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MINETA TRANSPORTATION INSTITUTE

# Impact of Dedicated Bus Lanes on Intersection Operations and Travel Time Model Development

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# Mineta Transportation Institute

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Report 22-19

# Impact of Dedicated Bus Lanes on Intersection Operations and Travel Time Model Development

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<tr><td colspan="4">16. Abstract<br>Over the years, public transit agencies have been trying to improve their operations by continuously evaluating best practices to better serve patrons. Washington Metropolitan Area Transit Authority (WMATA) oversees the transit bus operations in the Washington Metropolitan Area (District of Columbia, some parts of Maryland and Virginia). One practice attempted by WMATA to improve bus travel time and transit reliability has been the implementation of designated bus lanes (DBLs). The District Department of Transportation (DDOT) implemented a bus priority program on selected corridors in the District of Columbia leading to the installation of red-painted DBLs on corridors of H Street, NW, and I Street, NW. This study evaluates the impacts on the performance of transit buses along with the general traffic performance at intersections on corridors with DBLs installed in Washington, DC by using a "before" and "after" approach. The team utilized non-intrusive video data to perform vehicular turning movement counts to assess the traffic flow and delays (measures of effectiveness) with a traffic simulation software. Furthermore, the team analyzed the Automatic Vehicle Locator (AVL) data provided by WMATA for buses operating on the study segments to evaluate bus travel time. The statistical analysis showed that the vehicles traveling on H Street and I Street (NW) experienced significantly lower delays during both AM (7:00–9:30 AM) and PM (4:00–6:30 PM) peak hours after the installation of bus lanes. The approximation error metrics (normalized squared errors) for the testing dataset was 0.97, indicating that the model was predicting bus travel times based on unknown data with great accuracy. WMATA can apply this research to other segments with busy bus schedules and multiple routes to evaluate the need for DBLs. Neural network models can also be used to approximate bus travel times on segments by simulating scenarios with DBLs to obtain accurate bus travel times. Such implementation could not only improve WMATA's bus service and reliability but also alleviate general traffic delays.</td></tr>
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# Executive Summary

Dedicated bus lanes are those restricted to only buses either permanently or during certain hours of the day. The lanes are usually indicated with "Bus Only" posted signs and pavement markings along the route with specific regulations. These exclusive lanes provide opportunities for buses to bypass traffic congestion and avoid vehicular conflicts in mixed travel lanes to improve bus service reliability. Implementing these lanes can help increase the attractiveness of bus transit to prospective public transit users, thereby encouraging a mode shift from using single-occupancy vehicles to buses.

This report pres^ents the findings of a study that aimed to determine the impacts on the performance of transit buses as well as general traffic (transit and non-transit) performance after installing dedicated bus lanes (DBLs) at selected corridors in Washington, DC. Furthermore, a model for predicting bus travel times operating on such lanes was also developed using Artificial Neural Networks (ANN).

DDOT implemented a bus priority program on selected segments in the District of Columbia leading to the installation of red-painted DBLs on segments of H Street (NW) and I Street (NW). Hence, a "before" and "after" scenario approach was used to evaluate the impacts on the performance of transit buses and intersection performance on segments with DBLs. DDOT installed bus lanes by June 2019 on the segment of H Street (NW) between 19th Street (NW) and 13th Street (NW) and the segment of I Street (NW) between 21st Street (NW) and 13th Street (NW).

The matrices containing the variables required to conduct the studies were developed based on visual observation of intersection vehicular turning movement count (TMC) data, as well as the Automatic Vehicle Location (AVL) data for transit buses that were provided by Washington Metropolitan Area Transit Authority (WMATA) at the following five locations:

1. H Street and 14th Street, NW
2. H Street and 17th Street, NW
3. I Street and 15th Street/ Vermont Avenue, NW
4. I Street and 16th Street, NW
5. I Street and 17th Street, NW

AVL data were obtained from WMATA for the "before" months of May 2019 and June 2019 and the "after" months of September 2019 and October 2020 for bus routes 7Y, 32, 30S, and 30N.

These routes service the five locations. Non-intrusive video data at these intersections were reviewed to observe the compliance of buses and other passenger vehicles while using the DBLs at the intersections, in addition to vehicular TMCs. It was found that the average bus travel time on the segments generally decreased after the installation of these DBLs.

From field observations, TMC data and AVL data, relevant information for the analysis were obtained for the AM (7:00 AM–9:30 AM) and PM (4:00 PM–6:30 PM) peak periods before and after the installation of bus lanes. PetraPRO software was used to analyze the AM and PM TMCs, while Synchro 10 Simulation software was used to analyze the intersection operations, thereby obtaining the pertinent measures of effectiveness (MOE) such as approach delays and control delays (that determine the quality of traffic performance) at all intersections under both scenarios. Dependent t-tests were used for both measures to observe statistically significant differences for the before and after MOEs. Overall, statistically significant decreases in the approach and control delays were observed (at a 5% level of significance), signifying that vehicles experienced lower delays while traveling on the study intersections/segments.

The results of the multiple regression analysis showed that the length of the route between two serviced bus stops had the highest correlation with the travel time of the buses while the percentage of buses using the bus lane (or the rightmost lane of the corridors when the bus lanes were not installed) had the lowest correlation. Bus direction also had a negative correlation with travel time.

A summary of the input-target correlation, which is the measure of how the transit bus travel time (dependent or target variable) is correlated with varying independent variables (inputs), along with the measure of the probability (p-value or level of significance) is presented in Table 1.

Table 1. Inputs-Target Correlations

| Inputs | Correlation | p-value |
|---|---|---|
| L (X1) | 0.267 | 0.000 |
| DT (X2) | 0.075 | 0.000 |
| BD (X3) | -0.037 | 0.023 |
| BL (X4) | 0.033 | 0.182 |
| P (X5) | 0.026 | 0.042 |
| BC (X6) | -0.018 | 0.743 |

The coefficient of determination was 0.1. The coefficient of determination is the variation in the dependent variable explained by the set of independent variables. The multiple regression equation for the travel time was obtained as:

$$TT = 53.97 + 0.04L + 0.24DT - 8.32BD + 3.97BL + 6.2P + 0.03BC$$

An ANN model was also developed to predict buses' travel times using dedicated bus lanes. The analysis used an approximation method in the Neural Designer software in order to find an underlying function that explains the relationships between the independent variables and the dependent variable (namely, bus travel time). Hence, the goal of the approximation method for this research was to find the model that yielded the lowest error in predicting travel time.

For the prediction of bus travel time on segments with or without bus lanes, a minimum of 1,000 bus events (7Y, 32, 30S, and 30N) were used in the ANN model. ANN models are highly data-dependent and predict the outcomes by analyzing known data points. The independent variables included length of the route, average dwell time, bus travel direction, presence of bus lane, peak period, and the average percentage of buses using the rightmost lane (before) or bus lanes (after), while travel time was the dependent variable.

The project team documented the initial and final errors (training, selection, and testing) from the neural network training process. From the results, the approximation error metric (normalized squared error) for the testing dataset was found to be 0.97 (which is lower than the training error of 0.98 and selection error of 0.99). This indicates that the ANN model was predicting bus travel times based on unknown data with great accuracy.

The results of the analyses indicate that buses, as well as non-transit vehicles, generally experienced lower delays (resulting in better traffic flow) at all five study intersections. Hence, better traffic flow was observed when the bus lanes were present on the study segments. Transit buses' compliance with the dedicated bus lanes did not appear to affect the travel time of the buses when bus lanes were present. For future studies, additional analyses using data from additional segments with DBLs could be used to validate the models in addition to evaluating the benefits and limitations of such lanes. Moreover, the ANN model could be incorporated into future predictive models used by WMATA to provide patrons with travel time information. Such implementation can be beneficial to not only improve WMATA's bus service and reliability but also mitigate general traffic (transit and non-transit) operational delays.

# 1. Introduction

One of the main goals of public transit agencies is to provide patrons with the best services for them to plan their commute and get to their destinations on time. Hence, these agencies strive to improve their services by continuously evaluating best practices for better reliability and efficiency of their infrastructure. As for transit buses, technology has enabled the real-time tracking of buses and the prediction of approximate arrival times at bus stops with improved accuracy. Such efforts help public bus riders plan their trips without needing to rely on their personal vehicles for commuting. Despite these efforts, unforeseeable factors—including traffic congestion, roadway conditions, and inclement weather—tend to affect the efficiency of public transit services. Inaccuracies in the prediction of transit service travel times and arrival times may decrease patrons' perceptions of efficient and improved transit service.

One method that has been adopted by bus services to improve travel times and bus transit reliability is the implementation of designated bus lanes (DBLs). Designated bus lanes are those restricted to buses either permanently or during certain hours of the day. They are usually indicated by "Bus Only" signs posted along the route with specific regulations, and/or the lanes are painted red. DBLs allow buses to bypass traffic congestion and avoid vehicular conflicts in mixed travel lanes which helps to improve bus service reliability.[1] Implementing these lanes can help increase the attractiveness of bus transit, thereby encouraging the mode shift from using single-occupancy vehicles to buses.[2]

On the other hand, the installations of DBLs may disrupt existing traffic patterns, which may result in delays and violations by other vehicles. These violations may include deliberately traveling in bus lanes (by other vehicle types), right turns in front of buses, and parking in bus lanes, among others. These traffic violations may result in delays and obstruct bus operations, impacting the performance of the roadway and potentially creating safety issues.[3]

Siddique and Khan[4] conducted a study to investigate the capacity of Bus Rapid Transit (BRT) corridors in Ottawa, Canada. The study focused on the throughput of transit buses under prevailing conditions and compared it to the dynamic traffic microscopic analysis incorporating 2021 traffic conditions. The results showed that in saturated conditions with interference from other road users including turning vehicles at intersections, the average speed dropped by 75% while total bus delays and bus travel time increased by 135% and 96%, respectively. However, they noted that the bus delays and increased dwell times could be due to the manual fare collection and operation of high-floor buses. However, the research did not assess the control delays of vehicles in individual lane groups at the intersections where the bus lanes were present.

In 2014, Chen et al. investigated the interactions between the general traffic flow and buses operating in exclusive bus lanes.[5] The researchers found that there was a traffic saturation reduction of 16% with a 17% increase in bus travel time. However, the study was focused on only one BRT corridor and was not conducted for two scenarios (that is, it did not compare the scenarios before and after the implementation of BRT).

While implementation of the bus priority programs or dedicated bus lanes show that there are desirable and detrimental effects on the efficiency of the infrastructure, a study in Washington, DC has not been conducted to assess the operational logistics of such lanes. In 2019, a Bus Priority Program was implemented in the District of Columbia along the corridors of H Street (NW) and I Street (NW). This program consists of the installation of bus lanes and other street design improvements on different segments of the city.[6] Consequently, this research seeks to evaluate the impacts on the performance of transit buses and intersection performance on corridors with DBLs in Washington, DC. A "before" and "after" approach will be used to compare the measures of effectiveness at all intersections.

While simulations have been used to evaluate the measures of effectiveness for exclusive bus lanes, an actual study considering segments with and without such lanes has not been conducted in Washington, DC. This research employs a "before" and "after" approach to study the impact of DBLs in the District of Columbia. In addition, the team also used ANNs to predict the transit bus travel times for buses operating on networks with similar lanes in urban areas similar to DC. Most studies consider the average intersection delay, which is a measure of effectiveness used to interpret the level of service of an intersection. In this research, overall intersection control delays, as well as approach delays, will be analyzed to determine the impacts of implementing DBLs. The outcomes and the methodology of this study can be adopted and or/ modified by WMATA to significantly improve the prediction of bus arrival times, thereby increasing the reliability of public transportation for patrons.

# 2. Literature Review

## 2.1 Public Transportation in the United States

The popularity of public transportation as an alternative to personal vehicles in the United States came about in the 1970s following a collection of factors which included an increase in traffic congestion, pollution, and rising costs of car ownership.[7] Today, the public transportation system includes any generally accessible and publicly funded means of transport such as bus, rail, ferry, and airline transportation services. Although public transportation has been made available in most of the major cities in the US, only a few maintain an extensive public transit network.[8]

Currently, conventional or commuter buses, bus rapid transit, and intercity buses are the three most widespread bus service types in the United States. The hours, service frequency, and routes taken by these bus services are determined by the patrons' needs with the primary aim of providing accessibility, making them a rather popular option for commuters.[9]

The American Public Transportation Association (APTA) states that every dollar invested in public transportation generates $5 in economic returns, every $1 billion invested in public transportation invariably creates approximately 50,000 jobs and every $10 million of capital investment in public transportation results in increased business sales of approximately $30 million.[10]

Public transportation has been described as an efficient and eco-friendly alternative to private vehicle ownership, primarily because it enables a greater number of people to travel to various places in fewer vehicles, thus reducing traffic congestion and lowering the emissions of greenhouse gases.[11] The US Department of Transportation has reported that US transit buses emit an estimated 33% lower greenhouse gas emissions per passenger mile than an average US single-occupancy vehicle.[12] Furthermore, public transportation increases passenger safety. Several studies by APTA show that the use of public transportation reduces a person's risk of being involved in a motor vehicle accident by up to 90%.[13] This could be attributed to the level and regularity of public vehicle maintenance as well as the training and enforced driving habits of public transit drivers.[14]

Most cities and suburbs in the United States were built after the 1950s, just as passenger cars reached the height of their popularity among the general populace and became the dominant mode of transportation. Consequently, many US cities have roads that are largely favorable to smaller-sized vehicles, making it difficult to serve such areas with public transportation, nevertheless, its convenience ensures it remains a popular mode of transportation.[15]

## 2.2 Advantages of the Public Transport System

The Washington Metropolitan Area Transit Authority (WMATA) is a tri-jurisdictional government agency that operates transit services in the Washington Metropolitan Area and receives contributions to its operational costs from the various cities and counties in the District of Columbia, the state of Maryland, and the Commonwealth of Virginia (DMV) area.

WMATA operates under three distinct brand names to signify its different modes of service. Metrorail, under which it provides rapid transit services; Metrobus, under which it provides fixed-route bus services; and MetroAccess, which provides transportation assistance to patrons with disabilities. Metrobus consists of a fleet of approximately 1,580 buses which serve over 11,500 bus stops in the DMV area.[16] In addition, a separate bus system known as the DC Circulator operates in the downtown area and collaborates with WMATA in a public-private partnership bus system. The DC Circulator and the Metrobus are the two main options for bus commuters and provide services to a wide range of locations within DC and the larger DMV area. Figure 1 shows a WMATA Metrobus that operates in the District of Columbia-Maryland-Virginia region.

Figure 1. Photograph of a WMATA Metrobus


Public transportation is the most convenient way of moving around Washington, DC; however, to curb the spread of COVID-19 in 2020, Metrobus underwent several changes. Initially, as part of its Pandemic Flu Plan, Metrobus had a reduction in its hours of service, and buses operated according to the Saturday supplemental schedule throughout the week.[17] Following an increase in COVID-19 cases in the DMV, stricter measures were initiated and Metrobus further reduced its hours of operation. By then, the focus of WMATA had shifted to using public transportation as a means to support essential travel only, and bus operators were granted the authority to bypass bus stops if their vehicles had reached capacity in order to ensure social distancing in the vehicles.[18] These and other steps taken by Metrobus in the DMV highlight the continuous, though limited, availability of public transportation in the DMV area even during a pandemic.

As a result, while public transportation in the United States reportedly carried 34 million passengers a day despite significant increases in vehicle ownership in 2019,[19] these numbers significantly declined in 2020 due to the impacts of extensive quarantines and social distancing policies brought on as a result of the COVID-19 pandemic.[20] However, there has been a significant change in the numbers in recent months. While passenger vehicle miles traveled fell to approximately 40% of pre-pandemic levels in Washington, DC in 2020, it increased to approximately 90% (of the norm) in 2021. Nevertheless, public transit patronage is still comparatively low during weekdays.[21]

## 2.3 Issues Affecting the Bus Transit System

There have been numerous improvements to public transportation over the years that have resulted in increased patronage. Nevertheless, the system still encounters issues that make it a backup option or a last resort, especially for patrons with other options. Significant challenges include overcrowding, delays in arrival times, insufficient accessibility, longer commute times, and overall commute costs.[22]

Further, studies conducted by APTA indicate that approximately 45% of Americans do not have access to public transportation.[23] The rapid expansion of housing infrastructure development away from city centers is one of the main circumstances contributing to the uneven distribution of public transportation in the United States. Thus, the prevalence of housing communities situated at a great distance from downtown areas without significant public transportation access invariably leads to a heightened dependence on private vehicle ownership.[24]

On the other hand, public transportation services at city centers deal with challenges such as a consistent increase in patronage, particularly during peak hours. This leads to significant levels of overcrowding on buses, in which case riders become subjected to extensive periods of standing. Li and Hensher conducted a study on public transport crowding in some developed countries and discovered that overcrowding was prevalent in many public transit systems despite the many interventions implemented by transport authorities in order to monitor and curb it. Their findings suggested that apart from the discomfort related to standing for long periods, riders reported experiencing physical exhaustion, stress, health concerns, less privacy, and overall frustration.[25] Many of these issues are even more significant now due to the ongoing COVID-19 pandemic and the move to more socially distant habits. These issues are more than likely contributing factors which impact riders' preference for other modes of transportation (private vehicles, Uber, etc.).

Improvements in public transportation over the years have involved the application of technology to increase the efficiency and effectiveness of the sector thereby increasing rider satisfaction and patronage. Automatic vehicle location (AVL) technology has been one of the many technological advancements and is used specifically to deliver bus arrival prediction times by providing up-to-date real-time bus location. A study by Arhin et al. in 2013 to assess the reliability of transit buses in Washington, DC, indicated an overall performance of 75% with an average deviation of 2 to 5 minutes from the predicted arrival times. The results were consistent with WMATA's two-minute-early and seven-minute-late window for bus arrival times. However, the data from the study revealed that about 82% of the bus arrival times did not meet the general transit industry threshold.[26] Bus service reliability, however, is important for increased ridership, retention, and overall customer satisfaction.

One other major reason for rider dissatisfaction with public transportation is delayed commute times, which can be attributed to the contradictions in the predicted and actual arrival times of buses. A combination of factors, including traffic congestion, lower speed limits, traffic signal delays, and multiple passengers alighting or embarking along a bus route, can affect bus arrival times. A report by the District Department of Transportation (DDOT) on the automated enforcement of bus lanes and zones in 2017 stated that the average bus speed through downtown DC was less than 5 mph.[27] A study in 2016 evaluated bus travel time control strategies along routes with signalized intersections and concluded that buses traveling below the recommended segment speed as a result of delays and restrictions from signalized intersections experienced considerably higher roundtrip travel times.[28]

Traffic congestion in the United States for the year 2018 led to an average loss of 97 hours at an average cost of $1,348 per driver, totaling $87 billion.[29] This amount is estimated to increase to about $186 billion by 2030. Washington, DC, was identified as the third most congested city in the United States, with drivers spending about 102 hours in traffic per year. Congestion is more common in cities and urban areas with residential settlements in the outskirts or suburbs. Businesses or workplaces, on the other hand, are within town centers.[30] This situation leads to a heavy flow of traffic in one direction at any given time when people have to get to work and commute back home, leading to traffic congestion. The attempts of city and transport officials to designate bus-only lanes have not been entirely effective, because buses remain subjected to traffic congestion like other vehicles, especially during peak times when other vehicles ignore the restrictions of DBLs and utilize them as well. The effect of signalized intersections, though rather small, has been found to add up to a notable benefit, particularly on longer routes with more signalized intersections. A study conducted by Albright and Figliozzi found that there was an average bus travel time increase of 8 to 26 seconds per intersection on a bus route if the intersection was signalized.[31] In a research project that investigated the variability of time in public transport travel, results showed that travel time variation increased by up to 22% for each added intersection per kilometer.[32] Figliozzi and Feng discovered that for each stop sign on a bus corridor, an average of 12 to 16 seconds was added to bus travel time while left and right turns at intersections increased bus travel time by an average of 5 to 38 seconds.[33] Mazloumi, Currie, and Rose determined that the number of bus stops along a route had an impact on bus travel time variability, especially in the morning peak hours. The study further showed that the longer length of the route along with the higher number of bus stops affected the bus arrival and departure times and thereby increased the total bus travel time per commuter trip.[34]

Nevertheless, an issue of note to be addressed is that of the affordability of public transportation seeing how the price of a commute is a major factor that makes public transportation a favorable alternative to private vehicle ownership. Usually, public transportation offers more affordable pricing for getting around. This is especially the case in urban areas where riders are traveling shorter distances. If a rider would need two or more transfers to get to their destination, which in most cases includes different public transport options, the commute becomes costly in terms of both time and money. In addition, where riders had to wait for up to 30 minutes to access the next ride to continue their trip, they chose to use a different mode of transportation, preferably auto vehicles.[35] Fare integration has also been studied to further understand its potential impacts on transit ridership. A study on the effect of fare integration on travel behavior and transit ridership by Sharaby and Shiftan found that introducing a single fare system and providing free transfers to other buses along other routes led to a 25% increase in bus transit ticket sales, a 7.7% increase in passenger trips, and an 18.6% increase in bus boarding.[36] These findings suggested that the reduction or consolidation of fares into a single ticket purchase and free transfers for riders who had to use more than one bus on their commute increased rider patronage of the bus transit system.

## 2.4 Strategies to Improve the Bus Transit System

Over the years, there have been several additions to improve public transportation service to patrons in areas where it is widely used. Designated bus lanes, AVL technology, improved facilities, traffic management, and faster boarding at stops, among other measures, are used to enhance the efficiency of bus transit systems, address the concerns of riders, and attract more patronage.

Some studies have shown that designated bus lanes tend to decrease bus delay times by about 10%. A study conducted in New York indicated that after the introduction of designated and/or dedicated bus lanes, bus delay reduced from 76% to 42%, and rider patronage increased by 10%. In other areas within the United States, rapid bus transit services were supported by the introduction of two-lane busways on highways and freeways.[37]

In some other areas, traffic signal priority for buses has been implemented as an approach to reduce bus service delays and make it more appealing to riders. Through the years, two common types of systems have been used. The first involves a pre-installed electronic communications mechanism that allows the bus driver to advance the traffic signal cycle to green so they can pass through the intersection in cases where they need to maintain the bus schedule. The second system uses real-time bus tracking (AVL) technology combined with an advanced radio communications system that enables a computerized procedure to ascertain the position of the bus in relation to its schedule and then controls traffic signals to give buses priority as and when required.[38]

A study by Estrada et al. proposed a dynamic bus control model that used AVL data at stops to control bus speeds and possibly control signalized intersections by extending the green light phase for buses with significant delays. The simulated model considered passenger travel time, operating costs, and bus travel time variability and resulted in reduced total system cost for both the agency and the user (by 15–40%) and reduced bus time variability (by 53–78%).[39]

The overall satisfaction with the service provided is vital to retaining regular riders and attracting new ones. Enhancing facilities and amenities at subways, bus stops, and inside buses ensures that patrons have an enjoyable ride for the duration of their trip. A study of Curitiba's bus transit system in Brazil revealed that enhanced station platforms made same-level boarding access easier, protected riders from weather conditions, and allowed riders to pay fares before boarding. These improvements, coupled with a single fare with unlimited transfers, DBLs, signal priority for buses, buses with large-capacity doors, and express bus transit services, led to a reduction of bus dwell times by about 15 to 19 seconds, a reduction of 27 million auto trips per year, and the avoidance of 27 million liters of fuel used annually. Thus, Curitiba consumes about 30% less fuel per capita compared to eight similarly sized Brazilian cities.[40]

According to a report from Organization Gestion Marketing, results obtained from eight European cities indicated a substantial surge in public travel patterns in the initial two years after the introduction of a fare integration system.[41] These outcomes were similar to those from a study conducted by Sharaby and Shiftan (2012) which explored the effect of fare integration on transit ridership and travel patterns in Haifa, Israel. In Haifa, the complex pre-boarding fare system was converted into a single ticket system with free transfers between the different zones, ultimately leading to a reduction in fares for passengers. This implementation and ensuing results led to a 25% increase in single ticket sales, a 7.7% increase in passenger trips, and an 18.6% increase in bus boarding.[42]

## 2.5 Dedicated Bus Lanes

Dedicated bus lanes became one of the tools implemented to navigate through possible traffic congestion on transit routes, especially during peak hours. A DBL is a restricted lane reserved for buses that is used to increase the speeds of public transit buses thereby improving travel time. They are an essential component of a high-quality bus rapid transit (BRT) network, which ensures the reliability of public transport. Usually, a DBL occupies a section of a roadway that also has lanes serving general automotive traffic.[43]

Dedicated Bus Lanes prevent congestion on roads by restricting these lanes from private vehicles during peak hours. They could potentially lead to significant improvements in the performance of

BRT networks and encourage a switch from private vehicles to public transportation due to the significant increase in efficiency.[44] The implementation of DBLs in any city is very likely to increase the effectiveness and demand for public transportation.[45]

Nevertheless, some studies posit the opposite result for DBLs, claiming they are difficult to enforce, and little is done to prevent non-transit vehicles from using these lanes, even during peak hours.[46]

In Washington, DC, these bus lanes are usually installed on corridors with frequent bus service and high traffic congestion that causes reduced bus speeds and reliability issues.[47] DBLs are often located in the right curb lane. They are painted red to indicate they are restricted to buses only. The installation of red pavements on DBLs lead to a significant reduction in unauthorized use of the lanes by other vehicles, as is the case on Georgia Avenue (NW) in the present study area. Despite DBLs' restrictions, vehicles making right turns while approaching intersections are usually permitted.[48] In addition, DBLs can also be used by bicycles, charter buses, school buses, and marked taxis.

DBLs could potentially reduce travel times for buses between 15% and 50%, similar to other cities such as New York and Los Angeles.[49] So far, in Washington, DC, DBLs have been implemented on Georgia Avenue (NW), H Street (NW) and I Street (NW), M Street (SE), and Martin Luther King, Jr. Avenue (SE). The impact of DBLs on bus travel times on these routes has not been evaluated.

## 2.6 Assessing Intersection Measures of Effectiveness and Traffic Operational Performance

The operational characteristics of traffic can be determined by the movement of a group of vehicles or the whole traffic stream along a roadway.[50] In the literature, there are microscopic as well as macroscopic expressions to represent traffic operations. While microscopic traffic models focus on the movement of individual vehicles, macroscopic models are used to characterize the movement of groups of vehicles. The Highway Capacity Manual, Sixth Edition (HCM), published by the Transportation Research Board, provides information and procedures to compute the capacity of highway facilities (from freeways to unsignalized intersections) along with the effects of transit, pedestrians, and bicycles on the performance of such systems.[51] The speed-flow relationships for undersaturated flow (non-congested conditions) can be quantified using the HCM. There are three primary characteristics used in the HCM that help to describe the macroscopic operations of a roadway: flow, speed, and density.[52] These components have a vital role in the traffic simulation software analysis to obtain the measures of effectiveness, which has been discussed further in this report. The information presented in the following subsections is taken from the HCM, Sixth Edition.

