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Between the baseline year (2011) and HOT implementation year (2012), significant changes were noted in both the vehicle and person throughput on the corridor at Center Way. Vehicle throughput on the I-85 HOT corridor decreased by about 6.6% (2698 vehicles) during the morning peak period, but only by about 2.9% (1148 vehicles) during the afternoon peak period. Average vehicle occupancy (persons/vehicle) also decreased during the same period. Reduced vehicle throughput and decrease in observed vehicle occupancy had a synergistic impact on estimated corridor person throughput, which declined significantly at a much faster rate than vehicle throughput. While traffic volumes declined by 6.6%, person throughput concurrently declined by about 9.9% (4868 individuals). While traffic volumes declined by approximately 2.9% in the afternoon peak period, person throughput concurrently declined by about 6.3% (3123 individuals).
The data reveal that the majority of two-person carpools have been diverted from the HOV lane into the general purpose lanes after HOT lane implementation. Based upon vehicle throughput and occupancy distributions, the largest reduction in vehicle throughput in both the morning and afternoon peak periods came from a reduction in carpools (HOV2 and HOV3+ vehicles). Carpool mode share declined by more than 30% in the AM peak and by 25% in the PM peak, and average managed lane vehicle occupancy decreased from approximately 2.0 persons/vehicle to approximately 1.2 persons/vehicle.</td></tr>
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GDOT Research Project 10-03

Project Report

Atlanta I-85 HOV-to-HOT Conversion: Analysis of Vehicle and Person Throughput

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Executive Summary

This report summarizes the vehicle and person throughput analysis for the High Occupancy Vehicle to High Occupancy Toll Lane conversion in Atlanta, GA, undertaken by the Georgia Institute of Technology research team. The team tracked changes in observed vehicle throughput on the corridor and collected average vehicle occupancy (persons/vehicle) data to assess changes in person throughput. Traffic volumes were collected by VDS systems on the Georgia NaviGAtor system and the team implemented a large scale quarterly data collection effort for vehicle occupancy across all travel lanes. Center Way was selected as the control station for analysis based upon its location relative to inflow and outflow demand, and quality of available data. Only data between February and September in the base (2011) and HOT implementation years (2012) were employed in the analyses due to NaviGAtor I data compatibility issues (and an ice storm in January of the base year). An added focus was given to the February through April time period to control for seasonality (most travel demand studies are conducted in the spring) and to address potential issues with the phased system implementation that involved changes in weaving section locations, striping, and addition of rumble strips, all of which affected weaving behavior and potentially throughput.

Between the baseline year (2011) and HOT implementation year (2012), significant changes were noted in both the vehicle and person throughput on the corridor at Center Way. Vehicle throughput on the I-85 HOT corridor decreased by about 6.6% (2698 vehicles) during the morning peak period, but only by about 2.9% (1148 vehicles) during the afternoon peak period. The change in AM peak period activity was larger than experienced at control stations in other parts of the region, indicating that some of the reduction was likely the result of HOT implementation. Average vehicle occupancy (persons/vehicle) also decreased during the same period. Reduced vehicle throughput and decrease in observed vehicle occupancy had a synergistic impact on estimated corridor person throughput, which declined significantly at a much faster rate than vehicle throughput. Over the eight-month pre-and-post analysis (four months each), the combined effect on corridor person throughput during the AM and PM peaks was quite large. While traffic volumes declined by 6.6%, person throughput concurrently declined by about 9.9% (4868 individuals). While traffic volumes declined by approximately 2.9% in the afternoon peak period, person throughput concurrently declined by about 6.3% (3123 individuals).

The data reveal that the majority of two-person carpools have been diverted from the HOV lane into the general purpose lanes after HOT lane implementation. Based upon vehicle throughput and occupancy distributions, the largest reduction in vehicle throughput in both the morning and afternoon peak periods came from a reduction in carpools (HOV2 and HOV3+ vehicles). This indicates that the implementation of the HOT lanes did not incentivize, and may have dis-incentivized carpooling. Carpool mode share declined by more than 30% in the AM peak and by 25% in the PM peak, and average managed lane vehicle occupancy decreased from approximately 2.0 persons/vehicle to approximately 1.2 persons/vehicle. The decline in carpool retention on this corridor remains unexplained. Relevant behavioral data over time for these corridor commuters is not currently available and additional research into the impact of the implementation of the managed lanes on the formation and retention of carpools is warranted.

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List of Acronyms

ASCII	American Standard Code for Information Interchange
BRR	Beaver Ruin Road
CTR	Chamblee Tucker Road
DOT	Department of Transportation
FHWA	Federal Highway Administration, USDOT
Georgia Tech	Georgia Institute of Technology
GDOT	Georgia Department of Transportation
GP Lane	General purpose lane
GP1, GP2, etc.	General purpose lane 1, lane 2, etc.
GRA	Graduate research assistant
GRTA	Georgia Regional Transportation Authority
HD	High definition
HDV	Heavy-duty vehicle
HOT Lane	High-occupancy toll lane, allows SOVs to pay a toll to use the facility
HOT2+	High-occupancy toll lane, requiring a driver plus one or more passengers
HOT3+	High-occupancy toll lane, requiring a driver plus two or more passengers
HOV	High-occupancy vehicle, driver plus passenger(s)
HOV2	High-occupancy vehicle, driver plus one passenger
HOV2+	High-occupancy vehicle, driver plus one or more passengers
HOV3	High-occupancy vehicle, driver plus two passengers
HOV3+	High-occupancy vehicle, driver plus two or more passengers
HOV4+	High-occupancy vehicle, driver plus three or more passengers
HOV Lane	High-occupancy vehicle lane (a carpool lane)
HOV-to-HOT	Conversion of a HOV lane to a HOT lane
HPMS	Highway Performance Monitoring System
JCB	Jimmy Carter Boulevard
LDV	Light-duty vehicle
MARTA	Metropolitan Atlanta Rapid Transit Authority
ML	Managed Lane (Toll Lane, HOV lane, HOT lane, etc.)
NaviGAtor	The intelligent transportation system operated by the Georgia DOT
OPR	Old Peachtree Road
PHR	Pleasant Hill Road
PTZ	Pan, tilt, zoom (cameras)
RFID	Radio frequency identification
SOV	Single occupant vehicle (driver only)
SRTA	State Road and Tollway Authority
SUV	Sports utility vehicle
TMC	Traffic management center
USDOT	United States Department of Transportation
URA	Undergraduate research assistant
USB	Universal Serial Bus
USDOT	United States Department of Transportation
VDS	Vehicle detection systems (video-based in Atlanta)
VPHPL	Vehicles per hour per lane
VPSI	Vanpool Services, Inc.
VPTC	Vehicle and Person Throughput Calculator

1 Introduction

Many major metropolitan areas that are facing severe congestion problems have implemented transportation control measures designed to reduce the number of cars operating on the roadway in the morning and afternoon peak periods (Guensler, 1998). Incentives such as the provision of carpool lanes that allow high-occupancy vehicles (HOVs) to avoid congestion have become fairly commonplace. A network of managed lanes was implemented in Atlanta in the 1990's as part of a comprehensive freeway management strategy. However, in the early 2000's, the I-85 corridor managed lanes became congested and were no longer providing the appropriate incentives for carpooling (Guin, et al, 2008). Under congested conditions, neither the express bus system nor carpooling can offer significant travel time savings to riders. State transportation agencies had been seeking methods to provide a reliable travel time on this facility for carpools and express buses. However, conversion of the lane to a HOV-3 facility, requiring three persons per carpool, was not a viable option. Previous experience in Texas had shown that such a conversion would reduce demand for the HOV lane by 65%, which would result in many vehicles being diverted to the general purpose lanes, further increasing corridor congestion.

In 2008, the Georgia State Road and Tollway Authority (SRTA) and Georgia Department of Transportation (GDOT) applied to the US Department of Transportation for seed funding under a Congestion Reduction Demonstration Program Grant to convert the congested I-85 high-occupancy vehicle (HOV) lane into a high-occupancy toll (HOT) lane. HOT facilities had been successfully implemented in Minnesota and were slated for implementation in many areas across the country. Conceptually, the HOV lane occupancy requirement would change from 2-persons per vehicle to 3-persons per vehicle. Given the expected drop in carpool demand, congestion on the HOT lane would be eliminated. To fill the capacity vacated by 2-person carpools, the lane would open to additional traffic as a toll facility. That is, cars that contained fewer than 3-persons could opt to pay a toll to use the facility (i.e., the excess capacity on the lane was sold to those willing to pay a toll, or share the payment of a toll). By varying the toll price as a function of congestion, the demand for the facility is managed such that the facility will ensure that vehicles operated at 45 mph or greater speeds and the lane avoids congested conditions caused by too many vehicles trying to use the facility at the same time. Interestingly, when operated with proper pricing, the HOT lane can actually carry more vehicles per hour after conversion than it did as an HOV2+ lane. This means that the conversion of a congested HOV lane to a HOT lane should result in greater vehicle throughput on the managed lane during the peak-of-the-peak within the peak period , which should slightly reduce congestion on the general purpose lanes as well (as was observed in Minnesota where congested general purpose lane travel speeds increased by 7%). In November 2008, the USDOT awarded the demonstration grant to Georgia to begin the conversion of the 15.5-mile segment of HOV lanes on I-85, from Chamblee Tucker Road to Old Peachtree Road. The facility would later open on October 1, 2011.

As part of the demonstration project, a partnership with Georgia Tech established a research team that would assess changes in vehicle throughput, vehicle occupancy, and passenger throughput associated with the I-85 HOV-to-HOT conversion. The researchers were also assessing changes in weaving and effective roadway capacity from a traffic engineering perspective as well as performing initial reviews of changes in demographic profiles of users and non-users of the HOT lanes.

The effective capacity analysis (Guensler, et al., 2013) assessed the operating conditions on the managed lanes and general purpose lanes during the peak-of-the-peak period. In that report, researchers concluded that the maximum vehicle throughput appears to be higher in the section that was studied. Illegal weaving dropped significantly. With the significant decrease in illegal weaving, it may be that driver expectation associated with gap acceptance has changed. Speeds and densities may be running higher because managed lane drivers are not as worried as they used to be about someone jumping in front of them from the GP lane. Hence, the managed lane appears to handle more vehicles during the worst congestion conditions, when it is most needed. However, that effective capacity report (Guensler, et al., 2013) only assesses the performance of the lane under those peak conditions and is not meant to provide conclusions related to overall corridor performance and throughput. Because toll prices during the study period were not high enough to ensure that HOT lane demand always remained below capacity, HOT lane flow did break down. Hence, this research reported herein is designed to assess how the changes in the system have affected corridor vehicle and passenger throughput for the four-hour morning and afternoon peak periods.

To assess vehicle and passenger throughput, the research team assembled and reviewed traffic flow data (vehicles/lane/hour) from the Georgia NaviGAtor system, and collected vehicle occupancy data (persons/vehicle) via field data collection efforts for one year prior to HOT implementation and one year after the HOT lanes opened (October 2010 through September 2012). Quarterly occupancy data and daily vehicle flows were then employed in the assessment of throughput impacts of the new HOT facility.

Previous HOT lane studies have had mixed results in the area of person throughput, with some studies reporting decreases and some increases in person throughput (GAO, 2012). Previous studies have also had mixed results with respect to the impacts of HOT lane implementation on transit ridership (GAO, 2012). Some theories suggest that HOT lanes actually discourage transit ridership due to the travel time savings that can be gained from a functional HOT lane and the flexibility and privacy benefits of using a personal vehicle over transit. A survey in Houston’s efforts suggested that 1.6% of bus riders would switch to single occupancy vehicles for a 20 minute time savings at a $4.00 toll (Chum and Burris, 2008). However, the actual effect of an HOT lane on transit ridership was still unknown. The new Atlanta study reported herein is based upon passenger counts and concludes that the HOT lanes have had little impact on bus ridership and passenger throughput, but that the buses still carry a significant share of corridor users. There is still room to improve bus operations and passenger loads through incentives.

The biggest challenges associated with the assessment of changes in vehicle and person throughput were associated with quality and relevance of data available to the research team. Data from the NaviGAtor system were carefully assessed to identify data that could be considered reliable over the entire study period. In addition, the conversion of the lanes was completed in a three-phase process (described later), which complicated comparative analyses. The team developed new occupancy data collection methodologies for the HOT evaluation as the result of a comprehensive literature review, an examination of previous data collection methods, an evaluation of the physical characteristics of the I-85 corridor, and the testing of a variety of equipment/manpower strategies (D'Ambrosio, 2011).

The researchers found that vehicle throughput decreased by about 6.6% in the AM peak after HOT conversion for the months of February through April (comparing 2011 data to 2012 data), for Wednesdays-Thursdays at the Center Way station. This change was larger than expected, based upon comparisons of changes in throughput at other stations in the northern region of Atlanta. Hence, the economic downturn was not expected to be the sole contributing factor in the noted decrease in vehicle throughput. The more striking result was that accompanying the 6.6% reduction in vehicle throughput was an estimated 9.9% reduction in person throughput in the AM peak on the corridor for the same period based upon observed changes in vehicle occupancy.

Vehicle throughput decreased on average by about 2.9% during the PM peak after HOT conversion for the months of February through April (2011 data vs. 2012 data), for Wednesdays-Thursdays at the Center Way station. This change is comparable to decreases in demand noticed at other stations in the northern region of Atlanta during the same period. Hence, afternoon vehicle traffic changes were probably not as significantly impacted by the conversion. That reduction in vehicle demand remained fairly consistent from May through September. Accompanying the 2.9% reduction in vehicle throughput was an estimated 6.3% reduction in person throughput during the PM peak on the corridor for February through April based upon observed changes in vehicle occupancy. However, because vehicle occupancy continued to increase over the eight-month period, the decrease in passenger throughput for May through September was 3.9% (compared to the 6.3% reduction in person throughput for February through April).

The methods remained consistent throughout the study; hence, the predicted reduction in person throughput is expected to have been significant. The research effort was observational in nature, and did not include the originally-proposed large scale panel study and instrumented vehicle fleet, through which travel behavior data would have been collected. Hence, even though the decreases in vehicle and person throughput appear to have been large and significant, it is not possible to assess the reasons for the changes, and whether vehicles and passengers formerly served by the corridor have diverted to other routes, other times of day, or have curtailed trip-making.

This report is organized around the presentation of the throughput methodology and the results that arise during each step of the modeling effort. Chapter 2 describes the facility and describes the nature of the phased HOV-to-HOT conversion (which involved restriping of the HOV facility during the one-year baseline period). Chapter 3 provides an overview of the throughput calculation methodology and Chapter 4 provides a detailed discussion of vehicle activity data sources and treatments. Vehicle occupancy data collection, data processing, factors affecting occupancy, and occupancy results are provided in Chapters 5, 6, 7, and 8.

Because express buses and vanpools carry a large number of persons per vehicle, the person throughput methodology is modified to specifically address the impact of these modes (Chapter 9 and 10). The final vehicle and person throughput results are presented in Chapter 11 and conclusions and recommendations are presented in Chapter 12.

2 Study Area

The managed lane system plan (Smith, 2011) identified HOT operational goals and objectives:

- Protect mobility in the managed lanes
- Increase vehicle throughput
- Increase average travel speeds and reduce corridor travel times
- Decrease delay
- Decrease travel time variations
- Improve transit on-time performance
- Increase access to major activity centers
- Increase system efficiency

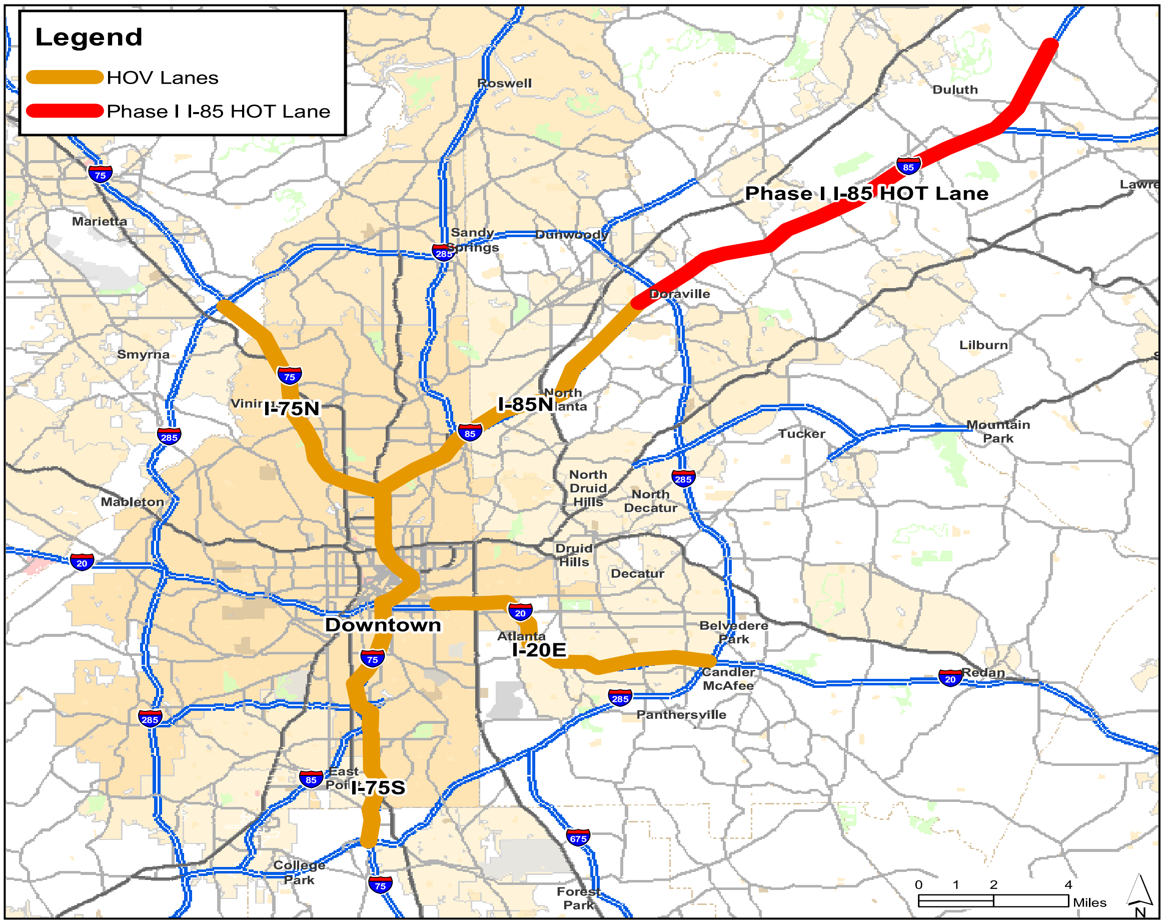
To accomplish these goals, GDOT made some major changes to the infrastructure along the I-85 corridor. The infrastructure changes included new signage for the HOT lane, addition of carved grooves on double white lines creating rumble strips to discourage illegal weaving across the lines, electronic collection of tolls, and implementation of an electronic enforcement barrier between the managed lane and the leftmost general purpose lane to discourage illegal weaving (see Vu, et al., 2007).

The I-85 corridor includes 13 different interchanges that allow entry and departure from I-85. In the northbound direction, there are 11 off-ramps and 10 on-ramps. In the southbound direction, there are 10 off-ramps and 11 on-ramps (Toth, et al, 2012). All except one of the interchange ramps are located on the right side of the Interstate. Signage notifying drivers to begin weaving towards their exit is found on the left hand side of the roadway. The SR-316 off-ramp in the northbound direction is located on the left side of the facility to give HOT lane users a direct exit from I-85. In the southbound direction, drivers coming from the 316 HOT lanes merge directly into the left hand HOT lane on I-85. In the conversion from HOV to HOT operations, the weaving zones were changed; some zones were eliminated and some zone lengths were modified.

The HOT lane is free for registered carpools carrying three or more occupants, motorcycles, transit vehicles, emergency vehicles, and Alternative Fuel Vehicles (AFV) with the proper license plates (GDOT). To use the HOT lanes, a Peach Pass is now required. The Peach Pass radio frequency identification (RFID) tag is used to electronically collect the toll. Even vehicles that are exempt from the toll require a Peach Pass; however, exempt vehicle Peach Passes are not charged when going through the system. Peach Pass occupancy status can be changed by any user from toll to toll-exempt status, and vice-versa. Police officers are placed along the system to check occupancy of the vehicle and discourage violation.

2.1 Phased HOT Conversion

The study area for this report is the I-85 HOT corridor in Atlanta, GA. The HOT corridor section being analyzed is 14.3 miles long between I-285 and SR-316 (see Figure 1). The physical infrastructure in the study was modified two times during data collection. The first change was a restriping, which eliminated or relocated some of the weaving sections. The second change was the opening of the HOT lane.



Source: GDOT, 2011

Figure 1: I-85 HOV-to-HOT Study Corridor

The research team collected traffic flow and quarterly vehicle occupancy data for one year before the opening and one year after implementation of the HOT lane. In converting the HOV lanes to HOT lanes, three distinct operational phases were observed, with additional sub-phases deserving specific attention:

- Phase I - Before April 18, 2011
  Phase I constitutes the baseline HOV operations period, prior to the opening of the HOT facility, but also prior to the date on which the HOV facility was restriped in preparation for the facility opening.

- Phase II - April 25, 2011 to October 1, 2011
  Phase II was the time period after the restriping of the facility was completed in preparation for HOT lane implementation, but before the HOT lanes opened. The

restriping decreased the cumulative length of weaving sections from 7.48 miles before the conversion to 4.45 miles after conversion and included the elimination and relocation of several weaving sections along the I-85 corridor.

- Phase III - After October 1, 2011
  The HOT lanes opened for business on October 1, 2011

The initial restriping of the corridor took place on April 18, 2011 and eliminated the southbound weaving zone on I-285 and the northbound weaving zone on Pleasant Hill Road. The initial restriping also relocated both the northbound and southbound weaving sections at Jimmy Carter Boulevard, Center Way, and Beaver Ruin. The second restriping event took place the following weekend on April 25, 2011. The second restriping eliminated the southbound weaving sections on Pleasant Hill Road, SR-120, and Old Peachtree Road and the northbound weaving section on Sugarloaf Parkway. Also, the SR-316 weaving section was relocated.

Before the restriping, there were 15 access points (legal weaving sections) between the general purpose lanes and the managed lane between Chamblee-Tucker Road and Old Peachtree Road (seven northbound, eight southbound). After restriping, the number of weaving sections into the managed lane decreased from 15 to 9 (five northbound, four southbound). Phase II began after the two-stage restriping was finished and continued until the HOT lanes opened (4/25/2011-10/1/2011).

Previous analysis demonstrated that vehicle activity during Phase II, after restriping, differed significantly from both the Phase I HOV baseline operations as well as the Phase III HOT operations in terms of weaving activity, speed differentials, and effective capacity (Guensler, et al, 2013). Hence, using data from the Phase II period to compare pre-and-post HOT operations is problematic and discussed in more detail later.

Further complicating the baseline period was the implementation of rumble strips on the facility. During the overnight hours of September 6-8, 2011, grooves were carved into the solid double-white lines separating the managed lane from the adjacent general purpose lane in the non-weave sections of the corridor. The rumble strips create significant vibration at high speed and are meant to remind and/or deter drivers from crossing the double lines. The research team did not specifically focus on this three-week time period, so analyses reported herein generally address the Phase II restriping period before September 6, 2011. In comparing Phase I and Phase III data, analysts should remember that the lanes were restriped and a rumble strip was added; hence, Phase II can be broken into two sub-phases.

- Phase IIa - April 25, 2011 to September 5, 2011
- Phase IIb - September 6, 2011 to October 1, 2011

Phase III operations represent the active operation of the HOT lane, which opened on October 1, 2011 and continues today. However, the initial operation of the facility was not representative of current operations. As discussed in other papers, and a variety of local newspaper articles that appeared in the Atlanta Journal Constitution in late 2011, the HOT lane operations during the startup phase were less than ideal, given the low usage of the HOT lane in the month after opening. Traffic on the HOT lanes was light, and congestion on the general purpose lanes was significant during startup. Some would argue that too few potential users had obtained Peach Passes prior to the opening of the toll facility, as evidenced by the high ongoing rate of Peach Pass sales during the first quarter of operation, and that initial tolls were too high, as evidenced by low usage and the Governor's decision to lower toll rates. October and November operations (prior to Thanksgiving week) should only be used to assess startup impacts. November and December contain residual startup impacts coupled with holiday travel. The first three months should not be included in a before-after analysis; hence, Phase III can be broken into two sub-phases.

- Phase IIIa - October 1, 2011 to December 31, 2011
- Phase IIIb - January 1, 2012 to September 30, 2012

The combined impact of restriping during the baseline period and non-representative startup conditions during the HOT operations period limits available data for valid before-after comparisons. Phased implementation effectively limits proper comparisons to a four month period that includes the months of January, February, March, and April (through April 25) in 2011 and 2012. Table 1 illustrates the Gantt chart of facility phases and identifies the overlap between Phase I and Phase IIIb as the best period to compare before-and-after operations. However, January has also been excluded from both baseline and HOT operations due to an ice storm in Atlanta in 2011 that closed freeways and major arterials for an extended period of time.

This report focuses on the comparisons of vehicle and passenger throughput during the months of February through April 2011 (Phase I - HOV operations) vs. 2012 (Phase III - HOT operations). Analyses of facility performance during the three month startup period (October 1, 2011 through December 31, 2011) will be left to other transportation policy forums. Similarly, changes between HOV operations after restriping and subsequent HOT operations with the same striping configurations will be left to other traffic engineering forums.

Table 1: I-85 HOT Lane Implementation Phases

		Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
		2010	2010	2010	2011	2011	2011	2011	2011	2011	2011	2011	2011
HOV Baseline	Phase I	xxxx	xxxx	xxxx	*xxx	xxxx	xxxx	xxx					
HOV w/Restriping	Phase IIa							x	xxxx	xxxx	xxxx	xxxx	x
HOV w/Rumble Strips	Phase IIb												xxx
		Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
		2011	2011	2011	2012	2012	2012	2012	2012	2012	2012	2012	2012
HOT Startup	Phase IIIa	xxxx	xxxx	xxxx									
HOT Stabilized	Phase IIIb				xxxx	xxxx	xxxx	xxxx	xxxx	xxxx	xxxx	xxxx	xxxx

* Snow/ice storm

3 Throughput Methodology Overview

The research team developed the Vehicle and Person Throughput Calculator (VPTC) to estimate hourly vehicle flow rates (vehicles/hour and vehicles/four-hour peak period) and person throughput (persons/hour and persons/four-hour peak period) at specific monitoring stations. VPTC outputs are compared over time to assess throughput changes that appear to be associated with the implementation of the HOT lane.

The original calculator was developed as an Excel spreadsheet, and then translated to a series of Perl Scripts for implementation. The scripting process allows the calculator to interface directly with the analytical database and the tables of pre-processed input data, including: 1) NaviGAtor ITS traffic volume data, after processing through quality assurance routines; 2) field-collected occupancy and vehicle classification data, after quality assurance processing and allocation of uncertain observations (described in later chapters), and 3) express bus and vanpool observation data. Outputs are in five-minute vehicle and person flows for the selected times and dates, which are aggregated to hourly and peak-period flows.

The calculator employs monitored traffic volumes by lane collected by the Georgia Department of Transportation (GDOT) Traffic Management Center (TMC) in Atlanta, GA. The video-based vehicle detection systems (VDS) located at monitoring stations along freeways throughout the region feed traffic volume data by lane back to the TMC and are aggregated from 20-second observations to five-minute summaries by station. For any given location, date, and time, the most relevant occupancy field data (i.e. quarterly field data collection results that are closest to the date, time, and location in question) are applied to the five-minute traffic volumes by vehicle class by lane to estimate passenger throughput.

Vehicle classification data from field data collection efforts are used to split NaviGAtor traffic volumes into the number of light-duty vehicles (LDVs), sport utility vehicles (SUVs), and heavy-duty vehicles (HDVs). Vehicle occupancy data by vehicle class, collected quarterly by field teams, are then applied to class-specific vehicle throughput data by lane. Hence, initial person throughput estimates are derived by multiplying vehicle class traffic volumes (e.g., vehicles/hour for sport utility vehicles), by vehicle-class-specific occupancy observations (persons/sport utility vehicle). Twelve consecutive five-minute vehicle volumes and person throughput results are aggregated to hourly values.

The initial hourly person throughput results are then corrected to account for the impact of vanpools and express buses. Vanpool and express bus impacts are handled via independent processes that effectively add persons to the hourly throughput results based upon the number of observed vanpools and buses and their relevant occupancies from survey data. Motorcycles, school buses, and tour buses are ignored, as they have no significant impact on the results due to their low and consistent volumes before/after conversion.

3.1 Vehicle and Person Throughput Calculator Steps

The VPTC operates in a stepwise process:

Step 1: Select Location, Date, and Time - The user selects a desired location (VDS Station ID), date, and time.

Step 2: Query Traffic Volume and Speed Data - The scripts pull the applicable five-minute resolution vehicle flow rates from the VDS database table for the station ID, date, and time. Data are tracked lane-by-lane. Hourly equivalent volumes are calculated by summing five-minute volumes for the hour. Hourly vehicle speeds are derived from five minute data using space-mean speed averaging. Speeds are used in online visualization processes and for subsequent data analysis efforts unrelated to throughput.

Step 3: Query Vehicle Classification Field Data - For any given station/lane/date/time, VDS traffic counts by lane are apportioned into hourly counts by vehicle class fraction (light-duty automobiles, sports utility vehicles, and heavy-duty vehicles) using the ratios obtained during quarterly field data collection (see Table 2). Vehicle class observations are available by lane and vehicle class by quarter. Lane-by-lane analysis is supported by this method, given that vehicle class fractions differ across lanes, as do average vehicle occupancy values (with higher occupancies on outside freeway lanes; discussed later).

Class	ML1	GP1	GP2	GP3	GP4	GP5	Sum
LDV	772	1192	962	898	748	807	5379
SUV	606	929	1001	727	687	798	4748
HDV	25	3	42	187	209	111	577
Total	1403	2124	2005	1812	1644	1716	10704

Table 2: Example of Vehicle Count Data Distributed by Classification and Lane

Step 4: Apply Occupancies - The counts by vehicle class are then linked to vehicle occupancy splits (percentage of 1-person, 2-person, 3-person, and 4+ person vehicles as described in Chapter 8) for each class to obtain estimates of vehicle throughput for each vehicle class, lane and time period (see Table 3).

Step 5: Calculate Person Throughput from Vehicle Throughput and Occupancy - The number of persons passing through the corridor per hour is calculated by multiplying each hourly vehicle count element by its applicable vehicle occupancy. LDVs and SUVs in the 4+ category are assigned an assumed occupancy value of 4.5 persons per vehicle (the team could not develop a better empirical value based upon field data).

Class	ML1	GP1	GP2	GP3	GP4	GP5	Sum
LDV1	685	1106	911	827	718	748	4995
LDV2	76	85	47	69	29	52	358
LDV3	9	0	3	1	1	7	21
LDV4+	2	0	0	1	0	0	3
SUV1	508	769	895	610	585	681	4048
SUV2	98	156	104	113	94	110	675
SUV3	0	1	2	2	6	5	16
SUV4+	0	3	0	2	3	3	11
HDV1	6	2	33	170	192	94	497
HDV2	5	2	8	15	15	10	55
HDV3	0	0	0	1	1	1	3
HDV4+	14	0	2	1	0	5	22
Total	1403	2124	2005	1812	1644	1716	10704

Table 3: Example of Field Data by Lane and Occupancy Class

Step 6: Adjust Vehicle and Person Throughput for Vanpools and Commuter Buses - In the final step, the calculator employs GRTA and Gwinnet County Transit bus route and vehicle occupancy data in the calculations. Buses operate on set schedules and bus throughput data are available for each hour. Each departing bus is allocated to the specific hour it is expected to arrive at a monitoring station based upon departure time, departure location, and average travel time to the station. Monthly vehicle occupancy data collection by route and departure time establishes applicable passenger occupancy of these buses as described in later chapters. HDV4+ person counts are adjusted downward by 4.5 persons per express bus, given the assumed 4.5 persons/vehicle for the 4+ class, and then adjusted upward to reflect the number of passengers on each passing bus. For vanpools, SUV4+ person counts are adjusted downward by 4.5 persons per vanpool, and then adjusted upward to reflect the passage of each vanpool.

3.2 Vehicle and Person Throughput Subroutines

The chapters that follow this one provide the complete descriptions of the methodology subroutines, data sources, and analytical results. Chapter 4 outlines the methodology for obtaining vehicle throughput estimates from the NaviGAtor system and discusses the field data collected to provide vehicle classification splits. Chapter 5 provides an overview of the occupancy study methodology and data collection efforts. Chapters 6, 7, and 8 provide the review and analysis of occupancy data, the resulting occupancy relationships identified across lanes and over time, and the final occupancy results. Chapters 9 and 10 provide the methods and results for the express bus adjustments and vanpool adjustments, respectively. Chapter 11 provides the final vehicle and person throughput analytical results.

4 Vehicle Throughput

Vehicle throughput data for the I-85 corridor were collected via the Georgia NaviGAtor system, housed in the GDOT Traffic Management Center (TMC). This system monitors more than 220 miles of freeway in Atlanta's metropolitan area providing data to improve safety and efficiency. Georgia NaviGAtor uses advanced signage, video, computer and communications systems (Lee and Bradford, 2004). Video-based vehicle detection systems (VDS) are located at monitoring stations approximately every 1/3-mile along freeways throughout the region. VDS data are generated by a machine vision process that counts vehicles that traverse the video system's field of view. The change in pixel colors occurring within a vehicle detection zone in the video field of view indicates the entry and departure of a vehicle. By establishing two detection zones, and using an estimated vehicle length, the system also provides vehicle speed estimates. Hence, data from the NaviGAtor system include: traffic volumes in the managed lane, traffic volumes in each general purpose lane, vehicle speeds in the managed lane, and vehicle speeds in each general purpose lane. Special vehicle classification (light-duty vehicles, heavy-duty vehicles, etc.) counts can be handled by some machine vision systems, but were not available for the specific study areas in the corridor. Hence, manual observation of vehicle classification was conducted (as described in Chapter 5). Traffic volume counts for the HOT lane are more accurate when collected via the State Road and Tollway Authority's (SRTA's) laser detection system (used to trigger RFID tag reads). However, baseline data are not available from the SRTA system (RFID tag readers did not go online until the system opened); hence, NaviGAtor VDS data were employed in all before-after studies for traffic volumes for consistency.

4.1 NaviGAtor Traffic Data

Traffic volumes and vehicle speeds are monitored by the Georgia Department of Transportation (GDOT) Traffic Management Center (TMC) in Atlanta, GA. Data flow to the Georgia Tech NaviGAtor archive through a remote GDOT TMC network monitoring station in the transportation research laboratory at Georgia Tech. The monitoring station is isolated from the Georgia Tech network for security purposes. The VDS data feed includes traffic volumes and spot speed data, by lane, at 20-second resolution. The research team manages an analytical archive of the TMC data, including the raw and processed 20-second data, aggregation of data to 5-minute bins, 15-minute bins, and hourly volumes. The Georgia Tech archives include 15-minute data, from January 2000 to date, and 20-second data, from October 2007 to date. The data are archived in near-real-time, with 20-second bin data arriving within 2 minutes. Figure 2 provides an overview of the NaviGAtor system.

Figure 3 shows the NaviGAtor web interface, which provides the NaviGAtor system camera locations used to collect traffic count data. Cameras are located roughly every 1/3 mile along the corridor and are usually mounted on 60' poles and pointed downward at the traffic. The location of the cameras relative to the lane monitored (vertical and horizontal angle) can significantly impact the accuracy and reliability of the data being collected (Grant, et al., 1999). Figure 3 illustrates the web interface provided by GDOT for the public to access camera views and visualize congestion conditions on the roadway.

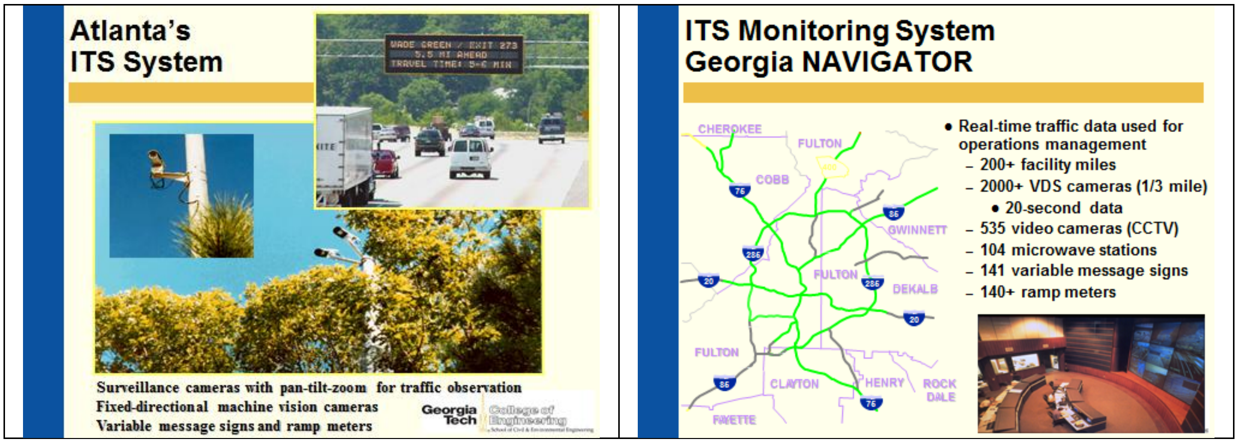


Figure 2: Overview of the NaviGAtor System

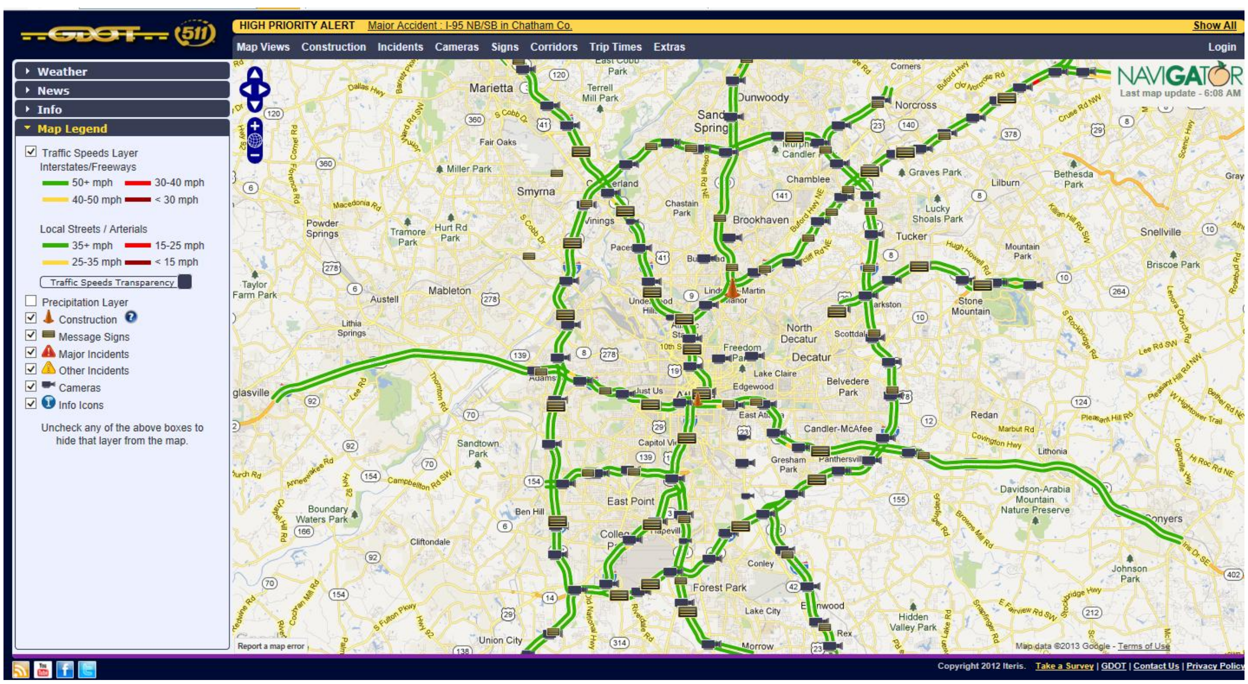


Figure 3: NaviGAtor Web Interface

The GDOT TMC uses pan-tilt-zoom and machine-vision cameras for incident identification and quick response dispatch of Highway Emergency Response Operators (HERO) units. The closed circuit pan-tilt-zoom (PTZ) cameras located along the corridor can also be used to collect traffic count data. Such data were employed in the HOT lane weaving and effective capacity analysis (Guensler, et al., 2013). Cameras along the corridor and the area covered at a high enough resolution for data collection (i.e. high enough resolution such that an observer can visually count vehicles and identify weaves between lanes) can be found in Figure 4. The donut areas between the yellow and the white lines in Figure 4 constitute the zones in which vehicles can be tracked using new software developed by Georgia Tech (Guensler, et al., 2013). The yellow line has a radius of 400', while the white line has a radius of 1000'. To obtain the maximum vehicle tracking distance, the camera must be pointed at this 600' area. Figure 4 also indicates that the PTZ cameras only cover about 25% of the corridor (Toth, 2011). For the purposes of the vehicle throughput study, the use of video-based traffic volume data taken from these PTZ cameras was not a practical consideration. Hence, the team used VDS data.

Figure 4: Locations of NaviGAtor PTZ Cameras on the HOT Corridor

As discussed above, the Georgia Tech data archive receives a direct feed from the NaviGAtor system. The research team processes the 20-second VDS data through a series of quality control measures to identify and eliminate highly improbable values. Gaps in real-time data do occur and are attributable to several different factors, such as sensor failures, data communications interruptions, etc. Georgia Tech researchers also process the 20-second data to impute missing data. After filtering and imputation, the 20-second data are re-aggregated to 5-minute and one-hour bins and retained in the separate analytical archive for use in research activities.

4.2 Quality Assurance/Quality Control (QA/QC)

The fundamental relationship between speed and flow is employed to filter VDS data in the data QA/QC process. Highly improbable 20-second paired speed and volume data points are removed from the data set and replaced with null values using a series of data filtering scripts applied to the raw data feed. Null values will be imputed in a later step.

