Vehicle Occupancy, Vehicle Throughput, and Person Throughput Assessment of Atlanta's HOV Managed Lane Facilities

May 2025

Authors:
Hongyu Lu,
Daniel Hunsaker, Ziming Liu, Abhiram Puppala, Meghan McGurk,
Angshuman Guin, and Randall Guensler

Georgia Institute of Technology
School of Civil and Environmental Engineering
790 Atlantic Drive, Atlanta, GA 30332-0355
randall.guensler@ce.gatech.edu

Sponsored by:

SRTA State Road & Tollway Authority

Abstract

This report presents the results of the 2024 vehicle occupancy and person throughput study conducted by the Georgia Institute of Technology for the State Road and Tollway Authority of Georgia (SRTA). The analysis focused on four high-occupancy vehicle (HOV) carpool corridors within the I-285 Perimeter in Atlanta, GA, with the goal of evaluating vehicle occupancy and person throughput on these corridors under current travel conditions. The research was based on consistent methodological design with the prior studies on HOV-to-HOT conversion (2010 to 2012) and on Express Lane facilities (2018 to 2020) in metro Atlanta. The research team collected vehicle occupancy data through structured field observation, and machine-vision-based vehicle classification to assess hourly vehicle and person throughput by lane and vehicle class. Express bus person throughput was integrated using schedule and ridership data provided by transit operators of Xpress, CobbLinc and Ride Gwinnett. Quality assurance procedures included regression tree analysis to identify any potential bias associated with data collectors as had been noted in prior studies; no biased data collectors were identified in this year's study. In the AM peak, 5th Street was the most active corridor and the other three sites exhibited comparable throughput levels. In the PM peak, 5th Street again remained the busiest, followed by North Druid Hills Road, Fair Drive, and Moores Mill Road. The vehicle occupancy results show consistently higher occupancy in HOV lanes than in general-purpose lanes, with HOV facilities moving a disproportionately high share of corridor passengers per lane, despite carrying fewer vehicles. Carpooling played a more prominent role on these inside-the-Perimeter corridors than in prior SRTA studies, with person throughput from HOV2 and HOV3+ modes exceeding 32% at all study sites across both peak periods, and exceeding even 40% at North Druid Hills Road and Fair Drive during the PM peak. Both HOV2 and HOV3+ contributions were notably higher on these HOV corridors compared with the Express Lane facilities outside the Perimeter that were noted in prior studies. Express buses, while small in volume, added meaningful person throughput at select locations. The study verifies that HOV lanes significantly contribute to high-efficiency person movement.

Acknowledgments

The authors of this report wish to thank the Georgia State Road and Tollway Authority, Georgia Department of Transportation, and the Atlanta Regional Commission for their data contributions, support, and assistance throughout this research effort.

Executive Summary

This report presents the results of a 2024 vehicle occupancy and person throughput study conducted by the Georgia Institute of Technology for the Georgia State Road and Tollway Authority (SRTA). The analysis focused on four HOV corridors located within the I-285 Perimeter: 1) Moores Mill Road NW at I-75 (I-75 North HOV Lanes), 2) North Druid Hills Road at I-85 (I-85 North HOV Lanes), 3) Fair Drive at I-75/I-85 (I-75/I-85 South HOV Lanes), and 4) 5th Street NW at I-75/I-85 (I-75/I-85 Connector HOV Lanes). The goal of this study was to assess vehicle occupancy, vehicle throughput, and person throughput in general-purpose and managed lanes under post-pandemic travel conditions.

Vehicle occupancy data were collected in the field through structured visual observations over ten sessions per site of Tuesdays, Wednesdays and Thursdays (five for morning peak hours and five for evening peak hours), with parallel video recording to support quality assurance and vehicle classification. Machine vision models were used to process overpass camera feeds and extract lane-level vehicle volumes and fleet composition. Unlike previous SRTA studies, GDOT NaviGAtor data were not used in this analysis due to extended data outages in 2024. Instead, vehicle volumes were obtained directly from machine vision video profiles that were temporally aligned with occupancy observations.

To ensure data integrity, the team conducted a regression tree analysis to evaluate data collector effects and potential observer bias. No such bias was detected, which reflects improvements in team selection, management, and training over previous cycles. Additional adjustments were made to account for express bus activity using recorded route schedules and ridership reports from Xpress, CobbLinc, and Ride Gwinnett.

In this study, SUVs consistently carried more passengers than passenger cars, particularly in GP lanes, across all sites, and lane type had a stronger influence on occupancy than vehicle class. The results also revealed consistently higher average vehicle occupancy in managed lanes relative to general-purpose lanes, with adjusted average vehicle occupancy in HOV lanes ranging from 1.56 to 1.74 persons per vehicle during AM peaks and 1.59 to 1.71 persons per vehicle in PM peaks.

Vehicle and person throughput were highest at 5th Street during the PM peak, with the corridor exceeding 13,200 persons per hour and managed lane headways falling to approximately 2.5 seconds per vehicle.

Across all sites, PM peaks showed higher occupancy than AM (except for 5th Street where the overall occupancy were comparable between the peak hours), with notable contributions from high-occupancy vehicle (HOV2 and HOV3+) travel. HOV3+ vehicles contributed approximately 7%-11% of total person throughput during the PM peak at several sites (considerably higher than in previous SRTA studies where their impact was generally below 5%). Field teams also observed time-clustered waves of three-person carpools, particularly in the PM peak at North Druid Hills Road (likely school-related trips).

HOV2 person throughput share were also higher compared with the 2018-2020 study, contributing approximately 20%-30% across sites (higher than the 19% maximum recorded in the 2018-2020 study). HOV2 remained the dominant carpool mode in managed lanes, often comprising 45%-60% of HOV lane person throughput.

Carpooling (HOV2 and HOV3+) played a more substantial role than in the previous corridor studies. PM peak periods at North Druid Hills Road and Fair Drive saw carpool shares exceeding 40% of total person throughput. The carpool person throughput shares exceeded 32% at all sites for both peak hour period. Even in cases where HOV lanes carried fewer vehicles, they consistently supported a disproportionate share of passenger movement. Express buses, while comprising less than 0.2% of vehicle throughput, contributed 0.6% to 2.3% of person throughput.

Overall, this study indicates that the HOV lanes within the I-285 Perimeter continue to support high-efficiency person movement under diverse demand conditions. It also captures a potential modal shift toward more frequent and meaningful carpooling (particularly among larger travel parties) in these urban freeway segments. With improved data reliability, higher occupancy rates, and robust HOV2 and HOV3+ performance, this study establishes a baseline for future corridor monitoring of managed lane facilities.

Table of Contents

List of Figures

List of Tables

List of Acronyms

5ST	5th Street
ABM	Activity-Based Model
AFV	Alternative Fuel Vehicle
ARC	Atlanta Regional Commission
AVO	Average Vehicle Occupancy
DOT	Department of Transportation
ETL	Express Toll Lane
FHWA	Federal Highway Administration, USDOT
FPS	Frames per second
FRD	Fair Drive
Georgia Tech	Georgia Institute of Technology
GDOT	Georgia Department of Transportation
GP Lane	General-purpose lane
GPU	Graphics processing unit
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 – A facility that allows vehicles that do not meet minimum required occupancy to pay a toll to use the facility
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 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
LDV	Light-duty vehicle
MARTA	Metropolitan Atlanta Rapid Transit Authority
ML	Managed Lane (Toll Lane, HOV lane, HOT lane, etc.)
MRM	Moores Mill Road
MV	Machine vision
NaviGAtor	The intelligent transportation system operated by the Georgia DOT
NRD	North Druid Hills Road
PPLPH	Persons per lane per hour
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
URA	Undergraduate research assistant
USDOT	United States Department of Transportation
VDS	Vehicle detection systems (video-based in Atlanta)
VPLPH	Vehicles per lane per hour
VPSI	Vanpool Services, Inc.
VPTC	Vehicle and Person Throughput Calculator
YOLO	You Only Look Once (object detection machine vision tool)

1 Introduction

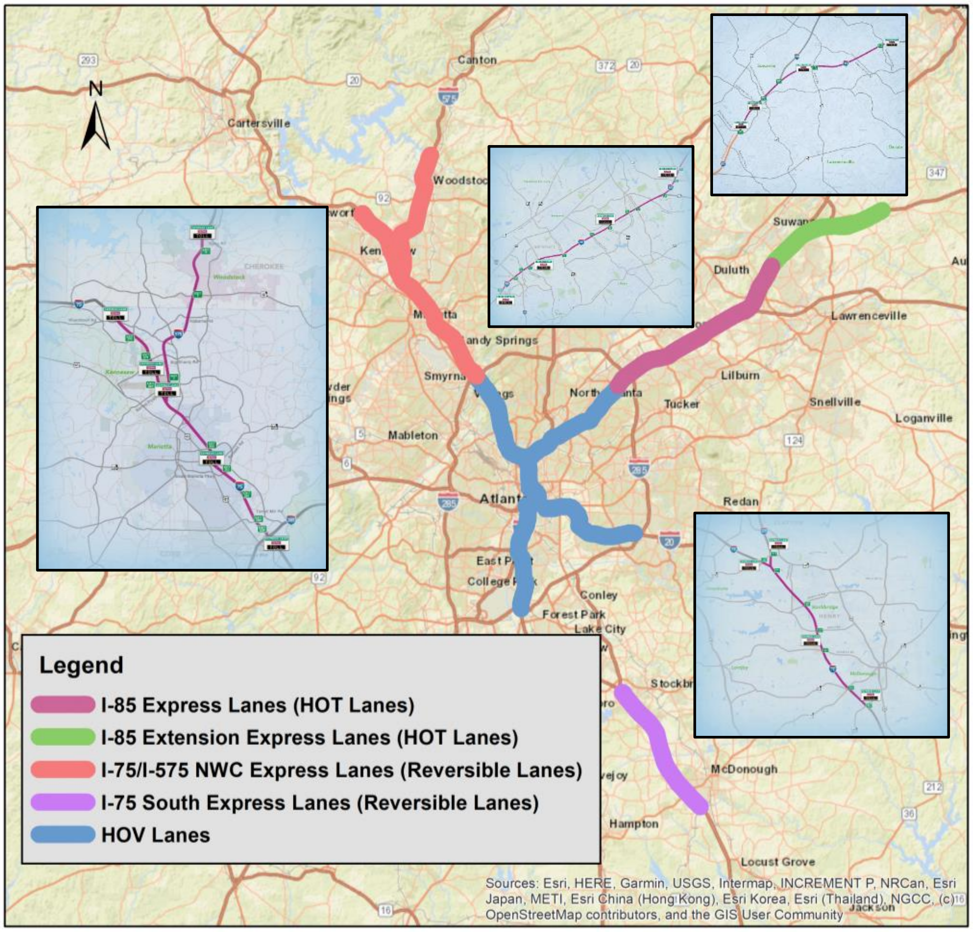
Major metropolitan areas that face severe congestion problems have been implementing a variety of transportation control measures designed to manage transportation demand and reduce congestion during morning and afternoon peak periods (Guensler, 1998; Guensler, et al., 2013a; Guensler, et al., 2013b; Guensler, et al. 2021a; Guensler, et al. 2021b). A growing congestion management trend has been the implementation of managed lanes, to enhance freeway operations (USDOT, 2012; FHWA, 2020). Managed lanes include high-occupancy vehicle (HOV) carpool lanes, high-occupancy toll (HOT) lanes, and express toll lanes (ETLs), which typically run within or alongside congested Interstate highways. Managed lanes provide commuters with an option to obtain more reliable travel speeds either by carpooling or paying a toll to access the managed lane. However, an important operational consideration with any managed lane is ensuring that demand for lane use remains below lane capacity, to ensure that congestion does not form on the lane (i.e., speeds remain above 45 mph during the peak period).

The demand for high-occupancy carpool lanes requiring 3+ persons per vehicle (HOV3+ lanes) typically remains below the lane capacity, because 3-person carpools are very difficult to form and retain. However, in large metropolitan areas, demand for carpool lanes that require only 2+ persons per vehicle (HOV2+) often exceed lane capacity, as they did on the Atlanta I-85 corridor prior to 2009 (Toth et al., 2014; Guensler, et al., 2013a; Guin, et al., 2008). When carpool demand exceeds capacity, congestion forms on the managed lane, which means that carpoolers and transit users do not attain their expected/promised levels of service. When a HOV2+ lane becomes congested, one might think that the logical approach is to convert the lane to an HOV3+ lane; however, 3-person carpools are very difficult to form. Converting an HOV2+ lane to an HOV3+ lane so drastically diminishes demand for use of the lane, that conversion results in an under-utilized managed lane and increases congestion on the regular (general-purpose or GP) lanes. For example, before-and-after data in Texas showed a reduction in demand for the HOV lane by 65% (Pratt, et al., 2000) after HOV2 to HOV3+ conversion, which pushed vehicles into the general-purpose (GP) lanes, and made corridor congestion worse than before the conversion (the lane was later converted back to HOV2).

To solve the reduction in demand associated with an HOV2+ to HOV3+ conversion, FHWA and others introduced the concept of high-occupancy toll (HOT) lanes. HOT lanes increase the occupancy requirement, which reduces demand for the lane, and then fills the free capacity on that lane with drivers who are willing to pay a toll. When tolls are low, demand for the lane is high. As demand increases and threatens to swamp the lane with congestion, facility operators increase the HOT lane toll price, which reduces demand. As demand decreases, the operators decrease the toll price to increase demand for the lane. With accurate anticipation of changes in demand for the lane, and proper setting of the toll price, demand never exceeds capacity and the lane achieves optimal flows. Express toll lanes (ETLs) work the same way as HOT lanes, increasing and decreasing toll pricing as needed to manage demand, with the difference that carpools and other vehicles that may be exempt on HOT lanes (e.g., electric vehicles) are also charged tolls in ETLs.

In the Atlanta Metropolitan area, the Georgia Department of Transportation (GDOT), in collaboration with relevant state and regional transportation agencies, designs, contracts, and constructs managed lane facilities that are part of the planned $16.1 billion managed lanes system (HNTB, 2015; HNTB, 2010). The State Road and Tollway Authority (SRTA) procures the financing for these systems and then operates the tolled transportation facilities within the State.

The previous vehicle occupancy projects conducted by Georgia Tech for SRTA in 2010-2012 and in 2018-2020 examined throughput on major managed lane facilities outside the I-285 Perimeter: the I-75/I-575 Northwest Corridor, the I-85 Express Lanes (original and extension), and the I-75 South Metro lanes. The first priced managed lane facility was an HOV-to-HOT conversion on the I-85 corridor that opened on October 1, 2011. The second facility, the I-75 South Metro Express Lanes, opened about five years later (January 2017). In September 2018, SRTA opened new reversible express toll lanes on the I-75/I-575 Northwest Corridor, and then extended the existing I-85 HOT Lanes north of Atlanta from Old Peachtree Road to Hamilton Mill Road in November 2018 (SRTA, 2018). All four facilities are within the metro area (Figure 1).



Sources: https://srta.ga.gov/georgia-express-lanes and https://peachpass.com/

Figure 1 – Map of Atlanta's Managed Lane Facilities

The 2024 vehicle occupancy update focuses on four specific locations within the I-285 Perimeter, to capture both I-75 and I-85 managed lane performance inside the urban core (Section 2.1 of this report describes the specific characteristics of each facility). The Georgia Tech team has been tasked in this 2024 project with assessing vehicle throughput, vehicle occupancy, and person throughput during the morning and evening peak periods on these HOV facilities, using the same methods employed in the previous managed lanes studies (Guensler, et al, 2013a; Guensler, et al, 2021a; Guensler, et al, 2021b). For this project, the team updated previous data collection methods and deployed students to collect vehicle throughput and vehicle occupancy data for use in the calculation of vehicle and person throughput under congested conditions. This research effort is observational in nature, and methods remained consistent throughout the entirety of the study.

- The team collected occupancy data in Fall 2024 at the four data collection sites to provide a contemporary snapshot of occupancy and person throughput at fully operational locations.

- All of the occupancy data associated with the above data collection efforts have been QA/QC-processed and summarized in this report.
- All of the collected license plates have been processed (a second graphics computer was dedicated to the analysis) to assess the presence of alternative fuel vehicles (AFVs) identified through license plate recognition.
- In the previous projects, traffic volumes from GDOT's NaviGAtor data were QA/QC-processed and served as input to the throughput assessment. However, due to a lack of available NaviGAtor data for the observation sites, the team used field-collected traffic counts derived from video profiles using machine vision to provide vehicle throughput.
- The previous studies employed before-and-after comparative occupancy and throughput results based upon field observations, with the substitution of average vehicle occupancy for vanpools and express buses. The study reported herein is for a snapshot in time and space and, therefore, does not include any before/after comparisons. Express bus ridership data were integrated into the study using the same methods as in previous efforts. However, vanpool data were not used because ridership data indicated relatively low average occupancy (ranges from 3.2 persons per vehicle to 7.0 persons per vehicle), and as demonstrated in prior studies (Guensler et al., 2021b), the low frequency of vanpool use has a negligible impact on vehicle occupancy and person throughput (less than 0.01 persons/vehicle impact on average occupancy across any lane).

Chapter 2 provides an overview of the vehicle and person throughput methodology, identifies available data sources, describes the managed lanes corridors and the occupancy field data collection efforts, and provides the throughput calculation methods. Vehicle occupancy data collection is described in Chapter 3, including the specific data collection deployment efforts. Machine vision algorithms and the identification of vehicle class and alternative fuel vehicles are presented in Chapter 4. Quality assurance and quality control (QA/QC) of field data collection is described in Chapter 5, and factors affecting occupancy are discussed in Chapter 6. Chapter 7 describe express bus data sources and person throughput adjustments used in adjusting field-observed average vehicle occupancy. Chapter 8 presents the field collected vehicle occupancy results. Final vehicle throughput and person throughput results by lane, by peak hours and by site (corridor) are presented in Chapter 9. Finally, the conclusions and recommended supplemental research are presented in Chapter 10. The majority of the chapter structure mirrors the previous reports to maintain consistency in analytical presentation.

2 Data Sources and Methodology

This study employed a consistent research design with the 2010-2012 and 2018-2020 studies to evaluate vehicle occupancy and person throughput across multiple managed lane corridors in the Atlanta metropolitan area. Manual roadside observations were performed to record vehicle occupancy and vehicle class, supplemented by field video profiles also capturing vehicle classes and capturing license plate images for post-processing. The observed occupancy profiles were examined for data quality through a regression tree analysis to identify potential data collector bias (documented in Chapter 5), and adjusted for uncertain observations (where not all persons inside a vehicle may be visible due to window tinting). Unlike the previous studies, which utilized GDOT's NaviGAtor system to source traffic volumes, this study relied on field-collected traffic counts derived from machine vision analysis of video footage. These counts were integrated with the occupancy data to calculate vehicle and person throughput by lane and mode. Express bus throughput was assessed separately, using reported ridership statistics. The final vehicle and person throughput were presented across sites (corridors) and between AM and PM peak hours.

2.1 Study Area

The overall Georgia Managed Lanes Plan calls for $16.1 billion in capital investments on managed lanes facilities (HNTB, 2010; HNTB, 2015). The managed lane system plan identifies the following operational goals and objectives (Smith, 2011):

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

GDOT and SRTA have endeavored to meet these goals through project implementation (corridor selection, design, and operations). Over the past fifteen years, the state has continued implementing managed lane corridors as part of the overall plan. As part of the planning and implementation process, SRTA has been committed to monitoring the outcomes of these new facilities. In 2010-2012, GDOT and SRTA conducted a before-and-after assessment of the HOV-to-HOT conversion on I-85 to see how the project affected vehicle and person throughput. In preparation for the opening of two new facilities, SRTA funded the 2018-2019 before-and-after study to also assess changes in vehicle and person throughput for the I-75/I-575 Northwest Corridor (NWC) and the I-85 HOT extension.

The HOV Lanes first opened in Atlanta on December 14, 1994, with 18 lane miles on I-20 from Downtown to I-285. In 1996, 60 additional lane miles opened on I-75 and I-85. Another 23.6 lane miles of HOV lanes opened on I-85 in Gwinnett County on October 31, 2001 (before they were converted to HOT lanes). These lanes are located in the inside (leftmost) lane and are designated for vehicles carrying two or more occupants (HOV2+). Lane separation is maintained by pavement markings only, with no dedicated barriers or pylons. Enforcement is managed via visual patrol and periodic compliance checks. Unlike dynamically priced Express Lanes, these HOV lanes do not utilize tolling or variable pricing mechanisms (no Peach Pass is required).

This study targets the following data collection sites within the I-285 Perimeter:

- I-75 North HOV Lanes: The facility operates through a dense urban segment between the I-285 Perimeter and the I-75/I-85 Downtown Connector. This corridor experiences high demand in both general-purpose and HOV lanes, particularly during peak commuting hours. Direct HOV lane access is provided by direct access ramps at Northside Drive and Akers Mill Road.

- I-85 North HOV Lanes: The I-85 North HOV lanes run through the northeastern quadrant inside the Perimeter. The segment endures directional congestion during peak periods, because it connects the urban core to major residential and employment centers. The corridor includes a direct northbound entrance ramp at Lindbergh Drive and a southbound exit ramp also at Lindbergh Drive (HOV travel to and from the Buckhead area).

- I-75/I-85 Connector HOV Lanes: The Downtown Connector includes continuous HOV lanes through central Atlanta, spanning from University Avenue to just north of 17th Street. This high-demand corridor accommodates bidirectional traffic demands for both peak hour periods. The northbound HOV lane has a direct entrance at Williams Street, with exits at Memorial Drive, Piedmont Road, and the Brookwood Interchange ramp to I-75. The southbound direction includes entrances from I-75 southbound Piedmont Road, and Memorial Drive, and an exit at Williams Street.

- I-75/I-85 South HOV Lanes: The I-75/I-85 South corridor extends from just south of I-20 to the I-285 Perimeter further south. This segment traverses a part of the metro area influenced by Hartsfield-Jackson Atlanta International Airport and distinct land uses (and therefore commuting pattern). The corridor features direct access ramps at C.W. Grant Parkway, enabling access to airport-related traffic flows.

2.2 Data Collection Overview

The research team selected one location to represent the performance of each of the four corridors (see Figure 2). Each data collection site was selected to be representative of the applicable facility. Each site had to be accessible to an appropriate roadside location, and a good view into the vehicle needed to be present for occupancy data collection (typically a slightly elevated view looking down into the vehicle as it passes by the observation site). The team conducted safety inspections for each site prior to finalizing the data collection plan, and safety reports were prepared for each site (safety plans are available under separate cover).

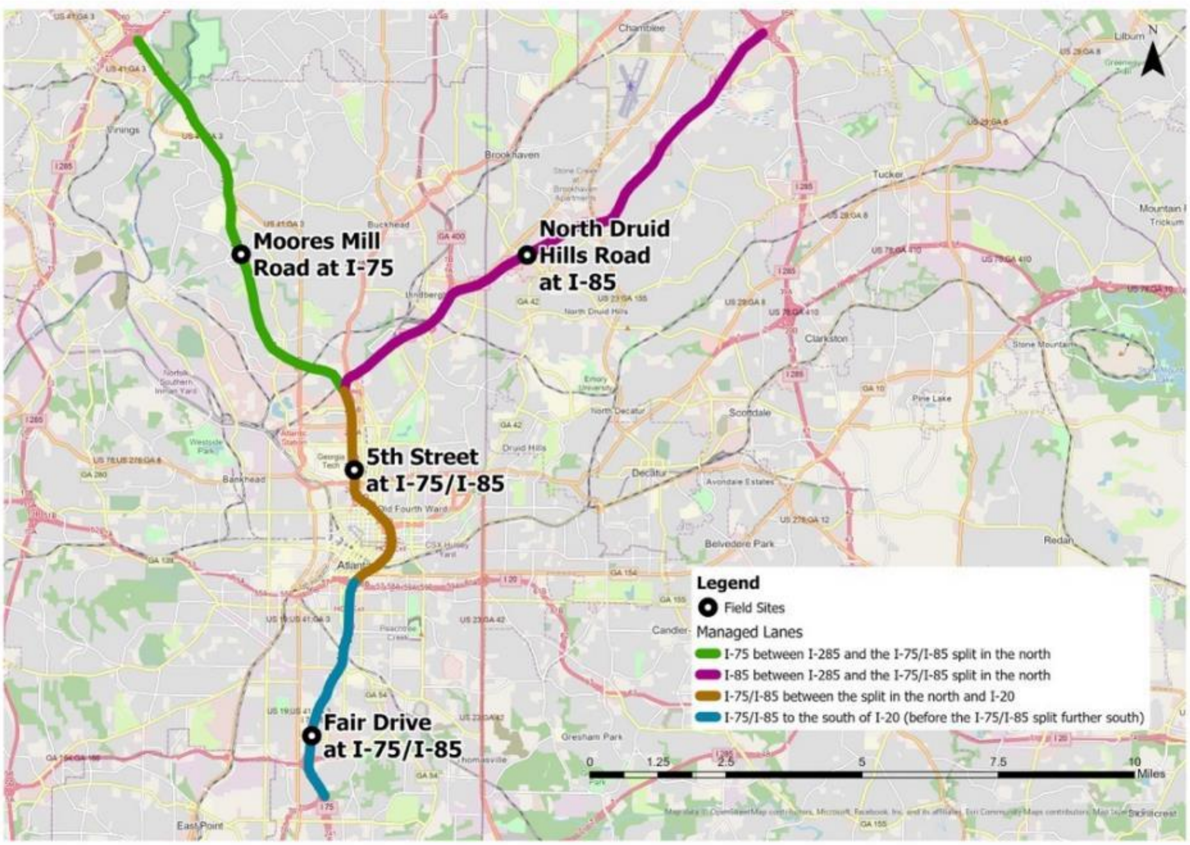


Figure 2 – Map of Data Collection Locations

At each site, the research team collected vehicle occupancy data on each facility for five morning and afternoon peak periods, typically over a two-week time span. As vehicles passed the observation location, student workers manually recorded the vehicle's occupancy on a specialized tablet using an app designed for occupancy data collection (see Chapter 3). The team concurrently collected video from the closest overpass while collecting the occupancy data. Each camera was set up to cover two lanes, and multiple cameras were used as needed, with the zoom set such that license plates in both lanes could be read clearly when played back in the laboratory. Video also allows the team to accurately count the number of vehicles traversing the roadways during each data collection session (video time-stamps provide second-by-second vehicle flow by lane). The team also used license plate icons to extract alternative fuel vehicle presences (as will be described in Chapter 4).

For this project, all data collection sites were selected based on the same principles as with previous studies: a combination of inspector safety, site accessibility, and site quality for collecting observational occupancy data. Safety was the primary criterion; no unsafe sites were considered. For each site, the team required safe parking locations, safe occupancy data collection spots (protection from traffic), and safe access routes between them. The occupancy data collection locations also needed to provide clear visibility for accurate data observation (e.g., an appropriate elevation above the roadway close enough to see vehicle occupants across all lanes). A nearby overpass bridge was desired where cameras could be set up to record license plates, which required safety and accessibility of the overpass sidewalk and visibility of the freeway traffic from the overpass. Northbound and southbound data collection points needed to be in close proximity (ideally on the same overpass), so that comparison between northbound and southbound traffic remained valid and consistent. The selection was based on examining all potential overpasses using maps, vehicle drive through video (to assess the vehicle occupancy locations), and in-person site visits (to take photos, verify parking locations, confirm safe access to and from the data collection locations, and perform vegetation trimming when needed).

The rationale behind the selection of each data collection site is described in the bullets below, and more details are provided on data collection methods and deployment dates provided in Chapter 4.

- Moores Mill Road NW at I-75 (I-75 North HOV Lanes): This site is located approximately midway between the I-285 Perimeter and the I-75/I-85 interchange, with both northbound and southbound data collected from gore areas just north of the overpass. The site was selected for its accessible configuration (after minor vegetation trimming), proximity to a safe parking area (at the nearby YMCA facility), and the unobstructed sight lines it provides for vehicle occupancy observation.

- North Druid Hills Road at I-85 (I-85 North HOV Lanes): Situated northeast of the overpass (and geographically closer to the I-75/I-85 connector than I-285), this site was selected to represent mid-corridor activity on I-85 North. It offers clear visibility for both travel directions (after minor trimming) and was the only feasible site in the corridor not obstructed by a U-turn connector structure. The data collection required daily coordination with an active construction project (new U-turn connectors), including enhanced safety protocols (hard hat uses), and was completed on schedule before visual access was compromised by bridge construction.

- Fair Drive at I-75/I-85 (I-75/I-85 Connector HOV Lanes): Positioned between the I-75/I-85 merge and I-20, this was the only location deemed both safe and accessible for monitoring traffic entering the connector from the southern metro region. The southbound site (based at Atlanta Metropolitan State College) was selected for its operational feasibility, and the northbound site was made accessible through extensive vegetation management.

- 5th Street NW at I-75/I-85 (I-75/I-85 South HOV Lanes): Positioned adjacent to Midtown and the Georgia Tech campus, this site captures central Atlanta flow north of I-20, where high volumes of commuter and student traffic converge. It was selected for its straightforward access, safe elevated viewpoints, and guaranteed parking permissions at Georgia Tech and the nearby FlexCar lots.

2.3 Vehicle and Person Throughput Assessment

The research team developed the Vehicle and Person Throughput Calculator (VPTC) to assess hourly vehicle flow rates (vehicles/hour and vehicles/three-hours during the morning and afternoon peak periods) and person throughput (persons/hour and persons/three-hour data collection period) using data collected for specific monitoring stations. The design of VPTC in this study remains consistent with the methodology applied in both previous studies.

The team developed the original calculator in a Microsoft® Excel spreadsheet, and then translated the code to a series of Python® scripts for implementation in the 2010-2012 study. The scripting process allowed the calculator to interface directly with the analytical database and the tables of pre-processed input data, including: 1) NaviGAtor ITS traffic volume data, or other monitoring data, after processing through quality assurance routines; 2) field-collected occupancy and vehicle classification data, after quality assurance processing and allocation of uncertain occupancy observations (described later in this report), and 3) express bus and vanpool vehicle occupancy data. Outputs are aggregated to five-minute bins for vehicle and person flows for the selected times and dates (which can be further aggregated to hourly and peak-period flow rates).

The implementation of this project was based on the Excel version of VPTC for easier verification, as with the 2018-2020 study. All data and calculation methods employed in this project can be found in the companion spreadsheets to this report.

In the 2010–2012 and 2018–2020 SRTA studies, vehicle throughput and speed profiles were derived from the Georgia NaviGAtor system, a network of video detection systems (VDS) operated by the Georgia Department of Transportation (GDOT) that monitors over 220 miles of Atlanta’s freeway network. This system provided 20-second interval data on traffic speed and volume at the lane level. The Georgia Tech research team developed and implemented a robust quality assurance/quality control (QA/QC) protocol using data filtering based on speed-flow rate fundamental diagrams. Speed variability was also reviewed through time-series plots to detect calibration anomalies, and free-flow speed calibration was validated with laser speed gun measurements across all lanes and sites. In the 2018-2020 study, only about 0.003% of NaviGAtor records were excluded after QA/QC processing.

Unlike prior studies, the 2024 assessment faced a significant limitation in the availability of NaviGAtor data. Although NaviGAtor was the planned data source, the transmission of data from GDOT to Georgia Tech's secured server failed between February and December 2024 (due to persistent server communication issues). After the Georgia Tech team identified the gap, GDOT was contacted to re-upload the missing data. However, the restored dataset was substantially incomplete, with data from only about 25% of devices across the metro Atlanta region being successfully recovered. Unfortunately, none of the functional stations were within 1.5 miles of the 2024 data collection sites or had consistent cross-sectional lane configurations. The team concluded that NaviGAtor data could not be used to derive throughput assessment at the necessary spatial resolution.

In response, the research team pivoted to using field-recorded video footage captured concurrently with vehicle occupancy observations. These video profiles were recorded from elevated positions (overpasses and protected gore sections) and were processed using machine vision techniques to extract vehicle volume data by lane. This approach also ensured that throughput assessment remained geographically and temporally consistent with the occupancy observations. The same manual volume verification developed in the previous study were applied to the video-derived data. Details of the video data processing methodology, including calibration and validation steps, are provided in Chapter 4 of this report.

The machine vision algorithms provided traffic volumes by the number of light-duty vehicles (LDVs), sport utility vehicles (SUVs), buses, motorcycles, vans, small heavy-duty trucks (small HDTs), and large heavy-duty trucks (large HDTs). The team assigned the observed vehicle occupancy data by vehicle class to class-specific vehicle throughput by lane. Hence, initial person throughput estimates were derived by multiplying vehicle class traffic volumes (e.g., vehicles/hour for sport utility vehicles), by corresponding vehicle-class-specific occupancy observations (persons/sport utility vehicle). More information on occupancy data collection and person throughput calculations is provided in later chapters.

Initial hourly person throughput results were later adjusted to account for the impact of express buses. Following the same process used in the previous analyses, express bus impacts were handled by replacing the persons in each applicable bus field observation (entered in the filed using the '4+' persons button) with the monitored ridership for these regularly scheduled vehicles (i.e., number of persons in each bus). The specific procedures for addressing express bus occupancy are presented in detail in Chapter 7 of this report. In previous studies, similar adjustments were also applied to vanpools; however, analysis indicated that average vanpool occupancy did not exceed 4.5 persons. Given the low volume of vanpool traffic and low vanpool occupancy in the current study, and the fact that vanpools had no significant impact on any prior calculations of average vehicle occupancy or person throughput in prior studies, vanpool occupancy substitution was not incorporated into this current study.

After the QA/QC process for vehicle throughput data are complete, the VPTC operates in a stepwise process:

Step 1: Select Location, Date, and Time:
The user selects a desired location, date, and time.

Step 2: Query Traffic Volume and Speed Data:
The scripts pull the applicable vehicle flow rates (at five-minute resolution) from the machine vision vehicle database table. Data are tracked lane-by-lane. Hourly equivalent volumes are calculated by summing five-minute volumes for the hour.

Step 3: Query Vehicle Classification Field Data:
For any given station/lane/date/time, machine vision traffic counts by lane come with vehicle class counts (motorcycles, light-duty automobiles, sports utility vehicles, buses, small HDTs, large HDTs) (see Table 1 for an example of the number of vehicle occupancy counts at North Druid Hills Road at I-85). Lane-by-lane analysis is supported by this method, given that vehicle class fractions vary across lanes, as do average vehicle occupancy values.

Table 1 – Number of Vehicle Occupancy Observations by Vehicle Type, North Druid Hills Road at I-85, 08/27/2024, PM Peak (3:30-6:30 PM)

Class	ML1	GP2	GP3	GP4	GP5	GP6	Sum
LDV	735	812	1,447	968	1,704	866	6,532
SUV	452	554	513	458	338	824	3,139
Small HDV	21	27	74	43	32	49	246
Large HDV	1	10	66	41	9	25	152
Bus	31	4	1	0	2	1	39
Van	162	111	169	122	155	97	816
MC	5	0	1	0	1	2	9
Total	1,407	1,518	2,271	1,632	2,241	1,864	10,933

Step 4: Apply Monitored Occupancy Data to Traffic Volumes:
The counts by vehicle class are then linked to vehicle occupancy counts (percentages of 1-person, 2-person, 3-person, 4-person and 4+ person vehicles, after allocation to certain occupancy values, as described in section 3.3 of this report) for each class of LDV, SUV, and HDTs to obtain estimates of vehicle throughput for each vehicle class, lane and time period (see Table 2 for an example of the occupancy observation data collected at North Druid Hills Road at I-85).

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 class count by the applicable vehicle class occupancy value. 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). Motorcycles are ignored in this process considering the small volume. Person throughput from vans and buses are processed separately in the next step.

Step 6: Adjust Vehicle and Person Throughput for Express Buses:
In the final step, the calculator employs Xpress, Ride Gwinnett, and CobbLinc 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 ridership data by route and departure time establishes applicable passenger occupancy of these buses as described in later chapters. The ‘4+’ person counts for buses 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 actual number of passengers on each passing bus. These processes and results are described in Chapters 7.

Table 2 – Vehicle Occupancy Observations by Vehicle Type and by Lane, North Druid Hills Road at I-85, 08/27/2024, PM Peak (3:30-6:30 PM)

Vehicle Class	Occupancy	ML1	GP2	GP3	GP4	GP5	GP6
LDV	1	64.3%	90.1%	89.6%	87.2%	86.8%	83.8%
	2	34.1%	8.5%	9.6%	11.5%	12.2%	14.6%
	3	1.5%	0.7%	0.7%	1.0%	0.6%	1.1%
	4	0.1%	0.5%	0.1%	0.0%	0.3%	0.4%
	4+	0.0%	0.2%	0.0%	0.3%	0.1%	0.1%
	Subtotal	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
SUV	1	34.3%	77.2%	69.0%	74.9%	69.4%	80.3%
	2	59.9%	22.4%	25.6%	20.5%	26.4%	16.9%
	3	4.6%	0.0%	2.1%	0.9%	1.9%	2.1%
	4	0.7%	0.2%	2.1%	0.0%	2.3%	0.2%
	4+	0.5%	0.2%	1.2%	3.7%	0.0%	0.5%
	Subtotal	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

* Table 1 and Table 2 employ the same field data (some vehicle classes are excluded here).

3 Vehicle Occupancy Data Collection

In this report, "vehicle occupancy" is defined as the number of persons in a vehicle (persons/vehicle), including the driver. A single-occupant vehicle (SOV) contains only the driver. In Georgia, a high-occupancy vehicle (HOV) is a 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, and so on. Vehicle occupancy data are needed to estimate person throughput for each managed lane 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, as well as numerous hybrid variations. In developing methods for the 2010-2012 and 2018-2020 data collection efforts, the Georgia Tech research team examined the advantages and disadvantages associated with each method via a literature review (Guensler, et al., 2013a). 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 site-specific constraints along the study corridor, as described in Section 2.2), the capabilities of available equipment, potential mental fatigue, and labor costs.

The traditional roadside/windshield method is the most common vehicle occupancy data collection method (Heidtman, et al., 1997) because of its simplicity and equipment requirements. This method positions a data collector such that they can see through a passing vehicle's windshield and the side windows to count the number of occupants as the vehicle passes. The data collector then records the occupancy value using a worksheet or electronic device. The strengths of this method are the minimal equipment required, ease of implementation, and high capture rate. However, there are several limitations to this method, including a relatively short view time into the vehicle (particularly at high speeds), restriction to daylight-only collection, 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 (fatigue). For this project, the team implemented a modified windshield survey method for collecting vehicle occupancy data as described in the following sections of this report.