*1. Flow (q)*

Flow is the number of vehicles passing a reference point per unit of time. It can also be referred to as throughput, volume, or intensity. Flow is the reciprocal of the average headway (distance between two vehicles measured in time) which is typically expressed in vehicles/hour.

*2. Speed (v)*

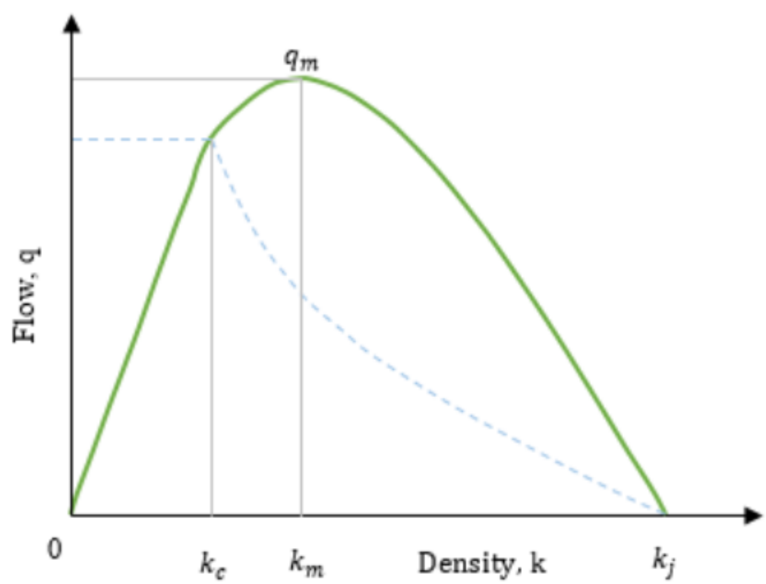
Speed is the amount of distance a vehicle travels per unit time (expressed in mile/ hour). For macroscopic expressions, the average speed is obtained by dividing the sum of all the instantaneous speeds by the total number of vehicles in the sample. The average speed can help determine whether a roadway segment is congested or not. Density, for a segment, is the reciprocal of the average spacing between vehicles. Density is expressed in vehicles/miles and helps determine the quality of service for roadway facilities.

The relationship between these two traffic stream parameters can be represented as:

Flow = Speed * Density

Figure 2 presents the relationship between traffic flow and density. As observed, free-flow speed is observed at critical density, after which the speed (as well as the flow) decreases with an increase in density.

Figure 2. Flow Density Relationship[53]




Additional performance measures for multimodal traffic operations include travel time, delay, and queue. These measures of assessment are discussed below.

*1. Travel Time*

Travel time is the time required to travel from an origin point to a destination. It is the inverse of speed and can be represented as:

$$TT = d/v$$

where D = distance from an origin to destination (in miles) and

V = average speed (in mph).

For transit agencies, the prediction of travel time is an essential component of providing reliable information for patrons to effectively plan their daily commute. According to the Transit Capacity and Quality of Service Manual (TCQSM), a transit vehicle is considered to be on time if the vehicle arrives within 5 minutes before or after the scheduled arrival time in contrast to WMATA's on-time bus arrival times window of two-minute-early and seven-minute-late after posted arrival time

*2. Delay*

Delay is the additional travel time required to travel across a particular corridor. There are three different types of delay that are used in traffic operations: stopped delay, travel time delay, and control delay.

a. Stopped Delay: A vehicle experiences a stopped delay while it is completely stopped.

b. Travel Time Delay: The difference between the actual travel time of a vehicle and the estimated "ideal" travel time corresponds to the travel time delay.

c. Control Delay: A vehicle experiences a control delay when it complies with traffic controls such as traffic signals and stop signs. The performance of intersections (signalized, unsignalized, and roundabouts) is generally assessed by measuring the control delay.

*3. Queue*

Queue or queue length is the number of vehicles stopped along a segment at a signalized (or unsignalized) intersection waiting to be served. Queue length is generally used at facilities with interrupted flow (such as intersections) rather than at facilities with uninterrupted flow (such as freeways/two-lane highways).

## Measures of Effectiveness and Level of Service

Level of service (LOS) for a facility is defined as the qualitative measurement of motor vehicle traffic service. LOS can be used to analyze the traffic performance based on several performance measures of the traffic flow. The scale of LOS ranges from A (best) to F (worst) and is evaluated by assessing measures of effectiveness (MOEs). The MOEs, which are performance measures, differ for interrupted and uninterrupted traffic flows. The MOEs for signalized intersections have been presented in Table 2.

Table 2. MOEs in the HCM 2010 for Signalized Intersection

| | | | |
|---|---|---|---|
| Signalized Intersections | Auto mode | Control delay (s/veh) | LOS can be computed for each lane group, each intersection approach (heading towards the intersection), and for the entire intersection; for approaches and intersection-wide assessment, |
| | Pedestrian and bicycle modes | LOS score based on traveler perception assessment | LOS score for pedestrians estimated for each crosswalk and intersection corner; LOS score |

From Table 2, control delay emerges as the primary MOE to determine the LOS of a signalized intersection. An increase in control delay due to a traffic signal directly corresponds to an increase in travel time experienced by vehicles. Different variables affect the control delay at signalized intersections such as signal phasing and coordination along a corridor, signal cycle length, and traffic volumes.[54] For unsignalized intersections, such as an All-Way Stop Controlled or a Two-Way Stop Controlled intersections, LOS is expressed as a weighted average of the control delay (at an all-way stop or a roundabout) or the weighted control delay experienced by vehicles traveling on the minor approaches (two-way stop). The LOS criteria for signalized and unsignalized intersections are presented in Table 3.

Table 3. Level of Service Criteria for Signalized and Unsignalized Intersections

| Level of Service | Average Control Delay (seconds/ vehicle) | | General Description |
|---|---|---|---|
| | For Signalized Intersections | For Signalized Intersections | |
| A | ≤10 | 0–10 | Free flow |
| B | >10–20 | >10–15 | Stable flow (slight delays) |
| C | >20–35 | >15–25 | Stable flow (acceptable delays) |
| D | >35–55 | >25–35 | Approaching unstable flow (tolerable delay, occasionally wait through more than one signal cycle before proceeding) |
| E | >55–80 | >35–50 | Unstable flow (intolerable delay) |
| F | >80 | >50 | Forced flow (congested and queues fail to clear) |

## 2.7 Impacts of Dedicated Bus Lanes on Traffic Performance

Several studies have been conducted over the years on the effects of a DBL on traffic operation. Different types of simulation, as well as operational practices, have been performed to observe the potential benefits of implementing either dedicated or intermittent bus lanes in a general urban setting similar to Washington, DC. In Lyon, France, a study utilized variable message signs and dynamic lane assignment to designate a bus lane with intermittent priority based on bus presence. The study evaluated overall intersection delays as well as movement delays to determine the benefits of an exclusive transit lane based on demand. Results demonstrated improvements in travel time (up to 14% reduction in travel time in the westbound direction during peak hours) with minimal impacts on traffic flow (no effects on the overall average intersection delays).[55] Impacts on the bus system's performance were studied to demonstrate the benefits of the combination of intermittent bus and transit signal priority. The authors compared results from four different configurations (Intermittent bus lanes, transit signal priority, both, and neither) for a 350-m case study on a selected corridor.

An approximately 10-second decrease in travel time was observed when intermittent bus lanes were deployed and there was also a reduction of time headways from 16.3% to 15%. There was an increase in average speed (by 15%) and a decrease in the time-headway variation (from 16.3% to 11.9%) when transit signal priority was deployed in addition to intermittent bus lanes, which can be a decisive measure for traffic management authorities to include transit signal priority in addition to exclusive bus lanes.[56] Similarly, a study was conducted in Kolkata City, India to investigate the signal priority for buses and the effectiveness of bus priority lanes at two signalized approaches. The results from that study demonstrated a positive impact on travel time, as well as a decrease in vehicular emissions, after introducing bus signal priority. Implementation of bus priority led to a 15–20% reduction in bus travel time, but it also led to a 6% increase in non-priority vehicular travel time. Moreover, the study pointed out that the road users showed a positive attitude after the implementation of bus priority lanes.[57]

A study was conducted in the United Kingdom where capacity and travel times were observed in a corridor with bus lanes. While the study pointed out the benefits of intermittent bus lane usage when combined with optimized transit signal priority, the authors also observed a reduction in capacity as well as an increase in travel times of the buses. This phenomenon occurred during times when the exclusive lane was active with the potential of reducing the bus travel time in subsequent intersections. Hence, the practice would not be ideal in a short corridor with an exclusive bus lane or if the bus stops were close to each other.[58] Another paper investigated the simulation of multiple bus lane combinations to evaluate a multiplier effect. The multiplier effect refers to higher road segment performance due to the combination of bus lanes than the road segment performance due to the sum of individual bus lanes). The simulations showed that conversion of a traffic lane to a dedicated bus lane when the upstream traffic volume is greater than the capacity of traffic lanes (>2,400 vehicles/hr) leads to higher bus travel times (>1,100 seconds). There was an observed 20% increase in bus travel time and a 60% increase in general traffic travel time. Hence, the authors concluded that bus lanes would generate negative effects during congested bottlenecks.[59]

On the contrary, another study that was conducted to find the ideal combination of exclusive bus lanes on the road segment network demonstrated that the total traffic travel time decreased after installing dedicated bus lanes. Two scenarios, with a bus lane on a different link along a segment in each scenario, were compared with the base case scenario (road segment with no dedicated bus lane). The results from the scenarios with the bus lanes showed that the passenger car travel times (non-transit traffic) decreased but the bus travel times increased. The decrease in non-transit vehicular travel times accounted for an overall improvement of the traffic flow (for bus and non-transit traffic) by 3.4%.[60] Similar results were also observed in a different study that considered changing the location of DBLs on an existing network. During under-saturated traffic conditions, a reduction in bus travel time was observed which outweighed the increase in the travel time of the non-transit traffic. The lane implementation helped in the reduction of bus travel times while slightly increasing car travel times. The authors also concluded that for saturated conditions, implementing dedicated bus lanes at strategic locations can be performed to achieve a significant decrease in bus travel times and the expense of only a minimal increase for passenger car travel times.[61]

Bus lane intermittent and dynamic priority was explored in an arterial in Changzhou, China, taking into consideration performance parameters such as clear distance (distance between bus and the downstream vehicle), degree of saturation, headway frequency, etc. Dynamic priority refers to the bus lane allocation dynamically depending on different traffic patterns or times throughout the day. For bus rapid transit, the authors noted a relatively small overall average delay when the volume-to-capacity ratio (saturation) was low, and an increase in average delay was observed with the increase in saturation. Based on the authors' findings, for a saturation of less than 0.7, dedicated bus lane implementation was not recommended. However, when the saturation is greater than 0.9, the implementation of a dedicated bus lane system demonstrated a significant decrease in delays.[62]

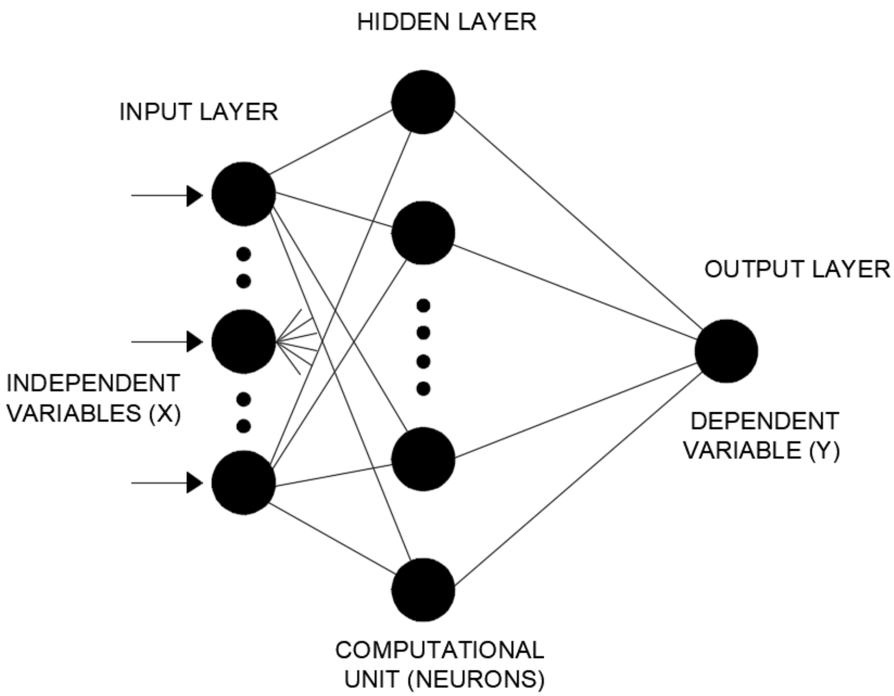
Red bus lanes were also introduced on First and Second Avenue in Manhattan, New York. Enforcement of red lanes led to a decrease in vehicular violations (vehicles illegally driving on dedicated bus lanes) and a decrease in vehicles parked on bus lanes by approximately 55% and 35%, respectively. However, there was an increase of vehicles illegally parking on the red lanes by 29%. Although the red lanes were installed to prioritize easier bus movement, less than 10% of the bus fleet operating on the segments used the bus lanes, which increased the average bus travel time.[63]

## 2.8 Artificial Neural Networks and Their Applications

Artificial Neural Networks (ANNs) are mathematical models that imitate the functioning of a human brain to solve computational problems. Due to the versatility of the learning mechanism of these networks, ANNs have been used in engineering and other disciplines to solve complex tasks such as data prediction/forecasting, pattern recognition, and classification by identifying the underlying relationships in a dataset. There is an interconnection of "neurons" in the ANN (like in the human brain) which enables learning through the process of training with enough data and good initialization.[64]

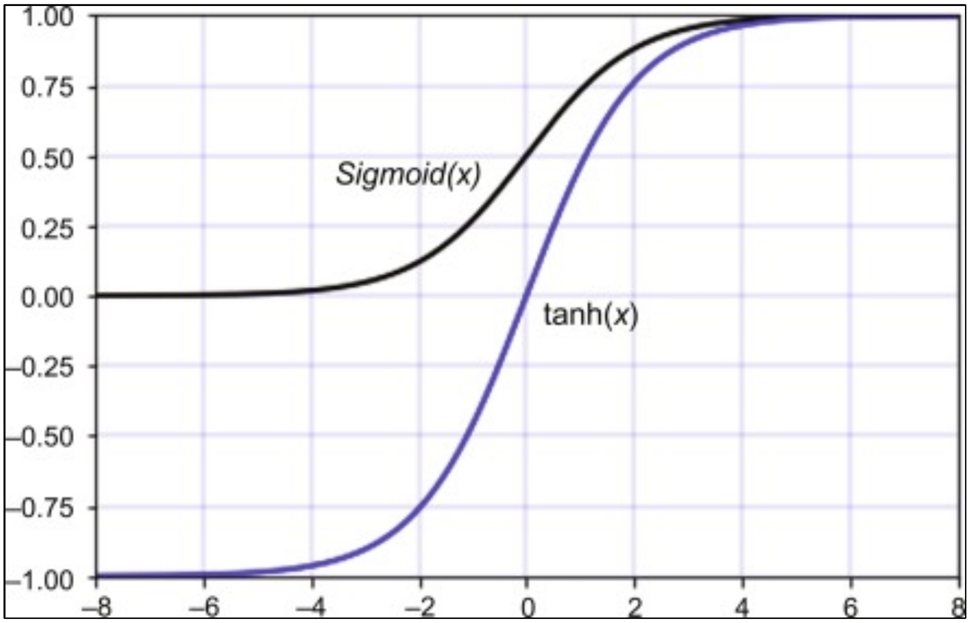
A variety of problems that are solved using ANN involve the use of multilayer perceptrons (MLP). The learning process involves building a model where the relationship between the inputs and the known outputs in the examples are mapped. The process is also known as supervised learning. MLP consists of a minimum of three layers—input layer, hidden layer, and output layer—where each layer has nodes (neurons) that are assigned different weights. These nodes are interconnected, which enables the flow of information from the input layer to the hidden layer. The learning takes place in the hidden layer and the information is then passed to the output layer to obtain results. The backpropagation algorithm occurs where the model starts with random weights and then adjusts the weights in each node for the model to make better or more accurate predictions. The process of predicting generates errors, and hence, the goal of the weight assignment is to reduce the final error to achieve ideal performance.[65] The errors obtained while predicting the output are placed back in the network to further adjust the assigned weights of the neurons, which is referred to as error backpropagation. This technique has been frequently used in transportation as well as other engineering studies.[66] An example of a three-layered neural network (one input, one hidden, and one output layer) has been presented in Figure 3.

Figure 3. Illustration of the MLP in an ANN




Activation functions or transfer functions are responsible to create nonlinearity in the ANN since physical world phenomena do not always follow linearity (graphically represented as a straight line). This is achieved through calculating the weighted sum of the inputs provided and adding a bias for the activation or deactivation of a neuron.[67] Different types of nonlinearity include sigmoid, tanh, ReLU, leakyReLU, softmax. The commonly used nonlinear activation functions are sigmoid and hyperbolic tangent activation functions. While the sigmoid activation function transforms the input into an output value between 0.0 and 1.0, the hyperbolic tangent function (*tanh*) yields output values between -1.0 and 1.0. A visual representation of these functions is presented in Figure 4. Since the hyperbolic function helps to center the data (by bringing the mean closer to 0), it can be a better tool in prediction models.[68]

Figure 4. Representation of Sigmoid and Hyperbolic Tangent Activation Function Curves[69]




Studies have been conducted to predict the travel times of buses using ANN and other mathematical models. One such study showed that ANN models to predict bus travel times could outperform regression models by obtaining lower mean absolute percentage error (MAPE) when compared to other models. For example, the results of a study that used AVL data in Houston, Texas, showed that the average MAPE obtained from the ANN model (4.76) was significantly lower than the historical data-based model (simple statistical model used by the authors) (9.96) and regression model (17.88).[70] Another study conducted in Washington, DC, demonstrated how ANN could outperform a multiple regression model when predicting travel times of the buses during different peak hours during the day in Washington, DC. It was determined that the approximation method using ANN to find the bus travel time based on the Quasi-Newton algorithm (with 2 perceptron layers) yielded the lowest errors in predicting the bus travel time.[71] However, in both studies involving ANN, neither considered the operation of buses on DBLs, nor did they study the transit operation before and after the implementation of such infrastructure.

In a study to implement transit signal priority by integrating traffic signal timing optimization using ANN, the authors concluded that implementing transit signal priority plans with pre-timed control would not improve schedule adherence. However, when a dynamic signal priority optimization in real-time traffic was utilized, general traffic delay was reduced by 5% to 90% while transit delay was reduced by 15% to 85% (depending on different congestion levels as well as control type).[72] While the results indicate better traffic flow at signalized intersections, the study did not consider segments with DBLs.

## 2.9 Summary of Literature Review

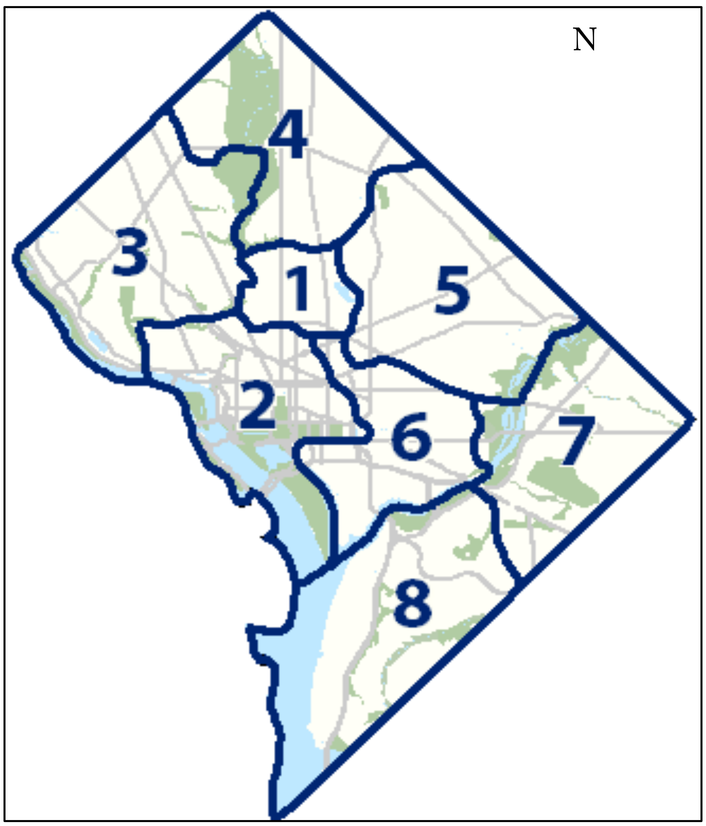
The public transport system has undergone several improvements in recent times to ensure the continued convenience and utility of public transportation to the populace even amid a debilitating pandemic. One of the mitigating strategies is the implementation of DBLs. Several studies have been conducted to determine the impacts of DBLs. In some cases, the impact appears positive with a significant decrease in delays for buses and private vehicles, alleviating traffic congestion. Nevertheless, other studies still show instances of increases in travel times and delays for buses or general traffic despite the presence of DBLs. The literature also indicates that transit signal priority and enforcement, in conjunction with dedicated bus lanes, improve the effectiveness of dedicated or exclusive bus lanes.

# 3. Research Methodology

## 3.1 Description of the Study Area

This research is conducted in Washington, DC, where the Washington Metropolitan Area Transit Authority (WMATA) oversees bus and rail operations. North Capitol, South Capitol, and East Capitol Streets divide DC into four unequal quadrants: Northwest (NW), Northeast (NE), Southwest (SW), and Southeast (SE). These quadrants are further divided into eight wards overlapping the quadrant boundaries. Figure 5 shows a map of Washington, DC, divided into wards. As of April 2020, the population of Washington, DC, was approximately 689,545.[73] The city is highly urbanized and is ranked as the sixth most congested city in the United States, with each driver spending an average of 63 hours per year in traffic.[74]

Figure 5. Map of Washington, DC, by Wards[75]




WMATA began overseeing the regional bus systems in the DC area in 1973. Currently, WMATA has a bus fleet of approximately 1,580 buses that operate on 325 routes in Washington, DC, in portions of Maryland, and Northern Virginia, servicing over 11,500 bus stops. The WMATA Metrobus network is the sixth-largest bus network in the United States. These buses operate 24 hours a day, seven days a week, and they make more than 400,000 trips each weekday. Currently, there are 14 bus priority corridors implemented in DC with the motive of making bus transit faster and more reliable.[76]

## 3.2 Data Collection

The following steps were followed to collect the data required for analysis.

### *3.2.1 Selection of Segments and Bus Routes*

The District Department of Transportation (DDOT) proposed a dedicated bus lane pilot during the summer of 2019 on the H Street and I Street (NW) corridors in downtown DC. The temporary bus lanes for H Street (NW) heading eastbound started from the bus stop located midblock between Pennsylvania Avenue, NW and 18$^{th}$ Street, NW to H Street and 14$^{th}$ Street, NW. The bus lanes for I Street, NW started at I Street and 13$^{th}$ Street, NW, and ended at the bus stop located midblock between 20$^{th}$ Street and Pennsylvania Avenue, NW.

WMATA buses are equipped with Automatic Vehicle Locator (AVL) technology which allows the real-time tracking and reporting of all logged buses. WMATA provided AVL data for buses operating on segments of H Street and I Street (NW) for the months before (May 2019, June 2019) and after (September 2019, October 2020) the installation of bus lanes.

The following bus routes operating on H Street and I Street (NW) were selected for the study: Route 7Y (Lincolnia-North Farlington Line), Route 32 (Pennsylvania Avenue Line), Route 30N (Friendship Heights-Southeast Line), and Route 30S (Friendship Heights-Southeast Line).

### *3.2.2 Route Characteristics*

The bus routes selected for this study have the following characteristics. Classifications of the primary operational roadways on which the transit buses operate are listed according to DDOT's 2016 Street Function Classification System, which is currently in use.

#### *1. Route 7Y*

Buses on Route 7Y operate primarily on Constitution Avenue (NW), Jefferson Davis Highway, and I-395 (Shirley Highway) with the main directions of travel being northeastbound/southwestbound. Constitution Avenue (NW) is classified as a principal arterial while Jefferson Davis Highway and I-395 are classified as interstate roads. Route 7Y buses run from Farragut North Station to Southern Towers in Virginia. The length of the route is approximately 7.5 miles, and the buses serve 31 bus stops in both the northeastbound (NEB) and southwestbound (SWB) directions of travel.

*2. Route 32*

Buses on Route 32 primarily operate on Pennsylvania Avenue (SE), Naylor Road (SE), Alabama Avenue (SE), Independence Avenue (SW), and Southern Avenue (SE) with the main directions of travel being NEB and SWB. The routes are round trips. Pennsylvania Avenue (NW) and Independence Avenue (SW) are classified as principal arterials, while Naylor Road, Alabama Avenue, and Southern Avenue (SE) are classified as minor arterials. Route 32 transit buses run from Virginia Avenue and E Street (NW) to Southern Avenue Bus Station in the Southeast DC round trip. The length of the route is approximately 8.75 miles, and the buses serve 47 bus stops along both the NEB and SWB directions of travel. There are 106 intersections between the first and the last bus stops. Route 32 operates from 4:00 AM–1:00 AM during weekdays (Monday–Friday) and from 5:00 AM–2:00 AM during weekends (Saturday and Sunday).[77]

*3. Route 30N*

Transit buses on Route 30N operate primarily on Wisconsin Avenue (NW), Pennsylvania Avenue (NW), Independence Avenue (SW), Branch Avenue (SE), and Naylor Road (SE) with the main directions of travel being northwestbound (NWB) and southeastbound (SEB). Pennsylvania Avenue (NW), Wisconsin Avenue (NW), Independence Avenue (SW), and Branch Avenue (SE) are classified as principal arterials while Naylor Road (SE) is classified as a minor arterial. Route 30N buses operated from Friendship Heights Station to Naylor Road Station and back. The length of the route was approximately 7.95 miles, and the buses served 75 bus stops along the NWB direction of travel and 71 bus stops along the SEB travel direction. Route 30N operated from 4:30 AM–11:30 PM during weekdays (Monday–Friday) and did not operate during weekends (Saturday and Sunday). The service has been discontinued due to redundancy since September 2021. The discontinuation of the service has no impact on the data used for the study or the data collection procedures.