Figure 5 shows an expected speed-flow plot. The blue regions represent the zones where no data points are expected to be observed based upon traffic engineering. A conservative approach was adopted, and only the data in the dark blue zones were eliminated as invalid. For example, data for which average vehicle speeds for 20-second bins exceed 110 mph are removed from the data stream, as are 20-second traffic volumes that exceed 20 vehicles (3600 vehicles/hour). The conditional logic and the thresholds used in data filtering are provided in Table 4. In general, if about 99% of the expected data points are available in a dataset, the QA/QC procedures trimmed the dataset to 97%; i.e. 97% of the data passed the validity tests and remain available.

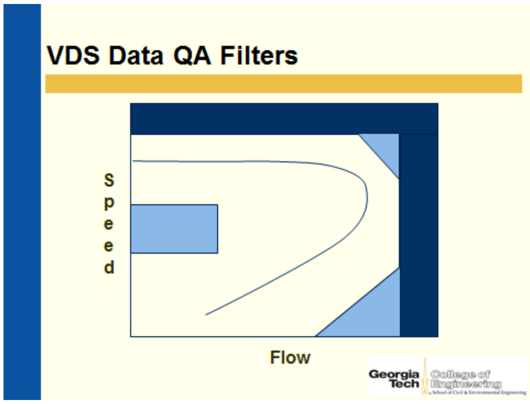


Figure 5: Data Validity Zones in a Speed-Flow Plot

Table 4: QA/QC Screening Threshold Values

Threshold Values		
Volume (veh/20sec)	**Speed (mph)**	**Density (veh/mi)**
(Two conditions must be true to be declared invalid)		
Zero (= 0)	**Zero (= 0)**	**Zero (= 0)**
(All conditions must be true to be declared invalid)		
All	**Low (< 20)**	**Medium (<120, >= 40)**
High (>= 15)	**All**	**Low(< 40) or High(>2 00),**
Nearly Zero (<= 2)	**Nearly Zero (<= 10)**	**Not Nearly Zero (>= 8)**
Too High (>= 20)	**All**	**All**
All	**All**	**Too High (> 290)**
All	**Too High (> 110)**	**All**

4.3 Vehicle Count Variability Issues

Figure 6 displays differences in cumulative 15-minute counts across three consecutive VDS stations for one example day. The plot includes volume differences between the upstream and center station and the downstream and center station. Given that there are no freeway entrances and exits between these stations, one would expect conservation of vehicles through the section. Hence, the differences should be approximately zero, unless there is a calibration issue with one or more of the stations. Even if the calibration is off, one would expect that the differences between stations would be consistent. However, volume differences differ by time of day.

Figure 7 displays an example of a single day cumulative vehicle count curve for three consecutive VDS stations. This figure is displayed as an oblique plot (relative to the average slope of the line at the center station count) to illustrate the differences more clearly. The counts have a time-delay factor such that the upstream counts begin at a free-flow volume region at initial time t, while the middle station starts counting at $t + \delta_{us}/ u$ and the downstream station begins at $t + (\delta_{us+}\ \delta_{ds})/u$ where δ_{us} *and* δ_{ds} represents the distance of the middle station from the upstream downstream stations respectively and u represents the free-flow speed. With the time translation of the starting time of counts, it is expected that cumulative counts will be roughly equal during free volume regions, and any upstream station counts are slightly higher than any downstream station counts at congested periods.

The upstream station exhibits lower cumulative counts than the other stations, while the downstream station exhibits higher cumulative counts. This happens quite consistently for every day in the data set. Given that there are no entrances and exits between stations, one would expect conservation of vehicles through the section which should yield nearly overlapping curves for the three stations. The large difference between the station cumulative traffic counts (0-8% between upstream and middle, and 8-18% between downstream and middle for a single day) suggests that there are substantial detector errors which are not consistent across stations and may vary by time period. The differences are most likely due to occlusion of vehicles, where larger vehicles hide smaller vehicles from video detection, or splashover errors, where large vehicles trigger counts in multiple lanes. Such errors are functions of different camera viewing angles and detector configurations (Grant, et al., 1999). Hence, as truck volumes and traffic densities vary during the day, departures in adjacent lane detector values may also vary.

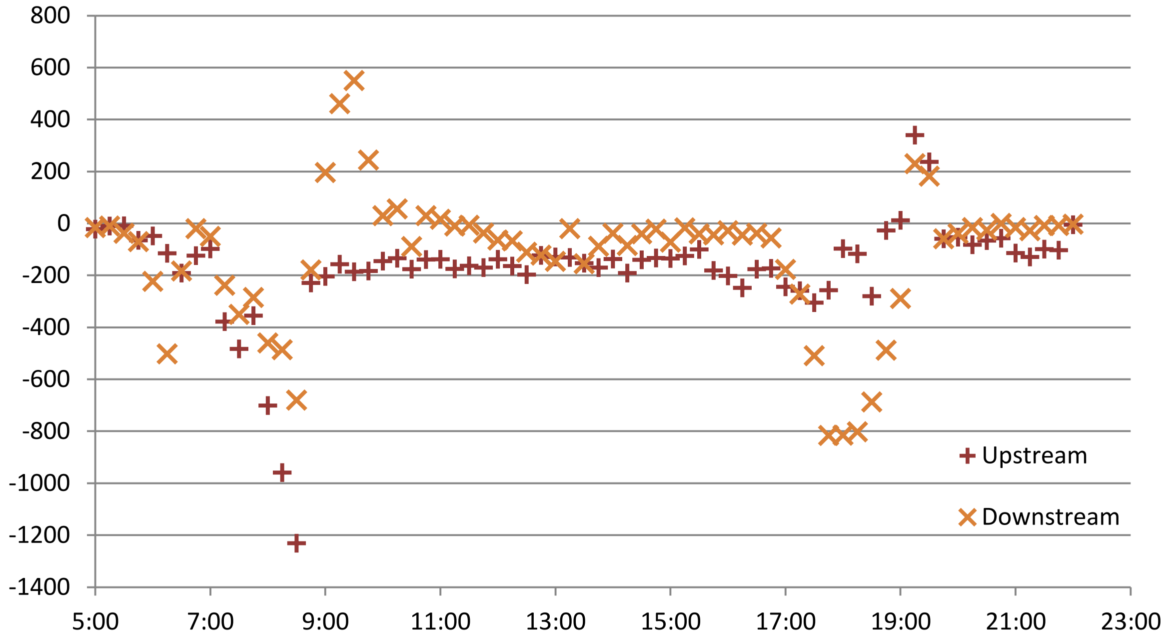


Figure 6: Example of Differences in Vehicle Counts for April 22, 2009 by Time

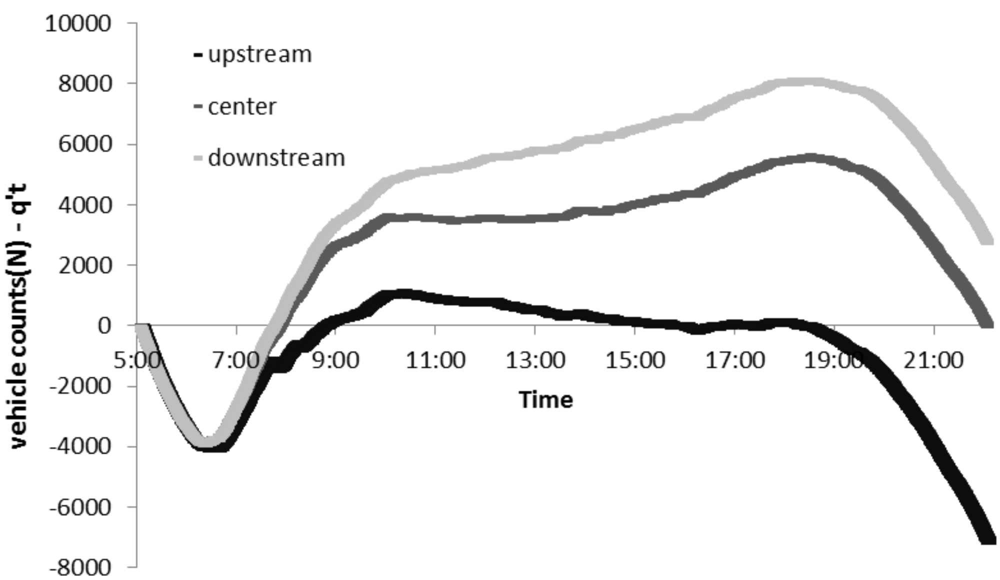


Figure 7: Example of Cumulative Vehicle Counts for May 8, 2009 (Oblique Plots)

4.4 Data Imputation

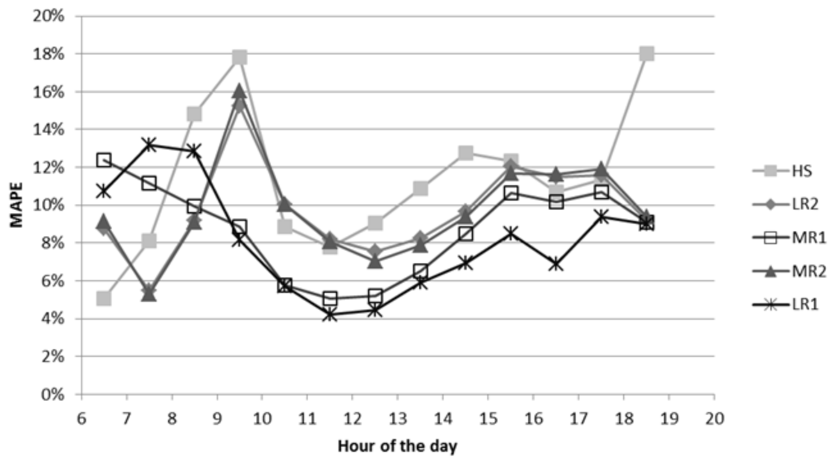
Regardless of the cause of missing data, gaps often have to be filled with reliable and reasonably accurate estimates before the data can be used for planning, operations, or congestion mitigation purposes. This research compares different methods for imputing missing values on Video Detection System (VDS) data, including historical averages, simple-linear regression, multiple-linear regression, spatial average and Newell's simplified kinematic wave model.

For corridor throughput volumes, station-level detector data (aggregated over all lanes at the station) are based upon the observation that in a VDS system, such as Georgia NaviGAtor, an overwhelming majority of missing data occurs at the station level. This is understandable because in most cases, all lane detectors are connected to a single video processing unit fed by a single camera view. Failure of an equipment component, or a communications failure between the central server and the video processing unit, can cause a complete outage at the detection station. In addition, it can be contended that a complete outage at a station is typically more severe and is also a more difficult problem to resolve.

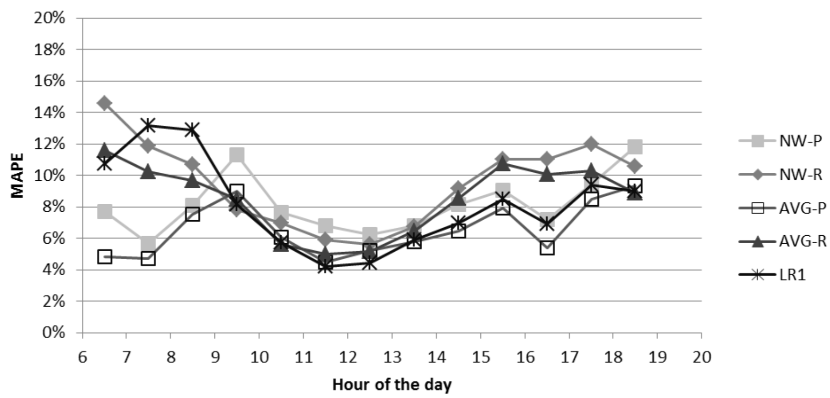
A total of nine imputation algorithms were analyzed in this study. Three algorithms came directly from previous research methods, and five hybrid methods were derived (Castrillon, et al., 2012). The nine algorithms compared were as follows:

1. HS- historical average, based upon raw detector training data and applied to raw testing data
2. LR1- simple linear regression model, calibrated using raw detector training data and applied to raw testing data
3. LR2- simple linear regression model with peak period dummy variables, calibrated using raw detector training data and applied to raw testing data
4. MR1- multiple regression model, calibrated using raw detector training data and applied to raw testing data
5. MR2- multiple regression model with peak period dummy variables, calibrated using raw detector training data and applied to raw testing data
6. NW-P- Newell's method with "period-of-day factor" adjusted curves, calibrated using Method A adjusted detector training data, applied to adjusted testing data
7. NW-R- Newell's method with Method B adjusted curves, calibrated using "regression factor" adjusted detector training data, applied to adjusted testing data
8. AVG-P- Upstream and downstream factored station averages with "period-of-day factor" adjusted curves, calibrated using adjusted detector training data, applied to adjusted testing data from the downstream and upstream stations.
9. AVG-R- Upstream and downstream factored station averages with "regression factor" adjusted curves, calibrated using adjusted detector training data, applied to adjusted testing data from the downstream and upstream stations.

Figure 8 and Figure 9 show the results of the comparison. Apart from algorithm LR1, the other algorithms that performed well all used some form of calibration to adjust the raw data before performing the imputation. The figures show the five-minute mean absolute percentage error (MAPE) averaged over one hour for (a) regression models and the historical model, and (b) Newell's models and factored models (and LR1 as reference for comparison).



(a)



(b)

Figure 8: Five-minute MAPE One-hour Averages (a) Regression Models and Historical Model, (b) Newell's Models and Factored Models (and LR1 as a reference for comparison)

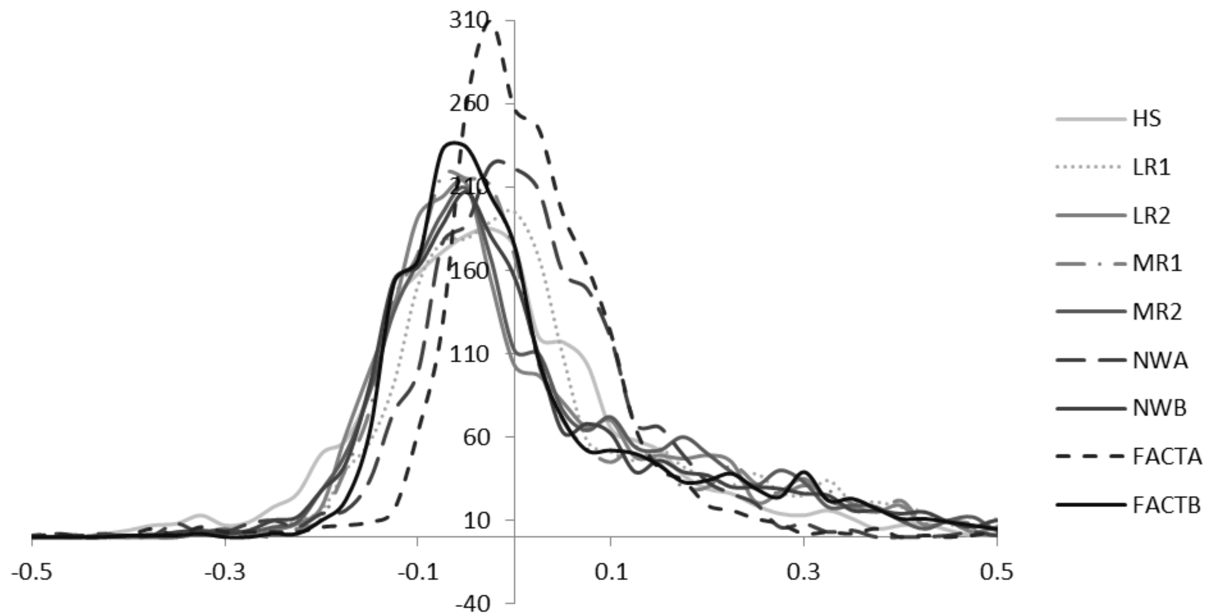


Figure 9: Distribution of the Percentage Errors for Five-minute Aggregate Results

A sensitivity analysis was performed to test the response of different methods to factors such as the size of training dataset, time-of-day adjustments to the algorithms and others. The results indicated that the time of day and volume adjustment factors have a non-trivial impact on the accuracy of the outputs. Despite the presence of significant errors in the base dataset, the Newell algorithm performed on par with the other methods, in terms of the bias and the mean absolute percentage, but the more simple factoring methods also provided comparable results and are easier to implement.

4.5 Final Imputation Strategy

The research into the imputation algorithms showed that the effectiveness of the imputation depends heavily on the calibration of the stations. Figure 10 is a plot of the average daily free-flow speeds at one of the detection stations between October 2010 and May 2012. The sudden shifts in the data across all lanes (December 2010 and October 2011) indicate potential calibration changes in the data. This affects the accuracy of the imputed data at an adjacent station that is based on data at this recalibrated station. To prevent such propagation of errors, cross station imputation strategies were abandoned. Imputation was only performed on the time scale. For example, for a 5-minute aggregate, if data was available only in 10 out of the fifteen 20-second time intervals, the count data was simply scaled by 15/10 to adjust for the missing data. The average speed was computed from the 10 data points that were available. If no data were available in an entire 5-minute period, these missing points were accounted for in a scaling factor when aggregated up to a larger period such as 15 minutes or an hour.

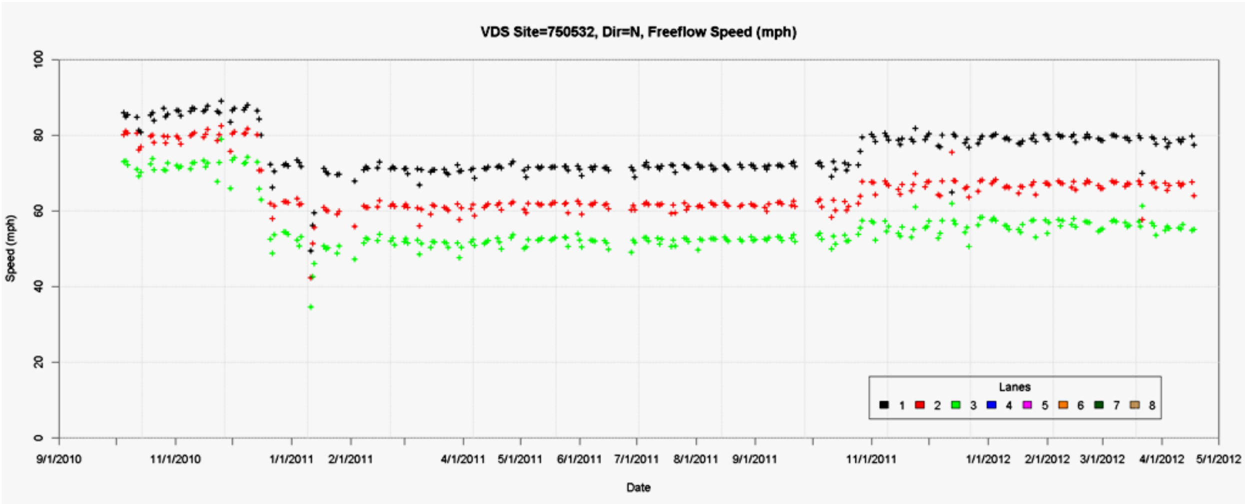


Figure 10: Time Series Plot of Daily Averages for Free-flow Speeds

4.6 Other Data Characteristics

The data in the HOT corridor as well as the control stations were analyzed on a station-by-station basis to identify confounding factors that can impact an analysis based on these data. For example for the same data shown in Figure 10, where speeds were problematic, the traffic counts were more stable, as can be seen in Figure 11, which plots the total daily vehicles counts over time.

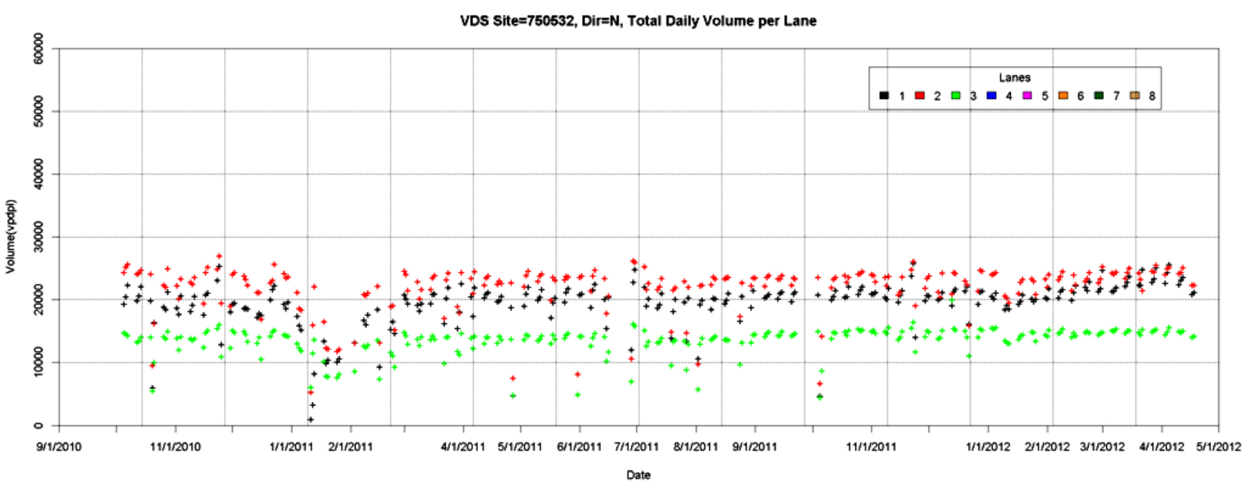


Figure 11: Time Series Plot of Total Daily Traffic Volume

Similarly, the speed-flow plots were studied on a lane-by-lane basis across the study period to look for possible changes in calibration or other issues. Figure 12 shows the plot of the 5-minute aggregated speed and count data converted to hourly numbers. Data from the same month but consecutive years are plotted in the same subplot but in different colors to look for possible changes while holding the seasonality factor constant.

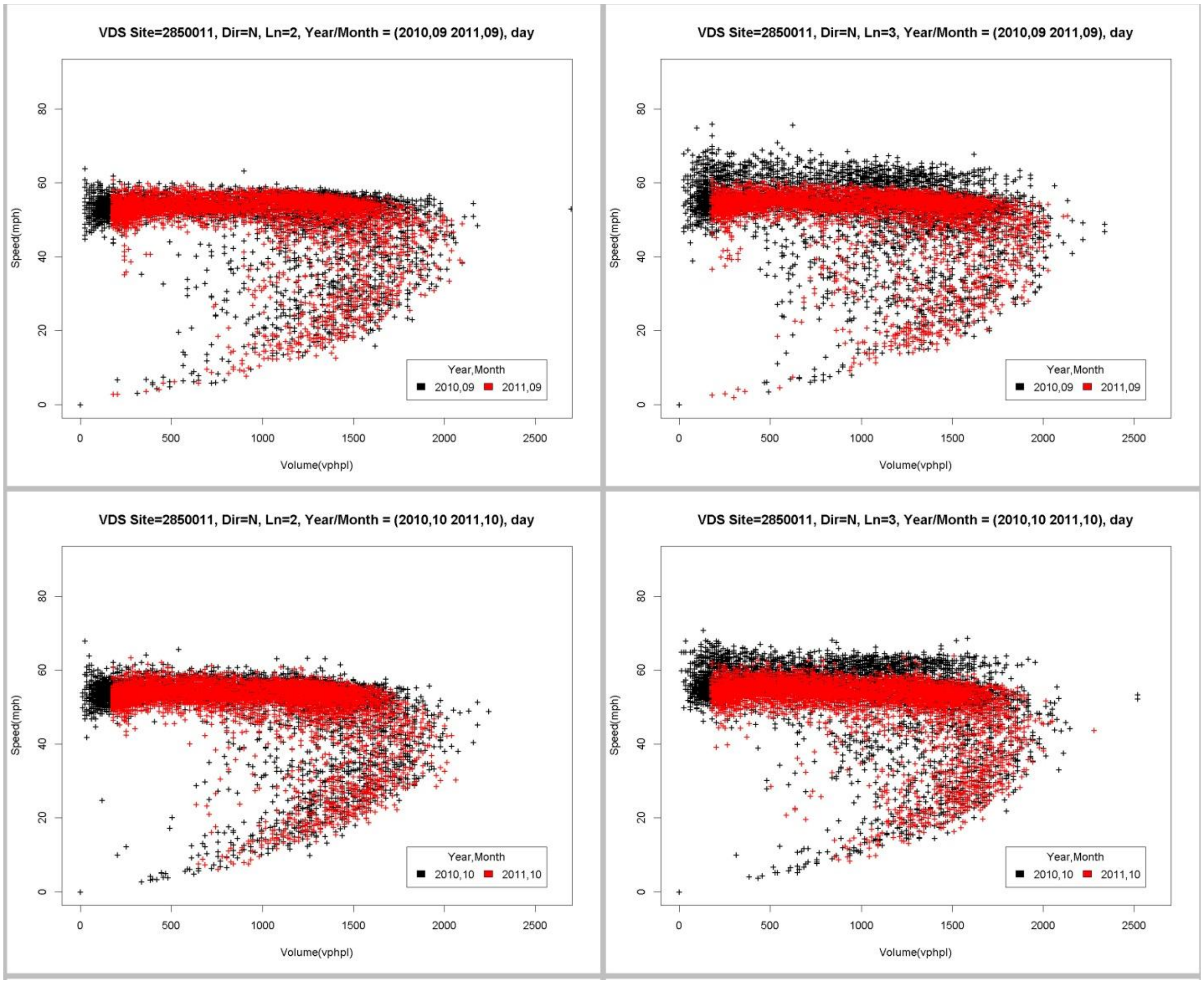


Figure 12: Speed-Flow Plots, 2010/2011 Overlays, September/October, Station 2850011

The speed-flow plots of raw lane by lane data at individual station, such as in Figure 13, helped identify reliable stations (e.g., Station 851485) versus unstable stations (e.g., Station 850501). These plots also helped identify and rectify a cross-lane mapping issue in the data. For example, the data corresponding to General Purpose Lane 5 at Station 851485 here show the characteristics of data in an HOV lane and the data tagged as HOV lane matches better with a general purpose lane's data. There is also a speed calibration issue for the HOV lane for which the average free-flow speeds seem to be reported near 90 mph.

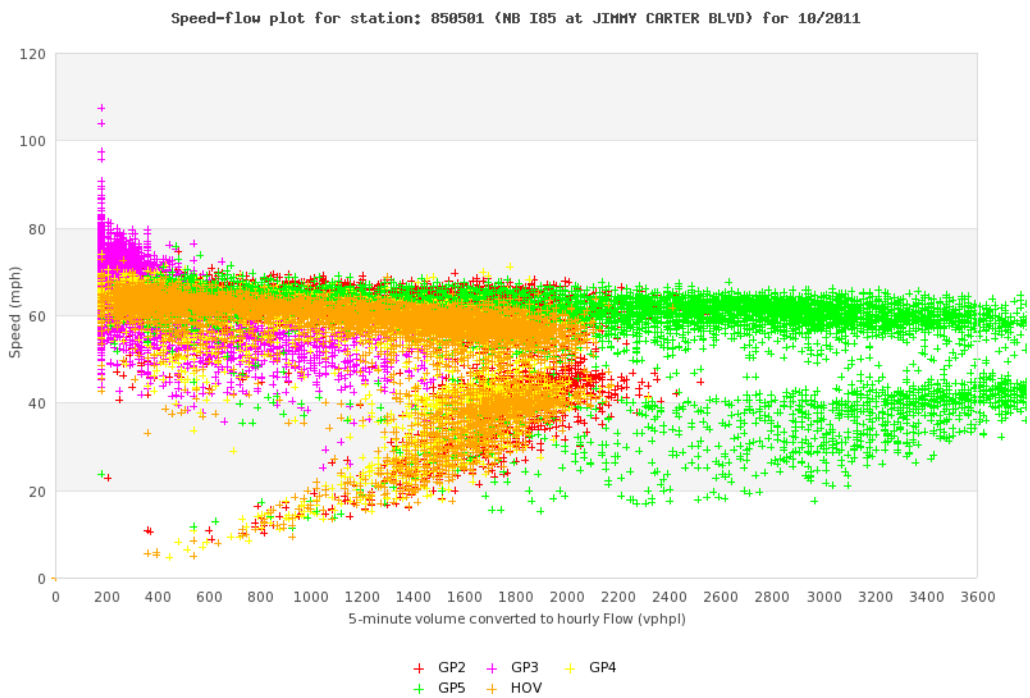


Figure 13: Raw Lane-by-Lane Data
(Reasonable Data vs. Data with Calibration Issues)

4.7 Study Area Data

Given the location relative to the overall corridor and facility demand, and given the quality of available data, Center Way serves as the control volume for before-after vehicle throughput comparisons. In the southbound direction, the Center Way station includes traffic volumes continuing south on I-85 as well as the volumes exiting in both directions at the I-285 interchange. Some additional vehicles do enter the facility after Center Way, usually from Jimmy Carter Boulevard, but fewer than 4% of total vehicles using the southbound managed lane enter the facility after Center Way. The northbound traffic observed at Center Way includes the vehicles that will ultimately reach the end of the managed lane and continue northbound on both I-85 and SR316. However, observations at this point exclude vehicles that enter the lane after Center Way, usually from the interchanges as traffic continues north from Center Way (i.e., Indian Trail, Beaver Ruin Road, and Pleasant Hill Road). About 7% of vehicles using the northbound HOT lane in the PM peak enter after Center Way based upon RFID tag reads. The VDS stations used in these analyses are Station 851498 for AM period and Station 850502 for PM period; locations are provided in Figure 14. The VDS data are of varying quality along the corridor. The data from these two stations were assessed by the research team and appear to be reasonable over the full analytical period.

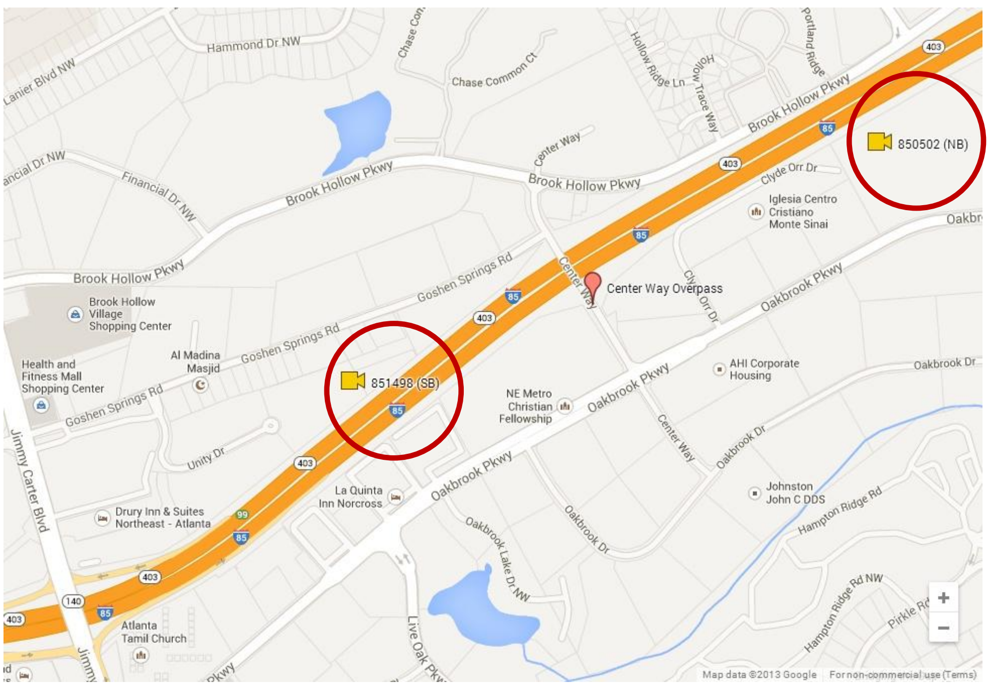


Figure 14: Location of Center Way VDS Stations

4.8 Changes in Vehicle Throughput on the HOV-to-HOT Corridor

Corridor peak period traffic volumes measured at Center Way in both the northbound and southbound directions in the morning and afternoon peak periods declined between the baseline year and the year post-implementation of the HOT lanes. The hours of 6:00 AM to 10:00 AM were used for the AM peak and 3:00 pm to 7:00 pm for the PM peak. The decline occurred over all months, with some monthly differences larger than others. The decline was slightly more pronounced in the morning peak period, with an overall 6.5% reduction in vehicle throughput for the February through September analysis period after HOT opening. The decline in the PM peak period was only 2.8% for the same eight-month analysis period. Figure 15 and Figure 16 present the monthly changes in AM and PM peak period vehicle throughput, respectively.

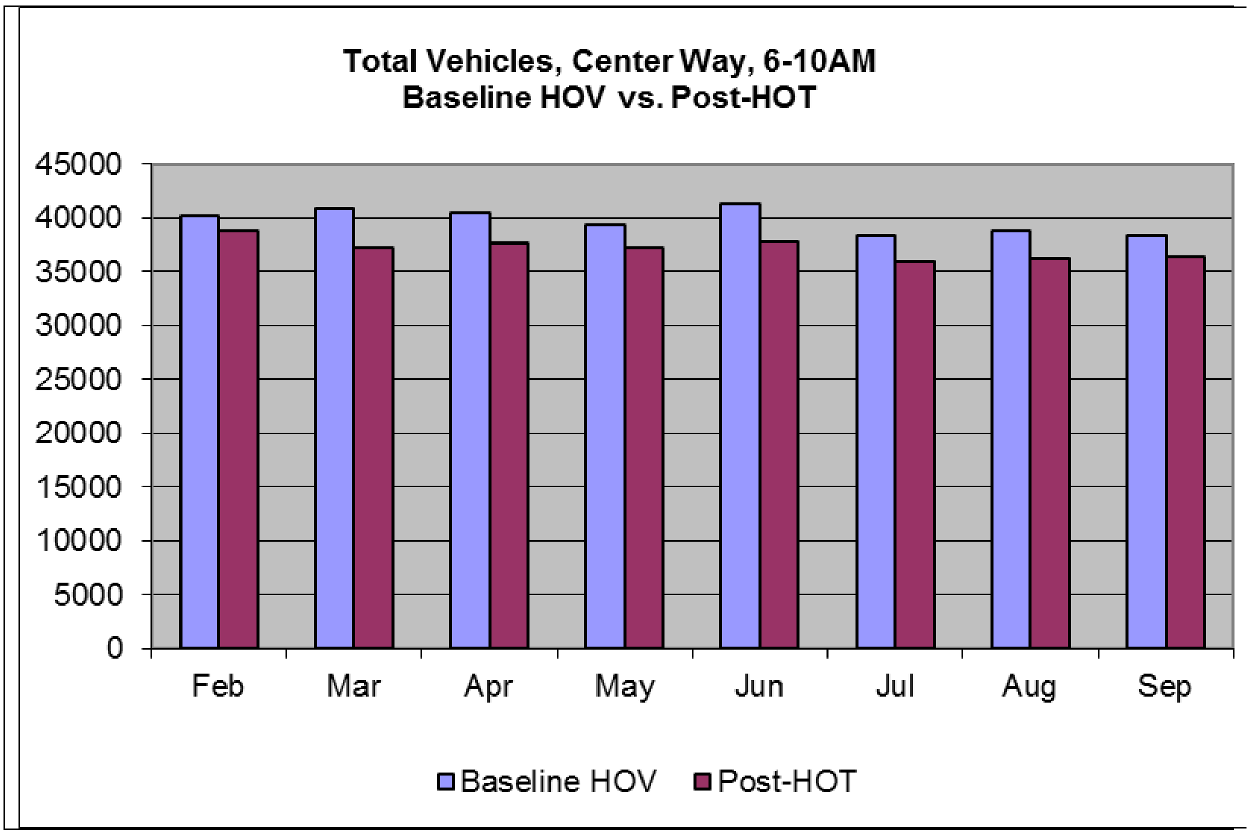


Figure 15: Vehicle Throughput in the AM Peak at Center Way Feb-Sep, Pre- and Post-HOT Implementation

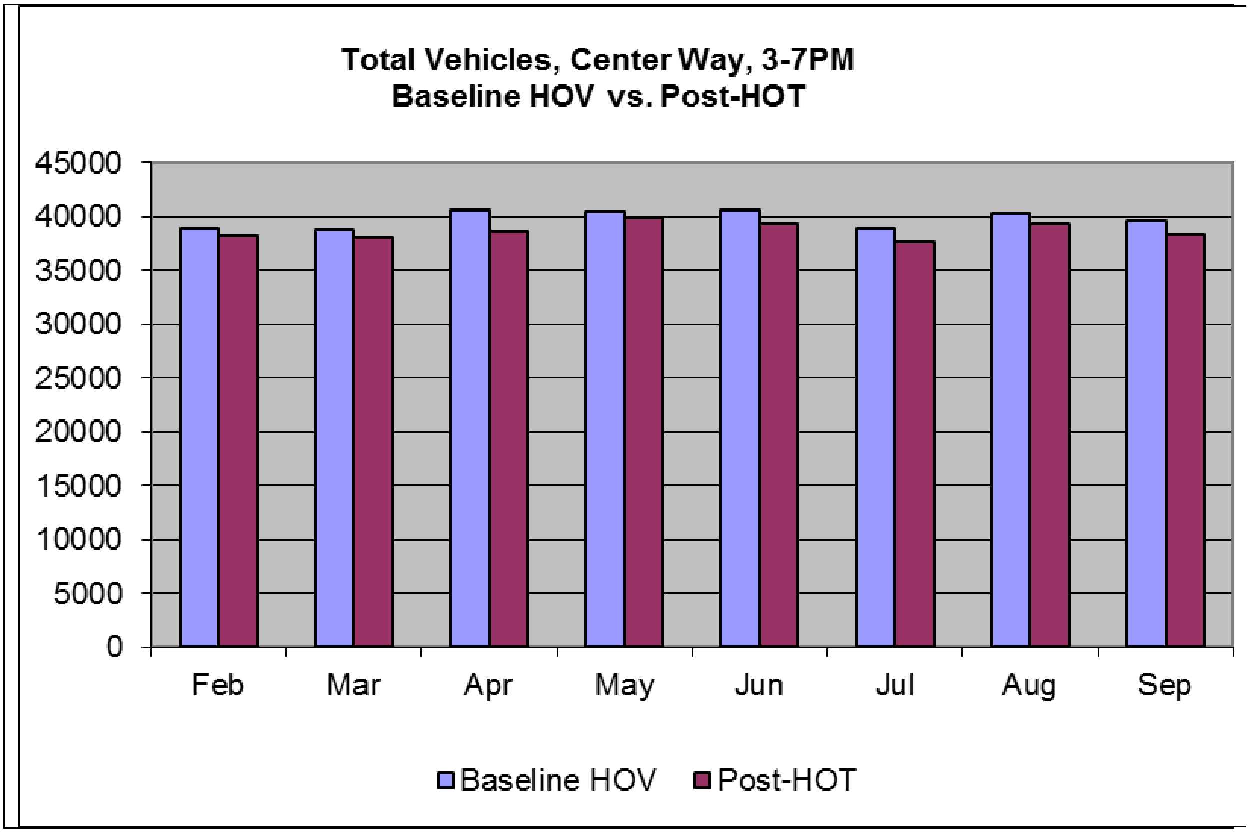


Figure 16: Vehicle Throughput in the PM Peak at Center Way
Feb-Sep, Pre- and Post-HOT Implementation

4.9 Comparative Baseline Analysis for Control Stations

Given the noted reduction in I-85 vehicle throughput between the baseline year and HOT operations, it was important to assess whether the economic downturn may have had region-wide impacts on travel demand that may have led to the reduction in vehicle activity. The research team selected five stations and compared the changes in vehicle activity across these stations for the same time period to the changes noted on the I-85 HOT corridor at Center Way. The following control stations were employed in the before-and-after assessment of vehicle activity:

- I-75 inside the I-285 perimeter, north of the Connector (Brookwood/I-75/I-85 Junction)
- I-75 outside the I-285 perimeter, between I-285 and I-575
- I-75 outside the I-285 perimeter, north of the I-575 junction
- I-285 north arc, between GA-400 and I-75
- GA-400 outside the perimeter, north of I-285

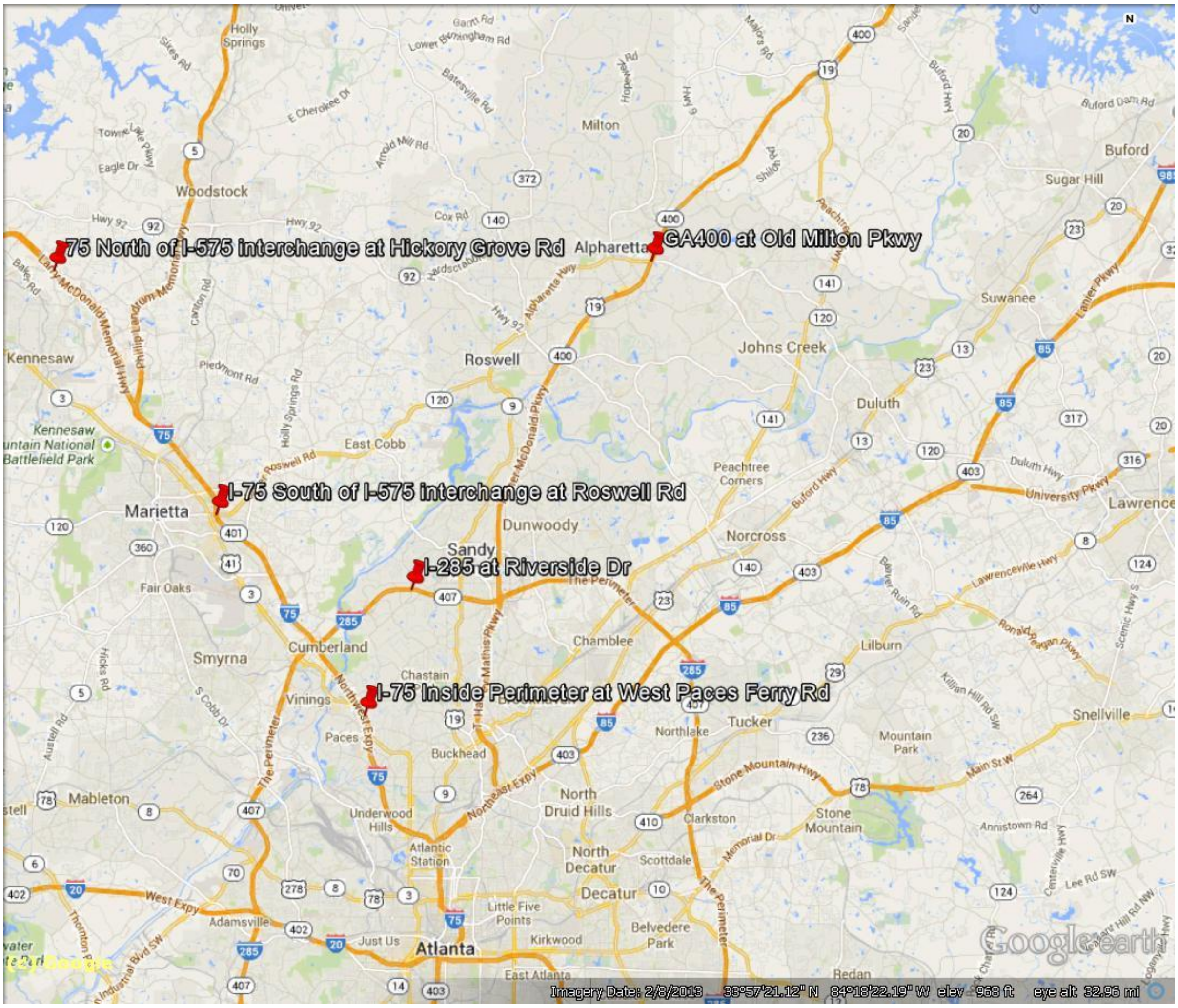


Figure 17: Control Station Map

Control stations were not chosen from the segments directly adjacent to the I-85 HOT corridor to avoid any potential direct or indirect impacts that may have resulted from changes in congestion levels on the nearby traffic network associated with the HOT corridor.