3.1 Vehicle Occupancy Field Data Collection

In selecting sites for occupancy and license plate data collection, the team visited the overpasses along each corridor and assessed each site for data collection potential (access and views) and for worker safety. As documented in Section 2.2, the four data collection sites were selected as they provided good data collection views, a good spatial distribution of coverage, and safe access and observation points (e.g., protected by guardrails, access via crosswalks and signals, etc.). The locations of the sites are mentioned below.

- I-75 North Corridor: Moores Mill Road at I-75 (between I-75/I-85 interchange and I-285 Perimeter in the north).

- I-85 North Corridor: North Druid Hills Road at I-85 (between I-75/I-85 interchange and I-285 Perimeter in the north).

- I-75/I-85 Connector Corridor: at 5th Street (between the I-75/I-85 interchange and I-20).

- I-75/I-85 South Corridor: Fair Drive at I-75/I-85 (between I-20 and I-285 Perimeter further south).

Traffic inbound to Atlanta was monitored for three hours during morning peak periods (usually 7:00 AM to 10:00 AM) and outbound traffic for three hours during the afternoon peak periods (usually 3:30 PM to 6:30 PM). Hence, the team monitored morning traffic in the southbound direction on the I-75 North Corridor, I-85 North Corridor, and I-75/I-85 Connector, and in the northbound direction on the I-75/I-85 South Corridor. The team monitored afternoon traffic in the northbound direction on the I-75 North Corridor, I-85 North Corridor, and I-75/I-85 Connector, and in the southbound direction on the I-75/I-85 South Corridor.

For tracking purposes, each lane was identified with two letters and one number in the database. The letters are lane type identifiers, where ML, GP, and RP represent managed lane (reversible lane, HOT lane, or HOV lane), general-purpose lane, and ramp, respectively. The number following the letter code is the lane number, where lanes are numbered from inside (leftmost) lane to outside (rightmost) lane. For example, in Figure 3, the managed lane is labeled as ML-1, and general-purpose lanes are labeled as GP-2 through GP-6.

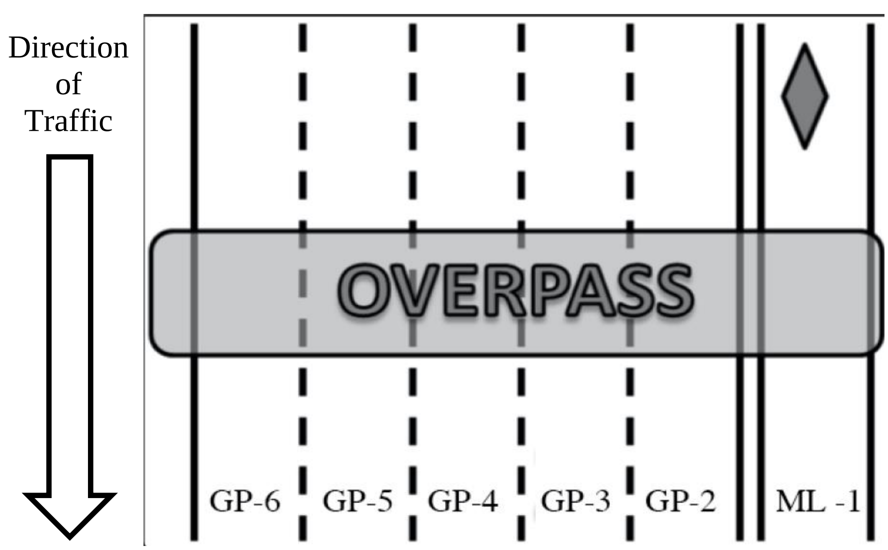


Figure 3 – Lane Numbering Configuration Example

The research team conducted vehicle occupancy data collection across five sessions during both the morning and afternoon periods at each site. During each session, about three hours of data were collected, depending upon light levels and visibility. Morning peak period data were collected between 7:00 AM and 10:00 AM and afternoon peak period data were collected between 3:30 PM and 6:30 PM. The research teams deployed well in advance so that data collection could begin on time. All sessions were conducted on Tuesdays, Wednesdays, and Thursdays, with days immediately following and preceding State of Georgia or federal holidays excluded. The sequence of sites was also arranged to avoid conflicts with school breaks in adjacent counties. Data collection was canceled during rain events, and make-up sessions were conducted as soon as practicable.

Field teams collected data from the elevated portion of the gore area at freeway exit ramps. These locations met 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 with safe access to the site, minimal expected weaving movements in observed traffic, and located to minimize glare given the angle of the sun. Figure 4 shows data collection by the undergraduate assistants.

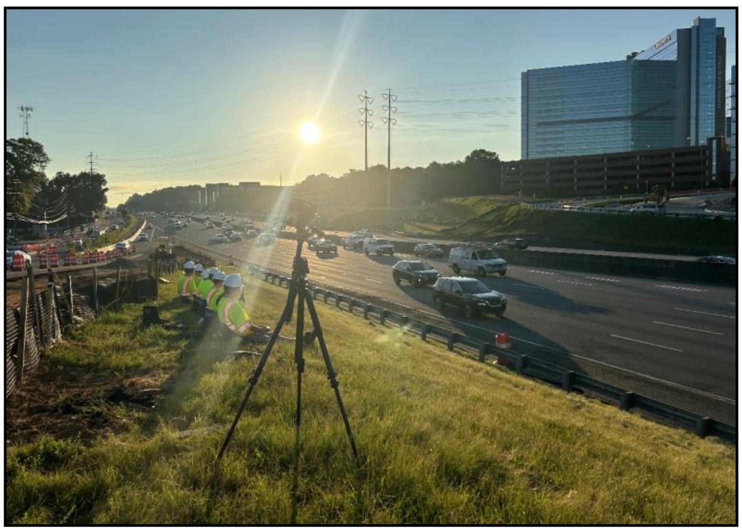


Figure 4 – Vehicle Occupancy Data Collection

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 provided the 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 the vehicle passed. Given the proximity to the traveled way, binoculars were not needed for data collection (in fact, binoculars and spotting scopes hinder data collection because vehicles are so close that visual tracking of the interior of the moving vehicle is more difficult). The field staff used a new tablet-based data collection system created specifically for this deployment. Table 3 provides the occupancy data collection schedules.

The team scheduled five data collection sessions at each site during both the morning and afternoon peak periods. In previous projects, the team employed regression tree analysis as part of the QA/QC process and identified a few data collectors who were not accurately recording vehicle occupancy (e.g., one data collector was repeatedly selecting a single button and was dismissed during the 2018–2020 study). In essence, a small number of human data collectors were identified as outliers whose recorded values deviated significantly from those of their peers. Approximately 6% of field occupancy observations were removed in that study, due to such inconsistencies to prevent potential bias in the final results. For this study, deployment management was optimized by using a smaller team of more experienced (and better) data collectors and introducing enhanced management protocols. These improvements included performance-based progression opportunities, a more structured operations and logistics team with designated roles, regular horizontal and vertical communication, and proactive planning for field sessions. The regression tree analysis (implemented with the same algorithm used in previous studies) was performed, and no data collector bias was detected or required removal (as further detailed in Chapter 5 of this report).

Table 3 – Schedule of Occupancy Data Collection Sessions, Fall 2024

Site	AM/PM	Session 1	Session 2	Session 3	Session 4	Session 5	Makeup	Makeup
Moores Mill Road at I-75	**AM**	06-Aug	07-Aug	08-Aug	13-Aug	14-Aug	24-Sep	25-Sep
	PM	06-Aug	07-Aug	08-Aug	13-Aug	14-Aug	24-Sep	01-Oct
North Druid Hills Road at I-85	**AM**	20-Aug	21-Aug	22-Aug	27-Aug	28-Aug		
	PM	15-Aug	20-Aug	21-Aug	22-Aug	27-Aug		
Fair Drive at I-75/I-85	**AM**	29-Aug	04-Sep	05-Sep	10-Sep	11-Sep	03-Oct	
	PM	28-Aug	29-Aug	04-Sep	5-Sep	10-Sep	02-Oct	
5th Street at I-75/I-85	**AM**	17-Sep	18-Sep	19-Sep	01-Oct	02-Oct		
	PM	11-Sep	12-Sep	17-Sep	18-Sep	19-Sep		

3.2 Occupancy Data Collection System

Building on the advancements made since the 2018-2020 study, the same data entry system was utilized for the 2024 field observations. This system was installed on Microsoft® tablets, which were carried in backpacks alongside portable power banks and charging cables. The digital keyboards were enhanced for usability by removing unnecessary keys and relabeling the remaining keys to represent vehicle classes, occupancy types, and other data elements. Observers recorded data by first selecting the appropriate vehicle class key, followed by the corresponding occupancy key. Additional keys were included to log missed vehicles (e.g., insufficient time to observe the next vehicle) and to mark the last record as incorrect.

In 2018, the Georgia Tech team developed a new Microsoft® tablet-based occupancy data collection app using Python®. The app has two UI windows, one to input meta-data associated with the data collection effort, and the other to input vehicle class and occupancy information. The layouts are shown in Figure 5 below. The left image shows the interface to enter the general information about the data collection session, including user's name, field location, assigned lane number, type of lane, position of lane, and tablet ID (each tablet is assigned a unique ID and the ID is labeled on a sticky tape). The selection options for each field are described below:

- "Select Username":
  - Dropdown list of field data collector names
- "Select Location":
  - Dropdown list of field data collection locations
- "Select Lane Number":
  - Dropdown menu from "Lane 1" to "Lane 10"
- "Lane Type":
  - Dropdown menu with three values
    - "Managed Lane"
    - "General-purpose Lane"
    - "Ramp"
- "Lane Position":
  - Dropdown menu with three values
    - "Inside" - Innermost (fast) lane
    - "Outside" - Outermost (slow) lane
    - "Middle" - Any other lane in between the inside and outside lane
- "Tablet ID":
  - Text entry field to record the tablet ID used in data collection

Figure 5 displays the input interface in the right-hand image. A horizontal line divides the window into two segments. The upper section displays basic information, which corresponds to the general information entered at login. The number of lanes, the type of lane, and position of the lane appear in the upper portion of the display (with the relevant buttons highlighted). These session data do not need to be changed during a data collection session (unless the data collector for some reason moves to another lane, in which case they shut down the app and log in again). Moreover, during data collection, if the recorder tries to change a session data selection in the upper window, an alert message pops up requiring the user to log in again and confirm the data change (starting a new session).

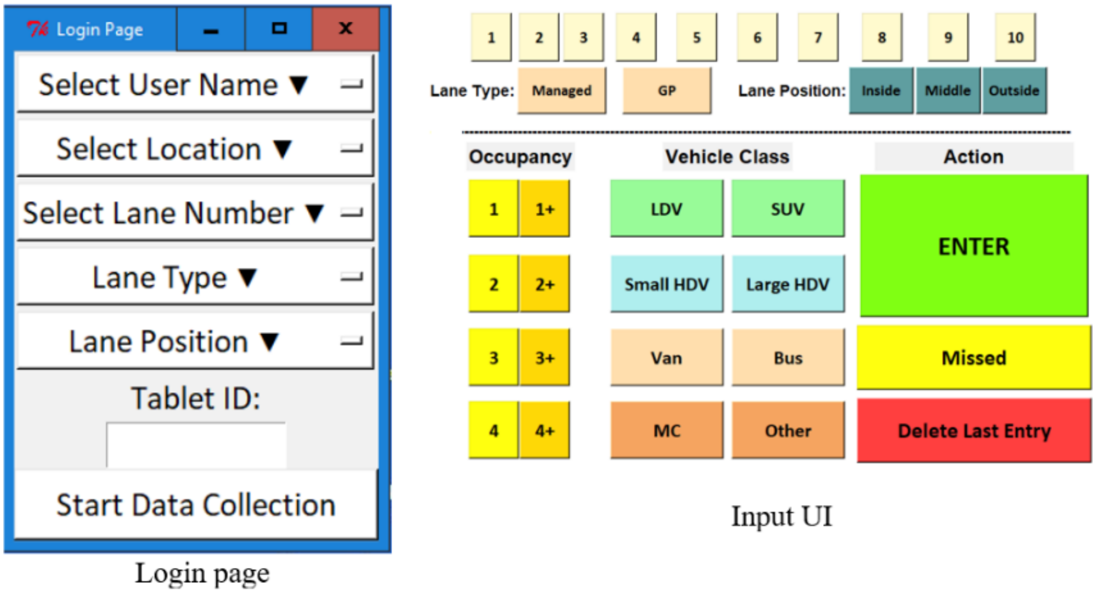


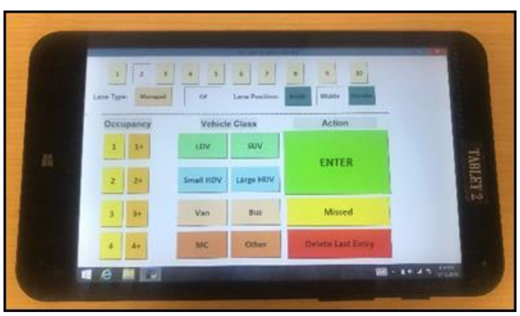
Figure 5 – UI Design for the Occupancy Data Collection System

The lower portion of the screen contains three classes of input buttons (vehicle occupancy buttons, vehicle class buttons, and action buttons. There are eight possible inputs for vehicle occupancy (‘1’, ‘1+’, ‘2’, ‘2+’, ‘3’, ‘3+’, ‘4’, and ‘4+’), corresponding to the occupancy observed by the recorder. If the observer sees exactly two people in a vehicle, they record ‘2’. Occupancy numbers with a plus sign indicate that the observer could definitely see that number of people in the vehicle, but that more persons might have been present. So, if a user can see two people in the front seat, but cannot see into the back seat due to window tinting, the observer records ‘2+’ as the vehicle occupancy. For occupied buses and large vanpools, observers click the ‘4+’ button. The second group of buttons allow observers to enter the class of the vehicle observed. The eight vehicle class values include ’LDV’, ‘SUV’, ‘Small HDV’, ‘Large HDV’, ‘Van’, ‘Bus’, ‘MC’, and ‘Other’ as described below:

- Light Duty Vehicle (LDV)
  - Sedans, sports cars, etc.
- Sports Utility Vehicle (SUV)
  - Pick-up trucks, crossover vehicles, station wagons, etc.
- Small Heavy-Duty Vehicle (Small HDV)
  - Box truck and medium-sized trucks without trailers

- Large Heavy-Duty Vehicle (Large HDV)
    - Trucks with trailing part for cargo
- Van
    - Family vans, large vanpools, food delivery cargo vans, etc.
- Bus
    - Small and large school buses, transit buses, inter-city buses, etc.
- Motorcycle (MC)
    - Two-wheel and three-wheel motorcycles
- Other
    - Police cars, fire engines, ambulances, etc.

The last column of buttons provides the user interface (UI) action buttons, used to submit the current input, reset the interface, or delete the previous input that was submitted. As the user selects each button in the first two columns, the non-selected buttons on the screen dim and change color, to indicate which button was selected. The user can also change their selection prior to entering the data and the new button will light up. When satisfied with the on-screen selections, the user selects the "Enter" button to submit the record into the data stream (see Figure 6) and clears the screen for the next data entry event. A Python® script records all of the keystrokes into a text file along with the timestamps. If a user cannot complete a record or is unsure about their selections, they hit the "Missed" button, which records that a vehicle was observed but not classified and the screen is reset. The "Delete Last Entry" button allows the user to recognize that the entry they just submitted was inaccurate and should not be used. The previous data record is immediately annotated to indicate that the record is inaccurate and flags the record for exclusion (the system adds a time stamp to the deletion time column).



Lane No.	Lane Type	Lane Position	Vehicle Class	Occupancy	Record Time	Deletion Time
4	General Purpose	Middle	LDV	1	2024-08-27 15:30:18	
4	General Purpose	Middle	SUV	1	2024-08-27 15:30:34	
4	General Purpose	Middle	LDV	1	2024-08-27 15:30:38	
4	General Purpose	Middle	LDV	2	2024-08-27 15:30:44	
4	General Purpose	Middle	Van	2	2024-08-27 15:30:53	
4	General Purpose	Middle	LDV	2	2024-08-27 15:30:58	
4	General Purpose	Middle	Van	1+	2024-08-27 15:31:09	
4	General Purpose	Middle	LDV	1+	2024-08-27 15:31:14	
4	General Purpose	Middle	LDV	1	2024-08-27 15:31:21	
4	General Purpose	Middle	LDV	1+	2024-08-27 15:31:28	
4	General Purpose	Middle	Van	2+	2024-08-27 15:31:35	
4	General Purpose	Middle	LDV	1	2024-08-27 15:31:40	
4	General Purpose	Middle	LDV	1	2024-08-27 15:31:44	
4	General Purpose	Middle	LDV	1	2024-08-27 15:31:47	
4	General Purpose	Middle	LDV	1	2024-08-27 15:31:53	
4	General Purpose	Middle	LDV	1	2024-08-27 15:31:56	
4	General Purpose	Middle	LDV	2+	2024-08-27 15:32:02	
4	General Purpose	Middle	SUV	1+	2024-08-27 15:32:08	

Figure 6 – Occupancy Data Collection System and Output

In the 2010-2012 assessment effort, the literature review did not identify any previous uses of 'uncertain' values; however, the research team demonstrated the importance of using 1+, 2+, and 3+ values in that study (Guensler, et al., 2013a). Had researchers not recorded these values, available information about occupancy would have been lost (carpool volumes were relatively low along the corridor). Discarding data for vehicles that were known to contain two or more persons, would have biased low the resulting percentage of carpools and average vehicle occupancy. The allocation of 'uncertain' values to vehicle occupancy is discussed in the next section.

3.3 Establishing Average Vehicle Occupancy for Uncertain Values

When collecting vehicle occupancy data, it is not always possible to see every person inside a vehicle. A driver is always present (at least until automated vehicles begin entering the Atlanta market), and data collectors can usually see any other occupants in the front seats. However, window tinting often obstructs the visibility of passengers in the rear seats. This study assumed that vehicles with and without window tinting have no systematic differences in occupancy. That is, a vehicle with extreme rear window tinting is no more likely to carry a passenger in the back seat than is a vehicle without severe window tinting.

Field observers recorded occupancy data using "certain" occupancy values ('1', '2', '3', and '4') when they were certain that they observed all seats and passengers in the vehicle. Field observers used "uncertain" occupancy values ('1+', '2+', '3+', and '4+'), when they were sure that they saw a specific number of persons in the vehicle, but additional passengers could not be ruled out. For example, a '2+' value indicates that two passengers were definitely observed, but visibility into other seats was obstructed (i.e., additional occupants may have been present).

The largest occupancy value employed ('4+') was uncommon for non-buses and vanpools. Based upon previous experiences, the '4+' values in the analyses did not significantly affect corridor person throughput estimates, because the throughput analyses handled the contributions of buses and vanpools to average vehicle occupancy as an independent calculation process (Guensler, et al., 2013a; Castrillon, et al., 2014; Guensler 2021a).

To calculate the average vehicle occupancy, "uncertain" values were first distributed to "certain" values using the relative ratio of applicable observed certain values. That is, the team distributed all '1+' occupancy values to occupancy categories '1', '2', '3', '4', and '4+' occupancy categories, using the relative ratios of those categories. For example, as an illustration of the calculation method, if the distribution of certain occupancy values was '1' = 85%, '2' = 10%, '3' = 4%, '4' = 1%, and '4+' = 0%, the team would assign the values to '1', '2', '3', '4', and '4+' categories as follows:

- 85% of the '1+' values to occupancy category '1'
- 10% of the '1+' values to occupancy category '2'
- 4% of the '1+' values to occupancy category '3'
- 1% of the '1+' values to occupancy category '4'
- 0% of the '1+' values to occupancy category '4+'

The analysis, however, never assigns uncertain values of ‘2+’ to occupancy category ‘1’, because the data collector observed at least one other passenger. Similarly, for ‘2+’ values, the team assigned the values to categories ‘2’, ‘3’, ‘4’, and ‘4+’ categories as follows:

- 66.66% (10%/(10%+4%+1%+0%)) of the ‘2+’ values to occupancy category ‘2’
- 26.66% (4%/(10%+4%+1%+0%)) of the ‘2+’ values to occupancy category ‘3’
- 6.66% (1%/(10%+4%+1%+0%)) of the ‘2+’ values to occupancy category ‘4’
- 0.00% (0%/(10%+4%+1%+0%)) of the ‘2+’ values to occupancy category ‘4+’

In summary, ‘1+’ values were redistributed to ‘1’, ‘2’, ‘3’, ‘4’, and ‘4+’ values, ‘2+’ values were redistributed to ‘2’, ‘3’, ‘4’ and ‘4+’ values, and ‘3+’ values were redistributed to ‘3’, ‘4’ and ‘4+’ values.

After redistribution of the uncertain values, the occupancy values remained in five occupancy categories (‘1’, ‘2’, ‘3’, ‘4’, and ‘4+’). As in the previous study, the occupancy category of ‘4+’ was assigned a value of 4.5 persons per vehicle for person throughput, in the absence of a more accurate empirical estimate. The majority of vehicles in the ‘4+’ category are vanpools and transit buses, which were typically removed from this portion of the calculation and handled separately in the person-throughput analysis (Castrillon et al., 2012; Guensler, et al., 2013a; Guensler, et al., 2021a). Previous studies indicated that vanpools do not significantly affect the ‘4+’ occupancy substitution process, as their actual ridership was generally modest (typically ranging from 4 to 5 persons), and they represented a relatively small share of the vehicle fleet. Therefore, in this study, the team applied individual occupancy substitutions only for express buses, while vanpools were handled within the general allocation framework.

Previous work by the research team demonstrated that deleting such uncertain data (rather than redistributing the data) leads to a significant downward bias in occupancy estimation (Guensler, et al., 2013a; Guensler, et al. 2021a). Table 4 illustrates the impact of excluding uncertain occupancy data from an analysis of average vehicle occupancy. The 513 occupancy records for sport-utility vehicles in Table 2 are for one data collector, one data collection session (general-purpose lane #3, August 2024, 3:30 PM to 6:30 PM). The average vehicle occupancy using the re-distribution method is 1.40 persons/vehicle. If uncertain values were excluded from an analysis as “missed vehicles,” as has been common in previous studies in the literature, the calculated average vehicle occupancy would only be 1.31 persons/vehicle. This would correspond to about a 6.3% biased underestimation of occupancy and person throughput.

Table 4 – Impact of Using and Allocating Uncertain Occupancy Values

Occupancy Category	Vehicles Observed	Percent Observed	Vehicles w/o Allocation	Percent w/o Allocation	Vehicles with Allocation	Percent with Allocation
1	301	58.6%	301	74.2%	354.4	69.0%
1+	72	14.0%				
2	92	17.9%	92	22.7%	131.1	25.6%
2+	26	5.1%				
3	5	1.0%	5	1.2%	10.6	2.1%
3+	9	1.8%				
4	5	1.0%	5	1.2%	10.6	2.1%
4+	3	0.6%	3	0.7%	6.4	1.2%
Total	513	100.0%	406	100.0%	513	100.0%
Average Occupancy (persons/vehicle)				1.31		1.40

4 Machine-Vision-Based Vehicle Identification

This section presents the methods used in the project to classify vehicle types and recognize alternative fuel vehicle (AFV) license plates, with the goal of extracting vehicle category and plate information from video recordings. The project primarily employed deep-learning-based machine vision techniques to process vehicle and license plate data. Vehicle images were extracted from each video frame using a vehicle detection model, and trained models were used to classify vehicle types and identify AFV plates. For quality assurance and control (QA/QC), manually annotated image samples were generated to verify license plate recognition results.

4.1 Video Data Preprocessing

At each observation site, the research team mounted overpass cameras to capture rear-view video of vehicles. Recordings were conducted during morning and evening peak hours on Tuesdays, Wednesdays, and Thursdays, with each session lasting three hours and a minimum of five sessions per site (concurrent with vehicle occupancy data collection). Whenever possible, cameras were positioned to capture two target lanes at a time, with additional cameras deployed specifically for ramp lanes. Once labeled by observation site and lane, the videos were processed using a YOLO-based vehicle detection model (YOLO stands for You Only Look Once, a real-time object detection algorithm) to automatically identify the video frame containing the best view of each vehicle and cropping vehicle images from that frame. More details of the model are presented in section 4.3.

Given the high traffic volumes during peak hours, vehicle occlusion was a common challenge. In some cases, the model failed to distinguish between closely spaced vehicles, resulting in traffic count underestimation. To mitigate these errors, the team implemented trajectory tracking methods to assign unique IDs to all vehicles. By analyzing the movements of vehicles across consecutive frames, the model was able to differentiate overlapping vehicles. Because most recordings included two lanes, a position detection algorithm was used to assign detected vehicles to either the left or right lane. This lane assignment was encoded in the output to provide additional context for downstream analysis. As will be described in the next section, the machine vision tools also identified the license plate within the video image, cropped and retained each plate image, and converted the image into alphanumeric characters via automatic license plate recognition (ALPR) algorithms.

4.2 Model Architecture

To support downstream vehicle and license plate analysis, the research team employed YOLO v11 (You Only Look Once version 11), a state-of-the-art image recognition model that detects objects, such as vehicles and license plates in video frames (Khanam, R., & Hussain, M. 2024). YOLOv11 improves upon previous versions by offering faster processing and more accurate results, making it well-suited for freeway video analysis where real-time detection and small-object localization are critical.

As shown in Figure 7, the YOLOv11 architecture consists of three main functional elements, known as the backbone, neck and head.

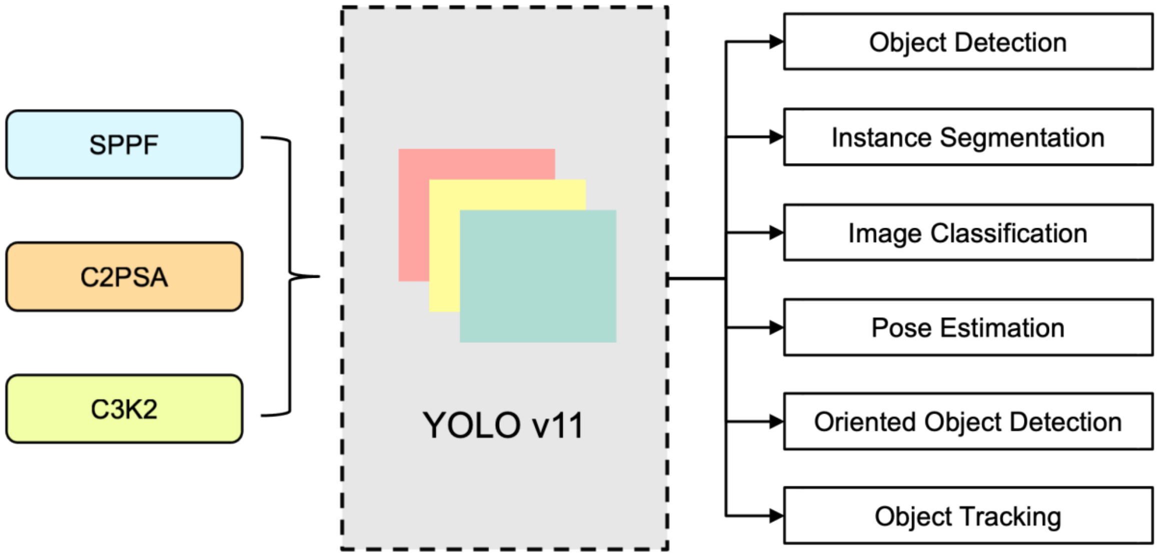


Figure 7 – Key Architectural Modules in YOLOv11

1. Backbone: Feature Extraction

This part of the model analyzes each video frame as an input image, and extracts visual features from the input image. YOLOv11 uses more efficient building blocks in the backbone than were used in previous versions:

- C3k2 Blocks: These components speed up image processing while still capturing visual detail (compact variants of the cross stage partial bottleneck with smaller kernel sizes of 2x3x3).
- SPPF (Spatial Pyramid Pooling – Fast): This facilitates the detection of small or distant objects (such as license plates in rear-view highway footage) by aggregating image features from various scales.

2. Neck: Feature Fusion

The neck of YOLOv11 combines features from various levels of the backbone to improve object recognition (enhanced object localization):

- Upsampling and Concatenation Layers: These modules combines fine and coarse image features at various scales, enhancing the ability to detect vehicles of various sizes.

- C2f and C2PSA Modules: These modules incorporate spatial attention mechanisms that help the model focus on likely object areas and suppress visual noise from busy traffic scenes or background clutter.

3. Head: Prediction Layer

The last stage (head) of YOLOv11 produces bounding boxes, object labels (e.g., vehicle, plate, etc.), and confidence scores in a single step:

- Multi-Scale Detect Layers: These allow the model to detect both large and small objects in various parts of the image, improving performance across vehicle types and different distances.

- Real-time Output Generation: It enables rapid processing of high-resolution video.

YOLOv11 offered several advantages for the project application.

- High Efficiency: Capable of over 40 frames per second (FPS) on modern GPUs with reduced parameter count compared to YOLOv8, enabling real-time detection from continuous video streams that can be many hours in duration.

- Improved Small-Object Detection: Enhanced ability to detect license plates and partially occluded vehicles through improved feature aggregation.

- Modular Flexibility: The same YOLOv11 structure was used for various tasks (vehicle detection, license plate cropping, plate type classification) with minimal retraining.

The YOLOv11 detection framework described above served as the foundation for subsequent automated classification tasks, including alternative fuel vehicle (AFV) leaf plate recognition and electric vehicle identification.

4.3 Model Verification Dataset

To evaluate the performance of the vehicle classification and license plate recognition models, the research team created a validation dataset consisting of 1,000 randomly selected vehicle images. The dataset was designed to ensure coverage across all observation sites, lanes, and both morning and evening peak periods. Undergraduate research assistants (URAs) were trained to identify Georgia license plate formats and vehicle types based on established design standards and classification criteria. To support accurate and consistent annotations, the team developed a new web-based labeling tool using JavaScript and HTML. As shown in Figure 8, the tool features a user-friendly layout with three panels:

• **Left Panel**: Displays a list of image filenames pending annotation, allowing users to select any image to label or review.

• **Center Panel**: Shows the current image being evaluated, with machine vision results displayed below.

• **Right Panel**: Serves as the labeling interface, where users verify the plate identification and enter license plate numbers, plate type and state, vehicle type, make, and model as needed.

This tool streamlined the annotation process and supported dual independent review to enhance overall accuracy and consistency in dataset preparation.

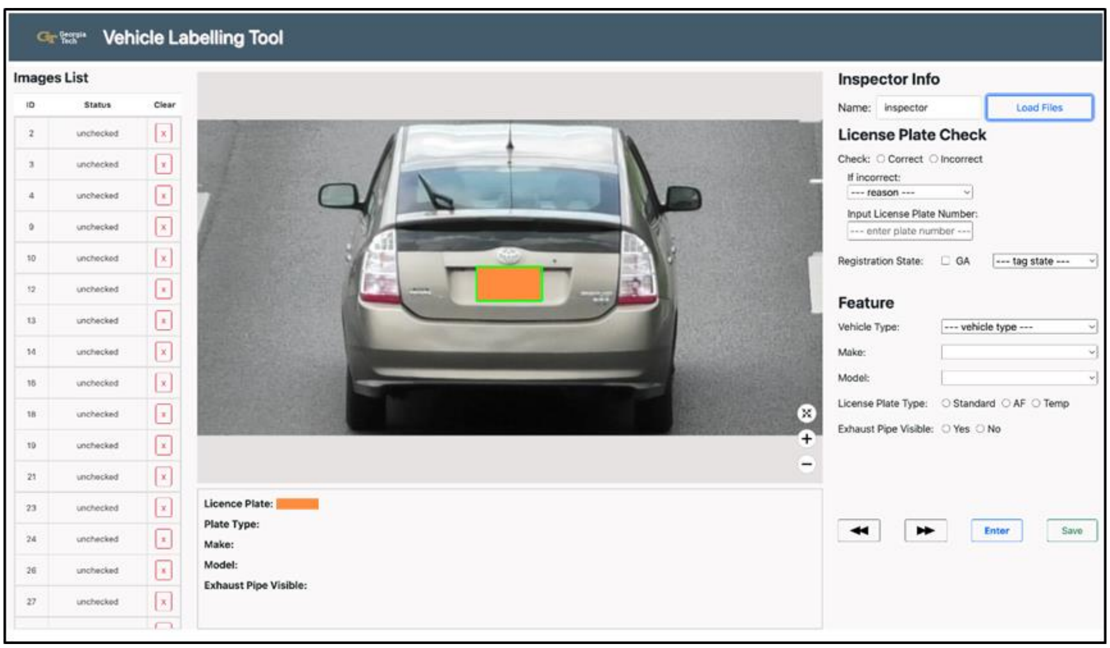


Figure 8 – The Main User Interface of the Vehicle Labelling Tool

4.4 Alternative Fuel Vehicle (AFV) Plate Recognition

To identify AFV plates with the Georgia leaf icon, the research team trained both a license plate detection model and a license plate classification model using the YOLOv11 architecture described in the previous section of this report. These new in-house models are based on the original YOLO framework (Khanam, R., & Hussain, M. 2024), and trained for these new purposes. After vehicle images were extracted, the detection model located the license plates and cropped them from each image. These cropped images were then classified using the trained model to classify plate type and identify AFV plates, as illustrated in Figure 9.

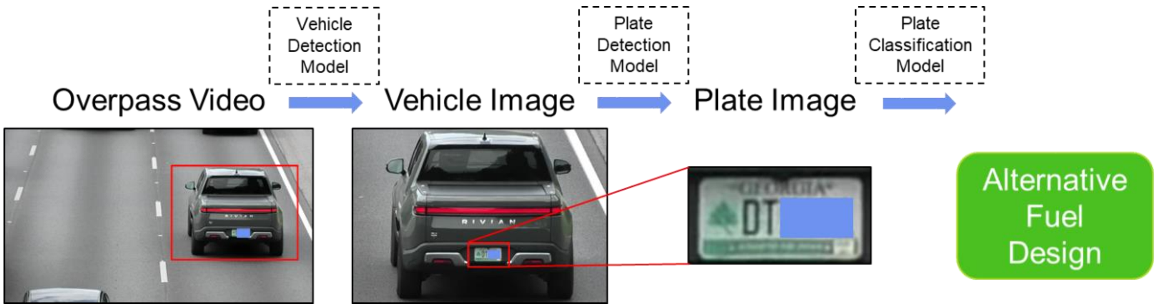


Figure 9 – AFV Plate Recognition Process

The license plate detection model was trained using a publicly available dataset consisting of 3,500 images. For the classification model, the training dataset was derived from project-collected license plate data. This dataset initially included 1,000 images and was expanded to 3,500 images through heuristic augmentation. The classification model was designed to categorize license plates into five types, shown in Table 5.

Table 5 – License Plate Categories in Classification Models

License Plate Type	Pattern
GA Standard Plates	
GA Alternative Fuel Plates	
GA Temporary Plates	
Other GA Specialty Plates	
Non-GA Plates	

The model demonstrated high accuracy in identifying AFV plates, with a 99% recognition rate and a very low false-positive rate of 1.4%. The model also effectively distinguished between Georgia and non-Georgia plates. The training results of the license plate classification model are summarized in Figure 10.

- Accuracy for identifying GA plates: 99.1%
- Misclassification rate of other plates as GA plates: 1.4%
- Accuracy for identifying non-GA plates: 90.1%
- Misclassification rate of GA plates as non-GA plates: 6.3%

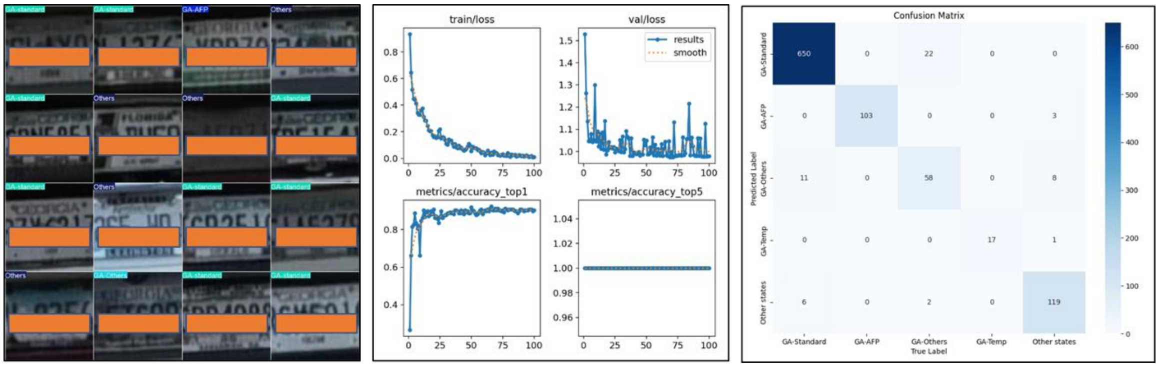


Figure 10 – License Plate Classification Model Prediction Samples, Training and Evaluation Metrics

4.5 Analysis of Alternative Fuel Vehicle (AFV) Plate Result

More than 1.1 million license plates (1,101,198 plates) were identified in this study, with Georgia plates representing 83.9% (923,768 plates) of the total plates observed. Among these 1.1 million plates, 20,986 (1.91%) were identified as AFV plates displaying the green leaf AFV icon. The share of these green leaf AFV plates varied by observation site (see Table 6): Moores Mill Road at I-75 recorded 2.03%, North Druid Hills Road at I-85 recorded 2.35%, Fair Drive at I-75/I-85 recorded 0.99%, and 5th Street at I-75/I-85 recorded 2.20%.

Table 6 – License Plate Results by Site

Site	Total Plates	GA Plates	AFV Green Leaf Plates	AFV Plate Percentage
Moores Mill Road at I-75	**299,669**	**247,554**	**6,071**	**2.03%**
North Druid Hills Road at I-85	**214,939**	**190,404**	**5,042**	**2.35%**
Fair Drive at I-75/I-85	**251,115**	**211,829**	**2,476**	**0.99%**
5th Street at I-75/I-85	**335,476**	**273,982**	**7,397**	**2.20%**
Total	**1,101,198**	**923,768**	**20,986**	**1.91%**

The AFV plate results for each site are shown in Table 7 through Table 14. At I-75 Moores Mill Road, HOV lanes exhibited a high proportion of AFV green leaf plates, with 8.76% in the morning and 8.98% in the afternoon. General-purpose lanes showed lower AFV rates, peaking at 1.20% on general-purpose lane #5 during the PM peak. Ramp lanes demonstrated a modest increase in AFV plate frequency in the afternoon, rising to 2.58% compared to 1.83% in the morning.

