Development of a Feeder Route Cyclist Demand Model for Dense Urban Areas

by

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ABSTRACT

This thesis provides a new way of forecasting bicycle demand in the urban core by using a feeder system approach. It uses a technique of predicting demand at a location for all of the demand feeding into that point. No other published research has been found to use bicycle count data flowing from upstream to downstream locations in this manner to forecast demand by using the socioeconomic and land use characteristics associated with these locations. This study, in particular, examines the behavior of bicyclists in the District of Columbia. This thesis forecasts a statistical relationship between socioeconomic characteristics and land use characteristics by using GIS and regression modeling techniques in order to determine what factors influence cycling behavior. Previous bicycle demand models fail to provide an accurate method of forecasting the demand because they do not consider the socioeconomic and land use characteristics associated with the flow of cyclists on particular bicycle lanes. This thesis demonstrates the development of two models which both prove to provide better results than the traditional "Point Location" Model (which is also modeled in this thesis for comparison against the two new methods). City officials, planners, and engineers should use the feeder system model so that they can make accurate predictions and design and construct bicycle facilities for the future urban area.

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LIST OF ABBREVIATIONS

ACS - American Community Survey

BLOS – Bicycle Level of Service

BTS - Bureau of Transportation Statistics

CBG – Census Block Group

CMAP - Chicago Metropolitan Agency for Planning

DC – District of Columbia

FHWA – Federal Highway Administration

GIS – Geographic Information Systems

ISTEA - Intermodal Surface Transportation Efficiency Act

MAP-21 - Moving Ahead for Progress in the 21st Century Act

MCE - Multi-Criteria Evaluation

MSA - Metropolitan Statistical Area

NYC DOT – New York City Department of Transportation

OLS - Ordinary Least Squares

PH – Peak Hour

PHBV – Peak Hour Bicycle Volume

SAFETEA-LU - Safe, Accountable, Flexible, Efficient Transportation Equity Act

TEA-21 - Transportation Equity Act for the 21st Century

US – United States

USDOT – United States Department of Transportation

1.0 INTRODUCTION

Vehicular commuting traffic puts numerous stresses on our metropolitan areas every year, including increased congestion, revenue loss due to extended travel times, strains on parking facilities, negative environmental impacts, and high highway maintenance costs (Bhat et al., 2005). As such, non-motorized transportation has become popular among individuals as well as at regional transportation planning agencies as a means of reducing these pressures. Of these non-motorized modes, urban cycling is perhaps the most prominent, as it offers an efficient, flexible, and cost-effective alternative to commuter driving (Turner et al., 2006). Specifically, urban bicycling not only reduces congestion and environmental emissions impacts but it also provides health benefits associated with increased daily physical activity.

To provide some perspective on the financial impact of cycling, according to the National Complete Streets Coalition, approximately three trillion miles were driven in the United States in 2008, and half of those trips were three miles or less. The National Complete Streets Coalition also reported that congestion in 2007 had cost the economy $87.2 billion due to the hours lost to traffic jams and the additional cost of wasted fuel (National Complete Streets Coalition 2012). Cycling, which is extremely competitive for trips less than three miles, greatly reduces the amount of traffic on the streets and requires no fuel consumption. According to Turner et al. (2006), if more people cycled, transportation systems would benefit from healthier air and reduced traffic congestion. On top of that, the FHWA explains that cycling is much cheaper than operating a motor vehicle, reporting that 5 to 22 cents per mile is saved for every automobile displaced by biking.

Additionally, the latest statistics from the District Department of Transportation show that urban cycling has an extremely low cost for one year compared to other modes of transportation. Figure 1 below compares the cost for operating a car, riding the metro, and taking a personal bike or using the capital bike share (CaBi) for one year in Washington DC (DDOT[1] 2012).

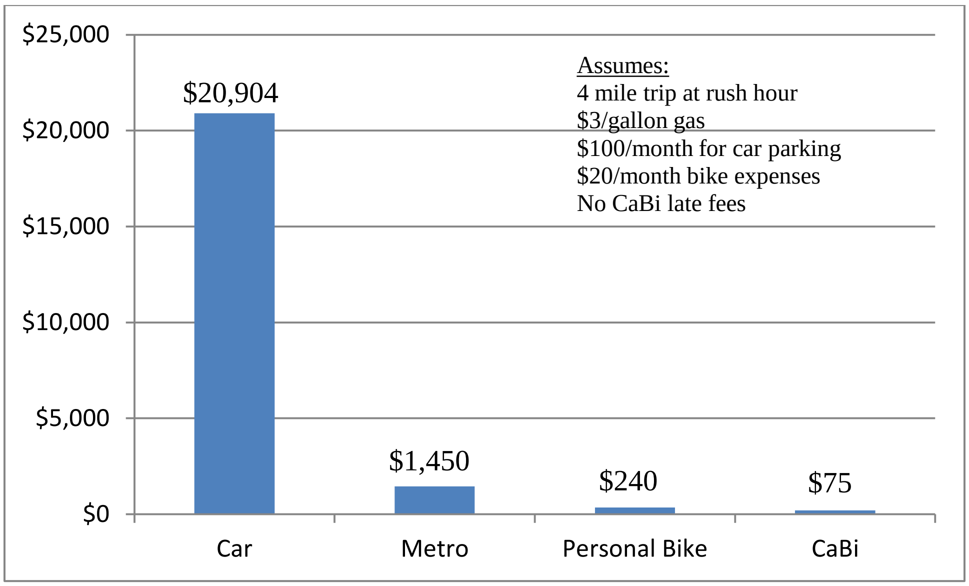

Figure 1: Cost of Transportation per Year (DDOT[1] 2012)

Not only does the increase in the use of the bicycle reduce fuel costs, but it also results in many health benefits. For example, Gutierrez (2009) found that a single rider could lose up to 60 pounds from their weight and save over 1,600 pounds of carbon dioxide exhaust from entering the environment by commuting to work via bicycle for just one year. Cavill and Davis (2007) performed extensive research in which it was found that cycling does, in fact, reduce the risk for cardiovascular disease, diabetes, cancer, and obesity. Bhat et al. (2005) also mentions how cycling can result in a lower risk of high blood pressure and psychological illnesses.

Despite the recognized benefits of promoting urban cycling, there are still many challenges to achieving this goal. These challenges include the city's financial ability to build and maintain safe bicycle infrastructure, overcoming of the convenience of a car, and uncertainty of the weather (Rietvel, Daniel 2004). Of these, securing funds to support bicycle infrastructure is the most challenging issue, because no matter how well a bicycle transportation system is planned, a city often requires additional funds beyond their annual budget to implement such a plan. For example, according to the Pedestrian and Bicycle Information Center (2012), the cost of installing a bike lane can range from $5,000 to $50,000 per mile. The cheapest installation occurs during reconstruction, resurfacing, or at the time of original construction.

There have, however, been several federal transportation authorization bills that have helped assist with this funding issue. The Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 promoted and funded many projects that included the enhancement and development of bicycle facilities (Turner et al. 1998). In 1998, the Transportation Equity Act for the 21st Century (TEA-21) also advanced the use of the bicycle by revising planning requirements to consider bicyclists in the design of facilities. Next, the Safe, Accountable, Flexible, Efficient Transportation Equity Act (SAFETEA-LU) of 2005 provided funding for projects that focused on the safety of the bicyclist (FHWA 1998). This act contained a program called "Safe Routes to School", which promoted actively commuting to school by incorporating bicycle infrastructure into the built environment (Wilson et al. 2009).

However, in 2012, the Moving Ahead for Progress in the 21st Century Act (MAP-21) combined and replaced programs, such as SAFETEA-LU's Safe Routes to School, for funding bicycling and pedestrian projects into a new Transportation Alternatives Program in order to reduce the federal budget deficit (FHWA 2012). Therefore, funding will still exist as an issue because the population of bicycle users is growing and cities will continue to compete with each other to receive funding. For example, in a recent article from the Chattanooga Times Free Press (2011), the cities surrounding Chattanooga, Tennessee, competed for federal grant money to build bike paths, walking trails, and stormwater control. The federal government aims to provide funding to projects that encourage people to actively commute. Therefore, these cities must battle with others from across the state in order to bring forth a creative and efficient way of improving cycling in their community.

One of the most effective methods for competing for these funds is to show (using performance measures) the potential impact that bicycle facilities will have on an urban area. The key performance measure used in these applications is 'bicycle demand'. Bicycle demand defines how many people desire to use a bicycle facility in a given area before it is built. As such, it is essential to accurately predict bicycle demand in an area because if these forecasts are being used to allocate funds, engineers need to be confident that their projects will benefit the most people. If done correctly, urban cycling facilities can be developed so that cyclists can operate under the safest and most efficient conditions.

A February 2003 Omnibus Survey (which is a quantitative marketing research study) conducted by the Bureau of Transportation Statistics (BTS) found that 41 percent of cyclists reported doing so for exercise or health reasons, and 37 percent reported doing so for recreation. According to this study, only 5 percent reported commuting to work by bicycle as its primary use (USDOT 2012). Because not all cyclists are biking for the same reasons, the planning process can be difficult when predicting what factors influence cyclists' behaviors to perform this activity. These factors can vary from socioeconomic components to land use characteristics. As a result, is it important to forecast all cyclist demand, regardless of their travel purposes.

This thesis introduces a new way of forecasting bicycle demand in the urban core by using a feeder system approach. While bicycle demand has been studied in the past, this technique considers the unique movement of cyclists in urban areas. Urban cyclists rarely only travel in a single bike lane corridor; instead, they tend to travel from surrounding areas (or feed) in to the corridor. This behavior is most common in areas that have dedicated non-redundant bike lanes that lead to important/ popular destinations, like a bridge or central business district. Surprisingly, no other research has used bicycle count data flowing from upstream to downstream locations in this manner when forecasting demand. This study, in particular, examines the behavior of bicyclists in the District of Columbia. The DC area was chosen because it represents a typical urban area in which cycling generally flows from the outskirts into the downtown area. It is important to model cyclists' true behavior so that the city can efficiently design for the use of bike facilities. This thesis develops a statistical relationship between socioeconomic characteristics and land use characteristics by using GIS and regression modeling techniques in order to determine what factors influence cycling behavior. The regression was performed on 27 different data collection locations using two types of feeder systems into those locations. A ¼ mile buffer was placed around the feeder paths so that the analysis zone would include those cyclists that may have come from locations surrounding the dedicated bike lanes. The dependent variable used in the regression was the peak hour bicycle volume. This research focuses on producing the best specifications of independent variables that would increase bicycling in the community. This thesis demonstrates the development of two models which both prove to provide better results than the traditional "Point Location" Model (which is also modeled in this thesis for comparison against the two new methods). City officials, planners, and engineers should use the feeder system model so that they can make accurate predictions and design and construct bicycle needs for the future urban area.