Average volumes (vehicles-per-hour-per-lane) and average speeds (miles/hour) were assessed at the six sites at two resolutions, averaged over four peak hours and averaged over two peak hours per day. The total peak demand was assumed to be reflected in the volumes averaged over a four-hour peak period since the flow is expected to go from free-flow to congested conditions and then back to free-flow within the period. The hours of 6:00 AM to 10:00 AM were used for the AM peak and 3:00 pm to 7:00 pm for the PM peak. In addition, a two-hour peak-of-the-peak analysis was conducted to assess throughput under the most congested conditions. The two-hour peak period is assumed to be 7:00 AM to 9:00 AM in the morning and 4:30 PM to 6:30 PM in the afternoon.

The control study was conducted using weekday data between February 2011 and September 2011 for the before period and February 2012 to September 2012 for the after period. October 2011 to January 2012 data were not used because of the impact of the transition effect of the HOV to HOT conversion (and the corresponding before data between October 2010 and January 2011 were also eliminated). January 2011 data were also eliminated because a significant NaviGAtor software system upgrade (data streaming) occurred during the last week of January 2011. The entire data set used in the analysis was obtained from the NaviGAtor-2 system for consistency.

Figure 18 show the before and after changes in average hourly volume speed in the four-hour AM and PM peak periods. Changes in average peak-of-the-peak throughput are reflected in the two-hour peak period charts presented in Figure 19. Looking closely at the AM Peak SB chart in Figure 18, the I-75 station inside the perimeter shows an increase in the demand as well as average speed. However, as presented in Figure 19 and Figure 20, this station stays in free-flow even in the peak-of-peak period. The I-85/I-75 connector serves as an internal bottleneck that limits the flow into that early section of I-75 such that commuters do not experience congestion at that location until reaching I-285 (Guensler, et al., 2001). Hence, the increase in demand at this location can be accommodated with existing capacity without imposing an impact on speed. The noted increase in the speed is more likely to have resulted from a recalibration of VDS equipment, rather than from a real increase in vehicle speeds. If there was a recalibration of the station, which should have involved a change in the view of the video-detection-camera, volume data may also have been affected, but it is not possible to verify the impact.

None of the control sites show any substantial difference (±5%) in traffic volumes. A couple of the stations indicate a sizeable variation in speeds which is more likely tied to recalibration of the equipment at these stations. For example it is known that the GA 400 stations were recalibrated just before the opening of the shoulder lanes in May 2012.

Appendix A: Baseline Station Traffic Volume Time Series Plots) provides time series plots of the flow rates for the six stations. The rates are averaged over weekdays from the eight-month periods in 2011 and 2012. The flow rate lines from 2011 and 2012 overlap across the majority of the plots. The plot for station 4000060, the GA400 NB station in the PM peak, shows a consistent but small change in the flow rate across the entire period as was noted earlier from the PM four-hour Peak NB plot in Figure 18.

In summary, the control stations did not show any particular direction of change in traffic demand as evidenced by no significant change in vehicle throughput or speeds across the five stations examined in detail. One of the stations showed an increase in demand beyond 5% while another showed a decrease beyond 5%. The rest varied within a 5% bound.

The peak-of-peak average over multiple lanes varies in the range of 1300 vphpl to 1700 vphpl. This seems to be on the lower side, considering the fact that some of these sites have HOV lanes and the averages include the volume in the HOV lanes. Normally the rates would be expected to be in the 1800+ vphpl range in the absence of geometric changes such as exit/entrance lanes, lane-drops/additions etc. Although, these data are averaged over a 2-hour period, and a better peak-of-peak comparison may need to be conducted over a shorter averaging period (say 15 to 30 minutes).

In light of the changes in traffic volumes noted at the five control stations during the same period, the noted 2.6% reduction in vehicle throughput on the I-85 HOT corridor during the afternoon peak seems to be within reasonable bounds of a natural change in regional demand. However, the reduction of vehicle throughput of 6.6% during the morning peak period seems unlikely to be associated solely with a regional change in demand. Given that afternoon traffic declined at a much lower rate, it seems reasonable that the reduction in morning traffic may be associated with a combined effect of natural reduction, foregone morning trips, trips deferred to the afternoon, and trips diverted to other routes. Unfortunately, a household panel study was not implemented for the corridor. The original planned study would have monitored changes in commute activity for 1200 households and gathered ongoing travel diary data. In the absence of such data, there is no way to assess whether the changes in corridor demand are directly linked to the implementation of the HOT lane.

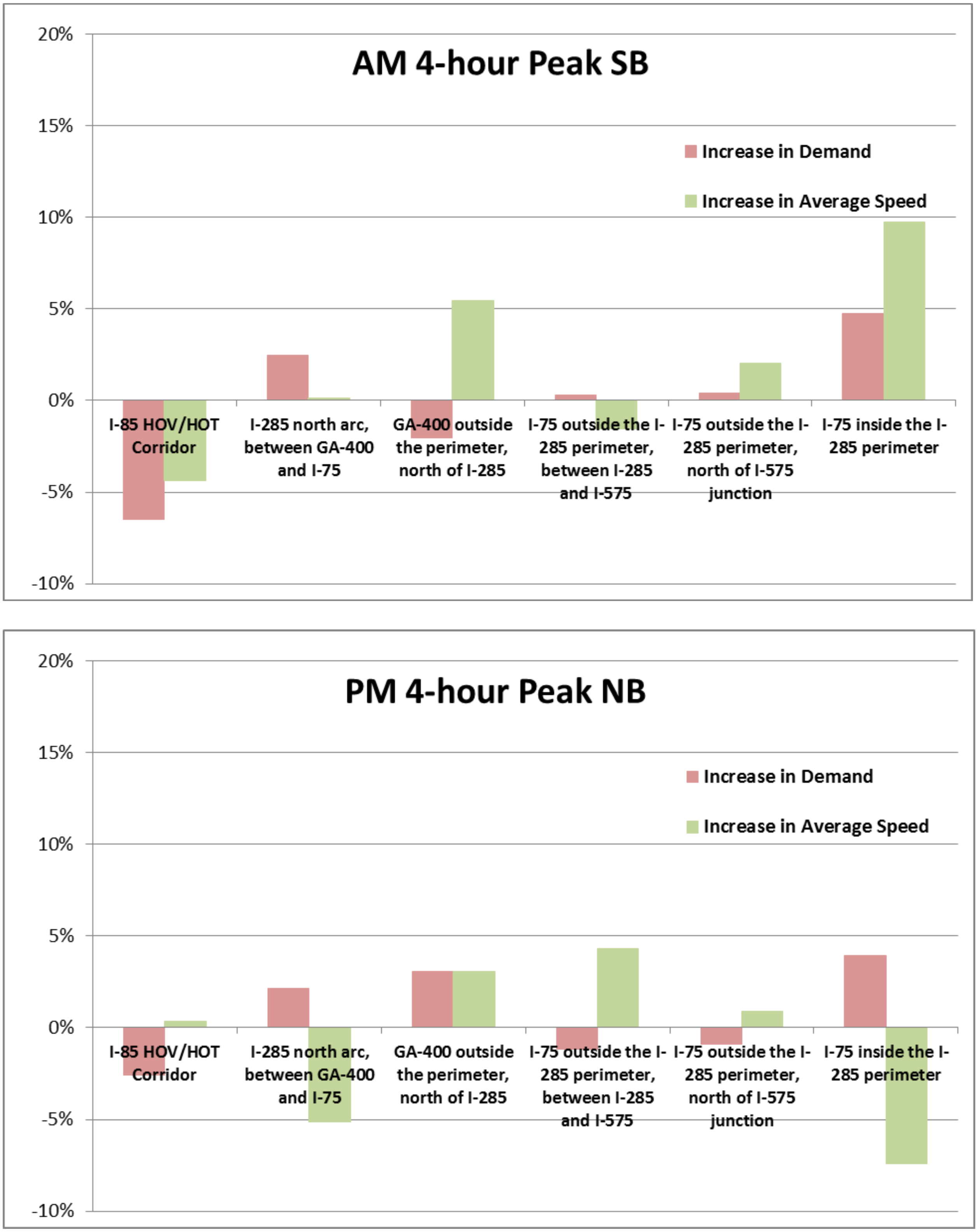


Figure 18: Percentage Change in Average Hourly Demand (four-hour peak)

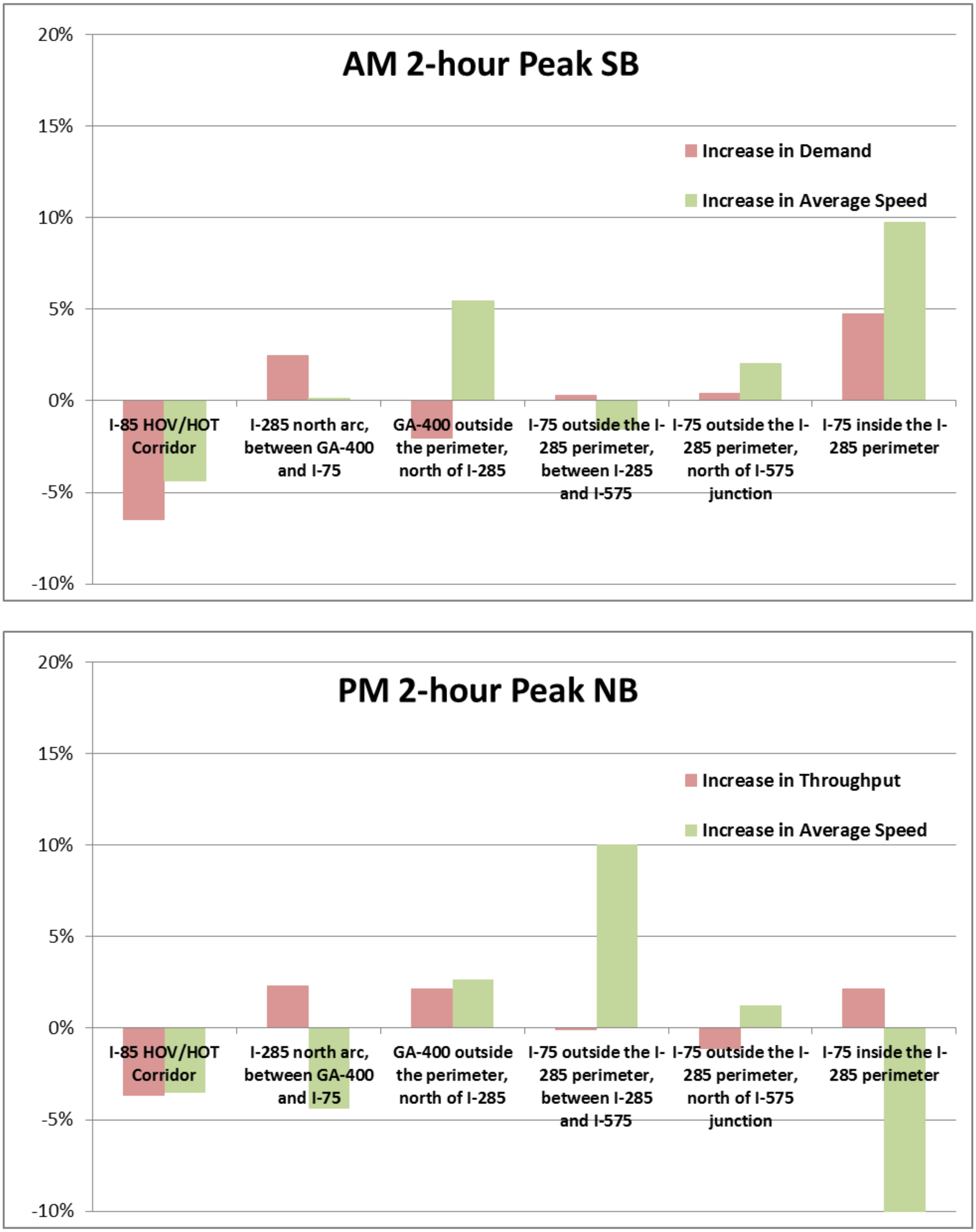
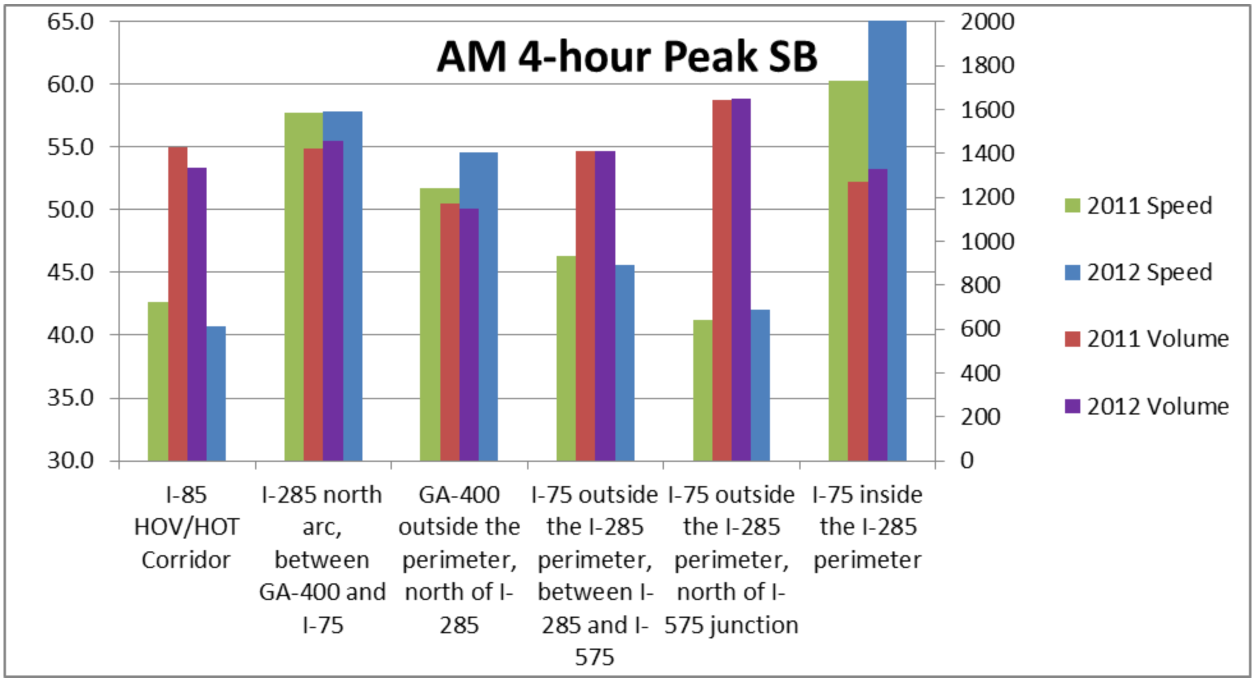


Figure 19: Percentage Change in Average Hourly Demand (two-hour peak)



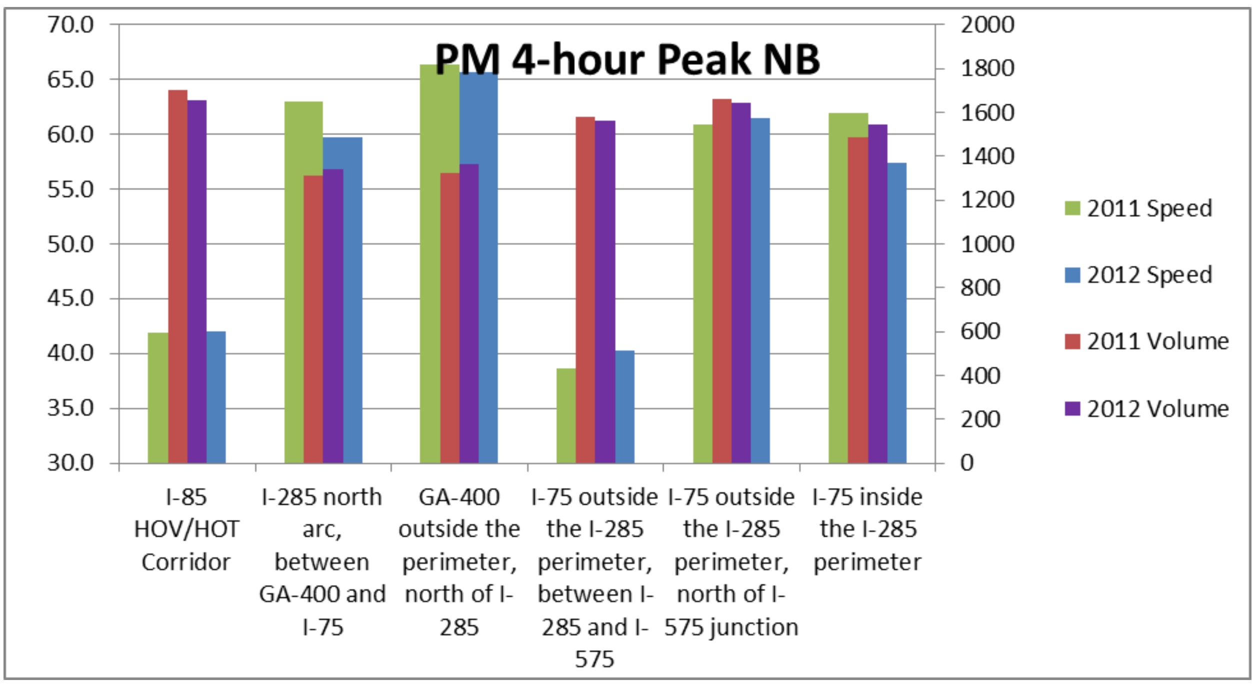
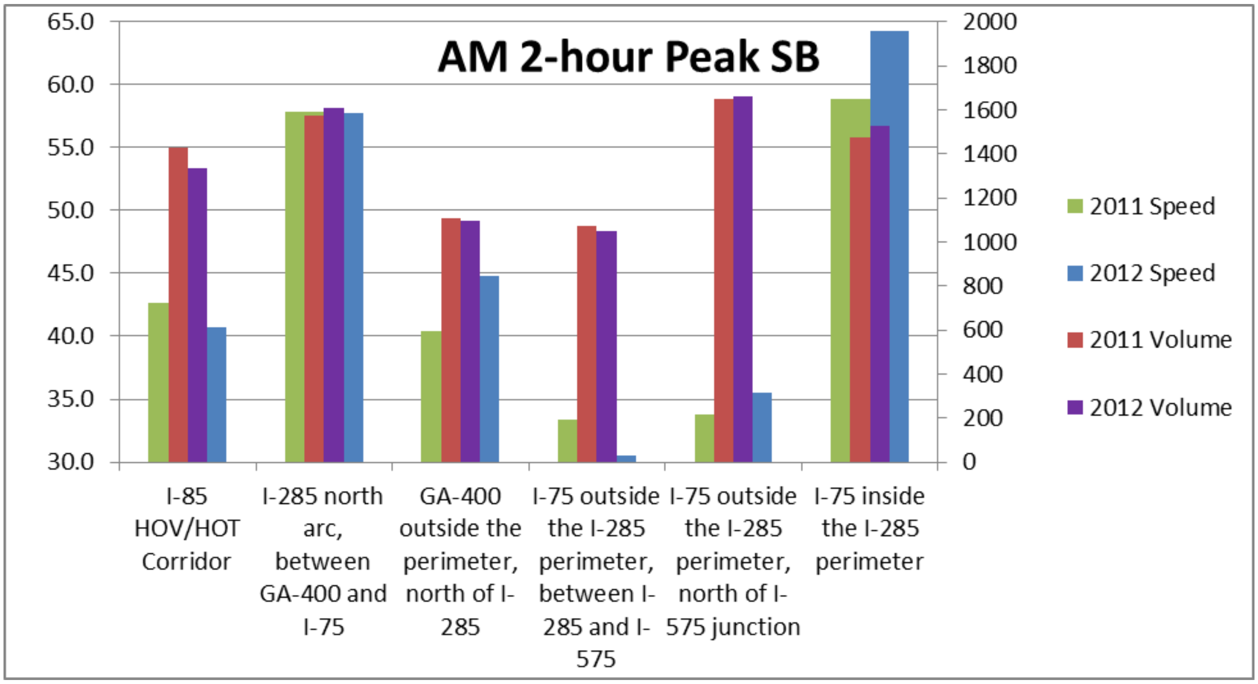


Figure 20: Average Hourly Demand (four-hour peak)



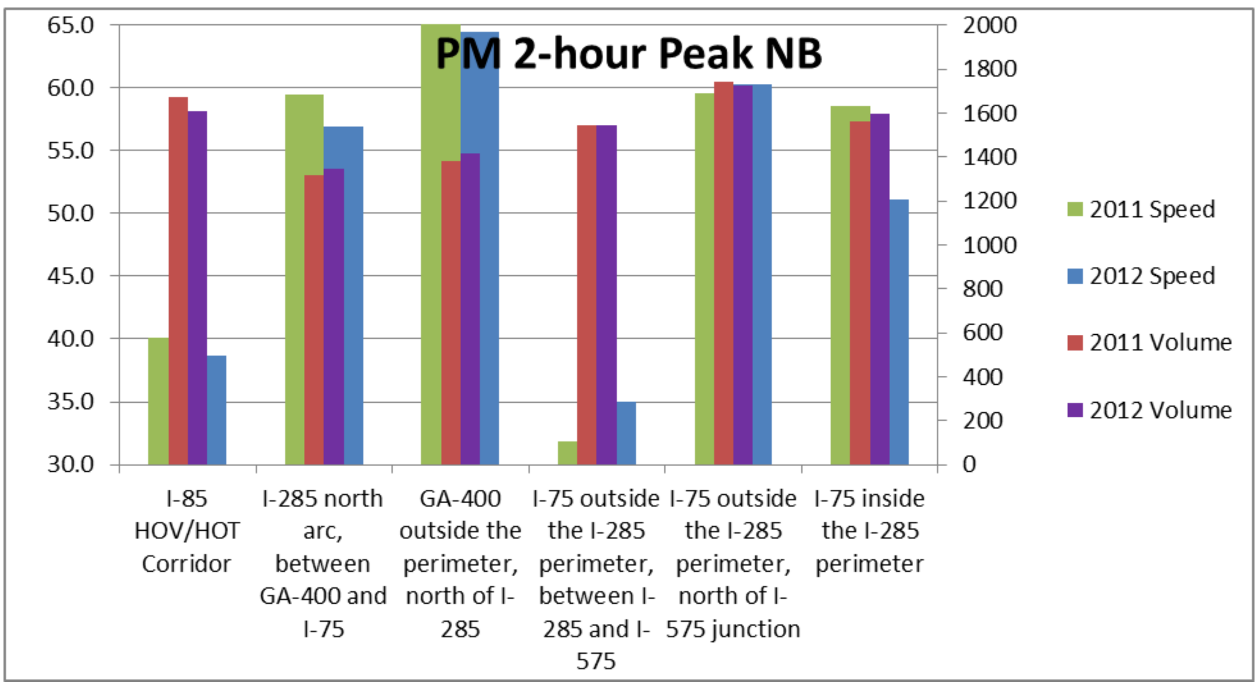


Figure 21: Average Hourly Vehicle Throughput and Speeds (two-hour peak-of-peak)

4.10 Vehicle Classification Data

The corridor does not include any permanent highway performance monitoring system stations (HPMS) that provide automated vehicle classification data, including counts by light-duty automobiles, medium duty trucks, heavy-duty trucks (by FHWA classification), buses, etc. As such, the classification scheme employed during occupancy data collection was implemented for this study. As occupancy data were recorded, vehicles were classified as light-duty automobiles, sports utility vehicles, and heavy-duty vehicles (see forthcoming Chapter 5, and Appendix B: Vehicle Class Definitions). Motorcycles were ignored in the analysis. Given the random sampling nature of data collection, the vehicle classification distributions (percentage LDVs, SUVs, and HDVs) were assumed to apply to the monitored traffic volumes discussed earlier. Because the occupancy data differ across these classifications, with SUVs generally carrying slightly more passengers on average compared to light-duty automobiles, the monitored traffic volumes (vehicles/hour) were split into vehicle class volumes, and then occupancy values by vehicle class were assigned to the vehicle throughput by class to estimate person throughput (persons/hour) by class.

Buses and vanpools carry a significant number of passengers through the corridor. These modes were also expected to be significantly impacted by HOT operations (improving level of service for alternative modes and providing a financial incentive for persons to carpool or take transit). Hence, methods specifically addressing the throughput of express buses and vanpools are implemented in later chapters of this report.

5 Vehicle Occupancy

In this work, "vehicle occupancy" is defined as the number of persons in a vehicle, including the driver (persons/vehicle). A single-occupant vehicle (SOV) contains only the driver. In Georgia, a high-occupancy vehicle (HOV) is considered to be vehicle that contains a driver plus at least one other person (i.e., one or more passengers). Thus, HOV2 is a carpool that includes the driver plus one passenger, HOV3 includes a driver plus two passengers, HOV3+ includes the driver plus two or more passengers, etc. Vehicle occupancy data are needed to estimate person throughput for the I-85 corridor, where person throughput (persons/hour) equals vehicle throughput (vehicles/hour) multiplied by vehicle occupancy (persons/vehicle).

Existing methodologies for collecting vehicle occupancy range from manual methods to automated technologies, and numerous hybrid variations. The research team examined the advantages and disadvantages associated with each data collection method in the literature and developed a Georgia Tech methodology for data collection on the Atlanta I-85 HOV-to-HOT conversion corridor. D'Ambrosio (2011) outlined the basis for the new methodology and data collection system. The method and system are based upon a comprehensive literature review of existing methods, assessment of safety considerations and other constraints and characteristics of the sites along the study corridor, and the capabilities of available equipment and manpower.

The traditional roadside/windshield method is the most commonly used method to collect data (Heidtman, et al., 1997) because of its simplicity and equipment requirements. With this method, a data collector is positioned such that they can see through a passing vehicle's windshield and side windows as the vehicle passes to visually count the number of occupants. The occupancy value is then recorded using an electronic counter or on a worksheet. The strengths of this method are the minimal equipment required, ease of implementation, and high percentage of collected data for passing vehicles, usually in the 75-90% range. However, there are several limitations to this method including a relatively short view time into the vehicle (particularly at high speeds), the limitation of collecting data only during daylight hours, and concerns with balancing the safety of the observer with the ideal perspective for viewing inside the vehicle. Another notable limitation is that the method is labor intensive, which can degrade observer performance over time. For this project, the team developed a modified windshield survey method for collecting vehicle occupancy data as described in the next report sections.

5.1 Vehicle Occupancy Field Data Collection

In selecting sites for occupancy and license plate data collection, each of the 15 overpasses within the corridor were visited and assessed for data collection capabilities and safety (D'Ambrosio, 2011). Four sites were initially selected for the data collection effort that satisfied safety and observation criteria that also allows sampling to be distributed throughout the 15.5-mile corridor. Before the data collection began, an additional northbound traffic monitoring site at the southern tip of the corridor was included to collect a data set for vehicles entering the HOT corridor. Data were collected at five sites: Chamblee Tucker

Road (CTR), exit 94; Jimmy Carter Boulevard (JCB), exit 99; Beaver Ruin Road (BRR), exit 102; Pleasant Hill Road (PHR), exit 104; and Old Peachtree Road (OPR), exit 109, during the morning and afternoon peaks (Figure 22). The southbound direction (towards downtown) was monitored during the morning peak and the northbound direction (away from downtown) was monitored during the PM peak. At the Chamblee Tucker Road site, only the afternoon peak was monitored since the site did not have a safe location to observe southbound traffic. Data were collected during both the morning and afternoon peak periods at all locations, except for Chamblee Tucker Road (northbound, afternoons only).

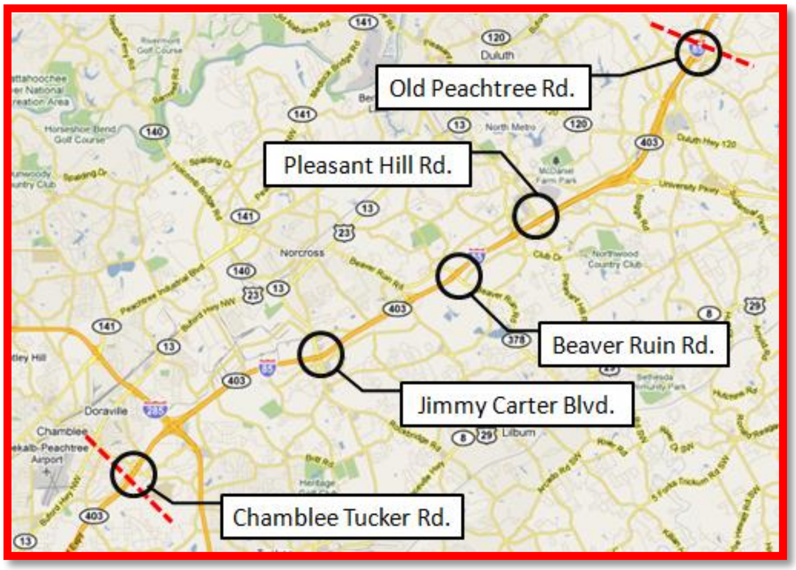


Figure 22: Occupancy Data Collection Locations

For tracking purposes, lanes at each site were numbered from the inside lane to outside lane. In the database, the managed lane (HOV or HOT lane) was labeled as lane "0." The lane directly to the right of the managed lane (the fast lane) was labeled general purpose lane "1", then "2", "3", etc. with the outside lane numbered the highest (see Figure 23). In this report, the managed lane will be labeled HOV or HOT, and general purpose lanes are labeled GP1 through GP5. For the selected data collection sites, all but Old Peachtree Road have a managed lane and five general purpose lanes. At Old Peachtree, there is 1 managed lane and only 4 general purpose lanes.

The team collected vehicle occupancy data for eight consecutive quarters. Four data collection sessions were pre-conversion HOV operations, and four sessions were post-conversion HOT operations. During each session, two hours of data were collected. Morning peak period data were collected from 7:00 AM to 9:00 AM and afternoon peak period data were collected from 4:30 PM to 6:30 PM on Tuesdays, Wednesdays and Thursdays. The research teams deployed well in advance so that data collection could begin on time. Data collection was cancelled during rain storms, and make-up sessions were conducted later in the same quarter. Data were collected for at least two days per week at each site, and almost always on all three days.

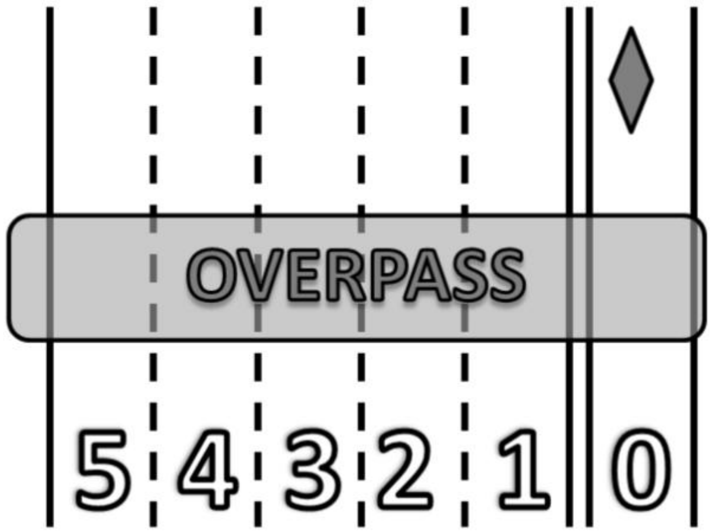


Figure 23: Lane Numbering Configuration

Data collection was conducted from the elevated portion of the gore area at freeway exit ramps. These locations meet the primary criteria for observation: 10-20 feet above the roadway, distances between 10 and 50 feet from the roadway, located where observers will not distract drivers, convenient parking and access to the site, minimal expected weaving movements in observed traffic, and located to minimize glare given the angle of the sun. Figure 24shows data collection by the undergraduate assistants.

Figure 24: Vehicle Occupancy Data Collection

Each data collector was assigned to record data from one lane during each deployment. Data collectors positioned themselves between the ramp and the mainline on the elevated slope of the overpass ramp at whatever location that gave them their best view into vehicles as they passed. Data collectors began watching the vehicle through the windshield as it approached, and visually scanned the vehicle seats through the side windows as well as the vehicle passed by. Given the proximity to the traveled way, no binoculars were needed for data collection (in fact, binoculars and spotting scopes were found to hinder data collection because the vehicles were so close that visual tracking of the vehicle interior as the vehicle passed by was more difficult). The field staff used a new netbook-based data collection system created specifically for this deployment.

5.2 Occupancy Data Collection System

The updated version of the traditional roadside/windshield method developed for this project employed small netbook computers and refaced wired USB numeric keypads (wireless were problematic) for vehicle class and vehicle occupancy input (D'Ambrosio, 2011). The data collectors carried the netbook in small backpacks. The numeric keypads were modified to remove keys that were not used. The keys were re-labeled to show vehicle classes, occupancy types, and other elements. Researchers observed the vehicle, pressed the applicable vehicle class key, followed by the applicable vehicle occupancy key. Keys to log a missed vehicle (e.g., not enough time to see into the next vehicle after recording a value) as well as to mark the last record as incorrect were included ("C", for 'clear'). Figure 25 illustrates the equipment employed during data collection. A Perl script recorded the keystrokes into an ASCII file along with the timestamps. The script also sent an audio alert to the data collector when a record was successfully entered.

To minimize data collection complexity, vehicles were divided into only three classifications:

- Light Duty Vehicle (LDV) - Sedans, sports cars, crossover vehicles, etc.
- Sports Utility Vehicle (SUV) - Pick-up trucks, minivans, and station wagons, etc.
- Heavy Duty Vehicle (HDV) - Large trucks, buses, 3+-axle vehicles, etc.

Motorcycles were flagged as LDVs, commuter vans were flagged as SUVs, and express buses were flagged as HDVs. Appendix B: Vehicle Class Definitions contains the visual identification charts that were used in the data collection.

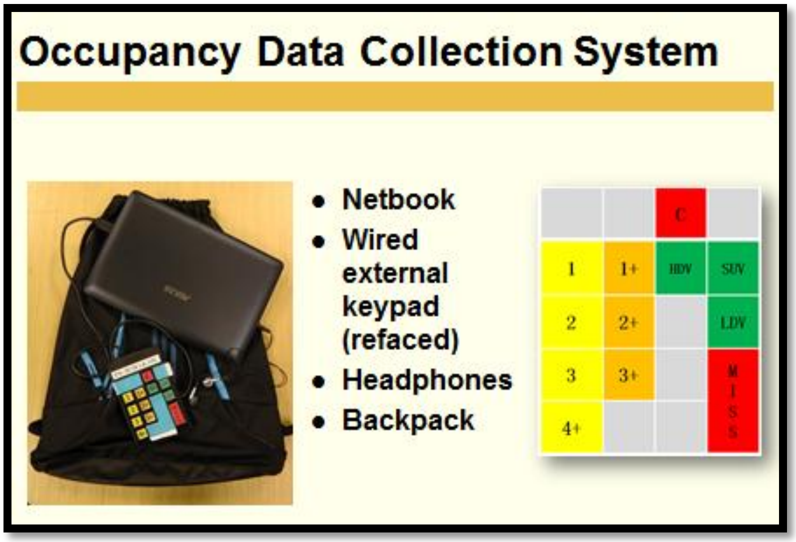


Figure 25: Occupancy Data Collection System

Vehicle occupancy types included 1, 1+, 2, 2+, 3, 3+, and 4+. The "plus" occupancy types were included to capture the uncertainty of data collection due to tinted glass, or sun glare due to reflection. The data collector recorded a 'certain' numeric value from the left hand keypad column (1,2,3,4+) when they were certain that there were only that number of persons in the vehicle. For example, if they could see two persons and see every seat, they would record a value of "2." However, if tinted windows obscured the back seat, the data collector would record "2+" to indicate that they were sure that they observed two persons, but that there may have been more individuals in the back seat.

Although the literature review did not identify previous use of 'uncertain' values, the 1+, 2+, and 3+ values were deemed important by the research team. Had researchers not recorded these values, some of the available information would have been lost. There are relatively few carpools operating on the corridor. Hence, had the team not recorded any data for vehicles that they knew contained a minimum of two persons but could not determine the total, the resulting percentage of carpools would have been biased low. The allocation of 'uncertain' values to vehicle occupancy is discussed below.

5.3 Establishing Average Vehicle Occupancy for Uncertain Values

To calculate the average vehicle occupancy, the uncertain values either need to be discarded or re-assigned to certain values. The research team considered assigning a standard value of 1.5 for 1+, 2.5 for 2+, 3.5 for 3+ and 4.5 for 4+. However, this assumes that almost half of the uncertain values have at least one more person in the car. Such an assumption cannot be substantiated. The uncertain values were assigned to those vehicles *because* the observer could not see the other seats in the vehicle, not because half of these vehicles contained an additional person. Hence, the team decided to redistribute the uncertain values to the certain values in the same proportion in which the certain values were observed in that session. The 1+ values were redistributed to 1, 2, 3, and 4+ values, the 2+ values were redistributed to 2, 3, and 4+ values, and the 3+ values were redistributed to 3, and 4+ values. By redistributing the uncertain values into certain values in proportion to the ratio of certain values during each session, we help ensure that the effects of all factors including the collector bias/error are not diminished by averaging.

As an example of the impact of using and allocating uncertain occupancy values, the LDV occupancy data collected for 529 vehicles using the HOV lane, from 7:00 AM to 8:00 AM, during the second day of data collection in the first week of February 2011, are provided in the first three columns of Table 5. If the uncertain values are not employed in the analysis of occupancy, the 1+, 2+, and 3+ counts are eliminated from the analysis. The resulting percentage of vehicles by 1, 2, 3, and 4+ categories appears in Table 5 Column 5. Applying 1, 2, 3 and 4.5 persons per vehicle to each applicable row yields an average vehicle occupancy value of 2.02 persons/vehicle. However, when the uncertain values are allocated to 1, 2, 3, and 4+ categories as outlined earlier, the resulting percentage of vehicles by 1, 2, 3, and 4+ categories appears in Table 5 Column 6, yielding an average vehicle occupancy value of 2.08 persons/vehicle. The allocation of the uncertain values always increases expected average vehicle occupancy if 2+ and 3+ values are present in the data stream. In this example, the estimated occupancy increased from 2.02 to 2.08 (2.7%) which is significant in terms of person throughput. However, given the low percentage of 2+ and 3+ values observed in the field, the reallocation of uncertain values has only a small overall impact on the final estimation of person throughput.

Table 5: Impact of Using and Allocating Uncertain Occupancy Values

OCC Value	Vehicles Observed	Percent Observed		Percent w/o Allocation	Percent with Allocation
1	7	1.3%		2.0%	1.4%
1+	29	5.5%			
2	335	63.3%		94.4%	90.3%
2+	120	22.7%			
3	12	2.3%		3.4%	7.6%
3+	25	4.7%			
4+	1	0.2%		0.3%	0.6%
Total	529	100%		100%	100.0%
Occupancy (persons/vehicle)				2.02	2.08

After redistribution of the uncertain values, the occupancy values remain in four occupancy categories: 1, 2, 3, and 4+. For each vehicle in each occupancy class, the number of persons in the vehicle is defined by the occupancy class. However, the 4+ occupancy type was assigned an occupancy of 4.5 persons/vehicle for lack of any better assumption that could be made. A significant portion of the vehicles in the 4+ occupancy category were vanpools and transit buses, which each carry numerous passengers. These vehicle classes are addressed through a supplemental process addressed in Chapter 9 and Chapter 10.

6 Review and Analysis of Vehicle Occupancy Field Data

The HOV-to-HOT performance evaluation study deployed teams of graduate and undergraduate students to collect vehicle occupancy (persons/vehicle) data by visually identifying the number of persons inside vehicles. Data collection procedures were standardized to minimize data collection and entry errors, with the help of instructions to data collectors, hardware, and software. However, the visual identification of the number of persons in a vehicle is subject to potential data collector bias. It was necessary to statistically assess the data to identify possible sources of bias or errors in occupancy data collected by individual data collectors and to filter such data from the analysis.

Intuitively, we expect factors such as season, data collection site, morning peak/afternoon peak, and lane type to affect vehicle occupancy. These factors continue to affect occupancy both before and after the conversion of HOV to HOT. Hence, it is important to understand the factors that affect vehicle occupancy along the I-85 corridor to assess the effects of the HOV to HOT lane conversion on vehicle occupancy. The objectives of this chapter are:

- Statistically asses bias/errors of data collectors on vehicle occupancy data
- Identify various factors that affect vehicle occupancy along the I-85 corridor

Standard predictive models, such as linear regression models are global models which have a single predictive formula designed to represent the entire data space [1]. However, when data have numerous features that interact in complicated non-linear ways, assembling a single global model may not effectively represent the data space. In such situations, partitioning or sub-dividing the data space into smaller regions where the interactions are manageable can be an effective solution. The data analysis reported in this chapter employs regression tree modeling (Cosma, 2013). In this process, the data space is recursively partitioned until small chunks of data space that can be fitted with simple models. The global model has two parts, the recursive portioning into cells and simple fit for the data in the cells.

Regression trees help to quickly assess data. The tree method highlights the important variables that affect variability in the data. Regression trees can handle jagged responses as well as smooth responses. The research team used these regression tree methods to analyze the data because the methods are easy to use and are effective for quickly identifying the factors that may be affecting observed vehicle occupancy.