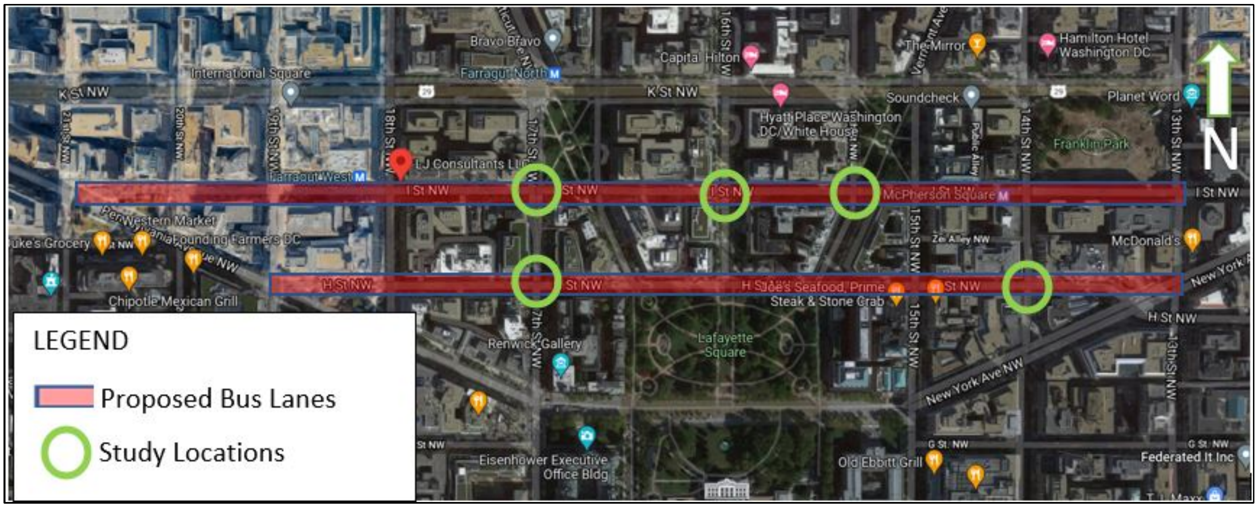
*4. Route 30S*

Route 30S transit buses operated primarily on Wisconsin Avenue (NW), Pennsylvania Avenue (NW), Independence Avenue (SW), Naylor Road (SE), Alabama Avenue (SE), and Southern Avenue (SE) with the main direction of travel being NWB/SEB. Pennsylvania Avenue (NW), Wisconsin Avenue (NW), and Independence Avenue (SW) are classified as principal arterials, while Naylor Road (SE), Southern Avenue (SE), and Alabama Avenue (SE) are classified as minor arterials. Route 30S buses operated from Friendship Heights Station to Southern Avenue Station and back. The length of the route was approximately 3.5 miles, and buses served 75 bus stops along the NWB direction of travel and 74 bus stops along the SEB travel direction. Route 30S operated from 4:00 AM to 10:00 PM (NWB) and 5:00 AM to midnight (SEB) Monday through Friday. The service has been discontinued due to redundancy since September 2021. The discontinuation of the service has no impact on the data used for the study or the data collection procedures.

*3.2.3 Study Intersections on Selected Segments*

In addition to obtaining WMATA data for bus routes operating on segments of H Street and I Street (NW), the project team also obtained turning movement count (TMC) data at five intersections on the study segments. Figure 6 shows the locations at which the video cameras were installed for the study intersections to obtain TMCs.

Figure 6. Locations of Video Cameras on Segments with Dedicated Bus Lanes




The researchers analyzed the measures of effectiveness before and after the installation of DBLs for the following locations. Brief descriptions of the study intersections based on field observations have also been provided.

*1. H Street and 14th Street (NW)*

The study segment of H Street (NW) is a one-way street that runs in the eastbound direction while 14th Street (NW) is a bi-directional street oriented in the north-south direction. The eastbound approach of H Street (NW) has an on-street residential parking lane on the north side followed by four travel lanes and a right-turn-only lane. The bus lane (painted in red) on H Street at the intersection can be seen in Figure 7. Fourteenth Street (NW) has a total of three lanes per direction on the northbound and southbound approaches with no on-street parking on either side. The pavement markings and surfaces on the northbound and southbound approaches are in good condition, as can be seen in Figures 8 and 9. The intersection is signalized with a statutory speed limit of 25 mph.

Figure 7. H Street (NW) Eastbound Approach

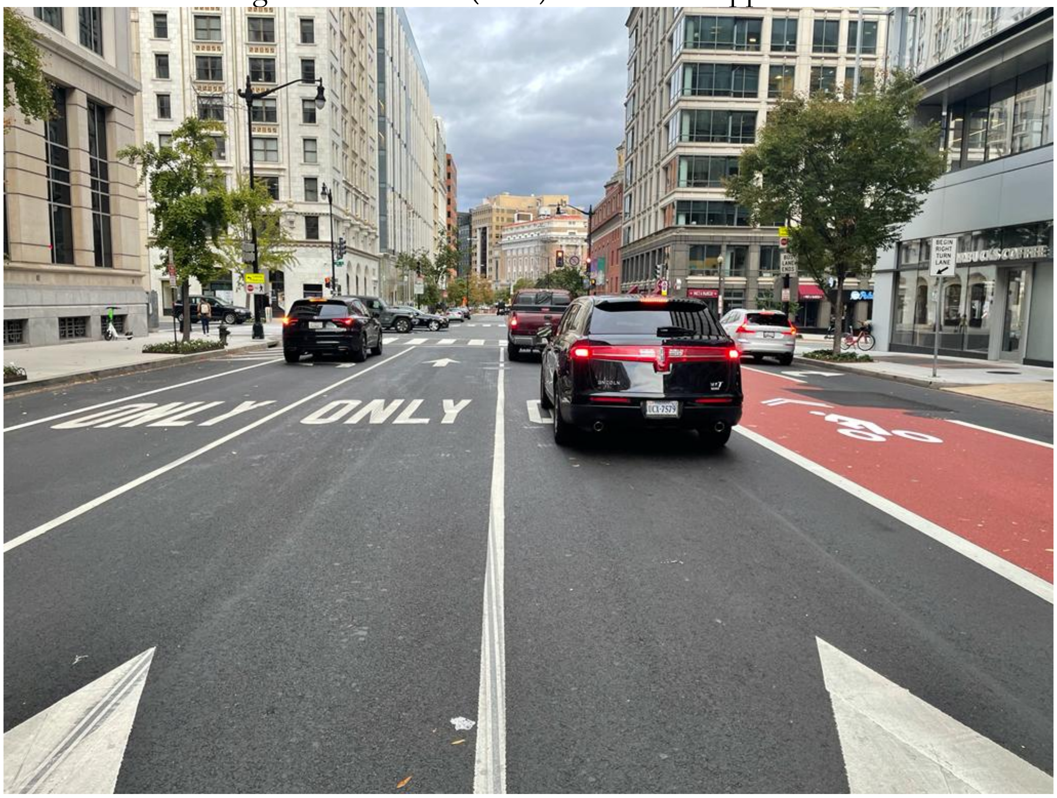


Figure 8. 14th Street (NW) Northbound Approach

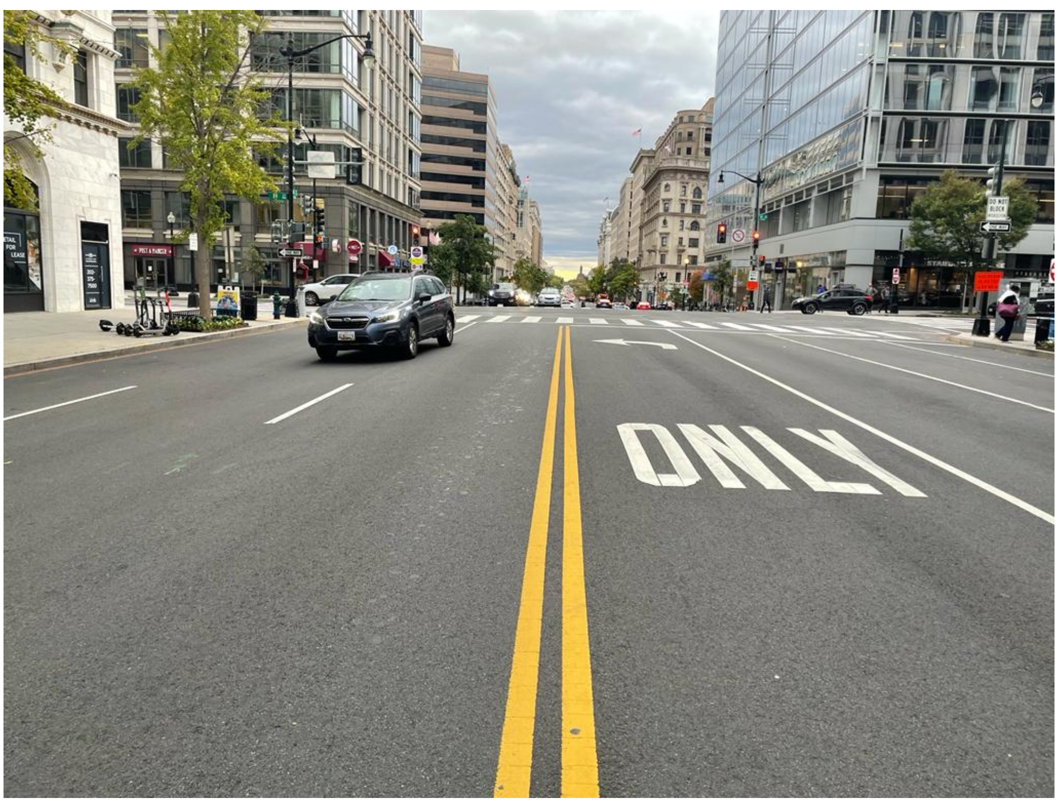


Figure 9. 14th Street (NW) Southbound Approach

*2. H Street and 17th Street (NW)*

The study segment of H Street (NW) is a one-way street that runs in the eastbound direction while 17th Street (NW) is a bi-directional street oriented in the north-south direction. The eastbound approach of H Street (NW) has on-street parking on the north side and four travel lanes. The bus lane on H Street (NW) at the intersection (in red) can be seen in Figure 10. Both the northbound and southbound approaches of 17th Street (NW) have four travel lanes (in the respective direction of travel) with three receiving lanes and no on-street parking. The pavement markings and surfaces on the northbound and southbound approaches of the intersection are in good condition, as can be seen in Figures 11 and 12. The intersection is signalized with a statutory speed limit of 25 mph.

Figure 10. H Street (NW) Eastbound Approach


Figure 11. 17th Street (NW) Northbound Approach

Figure 12. 17th Street (NW) Southbound Approach


*3. I Street and 15th Street/ Vermont Avenue (NW)*

The study segment of I Street (NW) is a one-way street oriented in the westbound direction whereas 15th Street and Vermont Avenue (NW) are bi-directional streets that run in the north-south direction. I Street (NW) has four travel lanes and a parking lane on the south side. The bus lane (painted in red) on the north side of I Street (NW) is shown in Figure 13. The northbound and southbound approaches of 15th Street/Vermont Avenue (NW) have two travel and receiving lanes. There is parking on both sides of the northbound and southbound approaches, as shown in Figures 14 and 15. The pavement markings and surfaces at the intersection are in good condition. The intersection is signalized with a statutory speed limit of 25 mph.

Figure 13. I Street (NW) Westbound Approach

Figure 14. Vermont Avenue (NW) Northbound Approach

Figure 15. 15th Street (NW) Southbound Approach

*4. I Street and 16th Street (NW)/Black Lives Matter Plaza*

The study segment of I Street (NW) is a one-way street oriented in the westbound direction whereas 16th Street (NW)/Black Lives Matter Plaza is a bi-directional street that runs in the north-south direction. I Street (NW) is classified as a principal arterial whereas 16th Street (NW)/Black Lives Matter Plaza is classified as a minor arterial. I Street (NW) has four travel lanes and no on-street residential parking, as shown in Figure 16. Sixteenth Street (NW) was renamed Black Lives Matter Plaza by DC Mayor Muriel Bowser on June 5, 2020. During the time of data analysis, vehicular entry has been restricted (only emergency vehicles have access on the left side) on the northbound and southbound approaches, as can be seen in Figures 17 and 18. The intersection is signalized with a statutory speed limit of 25 mph.

Figure 16. I Street (NW) Westbound Approach


Figure 17. 16th Street (NW)/Black Lives Matter Plaza Northbound Approach

Figure 18. 16th Street (NW)/Black Lives Matter Plaza Southbound Approach


*5. I Street and 17th Street (NW)*

The study segment of I Street (NW) is a one-way street oriented in the westbound direction, whereas 17th Street (NW) is a bi-directional street that runs in the north-south direction. I Street (NW) is classified as a principal arterial, and 17th Street (NW) is classified as a minor arterial. I Street (NW) has four travel lanes, and the bus lane is painted red, as shown in Figure 19. There are three travel and receiving lanes on the northbound and southbound approaches of 17th Street (NW), as can be seen in Figures 20 and 21, respectively. Additionally, the pavement markings and surfaces at the intersection are in good condition and there is no on-street parking on any of the approaches at the intersection. The intersection is signalized with a statutory speed limit of 25 mph.

Figure 19. I Street (NW) Westbound Approach


Figure 20. 17th Street (NW) Northbound Approach

Figure 21. 17th Street (NW) Southbound Approach


### *3.2.4 Data Extraction Metrics*

Video Data Extraction

The project team installed video data recording equipment for the “before” scenario observations in May and June of 2019 while recording equipment for the “after” scenario were installed in September 2019 and October 2020. Cameras were installed to record traffic flow and bus usage at the selected sites, after which the variables to be used as measurements of effectiveness were extracted. The video equipment was non-intrusive and thus had little to no influence on drivers’ behaviors. The video data for the study locations were obtained for five hours per day (7:00 AM–9:30 AM and 4:00 PM–6:30 PM) from Tuesday through Thursday twice a month. Table 4 shows the video data collection dates before and after the installation of bus lanes.

Table 4. Video Data Collection Days for "Before" and "After" Scenarios

| Before Data | | After Data | |
|---|---|---|---|
| May 2019 | May 7 | September 2019 | September 17 |
| | May 8 | | September 18 |
| | May 9 | | September 19 |
| | May 14 | | September 24 |
| | May 15 | | September 25 |
| | May 16 | | September 26 |
| June 2019 | June 11 | October 2020 | October 13 |
| | June 12 | | October 14 |
| | June 13 | | October 15 |
| | June 18 | | October 20 |
| | June 19 | | October 21 |
| | June 20 | | October 22 |

The vehicular TMCs were extracted from the video data, and the project team processed the information in JAMAR PetraPRO™ software. The team extracted essential traffic characteristics components from the AM and PM peak hour volumes such as peak hour factors and heavy vehicle percentages for further analysis in Synchro software (to obtain MOEs). In addition to TMCs at all the study intersections, the project team also tallied the variables such as buses traveling in bus lanes and other lanes, as well as non-transit vehicles parked/ stopped on bus lanes, and violations at the study intersection (such as illegal turns on red) using the video playbacks.)

AVL Data Extraction

WMATA officials provided the AVL data for the selected bus routes operating on the segments of H Street and I Street (NW) with the DBLs. Comma Separated Values (CSV) data files were obtained for the same days when the video data were collected (Table 4). A sample of the raw Excel data for a bus route obtained from the WMATA database is shown in Figure 22.

Figure 22. Sample Datasheet Obtained from WMATA (Route 32)

| | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q | R | S | T | U | V | W | X | Y | Z | AA |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | BUSTOOLS_VERSION | ROUTE_ID | STOP_SEQUENCE | Stop Desc | BUS_ID | EVENT_TIME | ODOMETER_DISTANCE | ROUTE_STATUS | DWELL_TIME | DELTA_TIME | STOP_SPEED | STOP_FRONT_DOOR_ENTRY | STOP_BACK_DOOR_ENTRY | STOP_FRONT_DOOR_EXIT | STOP_BACK_DOOR_EXIT | LATITUDE | LONGITUDE | HEADING | NAV_STATE | EVENT_TYPE | Event_Description | TRIP_ID | TRIP_TYPE | scheduled_time | TRIP_START_TIME | STOP_ID | TA_GEO_ID |
| 2 | S1000056 | 3201 | 0 | NULL | 2114 | 48:03.0 | 54100 | 0 | 0 | 603 | 0 | 0 | 0 | 0 | 0 | 38.8296 | -76.9905 | 49 | 1 | 9 | NULL | 9.41E+08 | 2 | NULL | 48:00.0 | NULL | BT-SH |
| 3 | S1000056 | 3201 | -1 | NULL | 2114 | 48:03.0 | 54100 | 4 | 0 | 2339 | 0 | 0 | 0 | 0 | 0 | 38.8296 | -76.9905 | 49 | 0 | 6 | NULL | 9.41E+08 | 2 | NULL | 48:00.0 | NULL | |
| 4 | S1000056 | 3201 | -1 | NULL | 2114 | 48:03.0 | 54100 | 4 | 0 | 603 | 0 | 0 | 0 | 0 | 0 | 38.8296 | -76.9905 | 49 | 0 | 720 | NULL | 9.41E+08 | 2 | NULL | 48:00.0 | NULL | |
| 5 | S1000056 | 3201 | 0 | NULL | 2114 | 00:01.0 | 54205 | 0 | 0 | 1321 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 1 | 104 | NULL | 9.41E+08 | 2 | NULL | 48:00.0 | NULL | BT-SH |
| 6 | S1000056 | 3201 | 0 | NULL | 2114 | 00:25.0 | 54205 | 0 | 0 | 1345 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 1 | 104 | NULL | 9.41E+08 | 2 | NULL | 48:00.0 | NULL | BT-SH |
| 7 | S1000056 | 3201 | 0 | NULL | 2114 | 00:51.0 | 54205 | 0 | 0 | 1371 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 1 | 104 | NULL | 9.41E+08 | 2 | NULL | 48:00.0 | NULL | BT-SH |
| 8 | S1000056 | 3201 | 0 | NULL | 2114 | 01:16.0 | 54205 | 0 | 0 | 1396 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 1 | 104 | NULL | 9.41E+08 | 2 | NULL | 48:00.0 | NULL | BT-SH |
| 9 | S1000056 | 3201 | 0 | NULL | 2114 | 01:40.0 | 54205 | 0 | 0 | 1420 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 1 | 104 | NULL | 9.41E+08 | 2 | NULL | 48:00.0 | NULL | BT-SH |
| 10 | S1000056 | 3201 | 0 | NULL | 2114 | 06:01.0 | 54205 | 0 | 229 | 1910 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 1 | 5 | NULL | 9.41E+08 | 2 | 09:50.0 | 48:00.0 | NULL | BT-SH |
| 11 | S1000056 | 3201 | 0 | NULL | 2114 | 06:02.0 | 54205 | 0 | 0 | 1681 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 1 | 101 | NULL | 9.41E+08 | 2 | NULL | 48:00.0 | NULL | BT-SH |
| 12 | S1000056 | 3201 | 0 | NULL | 2114 | 15:00.0 | 54205 | 0 | 0 | 2219 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 1 | 104 | NULL | 9.41E+08 | 2 | NULL | 48:00.0 | NULL | BT-SH |
| 13 | S1000056 | 3201 | 0 | NULL | 2114 | 30:00.0 | 54205 | 0 | 0 | 3120 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 1 | 104 | NULL | 9.41E+08 | 2 | NULL | 48:00.0 | NULL | BT-SH |
| 14 | S1000056 | 3201 | 0 | NULL | 2114 | 45:01.0 | 54205 | 0 | 0 | 4021 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 1 | 104 | NULL | 9.41E+08 | 2 | NULL | 48:00.0 | NULL | BT-SH |
| 15 | S1000056 | 3201 | 0 | NULL | 2114 | 00:01.0 | 54205 | 0 | 0 | 4921 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 1 | 104 | NULL | 9.41E+08 | 2 | NULL | 48:00.0 | NULL | BT-SH |
| 16 | S1000056 | 3201 | 0 | NULL | 2114 | 02:00.0 | 54205 | 0 | 0 | 5039 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 0 | 15 | NULL | 9.41E+08 | 2 | NULL | 02:00.0 | NULL | 1003537 |
| 17 | S1000056 | 3201 | 0 | NULL | 2114 | 02:00.0 | 54205 | 0 | 0 | 5039 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 0 | 720 | NULL | 9.41E+08 | 2 | NULL | 02:00.0 | NULL | 1003537 |
| 18 | S1000056 | 3201 | 21 | NULL | 2114 | 02:00.0 | 54205 | 0 | 0 | 5039 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 1 | 16 | NULL | 9.41E+08 | 2 | 02:00.0 | 48:00.0 | NULL | 1000593 |
| 19 | S1000056 | 3201 | 35 | NULL | 2114 | 02:00.0 | 54205 | 0 | 0 | 5039 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 1 | 16 | NULL | 9.41E+08 | 2 | 02:00.0 | 48:00.0 | NULL | 1000948 |
| 20 | S1000056 | 3201 | 2 | NULL | 2114 | 02:00.0 | 54205 | 0 | 0 | 5039 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 1 | 16 | NULL | 9.41E+08 | 2 | 02:00.0 | 48:00.0 | NULL | 3002667 |
| 21 | S1000056 | 3201 | 20 | NULL | 2114 | 02:00.0 | 54205 | 0 | 0 | 5039 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 1 | 16 | NULL | 9.41E+08 | 2 | 02:00.0 | 48:00.0 | NULL | 1000576 |
| 22 | S1000056 | 3201 | 13 | NULL | 2114 | 02:00.0 | 54205 | 0 | 0 | 5039 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 1 | 16 | NULL | 9.41E+08 | 2 | 02:00.0 | 48:00.0 | NULL | 1003927 |
| 23 | S1000056 | 3201 | 42 | NULL | 2114 | 02:00.0 | 54205 | 0 | 0 | 5039 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 1 | 16 | NULL | 9.41E+08 | 2 | 02:00.0 | 48:00.0 | NULL | 1001179 |
| 24 | S1000056 | 3201 | 25 | NULL | 2114 | 02:00.0 | 54205 | 0 | 0 | 5039 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 1 | 16 | NULL | 9.41E+08 | 2 | 02:00.0 | 48:00.0 | NULL | 1000702 |
| 25 | S1000056 | 3201 | 48 | NULL | 2114 | 02:00.0 | 54205 | 0 | 0 | 5039 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 1 | 16 | NULL | 9.41E+08 | 2 | 02:00.0 | 48:00.0 | NULL | 1003537 |
| 26 | S1000056 | 3201 | 0 | NULL | 2114 | 02:02.0 | 54205 | 3 | 0 | 5039 | 0 | 0 | 0 | 0 | 0 | 38.8297 | -76.9904 | 46 | 0 | 11 | NULL | 9.41E+08 | 2 | NULL | 02:00.0 | NULL | 1003537 |
| 27 | S1000056 | 3201 | 0 | NULL | 2114 | 22:35.0 | 149563 | 0 | 0 | 95 | 101 | 0 | 0 | 0 | 0 | 38.8685 | -76.9709 | 162 | 1 | 9 | NULL | 9.41E+08 | 2 | NULL | 22:33.0 | NULL | 1000437 |
| 28 | S1000056 | 3201 | -1 | NULL | 2114 | 22:35.0 | 149563 | 4 | 0 | 1508 | 101 | 0 | 0 | 0 | 0 | 38.8685 | -76.9709 | 162 | 0 | 6 | NULL | 9.41E+08 | 2 | NULL | 22:33.0 | NULL | |

From Figure 22, it can be seen that the AVL systems (for Route 32 buses) recorded information including odometer reading, geolocation, and dwell time, among others. The datasheets were filtered to display only the information required for the regression and neural network analyses. Based on the significance of their impact on the travel time of transit buses (from the previous literature), the following fields of a bus trip were filtered for the selected routes from the data: departure and arrival times (event times), length of routes, bus geolocation, dwell time, travel time, and bus stop ID.

The dwell times and the bus stop IDs were necessary to determine the duration a bus spent at the stops located on the segments with the bus lanes. For instance, the bus lane on H Street (NW) was installed from H Street and 18th Street (NW) to H Street and 14th Street (NW). The bus stops with following bus stop IDs are present within the H Street (NW) study segment:

a. H Street and 18th Street (NW) - 1001148

b. H Street (NW) and 17th Street (NW) - 1001133

c. H Street and Madison Place (NW) - 1001141

d. H Street and 14th Street (NW) - 1003467

The segment of I Street (NW) that has the bus lane includes the following bus stop IDs:

a. I Street and 14th Street (NW) - 1001191

b. I Street and 15th Street/ Vermont Avenue (NW) - 1001185

c. I Street and 17th Street (NW) - 1001183

d. I Street and 18th Street (NW) - 1001181

The information was used to further obtain the following variables used in the multiple regression and neural network analyses.

Length of Route between Bus Stops ($X_1$): The data provided by WMATA included the odometer readings of all the buses along a route. Hence, $X_1$ was obtained by taking the difference in the odometer readings between any two served bus stops.

Average Dwell Time at Served Bus Stops ($X_2$): The dwell time is the period during which the front and the rear doors of a bus at a bus stop remained open to serve patrons. Average dwell time ($X_2$) was regarded as mean of dwell times of the served bus stops between the origin and destination points. Thus, average dwell time was computed as

$$Average\ Dwell\ Time = \frac{\Sigma DT}{N}$$

where N = number of served bus stops between the origin and the destination (inclusive) along a route and DT = dwell time of the bus at the $n^{th}$ bus stop.

Bus Travel Direction ($X_3$): The segments of H Street and I Street (NW) are classified as principal arterials at the limits of the study. H Street (NW) is one-way oriented in the eastbound direction while I Street (NW) is one-way oriented in the westbound direction. Since the same bus routes (30N and 30S) operated on both H Street (NW) and I Street (NW), for multiple regression, $X_3$ data points were coded as 0 (EB) or 1 (WB) based on the direction of travel.

Presence of Dedicated Bus Lanes ($X_4$): To distinguish the data collected before and after the installation of bus lanes, the "before" scenario data points were coded as 0 and the "after" scenario data points were coded as 1 for $X_4$.

Peak Period ($X_5$): The event time provided in the CSV by WMATA was used to obtain data from the morning peak (7:00 AM–9:30 AM) as well as the evening peak (4:00 PM–6:30 PM). The AM and PM peak data points were hence coded as 0 and 1 for $X_5$, respectively.