This thesis is structured as follows. The next chapter provides a brief overview of the literature that was used in conducting this research. The investigation of this literature contributed to the understanding of the modeling process. Chapter 3 describes the data formulation, while Chapter 4 describes the methodology. A description of the collection and analysis of the data is explained in detail. Chapter 5 presents the model parameters and estimation results in which the generated results from the models are tabulated and further explained. Chapter 6 discusses a comparison of the models to each other and to the existing "Point Location" Model. Next, Chapter 7 concludes the thesis by summarizing the specified model and research findings. Finally, Chapter 8 lists the references made throughout the report, and Chapter 9 lists the tables that were not included in this report.

2.0 PREVIOUS METHODS FOR FORECASTING URBAN BICYCLE DEMAND

Bicycle demand defines how many people desire to use a bicycle facility in a given area, most often before it is built. Currently, there are a variety of different methods that planners use to forecast bicycle demand in urban areas. Specifically, there are four main techniques used to forecast bicycle demand: sketch planning models, aggregate models, four-step models, and disaggregate models.

Sketch planning models are models that describe the relationships between data using very little detailed information. While they are useful to quickly process data, they are not appropriate because they only provide a rough estimate of the model. Aggregate models are models that are formed by using data collected from a larger whole or, in this thesis, collected as census information at the level of a zone. Zones are defined as areas of land that are broken down and separated by specific characteristics. The decision makers, or determinants, in these models are the factors at the zonal level. Four step models are traditional forecasting models (mostly used in traffic modeling) that follow a four step process. These models can be used to predict demand but require the steps of determining trip generation, trip distribution, mode choice, and assigning routes that are often more complex than what is required for bicycle facilities. Disaggregate models are not analyzed at the broad level that aggregate model are analyzed at, but, instead, these models use data that is broken down into its unique parts. The decision makers in these models are not at the zone level but are examined at an individual level. These models typically include information on specific travel behavior such as travel origin and destination information, travel duration, and travel purpose.

The feeder system model structure introduced in this thesis is most consistent with aggregate-level models. As such, the following section summarizes some of the past work in the field to highlight trends in cycling that may be relevant to the feeder model. Additionally, while disaggregate models are less consistent with our work due to that fact that they require individual-level data collection, these models are useful to review because they provide insight into the potential factors influencing bicycle demand. Therefore, this section also identifies factor trends amongst disaggregate techniques before summarizing our feeder system model.

2.1. Aggregate Methods

Aggregate models are models that are formed by a collection of data from a larger whole, such as a zone. Jones et al. (2010) explains that aggregate models can use characteristics of an area from census data in order to study cyclists' travel behavior through a regression analysis. Simply put, aggregate models can be broken down into two types: aggregate *zone-level origin* models and aggregate *facility-level attraction* models. Aggregate zone-level origin models predict demand based on how many individuals are emerging from a particular zone or defined area (e.g., cyclists coming from a specific neighborhood). Aggregate facility-level attraction models use a "facility" or any other attraction in order to predict the demand in an area (e.g., cyclists on a specific bike lane). The main difference between them is that the aggregate zone-level origin model predicts demand based on the origin of the individual, while the aggregate facility-level attraction model predicts demand based on the route in which the individual is taking.

The aggregate zone-level origin model is beneficial when demand needs to be predicted for a zone in which the data is emerging. These models do not provide any information on where cyclists are traveling or where they might be found on the bicycle network. They only provide demand in a zone which is classified as the cyclist's origin. While on the other hand, the aggregate facility-level attraction model is beneficially used when the demand in that area is being predicted based on where the individual is travelling to. In this type of model, the path that the cyclist in traveling on (usually bicycle facilities) is considered and the demand along some point in that path is predicted. Therefore, the main challenge with each method is that the data (the zone data and the attractiveness data, respectively) required for each are assumed to be representative of the entire commuting population.

The following discussion summarizes a number of key examples of past studies performed by researchers using aggregate data. The purpose, data requirements, and findings of each study are described for each research approach.

First, An and Chen (2007) used an aggregate zone-level origin model in which a regression analysis was used to determine what specific factors influenced a cyclist's behavior by using socioeconomic data from the US Census Bureau and bike data from the 2001 National Household Travel Survey (NHTS) at the census block group (CBG) level. Because bike data from the ACS and NHTS was used for these studies, the analyses were able to be performed while isolating the people commuting to work, whereas this research includes the people cycling for a variety of other reasons. An and Chen (2007) found that the most significant factors (in order of most significant to least significant) were the percentage of the student population, the length of sidewalk segments, employment density, and the median household income. Employment density, the percentage of students in the zone, and the number of sidewalk segments resulted in a positive relationship with non-motorized travel. Median household income, however, developed a negative relationship with non-motorized travel demand.

Sheren and Deng (2011) also completed an aggregate zone-level origin model study on the bicycle demand for Bloomingdale Trail in the city of Chicago. Their study consisted of using an aggregate model that contained demographic, employment, and traffic data from the 2010 census, Chicago Metropolitan Agency for Planning's (CMAP) comprehensive regional plan, and the 2005-2009 American Community Survey (ACS) to forecast the bicycle demand while having limited count information. Because it was impractical to count cyclists on the trail being analyzed, a comparison study was used. Bicycle counts were performed at two similar locations surrounding the area (Lakefront Trail and North Milwaukee Avenue), and a trip generation rate was calculated from these locations to forecast data for Bloomingdale Trail. Several factors were determined to be related to the usage of the bicycle for work-related trips. These factors included bicycle ownership, vehicle ownership and availability, availability of faster mass transit, physical conditions, availability of bicycle infrastructure, availability of bicycle facilities at the destination, weather, terrain, and length of overall trip. Sheren and Deng believed that the greatest limitation in their study was the lack of origin-destination data, which is also a limitation in this study. Sheren's study is similar to this research in the fact that it uses aggregate data when performing the analysis. It differs, however, in the fact that the data in this research was collected for the actual streets being examined, and a trip generation rate was not adopted. However, a study by Xu et al. (2012), also displays that a rate model can be successfully used when determining how many bicycle parking facilities should be constructed. The study also determined that as trip distance and parking distance increased in an area these factors increased demand during different time intervals.

In a study performed by Rietvel and Daniel (2004), an aggregate zone-level origin model which incorporated regression analysis, was performed on the share of bicycle use for trips of up to 7.5 km using independent variables of physical aspects of municipalities, features of the population, and policy variables. It focused on to what extent municipality policies matter in determining bicycle use. Their research is very similar to the research discussed in this thesis because it uses a regression analysis to determine what aggregate factors influence cycling behavior. The main difference, however, is that they were concerned more on if municipal policies matter when forecasting bike demand. The findings include improving the attractiveness of a mode by reducing its generalized costs, making competing modes more expensive, maintaining the safety level of bicycle users, satisfying the needs of the cyclists, decreasing the travel time and accident risks. The cultural tradition of the area also played a significant role on whether people commuted to work by cycling.

Barnes and Krizek (2005) used an aggregate zone-level origin model for forecasting demand based on census commute-to-work data in the Minneapolis-St. Paul area. This approach consisted of obtaining data from the US Census Bureau that was specific to a particular area and using information about commuter cycling in that area. They explain that this would provide an area-specific baseline in which other socio-demographic factors could be added to the analysis. The bicycle count information had also been obtained from national travel surveys. Barnes and Krizek assumed, however, that much of the cycling was done by commuters, even though they believed this assumption could lead to slightly skewed results. The greatest finding in their study was that the attitudes of the local area and the history of the area influence a cyclist's decision to ride. For example, they mentioned that an area that presents itself with many commuter cyclists will also have more total cycling. Therefore, if an area already contains a high number of biking commuters, the attitude of the rest of the community is more likely to accept cycling as a desirable mode of transportation.

Another study performed by Baltes (1996) also used an aggregate zone-level origin model which included items such as demographic, economic, and climate factors that were most likely to influence the selection of the bicycle as a person's primary mode of transportation. These factors specifically include high urban densities, large student populations, and relatively temperate year-round climates. These data were taken from the 1990 US census, and was performed in 284 MSAs. This research analysis used a similar regression technique to determine significant aggregate variables that influence biking. The most notable difference in the techniques used in this thesis is the usage of the dependent variable. The dependent variable used in this thesis is the peak hour bicycle volume, while the dependent variable used in Baltes's study was the percentage of the modal split captured by bicycle for work trips in each MSA. The results did not provide any guidance on how to increase the amount of bicycling in the area because the results did not provide any unordinary useful information on the trends of cycling. The variables with the strongest correlation were the percentage of people ages 18 to 24 and enrollment in school. These two groups had the highest rates of commuting to work by bicycling.

Griswold (2011) used an aggregate zone-level origin model with a loglinear regression to determine what socioeconomic, intersection site, land use, and transportation system characteristics change when the bicycle intersection volume is changed. The study was performed at 81 intersections in Alameda County, California, and bicycle counts were taken on weekdays and weekends. The built environment variables were the most significant in Griswold's research, and the socioeconomic variables were too insignificant to include in the final model. Griswold's research uses a loglinear regression approach, whereas, this research uses a linear regression approach because it has been a more common method used for forecasting bicycle demand in the past.