Outliers are extreme observations that affect the mean response but that may be due to data collector bias or device error. The presence of extreme values in the data will move model results toward outlier values in the process of selecting beta coefficients that minimize model error. However, outliers may be true values that represent rare cases or cases that are influenced by another independent variable not used in model development [2]. If the extreme value is influenced by another independent variable not used in the model, these values carry significant information about the data and the mean response should include rare cases. Therefore, analysts must be very cautious about identifying extreme values as outliers and eliminating them from analysis. Neter, et al. (1990) suggests that outliers should only be discarded if there is direct evidence that they represent device error or data collection bias.

The research team has filtered data only when there was direct evidence of bias as will be explained step-by-step in the analysis sub-sections that follow.

6.1 Regression Tree Analysis

To statistically assess variables that may affect vehicle occupancy on the corridor and to identify potential bias that may have been introduced into the data by individual data collectors, regression tree modeling techniques were applied. Data that were significantly different from comparable data collected on the corridor over two-hour time periods that would significantly affect analytical results are identified, investigated manually, and ultimately filtered from the analysis if bias is identified. Regression trees examine the potential effect of variables on vehicle occupancy: data collection site, pre/post conversion, season/quarter, day of week, session (morning/afternoon peak), lane type (general purpose, high-occupancy vehicle lane and high-occupancy toll lane), and general purpose lane number (i.e., inside vs. outside lane impacts).

6.2 Day of Week Analysis

The first analysis was to see whether day of week had any significant effect on vehicle occupancy. Most of the data were collected on Tuesdays, Wednesdays, and Thursdays, but a few sessions were collected on Mondays (approximately 4%). Intuitively, the researchers expect to observer different travel behavior habits on Mondays than the other weekdays. The first regression tree run included all variables to see the relative effect of day of week compared to other variables (Figure 26).

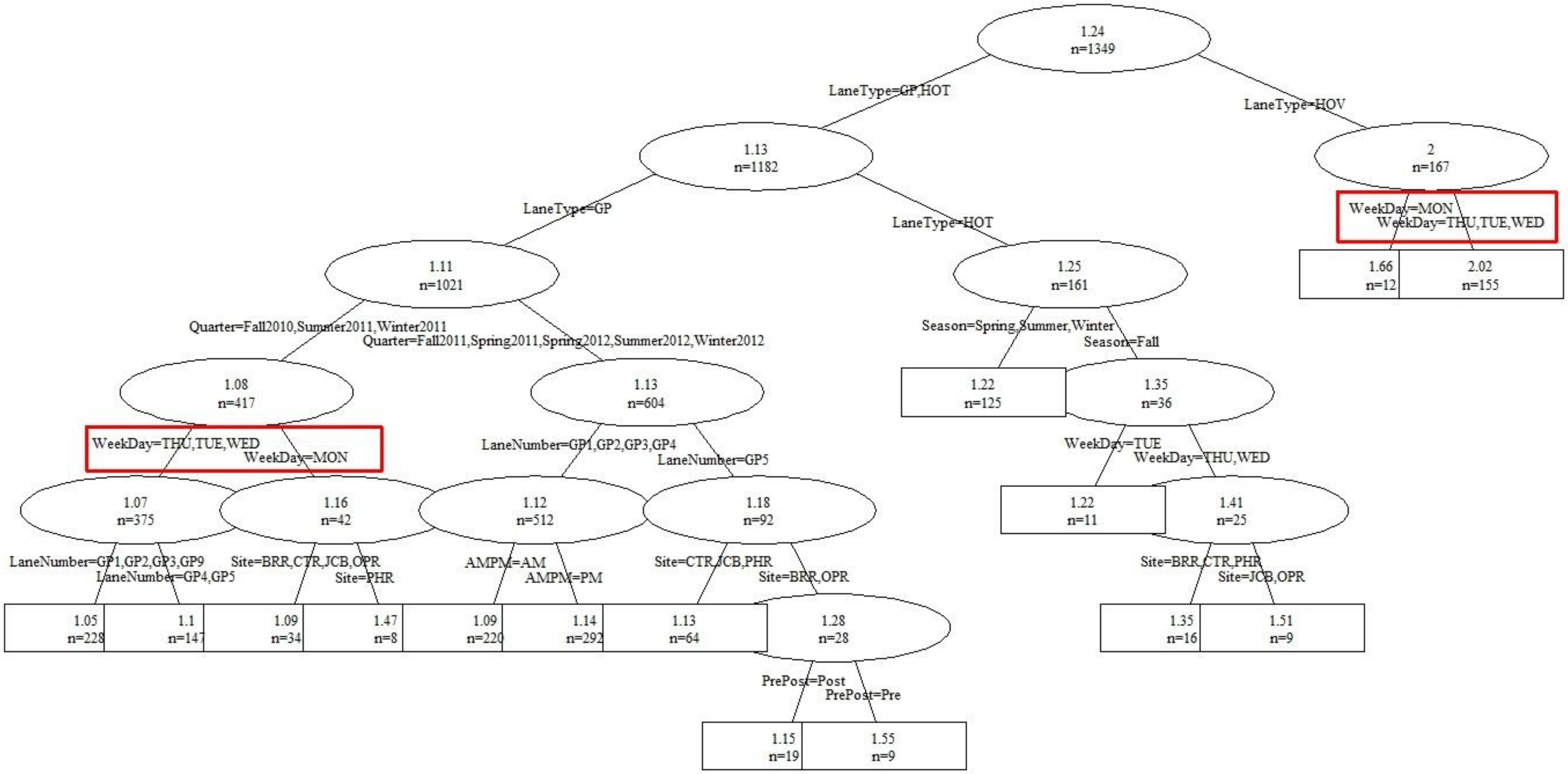


Figure 26: Regression Tree to Identify Day of Week Impacts

In Figure 26, the first split is by the lane type. On the high-occupancy vehicle (HOV) lane type branch of the tree, the next important factor was day of week, where Monday is different from other Weekdays as the researchers expected. On the general purpose (GP) and HOT side of the tree, Mondays again split from other weekdays at a level below the data collection quarter variable. The researchers conclude that occupancy data collected on Mondays were significantly different from other weekdays. Because these data represent only 4 percent of the total data collection sessions, and because there were no data collected on Mondays in the post-conversion HOT period, these data were excluded from the performance evaluation. Only data collected on Tuesdays, Wednesdays, and Thursdays are used in analysis throughout the rest of this report.

6.3 Average Vehicle Occupancy and Potential Data Collector Bias

The research team next studied the data to identify any potentially significant data collector bias that would affect average vehicle occupancy results, using a regression tree that included the data collector identification numbers along with the other variables. The resulting regression tree is shown in Figure 27. The data collector identification variable is significant next only to the lane type all through the tree. None of the other variables enter into the regression tree model.

To search for potential data collector bias, the research team looked for leaves on the tree representing a small number of data collection sessions (less than 15/1295 sessions). In Figure 27, four such nodes were identified. The research team next compared the data collector identifiers across these four leaves to identify data collectors who were repetitively different from other data collectors. Three data collectors repeated at least twice in these 4 leaves indicating that their data were very different than data collected by other data collectors. After reviewing the data from these three individuals, the research team concluded that there was a significant bias/error that made their data significantly different from others across multiple lane types. These data were removed from the data set to assess the impact of the data on overall average vehicle occupancy.

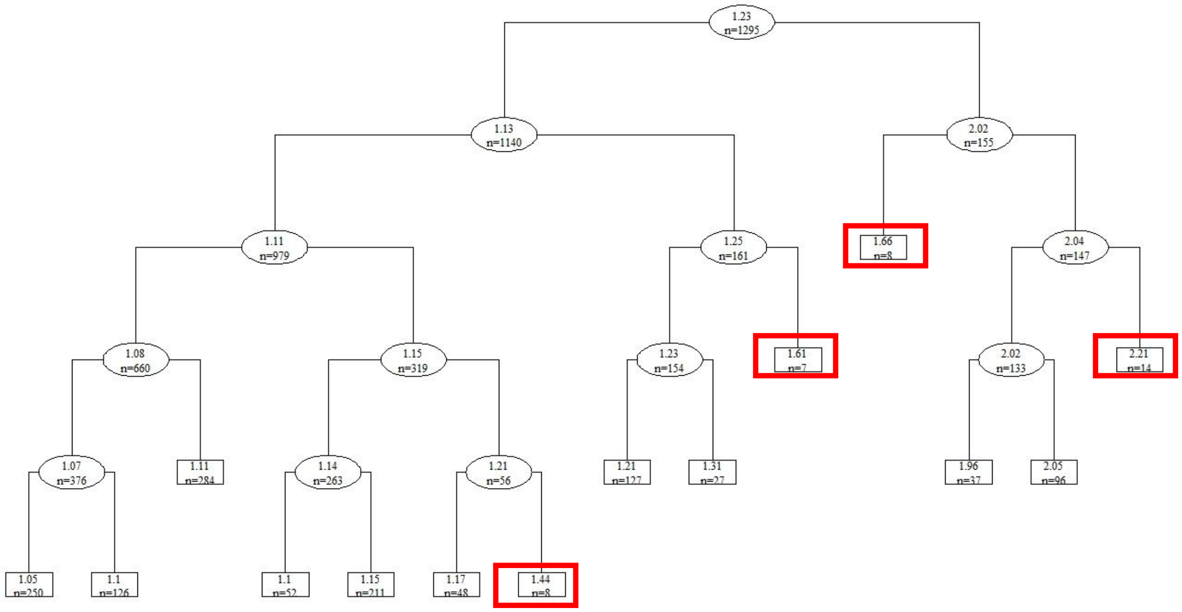


Figure 27: First Iteration Regression Tree to Identify Potential Data Collector Bias

A new regression tree model was generated excluding the data collected by the three data collectors and is shown in Figure 28. The research team applied the same criterion again to search for more data collectors who have consistent bias. Two leaves represented a small number of sessions and there were no repeat data collectors between the two leaves. No more data were identified for removal.

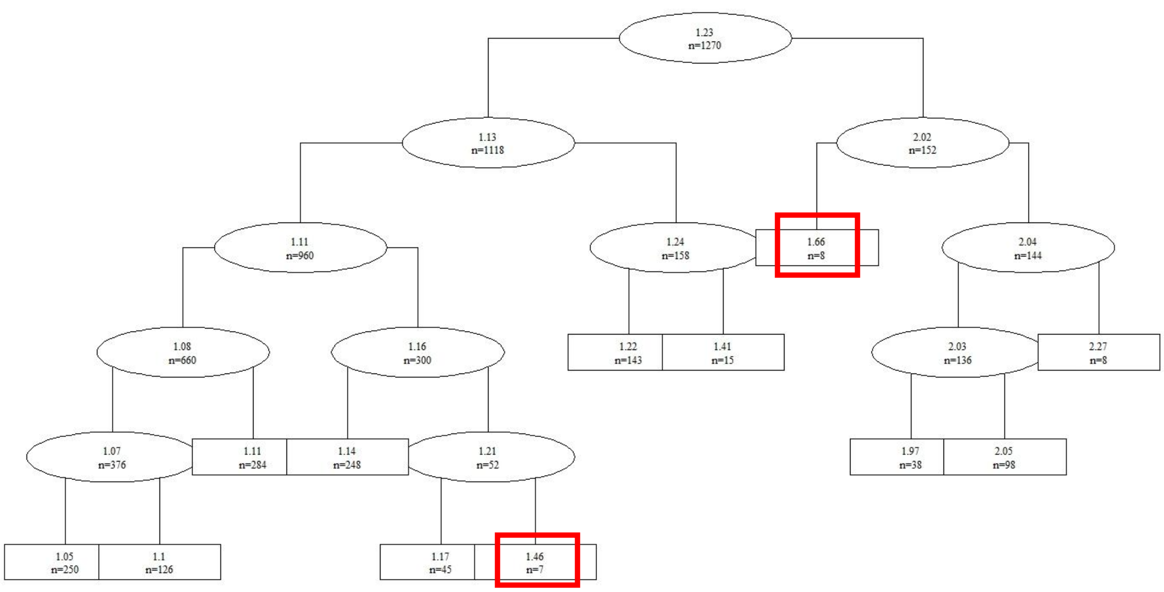


Figure 28: Second Iteration to Identify Potential Data Collector Bias

The team originally planned to move forward with the remaining data in the final data set. However, in plotting occupancy results across single occupancy vehicle (SOV) and carpool classifications (HOV2, HOV3, HOV4+) for use in the final report, some additional data quality issues were identified. The original data set was restored and a two-phase screening process was implemented as described in the next report section.

6.4 SOV and 3+ Vehicle Percentages and Potential Data Collector Bias

In evaluating the average occupancy and potential data collector bias and the impact on person throughput, it is important to analyze the distributions of each data collector across the different occupancy types. Screening based only on average vehicle occupancy does not account for the fact that biases in single occupancy vehicle and high-occupancy vehicle observations may cancel out in average vehicle occupancy. That is, two data collectors could achieve the same average vehicle occupancy values, but show significantly different fractions of SOVs and HOV3+ vehicles. This double-check is important because biased results will affect assessment of high-occupancy violation rates and overall passenger throughput. This section explores the data to identify potential data collector bias by analyzing the percent of single occupancy vehicles and three-person or more ('3+') occupancy vehicles using regression tree analysis.

As discussed earlier, the 1+, 2+ and 3+ uncertain values are redistributed to 1, 2, 3 and 4+ occupancy groups in proportion to certain values in that data collection session. Then the percentage of single occupancy vehicles and the 3+ person vehicles (3 and 4+) are calculated.

In analyzing Tuesday, Wednesday and Thursday data, the first split in the regression trees was observed by lane type, as was noted in previous analyses. HOV occupancy is very different from GP and HOT occupancy (which cluster together and are quite similar). The next regression tree nodes began to split on data collector identifiers, indicating that data collectors may be playing a significant role. However, data collectors were often assigned to the same lanes, and SOV percentages are significantly different across lanes, so the research team studied each lane separately to identify potential data collector bias. A stepwise series of ten regression tree analyses was performed to identify and filter potentially biased data.

6.5 Net Reduction in Sample Size due to Data Screening

Undergraduate students collected quarterly vehicle occupancy data over a period of two years. More than 100 students participated in data collection over this time period, and each student represented an opportunity for data quality issues to occur. Regression tree analysis was employed to identify significant deviations of data collected by individual data collectors from the data collected by their contemporaries, and to simultaneously control for differences expected across lanes, seasons, etc. Ten analytical iterations were employed (see Appendix C: Stepwise Analysis of Potential Data Collector Bias) to identify and remove potentially biased data from the vehicle occupancy data. Table 6 provides a summary of the results reported in the last chapter and the percentage of data removed from the analysis at each step. A total of 91 data collector records out of 1297 records, or 7.0 percent of the original data, were excluded from the analysis.

Table 6: Impact of Filtering Steps on Total Sample Size

Analysis Iteration	Regression Tree Type	Input Number of Records	Records Filtered	Percent Filtered
1	All HOV data SOV Percent	1297	55	4.24
2	All HOV data SOV Percent	1242	27	2.08
3	All HOV data SOV Percent	1215	0	0.00
4	All HOT data SOV Percent	1215	2	0.15
5	All HOT data SOV Percent	1213	0	0.00
6	All GP data SOV Percent	1213	0	0.00
7	All HOV data 3+ Percent	1213	7	0.54
8	All HOV data 3+ Percent	1206	0	0.00
9	All HOT data 3+ Percent	1206	0	0.00
10	All GP data 3+ Percent	1206	0	0.00
Total		1297	91	7.02

6.6 Net Impact of Data Screening on Average Vehicle Occupancy

The next chapter in this report discusses the final vehicle occupancy results. However, before presenting these findings, it is important to address the significance that data screening may have on average vehicle occupancy data, which will ultimately be used to assess changes in person throughput on the corridor (vehicle throughput multiplied by average vehicle occupancy). Figure 29 presents the average vehicle occupancy data by quarter by lane for the raw data (left) and filtered data (right) for the data collected at the three vehicle occupancy observation stations located between I-285 and SR316 in the PM peak. The impact of data screening on average vehicle occupancy was minor. Changes in average vehicle occupancy due to data screening were all less than 0.01 persons per vehicle, except for one increase of 0.06 persons/vehicle (a 3% increase) in winter 2011 HOV data and 0.03 persons/vehicle (a 1.5% increase) in summer 2011 HOV data.

Average Occupancy by Lane
Inside I-285 and SR 316, PM Peak (Raw Data)

	Fall 2010	Winter 2011	Spring 2011	Summer 2011	Fall 2011	Winter 2012	Spring 2012	Summer 2012
GP1	1.04	1.04	1.04	1.04	1.16	1.15	1.16	1.16
GP2	1.06	1.04	1.05	1.06	1.12	1.12	1.16	1.16
GP3	1.07	1.07	1.10	1.05	1.09	1.13	1.17	1.14
GP4	1.13	1.11	1.14	1.07	1.12	1.16	1.19	1.17
GP5	1.12	1.12	1.16	1.12	1.11	1.16	1.18	1.18
HOV/HOT	2.07	1.98	2.06	2.00	1.31	1.20	1.20	1.21

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Average Occupancy by Lane
Inside I-285 and SR 316, PM Peak (Filtered Data)

	Fall 2010	Winter 2011	Spring 2011	Summer 2011	Fall 2011	Winter 2012	Spring 2012	Summer 2012
GP1	1.04	1.04	1.04	1.04	1.16	1.16	1.17	1.16
GP2	1.06	1.04	1.05	1.06	1.12	1.12	1.16	1.16
GP3	1.07	1.07	1.10	1.05	1.09	1.13	1.17	1.14
GP4	1.13	1.11	1.13	1.07	1.12	1.16	1.19	1.17
GP5	1.12	1.12	1.16	1.12	1.11	1.16	1.18	1.18
HOV/HOT	2.07	2.04	2.06	2.03	1.31	1.21	1.20	1.21

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Figure 29: Observed Occupancy, PM Peak, All Data 2011 (left) and Filtered Data (right)

7 Resulting Factors Affecting Observed Vehicle Occupancy

The research team next studied the effects of different factors on vehicle occupancy using regression tree analysis and the filtered data presented in the previous chapter. The results of the regression tree are shown in Figure 30. The lane type is the most important factor that impacts vehicle occupancy. The first branch splits with HOV lanes being different from all other lane types. There are no further splits below HOV that improve the regression model's R-square value by more than 0.001. On the other side of the branch, the next split is between general purpose lanes and HOT lanes as expected. The HOT lanes further split by season, with Fall being different from all other seasons. This is expected since the HOT lane opened on October 1st just before the Fall data were collected and the HOT usage had not stabilized.

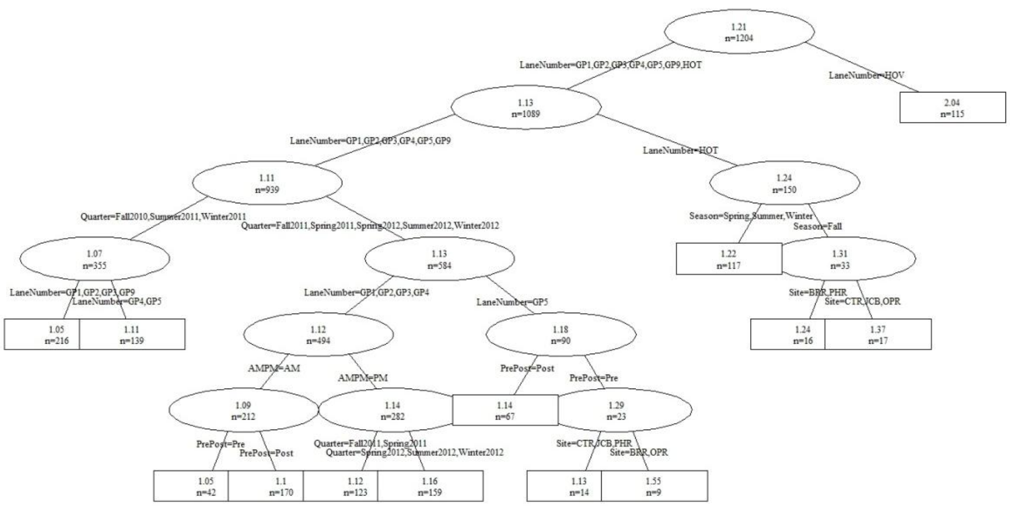

Figure 30: First Iteration - Regression Tree all Factors

On the general purpose side of the tree, the next split is by data collection quarter. One of the pre-conversion quarters, Spring 2011, is grouped with the post-conversion quarters. Table 7 shows the split of average occupancy by lane type and quarter and we notice that Spring 2011 is not very different from other pre-conversion quarters. The data collection quarter variable affects the model and produces a result that does not have significant meaning. Hence this variable is eliminated from the next run.

Table 7: Average Vehicle Occupancy by Data Collection Quarter

Lane Type	Fall |2010	Winter 2011	Spring 2011	Summer 2011	Fall 2011	Winter 2012	Spring 2012	Summer 2012
HOV	2.04	2.05	2.05	2.04	NA	NA	NA	NA
HOT	NA	NA	NA	NA	1.31	1.22	1.20	1.22
GP	1.07	1.07	1.12	1.07	1.11	1.13	1.14	1.15

The results of the regression tree without the data collection quarter variable are presented in Figure 31. The lane type is the top split and there are no further splits along the HOV branch. The HOT branch is split by seasons and the Fall season is further split by the sites. On the GP branch of the tree, the next split is pre-conversion and post conversion of HOV to HOT. The post-conversion is split by morning peak and afternoon peak. The pre-conversion is split by the lane numbers with the right two lanes having higher occupancy than the left lanes. The right two lanes are further split by the data collection sites with the sites between I-285 and Highway 316 grouped together.

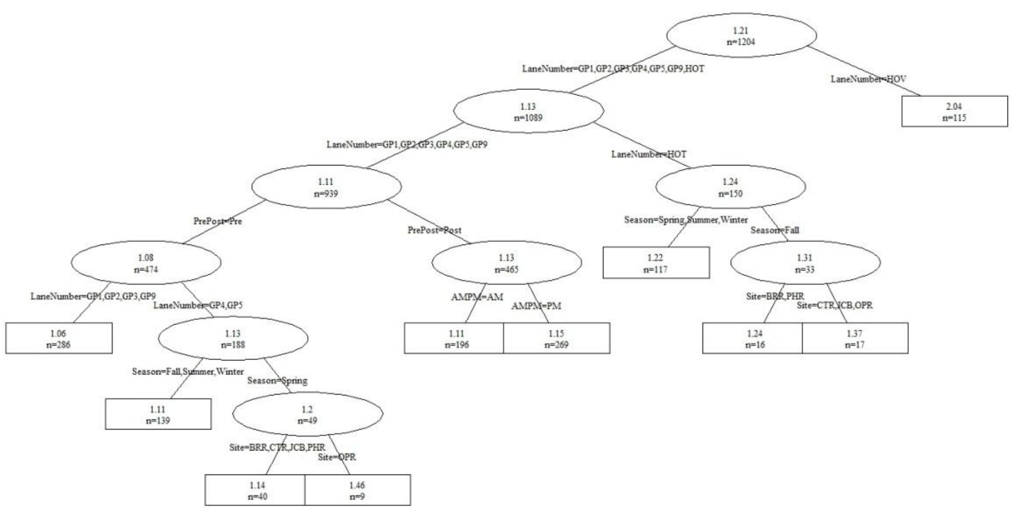

Figure 31: Second Iteration Regression Tree Excluding the 'Quarter' variable

7.1 Morning Peak Analysis

While the period of data collection, morning or afternoon peak, was not one of the most important variables in the classification tree, we expect the travel behavior characteristics to be different. A regression tree for the morning peak data is shown in Figure 32. As expected the first split is on HOV followed by GP and HOT split. The GP, HOT branch next split by lane number with HOT and GP5 having similar characteristics. On the HOT, GP5 side of the branch, the data are split by sites. On the general purpose lanes 1 through 4 branch, the next split is by pre- and post-conversion of HOV to HOT. The post conversion data are not further split. On the pre-conversion side, the right lane has higher occupancy than the left lanes. This is not surprising as we expect a significant amount of local traffic to be using the right-most lane traversing between local interchanges.

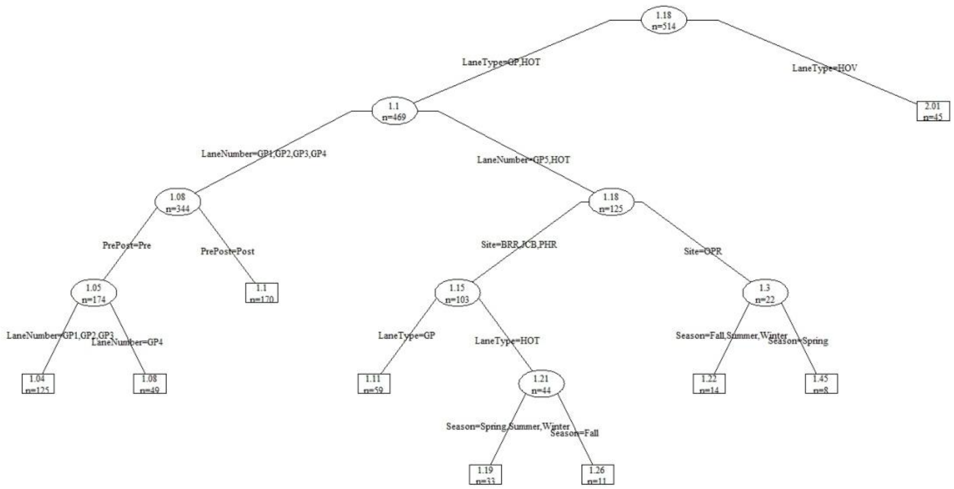

Figure 32: Regression Tree for Morning Peak Data

7.2 Afternoon Peak Analysis

A regression tree with data from the afternoon peak is shown in Figure 33. The first split is at the lane type as with other trees. The HOV branch is not further split. Under the HOT branch of the tree, fall is different from the other seasons, indicating that fall pre-opening and fall after opening remained fairly similar. In winter, spring, and summer, the CTR site is different from the other sites, which is as expected. In the afternoon peak direction CTR is upstream of the I-285 interchange.

On the general purpose lane branch, the first split is between pre- and post-conversion of HOV to HOT. The post-conversion branch does not have any further splits. In the pre-conversion period, again the right two lanes are different from the left lanes. There are no further splits for the left lanes. On the right two lanes branch, data are split by sites with BRR, CTR and OPR being different from the other two sites. The data on BRR, CTR and OPR are further split by seasons with the spring data being different from other seasons.

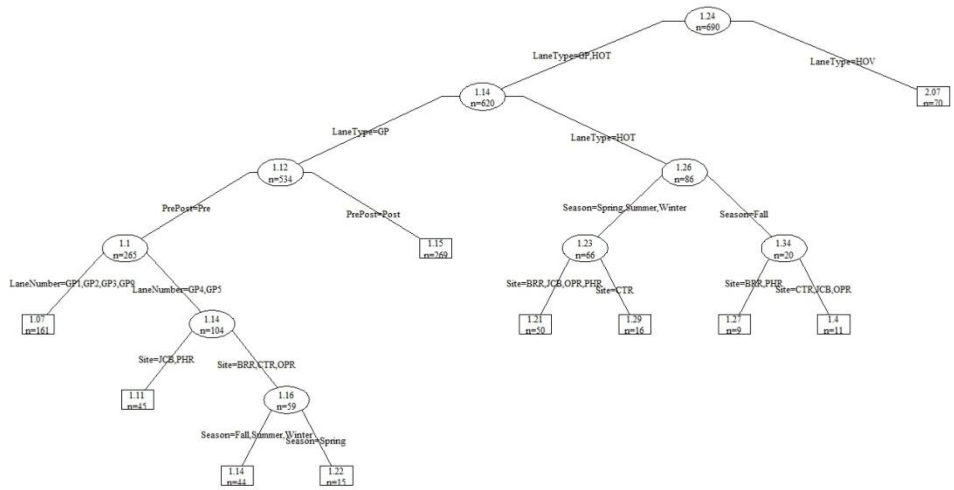

Figure 33: Regression Tree for Afternoon Peak Data

7.3 Summary of Regression Tree Analysis

The research team used regression tree methods to identify individual data collectors and data collection sessions that were statistically different from other sessions, to review each data set manually, and to filter potentially biased data from the final dataset. The first regression tree that included all variables and all data sessions indicated that data collected on Mondays were different from data collected on Tuesdays, Wednesdays and Thursdays. Only data from Tuesdays, Wednesdays, and Thursdays were included in the final dataset. The next regression tree analysis included data collector identification, and data collectors who were consistently statistically different from other data collectors were identified and all data collected by these data collectors were excluded from the final analysis.

The effects of site, season, session (morning/afternoon peak), day of week, data collection quarter, pre/post conversion, lane type, and lane number on vehicle occupancy were examined. The data collection quarter is correlated with season and pre/post-conversion variables. In the first regression tree, the data collection quarter variable indicated non-intuitive results and hence was not included as a variable in later analysis. Because morning and afternoon peak travel habits are different (different trip types) the data were analyzed separately. The lane type was the most significant variable from the regression tree analysis. For the HOV lanes, in the morning peak the day of the week was significant while in the afternoon peak the season was the significant variable. For HOT lanes, the season was the next significant variable with the fall season immediately after opening the HOT lanes very different from other seasons. Vehicle occupancy in the general purpose lanes was significantly different between the pre-conversion and post-conversion periods. In the pre-conversion periods, the right two general purpose lanes had higher vehicle occupancy than the other left lanes.

Based on the above results, the research team aggregated the vehicle occupancy data into three regions, the ‘Center Stations’ on the central portion of the corridor (three data collection stations between I-285 and SR316), North of SR 316 (one station), and South of I-285 (one station, where only afternoon data were collected). The aggregation of the three center stations increases sample size and should help to minimize any remaining potential bias due to individual data collectors, while not losing the effects of the other variables that impact vehicle occupancy. Other relevant factors include season, year (i.e., pre/post-conversion), morning/afternoon peak, and lane number. The final vehicle occupancy information is stored in the analytical database and applied in calculating person throughput across the I-85 study corridor.

8 Occupancy Results

Observed occupancy data were screened as described in Chapter 7 and assembled in a database for use in calculating person throughput across the I-85 study corridor (presented in final format in Chapter 11). This chapter presents the detailed comparative occupancy results for Spring 2011 and 2012 and then presents the trends noted across the eight quarters after the HOT lanes opened. As mentioned in the last chapter, vehicle occupancy data from the three data collection stations between I-285 and SR316 were aggregated into a 'Center Stations' occupancy result. Occupancy data were also collected North of SR 316 (one station), and South of I-285 (one station, where only afternoon data were collected).

8.1 Spring 2011 vs. 2012 Occupancy Results

The final observed breakdown of vehicle occupancy observation data for the three center stations between I-285 and SR 316 are presented in Table 8 through Table 11. The four tables provide results for observed spring occupancy data in 2011 (HOV operations) and 2012 (HOT operations), by lane, and by morning and afternoon peak period. The tables are accompanied by before-and-after, side-by-side comparisons in Figure 34 and Figure 35 for AM and PM periods.

The observed average vehicle occupancy results for each lane in the tables are derived by calculating total throughput (sum of vehicles x persons/vehicle for each observation class) and dividing by total vehicles. In these calculations, the occupancy observation class of 4+ is assigned 4.5 persons for the time being. In later chapters, the impacts of vanpools and express buses will be addressed. Hence, the occupancies are average vehicle occupancy based solely upon observation at this stage of the report.

In the HOV baseline period, occupancy results differ across lanes. As expected, based upon carpool lane restrictions, the HOV lane occupancy was greater than two persons per vehicle in Spring 2011. The general purpose lanes were much closer to a value of one person per vehicle, given the large percentage of single-occupant vehicles in these lanes. In both the AM and PM peak periods, the percentage of carpools increases across the general purpose lanes from the inside lane (fast lane adjacent to the HOV lane) to the outside lane. This may be the result of a significant number of local carpools (school-related trips, shopping trips, etc.) entering and exiting the corridor. After HOT lane implementation, the observed average vehicle occupancy of the HOT lane is nearly equal to the occupancy in the general purpose lanes, and the relative increase in occupancy across lanes nearly disappeared. The data reveal that the vast majority of two-person carpools have been diverted from the HOV lane into the general purpose lanes after HOT lane implementation. The overall average vehicle occupancy of each general purpose lane has increased as a result. Changes in person throughput are a function of changes in vehicle throughput and vehicle occupancy and the net impact on corridor person throughput will be presented in Chapter 11.

Table 8: Observed Occupancy Percent by Lane, Center Stations, Spring 2011, AM

Occupancy	HOV	GP1	GP2	GP3	GP4	GP5
1	9.8%	97.7%	97.7%	96.6%	92.6%	86.8%
2	83.2%	2.2%	2.2%	3.2%	6.7%	12.3%
3	4.4%	0.1%	0.1%	0.1%	0.5%	0.6%
4+	2.5%	0.1%	0.0%	0.1%	0.2%	0.4%
Sessions (n)	7	8	7	8	9	8
AVO	2.01	1.03	1.02	1.04	1.08	1.15

Table 9: Observed Occupancy Percent by Lane, Center Stations, Spring 2012, AM

Occupancy	HOT	GP1	GP2	GP3	GP4	GP5
1	86.8%	89.3%	88.9%	90.0%	89.4%	88.2%
2	10.9%	10.3%	10.6%	9.5%	10.0%	11.1%
3	0.7%	0.3%	0.4%	0.3%	0.4%	0.5%
4+	1.6%	0.1%	0.2%	0.2%	0.3%	0.2%
Sessions (n)	12	7	6	6	6	6
AVO	1.18	1.11	1.12	1.11	1.12	1.13

Table 10: Observed Occupancy Percent by Lane, Center Stations, Spring 2011, PM

Occupancy	HOV	GP1	GP2	GP3	GP4	GP5
1	7.3%	96.3%	95.5%	91.0%	88.6%	86.2%
2	84.0%	3.4%	4.3%	8.2%	10.3%	12.1%
3	5.4%	0.2%	0.1%	0.5%	0.7%	1.1%
4+	3.4%	0.1%	0.1%	0.3%	0.4%	0.6%
Sessions (n)	13	8	9	9	8	9
AVO	2.07	1.04	1.05	1.10	1.13	1.16

Table 11: Observed Occupancy Percent by Lane, Center Stations, Spring 2012, PM

Occupancy	HOT	GP1	GP2	GP3	GP4	GP5
1	85.3%	85.0%	86.0%	85.3%	83.7%	84.8%
2	12.2%	14.0%	12.9%	13.5%	14.6%	13.6%
3	0.8%	0.7%	0.6%	0.7%	1.2%	1.2%
4+	1.7%	0.4%	0.4%	0.6%	0.5%	0.5%
Sessions (n)	12	6	7	7	7	7
AVO	1.20	1.17	1.16	1.17	1.19	1.18

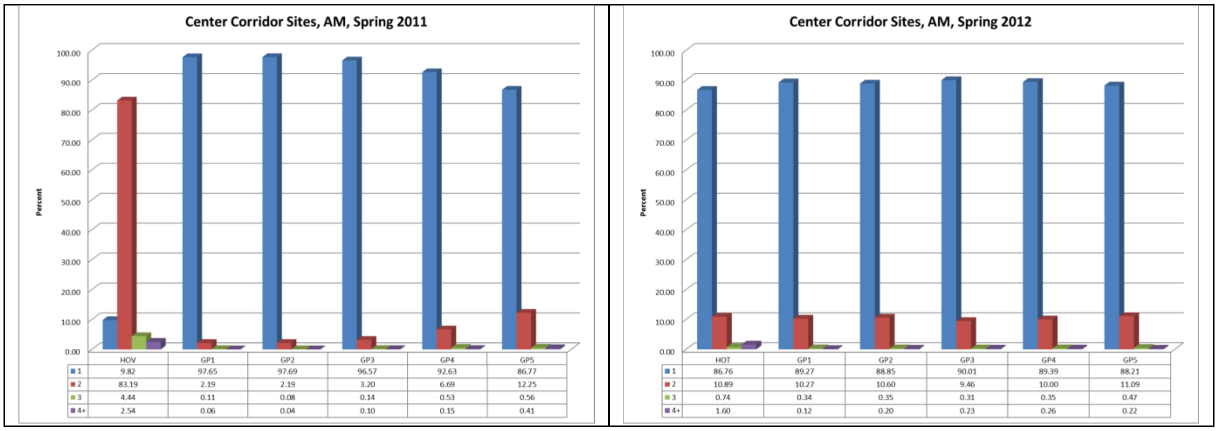

Figure 34: Observed Occupancy, AM Peak, Spring 2011 (left) and 2012 (right)

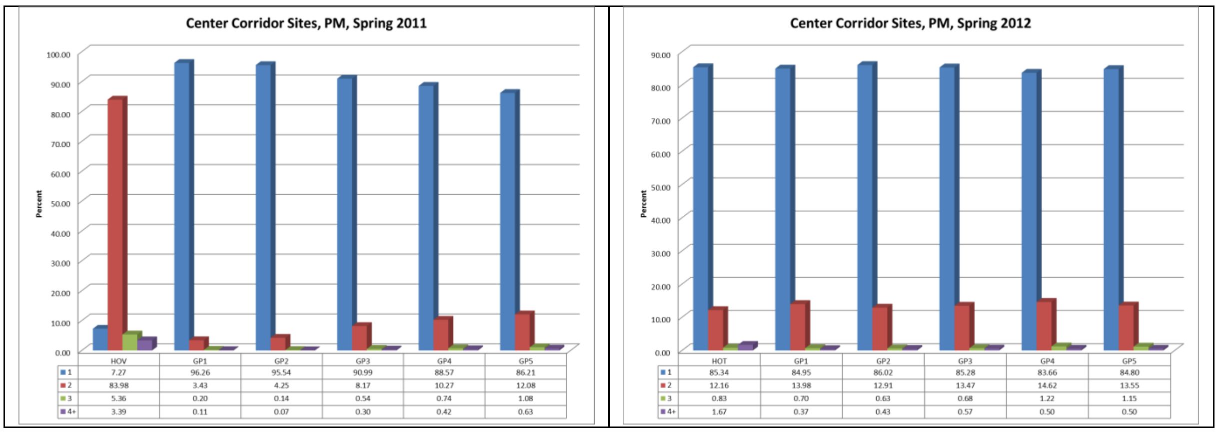

Figure 35: Observed Occupancy, PM Peak, Spring 2011 (left) and 2012 (right)

The observed changes in vehicle occupancy in the HOT lane after conversion were slightly larger than the research team expected to see. A large increase in single-occupant vehicles in the HOT lane was anticipated. However, given that three-person carpools can use the HOT lane for free (if they create a Peach Pass account), the significant reduction in 3 and 4+ occupant vehicles from 6.9% to 2.3% between Spring 2011 AM and Spring 2012 AM was surprising. Later chapters will indicate that the number of buses and vanpools per peak period is small, relative to the number of 3 and 4+ occupant vehicles that were originally operating on HOV lanes and that 3+ carpools either shifted to other lanes or broke into smaller carpools after the HOT lane opened. The percentage of 2-person carpools declined significantly, as expected. These carpools would have to either find a third commuter to operate on the HOT lane for free, or pay a toll to continue operating on the HOT lane. The percentage of 2-person carpools increased in all of the general purpose lanes, indicating that a significant number of carpools migrated to general purpose lanes and a significant fraction may also have disbanded.

8.2 Managed Lane Occupancy Changes over Time

Table 12 and Table 13 present the changes in managed lane vehicle occupancy distributions over time (by quarter) for the AM peak period and PM peak period, respectively. The tables present all four occupancy classifications and then condense the 3 and 4+ classification into a 3+ class for comparative purposes. The percentage of HOV3+ vehicles operating in the managed lane decreased from about 5-7% in the HOV baseline period to about 2-3% under HOT operations in the AM peak and from about 7-10% in the HOV baseline period to about 3-4% under HOT operations in the PM peak.

Table 12: Distribution of Occupancy Observation Records, Center Stations, AM Peak

AM	HOV Lane				HOT Lane			
	Fall 2010	Winter 2011	Spring 2011	Summer 2011	Fall 2011	Winter 2012	Spring 2012	Summer 2012
1	12.0%	2.4%	9.8%	5.6%	83.3%	86.0%	86.8%	85.9%
2	82.3%	92.2%	83.2%	90.1%	13.9%	11.8%	10.9%	11.4%
3	3.3%	2.8%	4.4%	2.1%	1.0%	0.7%	0.7%	0.9%
4+	2.4%	2.6%	2.5%	2.2%	1.9%	1.5%	1.6%	1.9%
AVO	1.97	2.07	2.01	2.02	1.22	1.18	1.18	1.20
	HOV Lane				HOT Lane			
1	12.0%	2.4%	9.8%	5.6%	83.3%	86.0%	86.8%	85.9%
2	82.3%	92.2%	83.2%	90.1%	13.9%	11.8%	10.9%	11.4%
3+	6.7%	5.4%	6.9%	4.3%	2.9%	2.2%	2.3%	2.8%
AVO	1.97	2.07	2.01	2.02	1.22	1.18	1.18	1.20

Table 13: Distribution of Occupancy Observation Records for Center Stations PM Peak

PM	HOV Lane				HOT Lane			
	Fall 2010	Winter 2011	Spring 2011	Summe r 2011	Fall 2011	Winter 2012	Spring 2012	Summe r 2012
1	8.1%	7.6%	7.3%	9.4%	78.3%	85.2%	85.3%	85.4%
2	82.2%	85.1%	84.0%	82.6%	17.6%	12.0%	12.2%	11.6%
3	6.1%	4.6%	5.4%	4.9%	1.3%	0.8%	0.8%	0.8%
4+	3.7%	2.7%	3.4%	3.1%	2.8%	2.0%	1.7%	2.2%
AVO	2.07	2.04	2.07	2.03	1.30	1.21	1.20	1.21
1	8.1%	7.6%	7.3%	9.4%	78.3%	85.2%	85.3%	85.4%
2	82.2%	85.1%	84.0%	82.6%	17.6%	12.0%	12.2%	11.6%
3+	9.8%	7.3%	8.8%	8.0%	4.1%	2.8%	2.5%	3.0%
AVO	2.07	2.04	2.07	2.03	1.30	1.21	1.20	1.21

There is some variability of note in the occupancy tables by lane presented in Table 12 and Table 13. Because the Fall 2010 quarter was the first deployment, the data may be less accurate than the subsequent quarters due to the data collection learning process. As the field team gained experience, there is a possibility that observers were less likely to record certain values, resulting in an increase in "uncertain" recordings. Hence, the percentage of "1" values in the AM peak may be too high. Because the research team did not record data collector identification numbers with the Fall 2010 data, it was not possible to identify any problem data collectors for screening (see discussion in Chapter 6). Winter data collection sessions began before sunrise (AM sessions) and end after sunset (PM sessions). Hence, the accuracy of data collected during the twilight periods may be different in winter than in other quarters. In addition, new students were added to the data collection team over the course of the study. However, it is important to keep in mind that the same methods were employed across all eight quarters.