Average Percentage of Buses Using Bus Lane ($X_6$): The rightmost lane in the H Street (NW) and I Street (NW) segments within the study boundaries were painted red, with additional pavement markings to designate them as DBLs. In addition to WMATA buses, the lane could be used by right-turning vehicles, bicycles, charter buses, school buses, and marked taxis. For this study, WMATA buses traveling on H Street and I Street (NW) were observed to see the compliance of buses for traveling on the bus lanes. A tally of the number of buses using the bus lanes and also the other travel lanes were extracted from the video files via playback. A sample of the DBL compliance tally sheet is presented in Figure 23. The summaries of bus lane usage for the "Before" and "After" scenarios during both the AM and PM peaks are presented in Appendix B.

Figure 23. Sample Compliance Tally Sheet

| Location | I Street and 16th Street, NW | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | In Bus Lane | | | | | | | In Other Travel Lanes | | | |
| | Buses | Taxis | Cyclists | Non-transit parked | Non-transit stopped | Right turning non-transit vehicles | Thru non-transit | Buses | Taxis | Cyclists | Non-transit |
| 7:00 | 4 | 2 | 3 | 0 | 0 | 20 | 1 | 11 | 6 | 0 | 196 |
| 7:15 | 5 | 4 | 0 | 0 | 0 | 17 | 0 | 14 | 8 | 4 | 229 |
| 7:30 | 5 | 3 | 2 | 0 | 0 | 21 | 0 | 9 | 10 | 1 | 200 |
| 7:45 | 3 | 2 | 2 | 0 | 0 | 34 | 0 | 14 | 16 | 2 | 175 |
| 8:00 | 4 | 6 | 1 | 0 | 0 | 27 | 1 | 10 | 16 | 5 | 185 |
| 8:15 | 7 | 4 | 3 | 0 | 0 | 26 | 2 | 15 | 16 | 1 | 205 |
| 8:30 | 3 | 5 | 2 | 0 | 0 | 40 | 1 | 11 | 22 | 7 | 198 |
| 8:45 | 7 | 5 | 7 | 0 | 1 | 26 | 3 | 13 | 21 | 4 | 178 |
| 9:00 | 2 | 6 | 3 | 0 | 0 | 27 | 1 | 12 | 15 | 6 | 212 |
| 9:15 | 2 | 7 | 6 | 0 | 1 | 26 | 0 | 18 | 16 | 3 | 194 |
| Total | 42 | 44 | 29 | 0 | 2 | 264 | 9 | 127 | 146 | 33 | 1972 |

The average monthly compliance for the AM and PM peak hours at all the study intersections (both before and after implementation) was obtained using the following formula:

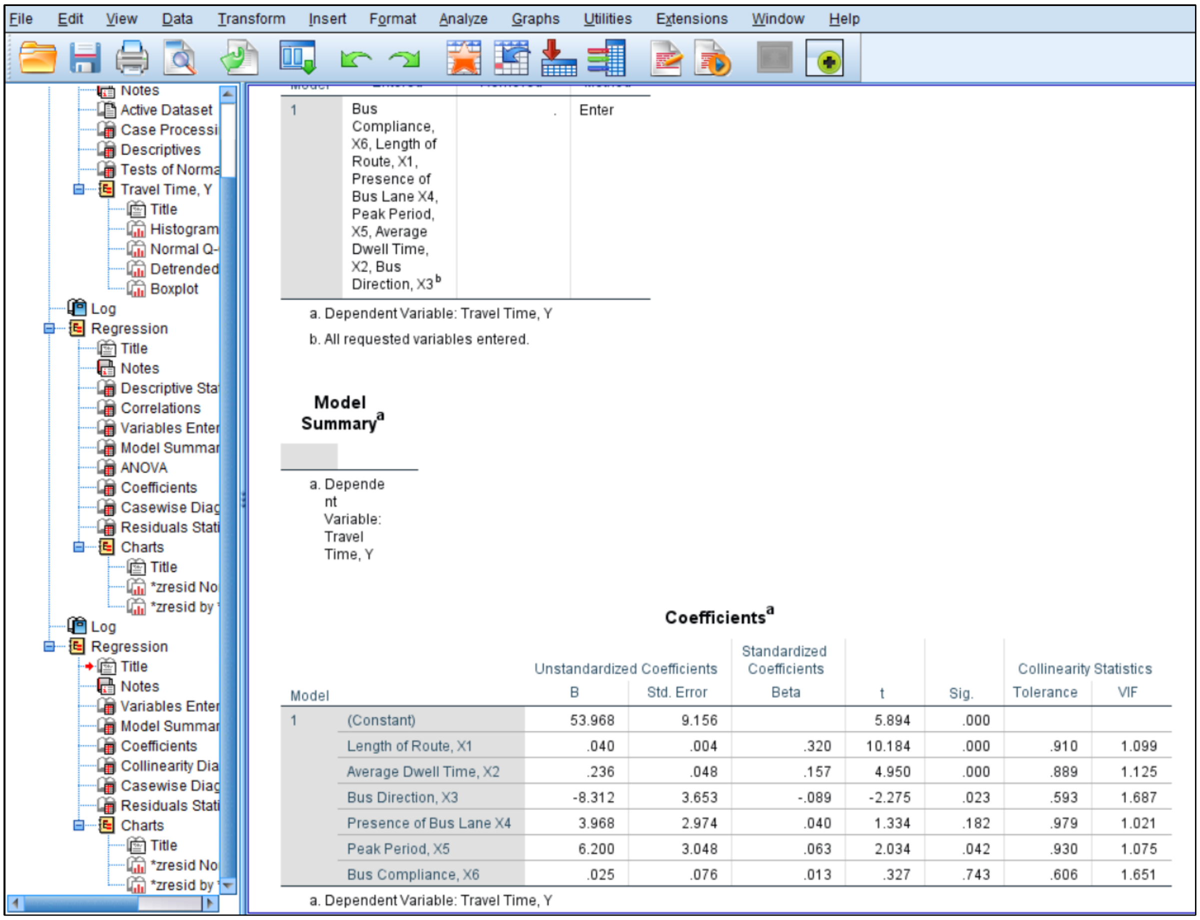
$$X6 = \frac{\Sigma(Buses\ using\ the\ bus\ lane)}{\Sigma(Buses\ using\ the\ bus\ lane) + \Sigma(Buses\ traveling\ on\ other\ lanes)}$$

## 3.3 Data Analysis

Two software programs were used for the data analysis. IBM's SPSS Statistics 25 software (SPSS) was used for the paired t-test and regression analysis of the "before" and "after" periods, while Neural Designer was used for the neural network analysis.

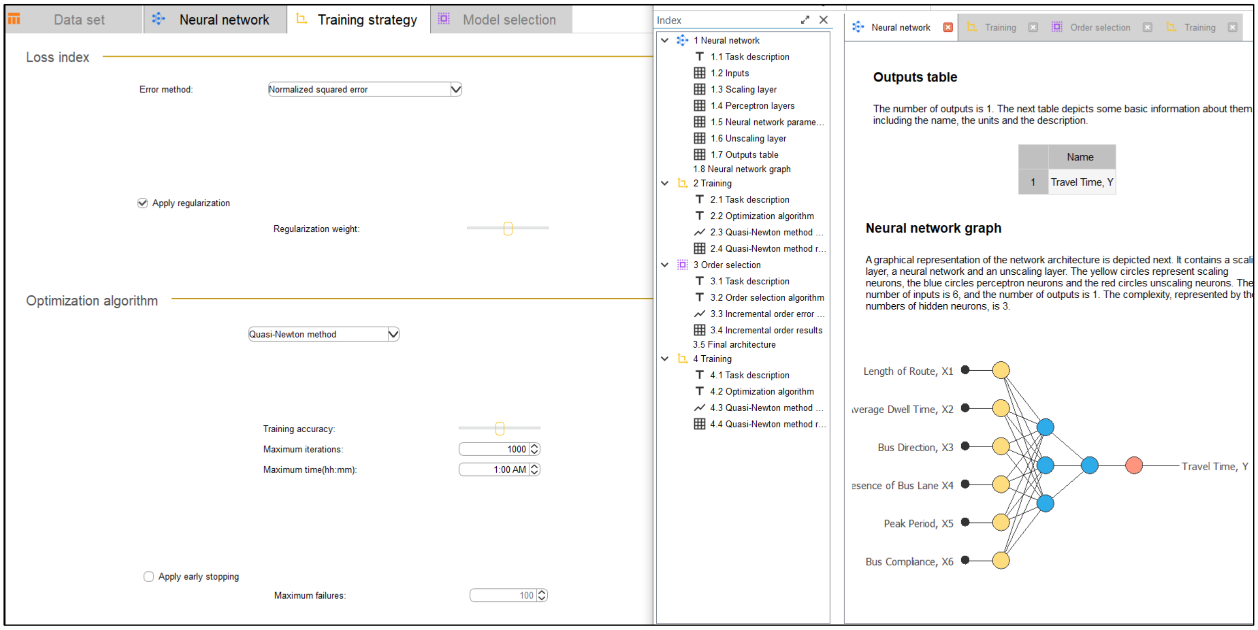
SPSS is a statistical software package that allows users to better understand the data under consideration based on the extraction of statistical insights. Figure 24 shows a sample analysis of a model in SPSS software.

Figure 24. Snapshot of SPSS Interface and Sample Output




Neural Designer is a software program that incorporates data science and machine learning techniques and which helps to build, train, and deploy neural network models. The high operability of Neural Designer allows it to be integrated into numerous projects from different sectors for approximation and classification problems. A snapshot of the software interface along with the sample output is presented in Figure 25.

Figure 25. Snapshot of Neural Designer Interface and Sample Output




### *3.3.1 Determination of Sample Size*

A dependent t-test was used to compare the differences in MOEs of the five study intersections before and after installing the bus lanes on the H and I Street (NW) segments, for a two-tailed t-test, setting the effect size to 0.5 (a medium effect size) and a significance of 0.05, a critical t-value of 2.00575 is obtained. Hence, a minimum sample of 54 events was required for statistical validity (actual power = 0.95) for the t-test. A significance level of 95% ensured that the team can be 95% confident that the obtained results are credible and not resulted from errors caused by randomness. For this study, five intersections were observed for 12 days (six days per month for two months) for both the “before” and “after” scenarios totaling 60 observations per scenario.

For the multiple regression analysis, there should be a minimum of 10 observations per independent variable. There are five independent variables (predictors) that were used in the study, and hence, a minimum of 50 observations is required. From the WMATA data, at least 50 observations were recorded for each bus route per peak period for both the “before” and “after” scenarios.

In the case of ANN, since ANNs are highly data-dependent, the complexity and accuracy of the model depend on the number of input variables. Training with a large dataset for ANNs would result in models that make better predictions on unknown data. Thus, data for a minimum sample of 1,000 origin-to-destination trips were extracted and exported into a Comma Separated Values (CSV) file for the ANN analysis. This dataset consisted of filtered WMATA AVL bus data points and not the MOE dataset that was used for the dependent t–test.

### *3.3.2 Descriptive Statistics*

The project team used Synchro 10™ to compute descriptive statistics (including the mean, median, and standard deviation) computed, and obtaining the intersection MOEs.

### *3.3.3 Dependent t-test*

Since H Street and I Street (NW) had a total of five intersections with bus lanes post-installation, a dependent t-test can be used to check for statistically significant differences for the same intersections over time. It is hypothesized that installing the bus lanes on the urban segments would result in better performance of intersections (Measures of Effectiveness). Hence, the Measures of Effectiveness used for the study will be more desirable (a lower value of MOE indicates better intersection performance) for traffic operation after installing the bus lanes. The hypothesis can be mathematically expressed as:

$H_o : \overline{MOE}_2 < \overline{MOE}_1$

$H_1 : \overline{MOE}_2 > \overline{MOE}_1$

where $\overline{\mathrm{MOE}}_1$ = measures of effectiveness before the installation of bus lanes and $\overline{\mathrm{MOE}}_2$ = measures of effectiveness after the installation of bus lanes.

The following formulas can be used to calculate the t-score:

$$t = \frac{\bar{d}}{SE\ (\bar{d})}$$

$$\bar{d} = \overline{(m1 - m2)}$$

Here, $t$ = t-statistic

$\bar{d}$ = mean difference in MOE

$SE(\overline{d})$ = standard error of differences

$m1$ = MOE at before scenario

$m2$ = MOE at after scenario

### *3.3.4 Regression Analysis*

The relationship between bus travel times and the independent variables was explored by conducting a multiple regression analysis. The regression model incorporated both the peaks (P) and also the presence/absence of bus lanes (BL). The multiple regression model for bus travel times can be represented as:

$$TT = \beta_o + \beta_1 L + \beta_2 DT + \beta_3 BD + \beta_4 BL + \beta_5 P + \beta_6 BC + \varepsilon$$

Where *TT* = Travel Time

*L* = Length of the Route between Served Bus Stops

*DT* = Average Dwell Time

*BD* = Bus Travel Direction

*BL* = Presence of Bus Lane

*P* = Peak Period

*BC* = Average Percentage of Buses Using Bus Lane

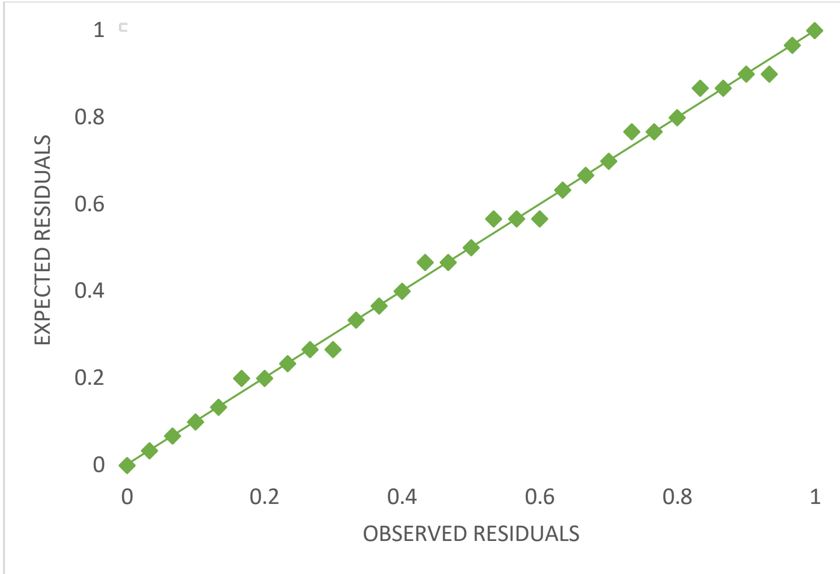
The term $\beta_o$ is the intercept and the items in the $\beta_k$ series ($k$ = 1 through 6) are the regression coefficients for the predictors. Further, $\varepsilon$ is the error residual (distributed error).

The assumptions of multiple linear regression were reviewed by testing for normality of errors, homoscedasticity, and multicollinearity, as discussed below.

Normality of Errors

The errors obtained for a multiple regression model (i.e., the residuals) should demonstrate a normal distribution. The errors should explain the relationship between predictor and target variables. This can be observed with a normal probability plot representing the observed cumulative probabilities versus the expected cumulative probabilities. An example of the normal probability plot displaying a straight line is shown in Figure 26. The project team presents a similar normal probability plot of the expected and obtained residuals in the results section of this report.

Figure 26: Example of a Normal Probability Plot



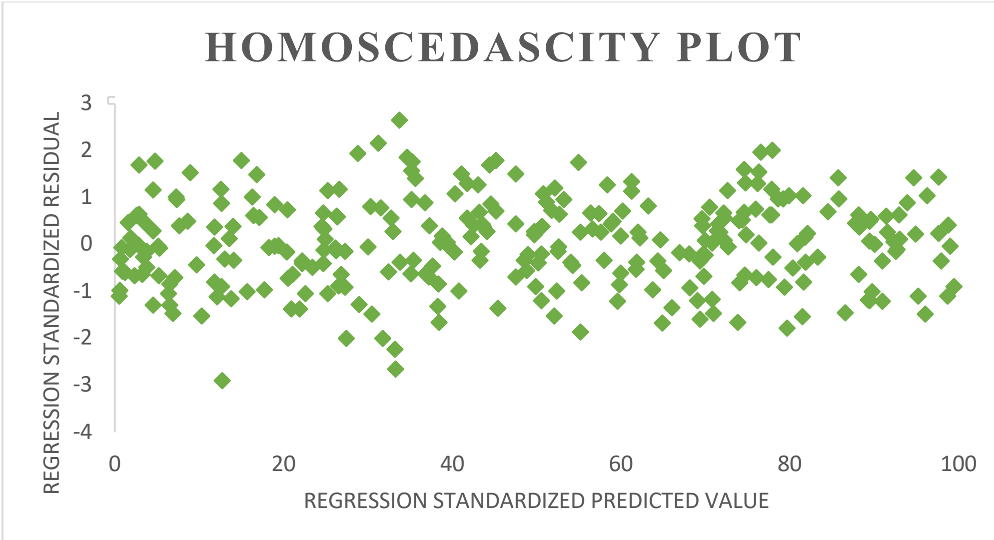

Multicollinearity

Multicollinearity exists if two or more predictor variables are highly correlated with each other. The prediction of a model is affected by multicollinearity since it becomes harder to determine which predictor variable affects the target the most. The Variance Inflation Factor (VIF), ratio of the variance of the model with multiple variables to the variance of the model with one variable, is one test that can be used to check for multicollinearity. VIF values of greater than 10 indicate multicollinearity. The tolerance level (values less than 0.1) and correlation values greater than 0.5 (positive or negative) also indicate the presence of multicollinearity.

Homoscedasticity

Homoscedasticity exists when the variances along the line of best fit remain similar at any point along the line. If there is no homoscedasticity, there is inaccuracy in the tests of regression coefficients. The regression standardized predicted value plotted against the regression standard residual is used to check for homoscedasticity. Homoscedasticity exists if distribution about the zero line appears to be even, as can be observed in Figure 27.  The project team checked for the homoscedasticity of the variables used in this study.

Figure 27. Example of a Scatter Plot Showing Homoscedasticity




### *3.3.5 Evaluation for Regression Analysis*

The multiple regression models were evaluated using the p-values of the F-test, $R^2$, and adjusted $R^2$ values. These evaluative parameters are typically used to assess the performance of the models.

#### *F-test*

The F-test evaluates the null hypothesis that all regression coefficients are equal to zero. The alternative hypothesis is that at least one regression coefficient is not zero. Hence, the F-test can be used to check whether the relationship between the target and the set of predictors is statistically significant. The F-test is given by:

$$F\ statistic = \frac{MSM}{MSE}$$

where *MSM* is the mean of squares for the model and *MSE* is the mean of squares for the error. The p-value is checked to see the statistical significance of the F-statistic. The significance level for this study was set at 5%.

#### *$R^2$ (Coefficient of Determination F-test)*

The coefficient of determination, $R^2$, is a measure of the goodness of fit of a model. It is defined as the percentage of the variance of the dependent variable that can be explained by the model. $R^2$ is expressed mathematically as:

$$R^2 = \frac{SST - SSE}{SST}$$

where

$SST$ = Sum of Squares Total (sum of the squares of the difference of the dependent variable and its mean)

$SSE$ = Sum of Squares of Error (sum of the squares of the difference of the predicted dependent variable from actual values of the data)

$R^2$ typically increases when predictors are introduced to the model. For this study, the multiple regression model used six predictor variables that have been discussed in section 3.3.4. However, the increase might not result in the actual improvement of the model and indicate overfitting of the model.

*Adjusted $R^2$*

$R^2_{adjusted}$ is a measure of the percentage of the total variance in the dependent variable that is explained by the model. $R^2_{adjusted}$ considers the model's degrees of freedom, penalizing the addition of too many predictor variables (in general) thereby increasing the $R^2$. Hence, $R^2_{adjusted}$ will decrease as independent variables are added if the increase in model fit is not enough to make up for the loss of degrees of freedom. It is expressed as:

$$R^2_{adjusted} = 1 - \frac{MSE}{MST}$$

where $MST$ = Mean of Squares Total

$MSE$ = Mean of Squares for Error

### *3.3.6 ANN Model Development*

Neural Designer software was used to develop a predictive ANN model and determine the bus travel times on the limits of the study where the bus lanes have been installed. The software is a data analytic tool that incorporates neural networks to recognize patterns and make predictions from the data. Since the bus lanes do not stretch over the entire length of the selected bus routes, data was only obtained from segments that were selected for the study.

The software uses a technique called approximation, whereby the neural network learns from the input-target examples provided by the user. The goal of the process is to obtain a good fit for the target variable (bus travel time, in this case) based on unknown data and represent it as a function.

The project team filtered WMATA data to obtain the bus travel times as well as other predictor variables that were assessed to predict travel times. The general form of the matrix containing the predictors and the target (bus travel time) is represented in Table 5.

Table 5. Sample Peak Period ANN Data Matrix Model for a Bus Route

| Trip ID | Length of Route, X1 | Average Dwell Time, X2 | Bus Travel Direction, X3 | Presence of Bus Lane, X4 | Peak Period, X5 | Average Percentage of Buses Using Bus Lane, X6 | Travel Time, Y |
|---|---|---|---|---|---|---|---|
| 1 | A | D | G | J | M | P | Y1 |
| 2 | B | E | H | K | N | Q | Y2 |
| 3.. | C | F | I | L | O | R | Y3 |
| … | - | - | - | - | - | - | - |
| 500 | S | T | U | V | W | X | YN |

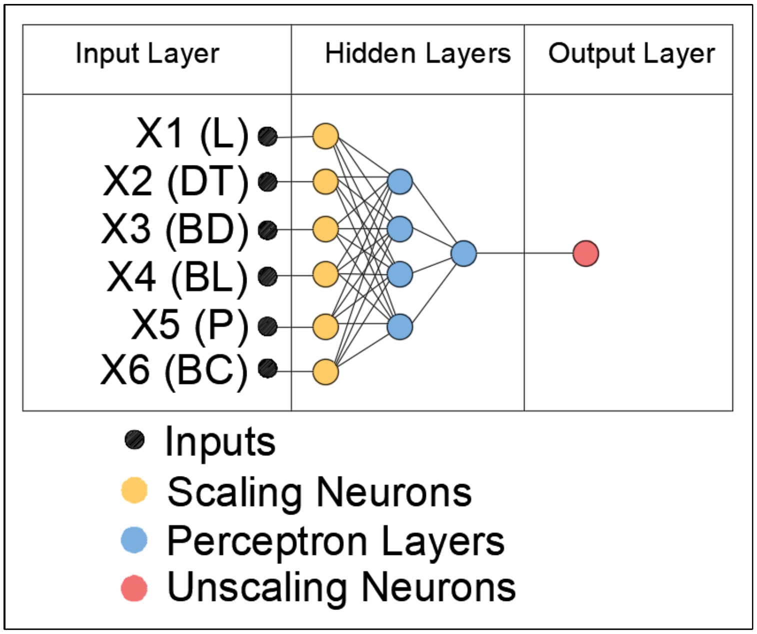
The data set was split in the Neural Designer software into a training set (75%) and a testing set (25%). Training was conducted through an iterative process of feed forward and error-back propagations until the gradient normalization goal or the stopping criterion of 1,000 epochs (iterations) was met. Development (learning) of the model was achieved using the training dataset while the testing dataset was used to validate the model. The parameters that were adjusted in the software to analyze the data set are as follows.

*Perceptron Layers*

The model was trained using multilayer perceptron (MLP). Perceptron layers consist of neurons that enable the neural network to learn. Numerical values are inputs ($X_1, \ldots, X_n$) for the perceptron neurons in a network to produce a numerical output y. The output is also affected by the combination of bias and the sum of individual weights of independent variables ($w_1, \ldots, w_n$).

The MLP used for this research consisted of three layers: input layer, hidden layer, and output layer. A typical ANN architecture is presented in Figure 28. The project team presents the ANN architecture obtained during the neural network process in this report.

Figure 28. Example of an ANN Architecture




*Data Standardization*

The range and the units of the predictor variables used in the study were not similar. For instance, a value X1 (length between two bus stops) could be greater than 1000 feet while the value for X6 (average bus compliance) could be 50%. To make the values of all predictor variables in the data set comparable, an automatic scaling layer was introduced in the neural network learning model. Hence, comparable values were processed by the software for neural network analysis. After the training, the output needed to be expressed in seconds, which is why the minimum and maximum unscaling method was employed for variables scaled for the analysis to scale it back to the original units.

*3.3.7 Training Strategy*

The goal of neural network approximation is to predict the value of the target with the minimum possible error by incorporating the loss function. The training strategy is the optimization process to obtain the minimum possible loss/model error. Lower error indicates better model accuracy. Minimizing the error can be achieved by finding a set of parameters that determine an ideal fit of the neural network. The training strategy consists of the optimization algorithm and the loss index.

*Optimization Algorithm*

The optimization algorithm involves varying the values of the independent variables during the training iteration or epoch to find the minimum loss. The optimization algorithm terminates the learning process after specific criteria are met. The common stopping criteria that stop the learning process are:

1. Loss reaching the minimum desired value,
2. Reaching maximum number of epochs,
3. Reaching maximum computing time, or
4. Increment of the selection subset error (error arising from selection dataset) while training.

For this study, the Quasi-Newton optimization algorithm was used to train the bus operation dataset model. The Quasi-Newton method is an optimization algorithm that is based on Newton's method that finds the stationary point of a function (where the slope is zero). In general, while Newton's method is used for approximating quadratic functions by using the first- and second-order derivatives to find the stationary point, Quasi-Newton method involves the analysis of the successive gradient vectors to reduce computational cost.[78]

The algorithm is the default optimization method in Neural Designer and is also recommended for training medium-sized data sets (10–1,000 variables, 1,000–1,000,000 instances) to yield functions with minimum loss.

*Loss Index*

The loss index evaluates the performance of a neural network by assessing its parameters. At the lowest value of the loss index, the slope is zero. It is a sum of a regularization term and an error term (or terms) which can be represented mathematically as:

$$LI = RT + ET$$

where $LI$ is the loss index, $RT$ is the regularization term, and $ET$ is the error term.

The gradient is zero when the loss index is at a minimum. To prevent overfitting of the data during the learning process, a regularization term is introduced to control the complexity of the neural network model. The error term measures how well the neural network fits the dataset.

### *3.3.8 Model Selection*

Model selection involves finding the optimal network architecture with the best generalization properties by adjusting the neurons or inputs to minimize the error for the neural network. To improve the accuracy of the training model, an order selection process was used after which another training was performed to generate an adequate fit for the bus travel time data. This process involves the optimization of the neural network architecture to present the optimal number of neurons in neural designer software thereby decreasing the errors. Hence the final neural network architecture that can be used to find the bus travel time for this project was obtained after the order selection process.