Because aggregate facility-level destination models predict the number of cyclists that will come to a facility based on the characteristics of the facility that will attract bicyclists, such as socioeconomic or land use characteristics of the region, it is appropriate to use this approach to modeling in this thesis. This method continues to remain significant when determining bicycle demand in other studies too. For example, the Contra Costa Transportation Authority (2009) completed a study on forecasting bicycle demand in Contra Costa County, California, using data from the 2000 census and the 2006-2008 ACS. The ACS data was used to calculate the current ridership in the several areas along a bike lane, then the estimated ridership was calculated from the current ridership by using a multiplying factor developed from a study in Portland, Oregon. This factor reflects the relationship between changes in the bikeway miles relative to the changes in ridership. Contra Costa estimated that the proposed 130 percent increase in bikeway miles in the year 2035 would lead to a 181 percent increase in ridership. Instead of determining what socioeconomic and land uses factors influence biking, Contra Costa predicted the increase in cycling with the addition of new cycling facilities. This demonstrates the use of the aggregate facility-level destination method mentioned above.

Aggregate models are typically used to identify the leading influential factors in the cyclists' decision making process in choosing which paths to ride (FHWA 1999). However, a downside to aggregate-based modeling is that the results tend to be less accurate because it is assumed that all the people in a given area were represented by the independent variables given and that the independent variables are directly related to cycling (Katz 2001). These assumptions can be greatly reduced by using disaggregate methods even though disaggregate methods still do not produce consistent and accurate results.

2.2 Disaggregate Methods

Disaggregate models use an individual's certain behaviors/characteristics to predict travel behavior. Even though the data collection is more extensive because it requires an "in depth" collection of data (usually through surveys), the produced results tend to provide more accurate predictions of travel behavior (FHWA 1999). Disaggregate data usually includes information about an individual's routing decisions. Most of an individual's routing choices lead them to take the most desired route into a downtown area. To incorporate the routing factor into this thesis, (since this thesis did not obtain any disaggregate data) the development of a feeder system was performed by assuming the flow on the bicycle lanes into the downtown area was the cyclist's most sought after route.

Now that an overview of disaggregate data has been provided, the rest of this section contains examples of past studies performed by researchers using disaggregate data. The purpose, data requirements, and findings of each study are described for each research approach.

Turner et al. (1998) recommended estimating bicycle demand by collecting specific bicycle trip information such as origin and destination locations, trip lengths, trip purpose, and trip frequency. Data from eight urban locations in four different cities in Texas were used to determine the bicycle travel demand using a sketch planning methodology. The results from his study suggest that people bicycle demand increases when there are favorable conditions for cyclists such as multi-use paths that are separated from traffic and bicycle lanes on scenic corridors or recreational corridors. His study is similar to a regional travel model. In a regional travel model, bicycle trips are predicted by using data such as trip purpose, mode, and origin/destination information (FHWA 1999). This closely relates to an activity-based regional model. It tends to be the most accurate disaggregate modeling method because it simulates an individual's travel patterns almost exactly. Therefore, all information about an individual's travel pattern (location, duration, mode of choice) is needed. However, this results in a costly and time consuming method for forecasting the bicycle demand in an urban area because of the extensive data requirements.

Ryley (2006) sent out 3,000 surveys to residents in the West Edinburgh, Scotland area to determine how their cycling preferences, socioeconomic factors, and attitudinal data affected their biking behavior. Cycling facilities enroute and at the biker's destination proved to be the most significant factor. Jones et al. (2010) also followed a disaggregate approach by collecting bicycle counts in the city of San Diego that included individuals' travel behaviors by surveys. He found that bicycle demand tended to increase when households did not own any vehicles, transit ridership was popular, and with the addition of bicycle lanes paths. Another similar modeling method that describes the relationship between route choice behavior and facility characteristics is proposed by Hyodo et al. (2000). Hyodo et al. (2000) finds that as a person's cognitive distance appears to increase, the chances of that person biking significantly decreases. In this study, cyclists in Japan were asked to fill out a questionnaire describing the individual's characteristics and the bicycle routes they commuted on every day. This thesis did not acquire the "in depth" data that Ryley (2006), Jones et al. (2010), and Hyodo et al. (2000) gained from their surveys. However, because three models were analyzed in this study, a fairly accurate bicycle demand can be obtained without undergoing the data accumulation of a disaggregate model.

Many of the previous studies have all linked the increase in bicycle demand to a few key components. Most of the studies found that people desire to bike when the built environment is fit for cycling. This fit occurs when there are numerous bicycle facilities along the individual's path. Also, it was commonly found that as the distance to a destination increased, the decision of the person was to not actively commute. One of the last most common factors discovered by past researchers was that age had a significant influence. A younger individual (especially one that is still in school) had a positive impact of bicycle demand.

2.3 Limitations of Past Work

Clearly, aggregate regression techniques are popular methods for forecasting bicycle demand. This is mainly due to the fact that the data for such models is commonly available, the technique is repeatable and understandable by most practitioners, and they can be applied to the proper scale of trip generation zones or bicycle facilities. Of these, however, the zone-based aggregate models are still quite limited in their scope. These models do not provide any information on where cyclists are traveling or where they might be found on the bicycle network.

Fortunately, the facility-based aggregate models are a step in the right direction. These models consider facilities in relation to areas that may generate cyclists and tie those cyclists to the facilities. Past work, as mentioned previously, sticks to considering sociodemographics/ land use (1) only at the start and end points of facilities, (2) along a corridor, or (3) around a single point at the beginning, middle or end of the corridor. These techniques are limited, especially in urban areas, where there is diverse development, and a dense network of bicycle lanes that feed into each other.

Another modeling limitation is that a high percentage of cyclists are biking not for commuting, but for recreational purposes. Barnes and Krizek (2005) discussed that facilities suitable for recreational biking are not necessarily suitable for commuters. They used the example that a dense development or a grid network would be ideal for a commuter, while less dense areas and infrequent intersections are more ideal for recreational riding. Most studies do not take this into consideration. Also, they implied that every study region is different. Regions vary by demographic, individual, economic, land use, terrain, and even climate characteristics. Therefore, it is extremely difficult to transpose a model from one city to another. This is seen in Chapter 6 of this thesis.

2.4 Feeder System Approach

This thesis introduces the feeder system approach to modeling, in response to the limitations of past efforts. This model represents a type of facility-level aggregate model that incorporates not just travel on a specific corridor, but all the cyclists that feed into a bicycle facility. For example, if you were to consider the cyclists at any given point on a bicycle lane network, they could have come from any neighborhood upstream from that location, which can branch out quite a bit from a single corridor. Past models would have assumed these cyclists all came from the same corridor, but this model predicts demand based on the sociodemographics/ land use of all the potential neighborhood sources upstream from that location.

This feeder system was developed by assuming which route an individual chooses while biking into an urban core. This study used a GIS-based approach, in which the aggregate data is analyzed at the census block group level. Implementing the model into GIS helped in visualizing the bicycle data through mapping and also buffering socioeconomic and land use characteristics around a bike lane.

3.0 DATA FORMULATION

This thesis utilizes bicycle network and surrounding population/development data from the District of Columbia. The DC region was selected primarily because its bicycle infrastructure is relatively new (i.e. over 56 miles of marked bicycle lanes built over the past 5 years), which makes it reasonable to assume that most of the users of the bicycle network most likely lived there before the infrastructure was constructed. This assumption is significant because this study can then effectively match existing sociodemographic and land use data with the bicycle ridership volumes along these corridors.

Additionally, DC's bicycle network is quite extensive, and covers a variety of urban settings, from dense business districts to residential neighborhoods to mixes of these land uses, from which bicycle ridership levels can be compared. Throughout all these areas, DC has seen an increase in cycling due to the citywide Bicycling Master Plan and pioneering the first public bicycle sharing program in the US (DDOT 2012). Bicycling is continuing to grow in the region due to the rising costs of owning an automobile, the negative environmental impacts, and the health benefits that it provides. Therefore, planners and engineers strive to develop safe and efficient infrastructure to support this mode of transportation by considering the use of the bicycle in future planning and design.

Interestingly, DC transportation planners did not use a traditional demand model when they developed their bicycle lane network. Instead, they sited the bicycle lane network relative to existing bicycle facilities, well-traveled (but undesignated) cyclist routes, bicycle level of service (BLOS) on every road segment, and locations of major activity centers/ metro stations (DDOT 2012). Of course, they also did extensive fieldwork, gathered public input through surveys and workshops, and worked with the District Department of Transportation staff. However, the fact that these facilities are so heavily used indicates that these factors heavily influence ridership and should be considered in such a model.

3.1 Bicycle Count Data

The first important piece of data needed for this analysis is bicycle count data, which was collected in the District of Columbia at twenty-seven separate locations every Tuesday, Wednesday, and Thursday during the month of June 2011. These days of the week during the month of June represent typical weekdays because people's travel behaviors and a city's traffic patterns tend to be the most normal (Talbot County 2006). Collection times spanned from 6:00am to10:00am and 3:00pm to7:000pm, in hopes of capturing the peak hour of bicycle traffic traveling from the outskirts into the downtown area. Specifically, the data were collected by employees of the Policy, Planning, and Sustainability Administration, which is a branch of the District Department of Transportation, by manually recording the time that every cyclist passed over a theoretical line perpendicular to the roadway. Cyclists were counted in both directions, whether they were in the bicycle lane or not. The twenty-seven line locations were chosen to highlight the major routes along the bicycle network that cyclists would take to travel downtown during the peak demand period. The pertinent information recorded during data collection was the number of cyclists, the time of day the cyclists passed the counter, the cyclists' traveling direction, and the location of the cyclist in the roadway. Weather was not considered in the analyses; however, it could have played a role in whether a cyclist decided to bike that day. It was also assumed that bicycle volumes and peak times were consistent across Tuesdays, Wednesdays and Thursdays. However, this assumption was not validated.

Figure 2 highlights the bicycle lane network within the District of Columbia as well as the twenty-seven locations at which bicycle count data was collected. Cycling counts were taken in all corners of the district. Counts were randomly taken on a variety of paths flowing from all types of land uses into the core downtown area. The flow of bicycle traffic generally depends on the time of day. Morning peak periods (which are what this thesis is concerned about) show that most cyclists are flowing into downtown, while evening peak periods show that cyclists tend to flow outwards from downtown. This assumption is proved when the peak hour was determined for the area.