At I-85 North Druid Hills Road, HOV lanes displayed the highest AFV plate proportions among all four sites, with 11.48% in the morning and 8.84% in the afternoon. General-purpose lanes at this site recorded rates ranging from 0.57% to 1.31%, with values generally increasing by lane number.

At I-75/I-85 Fair Drive, AFV plate shares in HOV lanes were notably lower than at other sites—3.42% in the morning and 2.33% in the afternoon. General-purpose lane rates ranged from 0.41% to 0.99%, and ramp lane proportions peaked at 1.15% in the afternoon. Overall, Fair Drive recorded the lowest AFV plate adoption among the four observation sites.

At I-75/I-85 5th Street, HOV lanes maintained relatively high AFV rates, with 8.66% in the morning and 8.71% in the afternoon. General-purpose lanes exhibited consistent results between 0.91% and 1.41%, while ramp lanes recorded the highest site-specific AFV rate, reaching 2.49% in the afternoon.

It is important to note that not all electric vehicles register as alternative fuel vehicles (AFVs) and receive Georgia's leaf plate design. An initial assessment conducted by the team indicates that only 30% to 40% of AFVs in the registration database back in 2022 (based upon vehicle make/model/fuel) carried the green leaf icon. Interestingly, the team also noted that the percentage of vehicles that obtained the AFV green leaf plates varied across zip codes and across vehicle makes (e.g., Rivian R1T trucks are much more likely to display the green leaf plate than are Ford F-150 Lightning trucks). Hence, while the application of machine vision tools to identify green leaf AFV license plates was extremely successful, the research team cannot identify more than half of the AFVs on the facility without access to the state of Georgia vehicle registration database, so that individual license plates can be used to look up individual vehicle make, model, model year and fuel type. Given the historic variability in plate acceptance across subregions and vehicle makes, we suggest that this analysis be re-run using the 2025 vehicle registration database to significantly improve the accuracy and representativeness of future electric vehicle identification and reporting. While Georgia law does require that SOV AFVs using the carpool lane display a green leaf plate (O.C.G.A. § 32-9-4, 2024), it is very likely that many of the EVs in the carpool lane do not have these plates. If vehicle registration data were available, it would be possible to assess the percentage of AFVs illegally using the HOV lanes, where vehicle owner may erroneously believe that they may use the lanes. With future plate-occupancy matching, post cards could be sent to inform these vehicle owners to notify them of their mistake.

Table 7 – AFV Plate Percentage Results, Moores Mill Road at I-75, AM Peak (7:30-10:30 AM)

AM/PM	Lane Number	Lane Type	AFV Plate Percentage	AFV Plates	GA Plates	Total Plates
AM	1	HOV	8.76%	1,841	14,658	21,006
AM	2	General-purpose	0.87%	316	30,855	36,366
AM	3	General-purpose	0.51%	167	27,592	32,510
AM	4	General-purpose	0.76%	226	25,322	29,800
AM	5	General-purpose	0.96%	202	18,106	21,115
AM	6	Ramp	1.83%	221	10,346	12,047

Table 8 – AFV Plate Percentage Results, Moores Mill Road at I-75, PM Peak (3:30-6:30 PM)

AM/PM	Lane Number	Lane Type	AFV Plate Percentage	AFV Plates	GA Plates	Total Plates
PM	1	HOV	8.98%	1,981	15,115	22,071
PM	2	General-purpose	0.70%	251	29,960	35,815
PM	3	General-purpose	0.65%	190	24,244	29,118
PM	4	General-purpose	0.82%	256	26,730	31,330
PM	5	General-purpose	1.20%	274	19,778	22,830
PM	6	Ramp	2.58%	146	4,848	5,661

Table 9 – AFV Plate Percentage Results, North Druid Hills Road at I-85, AM Peak (7:30-10:30 AM)

AM/PM	Lane Number	Lane Type	AFV Plate Percentage	AFV Plates	GA Plates	Total Plates
AM	1	HOV	11.48%	1,818	11,593	15,839
AM	2	General-purpose	0.75%	135	16,631	18,110
AM	3	General-purpose	0.75%	123	15,029	16,411
AM	4	General-purpose	0.88%	139	14,360	15,800
AM	5	General-purpose	1.21%	194	14,643	16,029
AM	6	General-purpose	1.31%	201	14,224	15,379

Table 10 – AFV Plate Percentage Results, North Druid Hills Road at I-85, PM Peak (3:30-6:30 PM)

AM/PM	Lane Number	Lane Type	AFV Plate Percentage	AFV Plates	GA Plates	Total Plates
PM	1	HOV	8.84%	1,525	13,072	17,242
PM	2	General-purpose	1.23%	257	18,659	20,899
PM	3	General-purpose	0.57%	126	19,856	21,939
PM	4	General-purpose	0.73%	148	18,548	20,384
PM	5	General-purpose	1.00%	212	19,431	21,234
PM	6	General-purpose	1.05%	164	14,358	15,673

Table 11 – AFV Plate Percentage Results, Fair Drive at I-75/I-85, AM Peak (7:30-10:30 AM)

AM/PM	Lane Number	Lane Type	AFV Plate Percentage	AFV Plates	GA Plates	Total Plates
AM	1	HOV	3.42%	412	9,971	12,039
AM	2	General-purpose	0.91%	161	15,582	17,620
AM	3	General-purpose	0.51%	81	13,836	15,755
AM	4	General-purpose	0.41%	60	12,570	14,490
AM	5	General-purpose	0.70%	96	12,201	13,745
AM	6	General-purpose	0.73%	91	11,087	12,499
AM	7	Ramp	1.10%	224	17,585	20,353

Table 12 – AFV Plate Percentage Results, Fair Drive at I-75/I-85, PM Peak (3:30-6:30 PM)

AM/PM	Lane Number	Lane Type	AFV Plate Percentage	AFV Plates	GA Plates	Total Plates
PM	1	HOV	2.33%	307	10,518	13,168
PM	2	General-purpose	0.41%	101	20,726	24,654
PM	3	General-purpose	0.52%	99	15,654	19,103
PM	4	General-purpose	0.90%	171	15,230	18,980
PM	5	General-purpose	0.96%	186	15,447	19,331
PM	6	General-purpose	0.99%	138	11,468	13,973
PM	7	Ramp	1.15%	174	12,840	15,146
PM	8	Ramp	0.86%	175	17,114	20,259

Table 13 – AFV Plate Percentage Results, 5th Street at I-75/I-85, AM Peak (7:30-10:30 AM)

AM/PM	Lane Number	Lane Type	AFV Plate Percentage	AFV Plates	GA Plates	Total Plates
AM	1	HOV	8.66%	1,789	14,027	20,669
AM	2	General-purpose	1.41%	365	21,270	25,832
AM	3	General-purpose	1.34%	301	18,271	22,400
AM	4	General-purpose	1.09%	236	17,303	21,723
AM	5	General-purpose	1.08%	231	17,467	21,488
AM	6	General-purpose	0.97%	221	19,199	22,897
AM	7	General-purpose	1.12%	195	14,115	17,479
AM	8	Ramp	2.49%	474	16,003	19,052

Table 14 – AFV Plate Percentage Results, 5th Street at I-75/I-85, PM Peak (3:30-6:30 PM)

AM/PM	Lane Number	Lane Type	AFV Plate Percentage	AFV Plates	GA Plates	Total Plates
PM	1	HOV	8.71%	1,991	16,599	22,853
PM	2	General-purpose	1.25%	325	22,003	25,987
PM	3	General-purpose	1.01%	254	21,103	25,041
PM	4	General-purpose	0.91%	221	20,381	24,273
PM	5	General-purpose	0.99%	267	23,074	26,945
PM	6	General-purpose	1.33%	288	18,844	21,716
PM	7	Ramp	1.39%	238	14,323	17,121

4.6 Vehicle Type Classification

Because GDOT NaviGAtor data were not available for the study areas, traffic volumes by vehicle class were derived from the video profiles. The research team trained a vehicle type classification model using YOLOv11. This model was applied to classify the vehicle images captured during field observations. The initial training dataset consisted of 1,000 images collected during this study. Additional images were added through multiple rounds of semi-automated classification, with each round followed by manual review to remove incorrect labels. This iterative process expanded the dataset to 5,000 images, after which the model was retrained using the augmented dataset.

During vehicle occupancy data collection, vehicles were initially grouped into eight categories. For classification purposes, some of these categories were further subdivided into more specific subcategories to improve granularity (the results were aggregated back to the vehicle classes before entering throughput assessment), as shown in Table 15.

Table 15 – Vehicle Classes in Occupancy Observations and Classification Models

Occupancy Vehicle Class	Classification Model Subclass
LDV	Sedan
	Hatchback
	Wagon
	Coupe
	Convertible
SUV	SUV/crossover
	Pickup truck
Van	Minivan
Small HDV	Box Truck
Large HDV	Large Box Truck
Bus	Bus
Motorcycle	Motorcycle
Others	Others

The training results of the classification model are presented in Figure 11. The model performed well in the major vehicle categories, particularly sedans, SUVs and crossovers, pickup trucks, buses, and motorcycles. While some minor misclassifications occurred between closely related categories (e.g., coupe vs. sedan or SUV vs. pickup truck), these were deemed acceptable for alignment with occupancy data, and the overall model performance remained strong. However, the model exhibited more frequent confusion between Small HDVs and Large HDVs.

- **Light Duty Vehicle (LDV)**: Accuracy for individual subcategories varied (e.g., Coupe: 100%, Hatchback: 71%, Convertible: 67%), though these intra-class differences did not impact the analysis.

- **SUV**: SUV and Crossover classification accuracy was 99%, while Pickup Trucks had a minor misclassification rate with 95% accuracy.

- **Minivan**: Achieved 95% classification accuracy, with some misclassification into the SUV and HDV categories.

- **Large HDV**: Classified with 68% accuracy, with moderate confusion observed with Small HDVs. Additional research is warranted on classifying HDVs into large and small categories, but this uncertainty did not affect corridor occupancy predictions.

- **Small HDV**: Achieved 71% accuracy, with occasional confusion with Large HDVs. Additional research is warranted on classifying HDVs into large and small categories, but this uncertainty did not affect corridor occupancy predictions.

- **Bus**: Reached 100% classification accuracy, with no misclassification.

- **Motorcycle**: Also achieved 100% classification accuracy with no misclassification.

The confusion between small and large HDVs was primarily due to the limitations of rear-view images, which often did not provide sufficient detail to distinguish between box trucks and tractor-trailers. This challenge can be mitigated by integrating overpass and roadside camera views. By tracking and re-identifying vehicles across both perspectives, the team can obtain side-view images to enhance classification reliability. To support this approach, the research team is currently developing a vehicle re-identification algorithm for a University Transportation Center project that will enable accurate cross-view analysis and improved HDV classification.

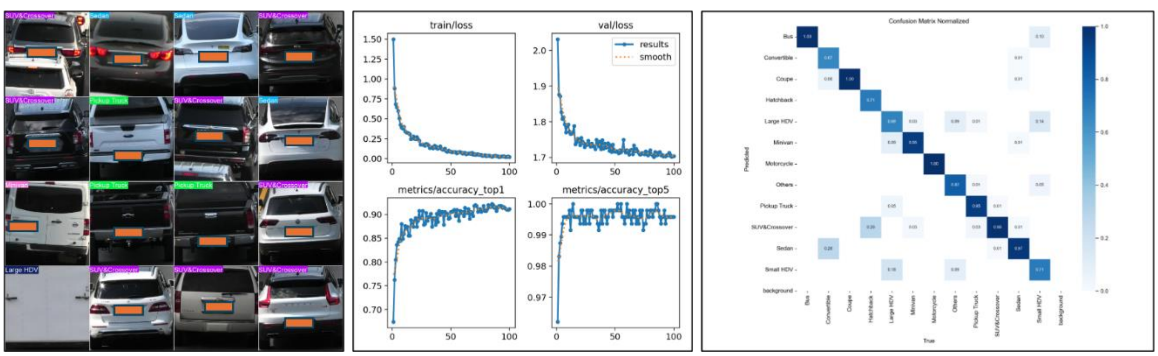


Figure 11 – Vehicle Type Classification Model Prediction Samples, Training and Evaluation Metrics

5 Review and Analysis of Vehicle Occupancy Data

Given the potential impact of technical malfunctions and human error associated with visual observation and manual data entry, a quality assurance/quality control (QA/QC) process is needed before undertaking final analysis of field-collected occupancy data (Elango and Guensler, 2014). In both the 2010-2012 and the 2018-2020 studies, the team found that some data collectors were "mashing" a single button; hence, their occupancy values differed significantly from their cohorts. That is, some data collectors may consistently make entry errors that potentially introduce bias into the dataset. To assess potential bias introduced by individuals collecting the occupancy data, the team first processed the data to remove known erroneous records and then applied regression tree analysis to the data sets (Wolf, et al., 1998). The analysis was used to assess whether any specific data collectors were primary contributors to variability in vehicle occupancy, which would indicate potential bias in observation. If one data collector consistently records different occupancy values for vehicles than their cohorts (after controlling for other factors), regression tree analysis will identify the data collector as being one of the main variables explaining differences in occupancy values.

The first step in the analysis involves filtering the raw data to remove known errors and create the final analytical dataset. In the raw data stream, blank records indicate that the user interface (UI) did not properly power down after a power loss. These records do not constitute real data; hence, a post-processing script automatically excludes blank records from project analysis. During live data collection, whenever a data collector realizes that they have just made a data input error (i.e., they selected the wrong button for occupancy or vehicle class), they are instructed to press the red "Delete Last Entry" key (Figure 5), which flags the previous data entry for deletion. The program appends a delete record mark to that data record. A post-processing script excludes the data-collector-reported erroneous data from project analysis.

To develop the final data set for regression tree analysis, the filtered data are aggregated to data collector records, based on site location, day of week (not needed for this study, because good weather conditions allowed data collection to avoid Mondays and Fridays), session (AM vs. PM), lane monitored, vehicle class, and data collector identifier (Elango and Guensler, 2014). That is, the occupancy data for each vehicle class, in the same lane, during the same session, collected by the same person, are used to generate an average vehicle occupancy data point for regression tree analysis. After controlling for vehicle class, facility, lane, and time of day (AM vs. PM sessions), large deviations in average vehicle occupancy across collectors indicate potential bias. The team excluded about 7.0% of the observations (91 out of 1,297 samples) in the 2010-2012 study (Guensler, et al., 2013a), and about 6.4% of the observations (90 out of 1,399 samples) in the 2018-2020 study (Guensler, et al., 2021a), from the final analyses, based upon the regression tree results.

The statistical term "outliers" refers to extreme observations that have an impact on resulting model response. In scientific research, outliers may result from data transcription errors, equipment malfunctions, or even data collector bias. However, many extreme values in a data set may simply represent rare cases, or may represent cases influenced by another independent variable not included in the data set and resulting model. Removal of rare cases that represent real-world effects will, by definition, bias model outputs (Neter, et al. 1990); hence, researchers must be very careful in removing data from analysis. Data should only be removed from statistical analyses when: 1) there is a clear case of data error (e.g., device error); 2) when there is a clear case of data collection bias that can be explained and supported; or 3) when the data belong in a separate model for some reason (i.e., the data reflect a subset of cause-effect relationships that warrants independent model development). As in the previous projects (Guensler, et al., 2013a; Guensler, et al., 2021a), the research team applied the same standard: data would only be removed from the working data set when there was clear evidence of error or direct evidence of bias (in this study, however, no such evidence was found, and no data were removed).

The occupancy assessment study deployed teams of graduate and undergraduate students to collect vehicle occupancy data (persons/vehicle) by visually identifying the number of persons inside each vehicle as the vehicle passes an observation station. The previous studies identified a number of factors that impact vehicle occupancy, including: data collection site, pre-/post-conversion status of the facility, season/quarter, day of week, session (morning/afternoon peak), lane type (general-purpose lane, HOV lane, and ramp), and lane number. The graphic user interface, standardized data collection procedures, and training of data collectors help minimize data entry errors. Nevertheless, the visual identification of the number of persons in a vehicle is still subject to potential data collector bias. Hence, a statistical assessment of collected data to identify possible sources of bias or errors in occupancy data collected by individual data collectors is required, so that researchers can assess whether there is a need to filter such data from occupancy analysis.

Regression tree analysis, adopted in the previous projects, proved to be a very effective analytical tool when data have numerous and complicated non-linear interactions (Guensler, et al., 2013a; Guensler, et al., 2021a). In this process, the data space is recursively partitioned using the explanatory variables that reduce total deviation error the most, until small chunks of data space can be fitted with simple models (Cosma, 2013). The global model consists of two parts: recursive partitioning of the data into clusters, and simple models fitted to each cluster. The tree method highlights the important variables that affect variability in the data. Regression trees can handle stepwise as well as continuous responses. Regression tree analysis facilitates rapid assessment of data to identify potential factors influencing observed vehicle occupancy. Regression tree analysis is not designed to assess causality, but to identify the relative influence of correlations on observed values. Analysts need to exercise caution in interpreting the outputs. It is possible to identify a factor as a cause of data variability, when that factor is simply highly correlated with another factor that is the real culprit.

5.1 Regression Tree Analysis

To assess variables that may affect vehicle occupancy on the corridor, and to identify variables that may have introduced potential bias into the data (e.g., whether specific data collectors are not accurately recording vehicle occupancy), the team applied regression tree modeling techniques (Elango and Guensler, 2014; Cosma, 2013; Wolf, et al., 1998; Washington, et al., 1997). Regression tree analysis (also known as binary recursive partitioning) is a standard technique in multivariate analysis that identifies the variables (and the cut points, or sub-classes, within each variable) that, when used to split a sample into two pools of data, can explain the greatest amount of variability within the original sample. For example, in a pool of human height data, the variable for gender is likely to explain more variability than any other variable associated with all of the data in the pool (race/ethnicity, education, household size, etc.). After splitting the data into two pools, subsequent analyses identify the most influential variables within each particular sub-pool. The resulting tree is made up of binary splits for those variables and cut points with the most influence, and these results are very useful for identifying potential cause-effect relationships. It is important to keep in mind that regression tree analysis is entirely dependent upon the sample and that causal variables are not always identified (strong correlations within the data can influence the results), but can be addressed in subsequent analysis (e.g., combining regression tree analysis for variable and interaction identification, followed by more advanced multivariate modeling).

In this report, the regression trees examine the potential effect of explanatory variables on observed vehicle occupancy, including data collection site, day of week, session (morning/afternoon peak), lane type (general-purpose, managed lane, and ramp), lane number, vehicle type, and data collector identifier. The research team is using regression tree analysis to search for clusters of data that exhibit significantly different occupancy values, collected on the same corridors, during the same time-periods, for the same vehicle types, etc. Once the regression tree analysis identified these data clusters with significantly different occupancy values, the team further investigates the differences. Those data deemed likely biased, due to specific data collector influence, were filtered from the analysis as outlined below.

Before conducting the regression tree analysis for identifying the data-collector-based bias, the raw data were aggregated into occupancy cases based on site location, day of week, session (AM vs PM), lane monitored, vehicle type, and data collector. The team excluded any data session where data collection time was shorter than one-half hour from the regression tree analysis (these are typically supervisor sessions where the data collector has taken a bathroom break). The team excluded any data session with fewer than 80 vehicle observations, to ensure a sufficient sample size and that the cases are likely to be representative. The analytical data set also excluded training sessions and experimental data collection efforts.

The team identified all data collectors by number, so that the individuals remain anonymous in this report. Table 16 provides the abbreviations of the data collection site names used in the analysis. The identifier for each lane used in regression tree analysis combines the site abbreviation and lane type. For example, MRM_ML1 refers to the leftmost managed lane (the HOV lane) of Moores Mill Road at I-75. The vehicle types included in the regression tree analysis were passenger car light duty vehicles, coded as LDVs and sport utility vehicles

(SUVs). The other vehicle types (motorcycles, HDVs, vans, buses, and others) were not included, due to their small sample sizes (i.e., comparisons would not be sufficiently representative). The raw fractions of all vehicle types are shown in Table 17. All categorical variables were set to nominal in the analysis.

Table 16 – Site Abbreviations for Regression Tree Analysis

Site	Abbreviation
Moores Mill Road at I-75	MRM
North Druid Hills Road at I-85	NDH
5th Street at I-75/I-85	5ST
Fair Drive at I-75/I-85	FRD

Table 17 – Number of Occupancy Observations by Vehicle Type (2024), All Locations

Vehicle Type	Number of Records	Fraction
LDV	126,797	40.26%
SUV	132,863	42.18%
Van	14,793	4.70%
Small HDV	7,316	2.32%
Large HDV	31,447	9.98%
Bus	961	0.31%
MC	629	0.20%
Other	170	0.05%
Total	314,976	100.00%

5.2 Average Vehicle Occupancy and Potential Data Collector Bias

In the 2010-2012 study, regression tree analysis revealed that day of the week (particularly Mondays and Fridays) significantly influenced observed vehicle occupancy. To account for this, the team flagged day-of-week effects prior to conducting tree analyses on average occupancy by data collector. In the 2018-2020 study, a preliminary regression tree analysis (excluding the data collector variable) was also performed to evaluate the influence of day-of-week patterns on average occupancy. These results in the prior study did not identify Mondays or Fridays as statistically significant sources of variation, because good weather allowed the team to avoid collecting make-up session data on likely due to the avoidance of Monday morning and Friday afternoon sessions during scheduling for the 2018-2020 project.

In the current (2024) study, no data were collected on Mondays or Fridays. Instead, all field sessions were deliberately scheduled on Tuesdays, Wednesdays, and Thursdays to reduce behavioral variability associated with weekend transitions. The data collection calendar also excluded dates immediately before or after federal and State of Georgia holidays and avoided public school breaks in the adjacent counties of each corridor, as described in section 3.1 of this report. As a result of this rigorous scheduling protocol, a separate day-of-week analysis was not necessary, and all valid samples were directly included in the average occupancy regression tree analysis.

The results from the first exploratory regression tree include all 46 data collectors (Figure 12). While the variable for data collector identifier entered the model, it did not produce any terminal nodes or leaf groupings indicative of potential bias. Specifically, the only instance where collector ID contributed to a split resulted in two large and nearly balanced subgroups (suggesting that the division reflected natural data variability rather than the influence of outlier behavior by individual collectors). No terminal leaf was defined solely or primarily by data collector identifier (with a small number of sessions and anomalous occupancy values), which would have warranted further investigation or removal. Instead, all terminal nodes were defined by more influential variables, such as vehicle class (nodes #7, #8, #9, and #10) and lane number (nodes #11 and #12).

Based on this result, the team concluded that data collector identity had no significant impact on observed vehicle occupancy in this dataset. Therefore, no records were excluded on the basis of potential collector bias, and all observations were retained for subsequent analysis.

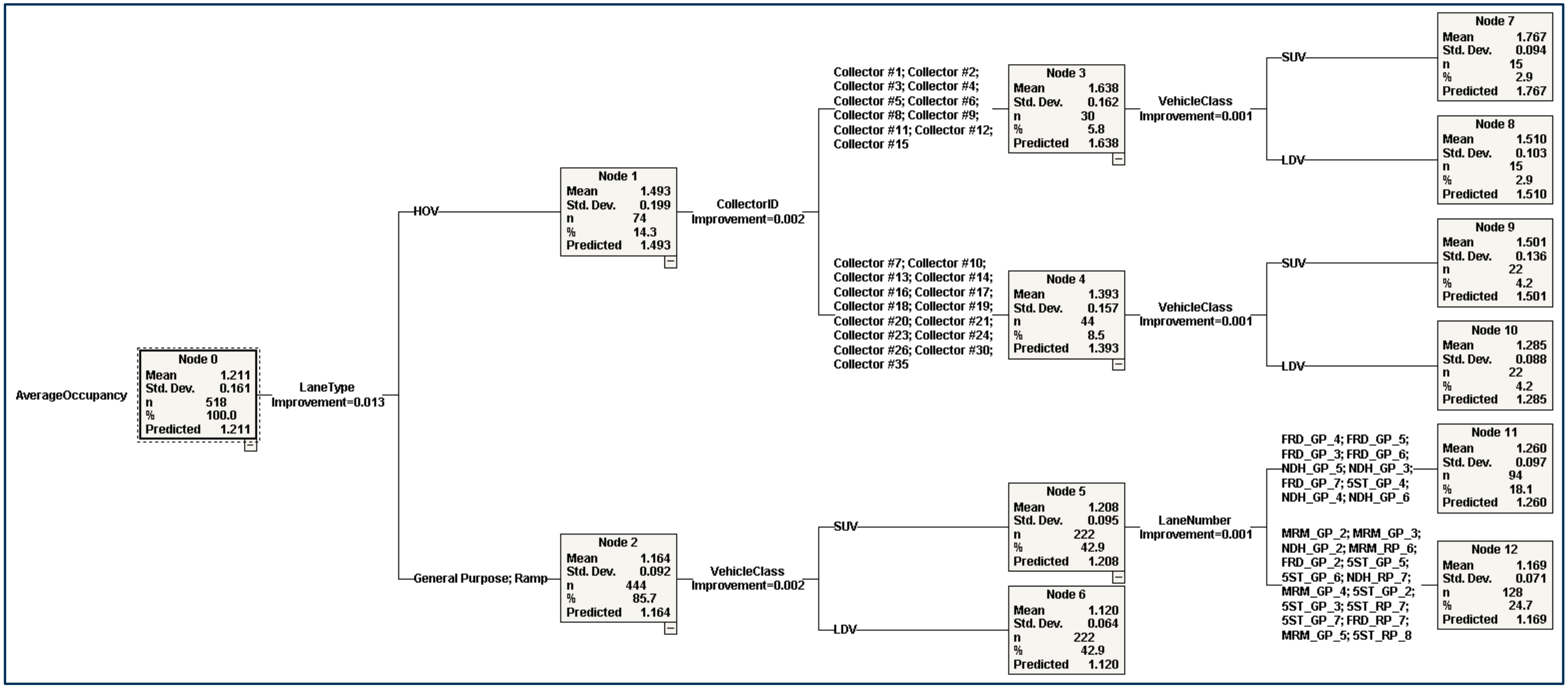


Figure 12 – Regression Tree on Average Occupancy to Identify Potential Data Collector Bias

5.3 SOV and HOV ‘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 a bias in single occupancy vehicle vs. high-occupancy vehicle observations may cancel out in average vehicle occupancy. That is, multiple data collectors could obtain the same average vehicle occupancy, but based upon significantly different fractions of SOVs and HOV ‘3+’ vehicles. This part of QA/QC is important because biased results will affect assessment of high-occupancy violation rates and overall passenger throughput. The team assessed potential data collector bias by analyzing the percent of single occupancy vehicles and three-person or more (‘3+’) occupancy vehicles using regression tree analysis using the same methods described above and for the previous studies (Guensler, et al., 2013a).

In the 2018 study, after all analyses, a total of four nodes (nine sessions) with SOV portions larger than 99.15% were excluded; they were significantly higher than other sessions. This may be because certain data collectors may inadvertently (or purposefully) over-input vehicles with only one passenger when they became overwhelmed by the number of vehicles passing their station (also known as “mashing an input button”). Qualified data collectors skip some vehicles in high volume traffic streams to ensure that they get a good field of view and time on target to measure their next vehicle.

The SOV/HOV analysis were conducted after uncertain occupancy records were allocated to certain records (see section 3.3), following the same methodology as in section 5.2. The SOV regression tree is presented in Figure 13, and the HOV ‘3+’ regression tree is shown in Figure 14. To evaluate potential data collector bias, the research team examined whether any terminal leaves were defined primarily by data collector identifier and contained a small number of sessions (fewer than 20 out of 518 total sessions), with notably different average occupancy values compared to adjacent branches. The team also examined the high/low portions, in addition to where data collector identifier contributed to a branch division.

The team manually reviewed the sessions associated with the data collectors. This included comparing their percentage values against those recorded by other collectors at similar times and locations. As an additional check, the team temporarily excluded the sessions from these collectors and re-ran summary statistics to assess whether their removal significantly affected overall average occupancy.

Based on these checks, the team concluded that these splits did not reflect bias introduced by any individual data collector. Therefore, no data were removed from the analytical dataset, and all observations were retained for subsequent analyses.

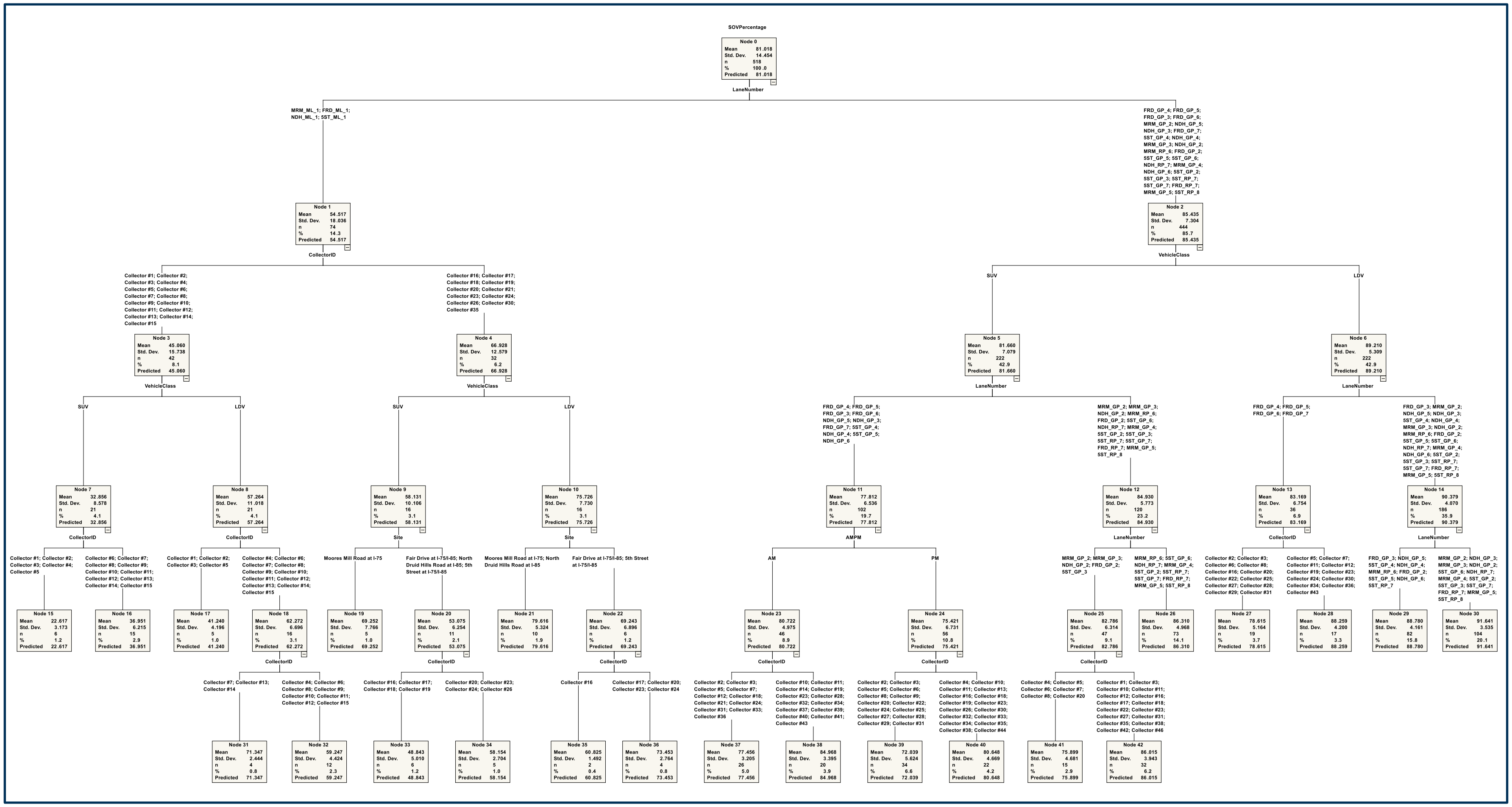


Figure 13 – Regression Tree on SOV Percentage to Identify Potential Data Collector Bias

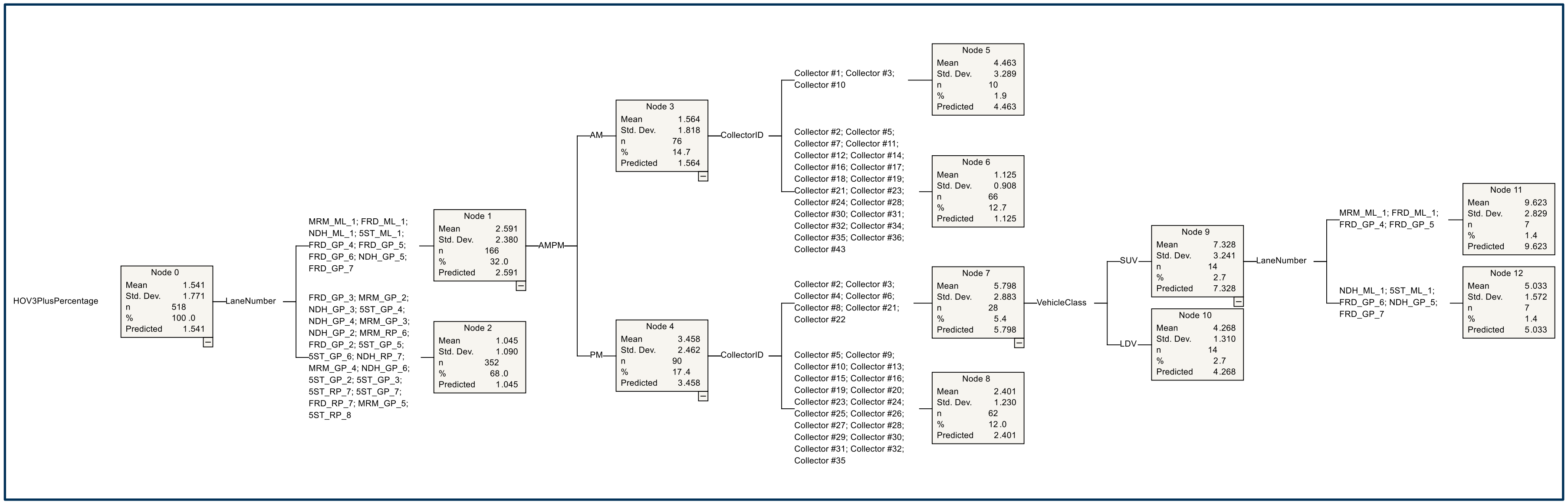


Figure 14 – Regression Tree on HOV '3+' Percentage to Identify Potential Data Collector Bias

5.4 Sample Sizes after Data Screening

In 2024 data collection, the undergraduate and graduate students collected vehicle occupancy data over a period of approximately two months. More than 40 students participated in this data collection, 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 vehicle classes, lanes, AM/PM, etc. A total of three analytical iterations were employed to identify and remove potentially biased data from the vehicle occupancy data.

Table 18 provides a summary of the results reported in this chapter and the sample sizes. In the 2010-2012 study, approximately 7.0% of the data were removed (Guensler, et al., 2013a), and in the 2018-2020 study, approximately 6.4% of the data were removed. In this 2024 study, no data was removed due to potential bias issue, and the QA/QC results indicated a better managed team. For this study, deployment management was optimized by using a smaller team of more experienced (and better) data collectors and introducing enhanced management protocols. These improvements included performance-based progression opportunities, a structured operations and logistics team with designated roles, regular horizontal and vertical communication, and proactive planning for field sessions.

Table 18 – Sample Size by Iteration of Regression Tree Analysis

Analysis Iteration	Regression Tree Type	Input Number of Records	Number of Records Filtered	Percent of Records Filtered	Input Number of Vehicles	Number of Vehicles Filtered	Percent of Vehicles Filtered
1	Average Occupancy	347	0	0.0%	588,633	0	0.0%
2	SOV Percentage	347	0	0.0%	588,633	0	0.0%
3	HOV ‘3+’ Percentage	347	0	0.0%	588,633	0	0.0%
Total		347	0	0.0%	588,633	0	0.0%

6 Factors Related to Observed Vehicle Occupancy

To evaluate the relative influence of explanatory variables on vehicle occupancy, the research team conducted a regression tree analysis with the QA/QC-filtered data developed in the previous chapter (excluding data collector identifiers). The goal was to understand how lane type, site characteristics, AM/PM, and lane positions contribute to observed variability in average vehicle occupancy (persons per vehicle). This chapter first presents the analytical results without considering vehicle type, as was done in the previous studies (Guensler, et al., 2013a; Guensler, et al., 2021a). Then, the team conducted additional analysis to assess the potential influence of vehicle type on vehicle occupancy (the detailed occupancy results are presented later, in Chapter 8).

6.1 Vehicle Occupancy by Site and Lane

The filtered occupancy records were aggregated by session (AM/PM and date), lane, and site. Data collector information was excluded from this portion of the analysis, as QA/QC procedures addressing collector influence had already been completed.

Variables that entered the regression tree included lane number (a combination of site, lane type, and lane ID, as described in Section 5.1), AM/PM indicator, lane position (inside, middle, and outside), lane type (general-purpose lanes, managed lanes, and ramps), site, and day of the week. Vehicle type was not included in the preliminary analysis, as it is examined later in Section 6.2. The resulting regression tree is shown in Figure 15.

The primary split in the tree was based on lane type, confirming it as the most influential factor (node 0, Figure 15). HOV lanes exhibited substantially higher average occupancies than GP lanes and ramp lanes, with vehicles in HOV lanes carrying approximately 0.39 more persons per vehicle on average.

Within the HOV branch, the next most influential factor was site location (Node 1, Figure 15). HOV facilities in downtown and southern corridors (5th Street and Fair Drive at I-75/I-85) showed higher average occupancies than those in northern corridors (Moores Mill Road at I-75 and North Druid Hills Road at I-85). This may reflect higher carpool demand, perhaps stronger enforcement or perceived violation risk in the more central corridors, and differences in land use, user demographics, and proximity to Hartsfield-Jackson International Airport for the southern portion of the network.