Because the occupancy data collection methods remained constant throughout the study, it is reasonable to expect that any methodological bias introduced by the method should be consistent across all eight quarters. That is, if there is some systematic problem in counting vehicle occupants, such as missing passengers in child seats or missing individuals that are prone in the back seat, the errors should be consistent throughout the study. The fact that observed vehicle occupancy changed so significantly after the HOT lanes opened indicates that the percentage of carpools has changed. One does have to be careful in comparing percentages. If the number of carpools remained constant (numerator), but vehicle throughput increased (denominator), the percentage of carpools declines. However, as will be discussed later, managed lane vehicle throughput declined during the same period. To identify other potential problems with the occupancy data, one needs to look for exogenous factors that may have changed during the study period and affected the use of the field data.

One potential problem that the team has identified is the fact that data were only collected for two hours during each peak period. In winter, the data collection window was even shorter because is too dark to collect data in early morning and late afternoon. If HOV3+ commuters modified their schedules such that they were passing through the corridor before or after data collection, then the percentages collected in the field are not applicable to the entire peak period. As such, we do not suspect that a change in HOV3+ vehicle temporal use patterns has occurred, but we cannot discount the possibility.

8.3 Overall Changes in Vehicle Occupancy

The previous chapter subsections addressed changes in average vehicle occupancy for spring 2011 vs. spring 2012, and addressed changes in HOV/HOT vehicle occupancy over time. This subsection addresses the changes in average vehicle occupancy over time for all lanes across all eight quarters. Detailed tables would clutter the report, so figures are used to communicate the observed changes in occupancy over time. A traditional bar plot is most appropriate to the data, presented in Figure 36 for AM and Figure 37 for PM. However, it is a bit easier to see the occupancy changes by lane in a linear plot (Figure 38 for AM and Figure 39 for PM). Average vehicle occupancy in the managed lane decreased from around 2.0 persons per vehicle (2-person carpool minimum requirement for use of HOV lane) to slightly above that of the general purpose lanes after conversion.

Vehicle occupancy results presented in the tables and figures that follow were based upon direct visual observation. As a reminder, the observational method included a maximum vehicle occupancy observation class of 4+. As discussed earlier, in calculating vehicle occupancy, the assumed number of passengers per vehicle in the 4+ class was 4.5 persons/vehicle. Unless a correction was made, every transit bus and vanpool on the corridor would have an associated occupancy value of 4.5 persons/vehicle in estimating person throughput. The following chapters address express bus and vanpool contributions to vehicle throughput and explain how the throughput methodology is modified to correct person throughput estimates to account for the significant impacts of vanpools and express buses on corridor passenger throughput.

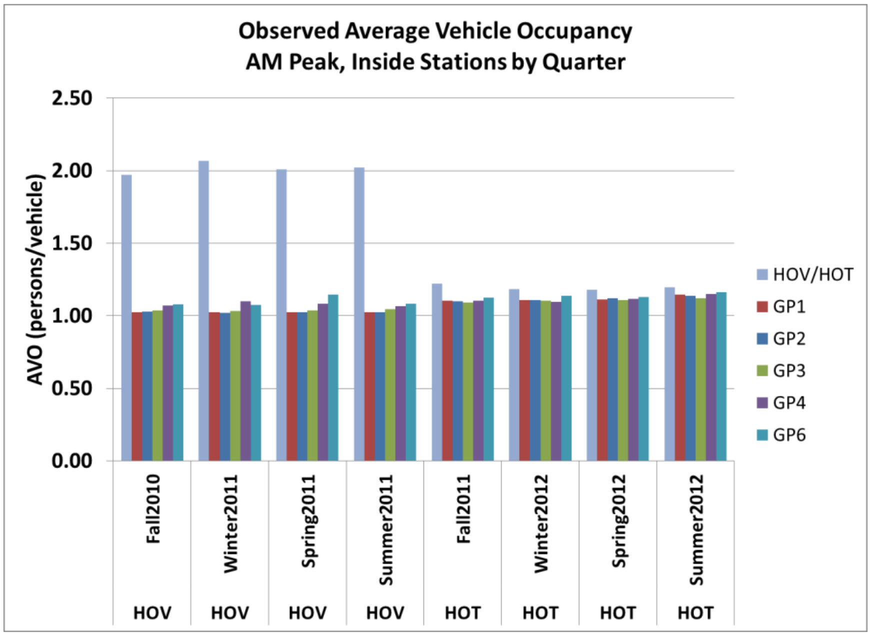

Figure 36: Changes in Vehicle Occupancy by Lane Over Time, Center Stations, AM

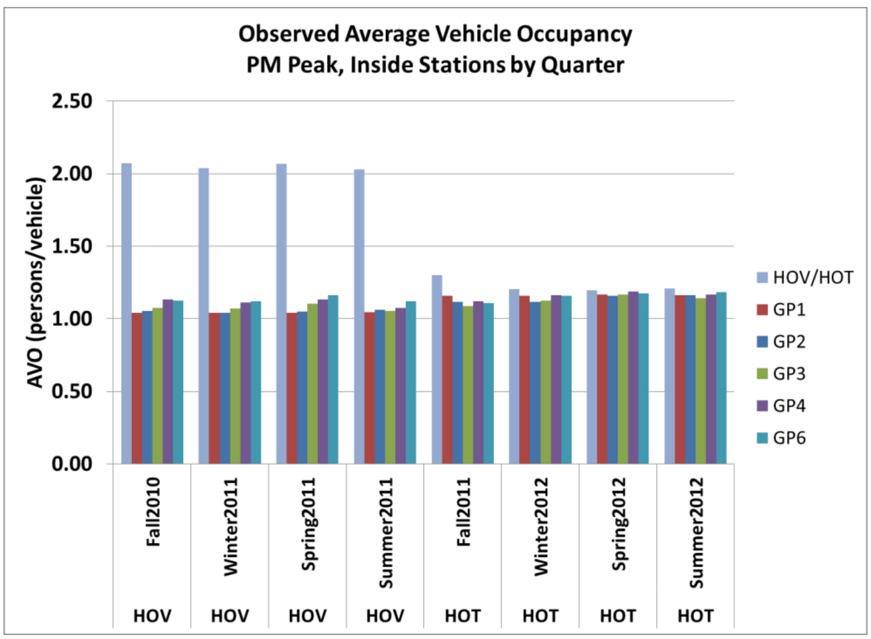

Figure 37: Changes in Vehicle Occupancy by Lane Over Time, Center Stations, PM

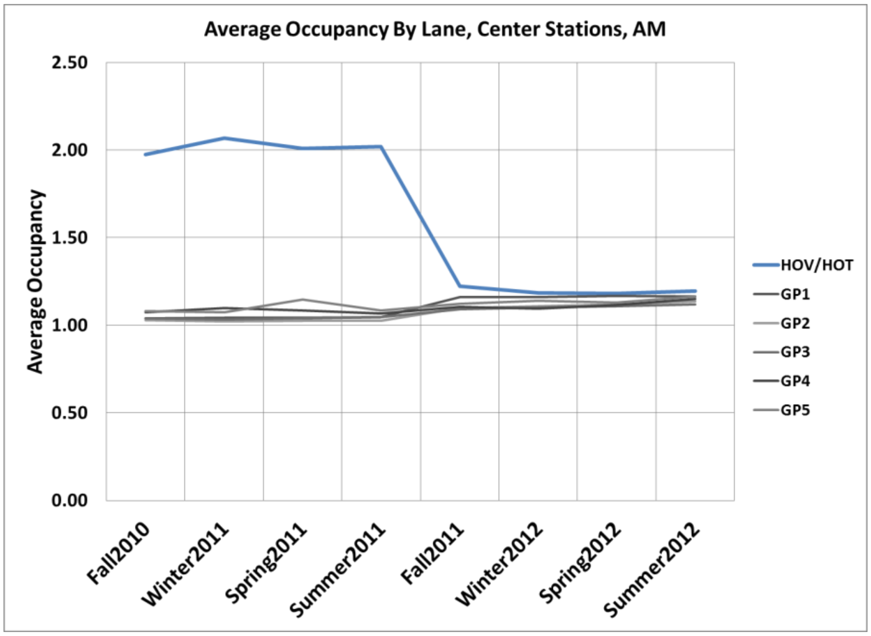

Figure 38: Changes in Vehicle Occupancy by Lane Over Time, Center Stations, AM

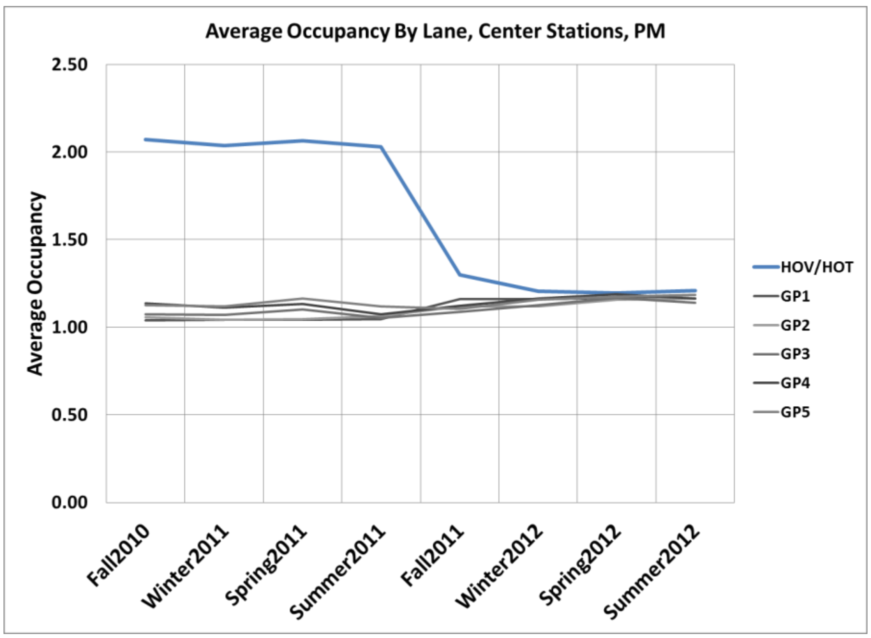

Figure 39: Changes in Vehicle Occupancy by Lane Over Time, Center Stations, PM

9 Express Bus Operations

The occupancy field data that were collected, and the occupancy results presented in the tables and figures of the previous chapter, do not explicitly account for the throughput of express buses and vanpools on the corridor. Express buses were simply identified by occupancy data collectors as heavy-duty vehicles containing 4+ persons. Similarly, vanpools were identified by data collectors as sport utility vehicles with 4+ persons. A significant number of persons are carried by express buses and vanpools, and the observed average vehicle occupancy values presented in the previous chapter are therefore understated, especially between the hours of 6 AM and 7 AM when buses and vanpools carry an even larger percentage of persons. This chapter discusses the explicit treatment of express buses and the following chapter addresses the explicit treatment of vanpools in the estimation of vehicle occupancy and calculation of corridor person throughput.

9.1 GRTA Express Bus Operations

A significant number of persons using the I-85 corridor during the peak periods are carried by express buses operated by GRTA and Gwinnett County Transit. One of the HOT lane goals was to reduce congestion delay and improve travel time reliability for these express buses. As discussed earlier, the pre-existing HOV lanes experienced significant congestion, which was preventing larger capacity alternative modes, such as express buses and vanpools from delivering the high level of service that users require to offset inconvenience they experience from using these modes. Furthermore, the majority of federal funding for the project was earmarked for transit operation improvements and implementation of park-and-ride lots for express bus operations. This chapter reports on the assessment of express bus activity on the corridor.

The Georgia Regional Transportation Authority (GRTA) is the state agency responsible for coordinating transit planning among all operators within its jurisdiction. Xpress is a regional public transportation service provided by the Georgia Regional Transportation Authority (GRTA), in collaboration with transit partners in Cobb County (CCT) and Gwinnett County (GCT). Xpress also provides convenient connections and free transfers to the Metropolitan Atlanta Rapid Transit Authority (MARTA).

The GRTA Xpress bus system includes 33 routes serving 12 metro Atlanta counties, carries more than two million passenger trips annually, and provides morning and afternoon peak-period service to commuters working in major employment centers such as Downtown, Midtown, Buckhead, and Perimeter Center (see Figure 40 for the route map). Xpress buses operate on five main corridors in Atlanta metro area: North corridor (I-75/I-575), West corridor (1-20 West), Northeast corridor (I-85/985 North and GA 400), East corridor (I-20 East/US 78) and, South corridor (I-75/I-85 South and US19/41). The main service corridors and the routes at each corridor are illustrated in Figure 40. GRTA/CCT Routes 101, 102, 103, 410, 411, 412, 413, and 416 operate on the I-85 HOT corridor.

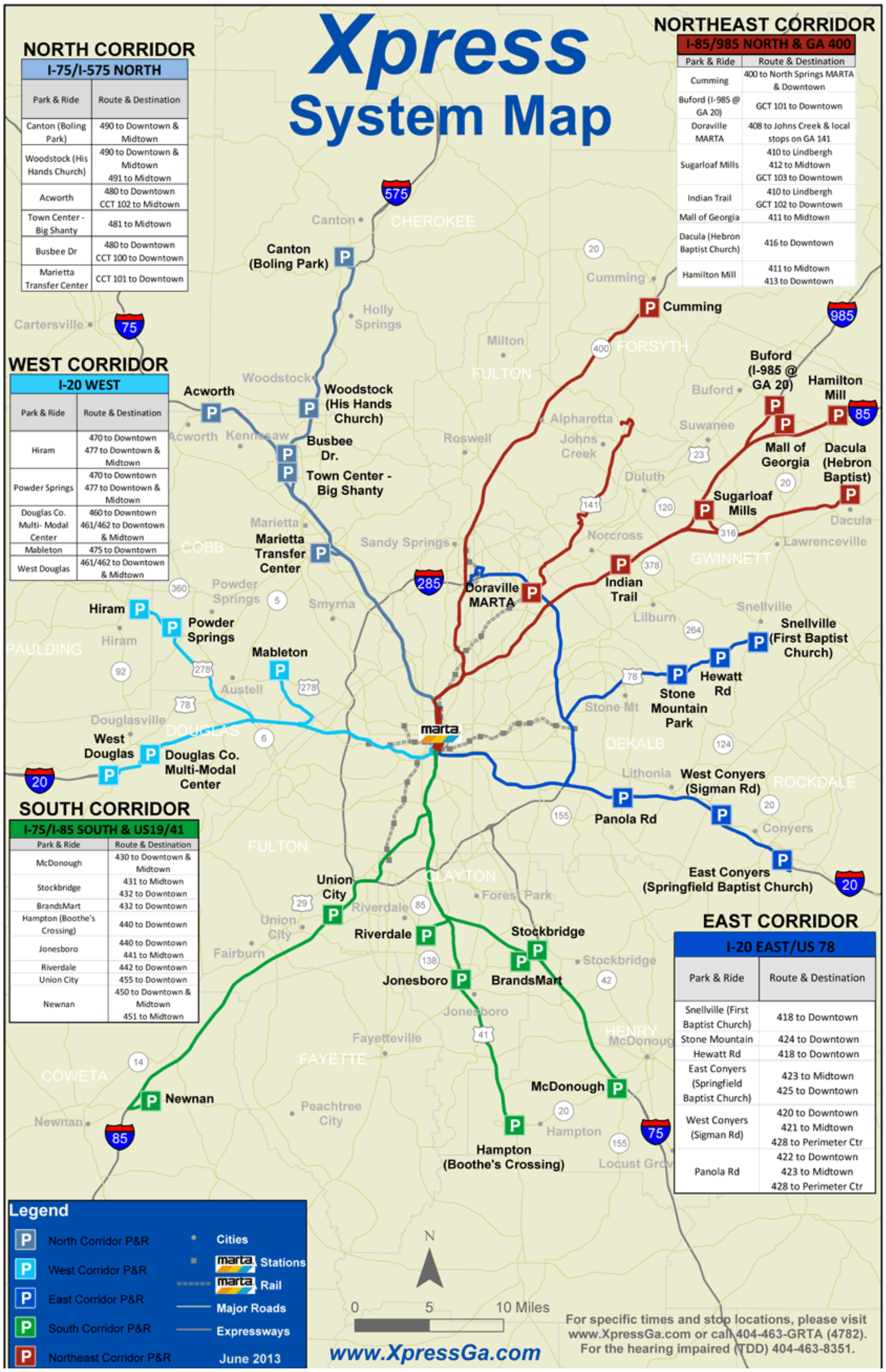

Figure 40: GRTA Express Bus Operations Map

9.2 Express Bus Data

Currently, GRTA drivers collect bus occupancy and travel time data every day for one week per month using passenger load and travel time report cards. The data allows GRTA to track impacts associated with changes in services, such as the introduction of new routes, schedules, and the HOT lane on the I-85 corridor. The fleet is currently not instrumented with GPS tracking, so in addition to number of passengers, the surveys include departure time and arrival time records for major stations. To avoid confusing downtown congestion with congestion on I-85, the first stop in downtown is used as the AM terminus station and the last stop in downtown is used as the PM departure station.

Travel time report cards are completed by the GRTA bus drivers. After data collection is complete, the cards are transferred to the Center for Urban Transportation Research at the University of South Florida. The cards are then entered into monthly Excel spreadsheets and quality checked by a second party, who compares each time card with the spreadsheet. There are many occurrence of missing data. The two primary reasons for this are that the entire time card was missing, or some discrepancy on the card rendered the data invalid.

To assess the accuracy of travel time card data, students from Georgia Tech were recruited to ride buses and collect data on the same days the bus drivers would be filling out time cards. Data collection took place during morning and afternoon peak periods on November 14th, 15th and December 14th. Five to seven undergraduates collected data during each collection period. Equipment consisted of a Qstarz BT-Q1000eX GPS device and a passenger count sheet. The GPS unit collected data automatically which was processed off-line, while the passenger counts were filled by the student as they saw riders board and alight. Two graduate students were in charge of drop-offs and pick-ups from Georgia Tech to the bus stations. All bus routes owned and operated by GRTA on the I-85 corridor at that time were collected, which were bus lines 410, 411, 413 and 416. Three additional bus lines, 101, 102, and 103 are operated by Gwinnett County, but were not included in the confirmation study. For the purpose of this report, only the passenger count data analysis will be included.

Passenger counts were obtained from undergraduate counts on their field worksheet, and these numbers were compared to the passenger counts collected by bus drivers. Figure 41 shows the difference between the bus driver records and the student records. From the histogram, the vast majority of data fall between the -2 and +2 count range. Only five occurrences fall outside this range. The two undergraduate students, who had recorded the counts with the greatest differences, reported that they were not able to clearly see when the passengers were getting on and off. The figure indicates that passenger counts from bus drivers are accurate more than 85% of the time by ±2. More research might provide insight into time card data errors based upon visual impairment of the data collectors, but the results indicate that the time card data could be trusted to be reasonably accurate and therefore the GRTA data are used in the throughput analysis.

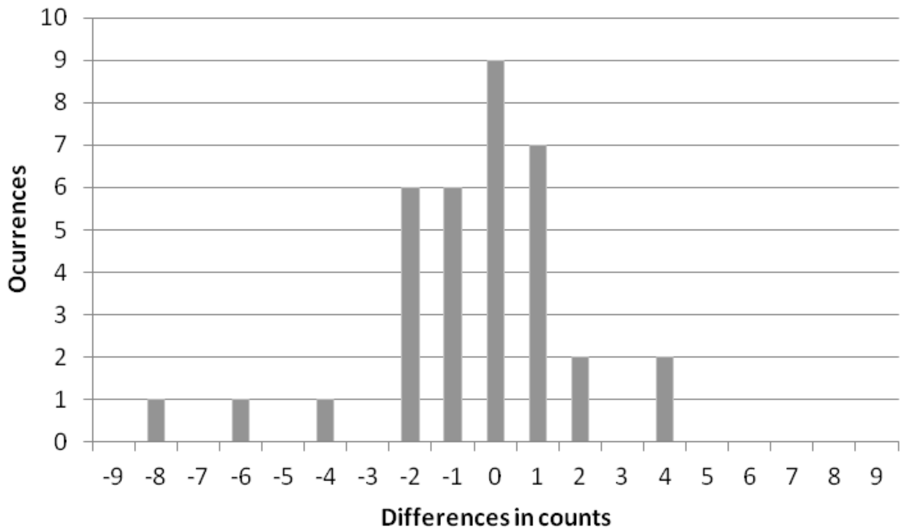

Figure 41: Passenger Count Histogram

9.3 Express Bus Occupancy

Driver-collected data as well as monthly revenue-based data were provided by GRTA to Georgia Tech for use in this study. Once received, the occupancy data for each route was entered into a table in the working database. The master table contains fields with bus route number, scheduled time of departure and arrival, and the occupancy as it is recorded in the travel time report cards. Monthly revenue data were added to a separate table.

Missing occupancy data were imputed to obtain expected bus occupancy values for every bus trip. In some cases, only one data point was missing for an individual bus, however, in other cases an entire route may be missing the entire week of data. Most of the missing occupancy data points are imputed by averaging data points directly to the right, left, above and below the missing data point by schedule. This method helps account for variation across days and times. This method is used to try to maintain the ratio of each. An example is provided below in Table 14 where there was a missing point for Route 101 at 7:15 AM on 02/23/2011. This cell, shown in red, is imputed through averaging the green cells around it. If a value is around the edges of the matrix, the same configuration is used without reaching into different months or routes. Some imputed values are therefore the average of only two or three values.

Table 14: Example of Bus Occupancy Data Imputation

Route	Peak Period	Scheduled Departure	2/21/2011	2/22/2011	2/23/2011	2/24/2011	2/25/2011
101	AM	7:00	29	39	33	32	15
101	AM	7:15	17	31	missing	27	34
101	AM	7:30	12	42	28	33	20
Imputed Bus Occupancy for Missing Cell							
101	AM	7:00	29	39	33	32	15
101	AM	7:15	17	31	30	27	34
101	AM	7:30	12	42	28	33	20

As previously mentioned, there were several cases where large segments of data were missing, such that it was not possible to use at least two data points abutting the missing value to determine its average. In these cases the previous or future month's occupancy values were used, depending on which of these months had the most reliable data. For example, all of the data for route 412 was missing in September 2011. In this case, the occupancy values from August's travel time report cards are used (the previous month), given that data from route 412 were also missing for October 2011. November 2011 data were then used to represent October 2011 data for route 412.

The other type of data used to calculate the expected occupancy of each bus is the monthly revenue-based ridership values. Because driver counts were only conducted for one week each month, the team assumed that the total ridership taken from the GRTA revenue source would provide the most accurate source of passenger throughput for the Xpress and Gwinnet County Transit lines. Ridership derived from monthly revenue totals is distinct and separate from the occupancy data collected each month through the travel time report cards. A monthly revenue report is assumed to be more accurate than a one-week count conducted by drivers. Hence, the revenue data serve as the control total for express bus passenger throughput, and the driver-collected data provide allocation ratios by route and time of day to disaggregate the total monthly bus ridership data to the scheduled vehicles for hourly and daily throughput estimation.

Monthly revenues comprise trips taken on all weekdays during the entire month (less official holidays when service is not provided). Express bus demand varies by day of week and across weeks in a month. Based upon driver counts, Monday ridership in February 2012 constituted only 17.3% of weekly ridership which is less than an expected 20% of weekly ridership (i.e., more trips are made Tuesday through Thursday). Hence, methods must account for the different number of days of the week that appear in each month. Months do not contain the same number of weekdays, nor do they contain the same number of each day of the week. For example, March 2011 contained four Mondays and four Fridays, but five Tuesdays, Wednesdays, and Thursdays. The passenger ridership allocation process starts by deriving a representative weekly person throughput from the monthly driver counts. The driver-collected traffic counts for each day of week are multiplied by the number of those days in that month (i.e., the Monday count is multiplied by the number of Mondays in that month, the Tuesday count by number of Tuesdays, etc.) to obtain a driver-count-equivalent monthly total that can be compared to the monthly revenue total. The monthly revenue total is generally higher than the monthly driver equivalent count total. For example, in February 2012, the ratio of equivalent monthly counts to revenue ridership was 0.876. This ratio of monthly driver-count-equivalent to monthly revenue counts is used to factor up observed driver counts for routes and departure times. For example, the Route 101 express bus departing at 7:00 am on Monday February 13th, 2012 carried a driver-reported occupancy of 24 riders. The February 2012 ratio of monthly driver-count-equivalent to monthly revenue ridership is 0.88. Hence, the adjusted count for this bus equals 24/0.876, or 27 riders. This count is applied to Route 101 departing at 7:00 AM on Monday February 13th and to the Route 101 buses on all other Mondays in February for the same departure time. As a side note, this bus represents 0.92% of Monday's total ridership, and 0.16% of total weekly ridership.

9.4 Temporal Allocation of Express Bus Operations

Express buses depart on a known schedule. The allocation of the bus and the passengers to a specific hour on the I-85 corridor is performed by estimating travel time from the departure location to specific stations along the HOT corridor. Travel times from departure station to the I-85 corridor were estimated using Google Maps arterial speed data and distance traveled. Times along the I-85 corridor were estimated using NaviGAtor speed data for the managed lane: the section lengths were used to estimate travel times for each. Table 15 provides the results employed for the Route 101 express buses. The arrival time in the table is used to assign the bus to a specific hour. For example, the Route 101 bus with 6:40 AM departure is expected to arrive at Jimmy Carter Boulevard at approximately 7:06 AM; hence, the bus and passengers are assigned to the 7:00 AM to 8:00 AM hour in the throughput analysis.

Table 15: GRTA Route 101 Estimated AM Arrival Times at Data Collection Locations

Departure I-985 @ SR-20	Old Peachtree Road	Pleasant Hill Road	Beaver Ruin Road	Jimmy Carter Boulevard	Chamblee Tucker Road
5:40	5:51	5:58	6:01	6:06	6:12
6:00	6:11	6:18	6:21	6:26	6:32
6:20	6:31	6:38	6:41	6:46	6:52
6:40	6:51	6:58	7:01	7:06	7:12
7:00	7:11	7:18	7:21	7:26	7:32
7:15	7:27	7:34	7:37	7:42	7:49
7:30	7:42	7:49	7:52	7:57	8:04
7:45	7:58	8:06	8:09	8:15	8:23
8:00	8:13	8:21	8:24	8:30	8:38

Give the departure times of some buses and the monthly differences in congestion levels, many buses may arrive at the station slightly before or after the hour. Hence, month-by-month hourly totals may vary by as many as 10 buses. However, monthly peak-period totals are all equal.

9.5 Changes in Express Bus Activity

The analysis of express bus activity shows an increase of 50 buses per week on the corridor in the morning (10 before the morning peak, and 40 during the morning peak) in winter/spring 2012, compared to the winter/spring 2011 baseline period. Two new routes were added in July and August 2011, but two early morning buses were also eliminated. Table 16 shows the breakdown of bus throughput by hour for February through April (winter/spring) for 2011 and 2012. January was not employed in the analysis because a major snow/ice storm in 2011 closed roads for more than one week (ridership returned to normal in February). The overall daily average increase in passenger throughput for the February-April morning peak in 2012 (winter/spring 2012) was about six riders. Afternoon ridership increased by about 42 riders, or 0.5%. Given that 50 buses were added to AM routes and 40 buses were added to PM routes, between zero and one rider was added per new bus. Table 17 shows the hourly break-down of passenger throughput. Table 18 shows the average difference in average bus occupancy (persons/bus) for each hour for February-April. Bus occupancy dropped significantly in the early morning hours, and increased in the later morning hours. Overall, however, bus occupancy declined in February-April by about 15% because bus service increased by about 14% while bus ridership increased by around 0.1%.

Table 16: Pre- and Post-HOT Average Weekly Express Bus Throughput Comparison

Weekly Average Express Bus Throughput	5-6 AM	6-7 AM	7-8 AM	8-9 AM	9-10 AM	AM Peak
February - April 2011	15	75	80	65	5	240
February - April 2012	25	90	100	70	5	290
Difference	10	15	20	5	0	50
Percent	66.7%	20.0%	25.0%	7.7%	0.0%	20.8%
Weekly Average Express Bus Throughput	3-4 PM	4-5 PM	5-6 PM	6-7 PM	7-8 PM	PM Peak
February - April 2011	35	75	85	80	20	295
February - April 2012	35	90	105	95	10	335
Difference	0	15	20	15	-10	40
Percent	0.0%	20.0%	23.5%	18.8%	-50.0%	13.6%

Table 17: Pre- and Post-HOT Weekly Express Bus Passenger Throughput Comparison

Weekly Average Passenger Throughput	5-6 AM	6-7 AM	7-8 AM	8-9 AM	9-10 AM	AM Peak
February - April 2011	316	2366	3234	2388	143	8447
February - April 2012	380	2266	3244	2415	148	8453
Difference	64	-100	10	27	5	6
Percent	20.3%	-4.2%	0.3%	1.1%	3.5%	0.1%
Weekly Average Passenger Throughput	3-4 PM	4-5 PM	5-6 PM	6-7 PM	7-8 PM	PM Peak
February - April 2011	1267	2564	2864	1545	228	8468
February - April 2012	991	2595	3162	1651	111	8510
Difference	-276	31	298	106	-117	42
Percent	-21.8%	1.2%	10.4%	6.9%	-51.3%	0.5%

Table 18: Pre- and Post-conversion Average Express Bus Occupancy Comparison

Express Bus Occupancy (persons/bus)	5-6 AM	6-7 AM	7-8 AM	8-9 AM	9-10 AM	AM Peak
February - April 2011	21.1	31.5	40.4	36.7	28.6	35.2
February - April 2012	15.2	25.2	32.4	34.5	29.6	29.1
Difference	-5.9	-6.4	-8.0	-2.2	1.0	-6.0
Percent	-27.8%	-20.2%	-19.8%	-6.1%	3.5%	-17.2%
Express Bus Occupancy (persons/bus)	3-4 PM	4-5 PM	5-6 PM	6-7 PM	7-8 PM	PM Peak
February - April 2011	36.2	34.2	33.7	19.3	11.4	28.7
February - April 2012	28.3	28.8	30.1	17.4	11.1	25.4
Difference	-7.9	-5.4	-3.6	-1.9	-0.3	-3.3
Percent	-21.8%	-15.7%	-10.6%	-10.0%	-2.6%	-11.5%

The compendium of express bus throughput and occupancy tables for January through April, for both AM and PM service, are located in Appendix D: Express Bus Throughput, February - April. Corridor throughput analyses presented later in the report will employ average daily vehicle and person throughput values for Tuesdays, Wednesdays, and Thursdays, to correspond with field data collection of vehicle occupancy. Hence, the average daily values for express bus ridership in those calculations will employ data only from mid-week ridership records.

9.6 Express Bus Occupancy and Throughput Discussion

Express bus ridership in winter/spring 2012 was practically unchanged, given the number of buses added to service. The lack of maturity of the newly added bus lines (implemented in September 2011 and evaluated for February through April) may have played a role. Another major factor specific to winter/spring 2012, however, was a significant fare increase. Of the eight lines servicing this corridor, five of them, operated by GCT, raised the fare starting in February 2012. Monthly passes for Zone 1 routes increased from $100.00 to $130.00 (30%) and for Zone 2 routes from $150.00 to $180.00 (20%). The fare increase may help explain why ridership did not increase. Assuming 20-commute-days per month, the new monthly Zone 2 fare of $180.00 allows a commuter $9.00/day that could be used toward HOT lane tolls; hence, potential express bus patrons may be driving alone in the HOT lane. Note that tolls have increased significantly since this study period, which may change future results. Collection and analysis of more detailed survey data and conduct of panel surveys of GRTA riders and non-riders is warranted to assess why the changes in travel behavior occurred and to identify factors that need to be addressed if ridership numbers are to improve.

The data from this study cannot be used to draw specific conclusions regarding the HOT lane's direct or indirect impact on the occupancy of buses and vanpools. Increased express bus service and reliability was concurrent with a fare increase. Behavioral data collection and analysis would be required to assess how HOT lane performance/price affected traveler decision making.

An increase in express bus throughput did occur as planned, but express bus passenger throughput remained essentially unchanged. A simultaneous decrease in bus occupancy resulted, given the number of buses introduced. Over time, express buses may have a larger impact on lane occupancy, especially if ridership continues to grow. As will be seen in the forthcoming passenger throughput assessment chapter of this report, express buses represent only about 0.1% of corridor vehicle throughput during the morning peak period, but carry nearly 4% of person throughput during the morning peak. Hence, the express bus mode has the potential to carry an even larger percentage of person throughput on I-85. Express buses provide excellent service and capacity, but there may be a need to further improve operational efficiency or implement targeted ridership incentives to increase person throughput.

9.7 Accounting for Express Bus Passengers in Total Corridor Throughput

The vehicle occupancy study conducted in the field and reported in Chapter 5 involved the collection of joint vehicle classification and vehicle occupancy records. Each record included vehicle class (light-duty vehicle, sports utility vehicle, or heavy-duty vehicle) and occupancy value. Few heavy-duty vehicles use the HOV and HOT lanes. Of the heavy-duty vehicles that were observed in the HOV and HOT lanes, many were utility trucks, such as lawn maintenance vehicles, and some did contain multiple passengers. Express buses, when observed, were always recorded as HDVs with 4+ occupancy. For every express bus, an occupancy value of 4.5 persons/vehicle would be assigned in the steps employed in calculating person throughput using observed occupancy data. However, express buses carry many more individuals

To properly account for express bus passenger throughput, an additional processing step was added to the person throughput methodology. For each hour, the number of scheduled express buses and corresponding number of persons are estimated via the methods outlined earlier in this chapter. The scheduled express buses traversing the corridor are assumed to have been present in the HDV throughput. For each bus traversing the corridor, 4.5 persons are removed from the person total and the estimated number of persons carried by each bus is added to the person total. This process significantly increases the total number of commuters and average vehicle occupancy, especially during the early morning periods when express buses carry a large faction of passenger throughput. A forthcoming chapter summarizes vehicle and person throughput and will specifically address the number of vehicles and persons served by each mode so that the impact of express buses on overall corridor throughput becomes more evident.

10 Vanpool Operations and Impacts on Occupancy

A subset of commuters using the I-85 corridor travel by vanpool. As discussed earlier, one of the goals of the HOT lanes was to provide a high level of service for, and to improve travel time reliability of, alternative modes. By improving the performance of the managed lane, individuals would be encouraged to form carpools, take vanpools, and use express bus transit. Very little research has been undertaken on the effect of HOT lane implementation on vanpool operations. This is likely due to vanpool's low ridership in recent years. Also, the lack of data availability for vanpools hinders research. This chapter reports on the assessment of vanpool activity pre- and post-HOT implementation.

Private vanpool ownership corporations constitute the majority of vanpools in operation across the country (Deitrick, et al., 2010). Typically, a vanpool ownership company will lease the van to a member of a group that has decided to form a vanpool. Typically, the lessee is the individual that serves as the primary driver of the vanpool. On some occasions, companies lease the vehicles on behalf of their employees. The primary driver typically garages the van at their residence. The vanpool group establishes standard morning and afternoon meeting locations (or pickup routes and stops) and sets departure times. The driver usually communicates with the members of their vanpool only when a problem arises. The primary vanpool ownership companies in the Atlanta region are Vanpool Services Inc. (VPSI) and Enterprise Vanpools. The vanpool agencies keep relatively little specific information about each vanpool's travel patterns as the vanpool may switch any aspect of their travel without informing the leasing company.

10.1 Vanpool Activity

Vanpool Services Inc. (VPSI) owns the vast majority of vans leased in the commutershed potentially used as vanpools on the I-85 HOT corridor (around 50). A second company, Enterprise, owns approximately 12 vans that may also be used on this corridor. Neither company collects operations data. The lack of available data made it difficult to assess the frequency of service and occupancy of the vanpools. Collecting operations data for the vanpools proved difficult given the vanpool business model; however, both companies they did assist the research team in contacting the lessees.

License plate data collected by the research team during the occupancy data collection studies were employed in socioeconomic impact assessment (see, Guensler, et al., 2013). License plate data served as a means to identify vehicles that were registered to the leasing company both before and after HOT lane operations commenced. With the assistance of VPSI and Enterprise, surveys were mailed to the primary drivers of all of the VPSI vanpools to gather additional information about the van's route, pickup locations, departure times, and occupancy. Readings taken by SRTA's Peach Pass RFID detectors were also examined and used to identify post-conversion vanpool operations data with respect to frequency and time of HOT facility use.

10.2 Survey of Vanpool Operations and Vanpool Occupancy

Surveys were sent to the primary drivers of the VPSI vanpools asking for information on their origins, destinations, time of departure, and occupancy. The survey instrument is contained in Appendix E: Vanpool Questionnaire. Of the approximately 60 VPSI vanpools using the corridor, only 11 drivers responded to the survey. The results are provided in Table 19 with the van ID number, occupancy of the vanpool, vanpool departure time in the morning and afternoon, origin location in the morning, whether they use a general purpose or managed lane, and in some cases where they travel to in the morning. These results show a great deal of variability in vanpool departure time. Most depart between 6:00 AM and 8:00 AM, but one van leaves at 5:00 AM. The departure times in the afternoon are more variable and have a broader range from 3:30 PM to 6:15 PM. Most of the vanpools in the survey used the HOT lane. Although this is a small sample size, the average occupancy of 8.9 persons/van is not unreasonable. This average is supported by the vanpools operated by Enterprise (Table 20), which yielded an average occupancy of 8.4 persons/van. For this study, the 8.6 persons/vanpool average occupancy value taken from all survey data was employed in calculating the throughput of vanpool passengers. Given the small sample size, additional analyses were conducted to estimate vanpool frequency.

Table 19: VPSI Survey Results

Van Number	Persons	AM Departure	PM Departure	AM Origin	AM Destination	Lane
28338	13	7:45 AM	6:10 PM	Discovery Mills	No Answer	ML
29150	6	7:50 AM	6:15 PM	South Hairston Rd.	No Answer	ML
29482	5	5:00 AM	No Answer	Buford I 985 P&R	Bluegrass Lakes	GP
29853	8	6:45 AM	5:30 PM	Snellville P&R	No Answer	GP(AM), ML(PM)
31494	7	6:00 AM	No Answer	Mall of GA	No Answer	ML
32038	6	6:30 AM	5:15 PM	Grayson Kroger	No Answer	ML
32519	7	6:30 AM	4:00 PM	Buford I 985 P&R	No Answer	ML
28992	13	6:50 AM	4:30 PM	Discovery Mills	Emory	ML
29873	9	6:20 AM	No Answer	Snellville Target	No Answer	ML
34141	15	6:15 AM	3:30 PM	Gwinnett P&R	Century Center	ML
Average	8.9					

Table 20: Enterprise Vanpool Data

Van Number	Persons (Occupancy)	AM Departure	PM Departure
VP 67	6	6:30 AM	5:30 PM
VP 133	9	4:45 AM	5:15 PM
VP 81	10	6:30 AM	5:30 PM
VP 58	6	6:30 AM	5:30 PM
VP 78	6	7:10 AM	6:00 PM
VP 91	7	6:05 AM	4:50 PM
VP 35	11	5:50 AM	5:10 PM
VP 4	11	6:50 AM	6:00 PM
VP 16	10	6:00 AM	5:00 PM
VP 99	10	5:45 AM	5:30 PM
VP 52	6	6:15 AM	5:00 PM
VP 89	9	6:20 AM	5:40 PM
Average	8.4		

10.3 Vanpool Throughput and Temporal Frequency

Relative frequencies of vanpool operations were estimated by analyzing the same video collected and processed to obtain license plate data for use in a demographic study (Guensler, et al., 2013). License plates in the video data stream were linked to a vehicle registration address through a secure process handled by a separate agency. Using a reverse search on VPSI's and Enterprise's corporate addresses, the team identified license plates belonging to VPSI and Enterprise vans. Video data were collected quarterly starting in October 2010 for five weeks from 7:00-9:00 AM and 4:30-6:30 PM at five overpass sites above the I-85 corridor; Chamblee Tucker, Jimmy Carter Boulevard, Beaver Ruin Road, Pleasant Hill Road, and Old Peachtree Road.

Table 21 and Figure 42 show the number of vanpools observed per hour in each season of data collection classified based on time (AM, PM) and lane (GP, HOV/HOT). The team selected Jimmy Carter Boulevard for AM, and Chamblee Tucker Road for PM, license plate counts. The reason for selecting these two sites is that they showed the highest frequency of vanpool observation for AM and PM respectively as well as being the closest sites to the Center Way where good NaviGAtor traffic volume data were also available for other elements of the study.

Based on the quarterly field data collection, the number of vanpools passing during the field data collection periods is significantly higher in the afternoon than it is in the morning. Because all vanpools that enter the city also return home, the vanpool frequencies should be the same in the morning and afternoon peak. Morning data collection was conducted from 7:00 AM to 9:00 AM (data collection effectively begins at 7:30 in the morning during the winter because of the lighting conditions). Hence, field observations missed a significant portion of vanpool activity from 6:00 AM to 7:00 AM. For throughput analysis, the missing morning peak period vanpools were all assigned to 6:00 AM to 7:00 AM for occupancy and throughput analysis.

Table 21: HOV/HOT Corridor Vanpools Frequency

Season	Time	Vanpools Observed per Peak Hour			
		AM GP	PM GP	AM HOV/HOT	PM HOV/HOT
HOV Q1	October 2010	0	1	1	6
HOV Q2	February 2011	0	1	1	7
HOV Q3	May 2011	0	1	2	7
HOV Q4	August 2011	0	1	2	7
HOT Q1	November 2011	0	1	2	9
HOT Q2	January 2012	0	1	2	8
HOT Q3	March 2012	0	0	2	8
HOT Q4	August 2012	na	na	na	Na

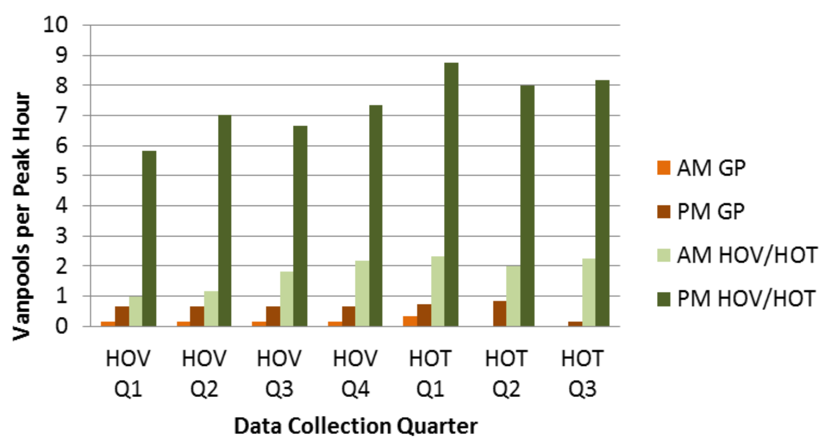

Figure 42: HOV/HOT Corridor Vanpool Observation Frequency

The research team also attempted to count the number of vanpools during AM and PM peak periods using low-resolution videos from GDOT's PTZ cameras along corridor. Unfortunately, because of the low quality of the video and the camera view angles, it was not possible to distinguish between utility vans, personal vans, and vanpools. The counts available from the quarterly occupancy data collection effort were the best available source of field data.