The peak hour one-direction bicycle volume was computed from the collected data by determining which hour had the most cyclists and the volume during that hour, considering only those cyclists traveling downstream into the city at all 27 data collection locations. In this research, the peak hour (PH) was determined to be 8:15 am to 9:15 am and the peak hour volume bicycle volume (PHBV) was 1,366 cyclists. Table 6 in the Appendix shows all of the locations and time periods in which the volumes were recorded.

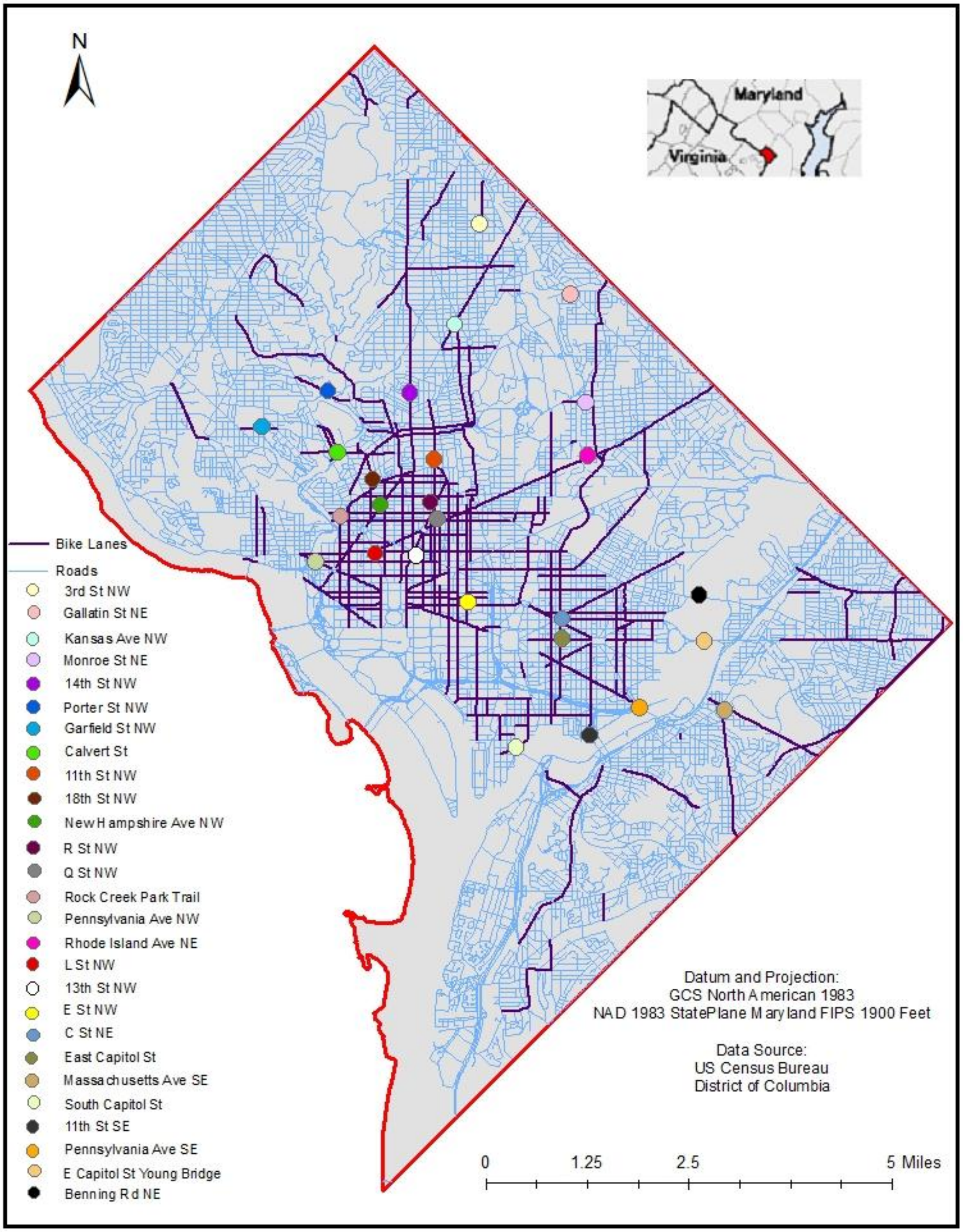

Figure 2: Map of Bicycle Count Locations in the District of Columbia

3.2 Land Use and Socioeconomic GIS Data

All of the land use and socioeconomic data were analyzed at the census block group (CBG) level because this was the smallest common spatial unit for which all data were available. CBGs are larger than census blocks and smaller than census tracts and normally contain 600 to 3,000 people (Iceland, Steinmetz 2003). The CBGs were downloaded from the US Census Bureau's TIGER files database. GIS features including the land uses, road network, and bike lanes were downloaded from the data catalog on district's government website (DDOT 2012). At the time of this research, the US Census Bureau was still releasing updated results from the 2010 census. Consequently, roughly half of the variables (mainly those concerning ethnicities and education levels) were available for 2010, and the remaining region characteristics were compiled from the 2000 dataset. Fortunately, there were not great differences in the data between the two years (433 CBGs in 2000 and 450 CBGs in 2010), so it was considered reasonable to work with data from both years. Both sets of variables were joined to their respective CBGs and compiled in ArcGIS. ArcGIS is a geographic information system used for geographic mapping. Next, the 2000 and 2010 CBGs were spatially joined together through a union, as a few zones were split between 2000 and 2010. This created one zone layer file with all of the 2000 and 2010 socioeconomic and land use characteristics attached to a census block group number. Finally, a point layer was drawn in GIS to represent the count locations.

Specifically, socioeconomic characteristics were collected from the US Census Bureau's Census Survey and American Community Survey (ACS) using the American FactFinder web tool. These data were selected for two major reasons: First, from a practitioner's perspective, these data are readily available (and familiar enough) to be applied to any urban area. Second, it is consistent with much of the findings on factors influencing bicycle demand from previous work. As such, this research focused on the important characteristics, as recognized by the previous literature, of the census block groups such as population, average household size, distributions of ages, income, education, employment, marital status, gender, and race (as seen in Table 1).

Table 1: Socioeconomic Characteristics Considered in the Analysis	
Population	Poverty
Average Household Size	Having a Child in Preschool/Nursery
Total Housing Units	Having a Child in Elementary/Middle School
Not a High School Graduate	Having a Child in High School
High School Graduate	In College
College Degree	Not Enrolled in School
People in the Labor Workforce	Age (0-14, 15-20, 21-49, 50+)
People Not in the Labor Workforce	
Unemployed	
Income (Less than 30K, 30K-60K, 60K-100K, 100K-200K, Greater than 200K)	Gender (Male, Female)
Not Married	Race (White, African American, Asian, Other)
Married	

As mentioned previously, land use has been shown to be highly correlated with different volumes of cycling. Therefore, land use information from the District of Columbia Department of Transportation was collected and characterized into a set of transferrable categories, as seen in Table 2. The residential land use consists of all the one and two family buildings and multi-family buildings in the district, while the mixed residential and commercial land use contains only the land that is used for both of these purposes. Commercial land use includes the district’s office buildings, and industrial and manufacturing consists of all of the space occupied by industries or factories. Transportation structures and utilities and public facilities and institutions are also considered important land uses for this research because they consist of a large portion of the land in the DC area. The final land use variable acknowledges all open space, parking, recreation, and vacant land in the DC area.

Table 2: Land Use Characteristics Considered in the Analysis
Residential
Mixed Residential and Commercial
Commercial
Industrial and Manufacturing
Transportation and Utility
Public Facilities and Institutions
Open Space

3.3 Final Datasets

This thesis utilizes three datasets (one for each of the models being analyzed) generated from the sociodemographic, land use, and bicycle count data. The models include two developed feeder models and the traditional point location model. Each model tested (i.e. local feeder, system feeder, and point location) has a similar dataset that differs only in the scope and spatial scale of the supporting data. As such, each dataset has 27 records, one for each bicycle count location in the city. Each record includes the peak hour bicycle volume at that location for all cyclists traveling in the direction towards the central business district. It is important to recognize that these values include all observed cyclists for the system feeder and point location models, but the local feeder model, by definition, includes only those cyclists that were not counted in the nearest upstream count location.

The supporting independent variables that will predict the PHBV (dependent variable) describe the population sociodemographics and land use at different spatial scales, depending on the type of model being used. For example, the local feeder model dataset considers all the bicycle lanes that lead up to a count location but do not feed into any upstream count locations. When analyzing the bicycle paths in the local feeder model, the average length of the 28 paths was 6.0 miles. This can be used as a reference point in future studies. The system feeder model dataset includes all the bicycle lanes that lead up to a count location including those that feed into any upstream count locations. Using this approach, the final system feeder model dataset produced an average bicycle lane length of 16.1 miles. The point location does not consider bicycle lanes leading to a counter location. In each, the quarter mile buffered distance around each bicycle lane was selected by considering that cyclists would most likely reach the bicycle lane from within this distance. Also, a variety of buffer distances were considered and this provided the most significant variables while preventing the overlap of the buffered areas on other bikes lanes.

4.0 FORECASTING METHODOLOGY

A relationship between the PHBV and the socioeconomic and land use characteristics is to be determined. An econometric regression model of bicycle corridor demand based on corridor land uses and socioeconomic characteristics was performed using three different methods of analysis. A single linear regression was chosen because it simply and easily models the relationship between the dependent variable and all of the independent variables. Regressions have been used in the past, but past research has not shown it to be used on a feeder system method. This feeder system method was developed in order to predict the bicycle demand in an urban area using the flow of cyclists in the peak demand period into the downtown DC area. In this case, the peak hour bicycle volume for each corridor feeder segment remained as the dependent variable throughout the regressions, while the census characteristics and the land uses served as the independent variables. This regression shows how the peak hour bicycle volume changes when any one of the independent variables is varied.