In the general-purpose and ramp lane branch, the second split was determined by lane number (node 2, Figure 15), suggesting spatial differences in how lanes are utilized. Higher occupancy was observed in: 1) GP4 to GP6 at North Druid Hills at I-85 (outer and middle lanes), 2) GP4 to GP7 at Fair Drive at I-75/I-85, and 3) GP4 at 5th Street at I-75/I-85 (the middle lane). These results suggest that outer and middle GP lanes at these sites may support more carpooling vehicles than inside lanes, potentially due to factors such as lane-change behavior or visibility to enforcement personnel. These findings are consistent with trends identified in previous studies. However, detailed occupancy patterns vary by corridor, as discussed further in Chapter 8.

The AM/PM variable entered the model at lower levels (nodes 5 and 9, Figure 15) but still demonstrated consistent explanatory influence. PM peak periods were associated with higher average occupancies than AM peaks, a trend consistent with prior studies and likely attributable to a greater mix of high-occupancy non-work trips (e.g., shopping and recreational travel) during afternoon hours.

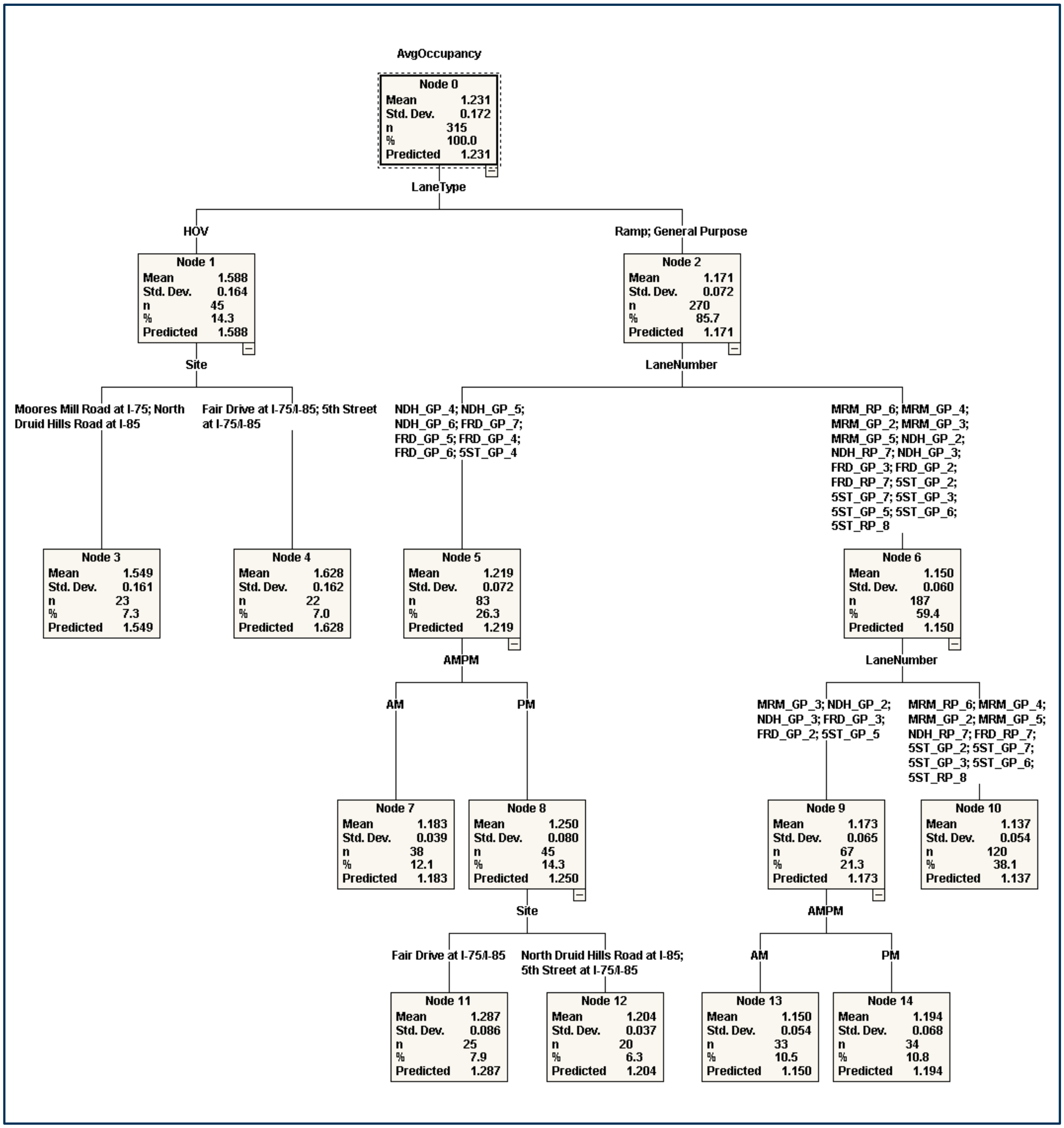


Figure 15 – Regression Tree for Corridor, Lane Number and AM/PM Impacts

6.2 Occupancy and Vehicle Type

To further investigate the factors influencing observed vehicle occupancy, the research team conducted a second regression tree analysis that incorporated vehicle class as an additional explanatory variable, as in the 2018-2020 study. This model included the same variables as the previous analysis (lane type, lane number, AM/PM indicator, lane position, and site) alongside vehicle class. Vehicles were grouped into LDVs and SUVs, which together comprised the vast majority of the observed fleet. The purpose of this analysis was to assess the impacts of vehicle class identifier, and evaluate whether LDVs and SUVs exhibited different occupancy patterns across spatial and temporal dimensions.

As shown in Figure 16, lane type once again emerged as the most influential factor, forming the primary split in the regression tree (node 0). Vehicles in HOV lanes exhibited significantly higher average occupancies (1.49 persons per vehicle, node 1) compared to those in general-purpose and ramp lanes (1.16 persons per vehicle, node 2), reaffirming the strong effect of facility type on carpooling activity.

Within each lane type category, vehicle class entered next in the tree structure, indicating that it was the second most important factor. SUVs generally carried more passengers than LDVs within the same facility type, while the extent of the differences varied. On HOV lanes, SUVs averaged 1.61 persons per vehicle (node 3), approximately 16% higher than LDVs, which averaged 1.38 (node 4). In GP lanes and ramp lanes, SUVs averaged 1.21 persons per vehicle (node 5), while LDVs averaged 1.12 (node 6), which is a difference of only about 8%. An exception to this pattern occurred in the outside lanes at Fair Drive on I-75/I-85, where LDVs exhibited an average occupancy of 1.19 persons per vehicle (Node 12), exceeding the 1.17 average observed for SUVs across multiple sites and lanes (Node 13). Fair Drive also tends to show higher occupancy in other branches of the tree, where site-level effects are expressed.

The remaining regression tree results also indicate the strong effect of lane type. LDVs operating on HOV lanes still had higher average occupancy than SUVs on general-purpose or ramp lanes (e.g., average occupancy in node 9 is larger than any branch after node 2).

Most of these findings are consistent with those of the 2018–2020 study. However, in the previous effort, vehicle class appeared to have a greater influence on occupancy than lane type. That study included Express Lanes in the I-75/I-575 Northwest Corridor (NWC) Express Lanes (reversible lanes), the I-85 Express Lanes and Extension (HOT lanes), and the I-75 South Express Lanes (reversible lanes), which were all located outside the I-285 Perimeter. By contrast, the current study (2024) focused exclusively on HOV lanes within the I-285 Perimeter, where lane type had a more dominant role in shaping occupancy patterns. This geographic and lane type distinction (and carpool requirement without tolling options) likely explains the relative shift in impacts between vehicle class and lane type.

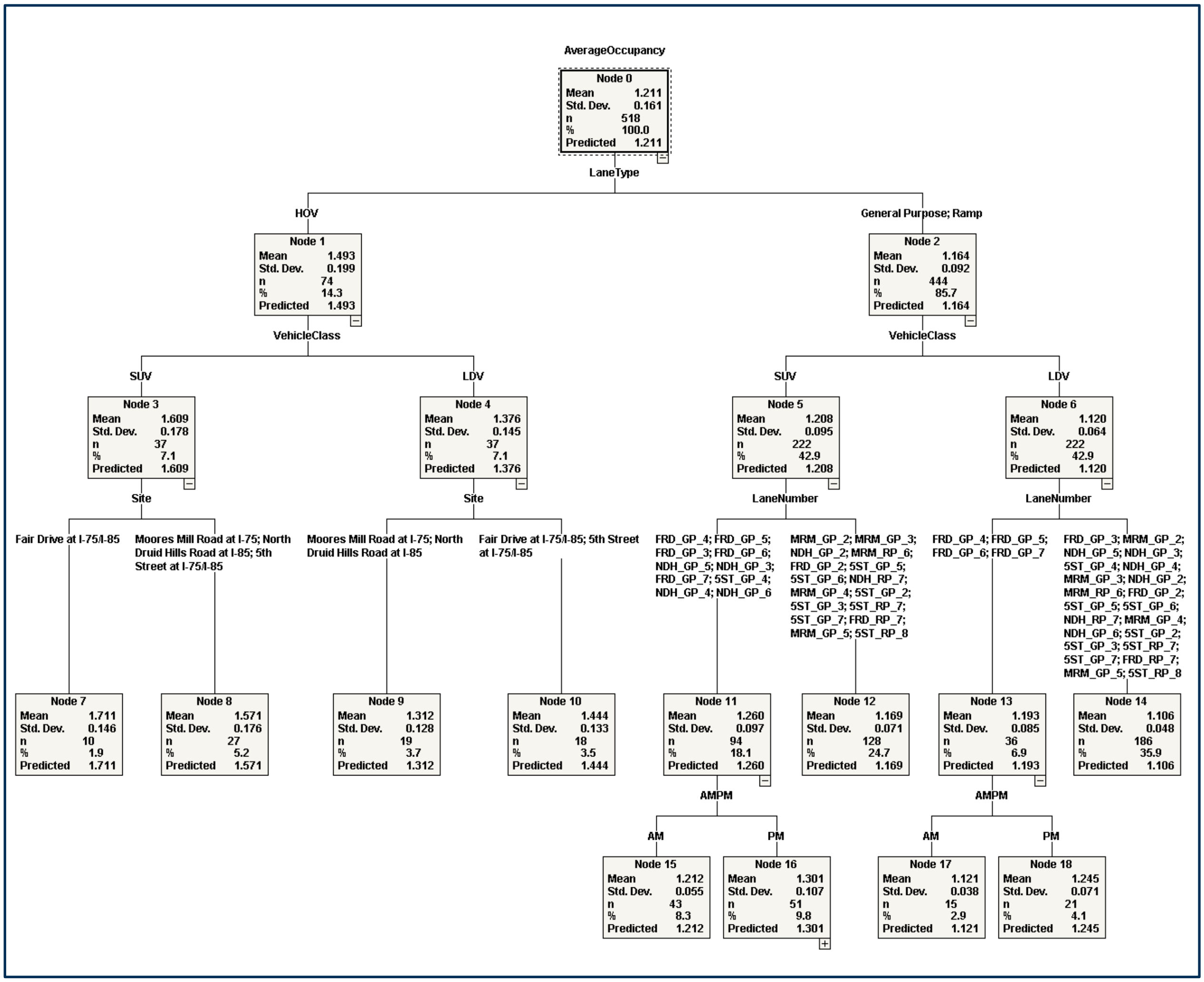


Figure 16 – Regression Tree for Vehicle Class, Corridor, Lane Number and AM/PM Impacts

6.3 Summary of the Exploratory Regression Tree Analysis for Occupancy

In the 2024 study, regression tree analysis was again employed to assess the relative influence of corridor, lanes, and vehicle class variables on observed vehicle occupancy. Two analyses were conducted: the first excluded vehicle class and focused on facility, site, lane, and morning vs. evening peaks; the second incorporated vehicle class to evaluate the effects for light-duty vehicles LDVs and SUVs.

When vehicle class is not included, lane type (i.e., HOV lanes vs. GP lanes and ramp lanes) emerges as the most influential factor affecting vehicle occupancy. HOV lanes consistently exhibit higher average occupancies than GP lanes and ramp lanes, which is not surprising to the team. Lane number, as a combination of site, lane type, and relative position within the facility, is also highly explanatory, particularly between middle, inside, and outside lanes.

The analysis reveals that middle and outer general-purpose lanes tend to exhibit higher occupancy, likely due to merging dynamics and enforcement visibility. Peak hours (AM vs. PM sessions) also plays a consistent role, with PM periods associated with higher average occupancy, a trend aligned with previous studies and likely driven by increased recreational and shopping travel in the afternoon.

In the second regression tree, which included vehicle class, lane type again emerged as the primary explanatory variable, with HOV lanes producing the highest occupancy levels. Vehicle class then entered as the second most influential variable, confirming that SUVs generally carry more passengers than LDVs across both lane types. These findings mirror those from the 2018–2020 study, though the relative importance of vehicle class was lower in this study. The shift likely reflects the study area context: the 2024 corridors are located entirely within the I-285 Perimeter and focus exclusively on HOV lanes, whereas the 2018–2020 study analyzed Express Lanes outside the Perimeter (with operational and pricing variabilities).

Fair Drive at I-75/I-85 emerged as a site with consistently higher occupancy across multiple splits, and an exception regarding vehicle class patterns was observed in the outside lanes at Fair Drive, where LDVs recorded higher average occupancy than SUVs at other sites and lanes.

Overall, the regression tree analyses confirm that lane type, vehicle class, lane position, site, and AM/PM are key drivers of vehicle occupancy variability across the study corridors. These findings reinforce the importance of stratifying further analysis by facility type and vehicle class. More detailed occupancy statistics will be presented in Chapter 8, following the treatment of express bus data in Chapters 7.

7 Express Bus Operations and Impacts on Occupancy

The field occupancy observations in this study capped maximum occupancy at ‘4+’, which was treated as 4.5 persons per vehicle when calculating average occupancy (as described in Section 3.3). However, express buses usually carry many more passengers than the ‘4+’ maximum default occupancy value used in field data collection. Given that express buses constitute a small fraction of the vehicle fleet but transport a disproportionately large share of commuters, it is important to substitute actual ridership data when assessing vehicle and person throughput. This chapter presents express bus activity on the studied corridors and discusses the explicit treatment of express buses in assessing vehicle occupancy, vehicle throughput and person throughput.

A subset of commuters using the studied facilities also travel by vanpool. Previous studies have substituted actual vanpool ridership data for the ‘4+’ default value; however, the 2018–2020 study indicated that vanpool operations do not significantly impact occupancy and throughput results (impacts of no larger than 0.01 persons per vehicle on average occupancy), due to their relatively low ridership and frequency of use. In this current project, the team received actual vanpool ridership data from SRTA for August and September 2024, which exhibited an average occupancy of approximately 4.31 persons per vehicle (these vans were recorded as 4.5 persons per vehicle). Consequently, the team decided not to perform vanpool substitution to replace HOV ‘4+’ vans with reported ridership data in this study.

7.1 Express Bus Operations

A significant number of commuters using the HOV corridors during peak periods are served by Xpress, CobbLinc, and Ride Gwinnett. No MARTA buses operated at the occupancy observation sites and were therefore not included in ridership substitution.

Xpress is a regional commuter coach system operated by the Atlanta-region Transit Link Authority (ATL), providing service across 12 metro Atlanta counties, as shown in Figure 17. Xpress operates 27 routes and historically has carried more than 1.8 million passenger trips annually. Xpress offers morning and afternoon peak-period services from Monday to Friday to major employment centers such as Downtown, Midtown, and Perimeter Center. Xpress began service on June 7, 2004, under the Georgia Regional Transportation Authority (GRTA), and was transferred to ATL in 2020. In this study, 19 Xpress routes traverse the data collection sites.

CobbLinc, operated by Cobb County, provides local bus service within Cobb County and commuter bus services to and from Downtown and Midtown Atlanta from Monday to Saturday. CobbLinc began operations in July 1989 (as Cobb Community Transit) and has maintained relatively strong ridership since then. It operates nine local routes and three express routes, with services connecting to MARTA at the Arts Center station. A total of 5 CobbLinc routes traverse the studied corridors during peak hours.

Ride Gwinnett (formerly known as Gwinnett County Transit, or GCT) is operated by Gwinnett County and provides local, paratransit, micro-transit, and express bus services.

Established in 2000, Ride Gwinnett operates 14 routes, including five commuter routes that connect to major employment centers in Atlanta (these five routes traverse the observation sites in this study). In January 2023, Gwinnett County rebranded its transit system to Ride Gwinnett to reflect its evolving focus on mobility.

The express bus routes passing each site are shown in Table 19 (morning peak) and Table 20 (evening peak). In this study, CobbLinc's operations are concentrated on the I-75 corridor (Moores Mill and 5th Street), whereas Ride Gwinnett's operations are focused on the I-85 corridor (North Druid Hills and 5th Street). Xpress buses are more evenly spread but vary in frequency and load depending on the route and site.

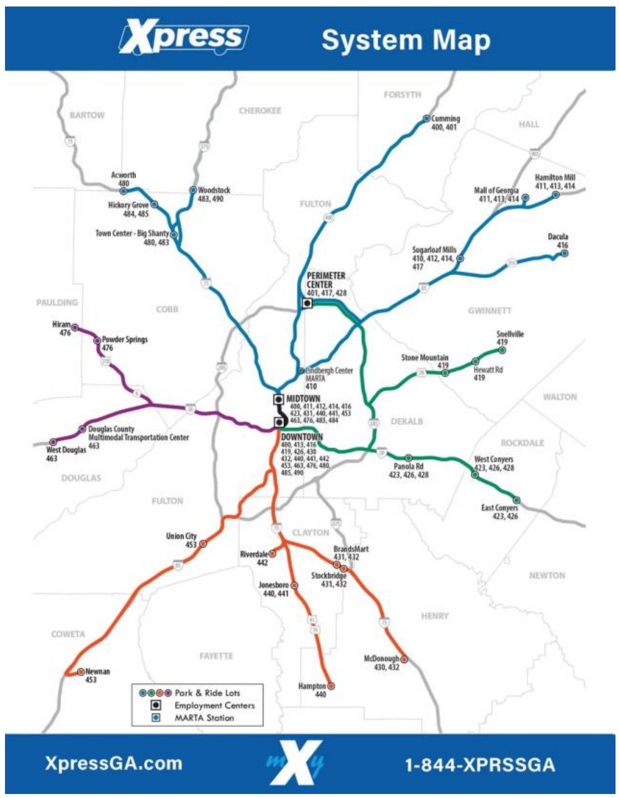


Figure 17 – Xpress System Map as of September 2024 (ATL, 2024)

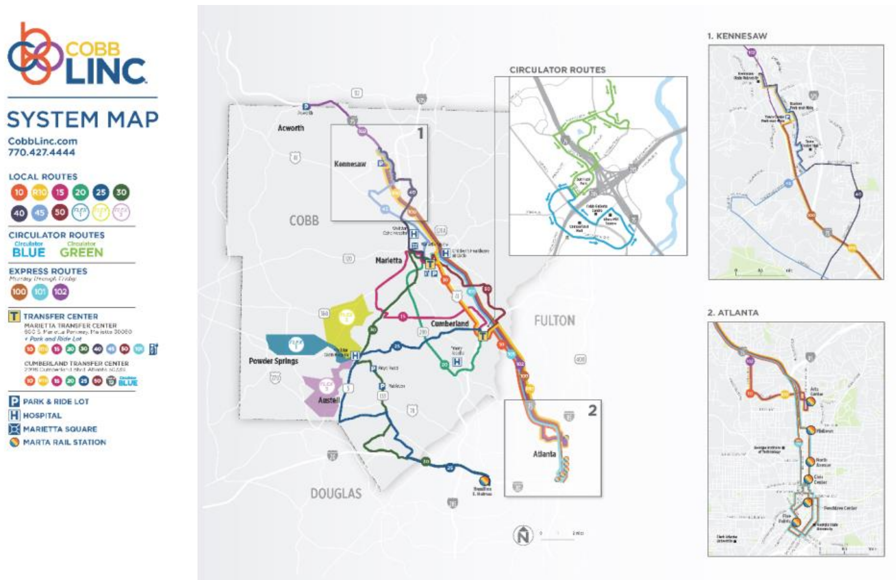


Figure 18 – CobbLinc System Map (CobbLinc, 2024)

Table 19 – Express Bus Routes by Site (7:30-10:30 AM), 2024

Site	Xpress	CobbLinc	Ride Gwinnett
Moores Mill Road at I-75	480, 483, 484, 485	Rapid 10, 10, 100, 101, 102	None
North Druid Hills Road at I-85	410, 411, 412, 413, 414	None	101, 102, 103, 103A
Fair Drive at I-75/I-85	430, 431, 432, 440, 441, 453	None	101, 103, 110
5th Street at I-75/I-85	400, 410, 411, 412, 413, 414, 480, 483, 484, 485	100, 101	101, 102, 103

Table 20 – Express Bus Routes by Site (3:30-6:30 PM), 2024

Site	Xpress	CobbLinc	Ride Gwinnett
Moores Mill Road at I-75	480, 483, 484, 485, 490	Rapid 10, 10, 100, 101, 102	None
North Druid Hills Road at I-85	410, 411, 412, 413, 414, 416	None	101, 102, 103, 103A
Fair Drive at I-75/I-85	430, 431, 432, 440, 441, 442, 453	None	101, 103, 110
5th Street at I-75/I-85	400, 410, 411, 413, 416, 480, 485, 490	None	101, 102, 103

An understanding of which routes pass each data collection site was necessary to assess average vehicle occupancy and throughput, as well as how many buses of each route passed the data collectors during the AM and PM peak period study hours. Because no automatic vehicle location (AVL) data were available at the time of study to provide actual vehicle trace data (i.e., the exact time that each bus passes a data collection site), the team assumed that all buses operate according to their scheduled times (no departure/arrival with deviations greater than10 minutes) and routes (no detour).

All buses were assumed to be running on the HOV lanes when they passed the data collection sites, even though several express bus routes approach the end of their trips near the Interstate exit at 5th Street on I-75/I-85 Southbound (e.g., CobbLinc Route 100). Under normal expectations, a bus preparing to exit the highway would typically shift to the rightmost GP lane to access a standard exit ramp. If this were the case, the buses would have been observed in the outside GP lane approximately half a mile upstream at the data collection site at 5th Street. However, based on routing review and the presence of the dedicated HOV exit ramp to Williams Street, the team assumed that these buses stayed in the managed lane.

The research team assigned the number of buses by route that traversed each observation site by hour, based on schedules for Xpress (Xpress 2024), CobbLinc (CobbLinc, 2024), and Ride Gwinnett (Ride Gwinnett, 2024). The bus route assignments were then integrated with Xpress, CobbLinc, and Ride Gwinnett ridership data (month-by-month profiles) to provide the average ridership profiles by month to assess express bus passenger throughput by site. The number of operational days for Xpress buses, CobbLinc buses, and Ride Gwinnett buses were extracted for each month, and coupled with average vehicle occupancy profiles. For Xpress buses and CobbLinc, the average vehicle occupancy by route was available for AM vs. PM periods. For Ride Gwinnett buses, time-of-day-specific ridership data were not available, so the team assumed identical average ridership for AM and PM periods.

7.2 Average Vehicle Occupancy Analysis for Express Buses

To assess the person throughput of buses and vanpools in this project, individual express bus trips were paired with applicable vehicle occupancy observations in time and space (i.e., for each data collection session). Because much of the raw ridership data were available only on a monthly average basis (not day-by-day data), ridership was assumed to be uniform across all operational days for each route and reflected by the average (total passengers/total trips). In the absence of specific occupancy data for the actual buses traversing through the data collection sites, the team assumed that express bus vehicle occupancy during field data collection at each site could be represented by these average ridership values. Express bus vehicle occupancy for each route was derived by integrating the ridership data provided by the contractors for the Xpress, CobbLinc, and Ride Gwinnett, with the number of buses for each route (weighted average) to obtain an average for each operator (by AM/PM and by site). Then, the observed occupancy entries for these buses (recorded as ‘4+’) were replaced by these higher average vehicle occupancy values.

Figure 19 and Figure 20 present average express bus ridership by site during the AM peak (7:30–10:30 AM) and PM peak (3:30–6:30 PM), respectively. If no buses from a particular operator passed a given site during the collection time of day, the average ridership is marked as "N/A."

During the AM peak, the highest observed ridership occurred at North Druid Hills Road at I-85, where Xpress buses averaged 15.7 passengers per vehicle. Moores Mill Road at I-75 also exhibited strong performance, with CobbLinc buses averaging 15.3 passengers. At 5th Street at I-75/I-85, Xpress and Ride Gwinnett buses recorded 14.1 and 11.9 passengers per vehicle, respectively. The lowest ridership was seen on CobbLinc buses at 5th Street, which averaged only 3.7 passengers per vehicle when data were being collected. This result is largely attributed to Routes 100 and 101, which traverse the segment but tend to carry much lighter loads compared to other express bus lines.

In the PM peak, overall ridership declined slightly across most locations. CobbLinc buses at Moores Mill Road again showed the highest average (17.5 passengers), followed by Xpress at North Druid Hills with 12.9. Express bus ridership at Fair Drive and 5th Street ranged between 10.0 and 10.7 for both Xpress and Ride Gwinnett. CobbLinc buses were not observed at these latter locations during the evening period.

These findings highlight the importance of route-level variances in shaping average ridership. Routes vary in length, stop structure, and regional coverage, all of which affect passenger volumes. For example, CobbLinc Route 10 (and its variant Rapid 10) consistently recorded the highest ridership among all routes across operators, averaging more than 4.5 additional passengers per trip than Routes 100 and 101. This contrast explains the higher CobbLinc average at Moores Mill and the much lower ridership at 5th Street.

Compared with prior studies, where Xpress buses often reported average occupancies exceeding 25 passengers per trip, the express bus ridership observed in this study were notably lower. No operator-site combination exceeded 17.5 passengers per vehicle, and most averages ranged between 10 and 15. This decline may reflect continued post-pandemic ridership recovery, as well as the shift in study geography, where all 2024 observation sites are located within the I-285 Perimeter, in contrast to the outer-suburban corridors examined in prior studies.

While the average per-bus occupancy levels in this study are lower than those reported in earlier studies, the express bus network remains an effective mode for moving large numbers of commuters. Despite comprising a small share of overall vehicle volume, express buses contribute disproportionately to person throughput across HOV corridors.

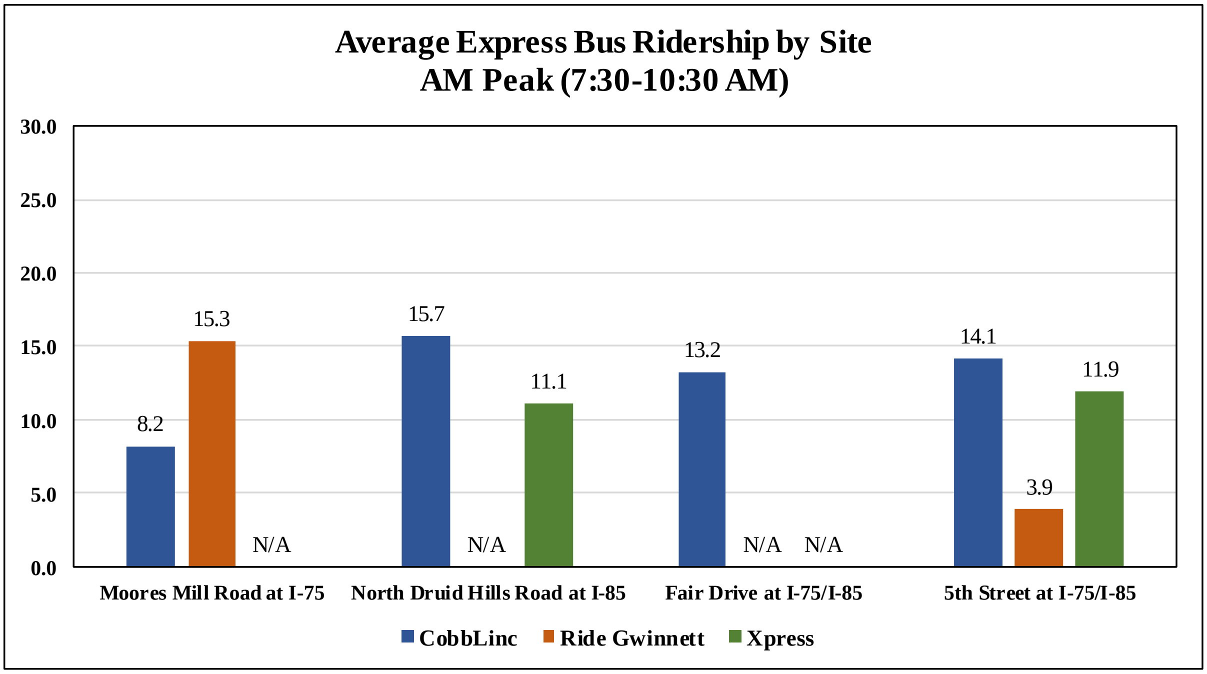


Figure 19 – Average Vehicle Occupancy on Express Buses by Site,
AM Peak (7:30-10:30 AM)

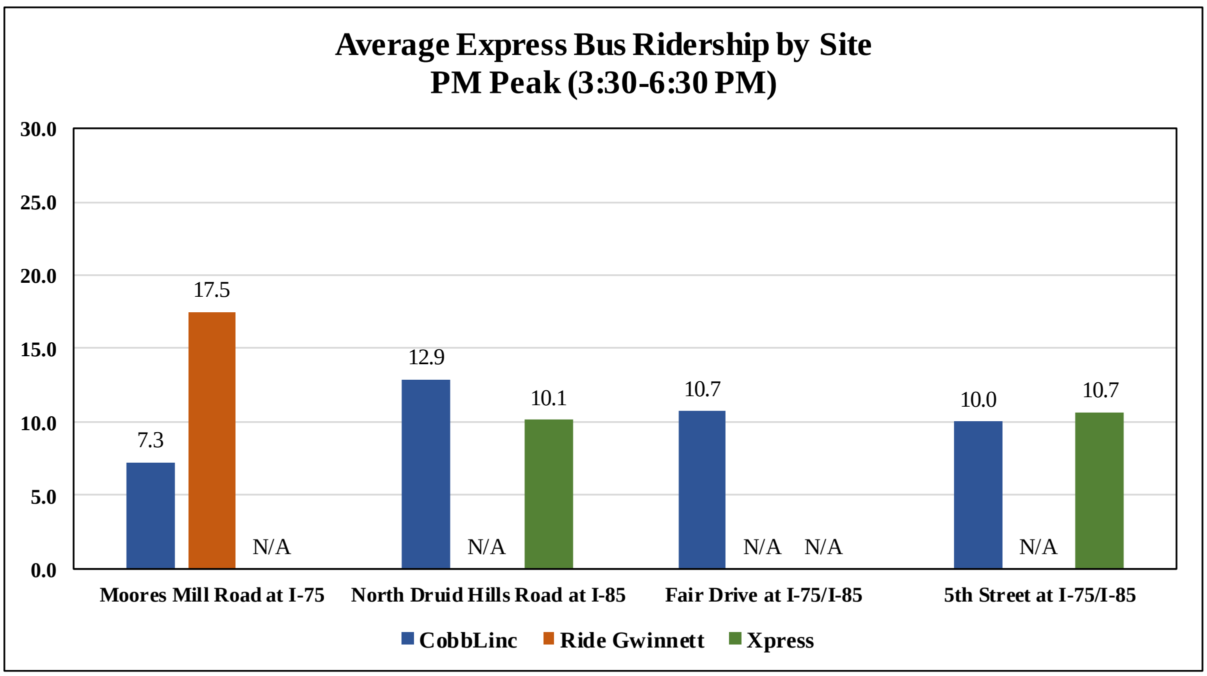


Figure 20 – Average Vehicle Occupancy on **Express Buses by Site,**
PM Peak (3:30-6:30 PM)

7.3 Accounting for Express Bus Passengers in Vehicle Occupancy and Person Throughput Assessment

The vehicle occupancy study conducted in the field and reported in previous chapters involved the collection of joint vehicle classification and vehicle occupancy records. Each record included vehicle class (passenger car, sports utility vehicle, heavy-duty vehicle, bus, vans, motorcycle, etc.) and occupancy value. Xpress, CobbLinc, and Ride Gwinnett buses, when observed, were always recorded as buses with '4+' occupancy. For every express bus, an occupancy value of 4.5 persons/vehicle was assigned in the steps employed in the regression tree analysis using observed occupancy data. However, express buses typically carry many more than 4.5 persons/vehicle.

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 were assessed via the methods outlined earlier in this chapter. The scheduled express buses were assumed to be operating on the HOV lanes, consistent with assumptions outlined earlier in this chapter. For each bus traversing the corridors, 4.5 persons were removed from the person total and the number of persons carried by each express bus was added to the person total. The additional processing steps described in this section essentially corrected for the inability of field observers to count the actual number of occupants in an express bus. The replacement of field placeholder values with onboard ridership values adjusted the occupancy values for buses, which were also used later in final calculations of average vehicle occupancy.

The numbers of passengers that needed to be added back (i.e., the average vehicle occupancy of the express buses) were consistent with the field occupancy collection, based on the corresponding occupancy data collection dates as described in the previous section. The substitution significantly increased the total number of express bus commuters and average vehicle occupancy, because the average vehicle occupancy of express buses was typically larger than 10 persons/vehicle.

The average occupancy adjustments for the Xpress, CobbLinc, and Ride Gwinnett passengers are shown in Table 21 (AM peak) and Table 22 (PM peak). For the I-85 corridor, the adjustment increased the average occupancy by approximately 0.11 persons per vehicle. Adjustments at other corridors raised the average occupancy by 0.04 to 0.10 persons per vehicle. At 5th Street at I-75/I-85 for morning peaks, the contribution of express buses resulted in only a modest increase in the average vehicle occupancy (an increase of approximately 0.02 persons/vehicle), not because of a limited number of buses, but rather due to an already high baseline occupancy in the HOV lane (highest across all sites and AM vs. PM peaks). This "ceiling effect" limited the additional impact of express bus riders on overall average occupancy. Nevertheless, the share of person throughput contributed by express buses at 5th Street remains significant and will be discussed further in Chapter 9. In the previous 2018-2020 study, for I-85 along the existing Express Lane, where many Xpress Bus routes traverse past the collection sites (Indian Trail Lilburn Road and Old Peachtree Road), the impacts of express buses on average Express Lane vehicle occupancy were as large as 0.19 to 0.43 persons/vehicle. This smaller adjustment, compared to the previous study, may reflect both geographic differences in corridor selection and the evolving nature of express bus operations during post-pandemic recovery.

Assigning all express buses to HOV lanes (many of which carry lower traffic volumes than their adjacent GP lanes) produced notable increases in person throughput for those lanes. Chapter 9 summarizes vehicle and person throughput at the corridor level 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. The vehicle and passenger throughput for express buses (after substitution) is presented in the following section.

Table 21 – Adjustment of Average Occupancy with Substitution of Express Buses, AM Peak (7:30-10:30 AM)

Site	Lane	AVO Before Adjustment	AVO After Adjustment	Impact of Adjustment
Moores Mill Road at I-75	MRM_ML1	1.51	1.56	0.04
North Druid Hills Road at I-85	NDH_ML1	1.48	1.59	0.11
Fair Drive at I-75/I-85	FRD_ML1	1.59	1.65	0.06
5th Street at I-75/I-85	5ST_ML1	1.72	1.74	0.02

Table 22 – Adjustment of Average Occupancy with Substitution of Express Buses, PM Peak (3:30-6:30 PM)

Site	Lane	AVO Before Adjustment	AVO After Adjustment	Impact of Adjustment
Moores Mill Road at I-75	MRM_ML1	1.57	1.67	0.10
North Druid Hills Road at I-85	NDH_ML1	1.58	1.70	0.11
Fair Drive at I-75/I-85	FRD_ML1	1.65	1.71	0.06
5th Street at I-75/I-85	5ST_ML1	1.51	1.59	0.08

7.4 Vehicle and Person Throughput of Express Buses

In this study, vehicle and person throughput were assessed on an hourly basis for peak periods: 7:30 AM to 10:30 AM for the AM peak and 3:30 PM to 6:30 PM for the PM peak. Total express bus vehicle throughput (combined Xpress, CobbLinc, and Ride Gwinnett services) by site is shown in Figure 21, and vehicle throughput by operator and site is shown in Figure 22 (AM peak) and Figure 23 (PM peak). Figure 24 presents the hourly person throughput of all express buses by site during the AM and PM peaks. Figure 25 and Figure 26 show the hourly person throughput by operator for both time periods.

Because express buses carry a large number of passengers with relatively few vehicles, and throughput was averaged across all three operational hours in the study window, both vehicle and person throughput are presented using one decimal place in this section. This level of precision reflects the averaging of scheduled buses and passenger loads per hour during peak periods. In Chapter 9, where final person and vehicle throughput figures are aggregated to the corridor level for reporting purposes, results will be rounded to the nearest whole number, as whole-person and whole-vehicle counts are more appropriate at that level of summary.

During the AM peak, the average express bus vehicle throughput ranged from a low of 3.3 buses per hour at Fair Drive at I-75/I-85 to a high of 10.7 buses per hour at 5th Street at I-75/I-85. Moores Mill Road at I-75 and North Druid Hills Road at I-85 each recorded 9.0 buses per hour. In the PM peak, throughput increased at all sites. North Druid Hills Road and Moores Mill Road each reached 13.0 buses per hour, 5th Street increased to 12.3 buses per hour, and Fair Drive increased to 9.0.

Person throughput results followed a similar pattern but were more sensitive to variabilities in average vehicle occupancy. In the AM peak, the highest hourly person throughput occurred at Moores Mill Road at I-75, with 128.5 persons per hour. North Druid Hills Road at I-85 followed at 113.5 persons per hour, and 5th Street at I-75/I-85 closely behind with 120.0 persons per hour. Fair Drive at I-75/I-85 had the lowest throughput during the morning period, at 44.1 persons per hour.

In the PM peak, person throughput increased at every site. Moores Mill Road at I-75 experienced the largest increase (reaching 189.8 persons per hour). North Druid Hills Road at I-85 rose to 147.3 persons per hour. Fair Drive at I-75/I-85 more than doubled its AM throughput, reaching 96.4 persons per hour, while 5th Street at I-75/I-85 increased modestly to 127.7 persons per hour.

