_rule[:6][-2:]):
    elif spd_rule[:3] == "ADD":
        spd += int(spd_rule[:6][-2:]):

    return spd"

arcpy.CalculateField_management(intable, speed_field, spd_expression, "PYTHON_9.3", spd_codeblock)

#### Calculate a temp ADT field to be used for LTS calc
ADT_field = 'ADT_Infer'
ADT_expression =
'getADT(!FEDERALFUN!,!qDirLanes!,!StOperNEU!,!GT15L!,!GT30L!,!GT10LO!,!GT20LO!,!LT10NO1!,!LT20NO1!,!LT802P2!,!LT56O2!,!GT5LO!,!LT15!,!LT30!)'
ADT_codeblock = """def getADT(fed_fun,dir_lanes,st_oper_neu,gt_15,gt_30,gt_10,gt_20,lt_10,lt_20,lt_80,lt_56,gt_5,lt_15,lt_30):
    if fed_fun == 7:
        if st_oper_neu in (0, 2):
            if gt_30 == 1:
                return 3001
            elif gt_15 == 1:
                return 1501
        else:

```
return 1499
else:
    if gt_20 == 1:
        return 3001
    elif gt_10 == 1:
        return 1501
    else:
        return 1499
elif dir_lanes <= 1:
    if st_oper_neu in (0, 2):
        if lt_15 == 1:
            return 1499
        elif lt_30 == 1:
            return 2999
        else:
            return 3001
    else:
        if lt_10 == 1:
            return 1499
        elif lt_20 == 1:
            return 2999
        else:
            return 3001
elif dir_lanes >= 2:
    if st_oper_neu in (0, 2):
        if lt_80 == 1:
            return 7999
        else:
            return 8001
    else:
        if lt_56 == 1:
            return 7999
        else:
            return 8001""]

arcpy.CalculateField_management(intable, ADT_field, ADT_expression, "PYTHON_9.3", ADT_codeblock)
### Calculation qLTS_Own without any pairing

```python
lts_own_field = 'LTS_2018'
lts_own_expression =
'getLTS(!qProtected!,!qNoAccess!,!qExclude!,!SPEED!,!qDirLanes!,!BL_WIDTH!,!BL_REACH!,!PARKALONG!,!ILLPARKING!,!bike_type!,!StOperNEU!,!ADT_In
fer!,!FEDERALFUN!)

lts_own_codeblock = """def
getLTS(protected,no_access,exclude,speed,dir_lanes,bl_width,bl_reach,parkalong,bl_block,bike_type,st_oper_neu,ADT,fed_fun):
    if no_access == 1:
        return 6

    elif exclude == 1:
        return 5

    elif fed_fun == 0 and exclude == 0:
        return 1

    elif protected == 1:
        return 1

    elif ( (bl_width < 4)
        or ((bl_width >= 4) and (bl_block == 1))
        or ((bl_width >= 4) and (parkalong > 0) and (bl_reach < 12)) )):
        ### Mixed Traffic
        if ( (dir_lanes >= 3 and speed >= 30)
            or (dir_lanes == 2 and ADT > 8000 and speed >= 30)
            or (dir_lanes == 2 and ADT <= 8000 and speed >= 40)
            or (dir_lanes == 1 and ADT > 1500 and speed >= 40)
            or (dir_lanes == 1 and ADT > 750 and speed >= 50)
            or (dir_lanes == 0 and ADT > 1500 and speed >= 40)
            or (dir_lanes == 0 and ADT > 750 and speed >= 50) ):
            return 4

    elif ( (dir_lanes >= 2)
or (speed >= 40)
or (dir_lanes == 1 and ADT > 3000)
or (dir_lanes == 1 and ADT > 1500 and speed >= 25)
or (dir_lanes == 1 and ADT > 750 and speed >= 35)
or (dir_lanes == 0 and ADT > 3000 and speed >= 25)
or (dir_lanes == 0 and ADT > 750 and speed >= 35)
: return 3

elif (dir_lanes == 1 and ADT > 750)
or (dir_lanes == 1 and speed >= 30)
or (dir_lanes == 0 and ADT > 1500)
or (dir_lanes <= 1 and speed >= 30)
: return 2

elif (dir_lanes == 1 and speed <= 25)
or (dir_lanes == 0 and speed <= 25)
: return 1

else:
 return 99

elif (bl_width >= 4) and (parkalong == 0):

## Bike lane with no adjacent parking
if (dir_lanes >= 3 and speed >= 40)
or (dir_lanes == 2 and speed >= 50 and bl_width < 6)
or (dir_lanes <= 1 and speed >= 50 and bl_width < 6)
: return 4

elif (dir_lanes >= 3)
or (speed >= 40)
: return 3

elif (dir_lanes == 2)
or (speed >= 30)
or (dir_lanes <= 1 and bl_width < 6)
: return 2
elif ( (dir_lanes <= 1) and (bl_width >= 6) ):  
    return 1

celse:
    return 98

eelif ( (bl_width >= 4) and (parkalong == 1) and (bl_reach >= 12) ):
    ### Bike lane adjacent to parking
    if speed >= 40:
        return 4

eelif ( (dir_lanes <= 1 and speed <= 25 and bl_reach >= 15 )):
    return 1

eelif ( (dir_lanes <= 1 and speed <= 30) 
    or (dir_lanes <= 2 and speed <= 25 and bl_reach >= 15) 
    or (dir_lanes <= 3 and speed <= 25 and st_oper_neu == 1 and 
        bl_reach >= 15) ):  
    return 2

eelif ( (speed >= 35) 
    or (dir_lanes >= 2) ):
    return 3

celse:
    return 97

celse:
    return 96"""