The formula below demonstrates how a basic regression model works.

$$Y = \beta X + \Sigma \tag{1}$$

In this equation, Y is the dependent variable, or in this thesis, the peak hour bicycle volume. The variable, X, is the independent variable, or the census and land use characteristics. Examples of these characteristics include age, gender, race, education, and residential or commercial land uses. The term, β, is the coefficient of the independent variable (which is found from the regression analysis). And finally, Σ is the regression constant.

A regression must have the assumptions of linearity, independence across factors and error terms, constant variance, and normality (Hunt et al. 2002). Linearity is the assumption of when the dependent variable changes, a proportional change happens in the independent variables. This is a major assumption considering that there is never an exact linear relationship between variables. However, this linear regression analysis is only used for the prediction of bicycle demand. The regression must also assume that the independent variables show signs of independence or no correlation from each other. In this case, when two independent variables were run together in the regression and were presumed too closely related, the regression analysis would not produce any results. Therefore, these related variables were taken out of the regression in order to produce a state of independence. Constant variance, also referred to as homoscedasticity, assumes that standard deviation and variance of the error terms are constant for all independent variables. This keeps the "scatter" of the independent variables uniform along the regression line which means that all of the variables are considered to be equally likely to influence bike demand. And finally, the last assumption of a regression analysis is that the variables have a normal distribution and are representative of the population. When variables are taken from many locations, they are assumed to follow a normal distribution, which is essential for performing a regression analysis. Past demand modeling researchers have used a confidence level of 95%. Therefore, at a 95% confidence level, the most influential independent variables were determined significant at a t-value of plus or minus 1.96. However, if some variables were close to this value and found to be significant in other studies, they were considered in this analysis. This is later described in section 5.1.

The goodness of fit of a model or r^2 value measures how well the results correspond to the model and is measured as the proportion of variability in the data set. An r^2 value of 1 indicates that the linear equation shows perfect correlation among the data, while an r^2 value closer to 0 indicates that there is no correlation among the data. Residuals are also important to consider in a regression analysis. A residual is simply the difference between each observed value and what the model predicts for that value. The goal is to minimize the residuals for every data point, and the r^2 value captures this as well.

Two methods were examined when determining the best way to forecast bicycle demand using the developed feeder system. These methods were modeled in GIS by mapping bicycle lanes that highlighted the two designed feeder systems into the downtown DC area and placing ¼ mile buffer around each system so that the land use and socioeconomic characteristics that fall in the buffered census block group will be incorporated as important factors in this study. These feeder system methods are described below including the description of the Point Location Model which has been a commonly used method in past research.

4.1 Explanation of the Feeder System

The definition of a feeder system is described as a way of modeling the flow of cyclists which "feed" into a location where the bicycle count is taken. In other words, counts are acquired at certain downstream points, and, in a feeder system, the distance upstream in which the cyclists are assuming to be coming from is variable. In this thesis, two types of feeder systems are discussed. Each system primarily differs by the upstream distance. The local feeder model uses only the bike lane distance from the closest upstream point (or end of the bike lane facility if no upstream point exists) to the desired downstream prediction location. However, the system feeder model includes all of the bicycle routes upstream of the prediction location. Each model will be explained in further detail below.

4.2 Local Feeder Model

The first option is the local feeder model. This model focuses on the impacts that nearby development/ populations may have on the demand for a bicycle facility. Practitioners may choose to vary this distance however they please. Similarly, the study data for this option ranged quite a bit from small areas limited to between count locations in the urban core to larger areas that extend to the end of the bicycle lane network in the suburbs. A local feeder model is demonstrated in the figure below.

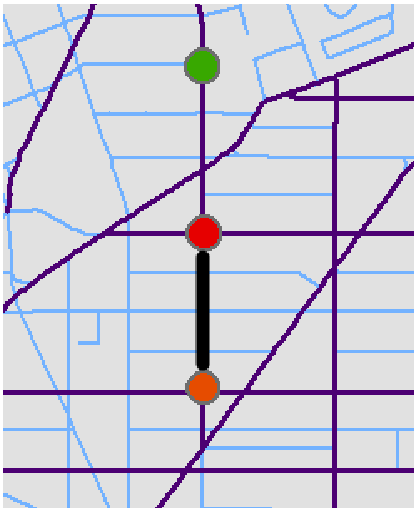

Figure 3: Demonstration of a Local Feeder Model

In Figure 3, the colored dots represent count locations. The orange dot pertains to the downstream count location in which bicycle demand is predicted. The purple lines are bicycle lanes, and the blue lines are the road network. The thick black line would represent a local feeder model. It only considers the cyclists flowing from the closest upstream location to the downstream location point in which the demand is calculated. Figure 3 shows the closest upstream location as the red dot. Therefore, in this case, the variable distance of the local feeder model would be set as shown above.

4.3 System Feeder Model

The second option is the system feeder model. This method considers the impact that development and population along the entire bicycle network up to a set point has on the bicycle volume at that location. Here, distance is not defined either, as any point one selects to measure demand must consider everything surrounding the bicycle network upstream of that point. In that respect, the system feeder model can be considered a very specific type of local feeder model. The one challenge of this option is that there is the potential to have such a wide variety of locations connected upstream from a point that model parameters may be confounded.

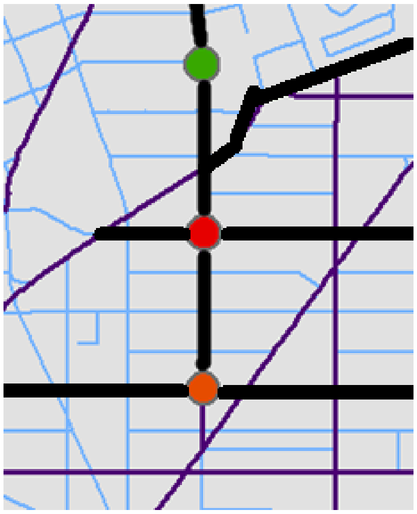

Figure 4: Demonstration of a System Feeder Model

In Figure 4, the colored dots represent count locations. The orange dot pertains to the downstream count location in which bicycle demand is predicted. The purple lines are bicycle lanes, and the blue lines are the road network. The thick black line would represent a system feeder model. It considers the cyclists flowing from all of the upstream locations to the corridor in which the downstream location point is being analyzed.

4.4 Point Location Model

The final method used in this analysis was called the point location model. A 1 mile buffer was placed around each data collection point so that the land use and socioeconomic characteristics could be summed in this area. This option is based on traditional point measurements that assume that demand is dependent on directly adjacent population/ development. The challenge with this method is that most cyclists pass through a region, and the demand is connected to the characteristics upstream and downstream of that point.

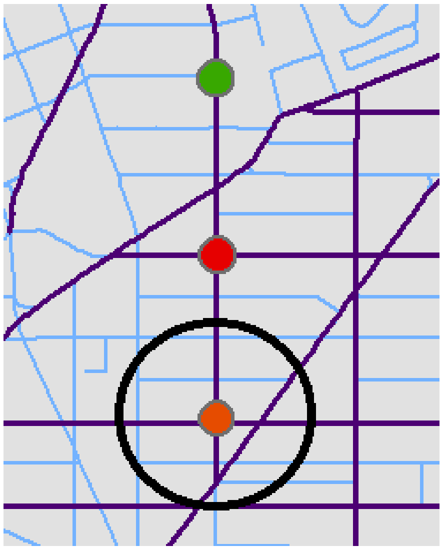

Figure 5: Demonstration of a Point Location Model

In Figure 5, the colored dots represent count locations. The orange dot pertains to the downstream count location in which bicycle demand is predicted. The purple lines are bicycle lanes, and the blue lines are the road network. The thick black line would represent a point location model. It considers the cyclists in a 1 mile buffered area around the count location.

The point location model is a more common way of modeling bicycle demand. Not only does it assume cyclists are biking from all directions (even when a bicycle lane is placed on a one-way street), but it also usually focuses on only changing the way the predictor variables are collected. For example, in the study performed by Jones et al. (2010), he simply develops modeling approaches by first figuring out either where high and low pedestrian activity is occurring or by predicting which areas consist of land uses that attract cyclists to use the bike lanes in these locations. The feeder system method was developed so that it can produce a forecast of bicycle demand that more closely models how cyclists are really flowing into a downtown core, while still being able to use simple aggregated data.

5.0 ESTIMATION RESULTS

The results of the District of Columbia bicycle forecasting demand model will now be explained in detail. Several socioeconomic and land use variables were determined to affect the PHBV for each of the three methods that were discussed above. Table 4 in this section displays the significant variables including their coefficients and t-values from the local feeder, system feeder, and point location models. The next sub-sections will describe the significance of the regression model and an explanation of which models produced the best results.

5.1 Significance using T-Values and r^2 Values

Table 4 in this section includes the coefficients and t- values for each significant socioeconomic characteristic, land use variable, and equation constants. The t-value is calculated by dividing the output of the coefficients by the standard error of the coefficients. The t-value is a measure of the likelihood that the actual value of the parameter is significantly different from zero and that the independent variables are not related. This study uses a 95% confidence level because it is common practice when selecting the significant variables that influence bicycle demand. Any variables with critical t-values greater than or equal to the absolute value of 1.96

(which is associated with the 95% confidence interval for a two-tailed test) were determined to be significant in this study. However, if some variables were close to this value and found to be significant in other studies, they were considered in this analysis. A two-tailed test was used because the interest was to consider 95% of the area under the normal curve excluding the first 2.5% and the last 2.5%.

The coefficient of determination (r^2 value) measures how well the results were predicted by the model. It was computed for each of the methods' linear regression equation. An r^2 value of 1 indicates that the linear equation shows perfect correlation to the data.

In this thesis, the local feeder model resulted in the largest r^2 value at 0.989. Therefore, this model proves to have the best correlation with the dataset and, therefore, will result in the best predictions. The system feeder model also displayed a high r^2 value of 0.975. As expected, the point location model had developed the lowest r^2 value of 0.856. From these results, it can be concluded that both of the feeder models will produce better predictions for bicycle demand in the DC area over the traditional point location model used by other researchers.