### *3.3.9 Model Testing and Evaluation*

Neural Designer was used to generate mathematical expressions for bus travel times within the limits of the study. Finally, the documented errors of the test data set were evaluated by obtaining the normalized squared error (NSE), which is the default error term for approximation problems, and mean percentage error (MPE), to determine the accuracy of the models. NSE can be mathematically represented as:

$$NSE = \frac{\sum(O - T)^2}{NC}$$

where

*NSE* = Normalized Squared Error

*O* = Outputs

*T* = Targets

*NC* = Normalized Coefficient.

MPE generates error while comparing the predicted values to the observed values and can be represented as:

$$MPE = \frac{1}{n}\frac{\sum|A-P|}{A} * 100$$

where

*A* = Observed values

*P* = Predicted values

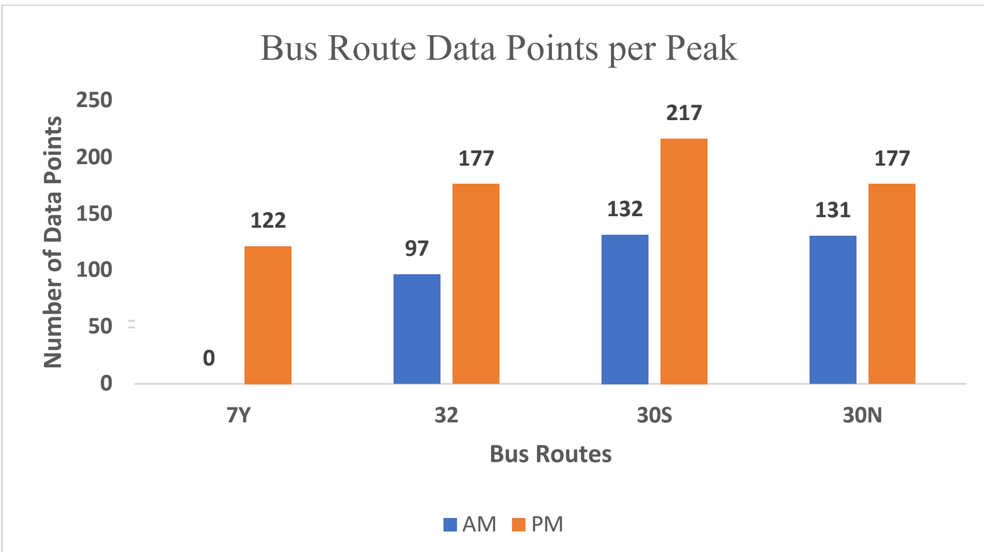
*n* = Number of observations.

# 4. Results

## 4.1 Summary Statistics

This section presents an overview of the WMATA bus data obtained for the selected routes before and after the installation of DBLs. The distribution of data points used to develop the models is presented in Figure 29 sorted by peak period. A data point for the purpose of the study was considered to be a valid bus event from which all variables ($X_1$ through $X_6$) could be extracted.

Figure 29. Total Number of Data Points Obtained per Peak Period




From Figure 29, note that a total of 122, 274, 349, and 308 data points were obtained for bus routes 7Y, 32, 30S, and 30N, respectively. Buses for route 7Y did not operate in the AM peak period throughout the duration of the study. In all, the data set for the multiple regression as well as the neural network analyses consisted of 1,053 bus events. Hence, the number of bus events for both the studies to provide meaningful results was adequate. Figure 30 presents a distribution of the data points before and after the installation of the bus lanes on H Street and I Street (NW). Figure 31 shows the total number of data points before and after installation.

Figure 30. Data Points Obtained for the "Before" and "After" Scenarios

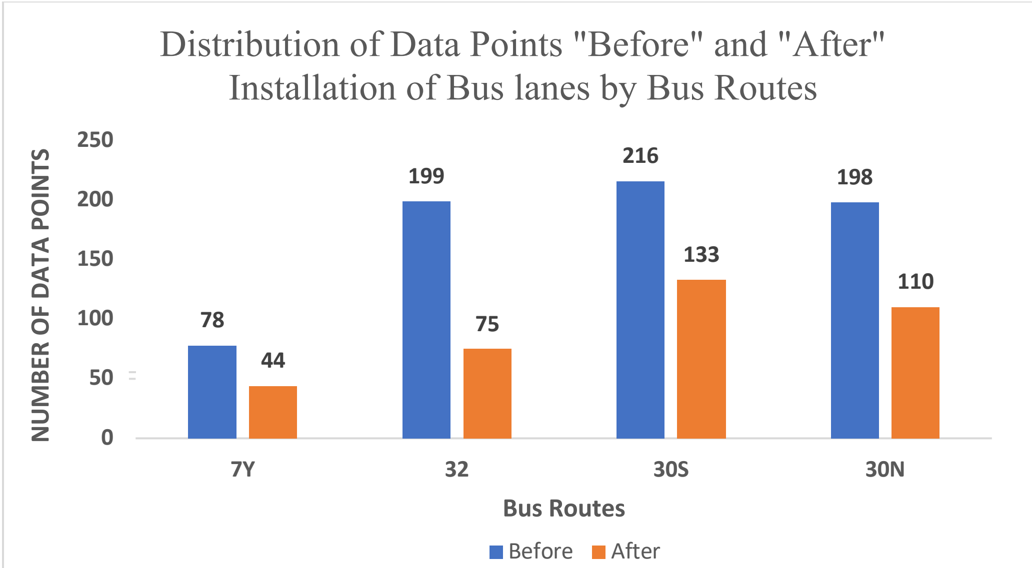



Figure 31. Distribution of "Before" and "After" Scenario Data

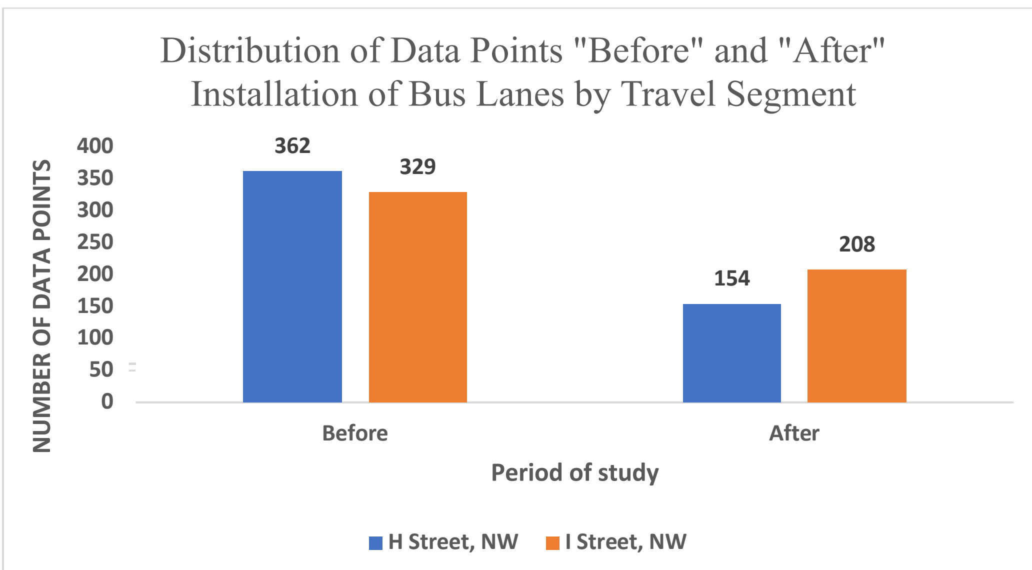
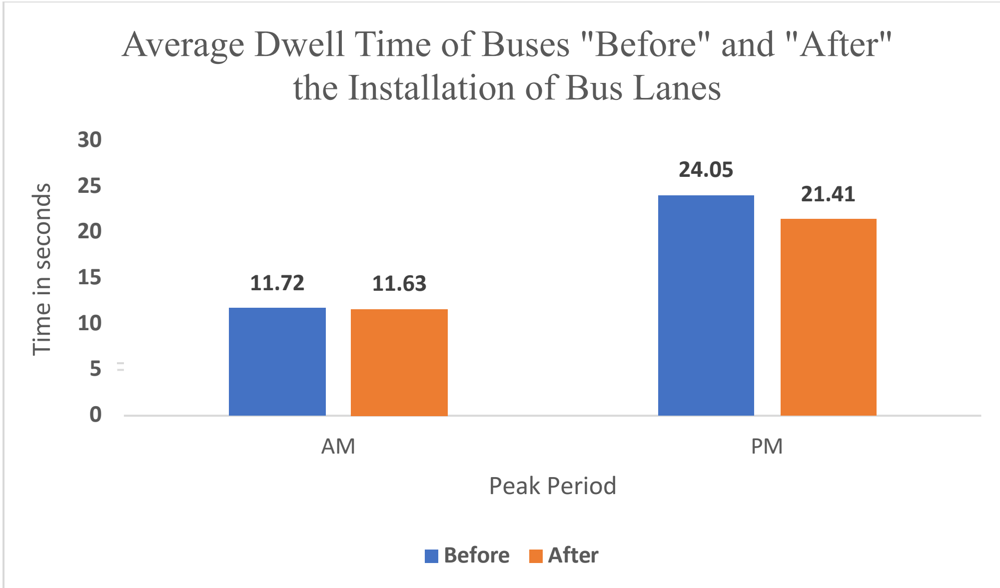


Table 6. Descriptive Statistics

| Scenario | Mean | | | Standard Deviation | | |
|---|---|---|---|---|---|---|
| | | Mean | Standard Deviation | Minimum | Maximum | 95% Confidence Interval |
| Before | L (X1) | 1240.62 | 382.92 | 126 | 3936 | 1212.02–1269.22 |
| | DT (X2) | 19.46 | 34.95 | 1 | 379 | 16.85–22.07 |
| | TT (Y) | 123.23 | 69.65 | 22 | 567 | 118.02–128.43 |
| After | L (X1) | 1225.95 | 370.11 | 214 | 2228 | 1187.69–1264.21 |
| | DT (X2) | 18.63 | 32.85 | 1 | 294 | 15.23–22.02 |
| | TT (Y) | 118.35 | 58.01 | 25 | 445 | 112.36–124.35 |

Table 6 presents the mean and standard deviation of independent and dependent variables such as length of the route, average dwell time of buses, and bus travel time obtained from the filtered WMATA AVL data (real-time bus logs recorded during bus operation). Finally, the average dwell time of WMATA buses during different peaks before and after the installation of bus lanes has been represented in Figure 32.

Figure 32. Average Dwell Times of Buses by Time of the Day




From Figure 32, note that the average dwell time for WMATA buses for both the AM and PM peaks decreased after the installation of DBLs. The study considered the overall average values during both peaks for the before and after scenarios and hence, did not account for the statistical significance of dwell times. The lowest average dwell time was obtained for the AM peak period after the installation of bus lanes (11.62 seconds).

## 4.2 Measures of Effectiveness

This section presents the results of the level of service (LOS) analysis conducted to determine the MOEs of the study intersections for the “before” and “after” scenarios. The 2016 Highway Capacity Manual (HCM) procedures were followed to conduct the LOS analysis in the Synchro 10™ software program. Turning movement counts obtained at all the intersections were analyzed in PETRAPro software to obtain the AM and PM peak hours along with respective peak hour factors and heavy vehicle percentages. These metrics were used in models developed in Synchro 10 ™ to obtain intersection MOEs. Synchro computes the MOEs through traffic simulation of existing criteria following the principles of the Highway Capacity Manual. The team modeled the H Street and I Street, NW networks in Synchro and used the metrics that were obtained from the PETRAPro software at every intersection. The team developed simulation models to represent all days of video data collection for both peaks. For the study, the project team has reported the approach delays for the vehicles traveling on H Street and I Street (NW), as well as intersection control delays (due to traffic signals) that were obtained from the Synchro simulations,. The approach delays for both the scenarios (during AM and PM peaks) for the five study intersections obtained from the Synchro Analysis have been presented in Table 7. Table 8 presents the intersection control delays at all intersections for both scenarios.

Table 7. Approach Delays (in seconds) at the Study Intersections

| | | AM PEAK | | | | | PM PEAK | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Month | Date | H & 14th | H & 17th | I & Vermont | I & 16th | I & 17th | H & 14th | H & 17th | I & Vermont | I & 16th | I & 17th |
| May 2019 | May 7 | 32.1 | 32.3 | 23.9 | 26 | * | 31.9 | 37.2 | 19.6 | 16.4 | * |
| | May 8 | 31.8 | 30.5 | 24.1 | 25.7 | 11.5 | 31.5 | 70.9 | 21.7 | 18.9 | 12 |
| | May 9 | * | 29.3 | 23.9 | 24.8 | 10.7 | * | 38 | 20.4 | 17.2 | 11.1 |
| | May 14 | 32.4 | 27.4 | 21.9 | 26.6 | 10.5 | 31.8 | 35.9 | 18.4 | 17.7 | 10.1 |
| | May 15 | 31.4 | 29.1 | 23 | 25.1 | * | 31.8 | 38.2 | 19.8 | 16.6 | * |
| | May 16 | 31.1 | 28.2 | 22.3 | 25.8 | 10.7 | 30.8 | 37.2 | 18.8 | 15.3 | 10.3 |
| June 2019 | June 11 | 34 | 25.4 | 22.8 | 25.8 | 11.7 | 33 | 32.1 | 20.3 | 17.1 | 11.8 |
| | June 12 | 32.3 | 25.5 | 23.2 | 25.8 | 13.8 | 32.9 | 30.5 | 19.4 | 16.7 | 14.1 |
| | June 13 | 33 | 26.1 | 22 | 27.2 | 12 | 32.1 | 30.7 | 20.5 | 16.6 | 11.7 |
| | June 18 | 30.9 | 26.3 | 21.9 | 24.9 | 13 | 33.4 | 33.4 | 21.4 | 16.3 | 12.8 |
| | June 19 | 31.3 | 29.1 | 24.6 | 25.9 | 11.7 | 33.8 | 32.2 | 19.9 | 16.2 | 12.3 |
| | June 20 | 31.7 | 28.3 | 22.4 | 25.8 | 12 | 30.9 | 35 | 20.9 | 15.3 | 14.8 |
| September 2019 | Sept 17 | 33 | 30.7 | 24.8 | 29.3 | 11.9 | 30.9 | 42.1 | 21.9 | 16.7 | 11.5 |
| | Sept 18 | 31.9 | 43.6 | 24.2 | 22.9 | 11.2 | 32.4 | 51.7 | 21.6 | 15.4 | 11.9 |
| | Sept 19 | 32.1 | 28.4 | 25.2 | 26.6 | 11.4 | 32.2 | 53.9 | 24.3 | 17 | 11.7 |
| | Sept 24 | 31.1 | 28.6 | 24.5 | 26.5 | 11.5 | 33.1 | 45.4 | 16.7 | 17.4 | 11.5 |

| | | AM PEAK | | | | | PM PEAK | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Sept 25 | 33.2 | 30.6 | 25.9 | 26 | 11.5 | 33.6 | 44.2 | 16.6 | 16.8 | 11.5 |
| | Sept 26 | 31.4 | 24.5 | 24.3 | 27 | 11.5 | 32.2 | 45.7 | 21.6 | 17.6 | 11.5 |
| October 2020 | Oct 13 | 26.2 | 22.8 | 18.9 | 22.7 | 9.5 | 26.1 | 27.6 | 16.6 | 14.4 | 9.1 |
| | Oct 14 | 26 | 23 | 18.5 | 22.5 | 9.5 | 26.9 | 28 | 16.4 | 14.4 | 9 |
| | Oct 15 | 26 | 22.7 | 18.4 | 22.5 | 9.4 | 26.2 | 27.7 | 16.5 | 14.4 | 9 |
| | Oct 20 | 25.9 | 23.3 | 18.7 | * | 9.6 | 27 | 28.3 | 16.9 | 12.8 | 9.4 |
| | Oct 21 | 26.4 | 23.2 | 18.9 | * | 9.5 | 26.3 | 27.7 | 16.6 | * | 9.3 |
| | Oct 22 | 26 | 23 | 18.7 | 22.8 | 9.5 | 26.1 | 27.9 | 16.7 | * | 9.3 |

* = MOE was not obtained

Table 8. Control Delays (in seconds) at the Study Intersections

| | | AM PEAK | | | | | PM PEAK | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Month | Date | H & 14th | H & 17th | I & Vermont | I & 16th | I & 17th | H & 14th | H & 17th | I & Vermont | I & 16th | I & 17th |
| May 2019 | May 7 | 22.8 | 29 | 32.4 | 23.4 | * | 23.8 | 32.6 | 27.3 | 20.5 | * |
| | May 8 | 23.5 | 67.9 | 27.6 | 23.2 | 253.4 | 24 | 48.5 | 27.3 | 20.5 | 258.6 |
| | May 9 | * | 23.5 | 31.2 | 22.4 | 27.3 | * | 24.3 | 27.2 | 20.7 | 22.1 |
| | May 14 | 23.2 | 24.3 | 31.8 | 23.9 | 30.2 | 23.7 | 22.7 | 33 | 21.4 | 24.1 |
| | May 15 | 22.7 | 31.9 | 26.9 | 22.7 | * | 23.3 | 24.4 | 27.5 | 20.1 | * |
| | May 16 | 22.4 | 31.6 | 35.6 | 23.2 | 23.7 | 22.4 | 23.1 | 52 | 19.6 | 25.3 |
| June 2019 | June 11 | 24.5 | 20.5 | 22.7 | 23.1 | 25.3 | 23.8 | 22 | 23.8 | 18.7 | 20.3 |
| | June 12 | 23.3 | 35.3 | 23 | 23.2 | 24.9 | 23.7 | 25.4 | 23.4 | 18.8 | 19.3 |
| | June 13 | 23.8 | 39.3 | 22.3 | 24.5 | 23.5 | 23 | 43.2 | 22.9 | 18.9 | 19.7 |
| | June 18 | 22 | 39.3 | 21.9 | 22.5 | 24.3 | 24.3 | 21.9 | 24 | 18.8 | 20.7 |
| | June 19 | 22.6 | 31.9 | 24.1 | 23.5 | 25.1 | 24.9 | 33 | 23.3 | 18.5 | 22 |
| | June 20 | 22.7 | 43.4 | 22.5 | 23.2 | 23.1 | 22.4 | 22.7 | 23.6 | 19.6 | 20.6 |
| September 2019 | Sept 17 | 25.3 | 23.9 | 24.2 | 26.6 | 24.9 | 22.9 | 37.1 | 22 | 20.6 | 19 |
| | Sept 18 | 24.4 | 45.5 | 23.7 | 22.9 | 24.7 | 24.1 | 28.8 | 21.7 | 19.1 | 18.6 |
| | Sept 19 | 23 | 33 | 24.6 | 23.9 | 22.2 | 25 | 29.8 | 24.2 | 19.6 | 19.1 |

| | | AM PEAK | | | | | PM PEAK | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Sept 24 | 24.5 | 46.2 | 24 | 23.8 | 24.3 | 23.3 | 27.5 | 18.4 | 21 | 21.9 |
| | Sept 25 | 26.8 | 40.4 | 25.3 | 23.4 | 25.4 | 30.2 | 26 | 18.4 | 19 | 20.5 |
| | Sept 26 | 50.5 | 23.5 | 43.8 | 24.1 | 25.4 | 30.9 | 42.1 | 21.9 | 19.7 | 20.5 |
| October 2020 | Oct 13 | 17.4 | 13.1 | 19.1 | 22.5 | 23.5 | 17.7 | 15.7 | 18.5 | 14.8 | 20.8 |
| | Oct 14 | 17.1 | 13.1 | 18.9 | 22.4 | 24.1 | 18.3 | 16.2 | 18.9 | 14.5 | 22.2 |
| | Oct 15 | 17 | 18.5 | 18.8 | 22.4 | 25.4 | 18 | 15.7 | 18.4 | 14.5 | 22.3 |
| | Oct 20 | 17.1 | 13.7 | 18.9 | * | 23.5 | 19 | 16.9 | 18.5 | 16.4 | 20.3 |
| | Oct 21 | 17.6 | 13.3 | 19 | * | 24.4 | 18.1 | 15.6 | 18.5 | * | 21.4 |
| | Oct 22 | 17.4 | 13.4 | 18.9 | 22.5 | 23.5 | 18 | 16.3 | 19.4 | * | 21.1 |

* = MOE was not obtained

The average approach delays, as well as the control delays for the "before" and "after" scenarios for all five study intersections in both AM and PM peaks, have been presented in Figures 33 through 36.

Figure 33. Comparison of Average Approach Delays during AM Peak at the Study Intersections Before and After Installing Bus Lanes

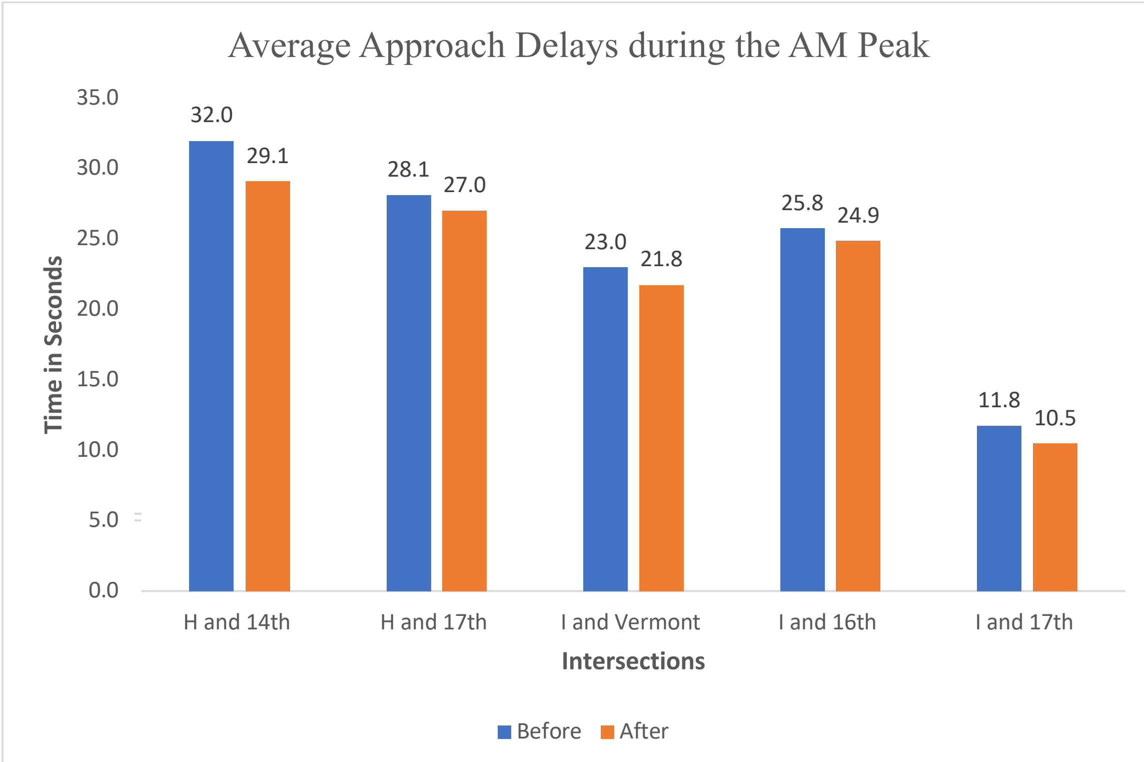



Figure 34. Comparison of Average Approach Delays during PM Peak at the Study Intersections Before and After Installing Bus Lanes

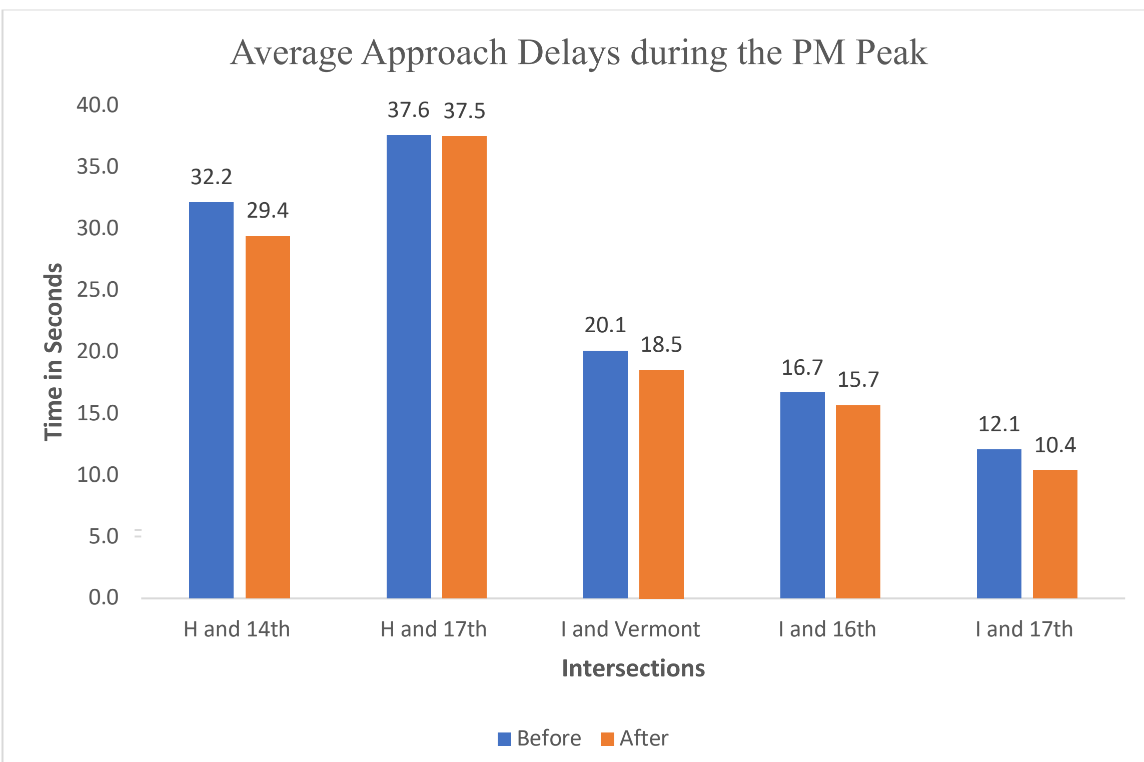


Figure 35. Comparison of Average Control Delays during AM Peak at the Study Intersections Before and After Installing Bus Lanes