Comparing the frequency of vanpools observation before and after the HOV to HOT conversion, a major increase in the number of vanpools was not observed. The method of data collection was consistent before and after the data collection. Hence, even if there is an undercounting error in the number of vanpools, this error should be consistent for all seasons of data collection before and after the conversion.

In comparing February 2011 to February 2012, an increase of one vanpool per hour is observed in the managed lane. Even if the vans were fully loaded with 15 passengers, the increase in passengers per hour on the HOV/HOT lane is insignificant, considering that more than 1500 vehicles per hour use the lane, including carpools and express buses with multiple passengers.

10.4 Current Vanpool Operating Schedules

To obtain a more accurate picture of vanpool frequency, the SRTA Peach Pass database was searched for the same VPSI license plates. This database contains the time of day when each Peach Pass is read by the detectors. The results of this search are shown in Table 22. Four cells (6-7 and 8-9 time periods on Feb 1st and 2nd) were imputed from the SRTA data because observation data were missing from the SRTA database. The median value from 8-9 AM was set to 1. The data in these tables are for VPSI vanpools only.

Table 22: Vanpool Frequency Observation Data

Date	Vans per Hour				Total
2012	6-7	7-8	8-9	9-10	Peak
31-Jan	20	5	0	0	25
1-Feb	20	6	1	0	26
2-Feb	20	6	1	0	26
7-Feb	19	6	0	0	25
8-Feb	21	7	0	0	28
9-Feb	18	7	0	0	25
14-Feb	20	6	0	0	26
15-Feb	20	6	0	0	26
16-Feb	19	4	0	0	23
21-Feb	20	5	1	0	26
22-Feb	20	5	0	0	25
23-Feb	21	5	0	0	26
Median	20	6	1	0	26

To obtain the frequency of vanpools before the conversion of the HOT lane, the observed vanpools from the video data collection of license plates was used. The percent change between February 2011 and February 2012 was multiplied by the observed numbers for 2012. In this case, the average observed frequency increased from 7 to 8 per peak hour. Therefore the actual frequencies in 2012 were multiplied by 0.875 to estimate 2011 frequencies (Table 23). The SRTA data confirm that most vanpools do travel between 6:00 and 7:00 AM and were therefore missed by video data collection in the morning. The estimates in these tables do not yet include a contribution from enterprise vanpools, which we expect to slightly increase vehicle and person throughput.

Table 23: Estimated 2011 Vanpool Frequency

Date	Vans per Hour				Total
2011	6-7	7-8	8-9	9-10	Peak
1-Feb	18	4	0	0	22
2-Feb	17	5	1	0	23
3-Feb	17	5	1	0	23
8-Feb	17	5	0	0	22
9-Feb	18	6	0	0	25
10-Feb	16	6	0	0	22
15-Feb	18	5	0	0	23
16-Feb	18	5	0	0	23
17-Feb	17	4	0	0	20
22-Feb	18	4	1	0	23
23-Feb	18	4	0	0	22
24-Feb	18	4	0	0	23
Median	18	5	1	0	23

For the vehicle and passenger throughput analysis, the SRTA-monitored Peach Pass RFID tag read data were used to establish 2012 observation counts. The ratios of vans observed in 2011 vs. 2012 via video analysis were then used to estimate the 2011 counts. The results indicate that about a 12.5% increase in vanpool activity occurred after the HOT lanes opened. Hence, the estimated increase in vanpool activity is about 15 vanpools per week in the morning and afternoon peaks. This total, along with the hourly breakdown, can be seen in Table 24. Assuming an average occupancy of 8.6 riders from the survey data, this translates to an increase of approximately 123 riders per week (Table 25). Table 26 is presented only to remind the reader that the team assumed that vanpool occupancy remained constant from 2011 to 2012, which may or may not be true. Yet, even if vanpool occupancy increased slightly, the impact on overall passenger throughput for the corridor will be very small.

Table 24: Pre- and Post-conversion Weekly Vanpool Throughput Comparison

Weekly Vanpool Throughput	5-6 AM	6-7 AM	7-8 AM	8-9 AM	9-10 AM	AM Peak
January-April 2011	0	87	25	1	0	113
January-April 2012	0	99	28	1	0	128
Difference	0	12	3	0	0	15
Percent	n/a	13.8%	12.0%	0.0%	n/a	13.3%

Table 25: Pre- and Post-conversion Weekly Vanpool Passenger Throughput Comparison

Weekly Person Throughput	5-6 AM	6-7 AM	7-8 AM	8-9 AM	9-10 AM	AM Peak
January-April 2011	0	748	215	9	0	972
January-April 2012	0	851	241	9	0	1101
Difference	0	103	26	0	0	129
Percent	n/a	13.8%	12.1%	0.0%	n/a	13.3%

Table 26: Pre- and Post-conversion Average Vanpool Occupancy Comparison

Vanpool Occupancy (persons/bus)	5-6 AM	6-7 AM	7-8 AM	8-9 AM	9-10 AM	AM Peak
January-April 2011	n/a	8.6	8.6	8.6	n/a	8.6
January-April 2012	n/a	8.6	8.6	8.6	n/a	8.6
Difference	n/a	0.0	-0.1	0.0	n/a	0.0
Percent	n/a	0.0%	0.0%	0.0%	n/a	0.0%

10.5 Vanpool Occupancy and Throughput Discussion

The vanpool data indicate that a small increase in vanpool throughput and vanpool passenger throughput has occurred since the HOT lanes opened. The increase is very small relative to total corridor throughput. Given the small increase, there is no way to be sure that the HOT lane implementation resulted in this change.

As will be seen in the forthcoming passenger throughput assessment chapter of this report, vanpools represent only about 0.1% of corridor vehicle throughput during the morning peak period, but carry about 0.4% of the person throughput given their higher occupancy. The 128 vanpools trips per week carry about 1100 passengers (8.6 passengers/vehicle), whereas 290 express bus trips in the peak carry more than 8510 passengers per week (29 passengers/vehicle). Express bus operations are more vehicle-efficient, but also service limited locations. Passenger throughput by vanpool might be increased for I-85 if the right TDM strategies are implemented. Over time, vanpools could have a larger impact on HOT lane throughput if ridership can be stimulated.

The increase in vanpool formation and ridership in winter/spring 2012 was probably smaller than anticipated, given the improved performance of the HOT lane compared to HOV operations and given the tolls that are in place for HOT lane use. However, the vanpool business model, where groups first must agree to form a vanpool and then lease the vans, is not necessarily conducive to vanpool formation without implementation of a more proactive planning process. More vanpools will likely form over time; however, there may be a need for state and local agencies and the business community to partner in an effort to increase the rate of vanpool formation.

In 2012, a 15-passenger VPSI van equipped with luxury captain chairs and with an allowance of 100 commute miles/day was leased for approximately $1534/month (VPSI, 2013). Assuming 20-commute-days per month, the cost divided by nine passengers is approximately $8.50 per person per commute day (plus fuel, shared maintenance, and insurance). The vanpool lease cost alone is more than $170.00/month/person, which is more expensive than express bus service from Zone 1 ($130.00/month) and comparable to Zone 2 express bus service ($180.00/month). When fuel, insurance, and maintenance are factored in, the cost of participating in vanpools is very high. In any case, this monthly alternative mode commute cost may be playing a significant role in the decision of commuters to drive alone in the HOT lane even though express buses and vanpools are available. Most commuters receive free parking at their workplace and weigh the sunk costs of automobile ownership much lower than out of pocket costs for transit fares and vanpool fees (Shoup, 2011). Collection and analysis of more detailed survey data and conduct of panel surveys of vanpool riders and non-riders is warranted to assess why significant changes in travel behavior have not yet occurred and to identify factors that need to be addressed if ridership numbers are to improve.

10.6 Accounting for Vanpool Passengers in Total Corridor Throughput

The vehicle occupancy study reported in Chapter 5 involved the collection of joint vehicle classification and vehicle occupancy records. Each record included vehicle class (light-duty vehicle, sports utility vehicle, or heavy-duty vehicle) and occupancy value. Vanpools, when observed, were always recorded as SUVs with 4+ occupancy. For every express bus on the corridor, 4.5 persons/vehicle is assigned in calculating initial person throughput using observed occupancy results. However, as discussed earlier, current vanpools are estimated to be carrying an average 8.6 persons/van.

To properly account for vanpool passenger throughput, an additional processing step was added to the person throughput methodology. For each hour, the number of vanpools and corresponding number of persons are estimated via the methods outlined earlier in this chapter. That set number of vanpools is assumed to have been present in the SUV throughput. For each vanpool traversing the corridor, 4.5 persons are removed from the person total and 8.6 persons are added to the person total. This process increases the total number of commuters and average vehicle occupancy, especially during the early morning periods when vanpools and express buses carry a large faction of passenger throughput. A forthcoming chapter summarizes vehicle and person throughput and specifically addresses the number of vehicles and persons served by each mode so that the impact of vanpools on corridor throughput becomes more evident.

11 Changes in HOT Corridor Vehicle and Person Throughput

For the purposes of this study, corridor vehicle and person throughput are assessed at Center Way, as discussed in Chapter 4. Vehicle throughput is monitored by VDS stations on the NaviGAtor system. Person throughput is a function of traffic flow coupled with vehicle occupancy. The implementation of the HOT lanes changed the minimum occupancy requirements on the managed lane from HOV2 (2-person carpools) to HOT3 (3-person carpools for free use of the lane) and then allowed single-occupant vehicles and 2-person carpools to pay a toll to fill the excess capacity on the HOT lane. Given the change in carpool requirements, it was essential to monitor changes in vehicle occupancy, as outlined in Chapters 5 through 8. Then, the impact on person throughput of express buses (which currently carry about 25% of persons using the HOT lane in the morning peak period) and vanpools had to be accounted for (Chapters 9 and 10). The resulting impacts of changes in vehicle throughput, changes in passenger vehicle occupancy, and changes in express bus and vanpool occupancy are presented in this chapter.

11.1 Changes in Vehicle Throughput by Lane and Mode

After the opening of the HOT lanes, traffic volumes were observed to have declined in both the morning and afternoon peak periods. Figure 43 presents the changes in AM (left) and PM (right) traffic volumes (previously presented as larger figures in Chapter 4). As discussed earlier, over the eight-month pre-and-post analysis (which excludes October-January due to lack of Navigator II data availability and a January ice storm), traffic volumes declined by approximately 6.5% in the morning peak period, and by about 2.8% in the afternoon peak period over the eight month period. Over the three month period of February-April, for which the research team believes that the best express bus data are available, traffic volumes declined by approximately 6.6% in the morning peak period, and by about 2.9% in the afternoon peak period.

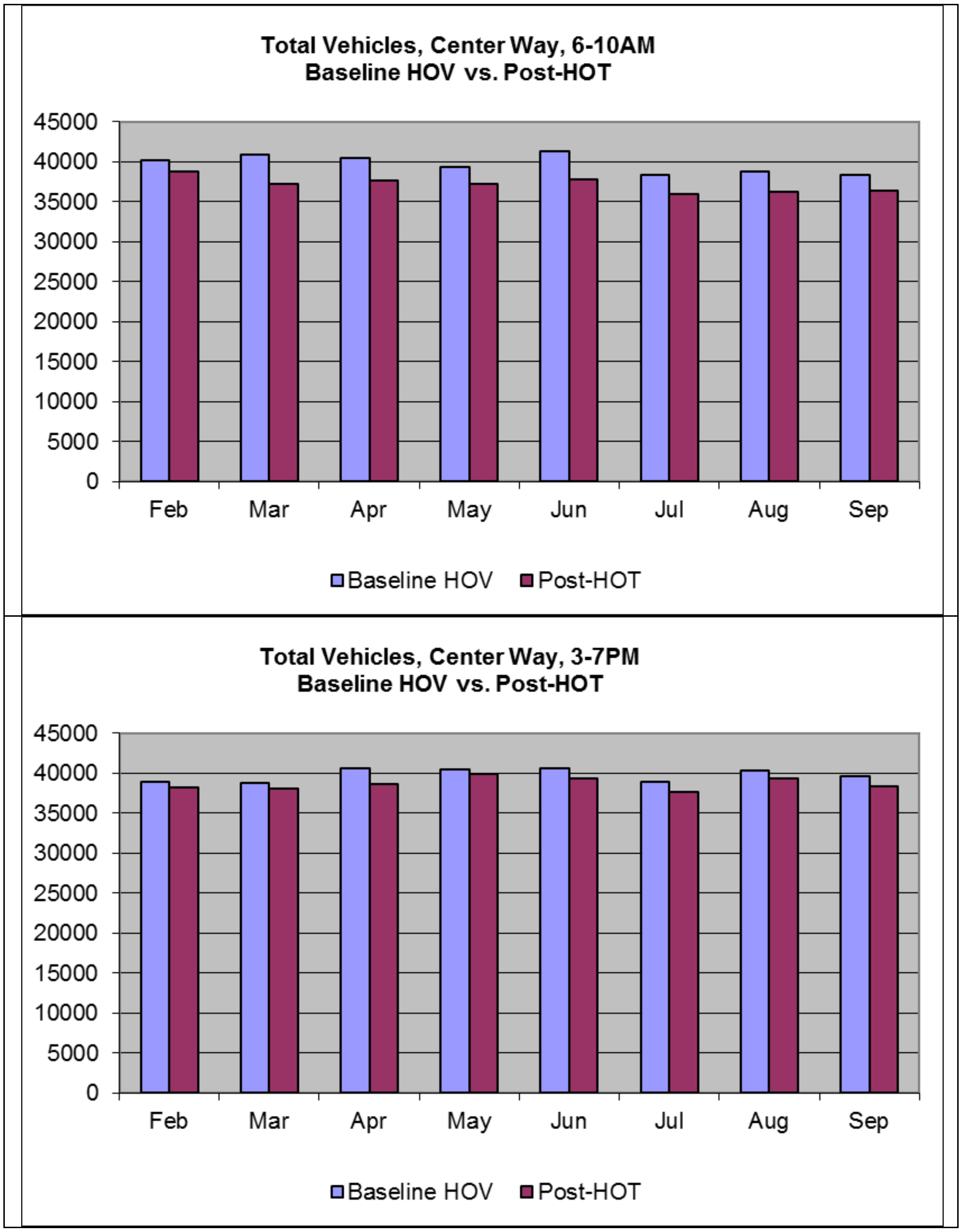

Figure 43: Vehicle Throughput in the AM and PM Peaks at Center Way Feb-Sep, Pre- and Post-HOT Implementation (Figure 15 and Figure 16)

Estimation of person throughput on the corridor in the next section necessarily involves the application of corridor vehicle occupancy results to the monthly lane volumes. The monthly lane volumes were extracted from the VDS system as described in Chapter 4. Table 27 and Table 28 break the corridor vehicle throughput figures into occupancy classifications for the months of February through April that will be used in this process. These tables indicate that the largest reduction in vehicle throughput in both the morning and afternoon peak periods came from carpools (HOV2 and HOV3+ vehicles). This is somewhat disconcerting as one of the goals of the implementation of the HOT lanes was to incentivize carpooling, or at least to not impact the percentage of carpools on the corridor. Carpool mode share declined by more than 30% in the AM peak and by 25% in the PM peak. As expected express bus operations increased (through the funding of increased bus service, as described in Chapter 9).

Table 27: Corridor Vehicle Throughput by Occupancy Mode, Feb-Apr, AM Peak

Mode	Baseline Volume	Baseline Mode %	Post-HOT Volume	Post-HOT Mode %	Volume Change	Percent Change
SOV	34407	84.8%	33707	88.9%	-700	-2.0%
HOV2	5819	14.3%	3921	10.3%	-1898	-32.6%
HOV3+	300	0.7%	189	0.5%	-110	-36.9%
Express Buses	45	0.1%	53	0.1%	8	17.5%
Vanpools	24	0.1%	27	0.1%	3	12.5%
Total	40595	100%	37897	100%	-2698	-6.6%

Table 28: Corridor Vehicle Throughput by Occupancy Mode, Feb-Apr, PM Peak

Mode	Baseline Volume	Baseline Mode %	Post-HOT Volume	Post-HOT Mode %	Volume Change	Percent Change
SOV	32438	81.9%	33108	86.1%	669	2.1%
HOV2	6542	16.5%	4868	12.7%	-1674	-25.6%
HOV3+	532	1.3%	377	1.0%	-155	-29.2%
Express Buses	55	0.1%	65	0.2%	10	18.2%
Vanpools	24	0.1%	27	0.1%	3	12.5%
Total	39592	100%	38444	100%	-1148	-2.9%

Table 29 and Table 30 break the same vehicle throughput results into managed lane and general purpose lane shares. The increase in SOV share using the HOT lane was by design; SOVs may pay a toll to use the lane (which fills excess capacity). The decline of both HOV2 and HOV3+ vehicles on the managed lane during both the AM and PM peak periods was significant and surprising, considering that HOV3+ vehicles can use the HOT lanes without paying a toll. On average, two-person carpools do not appear to have picked up a third passenger to avoid paying a toll. The shift of 2-person carpools to the general purpose lane, nearly doubling the number of HOV2 vehicles using the general purpose lanes, indicates that a significant share of HOV2 vehicles were not willing to pay a shared toll (split between two individuals). Most surprising, a large number of 3-person carpools shifted to the general purpose lanes, despite the fact that they can use the lanes for free. It seems likely that many of these vehicles may not have registered for use of the lanes and obtained an RFID tag. Additional research into the impact of the implementation of the managed lanes on the formation and retention of carpools is clearly warranted based upon the observational results.

Table 29: Corridor Vehicle Throughput by Occupancy Mode, Feb-Apr, AM Peak

Mode	Baseline Volume	Post-HOT Volume	Change Volume	Percent Change
SOV-ML	218	3635	3417	1567.7%
SOV-GP	34189	30073	-4117	-12.0%
HOV2-ML	4051	485	-3567	-88.0%
HOV2-GP	1767	3436	1669	94.4%
HOV3+-ML	199	16	-183	-92.1%
HOV3+-GP	101	173	73	72.5%
Express Buses	45	53	8	17.5%
Vanpools	24	27	3	12.5%
Total	40595	37897	-2698	-6.6%

Table 30: Corridor Vehicle Throughput by Occupancy Mode, Feb-Apr, PM Peak

Mode	Baseline Volume	Post-HOT Volume	Change Volume	Percent Change
SOV-ML	374	3668	3293	879.7%
SOV-GP	32064	29440	-2624	-8.2%
HOV2-ML	4250	520	-3730	-87.8%
HOV2-GP	2293	4348	2055	89.7%
HOV3+-ML	312	23	-289	-92.5%
HOV3+-GP	220	353	133	60.5%
Express Buses	55	65	10	18.2%
Vanpools	24	27	3	12.5%
Total	39592	38444	-1148	-2.9%

11.2 Changes in Person Throughput by Lane and Mode

After the opening of the HOT lanes, traffic volumes declined in both the morning and afternoon peak periods, as presented in the last section. However, the decline in traffic volume occurred concurrently with decreases in vehicle occupancy rates, as noted in Chapters 5 through 8. Over the eight month pre-and-post analysis (which excludes October-January due to lack of Navigator II data availability and a January ice storm), the combined effect on corridor person throughput during the AM peak is presented in Figure 44. Figure 45 presents the changes in PM person throughput. While traffic volumes declined by approximately 6.6% in the morning peak period for February through April, person throughput concurrently declined by about 9.9%. While traffic volumes declined by approximately 2.9% in the afternoon peak period for February through April, person throughput concurrently declined by about 6.3%.

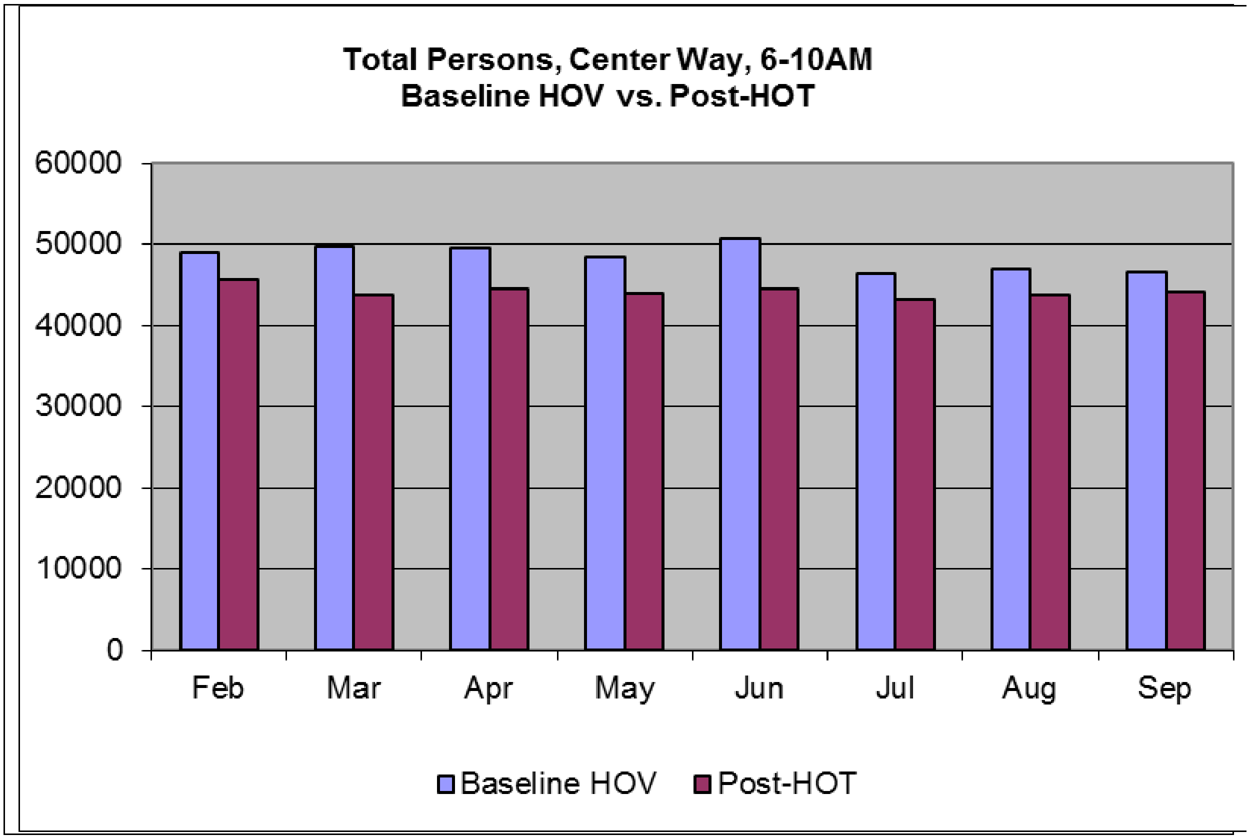

Figure 44: Vehicle Throughput in the AM Peak at Center Way
Feb-Sep, Pre- and Post-HOT Implementation

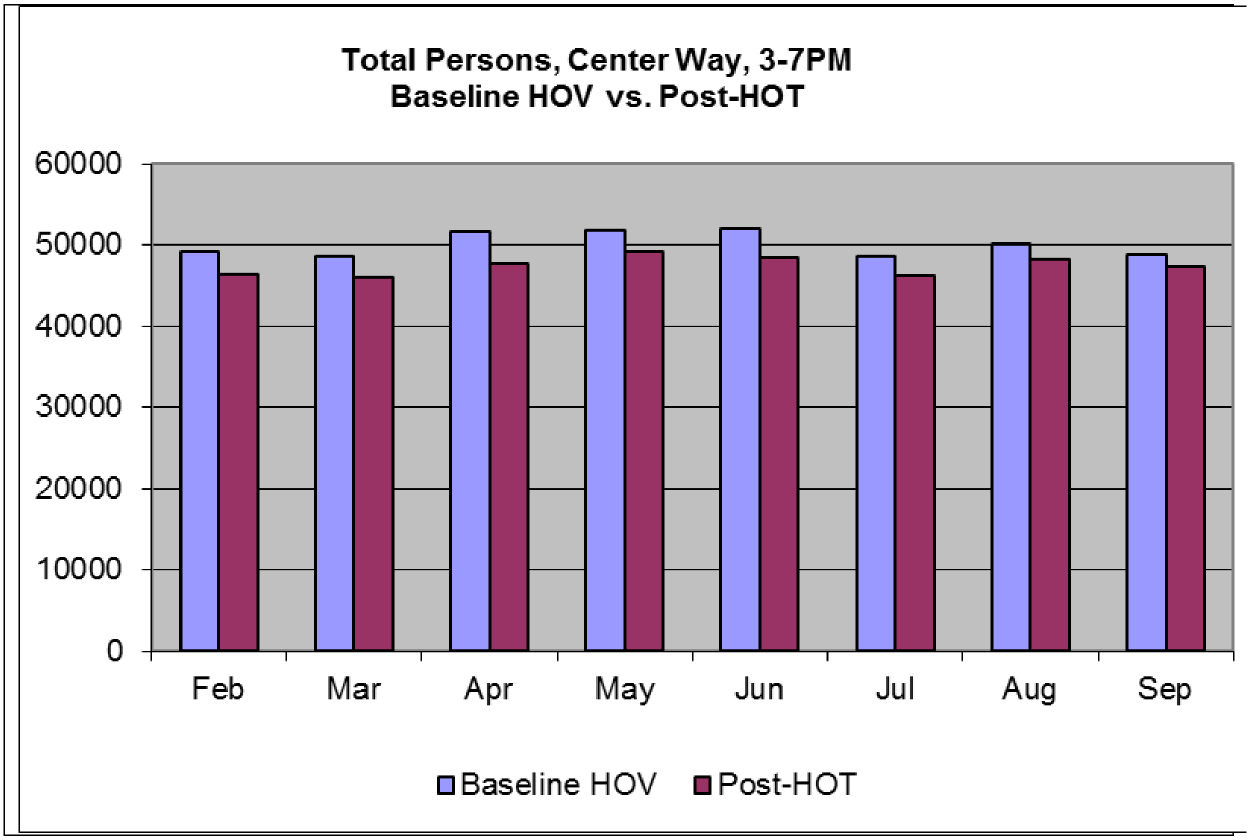

Figure 45: Person Throughput in the PM Peak at Center Way Feb-Sep, Pre- and Post-HOT Implementation

Estimation of person throughput involves the application of corridor vehicle occupancy results to the monthly lane volumes. Table 31 and Table 32 break the corridor person throughput figures into occupancy classifications for the months of February through April. As noted with vehicle throughput, these tables indicate that the largest reduction in person throughput in both the morning and afternoon peak periods came from carpools (HOV2 and HOV3+ vehicles). Person throughput via carpool modes declined by more than 30% in the AM peak period and by more than 25% in the PM peak period. The express bus person throughput presented in these tables is for Tuesdays-Thursdays. The throughput presented in Chapter 9 was for the entire week. Because express buses are used more frequently on Mondays and Fridays, the numbers are slightly different in these tables. As discussed earlier, person throughput via vanpools and express buses simply did not increase to any significant extent.

Table 31: Corridor Person Throughput by Occupancy Mode, Feb-Apr, AM Peak

Mode	Baseline Persons	Baseline Mode %	Post-HOT Persons	Post-HOT Mode %	Person Change	Percent Change
SOV	34407	70.2%	33707	76.4%	-700	-2.0%
HOV2	11637	23.7%	7841	17.8%	-3796	-32.6%
HOV3+	1015	2.1%	636	1.4%	-379	-37.4%
Express Buses	1748	3.6%	1729	3.9%	-19	-1.1%
Vanpools	206	0.4%	232	0.5%	26	12.5%
Total	49014	100%	44145	100%	-4868	-9.9%

Table 32: Corridor Person Throughput by Occupancy Mode, Feb-Apr, PM Peak

Mode	Baseline Persons	Baseline Mode %	Post-HOT Persons	Post-HOT Mode %	Person Change	Percent Change
SOV	32438	65.6%	33108	71.4%	669	2.1%
HOV2	13085	26.5%	9736	21.0%	-3349	-25.6%
HOV3+	1813	3.7%	1304	2.8%	-509	-28.1%
Express Buses	1920	3.9%	1960	4.2%	40	2.1%
Vanpools	206	0.4%	232	0.5%	26	12.5%
Total	49462	100%	46340	100%	-3123	-6.3%

Table 29 and Table 30 break the same person throughput results into managed lane and general purpose lane shares. The increase in SOV share using the HOT lane was by design; SOVs may pay a toll to use the lane (which fills excess capacity). The decline of persons using HOV2 and HOV3+ modes during both the AM and PM peak periods was significant. Based upon field observation of occupancy, there are 25 times more 3-person personal vehicle carpools using the general purpose lanes than using the HOT lane, even though the HOT lane is free for these vehicles. The person throughput findings affirm that additional research into the impact of the implementation of the managed lanes on the formation and retention of carpools is clearly warranted based upon the observational results. Barriers to the use of the lanes by 3-person carpools should be investigated. It is critical to identify the reasons why so many HOV2+ vehicles are choosing not to use the HOT lanes, even though tolls are free for HOV3+ and shared for HOV2 users.

Table 33: Corridor Person Throughput by Occupancy Mode, Feb-Apr, AM Peak

Mode	Baseline Volume	Post-HOT Volume	Change Volume	Percent Change
SOV-ML	218	3635	3417	1567.7%
SOV-GP	34189	30073	-4117	-12.0%
HOV2-ML	8103	969	-7133	-88.0%
HOV2-GP	3535	6872	3337	94.4%
HOV3+-ML	669	24	-645	-96.4%
HOV3+-GP	346	612	266	76.9%
Express Buses	1748	1729	-19	-1.1%
Vanpools	206	232	26	12.5%
Total	49014	44145	-4868	-9.9%

Table 34: Corridor Person Throughput by Occupancy Mode, Feb-Apr, PM Peak

Mode	Baseline Persons	Post-HOT Persons	Change Persons	Percent Change
SOV-ML	374	3668	3293	879.7%
SOV-GP	32064	29440	-2624	-8.2%
HOV2-ML	8500	1040	-7460	-87.8%
HOV2-GP	4585	8696	4111	89.7%
HOV3+-ML	1038	55	-983	-94.7%
HOV3+-GP	775	1249	474	61.1%
Express Buses	1920	1960	40	2.1%
Vanpools	206	232	26	12.5%
Total	49462	46340	-3123	-6.3%

11.3 Remaining General Purpose Lane Carpool Activity, Post-HOT

As noted earlier, a significant fraction of carpools are still using the general purpose lanes during both the morning and afternoon peak periods and these vehicles are handling a large share of corridor throughput. Approximately 9.5% of the corridor vehicle throughput in the AM peak consists of HOV2 and HOV3+ personal vehicles using the general purpose lanes, and nearly 12.2% in the PM peak (Table 35). These vehicles carry an even greater share of passengers; approximately 17.0% of the corridor person throughput in the AM peak is carried by HOV2 and HOV3+ personal vehicles in the general purpose lanes, and nearly 21.5% of persons in the PM peak (Table 36). In the afternoon peak, there are actually more HOV2+ vehicles using the GP lanes than there are total vehicles using the HOT lane (this is not true in the morning). One has to keep in mind that available carpool demand throughout the entire peak does not necessarily mean that there is the same level of pent-up demand during the peak-of-the-peak when the HOT lane is needed most.

Table 35: Corridor Vehicle Throughput by Lane and Occupancy Mode, Feb-Apr

Mode	AM Post-HOT Volume	AM Mode Share	PM Post-HOT Volume	PM Mode Share
SOV-GP	30073	79.4%	29440	76.6%
HOV2-GP	3436	9.1%	4348	11.3%
HOV3+-GP	173	0.5%	353	0.9%
SOV-ML	3635	9.6%	3668	9.5%
HOV2-ML	485	1.3%	520	1.4%
HOV3+-ML	16	0.0%	23	0.1%
Express Buses	53	0.1%	65	0.2%
Vanpools	27	0.1%	27	0.1%
Total	37897	100.0%	38444	100.0%

Table 36: Corridor Person Throughput by Lane and Occupancy Mode, Feb-Apr

Mode	AM Post-HOT Persons	AM Mode Share	PM Post-HOT Persons	PM Mode Share
SOV-GP	30073	68.1%	29440	63.5%
HOV2-GP	6872	15.6%	8696	18.8%
HOV3+-GP	612	1.4%	1249	2.7%
SOV-ML	3635	8.2%	3668	7.9%
HOV2-ML	969	2.2%	1040	2.2%
HOV3+-ML	24	0.1%	55	0.1%
Express Buses	1729	3.9%	1960	4.2%
Vanpools	232	0.5%	232	0.5%
Total	44145	100.0%	46340	100.0%

When GP lane traffic is isolated from ML traffic, approximately 10.7% of vehicles using the GP lanes in the AM peak and 13.8% of vehicles using the GP lanes in the PM peak are carpools (HOV2+). These vehicles carry about 19.9% and 25.3% of person throughput during the AM and PM peaks respectively. These vehicles operate on five general purpose lanes. With these volumes and throughput values in mind, additional research should be conducted on the feasibility of converting GP1 to a carpool lane, or converting GP1 to a second HOT lane and reducing the carpool requirement on the resulting two managed lanes from HOT3+ to HOT2+. Assessment of the demand for such a change requires a tolling and revenue analysis based upon hourly vehicle demand by lane and occupancy mode. Costs of such a change would include restriping and may require new gantry installation, as the final design of the system did not include gantries spanning all lanes. An increase in HOT capacity by adding the second lane might also reduce peak toll rates for both lanes, depending upon peak demand.

Table 37: GP Lanes Vehicle Throughput by Occupancy Mode, Feb-Apr

Mode	AM Post-HOT Volume	AM Mode Share	PM Post-HOT Volume	PM Mode Share
SOV-GP	30073	89.3%	29440	86.2%
HOV2-GP	3436	10.2%	4348	12.7%
HOV3+-GP	173	0.5%	353	1.0%
Total	33682	100.0%	34141	100.0%

11.4 Discussion and Caveats

Traffic counts indicate that corridor travel demand has declined by more than 6.6% in the morning peak period, but declined only by about 2.9% in the afternoon peak period. Corridor demand is not independent of corridor performance. The fact that demand declined at a greater rate in the morning peak than afternoon peak may be related to the fact that the HOT lane 45 mph uptime is only 90.8% during the morning peak. That is, 9.2% of the time, HOT lane commuters are not receiving their expected 45 mph service speeds. This may be resulting in the higher observed decline in morning corridor travel demand. A properly designed and properly priced corridor should be able to ensure that demand for use of the HOT lane does not exceed capacity. The lanes do appear to function properly during the shoulders of the peak (Guensler, et al., 2013); hence, the research team suspects that peak period pricing is insufficient to ensure that demand does not exceed capacity. Additional research should reveal whether the prices are adequate during the peak-of-the-peak period and once prices are adjusted, HOT lane performance should improve. When this happens, the team suspects that morning peak period trips that may have been postponed or diverted to other routes will return to the corridor.

In the process of performing the assessment, the research team determined that the existing sources of vehicle activity data were not as reliable as originally anticipated. Future studies should supplement existing VDS data sources with more accurate systems for vehicle counts, speeds, and travel times. For future HOT corridors, the team recommends that supplemental monitoring systems be deployed at least one year prior to HOT implementation. The systems should include new VDS systems that are carefully placed with respect to height and viewing angle to cover a limited number of lanes and ensure lane-by-lane count accuracy (requiring multiple cameras at specific benchmark locations). High-resolution video cameras can be used with new tracking technologies at these same locations to calibrate views (Toth, et al., 2012; Toth, et al., 2013). Loop detectors might also be recommended at specific locations. Finally, systems that allow for positive identification and re-identification of vehicles later in the corridor, such as Bluetooth or RFID, should be deployed. Deployment of the full span

RFID gantry systems, as implemented at specific locations on the I-85 HOT corridor, should be deployed one year in advance of HOT openings, along with free RFID tags to future users.

Because the occupancy data collection methods remained constant throughout the study, it is reasonable to expect that any methodological biases should be consistent across all eight quarters. That is, if there was some systematic problem in counting vehicle occupants, such as missing passengers in child seats or missing individuals that are prone in the back seat, the errors should be consistent throughout the study. The fact that observed vehicle occupancy changed so significantly after the HOT lanes opened indicates that the percentage of carpools has changed. Nevertheless, it is possible that data collection bias still remains after implementation of quality assurance methods described in this report. One potential problem that the team has identified is the fact that data were only collected for two hours during each peak period. In winter, the data collection window was even shorter because it was too dark to collect data in the early morning and late afternoon. If HOV3+ commuters modified their schedules such that they were passing through the corridor earlier and later than the data collection period, then the percentages collected in the field are not applicable to the entire peak period. As such, the researchers do not suspect that a major change in HOV3+ vehicle temporal use patterns has occurred, but cannot discount the possibility.

Probably the most surprising finding of the research effort was that carpool formation and/or retention appears to have declined significantly on the corridor, based upon vehicle occupancy studies. Free passage for HOV3+ carpools was expected to result in more 3-person carpools traversing the corridor. Three-person carpools appear to have declined on both the corridor and the managed lane. Additionally, more three-person carpools are using the general purpose lanes than the HOT lanes. On the other hand, three-person carpools are difficult to form and retain, and the elimination of the two-person carpools through the conversion of the HOV2 lane to a HOT3+ lane may have provided a significant negative incentive to the formation and retention of two-person carpools. As such, additional relevant data and further investigation is necessary to assess why carpool activity has declined on the corridor.

The research effort was observational in nature, and did not include the originally-approved large-scale panel study and instrumented vehicle fleet, through which travel behavior data would have been collected. Hence, even though the decreases in vehicle and person throughput appear to have been large and significant, it is not possible to assess the reasons for the changes. Vehicles and passengers formerly served by the corridor may have diverted to other routes, other times of day, or have curtailed trip-making. The fundamental reasons that might explain the significant observed breakup of carpools on the corridor remains unknown. Nor can the research data be used to assess why vanpool and express bus person throughput remained essentially unchanged in magnitude. Behavioral data collection and analysis would be required to assess how HOT lane performance/price affected traveler decision making. Given that the region is planning to build more than $16 billion in managed lanes, it is critical that future studies collect travel behavior data concurrently with field data, so that researchers can observe and assess the reasons behind behavioral change at the household level.

12 Conclusions and Recommendations

The vehicle and person throughput analysis for the High Occupancy Vehicle to High Occupancy Toll Lane conversion in Atlanta, GA required large scale data collection of vehicle occupancy over all travel lanes. Traffic volumes were collected by VDS systems on the Georgia NaviGAtor system. Center Way was selected as the control station for analysis based upon its location relative to inflow and outflow demand and quality of available data. The team developed occupancy data collection methodologies for the HOT evaluation. Primary data collection was then performed to obtain vehicle classification and occupancy data. Quarterly field data collection was conducted at five stations along the corridor, one year before and one year after HOT implementation. Only data between February and September in the base and HOT implementation year were employed in the analyses due to NaviGAtor I data compatibility issues (and an ice storm in January of the base year). An added focus was given to the February through April time period to control for seasonality (most travel demand studies are conducted in the spring) and to address potential issues with the phased system implementation that involved changes in weaving section locations, striping, and the addition of rumble strips. License plate data were collected for use in a separate set of demographic analyses (see Khoeini, et al., 2012; and Khoeini, et al., 2013), and separate analyses were also conducted to assess changes in weaving and effective capacity of the managed lane (Guensler, et al., 2013).

Between the baseline year and HOT implementation year, significant changes were noted in both the vehicle and person throughput on the corridor at Center Way. Average vehicle occupancy (persons/vehicle) also decreased during the same period. Reduced vehicle throughput and decrease in observed vehicle occupancy had a synergistic impact on estimated corridor person throughput, which declined significantly at a much faster rate than vehicle throughput.

The methods remained consistent throughout the study; hence, the predicted reduction in person throughput is expected to have been significant. The research effort was observational in nature, and did not include the originally-proposed large scale panel study and instrumented vehicle fleet, through which travel behavior data would have been collected. Hence, even though the decreases in vehicle and person throughput appear to have been large and significant, it is not possible to assess the reasons for the changes, and whether vehicles and passengers formerly served by the corridor have diverted to other routes, other times of day, or have curtailed trips. Specific findings are presented by major topic in the following sections:

12.1 Changes in Vehicle Throughput

- February-April 2011 vehicle throughput data from Center Way were compared with the same months in 2012, after the HOT lane became operational on October 1, 2011. Vehicle throughput on the I-85 HOT corridor decreased by about 6.6% during the morning peak period, but only by about 2.9% during the afternoon peak period.

- Changes in general regional economic conditions may have been responsible for some, or all, of the observed decline in HOT corridor traffic volumes. The research team examined changes in traffic volumes at five control sites to see whether the noted changes on the HOT corridor were in line with changes in other locations. The control stations did not show any particular direction of change in traffic demand. One of the stations showed an increase in demand beyond 5% while another showed a decrease beyond 5%. The rest varied within a 5% band. In light of the changes in traffic volumes for the control stations, the noted 2.6% reduction in HOT corridor vehicle throughput during the afternoon peak seems to be within reasonable bounds of a natural change in regional travel demand. However, the reduction of vehicle throughput of 6.6% during the morning peak period seems unlikely to be associated solely with a regional change in demand. Given that afternoon traffic declined at a much lower rate than morning traffic, it seems reasonable that the reduction in morning traffic may be associated with a combined effect of reduced regional demand, foregone morning trips, trips deferred to the afternoon, and trips diverted to other routes. Unfortunately, a long-term household panel study was not implemented for the corridor. Without travel diary data from a large number of households over that time period, there is no way to be sure that the observed changes in corridor demand are directly linked to the implementation of the HOT lane.