An F-test was also performed on all three models. The F value in all three cases is larger than the critical value found in the F distribution table. Therefore, it is appropriate to conclude that all three models are significantly different from each other. These F-values can be seen in Table 3.

Table 3: F-test Results

	Local Feeder - System Feeder	Point Location - Local Feeder	Point Location - System Feeder
F	35.96	62.21	14.53

The F-value for each test was computed using the equation below.

$$F = \frac{(SSE_1 - SSE_2)/\ R}{SSE_2\ /\ (N - m)}$$

In this equation, SSE stands for the sum of squared residual for each model. This value can be obtained from the analysis of variance results. $SSE_1$is the larger of the two sum of squared residuals and $SSE_2$is the smaller of the two for each model. R is the difference in the number of independent variables between the two models (the number of restrictions). N is the number of data points in each sample, and m is the number of variables in the SSE_2model plus the constant.

5.2 Final Model Results

Table 4 shows the coefficients and t-values of the variables that were determined to be significant in each model. Values left blank (-) mean that the variable did not become significant with the model listed in that column. The regressions constant and the r^2 values for each model are also listed in the table. By glancing at these results, the local feeder model (which was determined to be the most accurate way of modeling bicycle demand based on r^2 values) also produced the most statistically significant variables. These results are further explained in the following sections which are broken down into the 3 model types.

Table 4: Model Results						
	Local Feeder		System Feeder		Point Location	
	β	t-stat	β	t-stat	β	t-stat
Socioeconomic Characteristics						
Total Population…	-0.002	-6.39	-	-	-	-
Average Household Size…	1.041	5.13	-2.510	-6.28	-	-
Total Housing Units…	-	-	0.007	5.92	-	-
Ages 15 to 20 Years Old Per Sq Mile…	0.627	8.22	-	-	0.224	3.17
Ages 50 and Older Per Sq Mile…	0.201	7.41	0.425	5.05	-	-
People Who are Male Per Sq Mile…	0.068	3.78	-	-	0.085	2.89
People Who are Female Per Sq Mi…	-0.088	-3.62	-0.254	-5.93	-	-
People Who are Married Per Sq Mile…	0.122	7.71	-	-	0.249	2.88
Unmarried People Per Sq Mile…	-0.171	-5.03	-	-	-	-
People Who are of Asian Race Per Sq Mile…	-	-	-	-	-0.496	-3.68
Race Other Than White, African American, or Asian Per Sq Mile…	-	-	0.423	6.41	-0.156	-2.79
People Who have Graduated from High School Per Sq Mile…	-	-	-	-	-0.098	-2.71
People Who have not Graduated from High School Per Sq Mile…	-	-	0.413	6.41	0.260	3.42
People Who have College Degrees Per Sq Mile…	0.047	1.66	-	-	-	-
People Who have Kids that are in a Nursery Per Sq Mile…	-	-	7.400	6.80	1.126	2.08
People Who have Kids that are in High School Per Sq Mile…	-	-	-	-	-1.475	-3.14
People that are in College Per Sq Mile…	-0.151	-4.21	0.362	5.30	-	-
Income Less Than $30,000 Per Sq Mile…	-	-	-1.995	-6.28	-	-
Income from $60,000 to $100,000 Per Sq Mile…	-	-	1.234	5.10	-	-
Income from $100,000 to $200,000 Per Sq Mile…	-0.581	-3.61	-	-	-0.359	-2.37
Income of Greater Than $200,000 Per Sq Mile…	1.291	7.08	-	-	-	-
People in Poverty Per Sq Mile…	0.087	7.81	0.332	3.53	-	-
Unemployed People Per Sq Mile…	-1.199	-13.01	1.017	7.45	-0.295	-1.74
People in the Labor Workforce Per Sq Mile…	0.075	3.02	-	-	-	-
People Not in the Labor Workforce Per Sq Mile…	-	-	-0.332	-2.92	-0.114	-2.36
Land Use Characteristics						
Residential Land Use Per Sq Mile…	-0.006	-8.92	-	-	-	-
Commercial Land Use Per Sq Mile…	0.025	11.11	0.059	8.49	-	-
Mixed Residential and Commercial Land Use Per Sq Mile…	-	-	-	-	0.070	2.47
Industrial and Manufacturing Land Use Per Sq Mile…	-0.030	-10.72	-	-	-0.015	-3.47
Transportation and Utility Land Use Per Sq Mile…	-	-	0.003	2.04	-	-
Public Facility and Institutional Land Use Per Sq Mile	-	-	-0.014	-5.43	-	-
Open Space, Vacant Land, and Parking Land Use Per Sq Mile…	-	-	0.010	7.62	-	-
Constant	-71.90	-4.91	-1468.55	-4.79	67.69	1.44
r^2	0.989		0.975		0.856	

5.2.1. Local Feeder Model Results

After the regression analysis was performed on the local feeder method, the socioeconomic characteristics that became significant in predicting the bicycle demand in an urban area included the total population and the average household size. Total population had a slightly negative effect on the number of cyclists that chose to commute. In other words, as this population decreased, there would be a slight chance that the PHBV increased. The next paragraph proves this point by showing that as the area becomes more residential, the PHBV tends to decrease. As the average household size of an area increased, the peak hour bicycle volume also increased. This could possibly be a result because bicycling has become a popular mode of commuting because of the expenses associated with commuting by motorized travel.

Age also affects whether someone bikes or not. In this case, the younger population (ages 1 to 20 years old) and the oldest of the population (ages 50 and older) were more likely to commute by bicycle. Reasons for this could be because the youngest group does not have the required income for owning a vehicle, and the oldest population might find it a healthier lifestyle to bike. Additionally, this study, along with many others, confirmed that males typically commute by bicycle more than females. Emond et al. (2009) discussed how men are at least twice as likely to bike than women, and, therefore, performed a study on how gender influences cycling. It is also more likely for married couples to commute than for unmarried people possibly because married couples can bike together if they are heading in the same general direction. This study also found that people that are in college tend to bike less. Weather tends to be a huge factor when choosing what mode of transportation to take. The DC average annual temperature is approximately 54°F (City-Data.com). Unfortunately, this study did not allow the time to record this extensive data. Therefore, weather cannot be completely ruled out as a factor.

Households with an average income of $100,000 to $200,000 (which is above the median household income) showed a decrease in bicycling in the urban area. Pucher and Buehler (2011) admitted to finding that lower income families tend to commute by bicycle more than higher income families. This research, in turn, shows that as the number of people in poverty in the area increases, the PHBV will increase. Hence, lower income families tend to bike more.

Some unexplained variables that were determined to be significant are that people who have college degrees tend to bicycle more often and that when the area is made up of people who make an income of greater than $200,000, the PHBV is more likely to increase. Also, as the amount of unemployed people per square mile increase, the PHBV decreases. This could be explained by recognizing that unemployed people might be more inactive, and therefore, are less likely to commute by bicycle.

Not only did socioeconomic characteristics become significant, but land use characteristics also became significant. As mentioned above, the residential land use had a negative effect on PHBV. It was said that as the population of an area increased (or residential land use in this case) the PHBV would decrease. The only possible explanation is that these residential areas fell mostly on the outskirts of the downtown area at distances that were too far to commute by bike. Therefore, commercial land use would have the opposite effect on PHBV, as suggested by this study. However, if the land consists of industrial and manufacturing land use, the PHBV is more likely to decrease. This is a possibility because industries are normally built on the outskirts of town and in places that are not easily commutable by walking or biking.

5.2.2 System Feeder Model Results

The system feeder method also had several socioeconomic factors that highly influenced bicycle demand in the urban area. Using this method, as the average household size increased, the peak hour bicycle volume was more likely to decrease. The only possible explanation for this is that in the system feeder model, it includes households that are on the outskirts of the downtown area. So if there are multiple people in a household, it would be more likely that they carpool together or not bike for a long distance commute. In this model, as the total number of housing units increased in an area, the PHBV would also increase. This also has the opposite effect that the local feeder model had because in that model, the more residential the area, the less likely people are to bike.

However, it held true that people over the age of fifty tend to bike more often, and also that females tend to bike less often. PHBV increased as races other than white, African American, or Asian populated the area (the DC area consists mostly of African Americans). This is interesting since whites normally do most of the cycling (Pucher, Buehler 2011). This could instead relate to the fact that people who did not graduate from high school, which are most commonly the minorities or the lower income households, bike more often. Using this model, as the number of people that are in college increase, the PHBV tends to increase. This makes more sense because college students, in general, make less money and can better afford cycling. Also, they may conveniently live close to campus.

This study also shows that a positive relationship is developed with people who have incomes ranging from $60,000 to $100,000. Census data for 2010 show median household income was $84,523, and this range includes the average median income. As the poverty level increases in the area, the number of people that bike also increase. This, as mentioned above, is a common find in many research projects. Unlike the previous model, the number of unemployed people have a positive effect on the PHBV. As explained above, unemployment leads to bicycle ridership because it is related to the person's income level.

This model also had a few unexplained variables that were not commonly seen in past research. This could be because the DC area is unique in what factors influence cycling in the area. One was that as the number of people that have kids in a nursery increase, the PHBV is going to increase. Usually parents with very young children will commute by motorized vehicle since picking up or dropping off the child is normally in their daily routine. The second odd outcome of the study was that if the income of the area is less than $30,000, the PHBV will decrease. And finally, this research found that people recorded as not in the labor workforce tended to bike less. These both have an opposite effect from what was shown in other studies and the previous results in this study.

More land use characteristics were found to be significant in this method than in the local feeder model. Commercial land use had the same effect, while three different land uses also came into play. It was found that as the land became more transportation friendly (i.e. more roads, bike lanes) the PHBV increased. Moudon et al. (2005) proved that the perceived and actual built environment contribute to cycling behavior. And, also, as the amount of open land or vacant land increases, the PHBV increases. This system feeder method most likely contains more open space (which is commonly used for recreational biking) since it consists of the bike lanes on the outskirts of the district. And finally, this research found that as the amount of public facilities and institutional land use increases, the PHBV decreases. This was not expected since the downtown DC area contains a large amount of public facilities.