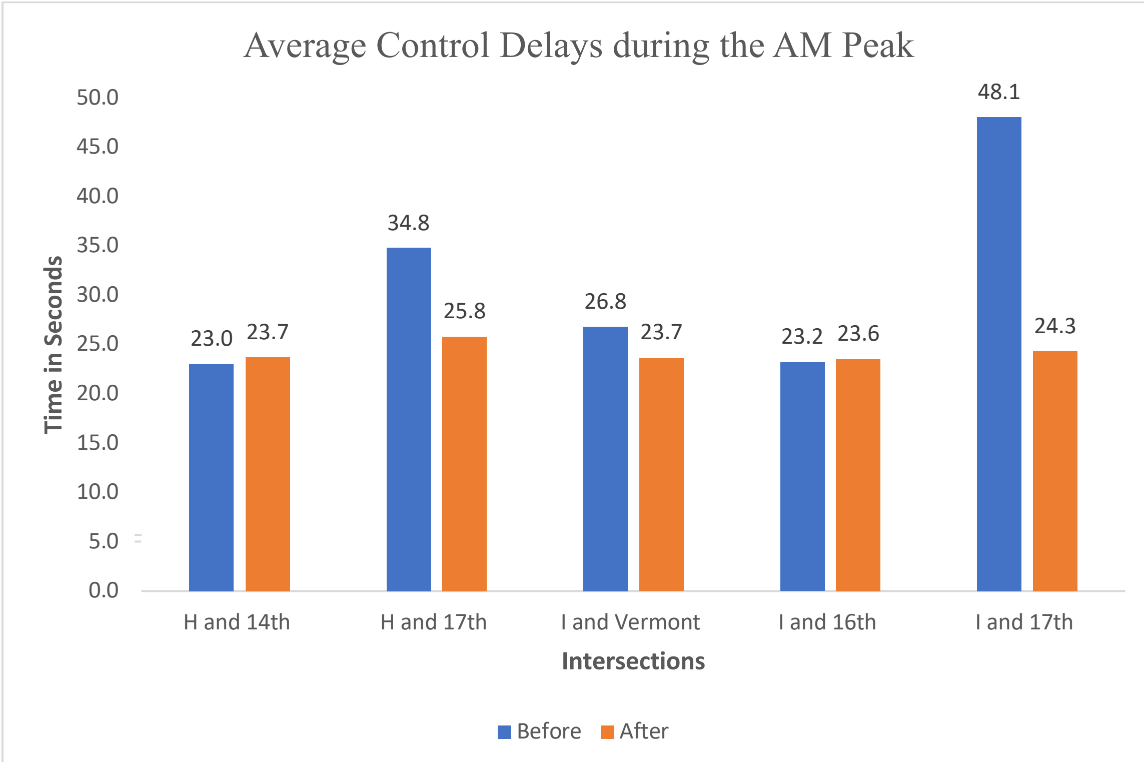
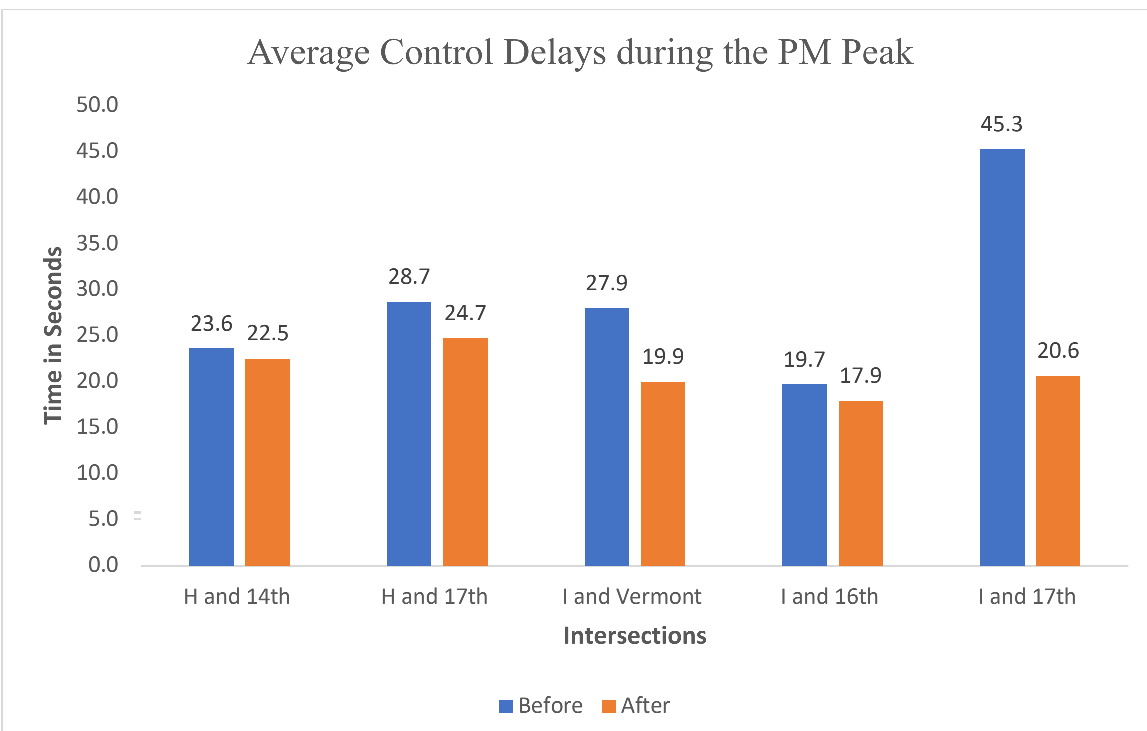



Figure 36. Comparison of Average Control Delays during PM Peak at the Study Intersections Before and After Installing Bus Lanes



From Figures 33 through 36, it can be observed that generally, the average approach delays, as well as the control delays at all the study locations for both AM and PM peaks, decreased slightly. It appears that only the average control delays for H Street and 14$^{th}$ Street (NW), as well as I Street and 16th Street (NW), increased during the AM peak after the implementation of bus lanes (Figure 35). Hence, the analysis demonstrates lower overall delays (both the approach as well as the control delays) after the installation of the bus lanes. This indicates that the quality of traffic flow at the intersections was better (on average) by implementing dedicated bus lanes on the corridors of H Street and I Street (NW). At the intersections where the control delays were observed to be higher post bus lane installation, DDOT could consider optimizing signal timing to improve general traffic flow.

## 4.3 Dependent T-Test

This section presents the results of the statistical analysis conducted in SPSS to test for statistically significant differences between the MOEs (approach delays and control delays) for both AM and PM peak periods due to the implementation of DBLs. The dependent t-test was used, which compares two means based on related/repeated data from matched samples. For this study, the matched samples are the MOEs obtained at the study intersections (for both peaks) before and after the installation of bus lanes. Table 9 presents the results of the paired t-test for approach delays on H Street (NW) and I Street (NW). The results of the t-test to determine any statistically significant differences between the control delays are presented in Table 10.

Table 9. T-Test Results for Approach Delays

| Paired Samples T-Test | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Peak Period | Variables | Mean Diff. | Std. Dev | Std. Error Mean | 95% CI of the Difference | | t | df | Sig. |
| | | | | | Lower | Upper | | | |
| AM | Approach Delay Before – Approach Delay After | 1.59 | 3.45 | 0.47 | 0.66 | 2.53 | 3.43 | 54 | 0.001 |
| PM | Approach Delay Before – Approach Delay After | 1.53 | 5.03 | 0.68 | 0.17 | 2.89 | 2.25 | 54 | 0.03 |

It can be observed from Table 9 that the mean differences in the approach delays of the study intersections in the AM and PM peaks were 1.59 and 1.53 seconds per vehicle. These differences were determined to be statistically significant at a 5% level of significance. On average, the vehicles traveling on approaches of H Street and I Street (NW) had significantly lower approach delays in the AM peak ($t(54) = 3.43$, $p = 0.001$) and PM peak ($t(54) = 2.89$, $p = 0.03$) after the installation of bus lanes.

Table 10. T-Test Results for Control Delays

| Paired Samples T-Test | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Peak Period | Variables | Mean Diff. | Std. Dev | Std. Error Mean | 95% CI of the Difference | | t | df | Sig. |
| | | | | | Lower | Upper | | | |
| AM | Control Delay Before – Control Delay After | 3.12 | 9.67 | 1.3 | .50 | 5.73 | 2.39 | 54 | .02 |
| PM | Control Delay Before – Control Delay After | 3.67 | 7.72 | 1.04 | 1.58 | 4.76 | 3.53 | 54 | <.001 |

From Table 10, note that the mean differences in the control delays of all vehicles at the study intersections in the AM and PM peaks were 3.12 and 3.67 seconds per vehicle. These differences were also determined to be statistically significant at a 5% level of significance. On average, the vehicles experienced significantly lower control delays in the AM peak ($t(54) = 5.73$, $p = 0.02$) and PM peak ($t(54) = 3.53$, $p < 0.001$) after the installation of bus lanes on H Street and I Street (NW) at all five intersections. Appendix A presents the complete results of the paired samples t-test analysis as SPSS output.

## 4.4 Regression Analysis

This section presents the results of the regression analysis developed to predict the travel time of buses within the limits of the study. A model was developed for the multiple linear regression assumed the form:

$$TT = \beta_o + \beta_1 L + \beta_2 DT + \beta_3 BD + \beta_4 BL + \beta_5 P + \beta_6 BC + \varepsilon i$$

where

TT = Travel Time

L = Length of the Route between Served Bus Stops

DT = Average Dwell Time

BD = Bus Travel Direction

BL = Presence of Bus Lane

P = Peak Period

BC = Average Percentage of Buses Using Bus Lane

The level of significance for testing the models in SPSS was set to 5%. The following evaluative criteria were used to measure the performance of the models:

1. Statistical significance (using the p-values of the F-statistics with 5% significance level)

2. Goodness of fit (using the $R^2$ and the adjusted $R^2$ values)

3. Statistical significance for the models' predictors (p-values of t-statistics).

While the t-test for each of the predictor variables tests the model against the null hypothesis that the MOEs of intersections improved after installing the bus lanes, the F-test compares the fit of the regression model with the fit of a null model with an intercept ($\beta_o$) but no predictor variables (where all regression coefficients are set to 0).

Correlations were obtained to represent the dependencies between predictors (independent variable) and the output (dependent variable). Correlation ranges from -1 to 1 where values close to -1 and 1 signify strong negative and positive correlations, respectively. A value close to 0 signifies a weak correlation or no correlation. Table 11 presents the correlations between the independent and dependent variables obtained from the AVL data.

Table 11. Input-Target Correlations

| Inputs | Correlation |
|---|---|
| L (X1) | 0.267 |
| DT (X2) | 0.075 |
| BD (X3) | -0.037 |
| BL (X4) | 0.033 |
| P (X5) | 0.026 |
| BC (X6) | -0.018 |

The highest and the lowest correlations with travel time were obtained for the variables $X_1$ (Length of Route) and $X_6$ (Average Percentage of Buses Using Bus Lane), respectively: see Table 11. The variables for bus direction ($X_3$) and bus compliance on the bus lane ($X_6$) were observed to have negative correlations with the dependent variable (bus travel time). Table 12 presents the results of the regression analysis using SPSS and the statistical significance.

Table 12. Results of the Regression Analyses for AM Peak Period

| | | | |
|---|---|---|---|
| MODEL SUMMARY | | | |
| R | R-Squared | Adjusted R-Squared | 44.552 |
| 0.321 | 0.103 | 0.098 | 158.240 |
| | | | |
| ANOVA SUMMARY | | | |
| Model | df | F | Sig . |
| Regression | 6 | 19.112 | 0.000 |
| | | | |
| COEFFICIENTS | | | |
| Variable | Unstandardized B | t | Sig. |
| Constant | 53.968 | 5.894 | 0.000 |
| L (X1) | 0.04 | 10.184 | 0.000 |
| DT (X2) | 0.236 | 4.95 | 0.000 |
| BD (X3) | -8.312 | -2.275 | 0.023 |
| BL (X4) | 3.968 | 1.334 | 0.182 |
| P (X5) | 6.2 | 2.034 | 0.042 |
| BC (X6) | 0.025 | 0.372 | 0.743 |

The results showed that the multiple regression model to determine the bus travel time within the study corridors is statistically significant, at a 5% level of significance. The obtained F-value was

19.11 with six degrees of freedom, which was significant (p-value < 0.05). The effects of all the independent predictor variables except the presence of bus lane (*BL*) and average bus lane usage compliance (*BC*) were determined to be statistically significant at the 5% significance level (p-values < 0.05). The equation obtained for the model, with an $R^2$ value of 0.103, was:

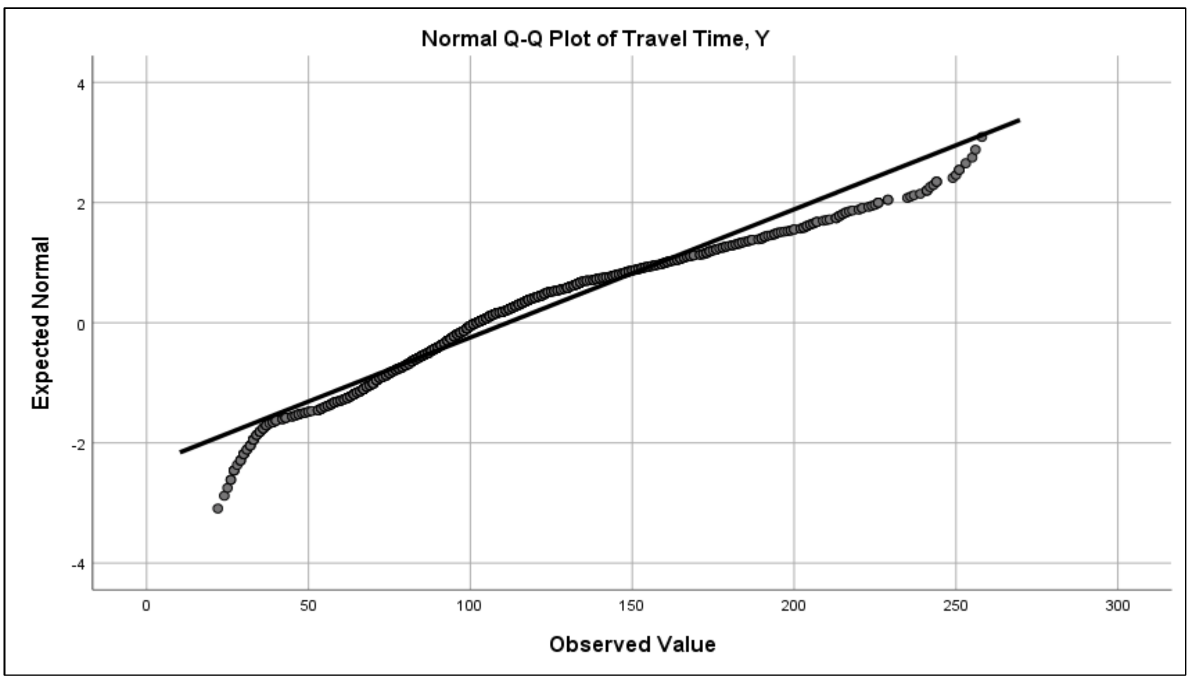
$$TT = 53.97 + 0.04L + 0.24DT - 8.32BD + 3.97BL + 6.2P + 0.03BC.$$

## 4.5 Model Testing

### *4.5.1 Normality of Errors*

Assumption for normality of errors was tested using the normal probability plot where the observed values of standardized residuals were plotted against the expected values of the standardized residuals. By visually inspecting the plots for the regression model presented in Figure 37, it can be observed that the curve closely follows the diagonal line of the plots. Hence, the errors were observed to be normally distributed.

Figure 37. Normality Probability Curve Obtained in SPSS




### *4.5.2 Multicollinearity*

The test for multicollinearity was performed and the collinearity statistics results are presented in Table 13. Generally, a variance inflation factor (VIF) above 10 indicates a high correlation and is cause for concern about the model developed. Other researchers suggest a more conservative level, indicating that a VIF of 2.5 or above prompts concern about multicollinearity. Also, in general, a tolerance value below 0.25 indicates that multicollinearity might exist, so further investigation is necessary. From the table, it can be observed that all values for tolerance were greater and 0.1 and the VIF values were lower than 10. Hence, there was no multicollinearity between the independent variables.

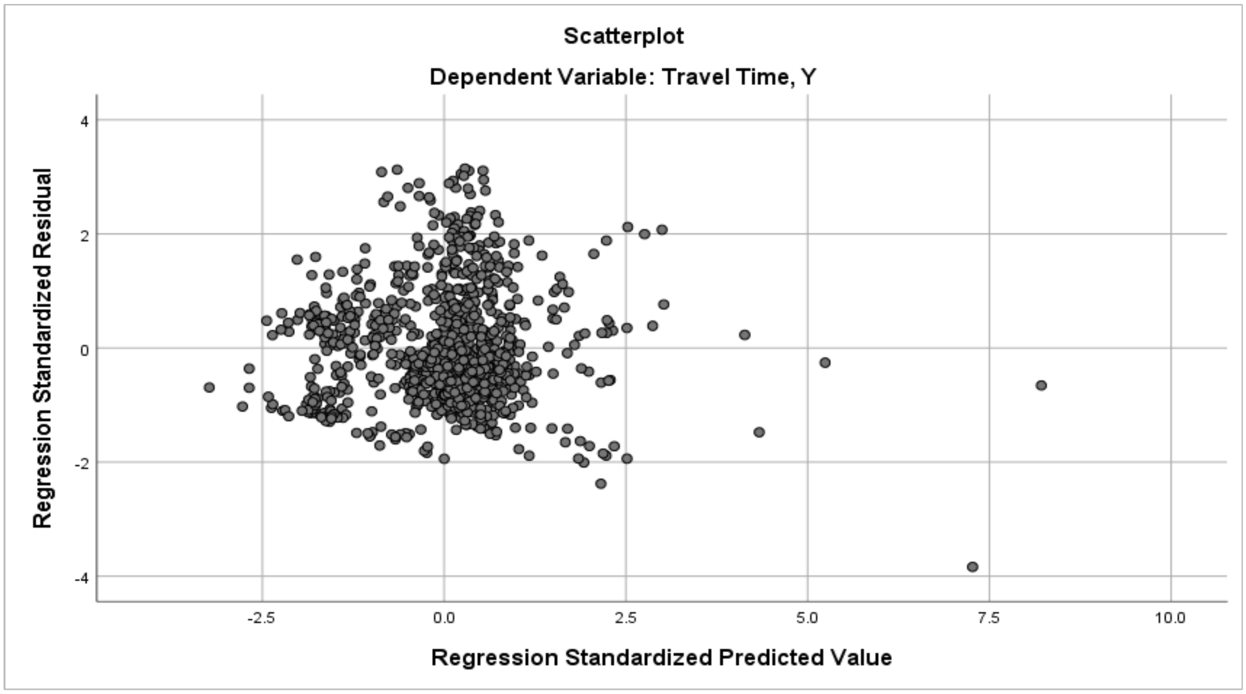
Table 13. SPSS Collinearity Statistics

| Coefficients | | |
|---|---|---|
| Model | Collinearity Statistics | |
| | Tolerance | VIF |
| (Constant) | | |
| L (X1) | 0.910 | 1.099 |
| DT (X2) | 0.889 | 1.125 |
| BD (X3) | 0.593 | 1.687 |
| BL (X4) | 0.979 | 1.021 |
| P (X5) | 0.930 | 1.075 |
| BC (X6) | 0.606 | 1.651 |

#### *4.5.3 Homoscedasticity*

The residual standardized predicted values were plotted against the regression standardized residuals in SPSS to check for homoscedasticity. Figure 38 represents the regression plot which shows a relatively even distribution about the zero line. Hence, the variances of the residuals of the predictors were the same for all values of the targets, and homoscedasticity was observed.

Figure 38. Homoscedasticity Regression Plot




## 4.6 Neural Network

The multiple linear regression analysis provided an overview of the linear fit of the data. Although the regression model was statistically significant, it could only explain approximately 10% of the variance in the bus travel time (see Table 10). However, neural networks can consider and analyze non-linear relationships in the data. The results of the neural network analysis to develop the travel time model are presented in this section. The AVL data matrix was analyzed using the Quasi-Newton algorithm in the Neural Designer software.

### *4.6.1 Quasi-Newton Optimization Algorithm*

The Quasi-Newton optimization algorithm is the default optimization strategy in Neural Designer software which is recommended for training data sets with 10–1,000 variables or 1,000–1,000,000 instances. A previous study conducted by Arhin et al. to predict bus travel time shows that Quasi-Newton algorithm with 2 perceptron layers yielded the lowest errors during the approximation process. Hence, the AVL data matrix was subjected to 2 perceptron layers for bus travel time prediction.

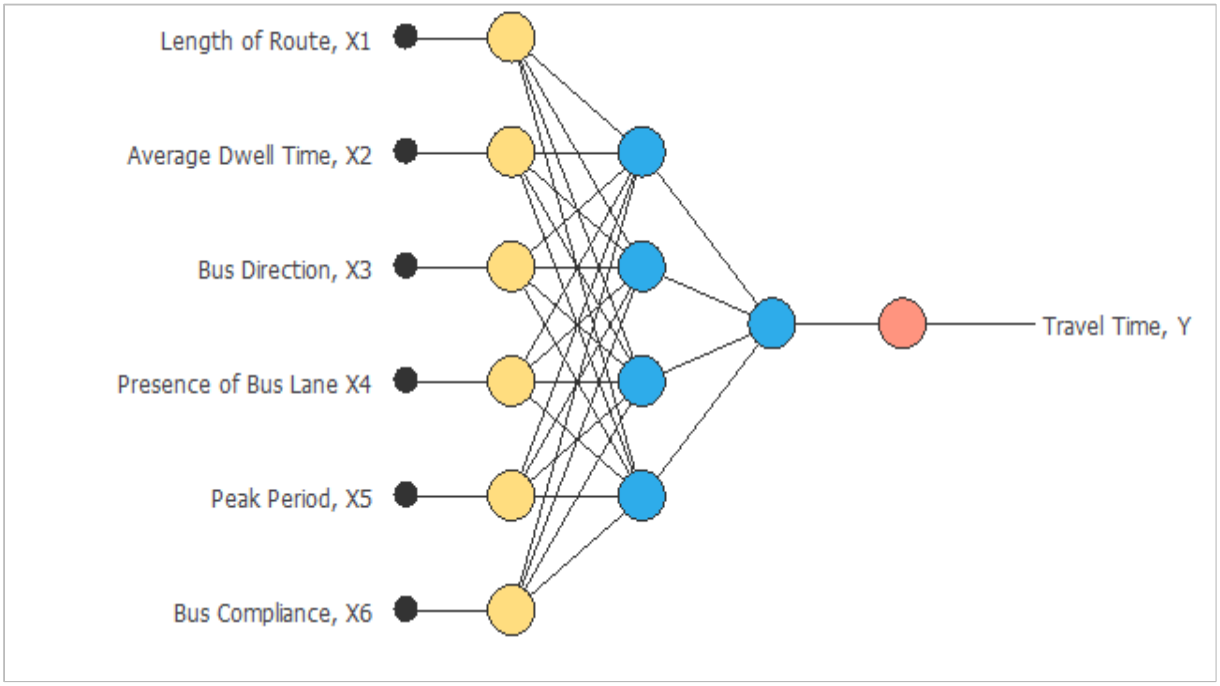
The inputs used for the analysis were scaled using the automatic scaling method where the size of the scaling layer was 6 (number of inputs). An unscaling layer was also used to scale output back to the original units. The minimum and maximum methods were used, and the size of the unscaling layer was 1 (number of outputs). The scaling and unscaling values are presented in Table 14.

Table 14. Scaling and Unscaling Values for Quasi-Newton Analysis (Three Perceptron Layers)

| Scaling Layers | | | | | |
|---|---|---|---|---|---|
| Peak Periods | | Minimum | Maximum | Mean | Deviation |
| Scaling Layer | X1 (L) | 126 | 4.29e+09 | 2.47e+07 | 3.25e+08 |
| | X2 (DT) | 1 | 4.29e+09 | 8.24e+06 | 1.88e+08 |
| | X3 (BD) | 0 | 1 | 0.496 | 0.5 |
| | X4 (BL) | 0 | 1 | 0.34 | 0.474 |
| | X5 (P) | 0 | 1 | 0.342 | 0.475 |
| | X6 (BC) | 3.9 | 75.8 | 43.8 | 23.7 |
| Unscaling Layer | Y (TT) | 22 | 567 | 121 | 65.8 |

Figure 39 shows the neural network architecture of the perceptron layers that was obtained for the model following the order selection. Of the two perceptron layers, the activation functions of the first and second layers for the analysis were set to hyperbolic tangent and linear (default software settings), respectively.

Figure 39. Neural Network Architecture Obtained in Neural Designer



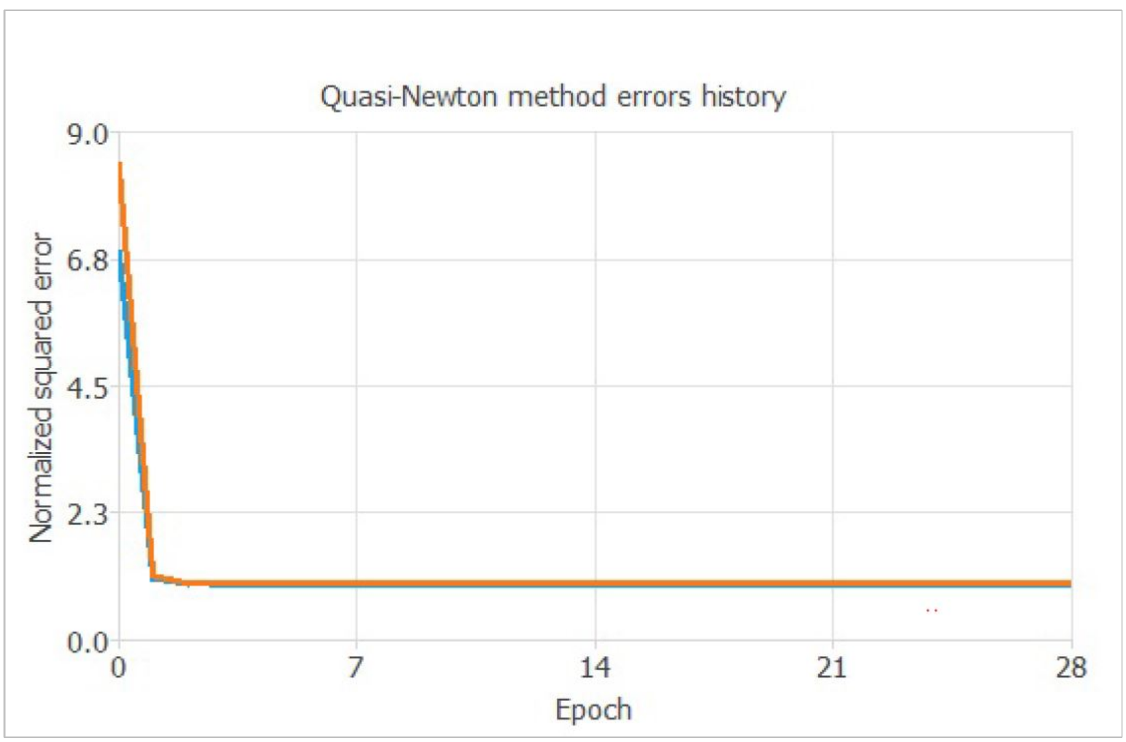

In Figure 39, the yellow, blue, and red circles represent the scaling neurons, the perceptron neurons, and the unscaling neurons, respectively. Perceptron layers are responsible for applying different weights to the input variables during the learning process to minimize the error made in approximation.