Figure 25 and Figure 26 break down the person throughput by operator. During the AM peak, Moores Mill Road at I-75 was served primarily by CobbLinc, which accounted for 117.6 persons per hour, and Xpress contributed an additional 10.9 persons per hour. At North Druid Hills Road at I-85, Ride Gwinnett and Xpress each contributed 66.5 and 47.0 persons per hour, respectively. Fair Drive at I-75/I-85 was served entirely by Xpress during the morning peak, while 5th Street at I-75/I-85 had a mixed contribution from Ride Gwinnett (63.5 persons per hour), Xpress (56.6 persons per hour), and a small number of passengers from CobbLinc (4.9 persons per hour).

In the PM peak, Moores Mill Road at I-75 saw a substantial increase in CobbLinc throughput to 163.2 persons per hour, with Xpress contributing an additional 26.6 persons per hour. North Druid Hills Road at I-85 continued to be served nearly equally by Ride Gwinnett and Xpress, which carried 74.1 persons per hour and 73.1 persons per hour, respectively. Fair Drive at I-75/I-85, which had no CobbLinc or Ride Gwinnett presence, was served entirely by Xpress, with 96.4 persons per hour. At 5th Street at I-75/I-85, Ride Gwinnett carried 71.1 persons per hour and Xpress carried 56.6, while CobbLinc buses did not pass through during the PM peak.

It is worth noting that vehicle throughput alone does not fully explain the variances in person throughput across sites. For example, although Fair Drive at I-75/I-85 had one of the lowest AM vehicle throughputs (3.3 buses/hour), it delivered 44.1 persons/hour, due to relatively high ridership on the Xpress buses operating in that corridor. Similarly, North Druid Hills Road at I-85 in the PM peak featured comparable person throughput from Ride Gwinnett and Xpress, even though their respective vehicle throughputs varied slightly.

Overall, these results demonstrate that operator mix, routing, vehicle frequency, and average ridership all play significant roles in shaping corridor-level person throughput. The overall person throughput results are comparable to the 2018-2020 study (except for Indian Trail Lilburn Road at I-85, which exhibited much higher express bus person throughput than all other sites). Express buses continued to move large volumes of commuters during both peaks, with a more pronounced impact during the evening period. These findings provide important context for interpreting the overall person and vehicle throughput values presented later in Chapter 9.

Over time, express buses are expected to have a growing impact on lane-level person throughput, particularly as ridership continues to recover and expand. As such, the express bus mode has the potential to carry an even larger share of total person movement on HOV corridors. While express buses already provide substantial capacity and high-quality service, there may be opportunities to further enhance their effectiveness by improving operational efficiency or introducing targeted ridership incentives. This is especially relevant for routes with lower ridership that serve the same corridors as higher-ridership lines from the same operator, yet consistently carry fewer passengers. Strategic interventions on these routes could help increase corridor-wide throughput and optimize the performance of express bus investments.

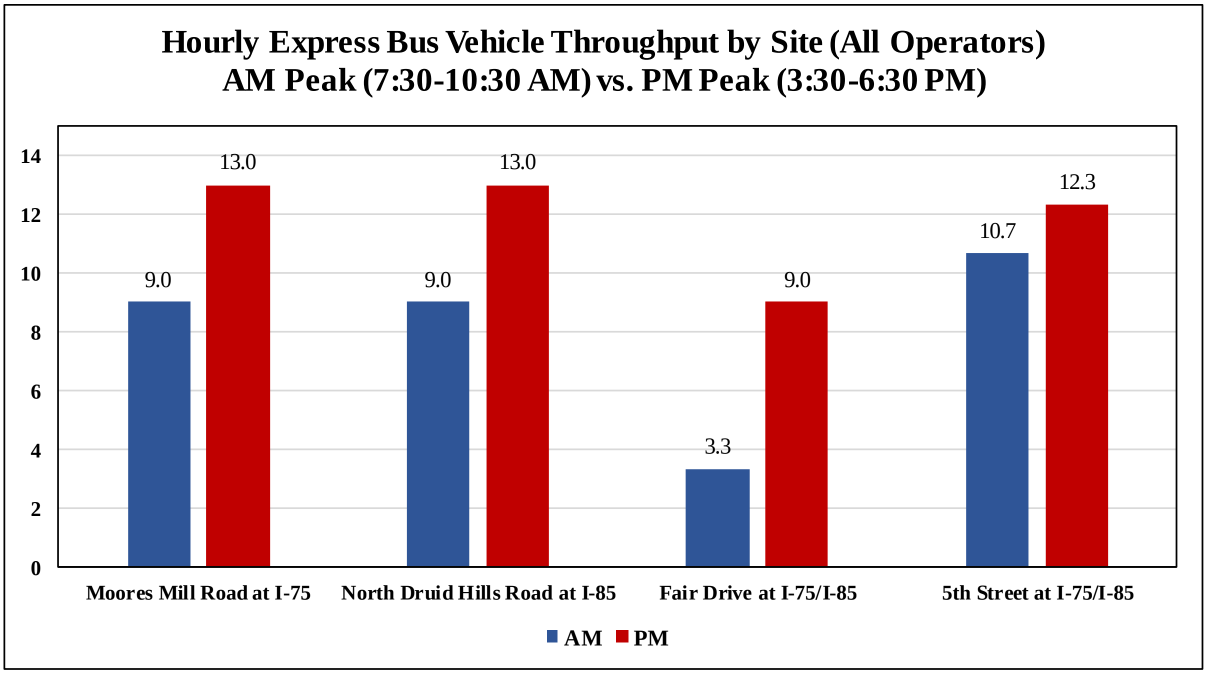


Figure 21 – Hourly Express Bus Vehicle Throughput, Combined Xpress, CobbLinc, and Ride Gwinnett Services, AM Peak (7:30-10:30 AM) and PM Peak (3:30-6:30 PM)

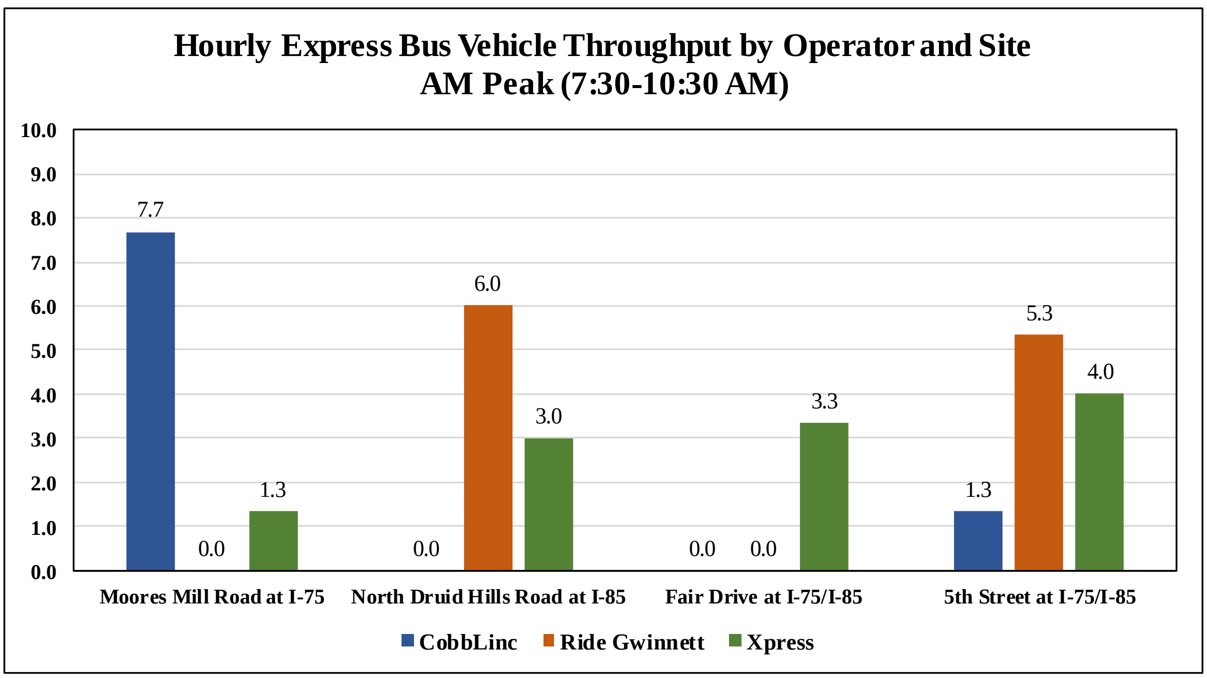


Figure 22 – Hourly Express Bus Vehicle Throughput by Operator, AM Peak (7:30-10:30 AM)

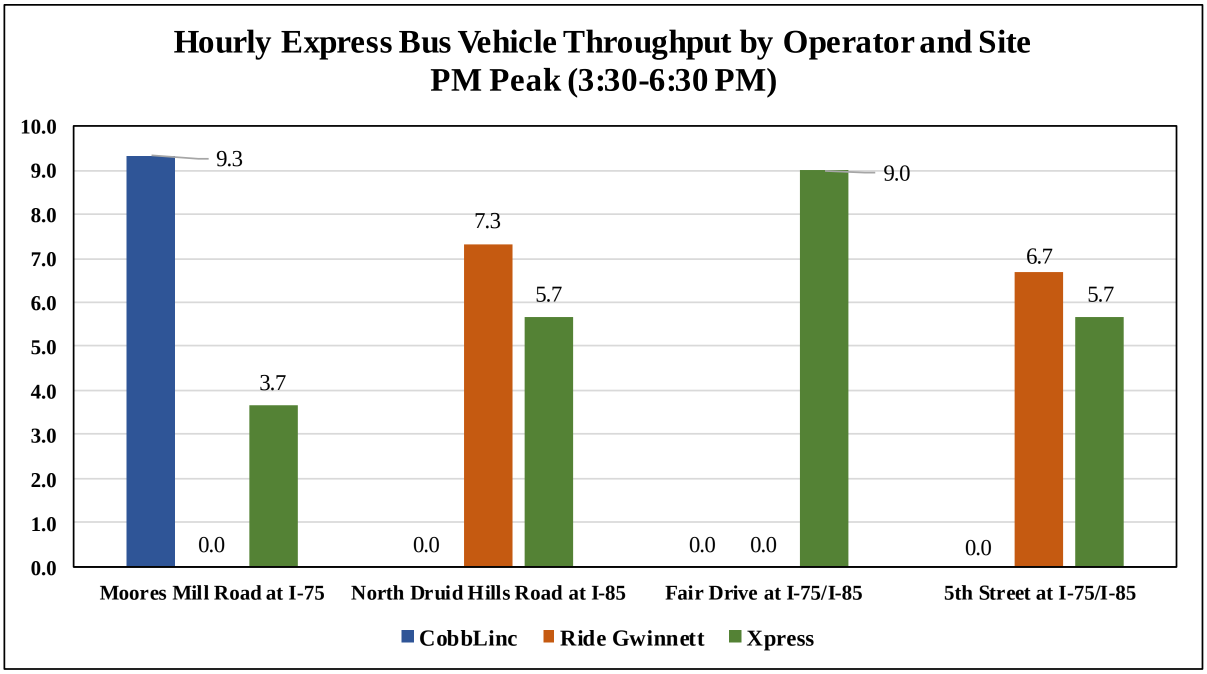


Figure 23 – Hourly Express Bus Vehicle Throughput by Operator,
PM Peak (3:30-6:30 PM)

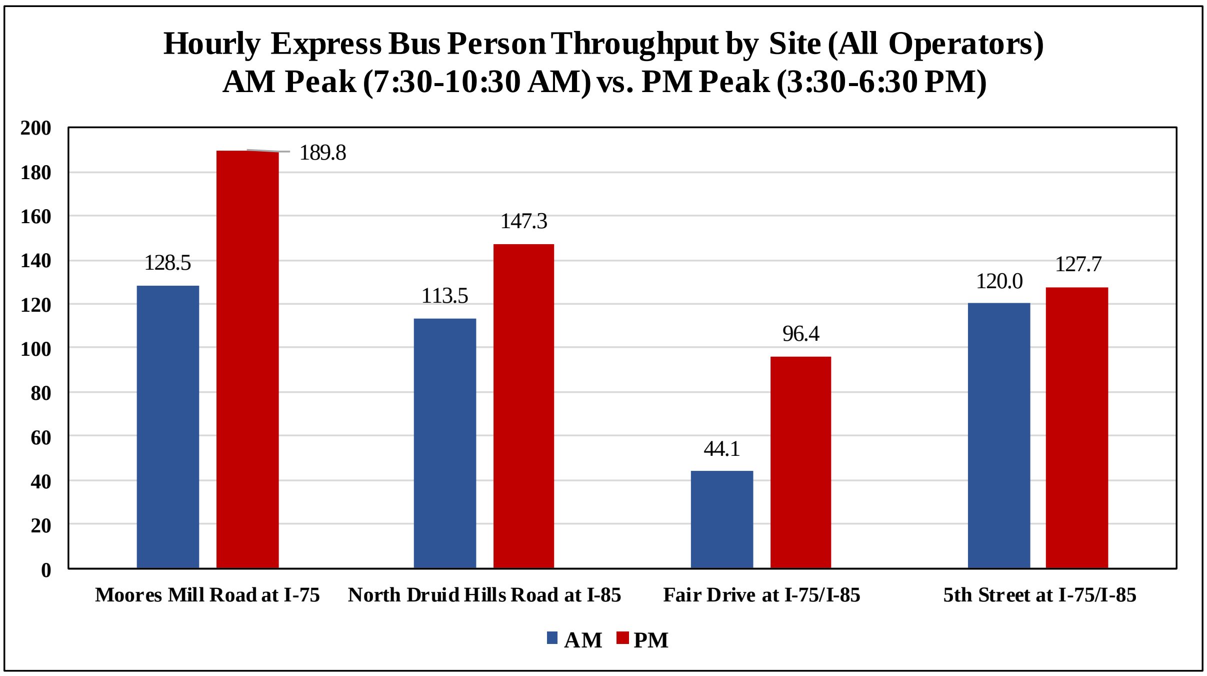


Figure 24 – Hourly Express Bus Person Throughput,
Combined Xpress, CobbLinc, and Ride Gwinnett Services,
AM Peak (7:30-10:30 AM) and PM Peak (3:30-6:30 PM)

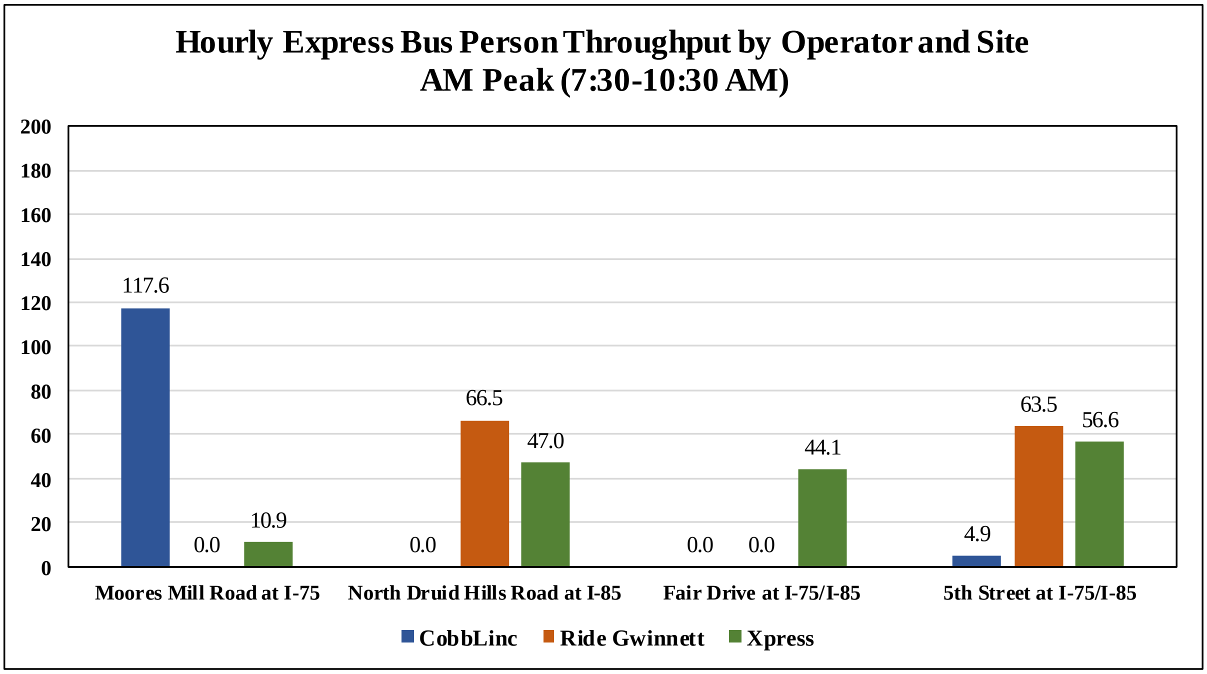


Figure 25 – Hourly Express Bus Person Throughput by Operator, AM Peak (7:30-10:30 AM)

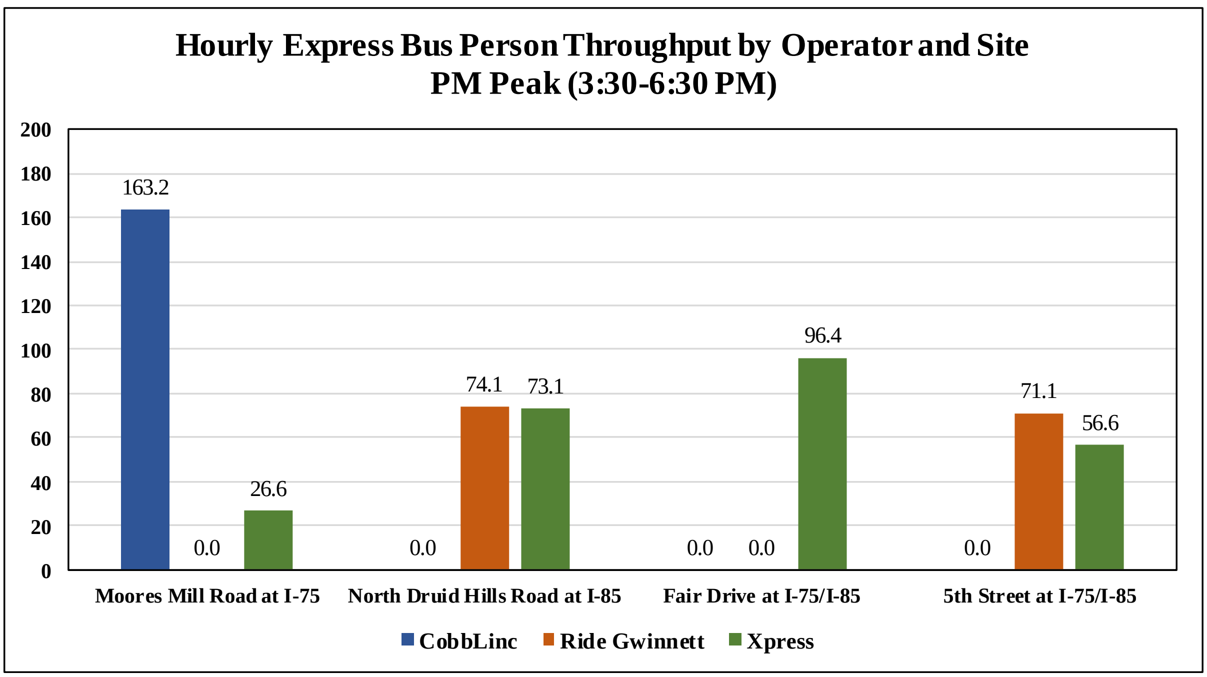


Figure 26 – Hourly Express Bus Person Throughput by Operator, PM Peak (3:30-6:30 PM)

8 Overall Vehicle Occupancy Results

The research team assembled all of the field-collected vehicle occupancy data in a database for use in calculating person throughput for each lane across the corridors. The data employed in the analyses presented in this Chapter have been QA/QC-processed and adjusted based on the average vehicle occupancy profiles of Express buses, as described in Chapter 5, and Chapter 7. Section 8.1 presents tables summarizing the occupancy data from the Fall 2024 field efforts (Table 23 through Table 30). Section 8.2 presents the same data in graphic format, broken down by vehicle class (Figure 27 through Figure 42).

It is important to note the percentages presented in this Chapter are rounded to one decimal place for presentation purposes, and that the rounding was performed separately for each cell. The team did not implement any post-processing to make the rounded percentages sum to 100% (e.g., the sum could be 99.9% or 100.1% instead of 100.0%), so that all numbers match the values in the full Microsoft® Excel spreadsheet that accompanies this report. All sums are actually 100.0% (i.e., any mismatch is simply due to rounding in each table cell), and the audience can refer to the Excel spreadsheet for verification. Similarly, the occupancy data presented in this Chapter is rounded to two decimal places, and all sums in the spreadsheet total to 100.0%. All assessments reported in the tables and figures are based upon the spreadsheet data, not on the rounded values that may appear in adjacent cells.

8.1 Observed Occupancy Results by Lane and by Site

The breakdown of vehicle occupancy observation data for all sites is presented in Table 23 through Table 30. Each lane is coded by site name, lane type, and lane ID (numbered from inside lane to outside lane), as described in Section 3.1 of this report.

Across the four study sites, the HOV lanes consistently reported higher average vehicle occupancy than their adjacent general-purpose (GP) lanes, as expected. The highest observed occupancy for a managed lane was at 5th Street at I-75/I-85 during the AM peak, with an adjusted AVO of 1.74 persons per vehicle. Fair Drive at I-75/I-85 followed with an adjusted AVO of 1.65, and Moores Mill Road at I-75 and North Druid Hills Road at I-85 showed adjusted values of 1.56 and 1.59, respectively. In the PM peak, occupancy increased further for all sites' HOV lanes (except for 5th Street), with values ranging from 1.67 at Moores Mill Road to 1.71 at Fair Drive. At 5th Street, the evening occupancy was lower (at 1.59 persons per vehicle) than the morning peaks, which could be due to the unique characteristics of midtown trips (a higher concentration of inbound morning work trips and more individualized outbound travel in the evening).

When comparing HOV lanes to their respective GP lanes within the same sites, occupancy in the HOV lane was consistently higher than all adjacent GP lanes. While GP lane occupancies were relatively uniform across the study network (typically ranging from 1.10 to 1.21 persons per vehicle), HOV lane occupancies generally exceeded GP lanes by 0.35 to 0.60 persons per vehicle, due to higher carpool rates and the inclusion of express bus riders.

In general-purpose lanes, the location of the highest-occupancy lanes varied by site but often occurred in the middle or outside lanes rather than the innermost GP lanes. At Moores Mill Road at I-75 and 5th Street at I-75/I-85, GP3 and GP4 (middle lanes) exhibited higher occupancy than GP2 (inside lane), especially during PM peaks. At North Druid Hills Road at I-85, GP4 and GP5 had slightly higher occupancy (1.21 and 1.22, respectively) than the other GP lanes, particularly in the evening period. Similarly, Fair Drive at I-75/I-85 showed a slight peak in occupancy in the outermost GP lanes (GP5 and GP6), where adjusted AVOs reached 1.29. This was likely shaped by merging activity, nearby exit locations, lane configuration, and surrounding land uses.

Notably, the highest adjusted AVO in a GP lane was 1.29, observed in the outermost GP lanes (GP5 and GP6) at Fair Drive during the PM peak, which is considerably higher than all other GP lanes in this study and the previous 2018-2020 study. As discussed before, the large evening occupancy observed at Fair Drive at I-75/I-85 could be due to a combination of regional land use, demographic factors in the southern metro area, and proximity to Hartsfield-Jackson International Airport. In addition, geometric constraints near the I-75/I-85 interchange may require vehicles traveling to and from I-85 to remain in the GP lanes, including high-occupancy commercial vehicles such as taxis, limousines, and rideshare services (which are likely more common near the airport). These operational factors likely contribute to the elevated occupancy observed in the GP lanes at this location.

The AM vs. PM comparisons indicate that vehicle occupancy was generally higher in the PM peak than in the AM peak across all sites. For each location, the adjusted AVO in the HOV lane increased from morning to afternoon by approximately 0.08 to 0.12 persons per vehicle. The same trend is also observed in the GP lanes. For example, at Fair Drive at I-75/I-85, the HOV lane increased from 1.65 to 1.71, and GP4 increased from 1.18 to 1.26. At 5th Street at I-75/I-85, the HOV lane decreased slightly from 1.74 to 1.59, but most GP lanes saw increases. These shifts likely reflect higher levels of carpooling, recreational travel, and express bus activity during the afternoon peak.

In summary, the following occupancy characteristics remain consistent with prior studies:

- The occupancy in GP lanes tends to increase from the inside lane toward the middle lanes and then decrease toward the outside lane, while the exact pattern varies by site. The highest occupancy can occur in the outermost lane, while in others, the peak appears in a middle lane or remains relatively flat across all GP lanes.
- Managed lanes continue to support significantly higher vehicle occupancy than adjacent GP lanes.
- PM peaks have higher occupancies than AM peaks.
- Express bus substitution increases the average occupancy, despite the small fleet volume.

In comparison with previous studies, several notable differences were observed:

- First, the HOV lanes in the 2024 corridors consistently exhibited higher occupancy than the Express Lanes studied in the 2018-2020 period outside the I-285 Perimeter, where adjusted AVOs were generally below 1.50 persons per vehicle (Guensler, et al.

2021a). However, these values remain below the pre-HOT conversion levels observed at Center Way on I-85, where AVO of the HOV lane exceeded 2.00 persons per vehicle (Guensler, et al. 2013a).

- Second, GP lanes in this study also demonstrated slightly higher occupancy than in prior studies, particularly during the PM peak at Fair Drive at I-75/I-85. These changes may reflect a variety of contextual factors, including different land use characteristics, user demographics, and fleet compositions within the I-285 Perimeter (e.g., smaller fractions of heavy-duty trucks), as well as differences in facility type (i.e., HOV vs. HOT/reversible lanes and tolling options). The proximity of Fair Drive to Hartsfield-Jackson International Airport may also contribute to higher vehicle occupancy observed at this location during evening periods.

Table 23 – Observed Occupancy Fraction and AVO by Lane,
Moores Mill Road at I-75, AM Peak (7:30-10:30AM)

Occupancy	MRM_ML1	MRM_GP2	MRM_GP3	MRM_GP4	MRM_GP5
1	55.9%	87.3%	83.3%	84.9%	90.4%
2	40.1%	11.6%	15.4%	14.0%	9.0%
3	1.8%	0.9%	1.0%	0.7%	0.4%
4	0.2%	0.1%	0.1%	0.2%	0.0%
4+	2.0%	0.1%	0.2%	0.1%	0.2%
AVO	1.51	1.14	1.18	1.17	1.10
Adjusted AVO	1.56	1.14	1.18	1.17	1.10

Table 24 – Observed Occupancy Fraction and AVO by Lane,
North Druid Hills Road at I-85, AM Peak (7:30-10:30AM)

Occupancy	NDH_ML1	NDH_GP2	NDH_GP3	NDH_GP4	NDH_GP5	NDH_GP6
1	58.5%	88.5%	85.2%	81.6%	82.7%	81.6%
2	37.7%	10.9%	13.7%	16.8%	15.5%	16.6%
3	2.0%	0.4%	0.7%	1.2%	1.3%	1.3%
4	0.3%	0.0%	0.1%	0.2%	0.3%	0.4%
4+	1.5%	0.2%	0.4%	0.1%	0.2%	0.1%
AVO	1.48	1.12	1.17	1.20	1.20	1.21
Adjusted AVO	1.59	1.12	1.17	1.20	1.20	1.21

Table 25 – Observed Occupancy Fraction and AVO by Lane,
Fair Drive at I-75/I-85, AM Peak (7:30-10:30 AM)

Occupancy	FRD_ML1	FRD_GP2	FRD_GP3	FRD_GP4	FRD_GP5	FRD_GP6
1	46.0%	88.0%	89.0%	84.4%	86.5%	85.6%
2	50.8%	11.4%	10.3%	14.4%	12.5%	13.3%
3	2.2%	0.5%	0.3%	0.7%	0.4%	0.7%
4	0.1%	0.1%	0.2%	0.0%	0.3%	0.2%
4+	0.9%	0.1%	0.2%	0.4%	0.4%	0.2%
AVO	1.59	1.13	1.12	1.18	1.15	1.16
Adjusted AVO	1.65	1.13	1.12	1.18	1.15	1.16

Table 26 – Observed Occupancy Fraction and AVO by Lane, 5th Street at I-75/I-85, AM Peak (7:30-10:30 AM)

Occupancy	5ST_ML1	5ST_GP2	5ST_GP3	5ST_GP4	5ST_GP5	5ST_GP6
1	40.9%	88.9%	86.3%	84.0%	87.2%	91.1%
2	53.3%	10.8%	13.1%	15.1%	11.7%	8.2%
3	1.2%	0.2%	0.4%	0.6%	0.5%	0.2%
4	0.3%	0.0%	0.1%	0.2%	0.2%	0.2%
4+	4.3%	0.1%	0.2%	0.2%	0.4%	0.3%
AVO	1.72	1.11	1.15	1.17	1.15	1.10
Adjusted AVO	1.74	1.11	1.15	1.17	1.15	1.10

Table 27 – Observed Occupancy Fraction and AVO by Lane, Moores Mill Road at I-75, PM Peak (3:30-6:30 PM)

Occupancy	MRM_ML1	MRM_GP2	MRM_GP3	MRM_GP4	MRM_GP5
1	54.0%	89.1%	86.9%	89.8%	89.7%
2	39.7%	9.8%	11.8%	9.2%	9.2%
3	2.8%	0.8%	0.8%	0.4%	0.7%
4	0.8%	0.1%	0.3%	0.3%	0.2%
4+	2.7%	0.2%	0.2%	0.3%	0.2%
AVO	1.57	1.12	1.15	1.12	1.12
Adjusted AVO	1.67	1.12	1.15	1.12	1.12

Table 28 – Observed Occupancy Fraction and AVO by Lane, North Druid Hills Road at I-85, PM Peak (3:30-6:30 PM)

Occupancy	NDH_ML1	NDH_GP2	NDH_GP3	NDH_GP4	NDH_GP5	NDH_GP6
1	52.5%	83.2%	83.7%	81.4%	81.4%	84.9%
2	42.1%	15.2%	14.7%	17.0%	16.2%	13.8%
3	2.0%	0.7%	0.9%	1.1%	1.5%	0.8%
4	0.4%	0.2%	0.2%	0.1%	0.5%	0.2%
4+	3.1%	0.6%	0.4%	0.4%	0.4%	0.2%
AVO	1.58	1.19	1.19	1.21	1.22	1.17
Adjusted AVO	1.70	1.19	1.19	1.21	1.22	1.17

Table 29 – Observed Occupancy Fraction and AVO by Lane, Fair Drive at I-75/I-85, PM Peak (3:30-6:30 PM)

Occupancy	FRD_ML1	FRD_GP2	FRD_GP3	FRD_GP4	FRD_GP5	FRD_GP6
1	47.3%	85.2%	81.3%	78.5%	76.1%	76.5%
2	45.5%	12.9%	16.8%	18.5%	20.2%	19.8%
3	3.2%	0.9%	1.2%	2.0%	2.2%	2.3%
4	1.7%	0.3%	0.3%	0.4%	0.7%	0.6%
4+	2.3%	0.7%	0.3%	0.6%	0.8%	0.8%
AVO	1.65	1.18	1.21	1.26	1.29	1.29
Adjusted AVO	1.71	1.18	1.21	1.26	1.29	1.29

Table 30 – Observed Occupancy Fraction and AVO by Lane, 5th Street at I-75/I-85, PM Peak (3:30-6:30 PM)

Occupancy	5ST_ML1	5ST_GP2	5ST_GP3	5ST_GP4	5ST_GP5	5ST_GP6
1	55.4%	88.8%	86.8%	81.6%	82.9%	85.8%
2	41.1%	10.5%	12.7%	16.7%	15.7%	13.0%
3	1.5%	0.4%	0.3%	1.1%	0.8%	1.0%
4	0.5%	0.2%	0.2%	0.3%	0.2%	0.2%
4+	1.5%	0.1%	0.0%	0.2%	0.4%	0.1%
AVO	1.51	1.12	1.14	1.21	1.19	1.16
Adjusted AVO	1.59	1.12	1.14	1.21	1.19	1.16

8.2 Observed Occupancy Results by Vehicle Class, by Lane, and by Site

The research team further disaggregated occupancy observations by vehicle class, and the distributions of passenger car LDVs and SUVs (GP lanes only). Occupancy results by vehicle classes are shown in Figure 27 through Figure 40.

Across all study sites and time periods, SUVs were more likely than passenger cars to carry multiple occupants, particularly in GP lanes. During both AM and PM peaks, the share of HOV2+ trips was consistently higher among SUVs than passenger cars. For example, in the PM peak on GP lanes at Fair Drive at I-75/I-85, 21.7% of SUVs carried two occupants, compared to 15.5% of passenger cars (Figure 36). This reflects a difference from the 2018-2020 study, in which SUVs had consistently lower occupancy than passenger cars.

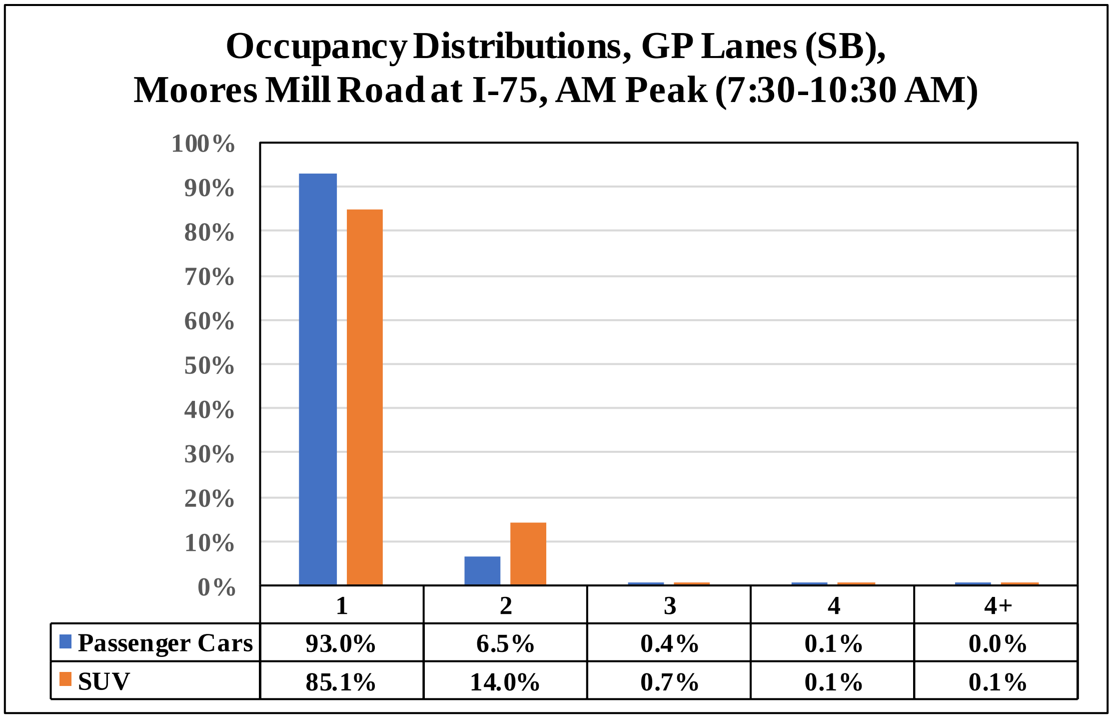
One reason for this shift might be related to fleet differences between the two study periods. In both studies (and in the 2010-2012 study), SUVs and pickup trucks were consistently grouped under the “SUV” category. The 2018-2020 study likely captured more pickup trucks (more common in the suburban corridors studied outside the I-285 Perimeter), which typically had lower occupancy than regular SUVs. In the current study (which focused on corridors within I-285), a greater proportion of regular SUVs (rather than pickups) were recorded. These vehicles are more commonly used for family and group travel, likely contributing to the observed increase in average SUV occupancy.

In examining differences between HOV and GP lanes, the gap between vehicle classes becomes more pronounced. In HOV lanes, SUVs carried a much higher proportion of two-person trips than passenger cars. For instance, in the HOV lane at 5th Street during the AM peak, 62.6% of SUVs had two occupants compared to just 45.4% of passenger cars (Figure 41). This trend held across all HOV lane observations.

One of the most notable findings was the relatively high occurrence of HOV3+ vehicles (three or more occupants) among SUVs and passenger cars in HOV lanes during the PM peak, particularly at North Druid Hills Road, Fair Drive, and 5th Street. These values exceed those observed at Moores Mill Road and also appear higher than observed on the 2018-2020 study corridors. While overall HOV3+ rates remain modest in absolute terms, the increase is consistent and meaningful across multiple sites.