5.2.3 Point Location Method Results

The last method results that are discussed are the point location method results. This method had results matching the previous methods and will only be briefly explained. People from ages 15 to 20 years old, who are males, and who are married had a positive effect on biking in the area and can be seen in the local feeder model results. This method also found that people who have not graduated high school bike more, and people who have graduated from high school bike less. This is further explained above in the system feeder method. People who have kids that attend high school are less likely to bike than people who do not. This effect seems likely because parents most often have to pick their kids up or drop them off at some point in time during their day.

An income of $100,000 to $200,000 also becomes significant in this study by concluding that people who make this income are much less likely to commute by bicycle. This was explained in the local feeder model above. Additionally, as the amount of unemployed people increase in an area, the PBHV decreases in that area. This produced the same result as the local feeder model. And finally, as the amount of people not in the labor workforce increase in an area, the PHBV also decreases. The result of this can be seen in the system feeder model.

The unexplained socioeconomic variables in this analysis were that people of Asian race and other races, not including white and African Americans, were less likely to bike. The system feeder model also explains how people who have children in a nursery are more likely to commute by bicycle. This method also produced these unexplainable results.

Only two land use variables were significant in this method. First, the amount of mixed-use land area (or mixed residential and commercial land use) produces a positive effect on PHBV. Many studies have proved that mixed-use areas promote cycling. In fact, Saelens et al. (2003) proved that residents that live in mixed-land-use communities have a higher rate of cycling than residents that live in single-land-use communities. And finally, people are less likely to cycle through an industrial and manufacturing area. This was previously explained in the local feeder model.

All of these methods proved to produce significant results when undergoing the regression analysis. But to further expand on the accuracy of the models, an application of the local feeder and system feeder models was carried out by comparing the DC model to data in Brooklyn, New York. This application is discussed in Chapter 6 below.

6.0 APPLICATION

6.1 Summary of Data Collected in the Brooklyn, New York, Study Area

Not only did this research compare the models based on the r^2 values, but an application of the models using data from Brooklyn, New York, was also performed and is discussed in this section. A regression analysis was already performed on the Brooklyn data, so it is applicable to apply the results from the DC model to the Brooklyn data in order to see how well it can predict the already forecasted Brooklyn model. Brooklyn bicycle counts, socioeconomic characteristics, and land use data was also collected in the same manner as the DC data. However, the Brooklyn data was only collected on one Tuesday and one Wednesday during the month of June 2012 during the hours of 7am-9am and 11am-1pm. Also, it was only collected for 8 locations (compared to 27 locations in DC). These locations are shown in the table and figure below. The peak hour was determined to be from 8am to 9am with a PHBV of 617 cyclists. This volume is shown in Table 7 in the Appendix. The flow in the Brooklyn study was determined to be from the residential Brooklyn borough into the very large commercial Manhattan borough using the dedicated bicycle lanes that exist on the Brooklyn Bridge, Manhattan, Bridge, and the Williamsburg Bridge. Using the local feeder model approach, the Brooklyn dataset produced an average bicycle lane length of 6.0 miles, while the system feeder model approach contained an average bicycle lane length of 11.4 miles. These are very close to the average lane lengths modeled in the DC data above.

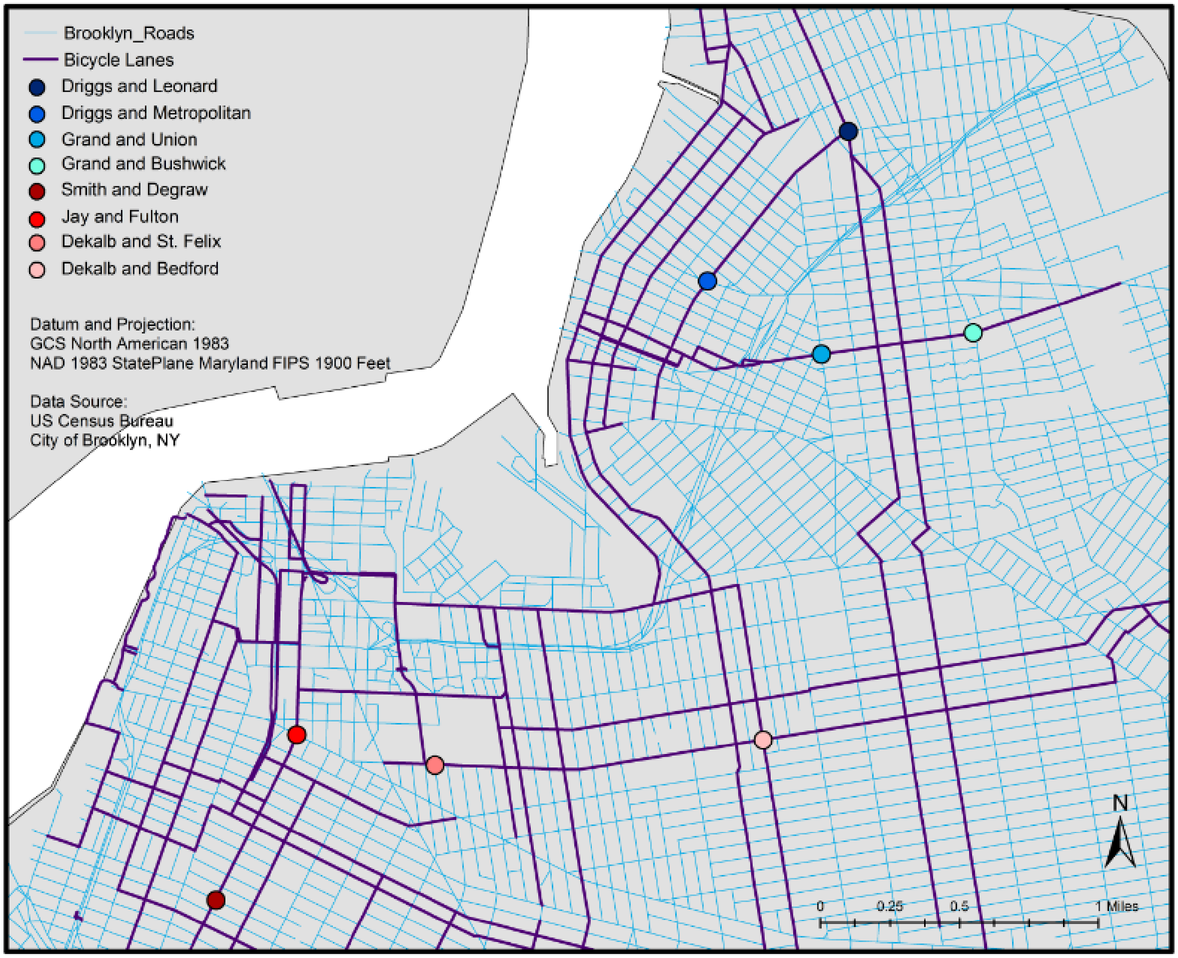

Figure 6: Map of Bicycle Count Locations in Brooklyn, New York

6.2 Application of the Models to Brooklyn, New York

From the regression analysis for the DC area, a linear equation was developed for each of the models. In this section, only the local feeder method and the system feeder method will be used in the application of the Brooklyn data. This is because those methods produced the best results, and time did not allow for the application of the point location method. The equation used in the application is as follows:

$$\textit{Estimated PHBV } (y_i) = \beta_{constant} + \beta_{independent\ variable_1} * independent\ variable_1 + \beta_{independent\ variable_2} * independent\ variable_2 + \beta_{independent\ variable_3} * independent\ variable_3 + \cdots \tag{2}$$

When both the local feeder and the system feeder models were applied to the data, the system feeder model proved to be slightly more accurate in predicting the already observed PHBV for each corridor in Brooklyn even though neither models successfully predicted the demand in the area, as seen in Table 5.

A correlation coefficient, or Pearson's r, was computed for the local feeder and system feeder models to measure the predictive strength. The coefficient was determined from the following formula.

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{3}$$

In this equation, n is the number of corridors, x_i is the observed PHBV for each corridor, $\bar{x}$ is the mean of the observed PHBVs, y_i is the estimated PHBV (for both local and system feeders), and $\bar{y}$ is the mean of the estimated PHBVs (for both local and system feeders).

Table 5: Correlation Coefficient Calculation						
	Local Feeder Model			System Feeder Model		
Location	**Observed PHBV**	**Prediction of PHBV**	**Difference**	**Observed PHBV**	**Prediction of PHBV**	**Difference**
Dekalb_Bedford	81	1675	1594	81	-1751	-1832
Dekalb_StFelix	19	-4	-23	100	-1789	-1889
Driggs_Leonard	66	1245	1179	66	-3305	-3371
Driggs_Metropolitan	8	1254	1246	74	-3304	-3378
Grand_Bushwick	56	-72	-128	56	-3025	-3081
Grand_Union	30	1239	1209	86	-2744	-2830
Jay_Fulton	66	1056	990	110	-759	-869
Smith_Degraw	44	328	284	44	-1028	-1072
		avg. of difference =	794		**avg. of difference =**	-2290
		r_{LF} =	0.29		**r_{SF} =**	0.31

As the r value approaches either -1 or +1, this suggests that the model is highly successful at predicting the observed bicycle volumes. Unfortunately, in this application, one can see that the correlation coefficients are extremely low, with 0.29 and 0.31 value, respectively. Therefore, the model calibrated with DC data is not appropriate for the Brooklyn New York City context. Barnes and Krizek (2005) mention that it is extremely difficult to transpose a model from one city to another. However, if this can be achieved, modeling bike demand in other areas would be much more efficient. If one looks at the predicted values, one can confirm that the predicted values are extremely different from the observed bicycle volumes, with many even being negative in scale.

This suggests that the DC model is not applicable to the Brooklyn data. There were some significant differences in the amount of people cycling in each region. For example, DC proved to have a slightly higher bicycling rate, on average, than Brooklyn. Additionally, the regions may have unobserved factors influencing demand that are not captured in the model that may require more extensive data collection methods using surveys. These factors include population density, attitudes, traffic behavior, transit accessibility/use etc. Also, the Brooklyn data was collected for only one Tuesday and Wednesday in June 2012 versus the DC data collection period of every Tuesday, Wednesday, and Thursday during June 2011. The Brooklyn study considered the morning and mid-day peak period, whereas the DC study considered the morning and afternoon peak periods. One final variation from the Brooklyn and DC models is that the DC models consider a variety of count locations. In all, consistency (by collecting data in the same manner from city to city) in modeling plays a huge role in comparison analyses.