- The HOT lane carries fewer vehicles during the peak period than it did as an HOV lane. This is by design and is not an issue. Two-person carpools were allowed to use the HOV lane at any time, but now only use the HOT lanes if they are willing to pay a toll. Because congestion is not prevalent during the entire four-hour-peak, the HOT lane is only needed for a portion of the peak. As such, the activity on the HOT lane is now mostly limited by driver choice to the peak of the peak period.

- As part of the Congestion Reduction Demonstration Program Grant, SRTA constructed park-and-ride lots and increased bus service by 18% during the morning peak period. This is a very large increase in bus level of service that was part and parcel of the proposed HOT implementation plan.

- The number of vanpools operating on the corridor during the peak period increased by about one vanpool per peak hour, or by about 13%. The number of vanpools operating on the corridor remains small. Additional incentives may increase vanpool formation.

12.2 Changes in Vehicle Occupancy

The research team deployed teams of graduate and undergraduate students to collect vehicle occupancy (persons/vehicle) data. Data collection procedures were standardized to minimize data collection and entry errors. To statistically assess variables that may affect vehicle occupancy on the corridor and to identify potential bias that may have been introduced into the data by individual data collectors, regression tree modeling techniques were applied. Data that were significantly different from comparable data collected on the corridor over two-hour time periods were identified, investigated manually, and filtered from the analysis if bias was identified via regression tree analysis. Approximately 7% of data collected were screened from the analyses. The net impact of data screening on vehicle occupancy was very small. The conclusions from the occupancy study are as follows:

- In the HOV baseline period, occupancy results differ across lanes. In both the AM and PM peak periods, the percentage of carpools increases across the general purpose lanes from the inside lane (fast lane adjacent to the HOV lane) to the outside lane. This may be the result of a significant number of local carpools (school-related trips, shopping trips, etc.) entering and exiting the corridor.

- As expected, based upon carpool lane use restrictions, the HOV lane occupancy was slightly greater than two persons per vehicle in Spring 2011. The general purpose lanes were much closer to a value of one person per vehicle, given the large percentage of single-occupant vehicles.

- After HOT implementation, the percentage of 2-person carpools using the managed lane declined significantly, as expected. Two-person carpools would have had to find a third commuter to operate on the HOT lane for free, or pay a toll to continue operating on the HOT lane. The percentage of 2-person carpools increased in all of the general purpose lanes, indicating that a significant number of carpools migrated to the general purpose lanes and a significant fraction may also have disbanded.

- Managed lane vehicle occupancy declined from around 2.05 as an HOV lane to between 1.20 and 1.30 after HOT implementation. The occupancy of the general purpose lanes increased from around 1.07 to 1.13 after HOT implementation due to the shift of carpools into the general purpose lanes.

- After HOT lane implementation, the observed average vehicle occupancy of the HOT lane is nearly equal to the occupancy in the general purpose lanes, and the relative increase in occupancy across lanes nearly disappeared.

- The percentage of HOV3+ vehicles operating in the managed lane decreased from about 5-7% in the HOV baseline period to about 2-3% under HOT operations in the AM peak and from about 7-10% in the HOV baseline period to about 3-4% under HOT operations in the PM peak. Given that three-person carpools can use the HOT lane for free (with Peach Pass account), the significant reduction in 3+ occupant was unexpected.

- The observed changes in vehicle occupancy in the HOT lane after conversion were larger than anticipated by the research team. The decrease in managed lane occupancy ultimately had a larger impact on person throughput than the increase in general purpose lane occupancy (as discussed in the person throughput section).

- The data reveal that the majority of two-person carpools have been diverted from the HOV lane into the general purpose lanes after HOT lane implementation. The overall average vehicle occupancy of each general purpose lane has increased as a result.

12.3 Changes in Person Throughput

- After the opening of the HOT lanes, traffic volumes declined in both the morning and afternoon peak periods. However, the decline in traffic volume occurred concurrently with decreases in vehicle occupancy rates. Over the eight-month pre-and-post analysis, the combined effect on corridor person throughput during the AM and PM peaks was quite large. While traffic volumes declined by approximately 6.6% in the morning peak period for February through April, person throughput concurrently declined by about 9.9%. While traffic volumes declined by approximately 2.9% in the afternoon peak period for February through April, person throughput concurrently declined by about 6.3%.

- Express bus ridership did not increase substantially even though bus service was increased by more than 18%. Express bus tolls were raised significantly prior to HOT implementation, which makes it impossible to decouple the positive effects of improved service and the negative effects of fare increase on passenger demand. Because the express buses use the HOT lane, the reliability of express bus service depends upon HOT lane reliability. As reported elsewhere (Guensler, 2013), the facility currently meets the federal 90% uptime requirement (90.8% of HOT operation during the morning peak at 45 mph or better). Express bus reliability is meeting base goals, but could be improved above the 90.8% level. Improvements in HOT lane performance translate to express bus reliability benefits. Efforts to improve the reliability of HOT service through proper peak-of-the-peak toll pricing should continue. It is important to keep in mind that although express buses constitute only 0.1% of vehicles using the I-85 corridor in the morning peak period and 0.2% in the afternoon peak period, they carry more than 3.9% of the total corridor person throughput across both peak periods. Express buses also constitute only 1.2% of vehicles using the HOT lane during the morning peak period, yet they carry 26% of the total HOT lane person throughput. Express bus service remains an important component of the HOT corridor.

- Although the number of vanpools increased by about one per hour during the peak periods, vanpools still only carry about 0.5% of corridor person throughput during both peak periods. While this is not an inconsequential number of persons, additional incentives may increase vanpool formation.

12.4 Changes in Carpool Activity

- Based upon vehicle throughput and occupancy distributions, the largest reduction in vehicle throughput in both the morning and afternoon peak periods came from a reduction in carpool throughput (HOV2 and HOV3+ vehicles). This indicates that the implementation of the HOT lanes did not incentivize carpooling. Carpool mode share declined by more than 30% in the AM peak and by 25% in the PM peak. The decline in carpool retention on this corridor remains unexplained. Relevant behavioral data over time for these corridor commuters is not currently available.

- The shift of HOV2 and HOV3+ vehicles from the managed lane to general purpose lanes during the AM and PM peak periods was significant. On average, two-person carpools do not appear to have picked up a third passenger to avoid paying a toll. The shift of 2-person carpools to the general purpose lane nearly doubled the number of HOV2 vehicles using the general purpose lanes. Hence, a significant share of HOV2 drivers and passengers were not willing to split the cost of the toll, or were unwilling to register to use the lanes. A large number of 3-person carpools also shifted to the general purpose lanes, despite the fact that they can use the lanes for free. It may be that these vehicles have not registered for use of the lanes and obtained an RFID tag. Additional research into the impact of the implementation of the managed lanes on the formation and retention of carpools is warranted based upon the observational results.

- A significant fraction of carpools are still using the general purpose lanes during both the morning and afternoon peak periods and these vehicles are handling a large share of corridor throughput. Approximately 9.5% of the corridor vehicle throughput in the AM peak consists of HOV2 and HOV3+ personal vehicles using the general purpose lanes, and nearly 12.2% in the PM peak. These vehicles carry an even greater share of passengers; approximately 17.0% of the corridor person throughput in the AM peak is carried by HOV2 and HOV3+ personal vehicles in the general purpose lanes, and nearly 21.5% of persons in the PM peak.

- Approximately 10.7% of vehicles using the GP lanes in the AM peak are carpools (HOV2+) and 13.8% of vehicles using the GP lanes in the PM peak are carpools. These vehicles carry about 19.9% and 25.3% of person throughput during the AM and PM peaks respectively. In the afternoon peak, more HOV2+ vehicles use the GP lanes than are carried in total by the HOT lane (not true in the morning). Available carpool demand across the entire peak does not necessarily mean that there is the same level of demand during the peak-of-the-peak when the HOT lane is needed most. However, additional research is warranted as to whether the corridor can support the addition of a carpool lane or second HOT lane.

12.5 Future Data and Research

The biggest challenges associated with the assessment of changes in vehicle and person throughput were associated with quality and relevance of data available to the research team. Data from the NaviGAtor system were carefully assessed to identify data that could be considered reliable over the entire study period. In addition, the conversion of the lanes was completed in a three-phase process, which complicated comparative analyses. Despite the uncertainties associated with the analyses, the significant changes in vehicle and person throughput, and the evidence of significant declines in carpool use on the facility indicate that additional research should be conducted.

- Given the problems noted with existing sources of vehicle activity data, future HOT performance studies should supplement existing VDS data sources with more accurate systems for vehicle counts, speeds, and travel times. Supplemental monitoring systems should be deployed at least one year prior to HOT implementation. The systems should include new VDS systems and high-resolution cameras that are carefully placed with respect to height and viewing angle to cover a limited number of lanes and ensure lane-by-lane count accuracy (multiple cameras at specific benchmark locations). Systems should also include Bluetooth or RFID systems to positively identify vehicles at multiple locations on the corridor to collect travel time data. Full span RFID gantry systems, as implemented at specific locations on the I-85 HOT corridor, should be deployed one year in advance of HOT openings, along with free RFID tags to future users.

- Vehicle and person throughput analysis indicates that the overall corridor carpooling rates in the AM peak have declined by more than 30%. It is important to evaluate the changes in carpooling activities before and after an HOV to HOT conversion, and most importantly, to understand the underlying forces driving the changes. Surveys and panel studies should be conducted to identify the reasons for the significant decrease in carpooling activity. Results will have significant policy implications for future HOV/HOT conversion projects with regard to formation and retention of carpools.

- The large percentage of HOV3+ vehicles using the general purpose lanes, despite the fact that registered carpools can use the HOT lane for free, indicates that additional research is warranted to try to identify why these vehicles are not using the HOT lanes. It may be that these vehicles are "fampools" (composed of family members) that are casual users of the corridor and will never register for the RFID tags. However, it may be that there are other reasons preventing these drivers from registering. Research to assess why these vehicles are not using the HOT lanes is warranted.

- The research effort was observational in nature, and did not include the originally-proposed large scale panel study and instrumented vehicle fleet, through which travel behavior data would have been collected. Hence, even though the decreases in vehicle and person throughput appear to have been large and significant, it is not possible to assess the reasons for the changes, and whether vehicles and passengers formerly served by the corridor have diverted to other routes, other times of day, or have curtailed trip-making. Future HOT implementation should include the major behavioral research elements that were originally planned and funded for the I-85 corridor, including monitoring of a large panel of commuting households to track changes in travel behavior before and after HOT implementation to quantify changes in origin-destination patterns, travel times, routes, carpool participation, etc.

- Given the large number of carpools still using the general purpose lanes in the peak period, additional research should be conducted on the feasibility of converting GP1 to a second HOT lane and reducing the carpool requirement on the resulting two managed lanes from HOT3+ to HOT2+.

- The HOT corridor effective capacity analysis (Guensler, et al., 2013) assessed the operating conditions on the managed lanes and general purpose lanes during the peak of the peak period. Maximum vehicle throughput appears to be higher in the section that was studied and illegal weaving dropped significantly. The managed lane appears to handle more vehicles during the worst congestion conditions, when it is most needed. However, the managed lane still experiences significant congestion based upon a corridor uptime performance analysis (Guensler, 2013). This indicates that current toll prices are not sufficient to ensure that HOT lane demand always remains below capacity and HOT lane flow remains uncongested. Additional research into proper pricing of the facility to prevent the impact of a bottleneck at the I-85/SR316 junction and other locations should be conducted. Similarly, additional econometric analysis of toll pricing across demographic groups would support this analysis.

- Accurate traffic counts are crucial for transportation impact studies and in planning activities for future HOT projects. All VDS stations that will be employed in before-after analysis in future HOT lane implementations should be calibrated monthly using the new Android Application (App) developed at Georgia Tech (Toth, et al., 2013). The traffic video processed by an observer will help assess changes in VDS accuracy by time of day (as a function of traffic volumes and truck percentages) and over the duration of the study. Detailed recordkeeping of camera recalibration should be required so that changes in VDS accuracy will not negatively impact future studies.

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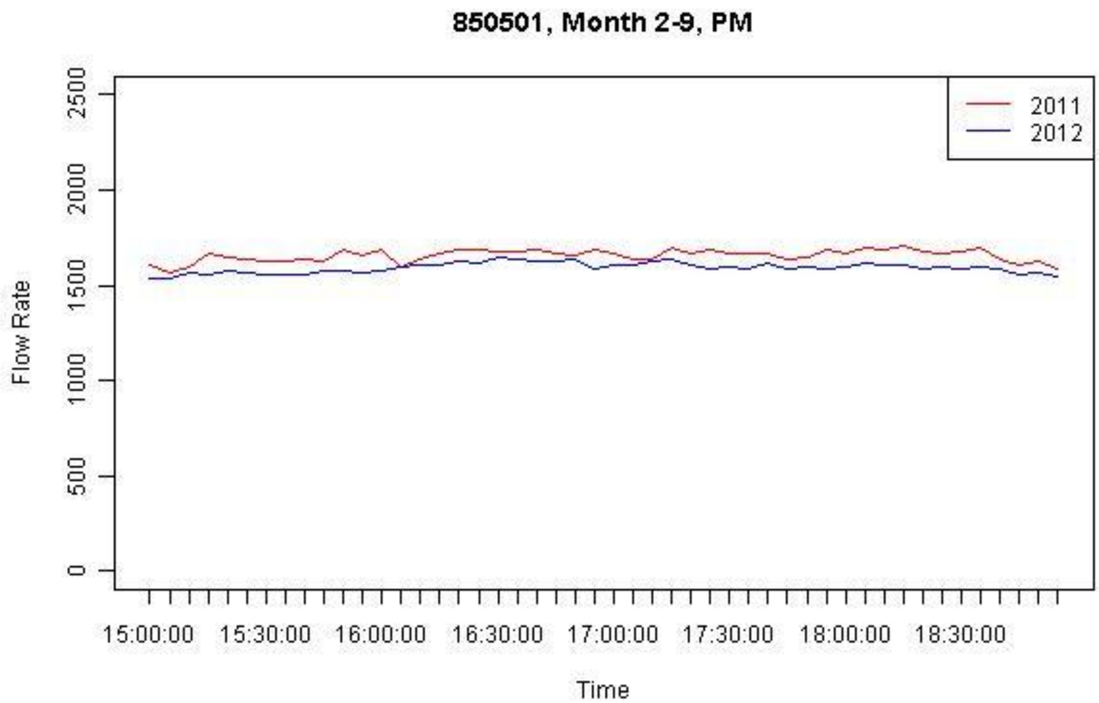
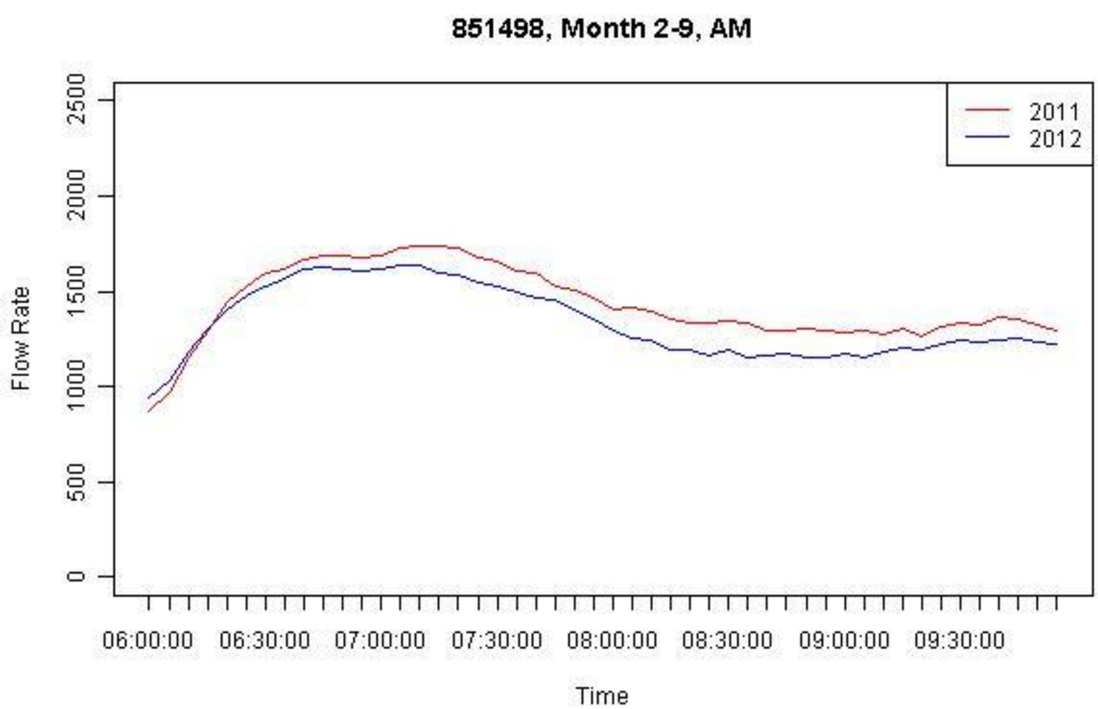
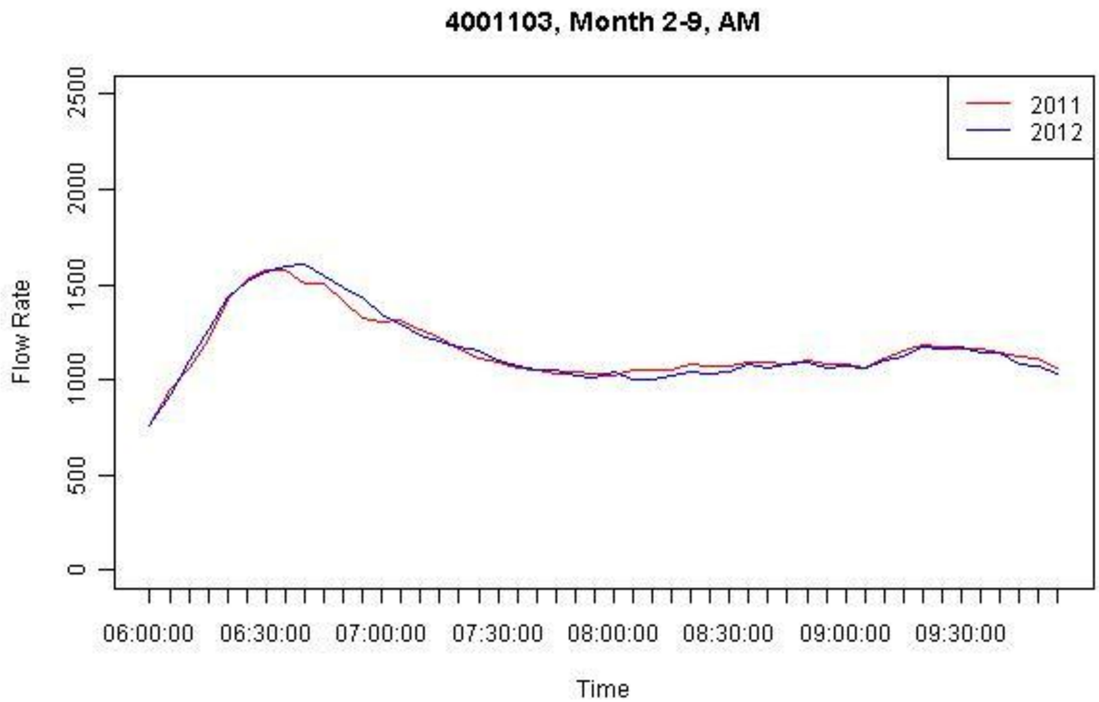
14 Appendix A: Baseline Station Traffic Volume Time Series Plots



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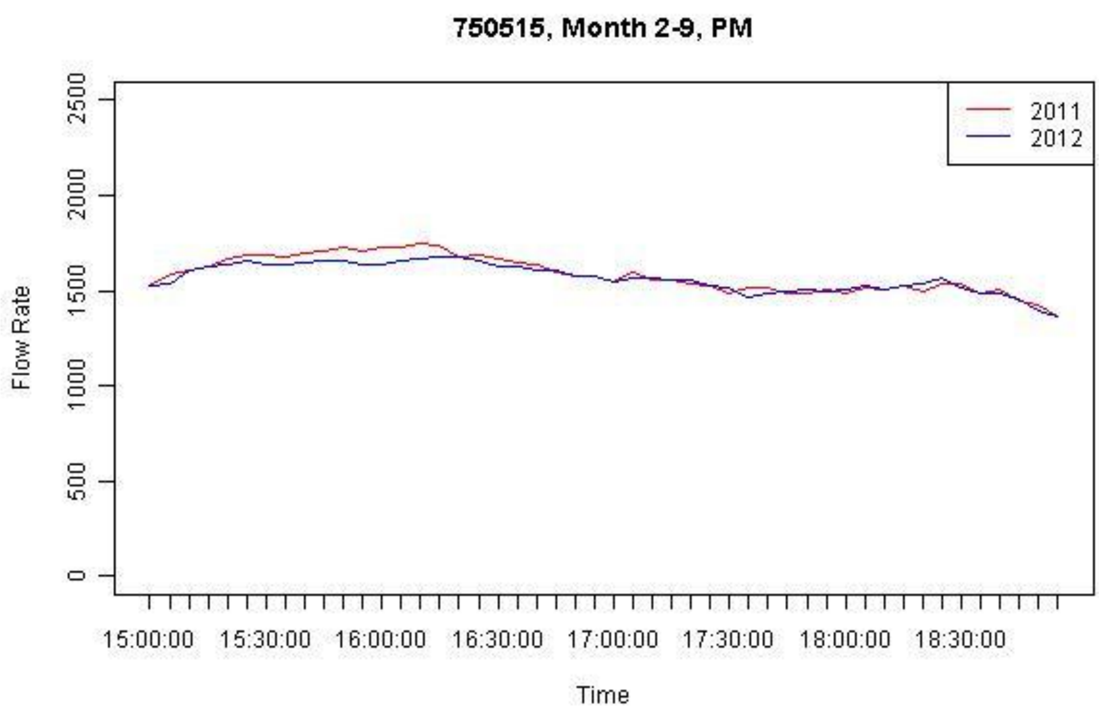
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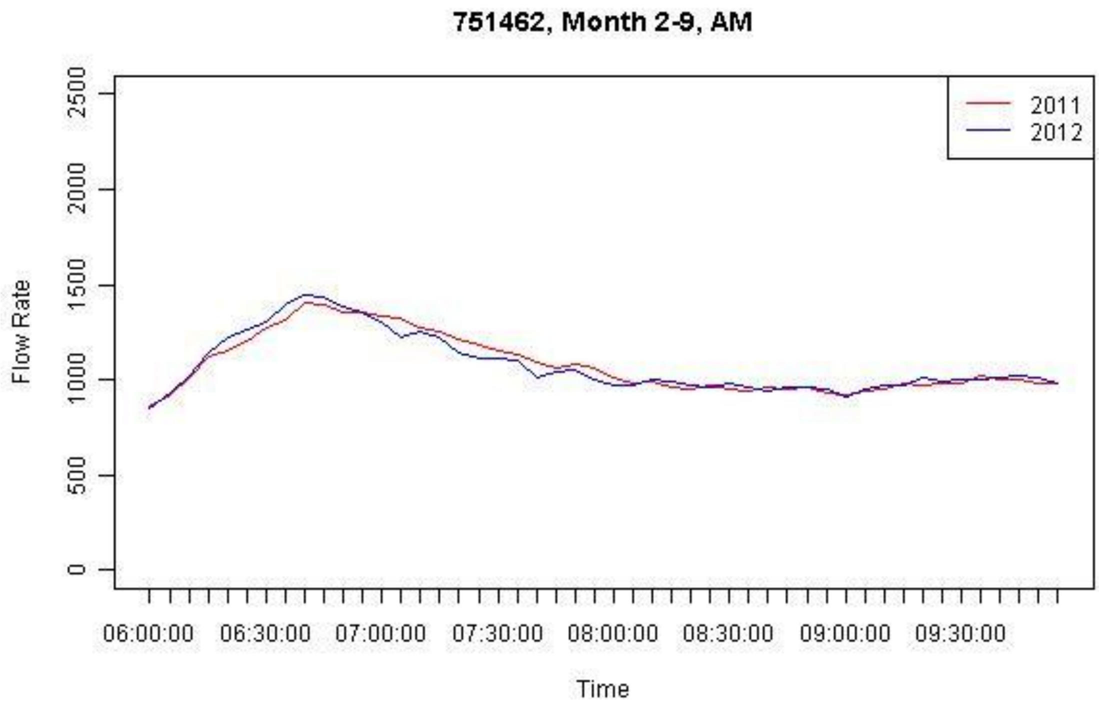

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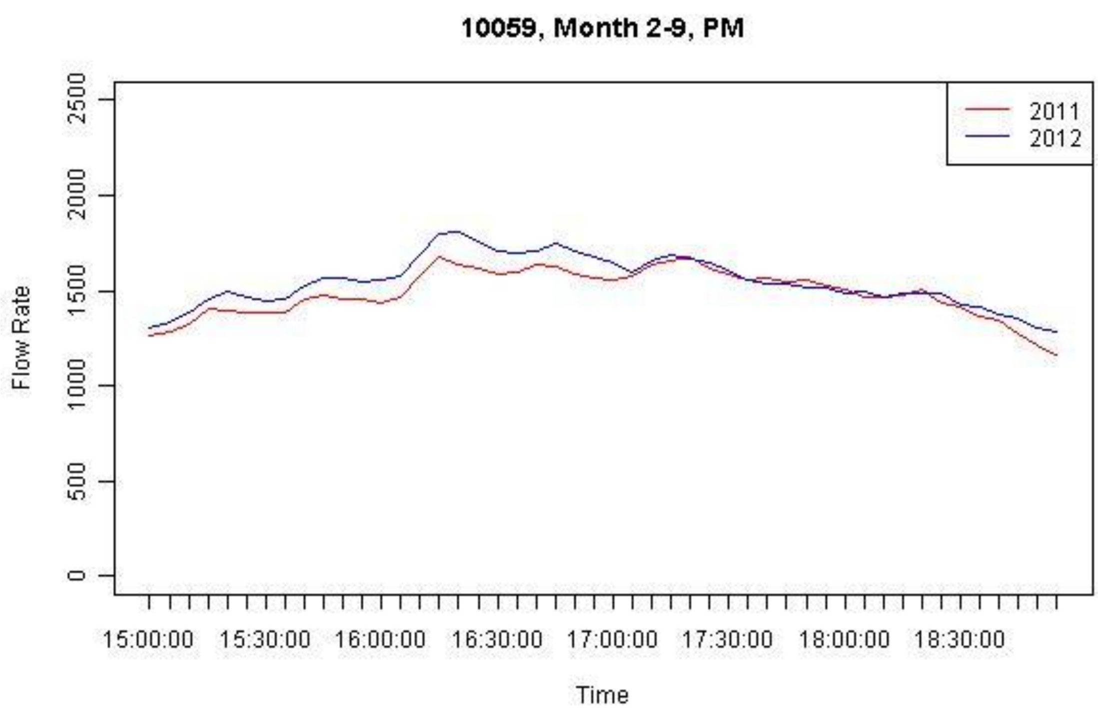

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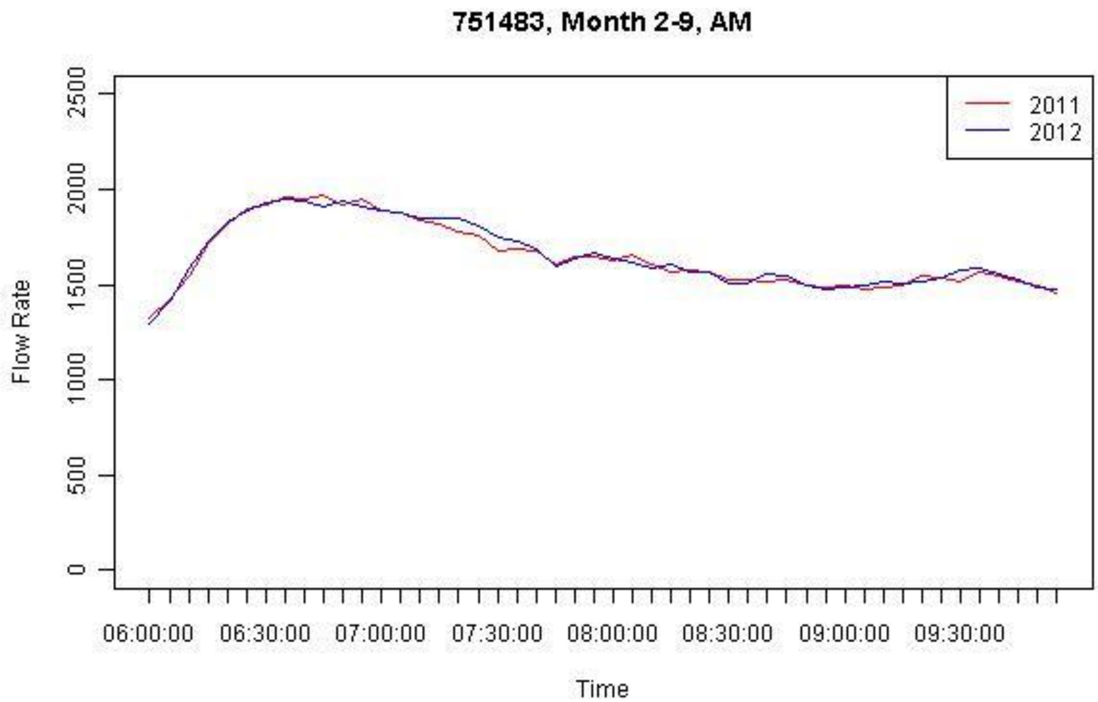
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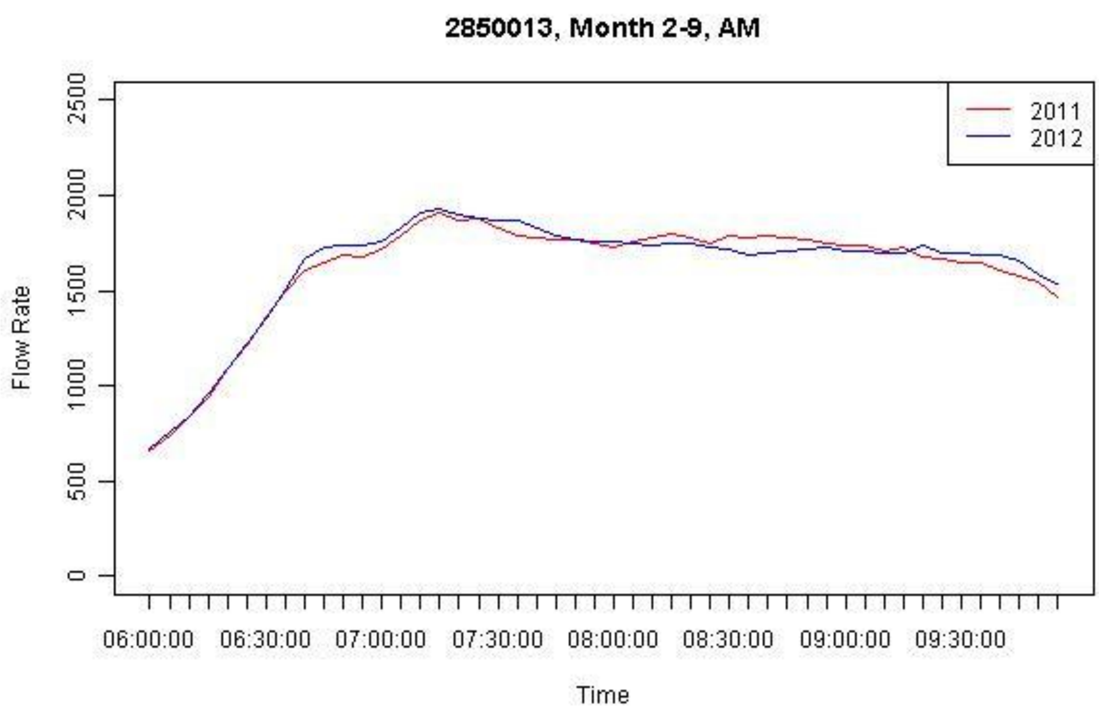
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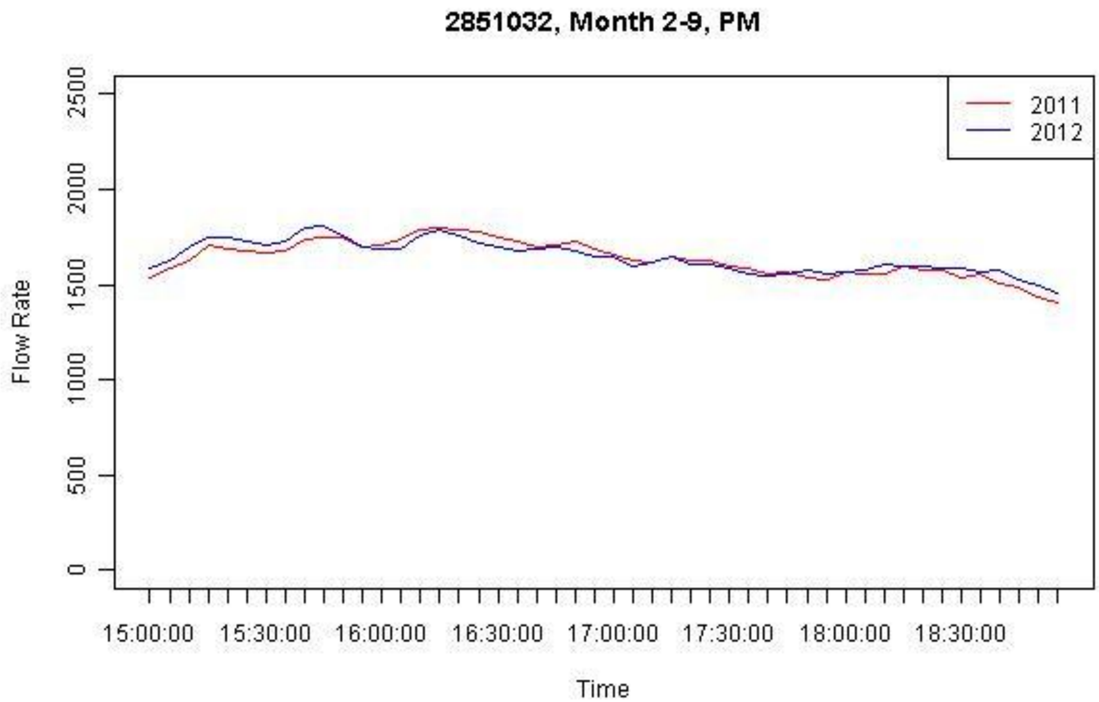
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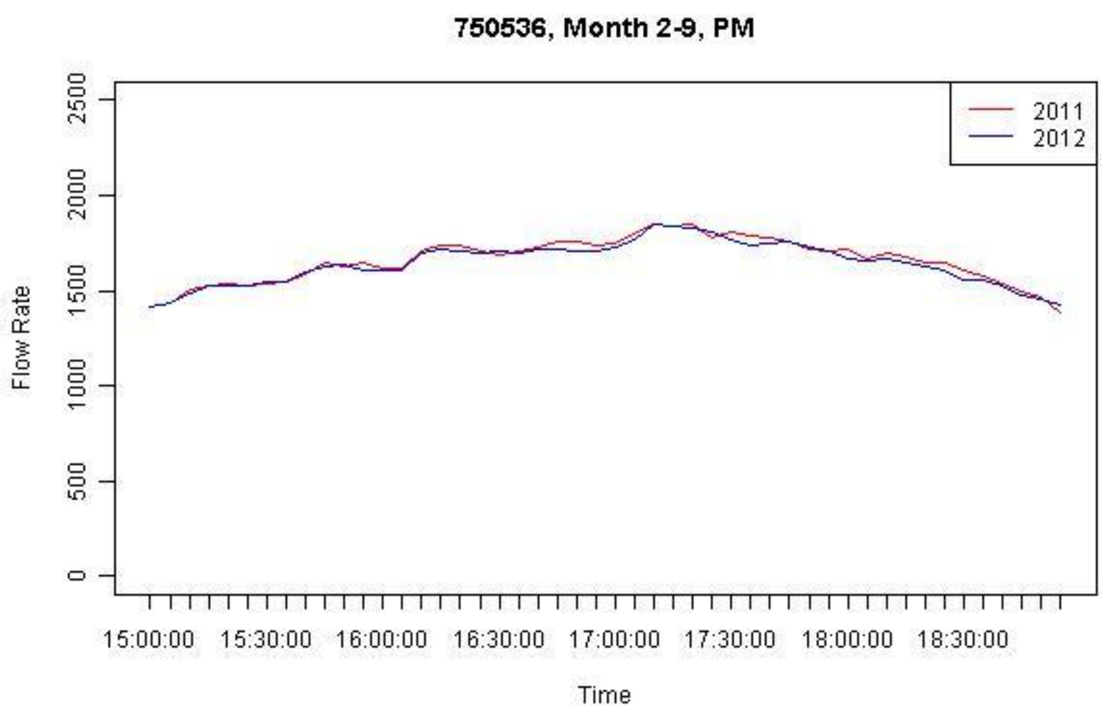
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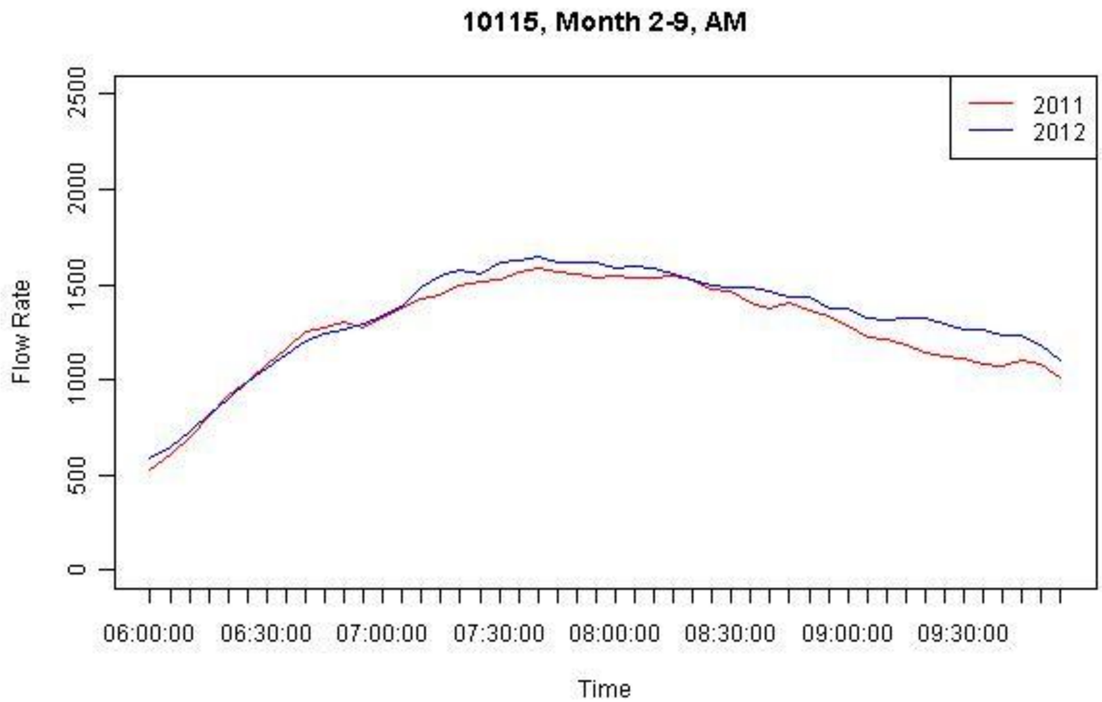
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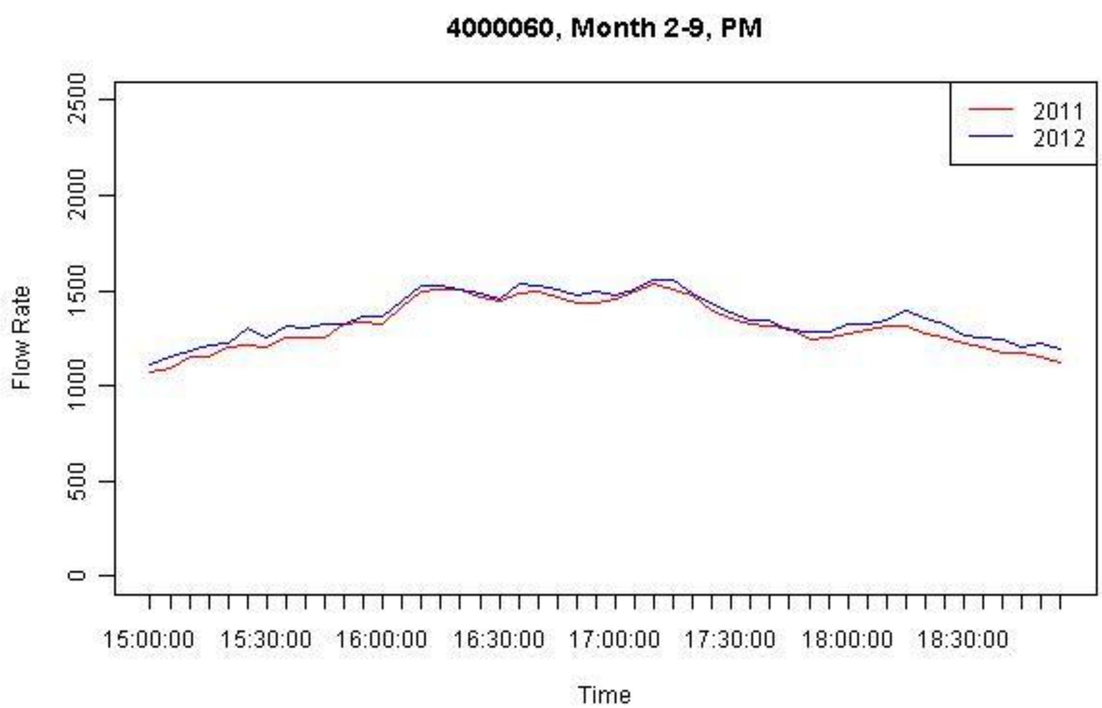
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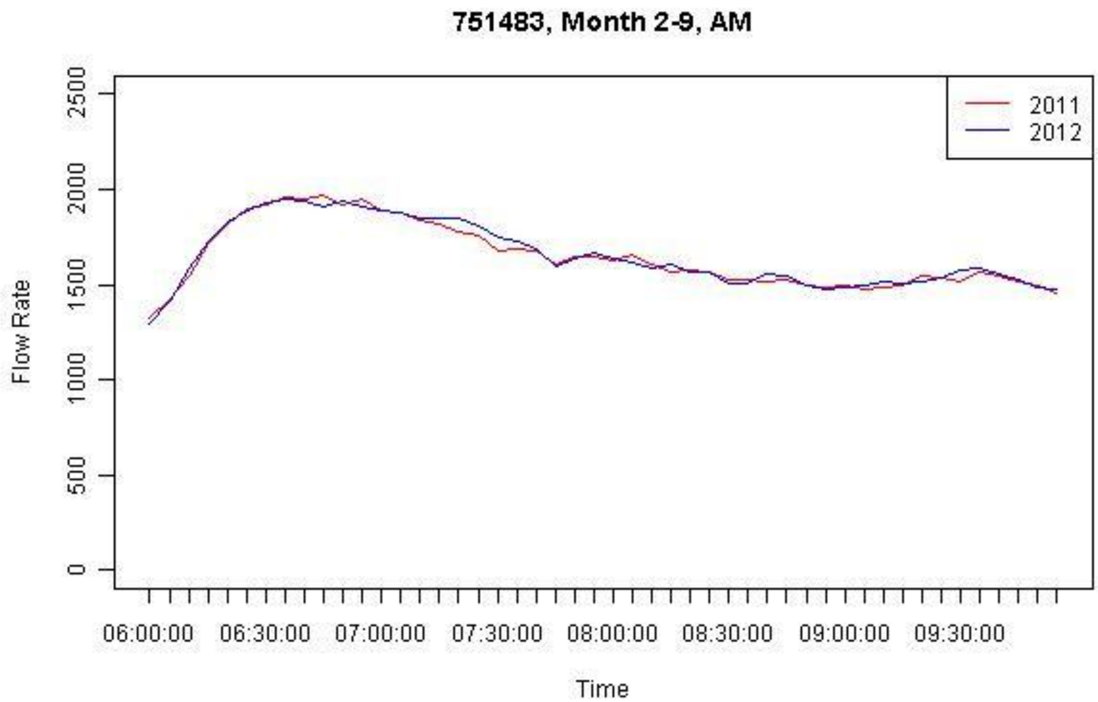
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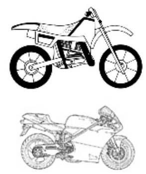
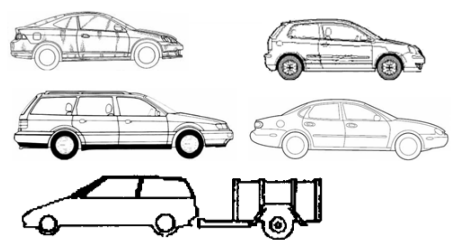
15 Appendix B: Vehicle Class Definitions