Neural network training was followed by order selection to obtain the ideal selection model providing an adequate fit for the neural network architecture. Another training was performed to obtain the final training and selection errors. The performance of an approximation model can be assessed by comparing the predicted values against the actual values of the testing data set. The results of the neural network training using the Quasi-Newton algorithm are presented in Table 15. Figure 40 shows the decrease in training and selection errors in each epoch during the training process.

Table 15. Quasi-Newton Method Results for Two Perceptron Layers

| | Error Value |
|---|---|
| Initial Training Error | 6.877 |
| Final Training Error | 0.984 |
| Initial Selection Error | 8.423 |
| Final Selection Error | 0.995 |
| Epochs Number | 28.00 |
| Elapsed Time | < 1 sec |
| Stopping Criterion | Gradient norm goal |

Figure 40. Neural Network Architecture Obtained in Neural Designer




In each epoch, the neural network evaluates all data in the training dataset only once whereby the Normalized Squared Error is calculated. As the training progresses, the model converges to not only reduce the error but also increase the predictive accuracy. The blue and orange lines in Figure 40 represent the decreasing trend of training and the selection errors, respectively. The initial values of training and selection errors at 0 epoch were 6.88 and 8.42. The training was completed in 28 epochs after which the training and selection errors (final) were reduced to 0.98 and 0.99, respectively.

The approximation error metrics were assessed using the normalized squared errors (NSE), the default error term for approximation problems. Table 16 presents the NSEs obtained during the neural network training, selection, and testing instances. In addition, mean absolute errors (MAE) and mean percentage errors (MPE) were also obtained following the neural network training to determine the model's accuracy. MAE is a measure of errors used to determine a model's predictive accuracy, and MPE is the average of percentage errors between paired observations. The mean absolute and percentage errors of the testing data set are presented in Table 17. The Neural Designer software output containing the decrease in errors during neural network training, together with the summary of the error statistics, is presented in Appendix C.

Table 16. Normalized Squared Errors for Training, Selection and Testing Instances (Two-Layer Quasi-Newton Method)

| | Error |
|---|---|
| Training Error | 0.984 |
| Selection Error | 0.995 |
| Testing Error | 0.973 |

Table 17. Error Statistics for Quasi-Newton Method

| | Error |
|---|---|
| Absolute Error | 42.03 |
| Percentage Error | 7.71 |

It can be observed from Table 16 that the lowest error was obtained for the testing dataset (0.97). A lower testing error compared to the training and selection errors indicate that there was no over-fitting of the model. Hence, the accuracy of the model is reliable to predict the bus travel time.

The testing data set resulted in a low MPE of 7.71%. A mathematical expression was also obtained following the neural network analysis to determine the bus travel time within the limits of the study. The equation is:

$$TT = 0.5*(\text{Scaled\_Y}+1)*545$$

The value of Scaled_Y is presented in Appendix D.

# 5. Discussion

This research aimed at determining the impacts on the performance of transit buses as well as the intersection performance after installing DBLs on selected corridors in Washington, DC. Moreover, neural network models for predicting the travel times of buses traveling on such bus lanes were also developed. The literature reviewed showed that the travel times of the buses may be impacted by time of the day, vehicle arrival and departure, passenger boarding and/or alighting, speed, distance, and en-route traffic conditions, among other factors.

The implementation of the DBLs on the segment of H Street (NW) between 19$^{th}$ Street (NW) and 13$^{th}$ Street (NW) and the segment of I Street (NW) between 21$^{st}$ Street (NW) and 13$^{th}$ Street (NW) by DDOT was completed by June 2019. The five study intersections within the segments that were selected for the study were:

1. H Street and 14th Street (NW)
2. H Street and 17th Street (NW)
3. I Street and 15th Street/ Vermont Avenue (NW)
4. I Street and 16th Street (NW)
5. I Street and 17th Street (NW)

Non-intrusive video data of the study intersections were reviewed to obtain the vehicular turning movement counts as well as observe the compliance of buses and other passenger vehicles while utilizing the DBLs at the intersection. "Before" data from May and June 2019 was compared with the "after" data from September 2019 and October 2020. Measures of Effectiveness required for the analysis were obtained by analyzing the AM and PM peak hour TMCs on PETRAPro and Synchro Traffic Simulation Software. Approach Delays on the eastbound approach of H Street (NW) and the westbound approach of I Street (NW) intersections along with the overall intersection control delays were obtained for the "before" and "after" scenarios. These measures of effectiveness were essential in determining the level of service (quality of intersection operations under fixed conditions like intersection geometry, signal timing, vehicular volume, etc.). Dependent t-tests were used to determine any statistically significant differences between the approach delays and intersection control delays "before" and "after" the DBLs for both AM and PM peak periods. The results showed that the approach delays and intersection control delays at the study intersections generally decreased after the installation of DBLs. In addition, the statistical analysis showed that the vehicles traveling on H Street and I Street (NW) experienced significantly lower approach delays as well as control delays during both AM and PM peaks after the installation of bus lanes (at 5% level of significance). Vehicles traveling on the eastbound approach of H Street (NW), the westbound approach of I Street (NW), and all approaches of the five study intersections generally experienced lower delays (in terms of seconds per vehicle). Lower delay directly translates to better traffic flow. The decrease in the approach delays indicates that the traffic flow (buses and non-transit vehicles) on the eastbound approach of H Street and westbound approach of I Street (NW) did not degrade in September 2019 and October 2020 (after scenario). Moreover, in general, the average control delay (a delay that arises due to the traffic signal) experienced by the vehicles at all study intersections was also low when the dynamic bus lanes were implemented. At the intersections where the average control delays were found to be higher, future studies could consider either optimizing traffic signals on the routes or implementing transit signal priority to review the general traffic performance. Hence, the results suggest that there was an improved level of service at the study intersections following the implementation of DBLs on the segments of H Street and I Street (NW).

Further, WMATA provided transit bus AVL data (real-time bus operation logs) for four selected bus routes (7Y, 32, 30N, and 30S) operating on H Street and I Street (NW). The data for the bus routes were filtered to extract variables including the length of the route between the bus stops and the dwell time of buses traveling in both east- and westbound directions in the AM and PM peak periods for the before (May 2019, June 2019) and after (September 2019, October 2020) months. AVL data points at WMATA bus stops with the following service IDs were used to extract variables for the study:

H Street and 18th Street, NW - 1001148

H Street, NW and 17th Street, NW - 1001133

H Street and Madison Place, NW - 1001141

H Street and 14th Street, NW - 1003467

I Street and 14th Street, NW - 1001191

I Street and 15th Street/ Vermont Avenue, NW - 1001185

I Street and 17th Street, NW - 1001183

I Street and 18th Street, NW - 1001181

The variables along with the average monthly percentage of buses using the bus lane for travel (i.e., compliance) were linked to the individual bus travel time data points to create a matrix which was used in the multiple linear regression analysis as well as the neural network analysis.

The regression analysis on the bus data was conducted to investigate the relationship between the independent variables and the travel times of the buses. The analysis also generated an equation based on all the variables (predictors) to predict bus travel time. The independent variable *length of the route between served bus stops* had the highest correlation values with the dependent variable bus travel time. The variables *presence of bus lane* and *average bus lane usage (compliance of the buses on DBLs)* did not display strong correlations with the bus travel time. The F-statistic showed that the model explained 10% of the variance in the bus travel time and was statistically significant at a 95% confidence interval (p-values < 0.05). Tests for normality of errors, multicollinearity, and homoscedasticity were conducted to ensure that there was no bias in the data, no multicollinearity, and approximately uniform distribution of variance between the residuals of the dependent, respectively. These tests were performed to meet the assumptions of multiple linear regression analysis. The multiple regression analysis, although statistically significant, could only explain around 10% ($R^2 = 0.103$) of the variance in the dependent variable (bus travel time). Hence, the non-linear relationships between the dependent and independent variables were not considered by the multiple regression analysis as the differences between the observed and predicted values were high.

Hence, a neural network analysis was conducted to develop a predictive model for bus travel time on dedicated bus lanes using Neural Designer software to consider non-linear relationships between the dependent and independent variables. Neural network learning was achieved through approximation, which is a process of finding the value of the dependent variable based on the combination of different predictor values. More specifically, the Quasi-Newton algorithm (with two perceptron layers) was applied to the matrix with all the variables to obtain an equation that approximated travel time. Hence, the analysis considered the presence or absence of bus lanes as one of the independent variables. An order selection process was also performed to obtain the final neural network architecture of the predictive model.

In the neural network training process, initial and final training, selection, and testing errors were obtained. Even though low errors are desired for a neural network, low training errors can result in overfitting. An overfit model performs well with the training data set but might yield higher errors while approximating the dependent variable with unknown data. The approximation error metrics (normalized squared errors) for the testing dataset was obtained to be 0.97 (lower than the training error 0.98 and selection error 0.99), which indicated that the model was predicting bus travel times based on unknown data with great accuracy. A testing error that is lower than the training and selection errors ensures that the neural network is good at making generalizations to predict the bus travel time, and at the same time, not overfitting. The quality of the approximation models was tested by gauging the mean absolute error and the mean percentage error. These measures of errors compared the difference between the predicted output and the actual values of bus travel time. The low values of MAE and MPE indicate that the neural network model was predicting the values of the dependent variable with good accuracy. Hence, for future studies, one constraint that can limit the potential of ANN predictability would be a lack of adequate data points since ANNs are highly data-dependent.

# 6. Conclusions and Recommendations

This research explored the impacts of installing dedicated bus lanes (DBLs) on traffic operation at intersections. Prior to this study, there had not been any study conducted in Washington, DC, that compared the qualitative measures of effectiveness of intersections before and after installation of bus lanes. Specifically, the project team evaluated the approach and control delays that were obtained from Synchro analysis. A neural network model was developed here that incorporated different variables such as time of the day (AM/PM peak) and presence/absence of bus lanes to predict the bus travel times on different segments. From the results, it can be concluded that for the H Street and I Street (NW) segments, the installation of bus lanes did not have a negative impact on the overall traffic operations. This could be supported by the fact that the measures of effectiveness such as approach delay and control delay experienced by a vehicle traveling on the same study segments/intersections were lower when the DBLs were present. Moreover, descriptive statistics conducted on the AVL bus data revealed that the average travel time of the buses traveling along the study segments in the "after" scenario was lower than the average travel time in the "before" scenario. The dwell times of the buses at the bus stops were also found to be lower after the installation of bus lanes during both AM and PM peak periods. Hence, WMATA can consider applying this methodology to other segments with busy bus schedules and multiple routes to evaluate the need for DBL implementation. Finally, neural network models can be used to approximate bus travel times on segments by simulating scenarios with DBLs to obtain accurate bus travel times. The performance of ANNs to accurately predict travel times by considering the presence and absence of dedicated bus lanes on segments of DC provides advantages over traditional models like historical data-based or multiple linear regression models. For instance, in this study, regardless of the multiple linear regression model being statistically significant, the obtained goodness of fit was a low of 10%. Hence, the accuracy of the ANN, which can be attributed to a low training error, outperforms the multiple linear regression model. Such implementation can be beneficial to not only improve WMATA's bus service reliability but also alleviate general traffic delays.

For future work, it is recommended that year-round data be analyzed to provide more insightful DBL usage (compliance) data as well as to improve the accuracy of the prediction models. Since ANN can perform better with more data, the same duration of post-DBL implementation data will also be required to compare the performance of intersections on other urban segments over time. This process would require working with WMATA to filter AVL data of existing bus routes to extract relevant variables for typical weekdays. The data along with simulation-based on bus lane usage by different vehicles from observational field studies can be used to assess the different measures of effectiveness of urban intersections.

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# Appendix A: SPSS Output

Figure 41. SPSS Output for Control Delay for AM Peak

**T-Test**

**Paired Samples Statistics**

| | | Mean | N | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| Pair 1 | CONTROL_DELAY_AM_BEFORE | 26.889 | 55 | 7.5660 | 1.0202 |
| | CONTROL_DELAY_AM_AFTER | 23.771 | 55 | 8.0077 | 1.0798 |

**Paired Samples Correlations**

| | | N | Correlation | Significance | |
|---|---|---|---|---|---|
| | | | | One-Sided p | Two-Sided p |
| Pair 1 | CONTROL_DELAY_AM_BEFORE & CONTROL_DELAY_AM_AFTER | 55 | .230 | .046 | .091 |

**Paired Samples Test**

| | | Paired Differences | | | | | t | df | Significance | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | 95% Confidence Interval of the Difference | | | | | |
| | | Mean | Std. Deviation | Std. Error Mean | Lower | Upper | | | One-Sided p | Two-Sided p |
| Pair 1 | CONTROL_DELAY_AM_BEFORE - CONTROL_DELAY_AM_AFTER | 3.1182 | 9.6695 | 1.3038 | .5042 | 5.7322 | 2.392 | 54 | .010 | .020 |

**Paired Samples Effect Sizes**

| | | | Standardizer[a] | Point Estimate | 95% Confidence Interval | |
|---|---|---|---|---|---|---|
| | | | | | Lower | Upper |
| Pair 1 | CONTROL_DELAY_AM_BEFORE - CONTROL_DELAY_AM_AFTER | Cohen's d | 9.6695 | .322 | .050 | .592 |
| | | Hedges' correction | 9.8064 | .318 | .049 | .584 |

Figure 42. SPSS Output for Control Delay for PM Peak

**T-Test**

**Paired Samples Statistics**

| | | Mean | N | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| Pair 1 | CONTROL_DELAY_PM_BEFORE | 24.660 | 55 | 6.5379 | .8816 |
| | CONTROL_DELAY_PM_AFTER | 20.989 | 55 | 5.3321 | .7190 |

**Paired Samples Correlations**

| | | | | Significance | |
|---|---|---|---|---|---|
| | | N | Correlation | One-Sided p | Two-Sided p |
| Pair 1 | CONTROL_DELAY_PM_BEFORE & CONTROL_DELAY_PM_AFTER | 55 | .166 | .113 | .225 |

**Paired Samples Test**

| | | Paired Differences | | | | | t | df | Significance | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | 95% Confidence Interval of the Difference | | | | | |
| | | Mean | Std. Deviation | Std. Error Mean | Lower | Upper | | | One-Sided p | Two-Sided p |
| Pair 1 | CONTROL_DELAY_PM_BEFORE - CONTROL_DELAY_PM_AFTER | 3.6709 | 7.7190 | 1.0408 | 1.5842 | 5.7576 | 3.527 | 54 | <.001 | <.001 |

**Paired Samples Effect Sizes**

| | | | | | 95% Confidence Interval | |
|---|---|---|---|---|---|---|
| | | | Standardizer[a] | Point Estimate | Lower | Upper |
| Pair 1 | CONTROL_DELAY_PM_BEFORE - CONTROL_DELAY_PM_AFTER | Cohen's d | 7.7190 | .476 | .195 | .753 |
| | | Hedges' correction | 7.8283 | .469 | .192 | .742 |

a. The denominator used in estimating the effect sizes.
Cohen's d uses the sample standard deviation of the mean difference.
Hedges' correction uses the sample standard deviation of the mean difference, plus a correction factor.

Figure 43. SPSS Output for Approach Delay for AM Peak

**Paired Samples Statistics**

| | | Mean | N | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| Pair 1 | APPROACH_DELAY_AM_BEFORE | 24.395 | 55 | 6.8379 | .9220 |
| | APPROACH_DELAY_AM_AFTER | 22.798 | 55 | 7.3725 | .9941 |

**Paired Samples Correlations**

| | | N | Correlation | Significance | |
|---|---|---|---|---|---|
| | | | | One-Sided p | Two-Sided p |
| Pair 1 | APPROACH_DELAY_AM_BEFORE & APPROACH_DELAY_AM_AFTER | 55 | .884 | <.001 | <.001 |

**Paired Samples Test**

| | | Paired Differences | | | | | t | df | Significance | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | 95% Confidence Interval of the Difference | | | | | |
| | | Mean | Std. Deviation | Std. Error Mean | Lower | Upper | | | One-Sided p | Two-Sided p |
| Pair 1 | APPROACH_DELAY_AM_BEFORE - APPROACH_DELAY_AM_AFTER | 1.5964 | 3.4552 | .4659 | .6623 | 2.5304 | 3.426 | 54 | <.001 | .001 |

**Paired Samples Effect Sizes**

| | | | Standardizer[a] | Point Estimate | 95% Confidence Interval | |
|---|---|---|---|---|---|---|
| | | | | | Lower | Upper |
| Pair 1 | APPROACH_DELAY_AM_BEFORE - APPROACH_DELAY_AM_AFTER | Cohen's d | 3.4552 | .462 | .182 | .738 |
| | | Hedges' correction | 3.5041 | .456 | .179 | .728 |

a. The denominator used in estimating the effect sizes.
Cohen's d uses the sample standard deviation of the mean difference.
Hedges' correction uses the sample standard deviation of the mean difference, plus a correction factor.

Figure 44. SPSS Output for Approach Delay for PM Peak

**Paired Samples Statistics**

| | | Mean | N | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| Pair 1 | APPROACH_DELAY_PM_BEFORE | 24.293 | 55 | 10.8882 | 1.4682 |
| | APPROACH_DELAY_PM_AFTER | 22.764 | 55 | 11.2397 | 1.5156 |

**Paired Samples Correlations**

| | | N | Correlation | Significance | |
|---|---|---|---|---|---|
| | | | | One-Sided p | Two-Sided p |
| Pair 1 | APPROACH_DELAY_PM_BEFORE & APPROACH_DELAY_PM_AFTER | 55 | .897 | <.001 | <.001 |

**Paired Samples Test**

| | | Paired Differences | | | | | t | df | Significance | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | 95% Confidence Interval of the Difference | | | | | |
| | | Mean | Std. Deviation | Std. Error Mean | Lower | Upper | | | One-Sided p | Two-Sided p |
| Pair 1 | APPROACH_DELAY_PM_BEFORE - APPROACH_DELAY_PM_AFTER | 1.5291 | 5.0305 | .6783 | .1692 | 2.8890 | 2.254 | 54 | .014 | .028 |

**Paired Samples Effect Sizes**

| | | | Standardizer[a] | Point Estimate | 95% Confidence Interval | |
|---|---|---|---|---|---|---|
| | | | | | Lower | Upper |
| Pair 1 | APPROACH_DELAY_PM_BEFORE - APPROACH_DELAY_PM_AFTER | Cohen's d | 5.0305 | .304 | .032 | .573 |
| | | Hedges' correction | 5.1017 | .300 | .032 | .565 |

a. The denominator used in estimating the effect sizes.

Figure 45. SPSS Output for Paired Sample T-Test of Intersection Delays

**Paired Samples Statistics**

| | | Mean | N | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| Pair 1 | BEFORE | 25.7745 | 110 | 7.12663 | .67950 |
| | AFTER | 22.3800 | 110 | 6.91415 | .65924 |

**Paired Samples Correlations**

| | | N | Correlation | Significance | |
|---|---|---|---|---|---|
| | | | | One-Sided p | Two-Sided p |
| Pair 1 | BEFORE & AFTER | 110 | .230 | .008 | .016 |

**Paired Samples Test**

| | | Paired Differences | | | | | t | df | Significance | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | 95% Confidence Interval of the Difference | | | | | |
| | | Mean | Std. Deviation | Std. Error Mean | Lower | Upper | | | One-Sided p | Two-Sided p |
| Pair 1 | BEFORE - AFTER | 3.39455 | 8.71295 | .83075 | 1.74803 | 5.04106 | 4.086 | 109 | <.001 | <.001 |

**Paired Samples Effect Sizes**

| | | | Standardizer[a] | Point Estimate | 95% Confidence Interval | |
|---|---|---|---|---|---|---|
| | | | | | Lower | Upper |
| Pair 1 | BEFORE - AFTER | Cohen's d | 8.71295 | .390 | .195 | .583 |
| | | Hedges' correction | 8.77348 | .387 | .194 | .579 |

a. The denominator used in estimating the effect sizes.
Cohen's d uses the sample standard deviation of the mean difference.
Hedges' correction uses the sample standard deviation of the mean difference, plus a correction factor.

Figure 46. SPSS Output for Paired Sample T-Test of Approach Delays

**Paired Samples Statistics**

| | | Mean | N | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| Pair 1 | Before | 24.30991 | 111 | 9.015592 | .855722 |
| | After | 22.76577 | 111 | 9.419414 | .894051 |

**Paired Samples Correlations**

| | | N | Correlation | Significance One-Sided p | Significance Two-Sided p |
|---|---|---|---|---|---|
| Pair 1 | Before & After | 111 | .893 | <.001 | <.001 |

**Paired Samples Test**

| | | Paired Differences Mean | Std. Deviation | Std. Error Mean | 95% Confidence Interval of the Difference Lower | Upper | t | df | Significance One-Sided p | Two-Sided p |
|---|---|---|---|---|---|---|---|---|---|---|
| Pair 1 | Before - After | 1.544144 | 4.280520 | .406289 | .738975 | 2.349314 | 3.801 | 110 | <.001 | <.001 |

**Paired Samples Effect Sizes**

| | | | Standardizer[a] | Point Estimate | 95% Confidence Interval Lower | Upper |
|---|---|---|---|---|---|---|
| Pair 1 | Before - After | Cohen's d | 4.280520 | .361 | .168 | .552 |
| | | Hedges' correction | 4.309984 | .358 | .167 | .548 |

a. The denominator used in estimating the effect sizes.
Cohen's d uses the sample standard deviation of the mean difference.
Hedges' correction uses the sample standard deviation of the mean difference, plus a correction factor.

Table 18. Multiple Regression Analysis Model Summary

| | | | | Change Statistics | | |
|---|---|---|---|---|---|---|
| R | R-Squared | Adjusted R-Squared | Std. Error of the Estimate | R Square Change | F Change | df1 |
| 0.321 | 0.103 | 0.098 | 44.552 | .103 | 19.112 | 6 |

Table 19. Multiple Regression Analysis Coefficients Table

| | Unstandardized Coefficients | | Standardized Coefficients | | |
|---|---|---|---|---|---|
| | B | Std. Error | Beta | t | Sig. |
| (Constant) | 53.968 | 9.156 | | 5.894 | .000 |
| Length of Route, X1 | .040 | .004 | .320 | 10.184 | .000 |
| Average Dwell Time, X2 | .236 | .048 | .157 | 4.950 | .000 |
| Bus Direction, X3 | -8.312 | 3.653 | -.089 | -2.275 | .023 |
| Presence of Bus Lane X4 | 3.968 | 2.974 | .040 | 1.334 | .182 |
| Peak Period, X5 | 6.200 | 3.048 | .063 | 2.034 | .042 |
| Bus Compliance, X6 | .025 | .076 | .013 | .327 | .743 |

Table 20. Travel Time Residuals Statistics Table

| | Minimum | Maximum | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Predicted Value | 62.84 | 235.25 | 111.50 | 15.064 | 1004 |
| Std. Predicted Value | -3.230 | 8.215 | .000 | 1.000 | 1004 |
| Standard Error of Predicted Value | 2.611 | 17.328 | 3.559 | 1.084 | 1004 |
| Adjusted Predicted Value | 63.36 | 237.54 | 111.52 | 15.183 | 1004 |
| Residual | -170.998 | 140.194 | .000 | 44.419 | 1004 |
| Std. Residual | -3.838 | 3.147 | .000 | .997 | 1004 |
| Stud. Residual | -3.965 | 3.153 | .000 | 1.001 | 1004 |
| Deleted Residual | -182.532 | 140.810 | -.019 | 44.815 | 1004 |
| Stud. Deleted Residual | -3.995 | 3.167 | .000 | 1.003 | 1004 |
| Mahal. Distance | 2.445 | 150.725 | 5.994 | 7.862 | 1004 |
| Cook's Distance | .000 | .152 | .001 | .006 | 1004 |
| Centered Leverage Value | .002 | .150 | .006 | .008 | 1004 |