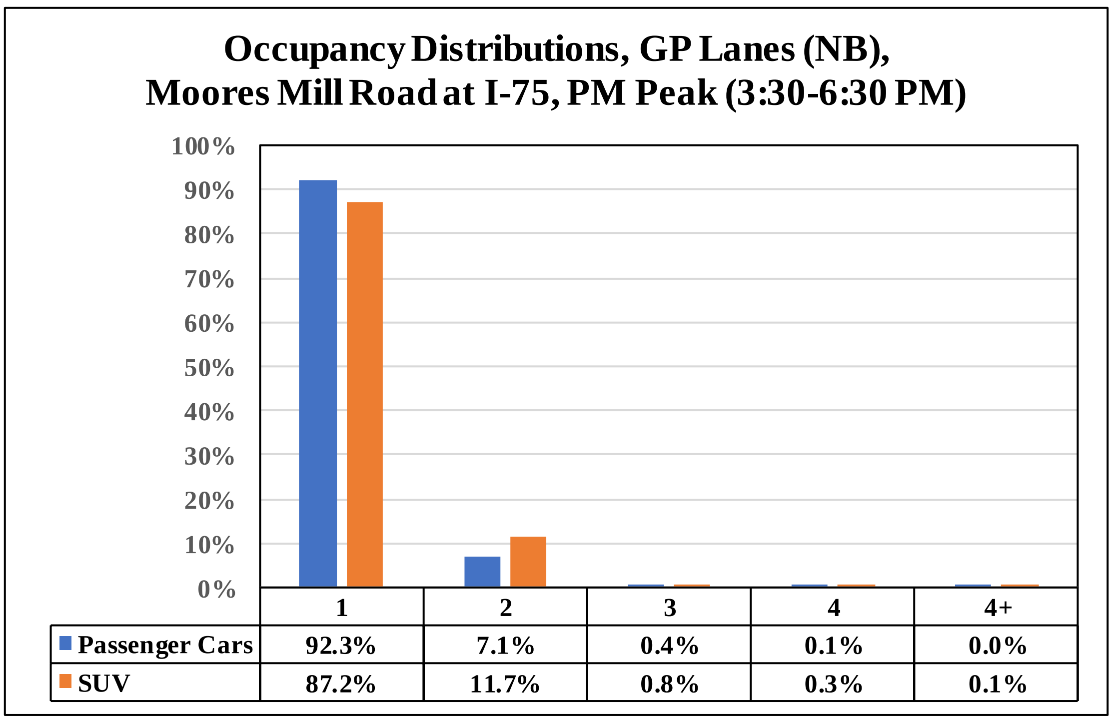
At North Druid Hills Road during the PM peak, field staff noted a recurring pattern of "waves" of HOV3+ vehicles, often composed of adults accompanied by school-age children. These short-duration bursts, during which several such vehicles passed within a few minutes, followed by intervals with none, suggest a potential influence of after-school pickup trips on HOV3+ occupancy. A deeper understanding of these behaviors would benefit from integrated demographic data (with access to the vehicle registration database to pair the recorded license plate numbers) and user travel surveys, which could help distinguish school-based group travel from other types of carpooling and support cross-site comparisons, particularly with I-75 corridor segments.

In summary, SUV occupancy characteristics in the 2024 study represent a departure from prior observations, with SUVs now often showing higher average occupancies and greater carpooling participation than passenger cars, particularly in HOV lanes. This shift may reflect regional vehicle mix differences, behavioral adaptation, or broader shifts in how SUVs (regular SUVs and pick-up trucks) are used within the I-285 Perimeter vs. outside the I-285 Perimeter where Express Lanes (HOT lanes and reversible lanes) provide a commute option.



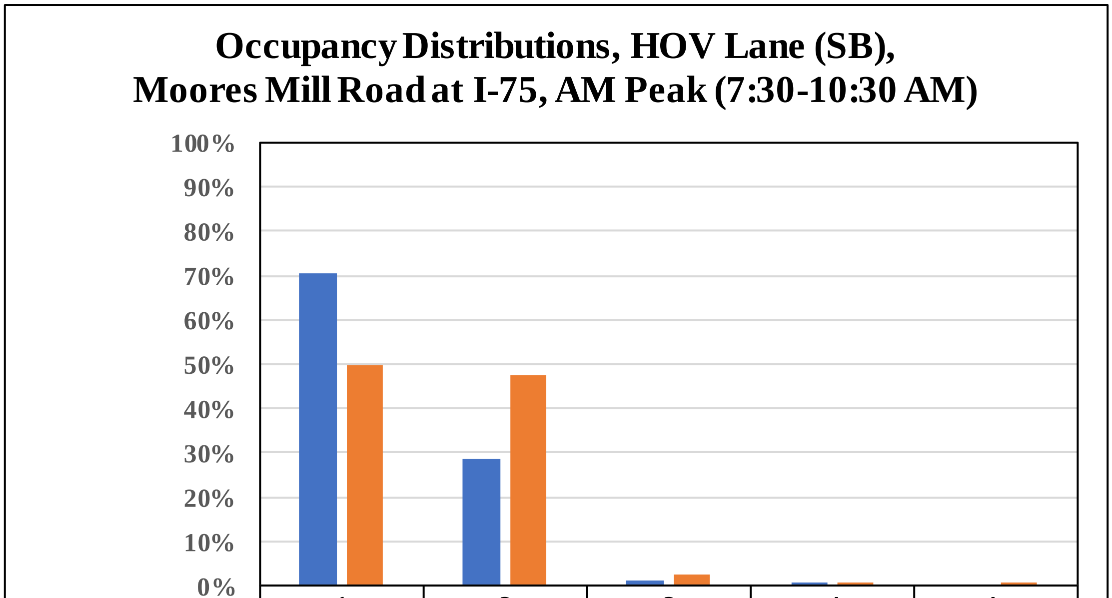
	1	2	3	4	4+
Passenger Cars	93.0%	6.5%	0.4%	0.1%	0.0%
SUV	85.1%	14.0%	0.7%	0.1%	0.1%

Figure 27 – Vehicle Occupancy Distributions, GP Lanes (SB), Moores Mill Road at I-75, AM Peak (7:30-10:30 AM)



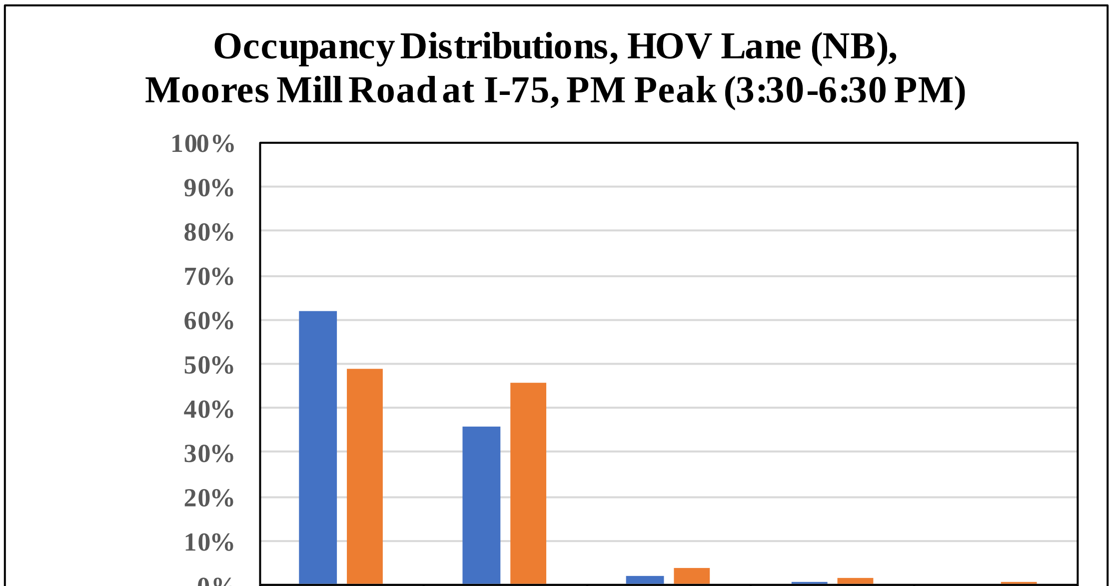
	1	2	3	4	4+
Passenger Cars	92.3%	7.1%	0.4%	0.1%	0.0%
SUV	87.2%	11.7%	0.8%	0.3%	0.1%

Figure 28 – Vehicle Occupancy Distributions, GP Lanes (NB), Moores Mill Road at I-75, PM Peak (3:30-6:30 PM)



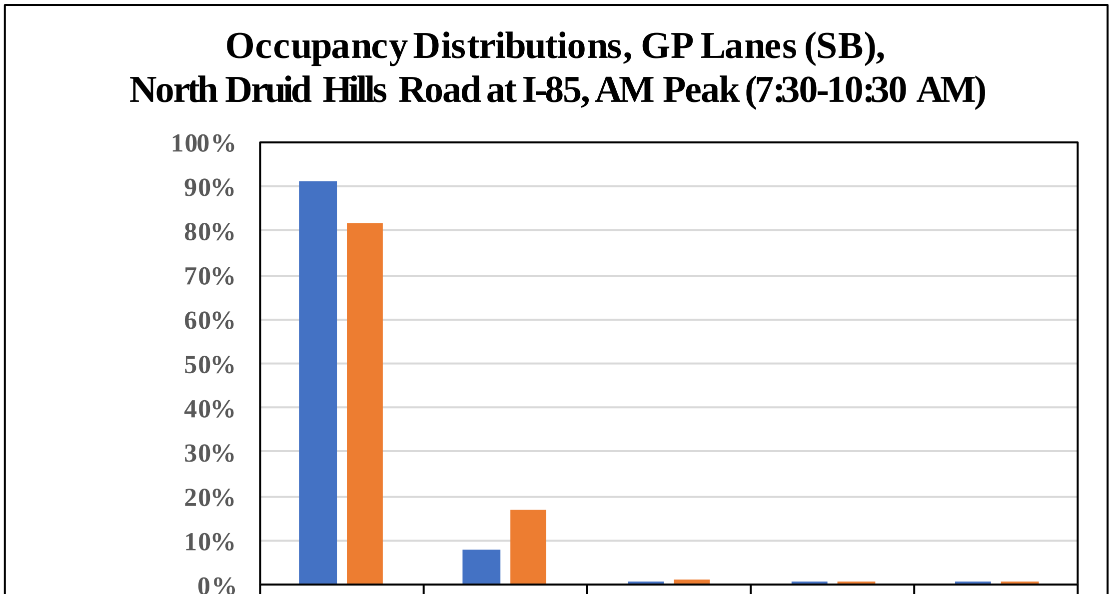
	1	2	3	4	4+
Passenger Cars	70.5%	28.5%	0.9%	0.1%	0.0%
SUV	49.7%	47.6%	2.4%	0.3%	0.1%

Figure 29 – Vehicle Occupancy Distributions, HOV Lane (SB), Moores Mill Road at I-75, AM Peak (7:30-10:30 AM)



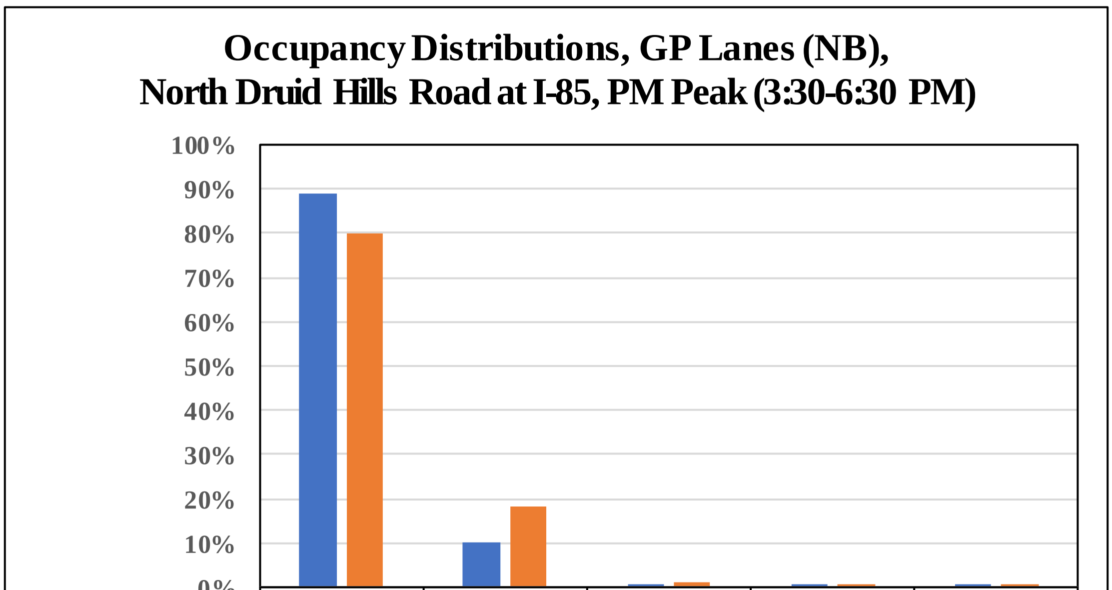
	1	2	3	4	4+
Passenger Cars	61.8%	35.8%	2.1%	0.3%	0.0%
SUV	48.8%	45.5%	3.9%	1.5%	0.2%

Figure 30 – Vehicle Occupancy Distributions, HOV Lane (NB), Moores Mill Road at I-75, PM Peak (3:30-6:30 PM)



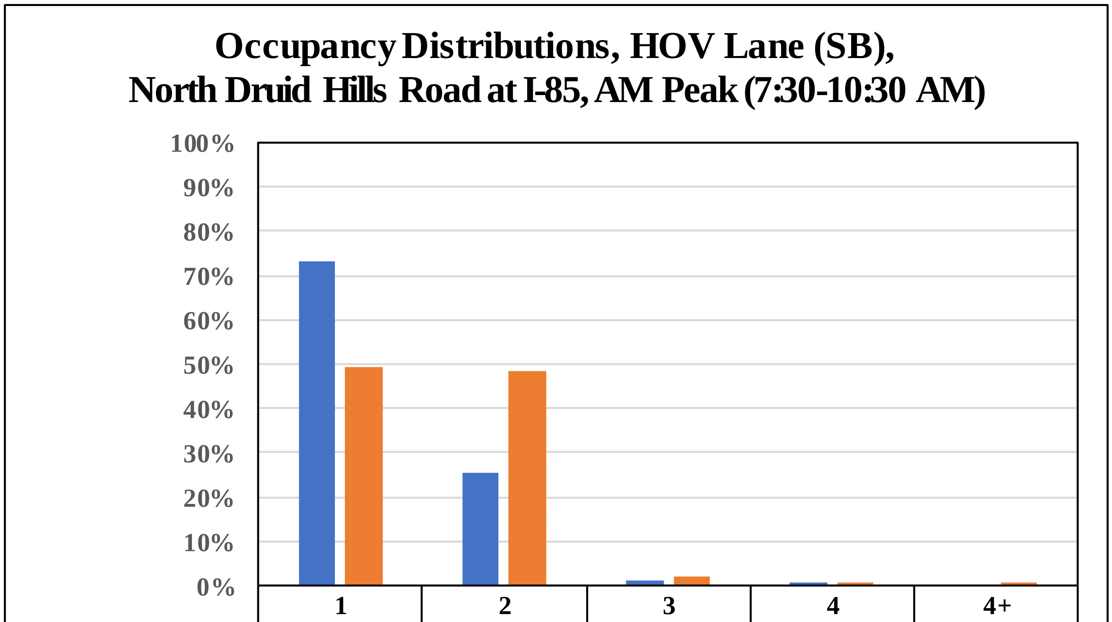
	1	2	3	4	4+
Passenger Cars	91.3%	8.1%	0.5%	0.1%	0.0%
SUV	81.6%	17.0%	0.9%	0.3%	0.2%

Figure 31 – Vehicle Occupancy Distributions, GP Lanes (SB), North Druid Hills Road at I-85, AM Peak (7:30-10:30 AM)



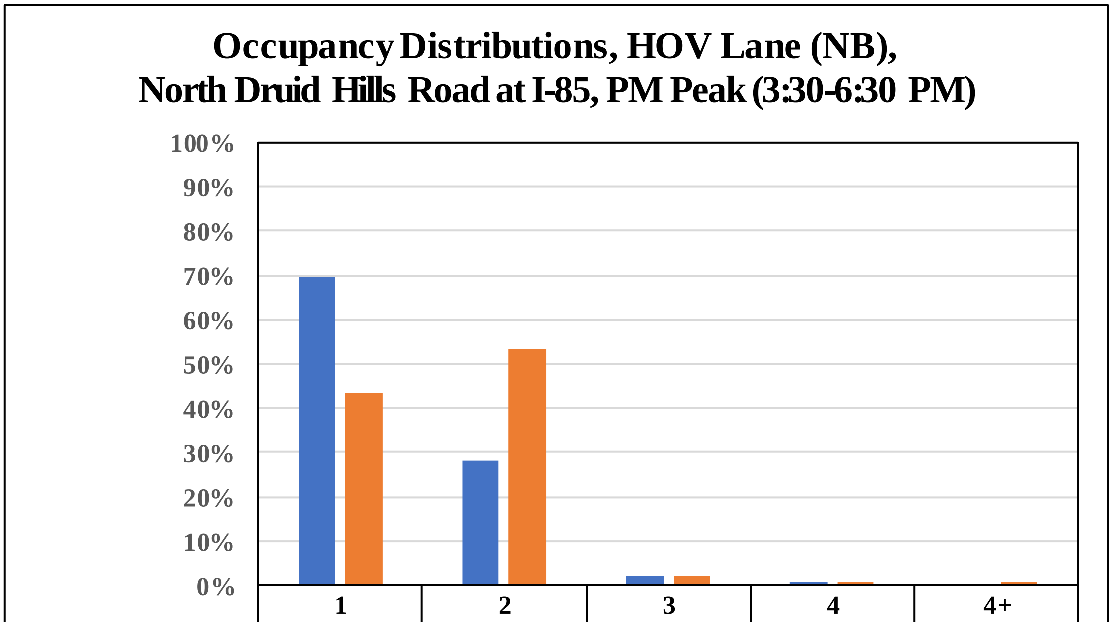
	1	2	3	4	4+
Passenger Cars	89.1%	10.0%	0.6%	0.2%	0.1%
SUV	79.9%	18.3%	1.0%	0.3%	0.5%

Figure 32 – Vehicle Occupancy Distributions, GP Lanes (NB), North Druid Hills Road at I-85, PM Peak (3:30-6:30 PM)



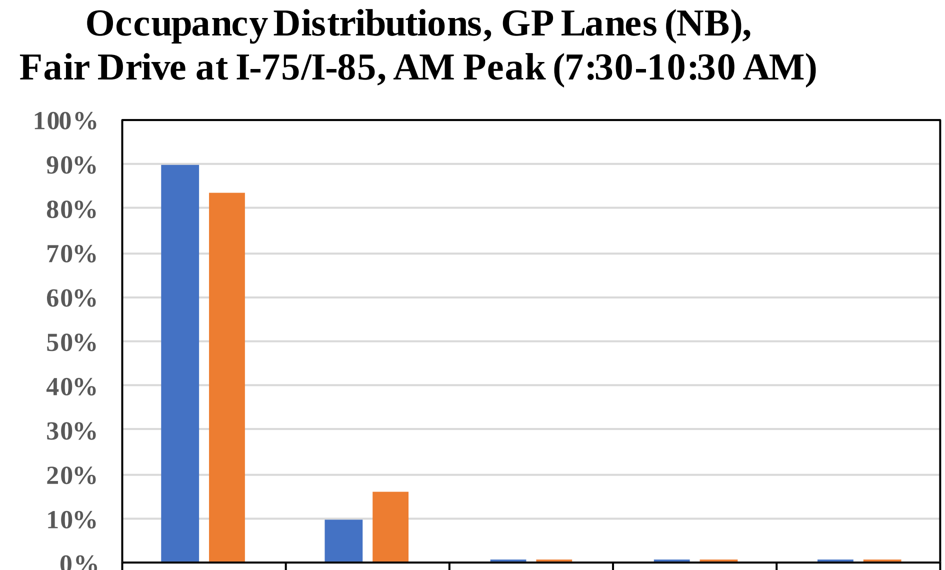
	1	2	3	4	4+
Passenger Cars	73.3%	25.3%	1.1%	0.3%	0.0%
SUV	49.1%	48.5%	1.9%	0.3%	0.1%

Figure 33 – Vehicle Occupancy Distributions, HOV Lane (SB), North Druid Hills Road at I-85, AM Peak (7:30-10:30 AM)



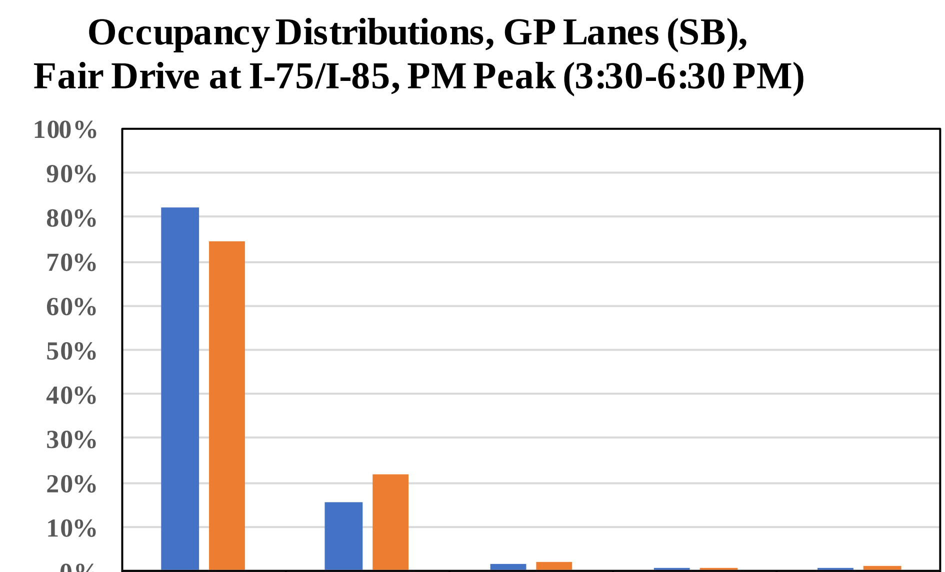
	1	2	3	4	4+
Passenger Cars	69.6%	28.1%	1.8%	0.4%	0.0%
SUV	43.5%	53.3%	2.2%	0.5%	0.6%

Figure 34 – Vehicle Occupancy Distributions, HOV Lane (NB), North Druid Hills Road at I-85, PM Peak (3:30-6:30 PM)



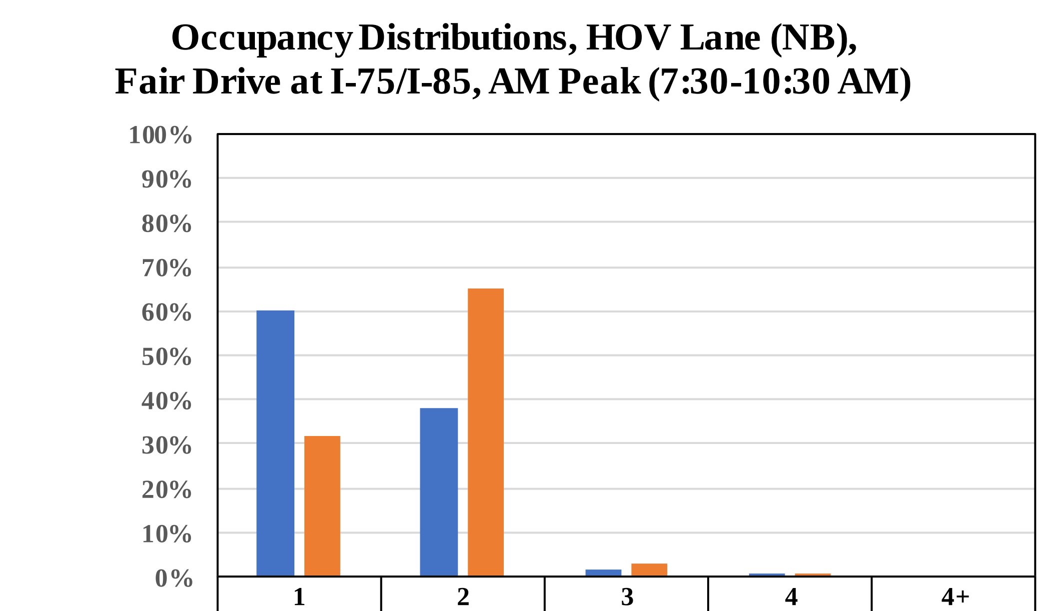
	1	2	3	4	4+
Passenger Cars	89.9%	9.6%	0.4%	0.1%	0.0%
SUV	83.4%	15.8%	0.6%	0.1%	0.1%

Figure 35 – Vehicle Occupancy Distributions, GP Lanes (NB), Fair Drive at I-75/I-85, AM Peak (7:30-10:30 AM)



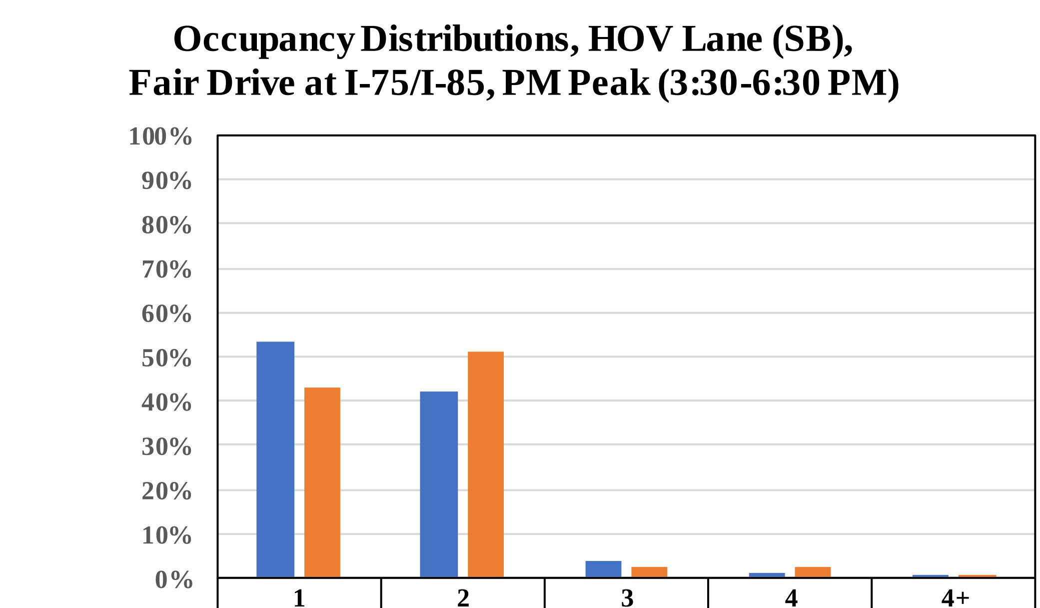
	1	2	3	4	4+
Passenger Cars	82.3%	15.5%	1.7%	0.3%	0.2%
SUV	74.8%	21.7%	1.9%	0.7%	0.9%

Figure 36 – Vehicle Occupancy Distributions, GP Lanes (SB), Fair Drive at I-75/I-85, PM Peak (3:30-6:30 PM)



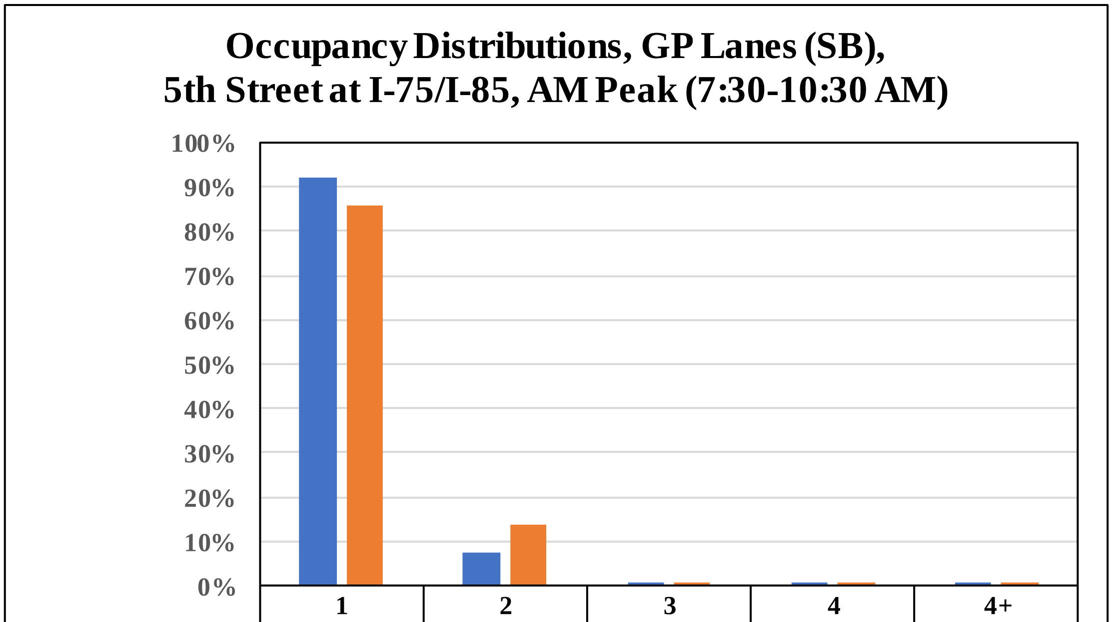
	1	2	3	4	4+
Passenger Cars	60.3%	37.9%	1.7%	0.1%	0.0%
SUV	31.9%	65.3%	2.8%	0.0%	0.0%

Figure 37 – Vehicle Occupancy Distributions, HOV Lane (NB), Fair Drive at I-75/I-85, AM Peak (7:30-10:30 AM)



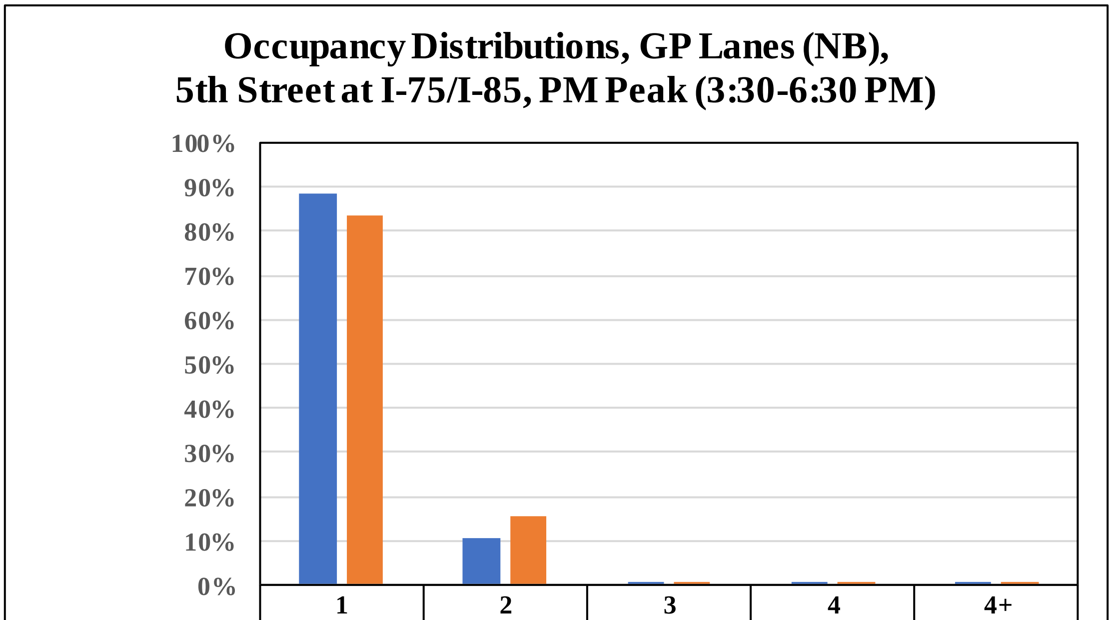
	1	2	3	4	4+
Passenger Cars	53.4%	42.0%	3.7%	0.9%	0.0%
SUV	43.2%	51.2%	2.5%	2.6%	0.6%

Figure 38 – Vehicle Occupancy Distributions, HOV Lane (SB), Fair Drive at I-75/I-85, PM Peak (3:30-6:30 PM)



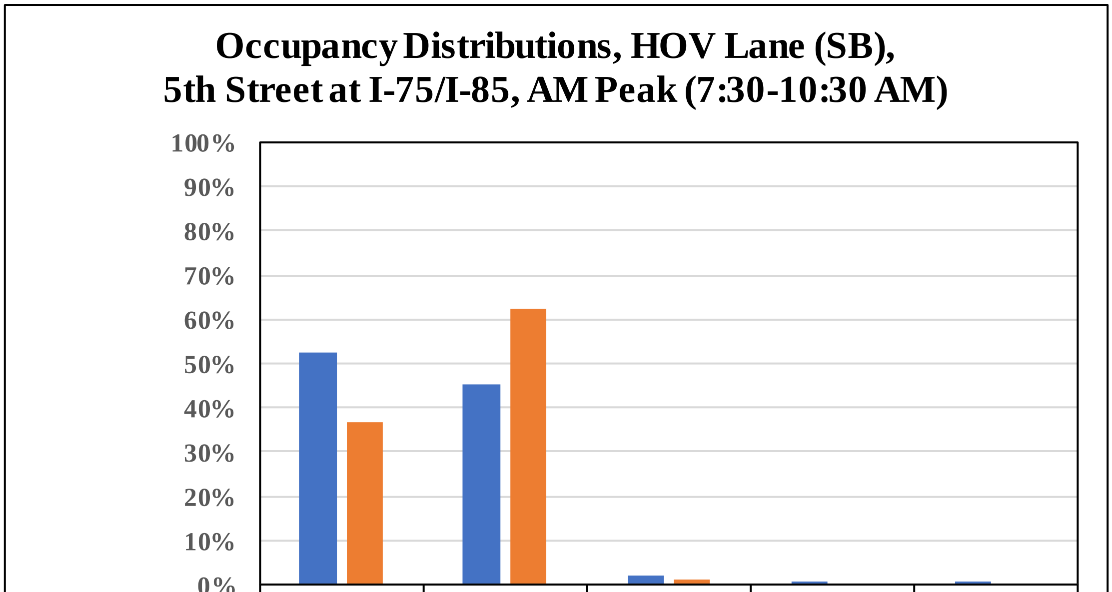
	1	2	3	4	4+
Passenger Cars	92.4%	7.2%	0.3%	0.1%	0.0%
SUV	85.9%	13.5%	0.4%	0.1%	0.1%

Figure 39 – Vehicle Occupancy Distributions, GP Lanes (SB), 5th Street at I-75/I-85, AM Peak (7:30-10:30 AM)



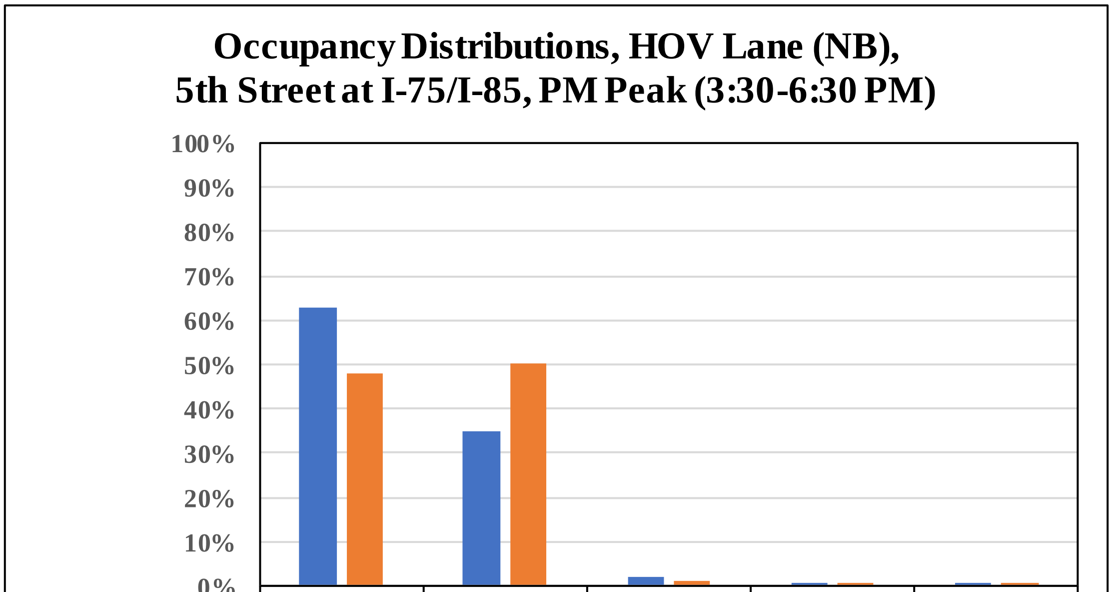
	1	2	3	4	4+
Passenger Cars	88.5%	10.5%	0.7%	0.2%	0.1%
SUV	83.4%	15.7%	0.6%	0.2%	0.1%

Figure 40 – Vehicle Occupancy Distributions, GP Lanes (NB), 5th Street at I-75/I-85, PM Peak (3:30-6:30 PM)



	1	2	3	4	4+
Passenger Cars	52.3%	45.4%	2.0%	0.1%	0.1%
SUV	36.5%	62.6%	0.9%	0.0%	0.0%

Figure 41 – Vehicle Occupancy Distributions, HOV Lane (SB), 5th Street at I-75/I-85, AM Peak (7:30-10:30 AM)



	1	2	3	4	4+
Passenger Cars	63.0%	34.9%	1.8%	0.3%	0.0%
SUV	47.9%	50.1%	1.1%	0.7%	0.1%

Figure 42 – Vehicle Occupancy Distributions, HOV Lane (NB), 5th Street at I-75/I-85, PM Peak (3:30-6:30 PM)

9 Person and Vehicle Throughput Results

Corridor vehicle and person throughput are assessed at all data collection sites. Vehicle throughput by vehicle class (light duty vehicles, SUVs, small HDVs, large HDVs, et al.) was obtained using video-based machine vision assessment (described in Chapter 4). The reported traffic volume profiles of 7:30 AM to 10:30 AM (morning peak), and of 3:30 PM to 6:30 PM (evening peak), which covered Tuesdays, Wednesdays and Thursdays, were processed on an hourly basis as input to throughput assessment.

Person throughput is a function of traffic flow coupled with observed vehicle occupancy, as outlined in previous chapters. The lane-by-lane volumes by vehicle class were integrated with the occupancy observations after QA/QC, and person throughput for each vehicle class was calculated by multiplying the vehicle throughput with its corresponding average vehicle occupancy. Vehicle and person throughput (unsubstituted) by lane, by lane type (GP lanes vs. managed lane), and of the corridor (all lanes) can be calculated by summing up all vehicle classes accordingly.

The substitution of express bus passengers was included in these analyses (presented as separate categories with ordinary SOV, HOV2, and HOV3+), following the methodologies described in Chapter 7 (express buses). The express bus vehicle throughput (scheduled Xpress, CobbLinc, and Ride Gwinnett buses) were assigned to the HOV lane in substituting actual vehicle occupancy for HOV '4+' buses. For each express bus substituted, 4.5 persons were removed from the person throughput of that lane, and the corresponding number of persons (average vehicle occupancy) was added to the person throughput. The final vehicle and person throughput for each site (corridor) were obtained by aggregating the throughput results. Person throughput calculation examples (occupancy by SOV, HOV2, HOV3, HOV4, and HOV4+ and volumes by vehicle class) are provided in Appendix B, and the full dataset can be found in the companion Microsoft® Excel spreadsheet.