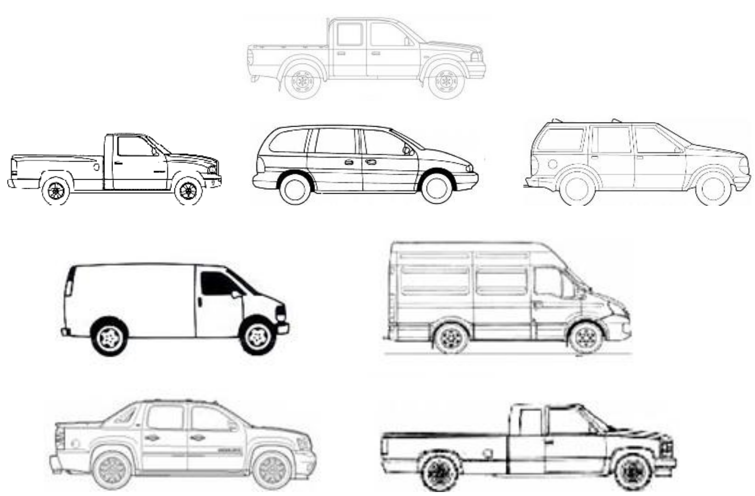
Motorcycle (not counted)



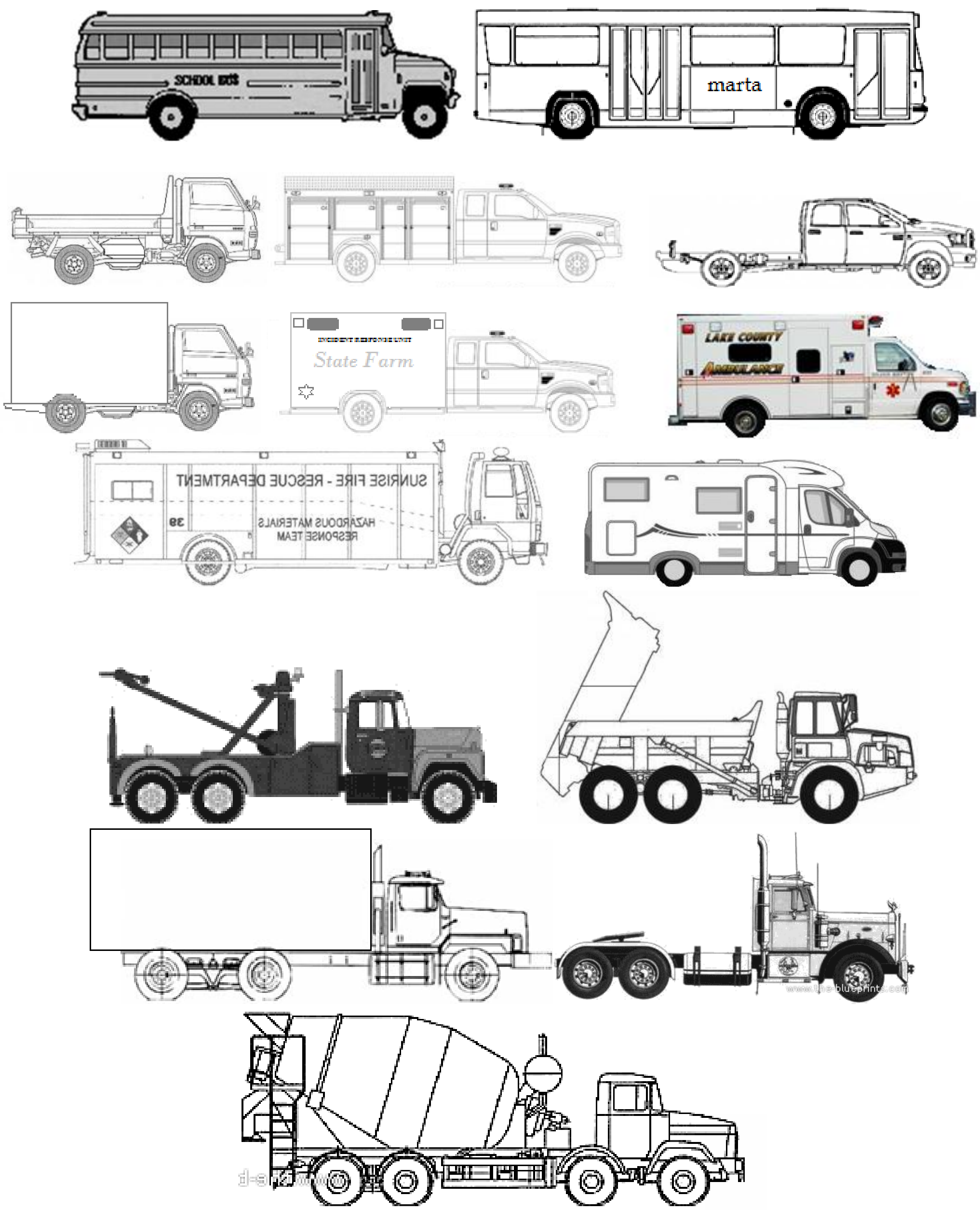
Light Duty Vehicles (LDVs)

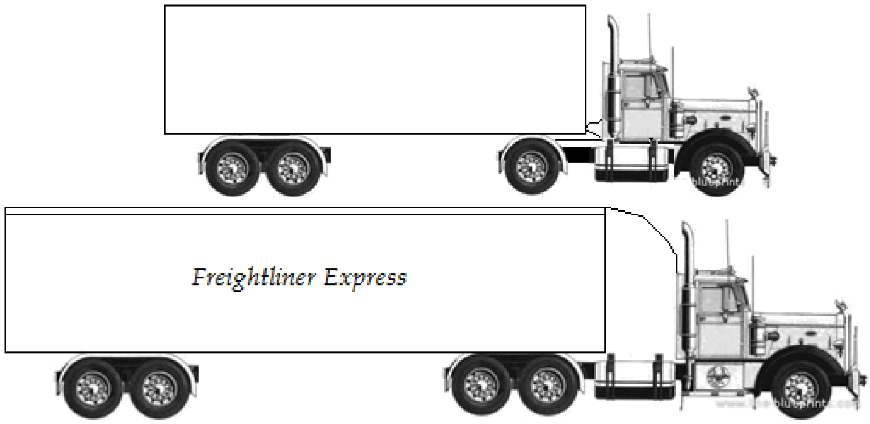


Sport Utility Vehicles and Light Utility Trucks (SUV)



Heavy-Duty Vehicles (HDV) - Buses, RVs, Single-unit Trucks, Large Trucks




Freightliner Express

16 Appendix C: Stepwise Analysis of Potential Data Collector Bias

After data collectors were screened based upon their reported average vehicle occupancy data, some regression tree nodes for SOV and HOV3+ percentages split on data collector identifiers. While data collectors achieved similar occupancy values during their observations, some appear to have done so by underestimating or overestimating SOV and HOV3+ percentages. To further assess potential data collector bias, the team conducted a stepwise series of ten regression tree analyses to identify and filter potentially biased data.

<u>Analysis 1</u>

Figure 46 shows the SOV percent regression tree for the HOV data. In this regression tree, the top levels are split on data collector identifiers, inferring that data collector bias may have had a significant impact on SOV percentiles. The extreme data under this dataset fall on the left and right corner leaves of the tree. The left most leaf which is the lower extreme has 2.9% from 36 data collection sessions (the overall average was 10.6%). However, on the right most leaf the tree has 35.3% from 9 data collection sessions. In the first analysis the research team explored all data across all lane types collected by the data collectors who fell into the leaf. The data from six data collectors were represented in the leaf. Data from four data collectors (URA023, URA033, URA038 and URA105) were inconsistent across different sessions within the same lane type and also different from other data collectors. All data collected by these four individuals were filtered from the analysis. Two other data collectors had one data session each on the HOV lane that was suspect; therefore, only those two sessions were filtered from the data. The next iteration of regression tree analysis was run with the filtered data.

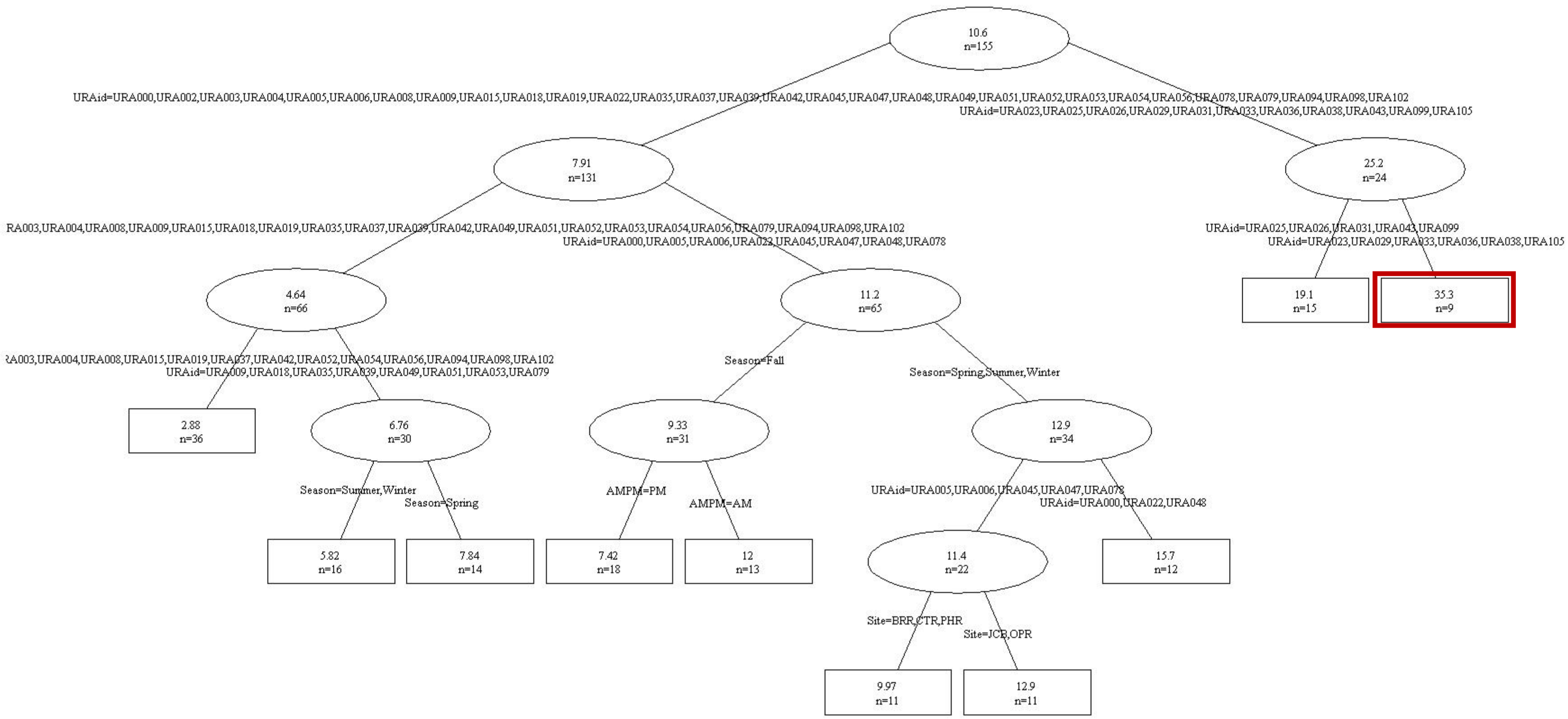


Figure 46: SOV Percent for the HOV Lane – Analysis 1

Analysis 2

Figure 47 shows the next regression tree run for the SOV percent. Again the two extreme values were explored for significantly different data. The left most leaf yields 1.97% SOV from thirteen sessions and the right most leaf yields 22.6% SOV from seven sessions. The node for the right-most leaf is split by site and that node was the result of a split on data collectors. Therefore we examine the right-most node, which had 18.1 percent SOV from twenty sessions. Data collected by ten data collectors are analyzed at this iteration.

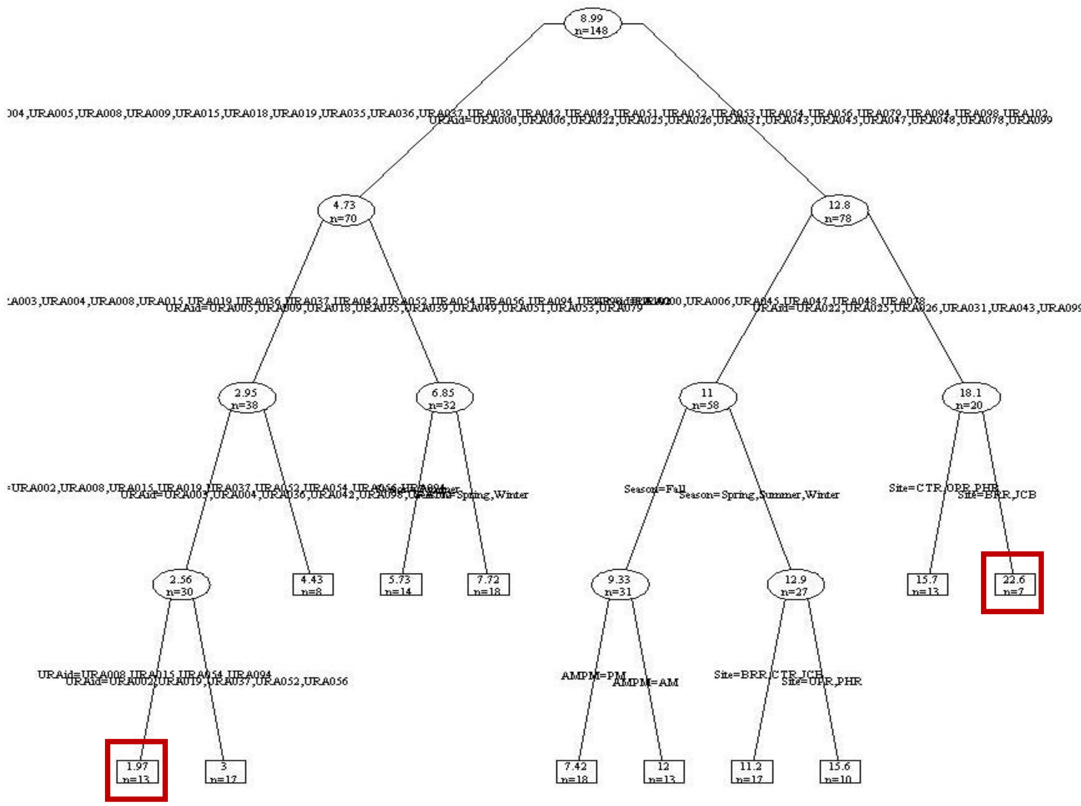


Figure 47: SOV Percent for the HOV Lane – Analysis 2

In exploring all data collected by these data collectors across all lane types, three data collectors had consistent data and all data collected by them were retained. One data collector (URA094) had six sessions out of a total seven sessions on the HOV lane and the SOV percentages were inconsistent, even within the same week. All data collected by this data collector were eliminated. Six other individuals collected fairly consistent data overall, but their HOV data were suspect in comparison to data collected by all of the other data collectors at the same site and session. HOV data collected by these six data collectors were eliminated, but all of the data from their other sessions were retained.

Analysis 3

The next regression tree analysis was run using filtered data. The results are shown in Figure 48 and no significant potential outliers remain. The next step is to evaluate HOT lane data and the general purpose lane data to identify potential data collector bias.

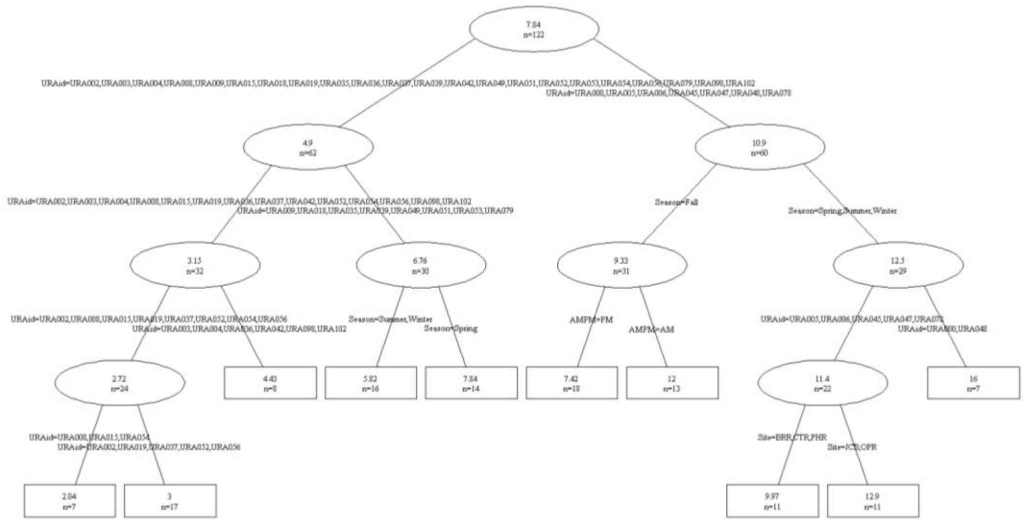


Figure 48: SOV Percent for the HOV Lane – Analysis 3

Analysis 4

Figure 49 shows the regression tree analysis for SOV percent in the HOT lane. Exploring the extreme leaves, the left most leaf yielded 50.8% SOV from 7 data collection sessions and the right most leaf yielded 88.9% SOV from 19 sessions. The right most leaf is not far from the overall SOV percent; therefore, only the left most leaf was explored in detail.

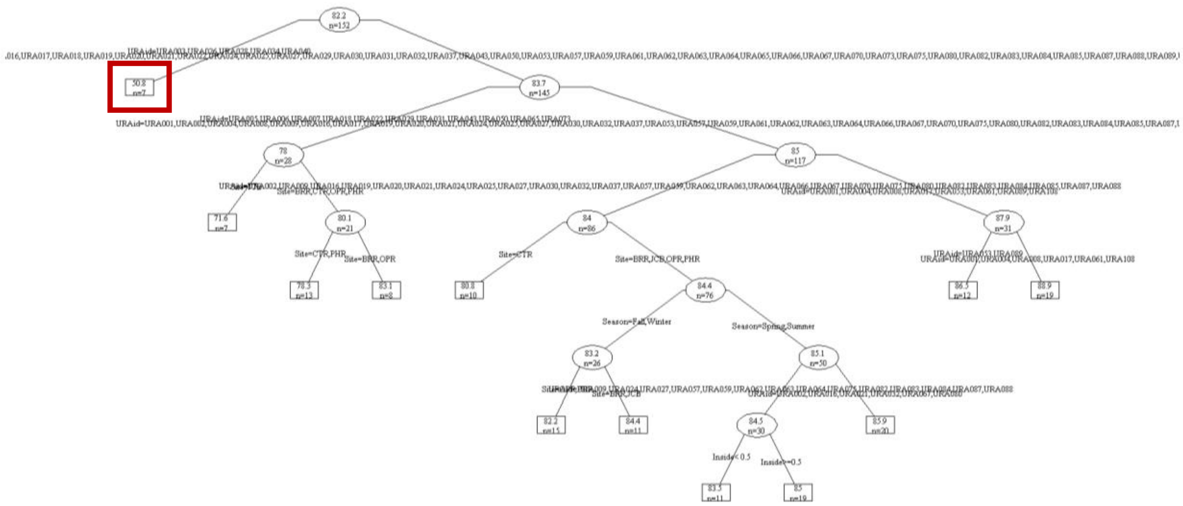


Figure 49: SOV Percent for HOT lane – Analysis 4

Exploring all data collected by the five data collectors who collected seven total sessions contained in the left most leaf, the research team found three data collectors had comparable data to the whole data set and their retained their data. Two other data collectors each had one session on the HOT with extreme values, but their other sessions were consistent and similar to other data collectors. Hence only the two extreme sessions were eliminated.

Analysis 5

The regression tree is run with the filtered data and show in Figure 50. No significant potential outliers remain in this regression tree and no further data filtering is required based on the HOT data. Next the research team explored the general purpose lane data.

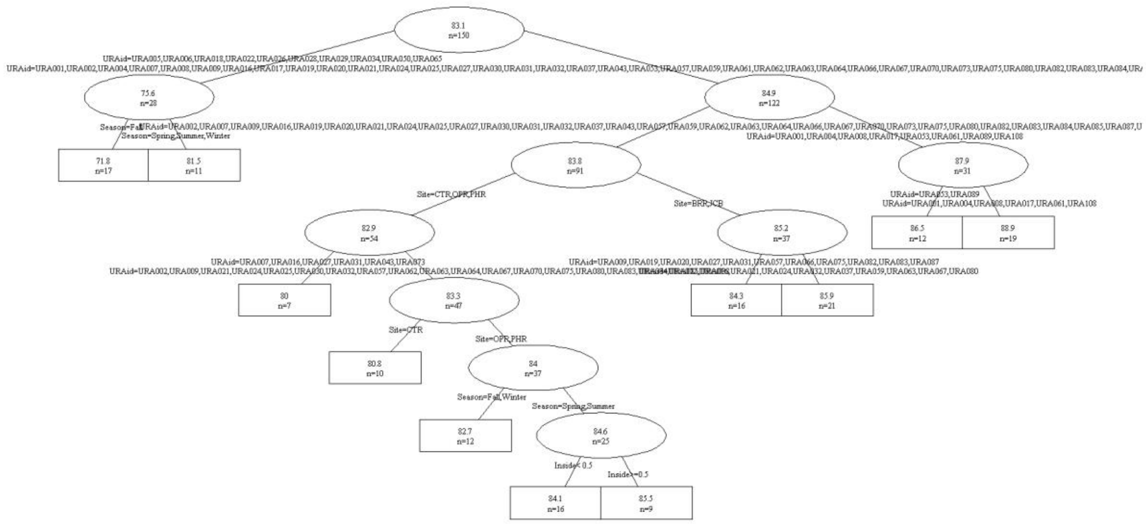


Figure 50: SOV Percent for the HOT lane – Analysis 5

Analysis 6

The regression tree on SOV percent of the general purpose lanes are presented in Figure 51. Examining the extreme values, the lowest value is 68% and it was split on the lane number and data collection quarter variables. No further outliers are present at this iteration. Next the research team explored the percentage of three or more ('3+') people occupancy vehicles using the regression tree methods.

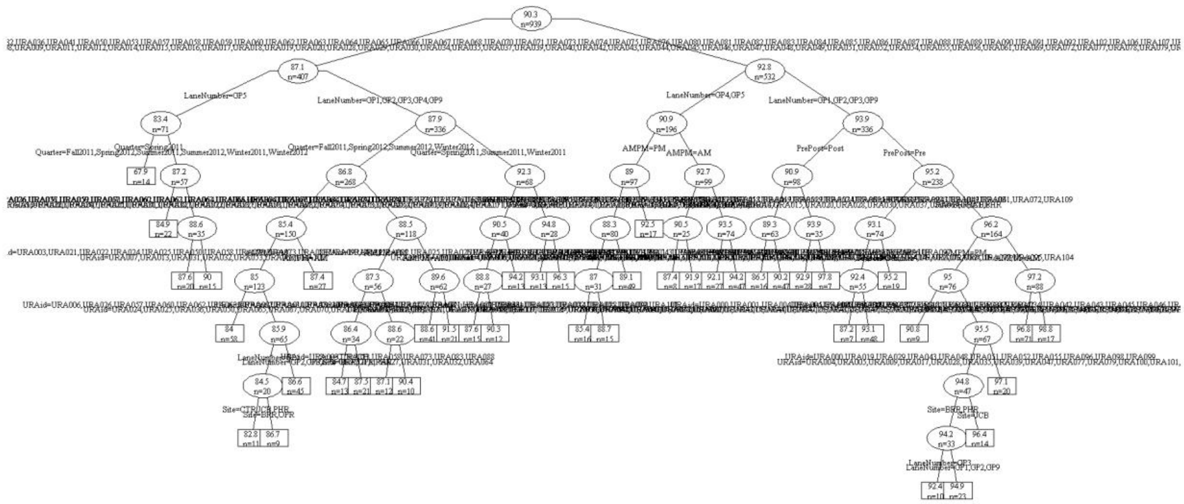


Figure 51: SOV Percent for the General Purpose Lanes – Analysis 6

Analysis 7

Figure 52 shows the regression tree for percentage of ‘3+’ occupancy for the HOV lane data. The extreme values the right leaf had only one individual with significantly different data from the overall average. The research team found major inconsistencies in that individual’s data. Hence, all data collected by this individual were eliminated.

Figure 52: ‘3+’ Occupancy Percent for the HOV Lane – Analysis 7

<u>Analysis 8</u>

Figure 53 show the '3+' Occupancy percent regression tree with the filtered HOV data. There are no extreme data that can be identified from this regression tree. Next the HOT dataset was tested for extreme data.

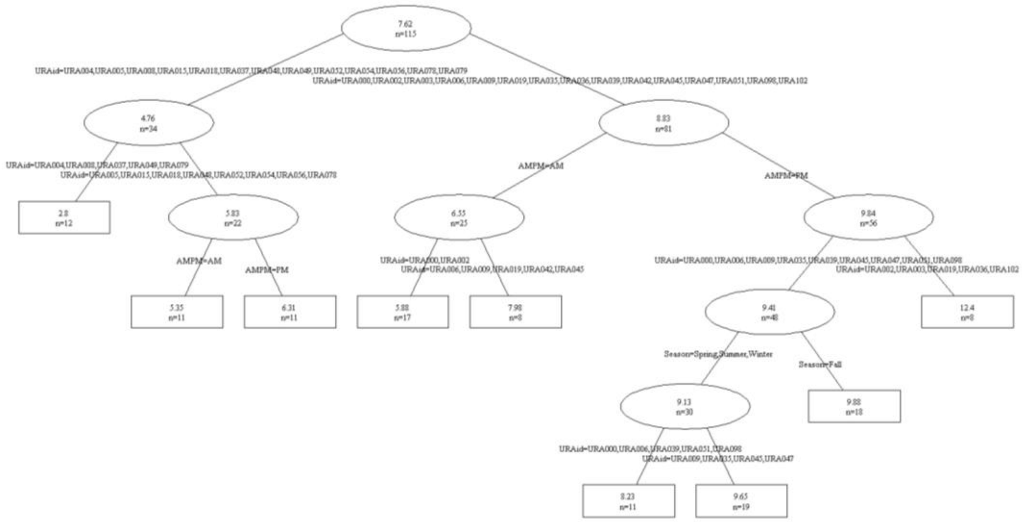


Figure 53: '3+' Occupancy Percent for the HOV Lane – Analysis 8

Analysis 9

Figure 54 shows the regression tree for '3+' Occupancy percentage in the HOT data. The right most leaf is explored further since it is almost twice the overall average value. The 12 sessions in that leaf were collected by six data collectors. Two of the six data collectors had good data and the remaining four data collectors had higher percentage only immediately after the HOT opened. Therefore no data were filtered at this iteration.

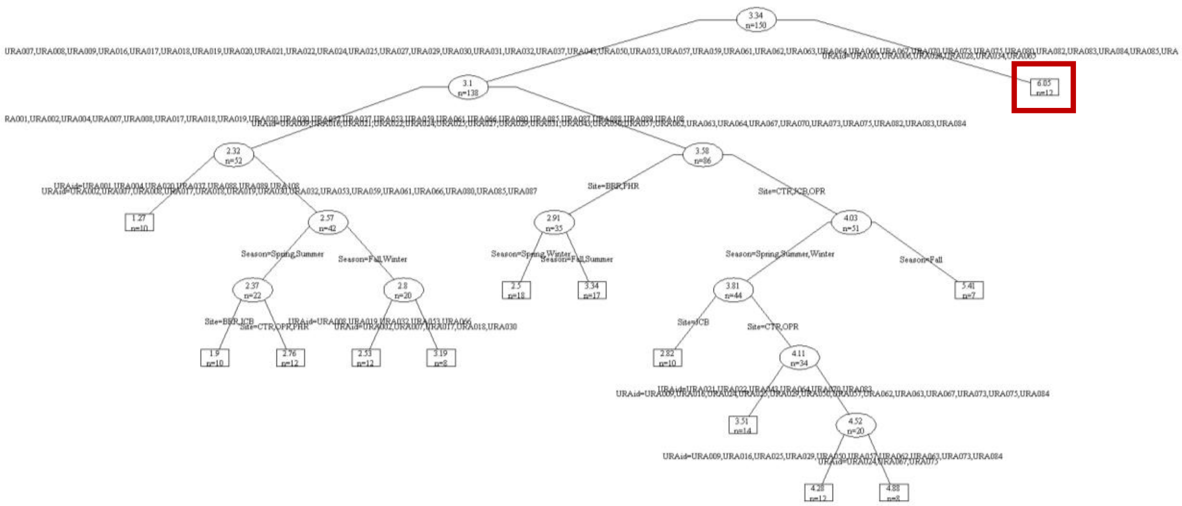


Figure 54: '3+' Occupancy Percent for the HOT lane – Analysis 9

Analysis 10

Figure 55 shows the '3+' Occupancy percent regression tree for the general purpose Lanes data. In this regression trees, the lane number is more significant variable than data collectors. Extreme data that were likely due to data collector bias have been eliminated and the dataset is finalized.

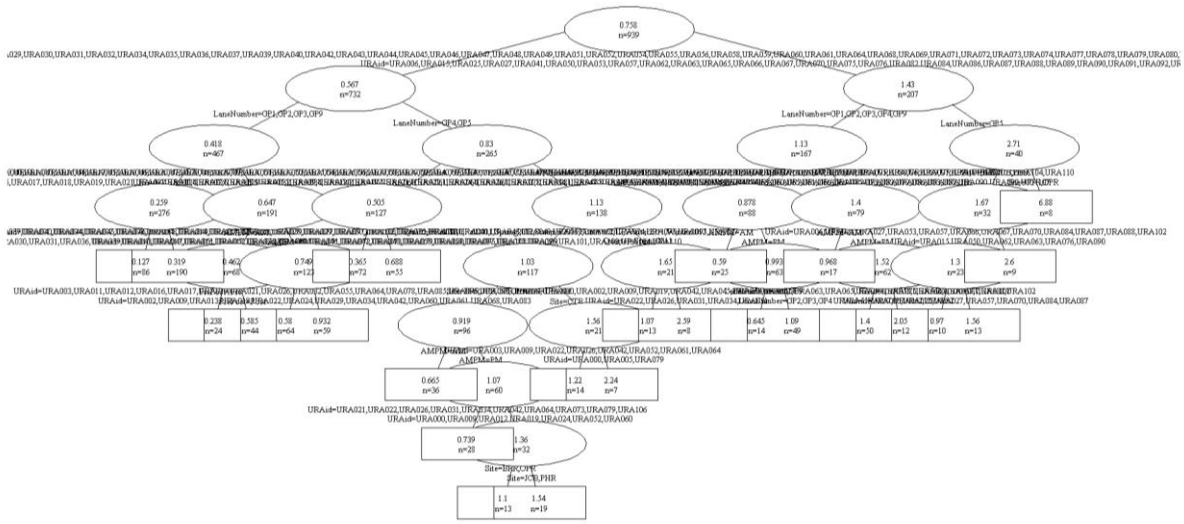


Figure 55: '3+' Occupancy Percent for the General Purpose Lanes – Analysis 10

17 Appendix D: Express Bus Throughput, February - April

Pre- and Post-HOT Average AM Weekly Express Bus Throughput

Weekly Express Bus Throughput	5-6 AM	6-7 AM	7-8 AM	8-9 AM	9-10 AM	AM Peak
February 2011	15	75	80	65	5	240
February 2012	25	90	100	70	5	290
Difference	10	15	20	5	0	50
Percent	66.7%	20.0%	25.0%	7.7%	0.0%	20.8%

Weekly Express Bus Throughput	5-6 AM	6-7 AM	7-8 AM	8-9 AM	9-10 AM	AM Peak
March 2011	15	75	80	65	5	240
March 2012	25	90	100	70	5	290
Difference	10	15	20	5	0	50
Percent	66.7%	20.0%	25.0%	7.7%	0.0%	20.8%

Weekly Express Bus Throughput	5-6 AM	6-7 AM	7-8 AM	8-9 AM	9-10 AM	AM Peak
April 2011	15	75	80	65	5	240
April 2012	25	90	100	70	5	290
Difference	10	15	20	5	0	50
Percent	66.7%	20.0%	25.0%	7.7%	0.0%	20.8%

Pre- and Post-HOT Average Weekly AM Express Bus Passenger Throughput

Weekly Passenger Throughput	5-6 AM	6-7 AM	7-8 AM	8-9 AM	9-10 AM	AM Peak
February 2011	323	2325	3191	2260	153	8251
February 2012	368	2211	3249	2544	172	8543
Difference	45	-114	58	284	19	291
Percent	14.0%	-4.9%	1.8%	12.6%	12.3%	3.5%

Weekly Passenger Throughput	5-6 AM	6-7 AM	7-8 AM	8-9 AM	9-10 AM	AM Peak
March 2011	300	2398	3185	2523	136	8542
March 2012	401	2358	3299	2483	156	8697
Difference	101	-40	115	-40	19	155
Percent	33.5%	-1.7%	3.6%	-1.6%	14.3%	1.8%

Weekly Passenger Throughput	5-6 AM	6-7 AM	7-8 AM	8-9 AM	9-10 AM	AM Peak
April 2011	326	2376	3326	2381	141	8550
April 2012	370	2228	3183	2219	116	8116
Difference	44	-148	-143	-163	-24	-435
Percent	13.5%	-6.2%	-4.3%	-6.8%	-17.4%	-5.1%

Pre- and Post-HOT Average Weekly AM Express Bus Occupancy

Express Bus Occupancy (persons/bus)	5-6 AM	6-7 AM	7-8 AM	8-9 AM	9-10 AM	AM Peak
February 2011	21.5	31.0	39.9	34.8	30.6	34.4
February 2012	14.7	24.6	32.5	36.3	34.3	29.5
Difference	-6.8	-6.4	-7.4	1.6	3.8	-4.9
Percent	-31.6%	-20.8%	-18.5%	4.5%	12.3%	-14.3%

Express Bus Occupancy (persons/bus)	5-6 AM	6-7 AM	7-8 AM	8-9 AM	9-10 AM	AM Peak
March 2011	20.0	32.0	39.8	38.8	27.3	35.6
March 2012	16.0	26.2	33.0	35.5	31.2	30.0
Difference	-4.0	-5.8	-6.8	-3.3	3.9	-5.6
Percent	-19.9%	-18.0%	-17.1%	-8.6%	14.3%	-15.7%

Express Bus Occupancy (persons/bus)	5-6 AM	6-7 AM	7-8 AM	8-9 AM	9-10 AM	AM Peak
April 2011	21.7	31.7	41.6	36.6	28.1	35.6
April 2012	14.8	24.8	31.8	31.7	23.2	28.0
Difference	-6.9	-6.9	-9.7	-4.9	-4.9	-7.6
Percent	-31.9%	-21.9%	-23.4%	-13.5%	-17.4%	-21.4%

Pre- and Post-HOT Average Weekly PM Express Bus Throughput

Weekly Express Bus Throughput	3-4 PM	4-5 PM	5-6 PM	6-7 PM	7-8 PM	PM Peak
February 2011	35	75	85	80	20	295
February 2012	35	90	105	95	10	335
Difference	0	15	20	15	-10	40
Percent	0.0%	20.0%	23.5%	18.8%	-50.0%	13.6%

Weekly Express Bus Throughput	3-4 PM	4-5 PM	5-6 PM	6-7 PM	7-8 PM	PM Peak
March 2011	35	75	85	80	20	295
March 2012	35	90	105	95	10	335
Difference	0	15	20	15	-10	40
Percent	0.0%	20.0%	23.5%	18.8%	-50.0%	13.6%

Weekly Express Bus Throughput	3-4 PM	4-5 PM	5-6 PM	6-7 PM	7-8 PM	PM Peak
April 2011	35	75	85	80	20	295
April 2012	35	90	105	95	10	335
Difference	0	15	20	15	-10	40
Percent	0.0%	20.0%	23.5%	18.8%	-50.0%	13.6%

Pre- and Post-HOT Average Weekly PM Express Bus Passenger Throughput

Weekly Passenger Throughput	3-4 PM	4-5 PM	5-6 PM	6-7 PM	7-8 PM	PM Peak
February 2011	1236	2553	2817	1532	203	8340
February 2012	1002	2741	3185	1651	112	8692
Difference	-233	188	368	119	-90	351
Percent	-18.9%	7.4%	13.1%	7.8%	-44.5%	4.2%

Weekly Passenger Throughput	3-4 PM	4-5 PM	5-6 PM	6-7 PM	7-8 PM	PM Peak
March 2011	1269	2644	2922	1500	248	8583
March 2012	997	2591	3203	1556	98	8445
Difference	-272	-53	281	56	-150	-138
Percent	-21.5%	-2.0%	9.6%	3.7%	-60.4%	-1.6%

Weekly Passenger Throughput	3-4 PM	4-5 PM	5-6 PM	6-7 PM	7-8 PM	PM Peak
April 2011	1298	2496	2854	1603	234	8484
April 2012	975	2452	3098	1745	121	8390
Difference	-323	-44	244	141	-113	-94
Percent	-24.9%	-1.8%	8.5%	8.8%	-48.2%	-1.1%

Pre- and Post-HOT Average Weekly PM Express Bus Occupancy Comparisons

Express Bus Occupancy (persons/bus)	3-4 PM	4-5 PM	5-6 PM	6-7 PM	7-8 PM	PM Peak
February 2011	35.3	34.0	33.1	19.2	10.1	28.3
February 2012	28.6	30.5	30.3	17.4	11.2	25.9
Difference	-6.7	-3.6	-2.8	-1.8	1.1	-2.3
Percent	-18.9%	-10.5%	-8.5%	-9.2%	11.0%	-8.2%

Express Bus Occupancy (persons/bus)	3-4 PM	4-5 PM	5-6 PM	6-7 PM	7-8 PM	PM Peak
March 2011	36.3	35.2	34.4	18.8	12.4	29.1
March 2012	28.5	28.8	30.5	16.4	9.8	25.2
Difference	-7.8	-6.5	-3.9	-2.4	-2.6	-3.9
Percent	-21.5%	-18.3%	-11.3%	-12.6%	-20.8%	-13.4%

Express Bus Occupancy (persons/bus)	3-4 PM	4-5 PM	5-6 PM	6-7 PM	7-8 PM	PM Peak
April 2011	37.1	33.3	33.6	20.0	11.7	28.8
April 2012	27.9	27.2	29.5	18.4	12.1	25.0
Difference	-9.2	-6.0	-4.1	-1.7	0.4	-3.7
Percent	-24.9%	-18.1%	-12.1%	-8.4%	3.6%	-12.9%

18 Appendix E: Vanpool Questionnaire

The Georgia Institute of Technology is currently researching the performance of the newly implemented high occupancy toll lane on I-85. This research requires accurate information on vanpools currently using the corridor. We are also preparing to distribute a survey to the users of I-85 and would like to gauge initial reactions to the HOT lane. We greatly appreciate your assistance by filling out this survey. Thank you very much!

Vanpool Group Number: ___________________________ Date: ________________

Vanpool Starting Date: _____________ Typical Number of Passengers: ___________

Location and Typical Times of Pick-ups

____

____

Location and Typical Times of Drop-offs

____

____

On what days is this van pool used in the…

Morning?

☐Monday ☐ Tuesday ☐Wednesday ☐Thursday ☐Friday

Evening?

☐Monday ☐ Tuesday ☐Wednesday ☐Thursday ☐Friday

Do you ever use the HOT lane on I-85?

☐Always ☐ Sometimes ☐ Never

If sometimes, which days do you usually use the HOT lane?

☐Monday ☐ Tuesday ☐Wednesday ☐Thursday ☐Friday

Does the HOT lane currently make your commuting easier or more difficult? Please feel free to add any information that will help us in evaluating how the HOT lane affects your commute.