# Appendix B: Bus Lane Usage "Before" and "After" Tally Summary

Table 21. Summary of Bus Lane Usage Operation for "Before" Data (May 2019)

| H Street and 14th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| AM | May 7th | 0 | 0 | 15.79 | 19.89 | 84.21 |
| | May 8th | 0 | 0 | 16.51 | 21.19 | 83.49 |
| | May 9th | 0 | 0 | 21.43 | 18.75 | 78.57 |
| | May 14th | 0 | 2 | 13.41 | 19.69 | 86.59 |
| | May 15th | 0 | 0 | 10.20 | 19.75 | 89.80 |
| | May 16th | 0 | 0 | 8.33 | 19.66 | 91.67 |
| PM | May 7th | 0 | 0 | 23.97 | 18.13 | 76.03 |
| | May 8th | 0 | 0 | 23.93 | 15.01 | 76.07 |
| | May 9th | 0 | 0 | 19.35 | 14.82 | 80.65 |
| | May 14th | 0 | 13 | 16.56 | 13.83 | 83.44 |
| | May 15th | 0 | 0 | 1.56 | 12.98 | 98.44 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | May 16th | 0 | 0 | 0 | 11.60 | 100 |
| H Street and 17th Street, NW | | | | | | |
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| AM | May 7th | 0 | 3 | 6.32 | 4.30 | 93.68 |
| | May 8th | 0 | 3 | 6.85 | 5.18 | 93.15 |
| | May 9th | 0 | 2 | 10.14 | 5.36 | 89.86 |
| | May 14th | 0 | 4 | 12.64 | 5.67 | 87.36 |
| | May 15th | 0 | 3 | 15.29 | 5.68 | 84.71 |
| | May 16th | 0 | 3 | 22.09 | 7.77 | 77.91 |
| PM | May 7th | 0 | 8 | 2.82 | 9.18 | 97.18 |
| | May 8th | 0 | 6 | 3.95 | 8.66 | 96.05 |
| | May 9th | 0 | 5 | 0 | 7.57 | 100 |
| | May 14th | 0 | 10 | 5.88 | 9.64 | 94.12 |
| | May 15th | 0 | 12 | 3.85 | 10.39 | 96.15 |
| | May 16th | 7 | 12 | 6.93 | 11.15 | 93.07 |

| I Street and Vermont Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| AM | May 7th | 0 | 0 | 52.55 | 16.98 | 47.45 |
| | May 8th | 0 | 1 | 47.06 | 22.96 | 52.94 |
| | May 9th | 0 | 0 | 3.19 | 19.24 | 96.81 |
| | May 14th | 39 | 0 | 60.61 | 20.10 | 39.39 |
| | May 15th | 52 | 4 | 54.70 | 15.32 | 45.30 |
| | May 16th | 22 | 6 | 63.86 | 17.26 | 36.14 |
| PM | May 7th | 0 | 7 | 62.12 | 22.27 | 37.88 |
| | May 8th | 0 | 4 | 63.19 | 25.55 | 36.81 |
| | May 9th | 0 | 3 | 64.44 | 21.41 | 35.56 |
| | May 14th | 22 | 27 | 42.62 | 22.36 | 57.38 |
| | May 15th | 47 | 63 | 46.58 | 20.05 | 53.42 |
| | May 16th | 29 | 167 | 52.48 | 20.82 | 47.52 |
| I Street and 16th Street, NW | | | | | | |

| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
|---|---|---|---|---|---|---|
| AM | May 7th | 0 | 0 | 29.65 | 14.72 | 70.35 |
| | May 8th | 0 | 0 | 29.27 | 16.97 | 70.73 |
| | May 9th | 0 | 0 | 31.11 | 20.51 | 68.89 |
| | May 14th | 5 | 5 | 32.85 | 15.75 | 67.15 |
| | May 15th | 13 | 42 | 17.16 | 7.26 | 82.84 |
| | May 16th | 6 | 1 | 24.85 | 13.91 | 75.15 |
| PM | May 7th | 0 | 0 | 37.44 | 16.15 | 62.56 |
| | May 8th | 0 | 8 | 36.07 | 17.73 | 63.93 |
| | May 9th | 0 | 4 | 33.95 | 16.97 | 66.05 |
| | May 14th | 13 | 8 | 37.76 | 12.19 | 62.24 |
| | May 15th | 11 | 58 | 37.68 | 16.87 | 62.32 |
| | May 16th | 12 | 61 | 31.40 | 17.65 | 68.60 |
| I Street and 17th Street, NW | | | | | | |
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |

| | | | | | | |
|---|---|---|---|---|---|---|
| AM | May 7th | 0 | 11 | 40.91 | 4.27 | 59.09 |
| | May 8th | 1 | 0 | 40.94 | 10.19 | 59.06 |
| | May 9th | 1 | 0 | 39.86 | 9.49 | 60.14 |
| | May 14th | 4 | 9 | 59.05 | 19.43 | 40.95 |
| | May 15th | 3 | 113 | 65.45 | 12.42 | 34.55 |
| | May 16th | 4 | 4 | 65.18 | 11.01 | 34.82 |
| PM | May 7th | 1 | 0 | 48.47 | 6.95 | 51.53 |
| | May 8th | 0 | 0 | 37.89 | 8.10 | 62.11 |
| | May 9th | 0 | 4 | 43.52 | 8.13 | 56.48 |
| | May 14th | 3 | 13 | 68.84 | 11.58 | 31.16 |
| | May 15th | 4 | 13 | 71.20 | 14.69 | 28.80 |
| | May 16th | 3 | 6 | 63.36 | 6.71 | 36.64 |

Table 22. Summary of Bus Lane Usage Operation for “Before” Data (June 2019)

| H Street and 14th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| AM | June 11th | 0 | 0 | 15.79 | 19.89 | 84.21 |
| | June 12th | 0 | 0 | 16.51 | 21.19 | 83.49 |
| | June 13th | 0 | 0 | 21.43 | 18.75 | 78.57 |
| | June 18th | 0 | 2 | 13.41 | 19.69 | 86.59 |
| | June 19th | 0 | 0 | 10.20 | 19.75 | 89.80 |
| | June 20th | 0 | 0 | 8.33 | 19.66 | 91.67 |
| PM | June 11th | 0 | 0 | 23.97 | 18.13 | 76.03 |
| | June 12th | 0 | 0 | 23.93 | 15.01 | 76.07 |
| | June 13th | 0 | 0 | 19.35 | 14.82 | 80.65 |
| | June 18th | 0 | 13 | 16.56 | 13.83 | 83.44 |
| | June 19th | 0 | 0 | 1.56 | 12.98 | 98.44 |
| | June 20th | 0 | 0 | 0 | 11.60 | 100 |
| H Street and 17th Street, NW | | | | | | |
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| AM | June 11th | 0 | 0 | 40.45 | 3.78 | 59.55 |

| H Street and 14th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| | June 12th | 0 | 0 | 50 | 5.24 | 50 |
| | June 13th | 0 | 0 | 49.41 | 6.15 | 50.59 |
| | June 18th | 0 | 0 | 61.82 | 8.74 | 38.18 |
| | June 19th | 0 | 3 | 62.16 | 7.78 | 37.84 |
| | June 20th | 0 | 9 | 62.86 | 3.59 | 37.14 |
| PM | June 11th | 0 | 0 | 37.89 | 10.12 | 62.11 |
| | June 12th | 0 | 0 | 34.62 | 12.41 | 65.38 |
| | June 13th | 0 | 0 | 38.83 | 11.07 | 61.17 |
| | June 18th | 0 | 0 | 56.06 | 15.04 | 43.94 |
| | June 19th | 0 | 12 | 57.89 | 13.02 | 42.11 |
| | June 20th | 0 | 6 | 46.97 | 9.36 | 53.03 |
| I Street and Vermont Street, NW | | | | | | |
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| AM | June 11th | 0 | 0 | 52.55 | 16.98 | 47.45 |
| | June 12th | 0 | 1 | 47.06 | 22.96 | 52.94 |
| | June 13th | 0 | 0 | 3.19 | 19.24 | 96.81 |

| H Street and 14th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| | June 18th | 39 | 0 | 60.61 | 20.10 | 39.39 |
| | June 19th | 52 | 4 | 54.70 | 15.32 | 45.30 |
| | June 20th | 22 | 6 | 63.86 | 17.26 | 36.14 |
| PM | June 11th | 0 | 7 | 62.12 | 22.27 | 37.88 |
| | June 12th | 0 | 4 | 63.19 | 25.55 | 36.81 |
| | June 13th | 0 | 3 | 64.44 | 21.41 | 35.56 |
| | June 18th | 22 | 27 | 42.62 | 22.36 | 57.38 |
| | June 19th | 47 | 63 | 46.58 | 20.05 | 53.42 |
| | June 20th | 29 | 167 | 52.48 | 20.82 | 47.52 |
| I Street and 16th Street, NW | | | | | | |
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| AM | June 11th | 0 | 0 | 29.65 | 14.72 | 70.35 |
| | June 12th | 0 | 0 | 29.27 | 16.97 | 70.73 |
| | June 13th | 0 | 0 | 31.11 | 20.51 | 68.89 |
| | June 18th | 5 | 5 | 32.85 | 15.75 | 67.15 |
| | June 19th | 13 | 42 | 17.16 | 7.26 | 82.84 |

| H Street and 14th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| | June 20th | 6 | 1 | 24.85 | 13.91 | 75.15 |
| PM | June 11th | 0 | 0 | 37.44 | 16.15 | 62.56 |
| | June 12th | 0 | 8 | 36.07 | 17.73 | 63.93 |
| | June 13th | 0 | 4 | 33.95 | 16.97 | 66.05 |
| | June 18th | 13 | 8 | 37.76 | 12.19 | 62.24 |
| | June 19th | 11 | 58 | 37.68 | 16.87 | 62.32 |
| | June 20th | 12 | 61 | 31.40 | 17.65 | 68.60 |

| I Street and 17th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| AM | June 11th | 0 | 11 | 40.91 | 4.27 | 59.09 |
| | June 12th | 1 | 0 | 40.94 | 10.19 | 59.06 |
| | June 13th | 1 | 0 | 39.86 | 9.49 | 60.14 |
| | June 18th | 4 | 9 | 59.05 | 19.43 | 40.95 |
| | June 19th | 3 | 113 | 65.45 | 12.42 | 34.55 |
| | June 20th | 4 | 4 | 65.18 | 11.01 | 34.82 |
| PM | June 11th | 1 | 0 | 48.47 | 6.95 | 51.53 |

| H Street and 14th Street, NW | | | | | | |
| --- | --- | --- | --- | --- | --- | --- |
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| | June 12th | 0 | 0 | 37.89 | 8.10 | 62.11 |
| | June 13th | 0 | 4 | 43.52 | 8.13 | 56.48 |
| | June 18th | 3 | 13 | 68.84 | 11.58 | 31.16 |
| | June 19th | 4 | 13 | 71.20 | 14.69 | 28.80 |
| | June 20th | 3 | 6 | 63.36 | 6.71 | 36.64 |

Table 23. Summary of Bus Lane Usage Operation for “After” Data (September 2019)

| H Street and 14th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| AM | September 17th | 0 | 0 | 51.16 | 16 | 88.14 |
| | September 18th | 0 | 0 | 72.97 | 14.14 | 91.38 |
| | September 19th | 0 | 0 | 41 | 15.59 | 88 |
| | September 24th | 0 | 2 | 22.11 | 18.81 | 80.83 |
| | September 25th | 0 | 0 | 46.82 | 15.70 | 86.21 |
| | September 26th | 0 | 1 | 47.06 | 18.17 | 82.30 |
| PM | September 17th | 0 | 0 | 68.57 | 13.55 | 98.60 |
| | September 18th | 0 | 0 | 47.37 | 14.06 | 91.60 |
| | September 19th | 0 | 0 | 42.62 | 17.97 | 91.91 |
| | September 24th | 0 | 11 | 52.94 | 9.54 | 87.41 |

| H Street and 14th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| | September 25th | 0 | 20 | 52.30 | 8.35 | 85.32 |
| | September 26th | 0 | 24 | 50.00 | 10.66 | 85.25 |

| H Street and 17th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| AM | September 17th | 0 | 0 | 27.14 | 3.78 | 59.55 |
| | September 18th | 0 | 0 | 17.91 | 5.24 | 50 |
| | September 19th | 0 | 0 | 19.44 | 6.15 | 50.59 |
| | September 24th | 0 | 0 | 37.50 | 8.74 | 38.18 |
| | September 25th | 0 | 3 | 46.29 | 7.78 | 37.84 |
| | September 26th | 0 | 9 | 29.66 | 3.59 | 37.14 |

| H Street and 14th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| PM | September 17th | 0 | 0 | 10.00 | 10.12 | 62.11 |
| | September 18th | 0 | 0 | 12.00 | 12.41 | 65.38 |
| | September 19th | 0 | 0 | 8.77 | 11.07 | 61.17 |
| | September 24th | 0 | 0 | 14.54 | 15.04 | 43.94 |
| | September 25th | 0 | 12 | 21.74 | 13.02 | 42.11 |
| | September 26th | 0 | 6 | 13.41 | 9.36 | 53.03 |
| I Street and Vermont Street, NW | | | | | | |
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| AM | September 17th | 41 | 20 | 47.33 | 14.28 | 27.27 |
| | September 18th | 41 | 30 | 57.19 | 13.20 | 25.13 |

| H Street and 14th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| | September 19th | 42 | 26 | 39.43 | 11.78 | 25.65 |
| | September 24th | 11 | 1 | 40.27 | 15.72 | 22.22 |
| | September 25th | 48 | 4 | 44.63 | 15.95 | 27.83 |
| | September 26th | 2 | 4 | 45.77 | 14.56 | 17.07 |
| PM | September 17th | 15 | 78 | 64.62 | 13.87 | 42.74 |
| | September 18th | 18 | 133 | 74.03 | 18.39 | 34.71 |
| | September 19th | 41 | 98 | 77.62 | 14.23 | 35.42 |
| | September 24th | 2 | 10 | 72.09 | 17.90 | 46.34 |
| | September 25th | 69 | 21 | 72.09 | 19.62 | 24.07 |
| | September 26th | 14 | 20 | 72.09 | 20.37 | 26.79 |
| I Street and 16th Street, NW | | | | | | |

| H Street and 14th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| AM | September 17th | 2 | 4 | 60.71 | 15.22 | 47.87 |
| | September 18th | 1 | 3 | 62.81 | 17.47 | 47.59 |
| | September 19th | 3 | 12 | 65.05 | 15.87 | 38.76 |
| | September 24th | 1 | 5 | 65.31 | 16.81 | 40.35 |
| | September 25th | 9 | 23 | 56.00 | 15.41 | 45.60 |
| | September 26th | 7 | 0 | 66.96 | 18.06 | 36.31 |
| PM | September 17th | 1 | 39 | 64.00 | 14.56 | 46.76 |
| | September 18th | 2 | 69 | 72.37 | 21.56 | 29.51 |
| | September 19th | 5 | 40 | 78.83 | 17.74 | 37.33 |

| H Street and 14th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| | September 24th | 23 | 0 | 72.66 | 17.39 | 35.68 |
| | September 25th | 2 | 9 | 69.23 | 20.82 | 35.71 |
| | September 26th | 8 | 65 | 77.12 | 26.29 | 35.24 |

| I Street and 17th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| AM | September 17th | 1 | 5 | 58.62 | 5.36 | 22.52 |
| | September 18th | 0 | 10 | 63.78 | 6.83 | 27.59 |
| | September 19th | 0 | 4 | 52.89 | 6.46 | 25.93 |
| | September 24th | 0 | 0 | 51.69 | 8.28 | 20.49 |
| | September 25th | 0 | 1 | 59.09 | 8.76 | 37.40 |

| H Street and 14th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| | September 26th | 0 | 0 | 57.94 | 8.63 | 33.10 |
| PM | September 17th | 1 | 3 | 74.51 | 5 | 21.85 |
| | September 18th | 1 | 5 | 69.81 | 5.12 | 25.62 |
| | September 19th | 1 | 4 | 67.65 | 2.96 | 27.07 |
| | September 24th | 0 | 0 | 63.45 | 8.47 | 15.86 |
| | September 25th | 0 | 6 | 69.40 | 6.24 | 48.99 |
| | September 26th | 1 | 1 | 70.80 | 7.57 | 19.08 |

Table 24. Summary of Bus Lane Usage Operation for “After” Data (October 2020)

| H Street and 14th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| AM | October 13th | 0 | 0 | 37.78 | 16 | 88.14 |
| | October 14th | 0 | 0 | 28.57 | 14.14 | 91.38 |
| | October 15th | 0 | 0 | 30 | 15.59 | 88 |
| | October 20th | 0 | 2 | 26.32 | 18.81 | 80.83 |
| | October 21st | 0 | 0 | 23.68 | 15.70 | 86.21 |
| | October 22nd | 0 | 1 | 27.78 | 18.17 | 82.30 |
| PM | October 13th | 0 | 0 | 39.58 | 13.55 | 98.60 |
| | October 14th | 0 | 0 | 37.04 | 14.06 | 91.60 |
| | October 15th | 0 | 0 | 31.71 | 17.97 | 91.91 |
| | October 20th | 0 | 11 | 36.17 | 9.54 | 87.41 |
| | October 21st | 0 | 20 | 31.91 | 8.35 | 85.32 |
| | October 22nd | 0 | 24 | 36.58 | 10.66 | 85.25 |
| AM | October 13th | 0 | 0 | 3.85 | 3.78 | 59.55 |
| | October 14th | 0 | 0 | 8.51 | 5.24 | 50 |
| | October 15th | 0 | 0 | 4.54 | 6.15 | 50.59 |

| H Street and 14th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| | October 20th | 0 | 0 | 2.22 | 8.74 | 38.18 |
| | October 21st | 0 | 3 | 8.33 | 7.78 | 37.84 |
| | October 22nd | 0 | 9 | 11.32 | 3.59 | 37.14 |
| PM | October 13th | 0 | 0 | 6.52 | 10.12 | 62.11 |
| | October 14th | 0 | 0 | 4.44 | 12.41 | 65.38 |
| | October 15th | 0 | 0 | 8.16 | 11.07 | 61.17 |
| | October 20th | 0 | 0 | 2.00 | 15.04 | 43.94 |
| | October 21st | 0 | 12 | 10.42 | 13.02 | 42.11 |
| | October 22nd | 0 | 6 | 8.69 | 9.36 | 53.03 |
| I Street and Vermont Street, NW | | | | | | |
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| AM | October 13th | 41 | 20 | 63.71 | 14.28 | 27.27 |
| | October 14th | 41 | 30 | 72.17 | 13.20 | 25.13 |
| | October 15th | 42 | 26 | 64.17 | 11.78 | 25.65 |
| | October 20th | 11 | 1 | 55.08 | 15.72 | 22.22 |

| H Street and 14th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| | October 21st | 48 | 4 | 48.80 | 15.95 | 27.83 |
| | October 22nd | 2 | 4 | 55.74 | 14.56 | 17.07 |
| PM | October 13th | 15 | 78 | 66.14 | 13.87 | 42.74 |
| | October 14th | 18 | 133 | 67.19 | 18.39 | 34.71 |
| | October 15th | 41 | 98 | 60.90 | 14.23 | 35.42 |
| | October 20th | 2 | 10 | 68.22 | 17.90 | 46.34 |
| | October 21st | 69 | 21 | 61.36 | 19.62 | 24.07 |
| | October 22nd | 14 | 20 | 61.03 | 20.37 | 26.79 |
| I Street and 16th Street, NW | | | | | | |
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| AM | October 13th | 2 | 4 | 0.00 | 15.22 | 47.87 |
| | October 14th | 1 | 3 | 0.00 | 17.47 | 47.59 |
| | October 15th | 3 | 12 | 0.00 | 15.87 | 38.76 |
| | October 20th | 1 | 5 | 0.00 | 16.81 | 40.35 |
| | October 21st | 9 | 23 | 0.00 | 15.41 | 45.60 |

| H Street and 14th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| | October 22nd | 7 | 0 | 0.00 | 18.06 | 36.31 |
| PM | October 13th | 1 | 39 | 0.00 | 14.56 | 46.76 |
| | October 14th | 2 | 69 | 0.00 | 21.56 | 29.51 |
| | October 15th | 5 | 40 | 1.28 | 17.74 | 37.33 |
| | October 20th | 23 | 0 | 0.00 | 17.39 | 35.68 |
| | October 21st | 2 | 9 | 0.00 | 20.82 | 35.71 |
| | October 22nd | 8 | 65 | 0.00 | 26.29 | 35.24 |

| I Street and 17th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| AM | October 13th | 1 | 5 | 46.39 | 5.36 | 22.52 |
| | October 14th | 0 | 10 | 44.56 | 6.83 | 27.59 |
| | October 15th | 0 | 4 | 30.48 | 6.46 | 25.93 |
| | October 20th | 0 | 0 | 41.84 | 8.28 | 20.49 |
| | October 21st | 0 | 1 | 38.68 | 8.76 | 37.40 |
| | October 22nd | 0 | 0 | 35.96 | 8.63 | 33.10 |

| H Street and 14th Street, NW | | | | | | |
|---|---|---|---|---|---|---|
| Peak | Date | Number of Illegal Turns on Red | Number of blocking the box incidents | Permitted Vehicles in Bus Lane (%) | Non-Permitted Vehicles in Bus Lane (%) | Buses in Other Travel Lanes (%) |
| PM | October 13th | 1 | 3 | 53.47 | 5 | 21.85 |
| | October 14th | 1 | 5 | 41.00 | 5.12 | 25.62 |
| | October 15th | 1 | 4 | 51.65 | 2.96 | 27.07 |
| | October 20th | 0 | 0 | 44.79 | 8.47 | 15.86 |
| | October 21st | 0 | 6 | 37.00 | 6.24 | 48.99 |
| | October 22nd | 1 | 1 | 33.67 | 7.57 | 19.08 |

# Appendix C: Neural Designer Output

Error Plots (Neural Designer Output):

Figure 47. Quasi-Newton Method Error History Plot with Two Perceptron Layers Before Order Selection

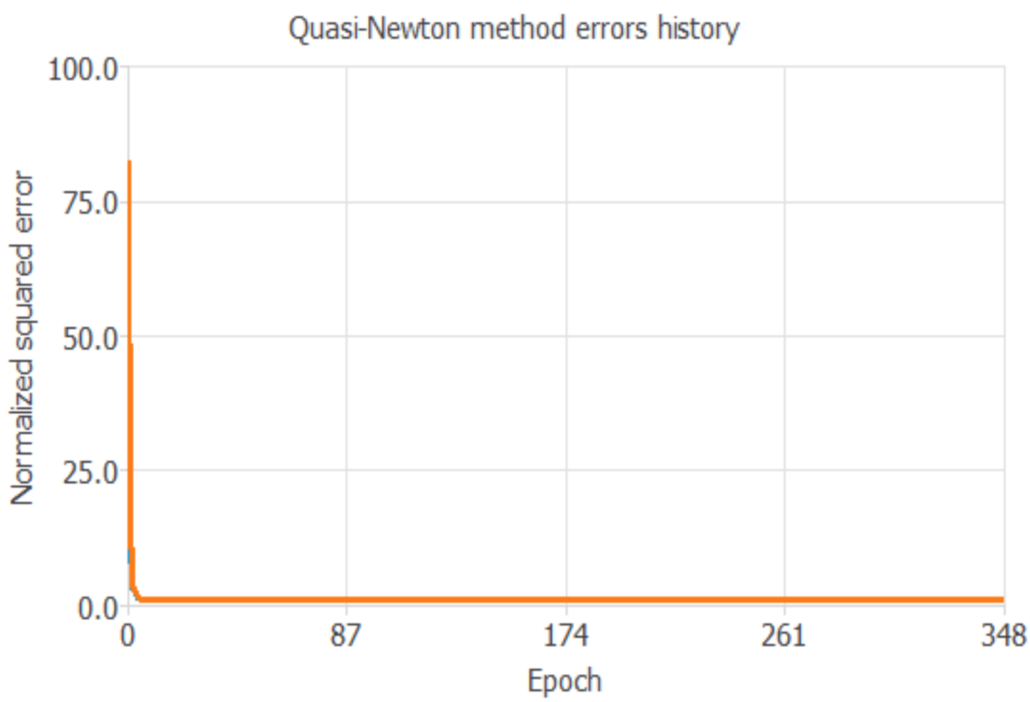

Figure 48. Incremental Order Error Plot

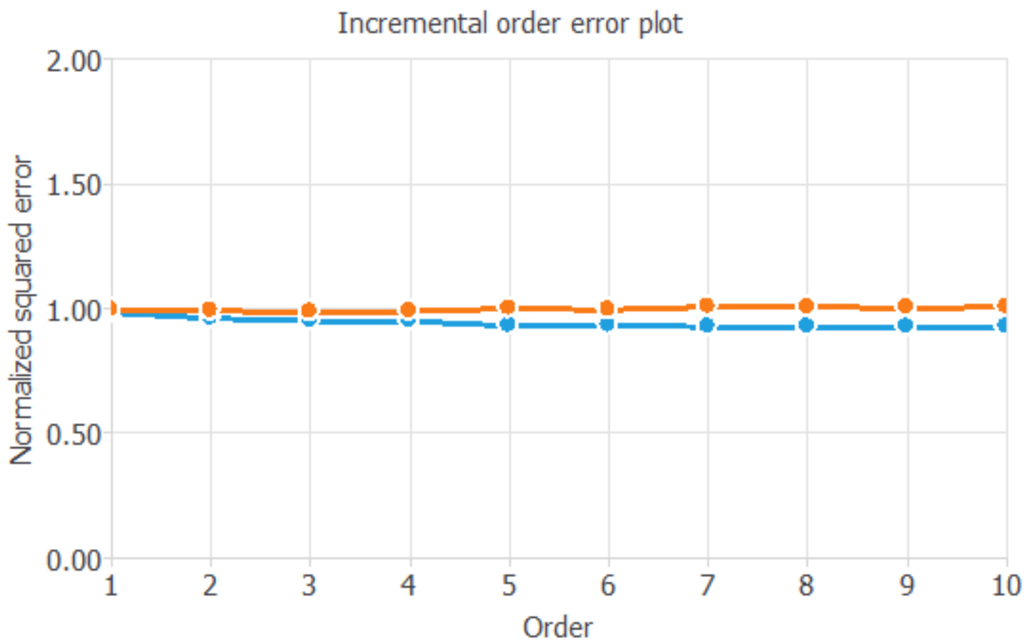


Table 25. Summary of Incremental Order Results

| | Value |
|---|---|
| Optimal Order | 1 |
| Optimum Training Error | 0.984 |
| Optimum Selection Error | 0.994 |
| Iterations Number | 10 |
| Elapsed Time | 00:42 |

Table 26. Summary of Travel Time Error Statistics

| | Minimum | Maximum | Mean | Deviation |
|---|---|---|---|---|
| Absolute Error | 0.025 | 341.354 | 42.032 | 42.687 |
| Percentage Error | 0.005 | 62.634 | 7.712 | 7.832 |

Table 27. Summary of Errors Table

| | Training | Selection | Testing |
|---|---|---|---|
| Sum Squared Error | 2.899e+06 | 798822 | 748262 |
| Mean Squared Error | 4623.52 | 3822.12 | 3580.2 |
| Root Mean Squared Error | 67.997 | 61.823 | 59.835 |
| Normalized Squared Error | 0.984 | 0.995 | 0.973 |
| Minkowski Error | 273525 | 81041.1 | 74677.6 |

# Appendix D: Neural Network Bus Travel Time Equation

Bus Travel Time Equation Obtained from Neural Network Analyses (Neural Designer Output):

Travel Time = 0.5*(Scaled_Y+1)*545

Where,

Scaled_Y = (-0.65213+ (y_1_1*0.181863));

y_1_1 = tanh (0.0965609 + (scaled_LengthofRoute,X1*0.120817)+ (scaled_AverageDwellTime,X2*-0.093415) + (scaled_BusDirection,X3*0.0850154) + (scaled_PresenceofBusLaneX4*-0.0552354) + (scaled_PeakPeriod,X5*-0.128569) + (scaled_BusCompliance,X6*-0.00506434));

scaled_LengthofRoute,$X_1$ = (LengthofRoute,$X_1$-24661300)/324664000;

scaled_AverageDwellTime,$X_2$ = (AverageDwellTime,$X_2$-8243720)/188076000;

scaled_BusDirection,$X_3$ = (BusDirection,$X_3$-0.495677)/0.500222;

scaled_PresenceofBusLane,$X_4$ = (PresenceofBusLane,$X_4$-0.339731)/0.473845;

scaled_PeakPeriod,$X_5$ = (PeakPeriod,$X_5$-0.342282)/0.474701;

scaled_BusCompliance,$X_6$ = (BusCompliance,$X_6$-43.7824)/23.7344;

# About the Principal Investigator

Dr. Arhin is an Associate Professor and the Interim Chair of the Department of Civil and Environmental Engineering of Howard University, the director of the Howard University Transportation Research and Traffic Safety Data Center (HUTRC), and the director of this transit research project, conducted under the Mineta Consortium for Transportation Mobility.

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