The percentages presented in the tables in this Chapter are rounded to one decimal place, and vehicle and person throughput is rounded to integer values. No further modification was made to these numbers (i.e., no revision was made for rounded fractions to summed to 100.0%) so that the tables remain consistent with the companion Excel spreadsheet. Hence, if a column adds up to 99.9% or 100.1%, be reassured that the total is 100.0% in the spreadsheet.

9.1 Vehicle and Person Throughput by Site

Table 31 summarizes hourly vehicle and person throughput for each study site by lane type and AM/PM sessions. Across the AM peak period, 5th Street at I-75/I-85 stood out as the busiest corridor in terms of both vehicle and person throughput, reaching nearly 7,418 vehicles per hour and 9,598 persons per hour, while the other three sites exhibited similar throughput levels. Fair Drive at I-75/I-85, while carrying fewer total vehicles (6,178 per hour), moved a comparable number of people (7,829 per hour), suggesting more efficient vehicle occupancy, which is consistent with the findings in Chapter 8.

In the PM peak, 5th Street again had the highest throughput, with 10,677 vehicles and 13,298 persons per hour, followed by North Druid Hills Road (7,584 vehicles per hour and 9,962 persons per hour), Fair Drive (7,090 vehicles per hour and 9,467 persons per hour), and lastly Moores Mill Road (6,589 vehicles per hour and 8,116 persons per hour) than the other sites. Across all sites, evening peak periods were generally busier than AM peaks (except for Moores Mill Road where both peak periods exhibited a similar level of throughput).

HOV lane utilization varied across corridors. The strongest HOV performance was consistently observed at 5th Street at I-75/I-85, which carried the largest number of HOV vehicles and passengers in both AM and PM peaks. HOV lane throughput at 5th Street reached 1,391 vehicles/lane/hour in the morning and 1,486 vehicles/lane/hour in the evening, equating to an average headway of approximately 2.5 seconds, which indicates strong and efficient usage of the midtown HOV facility during the commute hours. This was followed by North Druid Hills Road at I-85, Moores Mill Road at I-75, and lastly Fair Drive at I-75/I-85, which showed the lowest HOV lane throughput across both periods. Although Fair Drive's GP lanes exhibited higher-than-average occupancy, this did not translate into elevated HOV lane volumes. This suggests that many eligible carpoolers may have opted to remain in GP lanes, which could reflect preferences or limitations related to lane access, enforcement, or exit configuration relative to their trips.

Table 32 presents the overall average vehicle occupancy by site, by integrating machine vision vehicle counts and fleet composition. The results confirm several patterns observed throughout the analysis. At all sites except for 5th Street at I-75/I-85, occupancy increased during the PM peak relative to the AM peak. The highest occupancy overall was recorded at Fair Drive at I-75/I-85 during the PM peak (1.34 persons per vehicle), followed closely by North Druid Hills Road at I-85 (1.31). However, these patterns appear to arise from different sources. At North Druid Hills Road, the elevated occupancy is primarily driven by robust HOV lane utilization, while Fair Drive's high occupancy is concentrated in the GP lanes. This suggests that many carpooling vehicles either are choosing to remain in GP lanes, or are constrained to do so due to the roadway geometry near the I-75/I-85 interchange.

The slight decline in occupancy at 5th Street during the PM peak (1.25) compared to the AM (1.26) stands out as a unique trend among the four study sites. This may reflect Midtown's unique trip patterns, including a higher concentration of inbound morning work trips and more individualized outbound travel in the evening. The variation is also consistent with observations in Chapter 8 showing higher AM peak occupancy in the HOV lane at this location.

These results reinforce earlier findings that corridor performance is shaped not just by demand, but also by lane type usage patterns and modal distributions. While HOV lanes generally deliver higher average occupancies, their relative impact on person throughput depends on the willingness of carpoolers to use those lanes and the structural conditions that facilitate (or hinder) access, and the traffic conditions that affect both access to the lanes and re-entry into the GP lanes when approaching highway exits during heavy traffic.

Table 31 – Vehicle and Person Throughput per Hour by Site and Lane Type

AM/PM	Site/Corridor	Lane Type	Vehicle Throughput (Vehicles/hour)	Person Throughput (Persons/hour)
AM	Moores Mill Road at I-75	GP	5,715	6,565
AM	Moores Mill Road at I-75	HOV	1,000	1,584
AM	Moores Mill Road at I-75	All	6,716	8,149
AM	North Druid Hills Road at I-85	GP	5,531	6,727
AM	North Druid Hills Road at I-85	HOV	1,055	1,706
AM	North Druid Hills Road at I-85	All	6,585	8,434
AM	Fair Drive at I-75/I-85	GP	5,355	6,461
AM	Fair Drive at I-75/I-85	HOV	824	1,369
AM	Fair Drive at I-75/I-85	All	6,178	7,829
AM	5th Street at I-75/I-85	GP	8,588	10,074
AM	5th Street at I-75/I-85	HOV	1,391	2,451
AM	5th Street at I-75/I-85	All	9,978	12,526
PM	Moores Mill Road at I-75	GP	5,578	6,387
PM	Moores Mill Road at I-75	HOV	1,012	1,730
PM	Moores Mill Road at I-75	All	6,589	8,116
PM	North Druid Hills Road at I-85	GP	6,370	7,859
PM	North Druid Hills Road at I-85	HOV	1,214	2,102
PM	North Druid Hills Road at I-85	All	7,584	9,962
PM	Fair Drive at I-75/I-85	GP	6,210	7,928
PM	Fair Drive at I-75/I-85	HOV	880	1,540
PM	Fair Drive at I-75/I-85	All	7,090	9,467
PM	5th Street at I-75/I-85	GP	9,191	10,892
PM	5th Street at I-75/I-85	HOV	1,486	2,405
PM	5th Street at I-75/I-85	All	10,677	13,298

Note: Throughput in every cell is rounded to integers without further modification (i.e., the rounded HOV and GP values might not sum to the displayed values of ALL, but the total before rounding equals to the sum of these unrounded values).

Table 32 – Overall Vehicle Occupancy by Site

AM/PM	Site/Corridor	Overall Occupancy (Persons/vehicle)
AM	Moores Mill Road at I-75	1.21
AM	North Druid Hills Road at I-85	1.28
AM	Fair Drive at I-75/I-85	1.27
AM	5th Street at I-75/I-85	1.26
PM	Moores Mill Road at I-75	1.23
PM	North Druid Hills Road at I-85	1.31
PM	Fair Drive at I-75/I-85	1.34
PM	5th Street at I-75/I-85	1.25

9.2 Vehicle Throughput by Occupancy Mode

Table 33 through Table 40 summarize hourly vehicle throughput by occupancy mode at each study site for both AM and PM peak periods. The breakdown includes single-occupant vehicles (SOV), two-person carpools (HOV2), high-occupancy vehicles with three or more persons (HOV3+), and express bus modes (Xpress, CobbLinc, and Ride Gwinnett). Table 41 through

Table 48 further disaggregate these results by lane type (GP vs. HOV).

Across all sites and time periods, SOVs comprised the dominant share of vehicle throughput, typically ranging from 75.9% to 83.6%. Moores Mill Road at I-75 consistently exhibited the highest SOV share, reaching 83.6% in the PM peak. By contrast, North Druid Hills Road at I-85 and Fair Drive at I-75/I-85 showed relatively lower SOV shares and higher HOV2/HOV3+ proportions, particularly during the PM peak. All SOV percentages were lower compared to the results in 2019 (post opening of the Express Lane facilities), aligning with occupancy analysis findings indicating higher occupancies at 2024 study sites relative to 2018-2020.

Notably, Fair Drive in the PM peak had the highest share of HOV3+ vehicles in the entire dataset, with 3.2% of total vehicles carrying three or more passengers. Similarly, elevated HOV3+ activity was recorded at North Druid Hills Road at I-85 in the PM (2.1%). These findings align with the occupancy distributions discussed in Chapter 8, which highlighted an uptick in HOV3+ vehicles during the evening peak, especially among SUVs and family-style travel.

When disaggregated by lane type, several key insights emerge. SOVs remained the majority mode in both GP and HOV lanes, although their share was unsurprisingly higher in GP lanes, often exceeding 70%. In HOV lanes, HOV2 and HOV3+ combined accounted for approximately 6% to 8% of corridor traffic (depending on the site and peak hours). For example, at 5th Street during the AM peak (Table 47), the HOV lane carried slightly more HOV2 vehicles (741 vehicles/hour) than SOVs (568 vehicles/hour), plus 71 HOV3+ vehicles, making it one of the more balanced HOV facilities in terms of occupancy distribution.

A clear variability emerges in how carpools utilize HOV lanes. At 5th Street, a substantial portion of HOV2 and HOV3+ traffic occurs in the managed lane, whereas at Fair Drive, many of these high-occupancy vehicles remain in the GP lanes. This supports earlier conclusions from Chapters 8 and 9.1, where high GP lane occupancy at Fair Drive did not translate to high managed lane volume.

Table 33 – Vehicle Throughput per Hour by Occupancy Mode, Moores Mill Road at I-75, AM Peak (7:30-10:30 AM)

Mode	Vehicles per Hour	Mode %
SOV	5,483	81.6%
HOV2	1,132	16.9%
HOV3+	92	1.4%
Xpress	1	0.0%
CobbLinc	8	0.1%
Ride Gwinnett	0	0.0%
Total	6,716	100.0%

Table 34 – Vehicle Throughput per Hour by Occupancy Mode, Moores Mill Road at I-75, PM Peak (3:30-6:30 PM)

Mode	Vehicles per Hour	Mode %
SOV	5,506	83.6%
HOV2	959	14.6%
HOV3+	111	1.7%
Xpress	4	0.1%
CobbLinc	9	0.1%
Ride Gwinnett	0	0.0%
Total	6,589	100.0%

Table 35 – Vehicle Throughput per Hour by Occupancy Mode, North Druid Hills Road at I-85, AM Peak (7:30-10:30 AM)

Mode	Vehicles per Hour	Mode %
SOV	5,264	79.9%
HOV2	1,206	18.3%
HOV3+	106	1.6%
Xpress	3	0.0%
CobbLinc	0	0.0%
Ride Gwinnett	6	0.1%
Total	6,585	100.0%

Table 36 – Vehicle Throughput per Hour by Occupancy Mode, North Druid Hills Road at I-85, PM Peak (3:30-6:30 PM)

Mode	Vehicles per Hour	Mode %
SOV	5,916	78.0%
HOV2	1,495	19.7%
HOV3+	160	2.1%
Xpress	6	0.1%
CobbLinc	0	0.0%
Ride Gwinnett	7	0.1%
Total	7,584	100.0%

Table 37 – Vehicle Throughput per Hour by Occupancy Mode, Fair Drive at I-75/I-85, AM Peak (7:30-10:30 AM)

Mode	Vehicles per Hour	Mode %
SOV	5,023	81.3%
HOV2	1,078	17.5%
HOV3+	73	1.2%
Xpress	3	0.1%
CobbLinc	0	0.0%
Ride Gwinnett	0	0.0%
Total	6,178	100.0%

Table 38 – Vehicle Throughput per Hour by Occupancy Mode, Fair Drive at I-75/I-85, PM Peak (3:30-6:30 PM)

Mode	Vehicles per Hour	Mode %
SOV	5,379	75.9%
HOV2	1,477	20.8%
HOV3+	225	3.2%
Xpress	9	0.1%
CobbLinc	0	0.0%
Ride Gwinnett	0	0.0%
Total	7,090	100.0%

Table 39 – Vehicle Throughput per Hour by Occupancy Mode, 5th Street at I-75/I-85, AM Peak (7:30-10:30 AM)

Mode	Vehicles per Hour	Mode %
SOV	8,113	81.3%
HOV2	1,720	17.2%
HOV3+	135	1.3%
Xpress	4	0.0%
CobbLinc	1	0.0%
Ride Gwinnett	5	0.1%
Total	9,978	100.0%

Table 40 – Vehicle Throughput per Hour by Occupancy Mode, 5th Street at I-75/I-85, PM Peak (3:30-6:30 PM)

Mode	Vehicles per Hour	Mode %
SOV	8,671	81.2%
HOV2	1,850	17.3%
HOV3+	143	1.3%
Xpress	6	0.1%
CobbLinc	0	0.0%
Ride Gwinnett	7	0.1%
Total	10,677	100.0%

Table 41 – Vehicle Throughput per Hour by Occupancy Mode and by Lane Type, Moores Mill Road at I-75, AM Peak (7:30-10:30 AM)

Mode	Vehicles Per Hour	Mode %
SOV-GP	4,924	73.3%
HOV2-GP	731	10.9%
HOV3+-GP	60	0.9%
SOV-ML	559	8.3%
HOV2-ML	401	6.0%
HOV3+-ML	31	0.5%
Xpress	1	0.0%
CobbLinc	8	0.1%
Ride Gwinnett	0	0.0%
Total	6,716	100.0%

Table 42 – Vehicle Throughput per Hour by Occupancy Mode and Lane Type, Moores Mill Road at I-75, PM Peak (3:30-6:30 PM)

Mode	Vehicles Per Hour	Mode %
SOV-GP	4,959	75.3%
HOV2-GP	558	8.5%
HOV3+-GP	60	0.9%
SOV-ML	547	8.3%
HOV2-ML	401	6.1%
HOV3+-ML	51	0.8%
Xpress	4	0.1%
CobbLinc	9	0.1%
Ride Gwinnett	0	0.0%
Total	6,589	100.0%

Table 43 – Vehicle Throughput per Hour by Occupancy Mode and by Lane Type, North Druid Hills Road at I-85, AM Peak (7:30-10:30 AM)

Mode	Vehicles Per Hour	Mode %
SOV-GP	4,647	70.6%
HOV2-GP	809	12.3%
HOV3+-GP	75	1.1%
SOV-ML	617	9.4%
HOV2-ML	398	6.0%
HOV3+-ML	31	0.5%
Xpress	3	0.0%
CobbLinc	0	0.0%
Ride Gwinnett	6	0.1%
Total	6,585	100.0%

Table 44 – Vehicle Throughput per Hour by Occupancy Mode and Lane Type, North Druid Hills Road at I-85, PM Peak (3:30-6:30 PM)

Mode	Vehicles Per Hour	Mode %
SOV-GP	5,279	69.6%
HOV2-GP	984	13.0%
HOV3+-GP	107	1.4%
SOV-ML	637	8.4%
HOV2-ML	511	6.7%
HOV3+-ML	53	0.7%
Xpress	6	0.1%
CobbLinc	0	0.0%
Ride Gwinnett	7	0.1%
Total	7,584	100.0%

Table 45 – Vehicle Throughput per Hour by Occupancy Mode and by Lane Type, Fair Drive at I-75/I-85, AM Peak (7:30-10:30 AM)

Mode	Vehicles Per Hour	Mode %
SOV-GP	4,645	75.2%
HOV2-GP	660	10.7%
HOV3+-GP	50	0.8%
SOV-ML	379	6.1%
HOV2-ML	418	6.8%
HOV3+-ML	23	0.4%
Xpress	3	0.1%
CobbLinc	0	0.0%
Ride Gwinnett	0	0.0%
Total	6,178	100.0%

Table 46 – Vehicle Throughput per Hour by Occupancy Mode and Lane Type, Fair Drive at I-75/I-85, PM Peak (3:30-6:30 PM)

Mode	Vehicles Per Hour	Mode %
SOV-GP	4,963	70.0%
HOV2-GP	1,076	15.2%
HOV3+-GP	170	2.4%
SOV-ML	416	5.9%
HOV2-ML	400	5.6%
HOV3+-ML	55	0.8%
Xpress	9	0.1%
CobbLinc	0	0.0%
Ride Gwinnett	0	0.0%
Total	7,090	100.0%

Table 47 – Vehicle Throughput per Hour by Occupancy Mode and by Lane Type, 5th Street at I-75/I-85, AM Peak (7:30-10:30 AM)

Mode	Vehicles Per Hour	Mode %
SOV-GP	7,545	75.6%
HOV2-GP	979	9.8%
HOV3+-GP	64	0.6%
SOV-ML	568	5.7%
HOV2-ML	741	7.4%
HOV3+-ML	71	0.7%
Xpress	4	0.0%
CobbLinc	1	0.0%
Ride Gwinnett	5	0.1%
Total	9,978	100.0%

Table 48 – Vehicle Throughput per Hour by Occupancy Mode and Lane Type, 5th Street at I-75/I-85, PM Peak (3:30-6:30 PM)

Mode	Vehicles Per Hour	Mode %
SOV-GP	7,847	73.5%
HOV2-GP	1,240	11.6%
HOV3+-GP	104	1.0%
SOV-ML	824	7.7%
HOV2-ML	610	5.7%
HOV3+-ML	40	0.4%
Xpress	6	0.1%
CobbLinc	0	0.0%
Ride Gwinnett	7	0.1%
Total	10,677	100.0%

9.3 Person Throughput by Occupancy Mode

Table 49 through Table 64 present person throughput by occupancy mode and lane type for each study site and peak period. This includes single-occupant vehicle (SOV) passengers, two-person carpools (HOV2), high-occupancy vehicles with three or more persons (HOV3+), and riders on express bus services (Xpress, CobbLinc, Ride Gwinnett). The values reflect the total number of persons per hour carried by each mode across all lanes and are disaggregated further by lane facility type.

Across all sites and time periods, SOVs remain the largest contributor to person throughput, typically accounting for 53.0% to 67.8% of the total corridor person flow. However, their dominance is notably moderated in corridors with strong carpool and bus activity. Fair Drive, North Druid Hills Road, and 5th Street at I-75/I-85 consistently show higher shares of HOV2 and HOV3+ passenger movement, especially during the PM peak.

As documented in earlier sections, the PM peak generally yields higher person throughput than the AM peak at all sites. However, the modal composition shifts during this period are especially informative. For example, while Moores Mill Road retains a high SOV share in both peaks (67.3%–67.8%) (Table 49 and Table 50), the proportion of HOV3+ passengers increased significantly in the PM (from 3.4% in the morning to 6.2% in the afternoon).

For PM peaks, the influence of HOV3+ travel is particularly significant at North Druid Hills Road and Fair Drive. At Fair Drive during the PM peak, HOV3+ vehicles carried nearly 11% of all persons, making it the most carpool-dense site in the study (Table 54).

Across all corridors, GP lanes continued to carry the majority of person throughput, largely due to higher vehicle volumes and high SOV participation. However, HOV lanes made a disproportionate contribution to person movement. In contrast, Fair Drive, while exhibiting high occupancy in GP lanes, showed relatively modest person throughput in its HOV lane (although the occupancy of HOV lanes was still higher than their adjacent GP lanes, the gaps were not as significant as the rest of the sites). This pattern, consistent with findings in Chapter 9.1 and 9.2, underscores the apparent preference of eligible carpoolers to remain in general-purpose lanes at this location.

Table 49 – Person Throughput per Hour by Occupancy Mode, Moores Mill Road at I-75, AM Peak (7:30-10:30 AM)

Mode	Persons per Hour	Mode %
SOV	5,483	67.3%
HOV2	2,264	27.8%
HOV3+	274	3.4%
Xpress	11	0.1%
CobbLinc	118	1.4%
Ride Gwinnett	0	0.0%
Total	8,149	100.0%

Table 50 – Person Throughput per Hour by Occupancy Mode, Moores Mill Road at I-75, PM Peak (3:30-6:30 PM)

Mode	Persons per Hour	Mode %
SOV	5,506	67.8%
HOV2	1,918	23.6%
HOV3+	503	6.2%
Xpress	27	0.3%
CobbLinc	163	2.0%
Ride Gwinnett	0	0.0%
Total	8,116	100.0%

Table 51 – Person Throughput per Hour by Occupancy Mode, North Druid Hills Road at I-85, AM Peak (7:30-10:30 AM)

Mode	Persons per Hour	Mode %
SOV	5,264	62.4%
HOV2	2,413	28.6%
HOV3+	643	7.6%
Xpress	47	0.6%
CobbLinc	0	0.0%
Ride Gwinnett	67	0.8%
Total	8,434	100.0%

Table 52 – Person Throughput per Hour by Occupancy Mode, North Druid Hills Road at I-85, PM Peak (3:30-6:30 PM)

Mode	Persons per Hour	Mode %
SOV	5,916	59.4%
HOV2	2,990	30.0%
HOV3+	909	9.1%
Xpress	73	0.7%
CobbLinc	0	0.0%
Ride Gwinnett	74	0.7%
Total	9,962	100.0%

Table 53 – Person Throughput per Hour by Occupancy Mode, Fair Drive at I-75/I-85, AM Peak (7:30-10:30 AM)

Mode	Persons per Hour	Mode %
SOV	5,023	64.2%
HOV2	2,157	27.5%
HOV3+	605	7.7%
Xpress	44	0.6%
CobbLinc	0	0.0%
Ride Gwinnett	0	0.0%
Total	7,829	100.0%

Table 54 – Person Throughput per Hour by Occupancy Mode, Fair Drive at I-75/I-85, PM Peak (3:30-6:30 PM)

Mode	Persons per Hour	Mode %
SOV	5,379	56.8%
HOV2	2,954	31.2%
HOV3+	1,038	11.0%
Xpress	96	1.0%
CobbLinc	0	0.0%
Ride Gwinnett	0	0.0%
Total	9,467	100.0%

Table 55 – Person Throughput per Hour by Occupancy Mode, 5th Street at I-75/I-85, AM Peak (7:30-10:30 AM)

	Persons per Hour	Mode %
SOV	8,113	64.8%
HOV2	3,440	27.5%
HOV3+	848	6.8%
Xpress	57	0.5%
CobbLinc	5	0.0%
Ride Gwinnett	63	0.5%
Total	12,526	100.0%

Table 56 – Person Throughput per Hour by Occupancy Mode, 5th Street at I-75/I-85, PM Peak (3:30-6:30 PM)

Mode	Persons per Hour	Mode %
SOV	8,671	65.2%
HOV2	3,700	27.8%
HOV3+	799	6.0%
Xpress	57	0.4%
CobbLinc	0	0.0%
Ride Gwinnett	71	0.5%
Total	13,298	100.0%

Table 57 – Person Throughput per Hour by Occupancy Mode and Lane Type, Moores Mill Road at I-75, AM Peak (7:30-10:30 AM)

Mode	Persons per Hour	Mode %
SOV-GP	4,924	60.4%
HOV2-GP	1,462	17.9%
HOV3+-GP	180	2.2%
SOV-ML	559	6.9%
HOV2-ML	802	9.8%
HOV3+-ML	95	1.2%
Xpress	11	0.1%
CobbLinc	118	1.4%
Ride Gwinnett	0	0.0%
Total	8,149	100.0%

Table 58 – Person Throughput per Hour by Occupancy Mode and Lane Type, Moores Mill Road at I-75, PM Peak (3:30-6:30 PM)

Mode	Persons per Hour	Mode %
SOV-GP	4,959	61.1%
HOV2-GP	1,115	13.7%
HOV3+-GP	312	3.8%
SOV-ML	547	6.7%
HOV2-ML	803	9.9%
HOV3+-ML	191	2.4%
Xpress	27	0.3%
CobbLinc	163	2.0%
Ride Gwinnett	0	0.0%
Total	8,116	100.0%

Table 59 – Person Throughput per Hour by Occupancy Mode and Lane Type, North Druid Hills Road at I-85, AM Peak (7:30-10:30 AM)

Mode	Persons per Hour	Mode %
SOV-GP	4,647	55.1%
HOV2-GP	1,618	19.2%
HOV3+-GP	463	5.5%
SOV-ML	617	7.3%
HOV2-ML	795	9.4%
HOV3+-ML	181	2.1%
Xpress	47	0.6%
CobbLinc	0	0.0%
Ride Gwinnett	67	0.8%
Total	8,434	100.0%

Table 60 – Person Throughput per Hour by Occupancy Mode and Lane Type, North Druid Hills Road at I-85, PM Peak (3:30-6:30 PM)

Mode	Persons per Hour	Mode %
SOV-GP	5,279	53.0%
HOV2-GP	1,968	19.8%
HOV3+-GP	613	6.1%
SOV-ML	637	6.4%
HOV2-ML	1,022	10.3%
HOV3+-ML	296	3.0%
Xpress	73	0.7%
CobbLinc	0	0.0%
Ride Gwinnett	74	0.7%
Total	9,962	100.0%

Table 61 – Person Throughput per Hour by Occupancy Mode and Lane Type, Fair Drive at I-75/I-85, AM Peak (7:30-10:30 AM)

Mode	Persons per Hour	Mode %
SOV-GP	4,645	59.3%
HOV2-GP	1,321	16.9%
HOV3+-GP	495	6.3%
SOV-ML	379	4.8%
HOV2-ML	836	10.7%
HOV3+-ML	110	1.4%
Xpress	44	0.6%
CobbLinc	0	0.0%
Ride Gwinnett	0	0.0%
Total	7,829	100.0%

Table 62 – Person Throughput per Hour by Occupancy Mode and Lane Type, Fair Drive at I-75/I-85, PM Peak (3:30-6:30 PM)

Mode	Persons per Hour	Mode %
SOV-GP	4,963	52.4%
HOV2-GP	2,153	22.7%
HOV3+-GP	812	8.6%
SOV-ML	416	4.4%
HOV2-ML	801	8.5%
HOV3+-ML	227	2.4%
Xpress	96	1.0%
CobbLinc	0	0.0%
Ride Gwinnett	0	0.0%
Total	9,467	100.0%

Table 63 – Person Throughput per Hour by Occupancy Mode and Lane Type, 5th Street at I-75/I-85, AM Peak (7:30-10:30 AM)

Mode	Persons per Hour	Mode %
SOV-GP	7,545	60.2%
HOV2-GP	1,959	15.6%
HOV3+-GP	571	4.6%
SOV-ML	568	4.5%
HOV2-ML	1,481	11.8%
HOV3+-ML	277	2.2%
Xpress	57	0.5%
CobbLinc	5	0.0%
Ride Gwinnett	63	0.5%
Total	12,526	100.0%

Table 64 – Person Throughput per Hour by Occupancy Mode and Lane Type, 5th Street at I-75/I-85, PM Peak (3:30-6:30 PM)

Mode	Persons per Hour	Mode %
SOV-GP	7,847	59.0%
HOV2-GP	2,480	18.6%
HOV3+-GP	566	4.3%
SOV-ML	824	6.2%
HOV2-ML	1,220	9.2%
HOV3+-ML	233	1.8%
Xpress	57	0.4%
CobbLinc	0	0.0%
Ride Gwinnett	71	0.5%
Total	13,298	100.0%

9.4 Throughput Percentage by Occupancy Mode and by Lane Type

Table 65 and Table 66 present the proportional composition of vehicle and person throughput by occupancy mode and lane type for both AM and PM peak periods. As expected and consistent with earlier findings, SOVs dominate vehicle throughput in both GP and HOV lanes, particularly in the morning. However, in most corridors, SOVs accounted for less than 40% of HOV lane person throughput during peak periods, despite making up more than half of the vehicles in those lanes.

One of the most distinct findings of this study is the elevated contribution of HOV3+ vehicles to person throughput, particularly in HOV lanes and at the corridor level. Across all four study sites, HOV3+ modes account for 6.0%-11.3% of HOV lane person throughput in the AM and up to 14.7% in the PM peak, with corridor-level totals reaching 11.0% at Fair Drive and 9.1% at North Druid Hills Road during PM peaks. These figures contrast with the 2018-2020 study, in which HOV3+ vehicles were rare and contributed less than 5% of total person throughput in most corridors.

HOV2 vehicles also contributed a larger share of person throughput compared to the 2018-2020 study. Across the four study sites, HOV2 vehicles contributed between 27.5% and 28.6% of corridor person throughput in the AM peak, and between 23.6% and 31.2% in the PM peak. By comparison, the 2018–2020 study found the highest HOV2 contribution to be 19.0% (at Chastain Road at I-575).

In HOV lanes, HOV2 vehicles consistently emerged as the primary contributor to person throughput, often representing 45%-60% of the HOV person throughput. For example, at 5th Street during the PM peak, HOV2 vehicles accounted for 50.7% of managed lane person throughput, compared to 34.3% from SOVs and 9.7% from HOV3+. A similar pattern was observed at North Druid Hills Road and Fair Drive, where HOV2 made up nearly half of the person throughput in managed lanes.

The contribution of express bus services remains modest in terms of vehicle share but significant in terms of person throughput in select corridors. At Moores Mill Road and Fair Drive, for example, Xpress and CobbLinc buses together carried 6.3%–10.9% of HOV lane passengers in the PM peak.

Table 65 – Vehicle and Person Throughput by Occupancy Mode and by Lane Type, AM Peak (7:30-10:30 AM)

AM		% of Vehicle Throughput	% of Person Throughput	% of Vehicle Throughput	% of Person Throughput	% of Vehicle Throughput	% of Person Throughput
Data Collection Site	Mode	GP Lanes	GP Lanes	HOV Lane	HOV Lane	Corridor	Corridor
Moores Mill Road at I-75	SOV	86.2%	75.0%	55.9%	35.3%	81.6%	67.3%
Moores Mill Road at I-75	HOV2	12.8%	22.3%	40.1%	50.6%	16.9%	27.8%
Moores Mill Road at I-75	HOV3+	1.1%	2.7%	3.1%	6.0%	1.4%	3.4%
Moores Mill Road at I-75	Xpress	0.0%	0.0%	0.1%	0.7%	0.0%	0.1%
Moores Mill Road at I-75	CobbLinc	0.0%	0.0%	0.8%	7.4%	0.1%	1.4%
Moores Mill Road at I-75	Ride Gwinnett	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Moores Mill Road at I-75	Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

AM		% of Vehicle Throughput	% of Person Throughput	% of Vehicle Throughput	% of Person Throughput	% of Vehicle Throughput	% of Person Throughput
Data Collection Site	Mode	GP Lanes	GP Lanes	HOV Lane	HOV Lane	Corridor	Corridor
North Druid Hills Rd. at I-85	SOV	84.0%	69.1%	58.5%	36.2%	79.9%	62.4%
North Druid Hills Rd. at I-85	HOV2	14.6%	24.0%	37.7%	46.6%	18.3%	28.6%
North Druid Hills Rd. at I-85	HOV3+	1.4%	6.9%	2.9%	10.6%	1.6%	7.6%
North Druid Hills Rd. at I-85	Xpress	0.0%	0.0%	0.3%	2.8%	0.0%	0.6%
North Druid Hills Rd. at I-85	CobbLinc	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
North Druid Hills Rd. at I-85	Ride Gwinnett	0.0%	0.0%	0.6%	3.9%	0.1%	0.8%
North Druid Hills Rd. at I-85	Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

AM		% of Vehicle Throughput	% of Person Throughput	% of Vehicle Throughput	% of Person Throughput	% of Vehicle Throughput	% of Person Throughput
Data Collection Site	**Mode**	**GP Lanes**	**GP Lanes**	**HOV Lane**	**HOV Lane**	**Corridor**	**Corridor**
Fair Drive at I-75/I-85	**SOV**	**86.7%**	**71.9%**	**46.0%**	**27.7%**	**81.3%**	**64.2%**
Fair Drive at I-75/I-85	**HOV2**	**12.3%**	**20.4%**	**50.8%**	**61.1%**	**17.5%**	**27.5%**
Fair Drive at I-75/I-85	**HOV3+**	**0.9%**	**7.7%**	**2.8%**	**8.0%**	**1.2%**	**7.7%**
Fair Drive at I-75/I-85	**Xpress**	**0.0%**	**0.0%**	**0.4%**	**3.2%**	**0.1%**	**0.6%**
Fair Drive at I-75/I-85	**CobbLinc**	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**0.0%**
Fair Drive at I-75/I-85	**Ride Gwinnett**	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**0.0%**
Fair Drive at I-75/I-85	**Total**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

AM		% of Vehicle Throughput	% of Person Throughput	% of Vehicle Throughput	% of Person Throughput	% of Vehicle Throughput	% of Person Throughput
Data Collection Site	**Mode**	**GP Lanes**	**GP Lanes**	**HOV Lane**	**HOV Lane**	**Corridor**	**Corridor**
5th Street at I-75/I-85	**SOV**	**87.9%**	**74.9%**	**40.9%**	**23.2%**	**81.3%**	**64.8%**
5th Street at I-75/I-85	**HOV2**	**11.4%**	**19.4%**	**53.3%**	**60.4%**	**17.2%**	**27.5%**
5th Street at I-75/I-85	**HOV3+**	**0.7%**	**5.7%**	**5.1%**	**11.3%**	**1.3%**	**6.8%**
5th Street at I-75/I-85	**Xpress**	**0.0%**	**0.0%**	**0.3%**	**2.3%**	**0.0%**	**0.5%**
5th Street at I-75/I-85	**CobbLinc**	**0.0%**	**0.0%**	**0.1%**	**0.2%**	**0.0%**	**0.0%**
5th Street at I-75/I-85	**Ride Gwinnett**	**0.0%**	**0.0%**	**0.4%**	**2.6%**	**0.1%**	**0.5%**
5th Street at I-75/I-85	**Total**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Table 66 – Vehicle and Person Throughput by Occupancy Mode and by Lane Type, PM Peak (3:30-6:30 PM)

PM		% of Vehicle Throughput	% of Person Throughput	% of Vehicle Throughput	% of Person Throughput	% of Vehicle Throughput	% of Person Throughput
Data Collection Site	**Mode**	**GP Lanes**	**GP Lanes**	**HOV Lane**	**HOV Lane**	**Corridor**	**Corridor**
Moores Mill Road at I-75	SOV	88.9%	77.7%	54.0%	31.6%	83.6%	67.8%
Moores Mill Road at I-75	HOV2	10.0%	17.5%	39.7%	46.4%	14.6%	23.6%
Moores Mill Road at I-75	HOV3+	1.1%	4.9%	5.0%	11.0%	1.7%	6.2%
Moores Mill Road at I-75	Xpress	0.0%	0.0%	0.4%	1.5%	0.1%	0.3%
Moores Mill Road at I-75	CobbLinc	0.0%	0.0%	0.9%	9.4%	0.1%	2.0%
Moores Mill Road at I-75	Ride Gwinnett	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Moores Mill Road at I-75	Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

PM		% of Vehicle Throughput	% of Person Throughput	% of Vehicle Throughput	% of Person Throughput	% of Vehicle Throughput	% of Person Throughput
Data Collection Site	**Mode**	**GP Lanes**	**GP Lanes**	**HOV Lane**	**HOV Lane**	**Corridor**	**Corridor**
North Druid Hills Rd. at I-85	SOV	82.9%	67.2%	52.5%	30.3%	78.0%	59.4%
North Druid Hills Rd. at I-85	HOV2	15.4%	25.0%	42.1%	48.6%	19.7%	30.0%
North Druid Hills Rd. at I-85	HOV3+	1.7%	7.8%	4.4%	14.1%	2.1%	9.1%
North Druid Hills Rd. at I-85	Xpress	0.0%	0.0%	0.5%	3.5%	0.1%	0.7%
North Druid Hills Rd. at I-85	CobbLinc	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
North Druid Hills Rd. at I-85	Ride Gwinnett	0.0%	0.0%	0.6%	3.5%	0.1%	0.7%
North Druid Hills Rd. at I-85	Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

PM Data Collection Site	Mode	% of Vehicle Throughput GP Lanes	% of Person Throughput GP Lanes	% of Vehicle Throughput HOV Lane	% of Person Throughput HOV Lane	% of Vehicle Throughput Corridor	% of Person Throughput Corridor
Fair Drive at I-75/I-85	SOV	79.9%	62.6%	47.3%	27.0%	75.9%	56.8%
Fair Drive at I-75/I-85	HOV2	17.3%	27.2%	45.5%	52.0%	20.8%	31.2%
Fair Drive at I-75/I-85	HOV3+	2.7%	10.2%	6.2%	14.7%	3.2%	11.0%
Fair Drive at I-75/I-85	Xpress	0.0%	0.0%	1.0%	6.3%	0.1%	1.0%
Fair Drive at I-75/I-85	CobbLinc	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Fair Drive at I-75/I-85	Ride Gwinnett	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Fair Drive at I-75/I-85	Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

PM Data Collection Site	Mode	% of Vehicle Throughput GP Lanes	% of Person Throughput GP Lanes	% of Vehicle Throughput HOV Lane	% of Person Throughput HOV Lane	% of Vehicle Throughput Corridor	% of Person Throughput Corridor
5th Street at I-75/I-85	SOV	85.4%	72.0%	55.4%	34.3%	81.2%	65.2%
5th Street at I-75/I-85	HOV2	13.5%	22.8%	41.1%	50.7%	17.3%	27.8%
5th Street at I-75/I-85	HOV3+	1.1%	5.2%	2.7%	9.7%	1.3%	6.0%
5th Street at I-75/I-85	Xpress	0.0%	0.0%	0.4%	2.4%	0.1%	0.4%
5th Street at I-75/I-85	CobbLinc	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
5th Street at I-75/I-85	Ride Gwinnett	0.0%	0.0%	0.4%	3.0%	0.1%	0.5%
5th Street at I-75/I-85	Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

9.5 Carpool (HOV2 and HOV3+) Activity

Table 67 and Table 68 present carpool (HOV2 and HOV3+) mode shares by site, peak period, and lane type. Results show that carpool mode shares in the 2024 study are markedly higher than those observed in previous studies, both in terms of vehicle share and person throughput. In PM at North Druid Hills Road at I-85 and at Fair Drive at I-75/I-85, person throughput from carpools exceeds 40% of total corridor passengers (contrast to earlier findings where carpool contributions were consistently smaller than 25%). Even in the AM peak, all sites showed carpool person shares above 30%, with North Druid Hills Road reaching 37.6%.

Lane-level breakdowns further verify that carpool carry a disproportionate share of passengers, especially on HOV lanes. For example, carpooling vehicles on the HOV lane at 5th Street moved 65.7% of passengers with 44.6% of PM peak vehicles. A similar pattern also appears at other sites and during AM peak hours.

These findings indicate stronger carpool activity than any previously studied corridor, including those examined in the 2010-2012 and 2018-2020 studies. While earlier studies documented HOV2 and HOV3+ participation in the 10%-35% range of person throughput, the current results show that almost half of all passengers at certain sites are traveling in carpools. This increase is consistent with the occupancy patterns described in Chapters 8 and 9.3, particularly the observed growth in HOV3+ movement in the PM peak.