7.0 CONCLUSIONS

Since biking has recently became a more common mode of transportation because of rising gas prices, constant congestion, growing environmental problems, and the promotion of health benefits, it is important that we plan and design for cyclists to use the area around them to actively commute rather than taking a motorized vehicle. Modeling of bicyclists' behavior has helped acquire information about how we can make our areas more efficient, safe, and attractive to cyclists. The models in this research allow us to predict cyclists' behaviors in the District of Columbia based on predicting the demand at a point for all the demand feeding into that point. This modeling technique has never been used before and can further be developed to fit any other urban location because accurately predicting this demand can provide better results for cities which are competing for grant money to build bicycle infrastructure.

Past researchers have used the traditional point location model which does not accurately model a cyclist's actual behavior. This model simply calculates demand using the characteristics around the count location instead of along the bike path in which a cyclist would actually take. Therefore, the two new methods are proposed in this thesis that more closely model cycling behavior. These feeder systems allow one to predict demand at a location for all of the demand feeding into that point using a variable upstream distance.

Three methods were used in this research: local feeder, system feeder, and point location models. The feeder models were shown to produce the best results because the traditional point location model lacked in the understanding of how bicyclists flow into a downtown urban core during the morning peak hours in which the cyclists would be biking into the city. Therefore, it is recommended that a feeder system approach be used (specifically the local feeder model) when analyzing the bicycle demand of an urban area. It produced the most significant socioeconomic and land use variables that can be used in the design and construction of future bicycle infrastructure projects, while also proving to have the best goodness of fit. The local feeder model was able to capture the actual behavior of cyclists flowing from one location to the next into downtown DC. Using these routes, the ¼ mile buffer was able to pick out the specific socioeconomic and land use characteristics of the area that influenced the cyclists to bike on that corridor. This model can be accurately used to predict the bicycle demand if it used in a way to model the flow of cyclists from the outskirts of the city into the downtown urban core.

In this thesis, several factors were determined to be significant influences (using the feeder models) on the bikers into the downtown DC area. These factors include population, household size, age, gender, marital status, education, income, employment, residential land use, commercial land use, and industrial and manufacturing land use. All of these factors result in either a positive or negative impact on bicycle demand in the urban core.

Planners and engineers should use the feeder model when predicting the demand into a urbanized area. It is very important that bicycle demand is modeled specifically so that the city itself knows how costly the addition of bicycle infrastructure would be. Predicting demand can also be used to evaluate the level of service of an area while also considering the safety of its users.

It was found, however, that when the feeder model was applied to Brooklyn, New York, it was not as strong in its prediction. This could indicate that the model may need to be calibrated for different areas before being applied. However, it is more likely that the feeder model can still be generalized to other areas. The New York City area is unlike any other city in the United States of America with respect to socioeconomic and land use characteristics. This is because the New York City area is so different from any other urban areas in the United States in relation to population size and commercial and financial business. Also, the Brooklyn data was collected for a lesser amount of days and different peak hour periods than the DC data. It also emphasizes that travel behavior in Brooklyn is much different than in DC. And finally, the DC models consider a variety of count locations, whereas the Brooklyn models do not. Therefore, the feeder system model would only produce accurate results if it is applied to an area with many count locations, while consistently using measurements during the same peak times.

The model developed in this thesis may be applicable if it is developed for the specific city in which bicycle demand is an achievement. However, just because this approach provides a more accurate method of modeling the actual flow of bicyclists, there is still much to learn on this subject. Future research should consider using a feeder model approach when examining rural areas. These areas usually possess little to any cycling behavior, but a model could be produced to determine the factors that quantify this behavior. And finally, future research using the feeder system approach to determine pedestrian habits, traffic demand, or freight usage can prove to have beneficial results when determining the best ways for cities to handle this demand.

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9.0 APPENDIX

Table 6: DC Bicycle Volumes During the Count Period														
Time	3rd St NW	Gallatin St NE	Kansas Ave NW	Monroe St NE	14th St NW	Porter St NW	Garfield St NW	Calvert St	11th St NW	18th St NW	NH Ave NW	R St NW	Q St NW	Rock Creek Park Trail
6:00-7:00	6	0	4	9	38	8	7	10	40	12	24	12	2	2
6:15-7:15	14	0	8	11	43	13	7	25	56	14	31	19	6	7
6:30-7:30	16	0	8	15	53	13	6	36	70	17	36	22	8	9
6:45-7:45	20	0	8	19	72	13	6	49	96	18	46	30	13	13
7:00-8:00	26	0	13	22	83	15	8	69	120	19	73	37	19	20
7:15-8:15	21	0	14	28	88	14	9	73	149	27	97	45	23	19
7:30-8:30	23	1	20	29	89	10	14	88	182	32	127	56	29	17
7:45-8:45	20	1	31	27	89	9	13	105	214	38	151	68	34	14
8:00-9:00	17	1	28	26	109	6	12	110	263	49	168	84	38	15
8:15-9:15	14	1	27	23	116	3	11	103	280	52	178	96	37	16
8:30-9:30	12	1	24	19	109	4	6	90	280	55	184	90	35	16
8:45-9:45	11	2	17	15	93	5	5	73	249	53	177	80	29	22
9:00-10:00	6	2	15	13	65	10	6	58	182	39	150	55	19	16
15:00-16:00	3	1	2	2	82	10	8	65	59	30	54	4	3	13
15:15-16:15	3	0	2	3	95	11	10	67	78	28	53	7	4	13
15:30-16:30	2	0	1	6	103	13	7	76	90	31	56	11	10	13
15:45-16:45	4	0	3	14	93	14	9	72	94	34	51	18	11	10
16:00-17:00	4	0	7	16	98	13	7	87	103	29	63	22	13	4
16:15-17:15	7	0	10	24	88	18	6	94	91	33	75	28	20	14
16:30-17:30	9	0	15	22	99	16	8	96	103	33	98	26	22	17
16:45-17:45	12	0	14	19	112	16	6	102	128	52	120	26	29	20
17:00-18:00	20	0	17	27	121	20	7	95	166	73	146	32	43	25
17:15-18:15	18	0	24	25	132	18	11	99	212	83	169	41	46	18
17:30-18:30	18	6	20	27	135	18	11	107	227	101	173	52	49	18
17:45-18:45	15	6	20	36	135	18	10	108	237	88	180	61	62	16
18:00-19:00	6	6	14	31	105	12	9	120	215	67	162	60	53	16

Table 6 Continued: DC Bicycle Volumes During the Count Period													
Time	PA Ave NW	RI Ave NE	L St NW	13th St NW	E Street NW	C St NE	East Capitol St	MA Ave SE	South Capitol St	11th St SE	PA Ave SE	East Capitol St Young Bridge	Benning Rd NE
6:00-7:00	15	5	6	9	9	8	23	1	6	2	9	4	5
6:15-7:15	32	8	12	13	9	9	35	1	9	3	12	4	6
6:30-7:30	30	10	12	9	18	7	43	1	8	3	11	4	9
6:45-7:45	47	10	16	13	23	8	50	0	8	4	7	2	10
7:00-8:00	69	14	24	15	23	8	52	0	6	4	7	2	11
7:15-8:15	65	12	24	19	26	10	50	1	6	3	10	2	11
7:30-8:30	86	10	38	22	23	20	58	2	5	1	8	4	12
7:45-8:45	91	9	49	28	28	26	64	2	6	0	11	4	18
8:00-9:00	93	5	53	42	29	30	72	2	7	1	10	3	19
8:15-9:15	111	4	71	46	35	29	74	1	4	3	5	3	23
8:30-9:30	97	6	77	55	33	19	66	0	5	3	10	3	18
8:45-9:45	99	6	77	63	27	12	56	0	3	3	8	11	11
9:00-10:00	91	6	77	51	22	8	43	0	2	3	11	12	14
15:00-16:00	50	7	17	20	24	4	19	1	4	1	12	0	14
15:15-16:15	50	8	31	17	21	2	18	1	8	1	14	0	17
15:30-16:30	43	3	34	17	19	2	24	1	11	1	10	1	16
15:45-16:45	38	4	41	14	18	1	25	0	15	7	8	1	16
16:00-17:00	37	4	45	8	23	2	41	1	15	8	3	1	17
16:15-17:15	59	6	42	18	28	2	47	1	12	9	4	3	18
16:30-17:30	69	20	48	25	34	4	44	1	10	15	6	2	20
16:45-17:45	85	27	48	41	37	6	57	2	10	10	11	2	16
17:00-18:00	94	28	59	43	38	6	46	2	7	9	12	3	15
17:15-18:15	72	29	75	36	33	7	49	2	8	8	15	2	12
17:30-18:30	74	16	73	35	29	5	63	2	7	2	18	2	8
17:45-18:45	60	10	77	26	29	5	62	1	5	2	16	8	14
18:00-19:00	54	11	68	21	20	4	54	1	6	3	19	7	13

Table 7: Brooklyn Bicycle Volumes During the Count Period								
Time	**Smith & Degraw**	**Jay & Fulton**	**Dekalb & St Felix**	**Dekalb & Bedford**	**Grand & Bushwick**	**Grand & Union**	**Driggs & Leonard**	**Driggs & Metropolitan**
7:00-8:00	30	45	52	32	41	47	12	17
7:15-8:15	31	67	63	48	46	62	27	32
7:30-8:30	38	89	70	65	46	80	45	44
7:45-8:45	40	93	82	74	46	87	57	58
8:00-9:00	44	110	100	81	56	86	66	74
11:00-12:00	17	29	47	41	41	61	32	43
11:15-12:15	25	32	45	40	43	61	34	44
11:30-12:30	30	33	36	33	41	70	33	45
11:45-12:45	37	33	30	34	39	64	35	42
12:00-13:00	38	38	22	23	33	59	35	41