Table 67 – Carpool (HOV2 and HOV3+) Mode Percentages by Site

Site	AM Carpool Vehicle Throughput Mode %	AM Carpool Person Throughput Mode %	PM Carpool Vehicle Throughput Mode %	PM Carpool Person Throughput Mode %
Moores Mill Road at I-75	18.4%	32.7%	16.4%	32.2%
North Druid Hills Road at I-85	20.1%	37.6%	22.0%	40.6%
Fair Drive at I-75/I-85	18.7%	35.8%	24.1%	43.2%
5th Street at I-75/I-85	18.7%	35.2%	18.8%	34.8%

Table 68 – Throughput Mode Percentage of Carpool (HOV2 and HOV3+) by Site

Site	Lane Type	AM Carpool Vehicle Throughput Mode %	AM Carpool Person Throughput Mode %	PM Carpool Vehicle Throughput Mode %	PM Carpool Person Throughput Mode %
Moores Mill Road at I-75	GP	13.8%	25.0%	11.1%	22.3%
Moores Mill Road at I-75	ML	44.1%	64.7%	46.0%	68.4%
North Druid Hills Road at I-85	GP	16.0%	30.9%	17.1%	32.8%
North Druid Hills Road at I-85	ML	41.5%	63.8%	47.5%	69.7%
Fair Drive at I-75/I-85	GP	13.3%	28.1%	20.1%	37.4%
Fair Drive at I-75/I-85	ML	54.0%	72.3%	52.7%	73.0%
5th Street at I-75/I-85	GP	12.1%	25.1%	14.6%	28.0%
5th Street at I-75/I-85	ML	59.1%	76.8%	44.6%	65.7%

9.6 Express Bus Throughput

Table 69 summarizes the share of vehicle and person throughput attributed to express buses (Xpress, CobbLinc, and Ride Gwinnett). As in prior studies, express buses continue to represent a very small fraction of vehicle throughput (typically between 0.1% and 0.2% per corridor) yet contribute a disproportionately larger share of person throughput, ranging from 0.5% to 2.3% during the peak hours. The highest express bus person mode shares were observed at Moores Mill Road at I-75, reaching 2.34% of all persons during the evening peak, with similar, though slightly lower, values at North Druid Hills Road and Fair Drive.

The 2024 express bus shares are broadly similar to those seen in prior years, and they remain a critical component of managed lane strategy, particularly where they complement high carpool volumes in peak periods. As discussed in Chapter 7, express buses help stabilize occupancy and increase person throughput in corridors where vehicle capacity is constrained, or user demand is surging.

Looking ahead, express buses are likely to play an increasingly important role in person throughput, particularly as system-wide bus ridership continues to rebound and expand. Although these services already contribute considerably to corridor efficiency, there remains room to further strengthen their impact, either through operational improvements or through strategic incentives designed to boost ridership. This is especially pertinent for lower-ridership routes that operate alongside higher-ridership services within the same corridor (but consistently carry fewer passengers). Tailored interventions on such routes could help improve utilization, increase overall person throughput, and optimize the return on investment for express bus infrastructure.

Table 69 – Throughput Mode Percentage of Express Bus by Site (Combined Xpress, Ride Gwinnett, and CobbLinc)

Session	Site	Mode Share of Vehicle Throughput	Mode Share of Person Throughput
AM	Moores Mill Road at I-75	0.13%	1.58%
AM	North Druid Hills Road at I-85	0.16%	1.35%
AM	Fair Drive at I-75/I-85	0.06%	0.56%
AM	5th Street at I-75/I-85	0.14%	1.00%
PM	Moores Mill Road at I-75	0.20%	2.34%
PM	North Druid Hills Road at I-85	0.20%	1.48%
PM	Fair Drive at I-75/I-85	0.15%	1.02%
PM	5th Street at I-75/I-85	0.15%	0.96%

9.7 Discussion and Caveats

Unlike prior studies which relied on GDOT NaviGAtor data, this study utilized machine-vision-derived volume data as described in Chapter 4. These data offered several advantages: they were directly validated through co-recorded field videos and were temporally aligned with the occupancy observation sessions. This ensured consistency between vehicle classification, occupancy assignment, and throughput assessment. However, these machine vision profiles only covered the data collection dates and did not capture broader temporal variability (seasonal or day-to-day). As a result, the findings provide a reliable snapshot of typical weekday peak conditions but may not capture variability related to weather and other traffic incidents. Broader integration with probe data, or longer-duration video deployments, could help enhance representativeness in future studies.

The QA/QC analysis using regression tree modeling found no observable collector bias in the occupancy dataset. In this study, a smaller, more experienced group of data collectors was deployed, supported by structured team management protocols. These included role specialization, performance-based progression, and improved communication between field and supervisory teams. As a result, the data collected for this cycle may be considered among the more internally consistent of SRTA occupancy study to date, and the 2024 dataset may serve as a strong baseline for future comparison.

The results verify that HOV lanes carry more passengers per vehicle than GP lanes, contributing disproportionately to person throughput (even when vehicle throughput is lower). For example, at sites like Fair Drive at I-75/I-85, the GP lanes exhibited relatively high occupancy compared to other sites, but the HOV lane still moved a greater number of people per vehicle. This suggests that even in corridors where carpoolers opted to remain in GP lanes, the presence of a managed lane likely have encouraged carpool formation and helped maintain system-wide person throughput efficiency.

Without the managed lanes, these carpooling behaviors might not have occurred at such extent.

The study observed a notably higher share of HOV3+ vehicles and person throughput than in prior SRTA studies. At several sites, HOV3+ accounted for more than 20% of person throughput. Field teams at North Druid Hills Road at I-85 noted that clusters of HOV3+ vehicles often appeared in short waves during the PM peak, likely representing after-school pickup travel involving families with children. These observations suggested a shift in how carpooling was being utilized in the corridor, with non-work trips playing a larger role. The study team has field-recorded video profiles that could support additional investigation of these patterns, pending data access to the vehicle registration database to link these with demographic information.

10 Conclusions

This study was conducted to evaluate vehicle occupancy and person throughput performance across four HOV corridors located within the I-285 Perimeter in Atlanta: 1) I-75 North HOV Lanes (at Moores Mill Road NW at I-75), 2) I-85 North HOV Lanes (North Druid Hills Road at I-85), 3) I-75/I-85 Connector HOV Lanes (Fair Drive at I-75/I-85), and 4) I-75/I-85 South HOV Lanes (5th Street NW at I-75/I-85). Building on the methodologies established in previous SRTA studies, the 2024 effort assessed vehicle occupancy, vehicle throughput, and person throughput with field data collection consistency augmented with machine vision (MV) technologies for vehicle throughput analysis.

Field data collection included five observation sessions per site across AM and PM peak periods (7:30-10:30 AM and 3:30-6:30 PM). Vehicle occupancy was recorded visually by trained observers using a standardized tablet interface, supported by elevated positioning and enhanced QA/QC protocols. In parallel, video footage was recorded from overpass and from side of the roadway to enable independent vehicle classification using deep learning-based machine vision models. These MV outputs were used to derive vehicle volume and fleet composition, which were then integrated with occupancy observations to assess hourly vehicle and person throughput by site, lane, and occupancy mode.

To ensure data validity, a regression tree analysis was conducted to identify potential observer bias. No collector effects were identified, reflecting the effectiveness of an optimized deployment strategy that prioritized a smaller, experienced field team and structured management protocols. Express bus person throughput was substituted using operator-reported ridership and scheduled pass-throughs during the observation periods.

The key findings of the study are summarized as follow.

1) Alternative Fuel Vehicles (AFVs)

> The MV-identification of leaf icons indicated that AFV plate shares were highest in HOV lanes across all sites, reaching up to 11.5% at North Druid Hills Road at I-85 in the AM peak. In contrast, general-purpose lanes typically exhibited much lower AFV rates, ranging from 0.4% to 1.4%, and Fair Drive at I-75/I-85 showed the lowest overall AFV adoption among the four corridors. The total observed AFV plate share across all 1.1 million identified plates was 1.91%, with Georgia-issued plates comprising 83.9% of the dataset.
>
> AFV plate identification using the leaf icon clearly underrepresents actual EV adoption and use on these corridors, as it is likely that only 30% to 40% of registered AFVs in Georgia carry the green leaf plate. The use of these plates also appears to vary by location, time of day, and vehicle make and model. Without access to the 2025 vehicle registration database, reliance on the plate icon alone will likely identify fewer than 50% of the electric vehicles using the corridor and

will be unrepresentative over space (i.e., distribution of households that choose to pay for the green leaf plates and variability in make/model purchase decisions, given the noted differences in plate uptake across makes/models).

2) Vehicle Occupancy

HOV lanes exhibited consistently higher average vehicle occupancy (AVO) than adjacent general-purpose lanes, with adjusted AVOs ranging from 1.56 to 1.74 persons per vehicle in the AM peak and 1.59 to 1.71 persons per vehicle in the PM peak.

General-purpose lanes at Fair Drive at I-75/I-85 and North Druid Hills Road at I-85 recorded relatively high occupancy compared to the sites in prior studies, in some cases exceeding 1.30 persons per vehicle, largely due to elevated HOV2 and HOV3+ activity in the PM peak.

Within each lane type, SUVs generally carried more passengers than LDVs, especially in GP lanes, reversing the pattern observed in the 2018-2020 study. This difference is likely due to the current study capturing a larger proportion of regular SUVs used for family or group trips within the I-285 Perimeter, rather than the higher share of pickups (typically lower occupancy) observed in the previous suburban-focused study.

Lane type had a notably stronger influence than vehicle type on vehicle occupancy in the current 2024 study (focused on HOV lanes within the I-285 Perimeter), compared to the 2018-2020 study (which included reversible and HOT lanes outside the Perimeter).

Across sites, vehicle occupancy was generally higher in the PM than in the AM peak (except for 5th Street at I-75/I-85, likely attributable to the unique characteristics of Midtown travels), a trend consistent with increased group travel and non-work trips during the afternoon period.

3) Vehicle and Person Throughput

In the AM peak, 5th Street was the busiest corridor in both vehicle and person throughput, while the other three sites exhibited similar throughput levels. In the PM peak, 5th Street again ranked highest, followed by North Druid Hills Road, Fair Drive, and Moores Mill Road.

The highest person throughput was recorded at 5th Street at I-75/I-85 during the PM peak, with over 13,200 persons per hour, supported by high GP lane volumes and substantial HOV lane usage.

All corridors showed higher PM peak vehicle throughput than AM, with especially balanced volumes at Moores Mill Road, North Druid Hills Road, and Fair Drive.

Despite carrying fewer vehicles, HOV lanes consistently delivered a disproportionate share of person throughput, moving 20%-30% of corridor passengers with only 12%-16% of vehicles. The HOV lane at 5th Street PM operated at an average headway of approximately 2.5 seconds, indicating efficient utilization of the managed lane facility.

4) Occupancy Mode Performance

HOV3+ vehicles accounted for approximately 7% to 11% of total person throughput at several corridors in the PM peak, marking a considerably higher fraction compared to previous studies where HOV3+ was a minor contributor (less than 5%).

Observed "waves" of HOV3+ vehicles during the PM peak, particularly at North Druid Hills Road, are likely school-related travel and family-based trips.

HOV2 person throughput shares were also higher compared with the 2018-2020 study, contributing approximately 20%-30% across sites (higher than the 19% maximum recorded in the 2018-2020 study). HOV2 vehicles remained the dominant carpool mode in managed lanes, contributing 45%-60% of HOV lane person throughput in most cases.

Express buses, though representing less than 0.2% of vehicles, consistently contributed 0.5%-2.3% of corridor person throughput, with higher values at Moores Mill Road and North Druid Hills Road.

5) Carpool Mode Shares

Carpool person throughput exceeded 40% at Fair Drive and North Druid Hills Road during the PM peak. These levels are higher than any previous SRTA-observed corridor, including Center Way at I-85 (pre-HOT conversion), which was approximately 35% during PM peak.

Carpooling continues to carry the majority of HOV person throughput. For example, at 5th Street in the AM peak, 76.8% of the person throughput was moved via carpool activities.

The integration of machine vision classification and synchronized field-recorded video significantly improved consistency between volume and occupancy inputs. These data were easier to validate and ensured precise alignment with the observed peak periods. However, machine vision data were limited to the specific dates of observation sessions, and consequently do not account for week-to-week, seasonal, or weather-related variability (all data collection sessions were scheduled to avoid such weather events). Broader temporal coverage would enhance the generalizability of throughput estimates.

The high reliability of field occupancy data in this cycle, supported by regression tree QA/QC and optimized team management, makes the 2024 study a strong candidate as a baseline for future trend evaluation.

The observed growth in HOV2 and particularly HOV3+ person throughput represents a noteworthy behavioral shift. This highlights a need for further investigation using license plate linkage and demographic data to better understand who is contributing to these high-occupancy trips.

This study reinforces the critical role of managed lanes in maximizing person throughput, even in cases where vehicle volumes remain modest. The differences observed between the corridors in this study and those examined in previous projects (outside the I-285 Perimeter) are also worth further exploration. Additionally, the findings suggest a potential shift toward more frequent and meaningful carpooling (particularly among larger travel parties) within corridors located inside the I-285 Perimeter where managed lanes have not been converted to Express Lane facilities (HOT and reversible lanes). As SRTA and GDOT continue to evaluate lane policy, facility design, and investment strategies, these results can help inform decisions aimed at supporting high-efficiency, multimodal freeway operations across metro Atlanta.

11 References

Atlanta-region Transit Link Authority. (2024). Xpress routes and schedules. Retrieved May 2025, from https://xpressga.com/

Araque, S. (2013). Statistical analysis of weaving before and after managed lane conversion (Master's thesis). Georgia Institute of Technology, School of Civil and Environmental Engineering, Atlanta, GA.

Castrillon, F., Guin, A., Guensler, R., & Laval, J. (2012). Comparison of modeling approaches for imputation of video detection data in intelligent transportation systems. Transportation Research Record: Journal of the Transportation Research Board, 2308(1), 138–147. https://doi.org/10.3141/2308-15

CobbLinc. (2024). CobbLinc routes and schedules. Retrieved May 2025, from https://www.cobbcounty.org/transportation/transit/routes-and-schedules

Cosma, S. (2013). Classification and regression trees, Carnegie Mellon University, Lecture 22. Retrieved May 28, 2025, from http://www.stat.cmu.edu/~cshalizi/350/lectures/22/lecture-22.pdf

D'Ambrosio, K. (2011). Methodology for collecting vehicle occupancy data on multi-lane interstate highways: A GA 400 case study (Master's thesis). Georgia Institute of Technology, School of Civil and Environmental Engineering, Atlanta, GA.

Elango, V., & Guensler, R. (2014). Collection, screening, and evaluation of vehicle occupancy data. Transportation Research Record, 2470, 142–151.

Federal Highway Administration (FHWA). (2020). Managed lanes. Retrieved May 2025, from https://ops.fhwa.dot.gov/freewaymgmt/managed_lanes.htm

Ride Gwinnett. (2021). Routes and schedules. Retrieved May 2025, from https://www.gwinnettcounty.com/web/gwinnett/Departments/Transportation/GwinnettCountyTransit/RoutesandSchedules

Guensler, R., Liu, H., Lu, H., Chang, C. H., Dai, Z., Fu, Z., Liu, D., Kim, D., Zhao, Y., & Guin, A. (2021a). Atlanta metro area managed lane 2018–2020 vehicle and person throughput analysis. Volume II: Commutershed and demographic analysis for the I-75 Northwest Corridor and I-85 Express Lanes. Georgia State Road and Tollway Authority. Atlanta, GA.

Guensler, R., Liu, H., Lu, H., Chang, C. H., Dai, Z., Fu, Z., Liu, D., Kim, D., Zhao, Y., & Guin, A. (2021b). Atlanta metro area managed lane 2018–2020 vehicle and person throughput analysis. Volume I: Vehicle occupancy, vehicle throughput, and person throughput analysis for the I-75 Northwest Corridor and I-85 Express Lanes. Georgia State Road and Tollway Authority. Atlanta, GA.

Guensler, R. (2013). HOT lane 45 mph uptime results [Memorandum to Ben Rabun, GDOT]. Georgia Institute of Technology, May 17, 2013.

Guensler, R., Elango, V., Guin, A., Hunter, M., Laval, J., Araque, S., Colberg, K., Castrillon, F., D'Ambrosio, K., Duarte, D., Khoeini, S., Peesapati, L., Sheikh, A., Smith, K., Toth, C., & Zinner, S. (2013a). Atlanta I-85 HOV-to-HOT conversion: Analysis of vehicle and person throughput. Georgia Department of Transportation Report FHWA-GA-13-10-03.

Guensler, R., Khoeini, S., Guin, A., & Elango, V. (2013b). Atlanta I-85 HOV-to-HOT conversion: Analysis of user socio-spatial demographic changes. School of Civil and Environmental Engineering, Georgia Institute of Technology, Atlanta, GA.

Guensler, R. (1998). Increasing vehicle occupancy in the United States. In Odile Andan et al. (Eds.), L'Avenir Des Deplacements en Ville (The Future of Urban Travel) (Vol. 2, pp. 127–155). Laboratoire d'Economie des Transports, Lyon, France.

Guin, A., Hunger, M., & Guensler, R. (2008). Analysis of reduction in effective capacities of high-occupancy vehicle lanes related to traffic behavior. Transportation Research Record, 2065, 47–53.

Heidtman, K., Skarpness, B., & Tornow, C. (1997). Improved vehicle occupancy data collection methods. Federal Highway Administration, Office of Highway Information Management.

HNTB Corporation. (2010). Atlanta Regional Managed Lane System Plan, Final Report. Prepared for the Georgia Department of Transportation. Atlanta, GA. Available at: http://www.dot.ga.gov/BuildSmart/Studies/Documents/ManagedLanesSystemPlan/FINALREPORT.pdf. January 2010).

HNTB Corporation. (2015). Atlanta Regional Managed Implementation Plan, Final Report. Prepared for the Georgia Department of Transportation. Atlanta, GA. Available at: www.dot.ga.gov/BuildSmart/Studies/ManagedLanesDocuments/MLIP/MLIP02 Report FINAL.pdf. December 2015).

Khanam, R., & Hussain, M. (2024). Yolov11: An overview of the key architectural enhancements. arXiv preprint arXiv:2410.17725.

Neter, J., Wasserman, W., & Kutner, M. (1990). Applied linear statistical models: Regression, analysis of variance, and experimental designs (3rd ed.). Irwin Inc.

Official Code of Georgia Annotated § 32-9-4 (2024). Designation of special or exclusive use travel lanes; use of such lanes. Section 32-9-4, 2024 Code of Georgia.

Pratt, R., Turnbull, K., Evans, J. IV, McCollom, B., Spielberg, F., Vaca, E., & Kuzmyak, J. (2000). Traveler response to transportation system changes: Interim handbook. Transit Cooperative Research Program Report 95, Transportation Research Board, Washington, DC.

Smith, K. (2011). A profile of HOV lane vehicle characteristics on I-85 prior to HOV-to-HOT conversion (Master's thesis). Georgia Institute of Technology, School of Civil and Environmental Engineering, Atlanta, GA.

State Road and Tollway Authority (SRTA). (2025). Georgia express lanes. Retrieved May 2025, from https://www.srta.ga.gov/georgia-express-lanes/

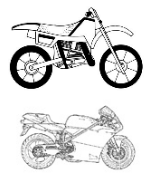
Toth, C., Guensler, R., Araque, S., Guin, A., Elango, V., & Hunter, M. (2014). Atlanta I-85 HOV-to-HOT conversion: Impacts on weaving and effective capacity (14-5580). 93rd Annual Meeting of the Transportation Research Board, Washington, DC.

Washington, S., Wolf, J., & Guensler, R. (1997). A binary recursive partitioning method for modeling hot-stabilized emissions from motor vehicles. Transportation Research Record, 1587, 96–105.

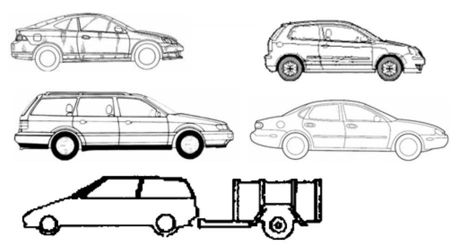
Wolf, J., Guensler, R., & Washington, S. (1998). High emitting vehicle characterization using regression tree analysis. Transportation Research Record, 1641, 58–65.

Appendix A: Vehicle Class Definitions

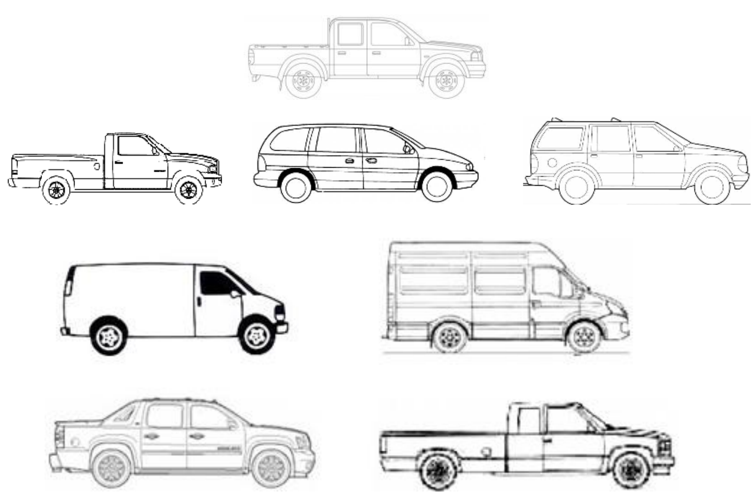
Motorcycle



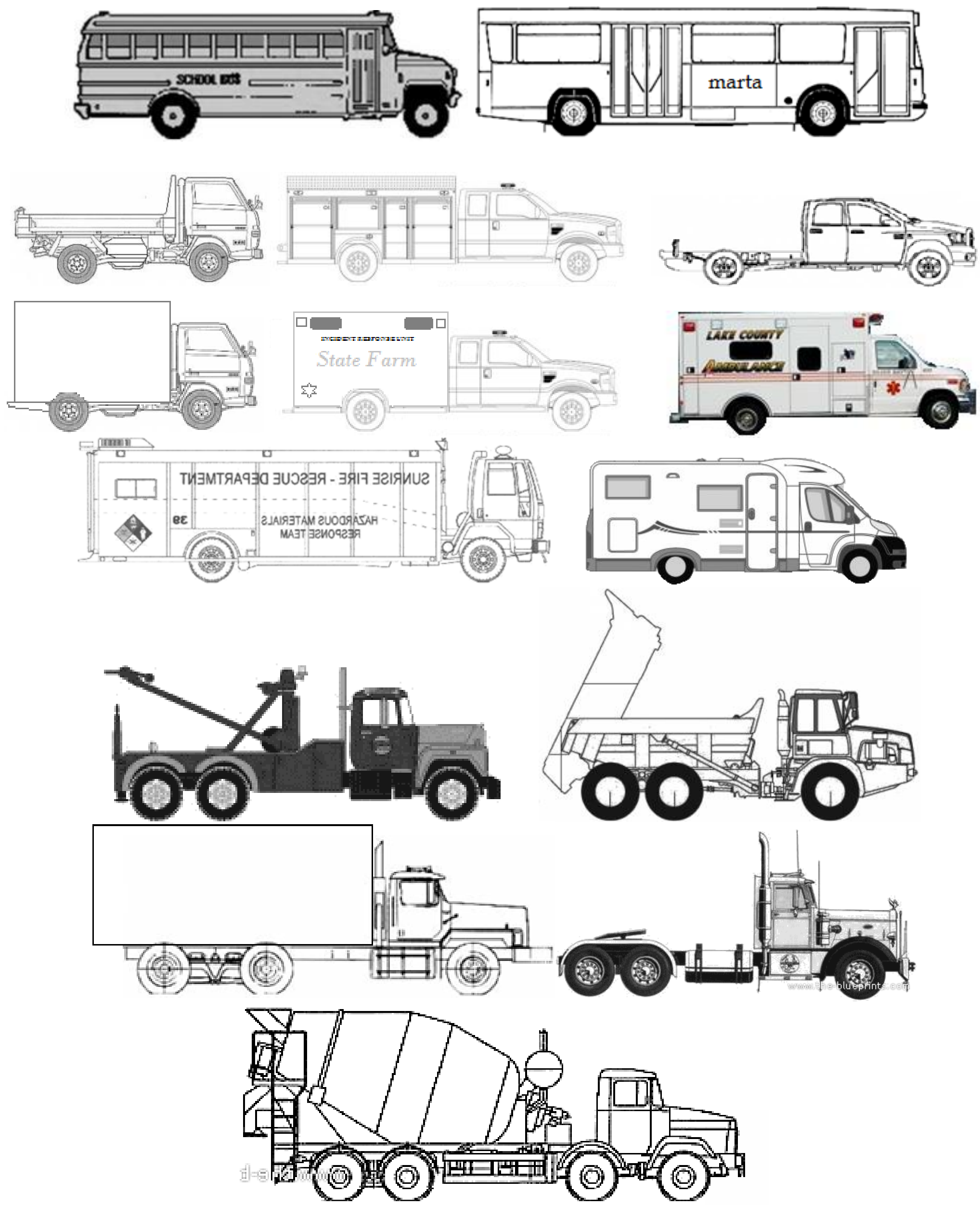
Light Duty Vehicles (LDVs)

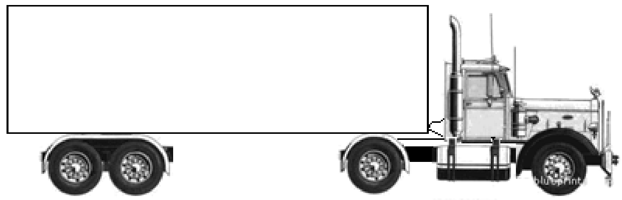


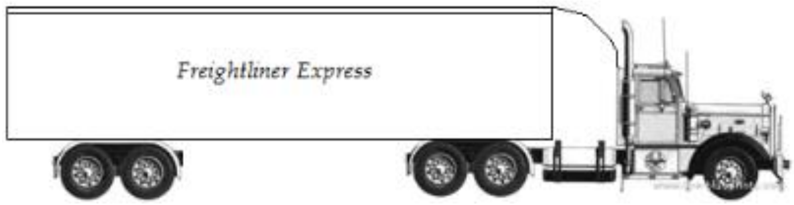
Sport Utility Vehicles and Light Utility Trucks (SUV)



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






Freightliner Express

Appendix B: Sample Step-by-Step Calculation for Express Bus Occupancy Substitution and Throughput Assessment

The morning peak (7:30 to 10:30 AM) of Moores Mill Road at I-75 is presented as a sample to show each step of the adjustment of average occupancy, vehicle throughput, and person throughput in substitution of express buses ridership profiles. This Appendix starts with the substitution of express buses, followed by the substituted occupancy and throughput outcomes, with the input data, formulas, step-by-step results, and then the final outputs of the calculation. Please note that decimals are not omitted in the step-by-step results (although in certain cases it makes more sense to use integers, such as vehicle throughput and person throughput) to minimize in-process rounding errors (only final results are rounded). The team did not implement any post-processing to make the rounded percentages sum to 100% (e.g., the sum could be 99.9% or 100.1% instead of 100.0%), so that all numbers match with the Microsoft® Excel® spreadsheet attached with this report. All sums are essentially 100.0% (i.e., any mismatch of sum is due to the rounding), and the audience can refer to the Excel spreadsheet for validation. Similarly, the occupancy data presented in this chapter is rounded to two decimal places, and any changes (differences) were based on the raw values before rounding to be consistent with the spreadsheet. Therefore, it could be that the changes do not pair with the presented before-and-after occupancy (rounded), and these mismatches are not erroneous.

Adjustment of average vehicle occupancy, vehicle throughput, and person throughput to accommodate the ridership of express buses follows the methodology described in Chapter 7. The express buses were recorded as HOV4+ buses (which includes both regular and express buses) during field observations of vehicle occupancy, and the number of Xpress, CobbLinc and Ride Gwinnett buses (based on the express bus schedules) were taken from the observed number of buses in the adjustment. For each express bus taken, 4.5 persons were subtracted from the total person throughput, and the number of passengers from the operation data (provided by the contractors) was added back to the person total. The substitution of Moores Mill Road at I-75, AM peak is presented as an example of the calculation, and the adjustment of all sites can be found in the attached spreadsheet.

1. Unadjusted Vehicle and Person Throughput by Class

There are four GP lanes (numbered as GP lane #2 to GP lane #2 from inside to outside) at Moores Mill Road at I-75 Southbound (AM peak observations capture Southbound traffic), along with the HOV lane (numbered as HOV lane #1). The vehicle throughput was presented by vehicles classes and by lane, based on the machine vision traffic volumes and vehicle class distributions, as shown in Table 70. The unadjusted person throughput was calculated by multiplying the number of vehicles (by class) with the observed average occupancy (shown in Table 71), as shown in Table 72.

Table 70 – Unadjusted Vehicle Throughput by Class and by Lane, Moores Mill Road at I-75, AM Peak (7:30-10:30 AM)

Vehicle Class	GP Lane #2	GP Lane #3	GP Lane #4	GP Lane #5	HOV Lane #1	All Lanes
Passenger Car LDVs	866.87	680.90	642.29	472.97	488.77	3,151.80
SUV	762.55	726.41	625.16	459.20	434.91	3,008.23
Bus (Regular and Express Buses)	47.32	67.00	64.04	35.67	42.57	256.60
Van	10.95	37.16	54.32	25.67	7.36	135.46
Large HDV	13.42	34.81	47.56	25.53	10.91	132.23
Small HDV	1.14	1.41	2.39	2.74	12.10	19.78
MC	0.95	0.38	0.47	0.42	3.04	5.25
Other	0.90	1.60	2.02	0.99	0.66	6.17
Total	1,704.11	1,549.66	1,438.24	1,023.19	1,000.32	6,715.52

Table 71 – Observed Average Vehicle Occupancy by Class and by Lane, Moores Mill Road at I-75, AM Peak (7:30-10:30 AM)

Vehicle Class	GP Lane #2	GP Lane #3	GP Lane #4	GP Lane #5	HOV Lane #1	All Lanes
Passenger Car LDVs	1.09	1.09	1.08	1.05	1.31	1.11
SUV	1.16	1.19	1.18	1.12	1.53	1.22
Bus (Regular and Express Buses)	1.00	1.00	2.64	2.17	3.15	2.91
Van (Mini Van and Vanpool)	1.38	1.49	1.35	1.26	1.78	1.46
Large HDV	1.00	1.11	1.14	1.07	1.50	1.11
Small HDV	1.41	1.52	1.41	1.28	1.82	1.41
MC	1.00	1.00	1.00	1.00	1.05	1.04
Other	1.00	1.29	1.00	N/A	1.50	1.21
Total	1.14	1.18	1.17	1.10	1.51	1.21

Table 72 – Unadjusted Person Throughput by Class and by Lane, Moores Mill Road at I-75, AM Peak (7:30-10:30 AM)

Vehicle Class	GP Lane #2	GP Lane #3	GP Lane #4	GP Lane #5	HOV Lane #1	All Lanes
Passenger Car LDVs	942	745	697	496	639	3,517
SUV	883	863	739	512	667	3,665
Bus (Regular and Express Buses)	47	67	169	77	134	494
Van (Mini Van and Vanpool)	15	55	73	32	13	189
Large HDV	13	39	54	27	16	150
Small HDV	2	2	3	3	22	33
MC	1	0	0	0	3	5
Other	1	2	2	1	1	7
Total	1,904	1,773	1,738	1,150	1,496	8,061

2. Throughput Adjustment of Express Buses

The processed express bus operation data (from SRTA) is used to substitute the number of Xpress, CobbLinc and Ride Gwinnett Express Commuter Buses that need to be taken from the bus vehicle throughput, as shown in Table 73 (per morning session). Ride Gwinnett routes do not traverse Moores Mill Road at I-75 during AM peak hours (zero vehicle count and vehicle occupancy), and all Xpress and CobbLinc buses are assigned to the HOV lane.

For each Xpress and CobbLinc bus, 4.5 persons are taken from the person total, and the express bus passengers are added back, as shown in Table 74. The person throughput that needs to be added back is the number of express bus per hour multiplied by its average vehicle occupancy (e.g., 4.00 vehicles/session / 3 hours/session × 8.21 persons/vehicle ≈ 10.95 persons/hour for the Xpress buses on the HOV lane, and 23.00 vehicles/session / 3 hours/session × 15.34 persons/vehicle ≈ 117.59 persons/hour for the CobbLinc buses on the HOV lane). The vehicle and person throughput of regular buses is calculated by bus (regular and express buses) throughput minus express bus throughput, and when the initial person throughput is not large enough to subtract 4.5 times the number of express buses without leaving 1.0 persons per vehicle in the remaining vehicles, an extra vehicle must be manually added (with 4.5 persons) to compensate (the compensation was not needed in this study as all substitutions ended up with enough remaining regular buses). In this sample case, the change of vehicle throughput after the adjustment is 0, and the change of person throughput after the adjustment is the HOV4+ passengers taken (4.5 persons multiplied by the number of HOV4+ buses taken) plus the express passengers, which is -4.5 persons/vehicle × 4.00 vehicles/session / 3 hours/session (Xpress buses taken) - 4.5 persons/vehicle × 23.00

vehicles/session / 3 hours/session (CobbLinc buses taken) + 10.95 persons (Xpress passengers) + 117.59 persons (CobbLinc passengers) ≈ 88.03 persons. Again, all the calculations were based on raw values (no rounding), and a mismatch in the step-by-step results is not erroneous.

Table 73 – SRTA-Reported Express Bus Operation Data by Lane, Moores Mill Road at I-75, AM Peak (7:30-10:30 AM)

Vehicle Class	GP Lane #2	GP Lane #3	GP Lane #4	GP Lane #5	HOV Lane #1	All Lanes
Xpress Bus Count per Morning Peak Session from SRTA *	0.00	0.00	0.00	0.00	4.00	4.00
Xpress Bus Average Ridership for Throughput Calculation	0.00	0.00	0.00	0.00	8.21	8.21
CobbLinc Bus Count per Morning Peak Session from SRTA *	0.00	0.00	0.00	0.00	23.00	23.00
CobbLinc Bus Average Ridership for Throughput Calculation	0.00	0.00	0.00	0.00	15.34	15.34
Ride Gwinnett Bus Count per Morning Peak Session from SRTA *	0.00	0.00	0.00	0.00	0.00	0.00
Ride Gwinnett Bus Average Ridership for Throughput Calculation	0.00	0.00	0.00	0.00	0.00	0.00
Xpress Bus Count per Morning Peak Session from SRTA *	0.00	0.00	0.00	0.00	4.00	4.00
Xpress Bus Average Ridership for Throughput Calculation	0.00	0.00	0.00	0.00	8.21	8.21
CobbLinc Bus Count per Morning Peak Session from SRTA *	0.00	0.00	0.00	0.00	23.00	23.00

* Note: Express Buses are allocated to the HOV lane.

Table 74 – Throughput Adjustment with Substitution of Express Buses, Moores Mill Road at I-75, AM Peak (7:30-10:30 AM)

Vehicle Class	GP Lane #2	GP Lane #3	GP Lane #4	GP Lane #5	HOV Lane #1	All Lanes
Xpress Person Throughput per Hour after Adjustment	0.00	0.00	0.00	0.00	10.95	10.95
CobbLinc Person Throughput per Hour after Adjustment	0.00	0.00	0.00	0.00	117.59	117.59
Ride Gwinnett Person Throughput per Hour after Adjustment	0.00	0.00	0.00	0.00	0.00	0.00
Changes of Vehicle Throughput per Hour after Adjustment for Express Buses***	0.00	0.00	0.00	0.00	0.00	0.00
Changes of Person Throughput per Hour after Adjustment for Express Buses *	0.00	0.00	0.00	0.00	88.03	88.03
Regular Bus Vehicle Throughput per Hour after Adjustment **	47.32	67.00	64.04	35.67	33.57	247.60
Regular Bus Person Throughput per Hour after Adjustment**	47.32	67.00	168.82	77.29	93.53	453.96

4. Throughput and Average Occupancy after Adjustment

The adjusted vehicle throughput is presented in Table 75, and the adjusted person throughput presented in Table 76. The adjusted average occupancy is calculated as person throughput divided by vehicle throughput, as shown in Table 77.

Table 75 – Adjusted Vehicle Throughput by Class and by Lane, Moores Mill Road at I-75, AM Peak (7:30-10:30 AM)

Vehicle Class	GP Lane #2	GP Lane #3	GP Lane #4	GP Lane #5	HOV Lane #1	All Lanes
Passenger Car LDVs	867	681	642	473	489	3,152
SUV	763	726	625	459	435	3,008
Regular Bus	47	67	64	36	34	248
Xpress	0	0	0	0	4	4
CobbLinc	0	0	0	0	23	23
Ride Gwinnett	0	0	0	0	0	0
Van	11	37	54	26	7	135
Large HDV	13	35	48	26	11	132
Small HDV	1	1	2	3	12	20
Motorcycle	1	0	0	0	3	5
Other	1	2	2	1	1	6
Total	1,704	1,550	1,438	1,023	1,018	6,734

Table 76 – Adjusted Person Throughput by Class and by Lane, Moores Mill Road at I-75, AM Peak (7:30-10:30 AM)

Vehicle Class	GP Lane #2	GP Lane #3	GP Lane #4	GP Lane #5	HOV Lane #1	All Lanes
Passenger Car LDVs	942	745	697	496	639	3,517
SUV	883	863	739	512	667	3,665
Regular Bus	47	67	169	77	94	454
Xpress	0	0	0	0	11	11
CobbLinc	0	0	0	0	118	118
Ride Gwinnett	0	0	0	0	0	0
Van	15	55	73	32	13	189
Large HDV	13	39	54	27	16	150
Small HDV	2	2	3	3	22	33
Motorcycle	1	0	0	0	3	5
Other	1	2	2	1	1	7
Total	1,904	1,773	1,738	1,150	1,584	8,149

Table 77 – Adjusted Average Vehicle Occupancy (AVO) by Lane, Moores Mill Road at I-75, AM Peak (7:30-10:30 AM)

Vehicle Class	GP Lane #2	GP Lane #3	GP Lane #4	GP Lane #5	HOV Lane #1	All Lanes
Adjusted AVO w/Substitution of Express Buses	1.12	1.14	1.21	1.12	1.56	1.21