FINAL REPORT

EFFECT OF REAL-TIME TRAFFIC DATA ON TRUCK DIVERSION ROUTING ON I-75

BDV24-977-28

Master University Agreement: BDV24

Submitted to

Mr. Jeremy Dilmore, P.E.
District Five TSM&O
Department of Transportation
133 S. Semoran Blvd
Orlando FL 32807

Submitted By

Amr A. Oloufa, Ph.D., P.E.
College of Engineering and Computer Science
Center for Advanced Transportation Systems Simulation
University of Central Florida
PO Box 162450
Orlando, FL 32816-2450
Phone: (407) 823-5657, Fax: (407) 823-4676
E-mail: aoloufa@mail.ucf.edu

Samar Younes, Ph.D.
College of Engineering and Computer Science
Center for Advanced Transportation Systems Simulation
University of Central Florida
Phone: (407) 683-4378, E-mail: samar@knights.ucf.edu

Haluk Laman, Ph.D.
College of Engineering and Computer Science
Center for Advanced Transportation Systems Simulation
University of Central Florida
Phone: (407) 414-4764, E-mail: haluklaman@knights.ucf.edu

November 2020

DISCLAIMER

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Effect of Real-time Traffic Data on Truck Diversion Routing on I-75		5. Report Date October,2020 6. Performing Organization Code
7. Author(s) Amr A. Oloufa, Ph.D., P.E. ; Samar Younes, Ph.D.; Haluk Laman, Ph.D.		8. Performing Organization Report No.
9. Performing Organization Name and Address University of Central Florida PO box 162450 4000 Central Florida Blvd. Orlando FL, 32816-2450		10. Work Unit No. (TRAIS) 11. Contract or Grant No. BDV24-977-28
12. Sponsoring Agency Name and Address District Five TSM&O Florida Department of Transportation 133 S. Semoran Blvd Orlando FL 32807		13. Type of Report and Period Covered Final Report 14. Sponsoring Agency Code
15. Supplementary Notes		

16. Abstract

Successful development of effective real-time traffic management and information systems requires high quality traffic data in real time. The challenge over the years has been the massive expenses in both time and cost related to the collection of such data. This is true for both passenger vehicle and freight traffic where origin-destination (O/D) data collection relied heavily either on manual counts or the traditional four-step planning model where surveys and interviews are required or on expensive ITS technologies that required excessive MOT and traffic stoppages for installation.

This research project aims to develop a novel method of automated real-time O–D data collection that is reliable, inexpensive, and portable using a mix of commercial off-the-shelf hardware and custom software. As such, the researchers conducted an automated license plate reading methodology at three locations on the I-75 corridor. Collected data via the system design, hardware, and software were extensively evaluated. Data collected from the two test sites were compared with the loop detector counts under the supervision of FDOT District 5.

Finally, an ArcGIS-based real-time truck diversion framework methodology has been developed, and the benefits are presented along with case studies in this report.

17. Key Word Real-time traffic data, Freights, O-D data, ArcGIS, Truck diversion, Incident management	18. Distribution Statement No restrictions.

19. Security Classif. (of this report) Unclassified.	20. Security Classif. (of this page) Unclassified.	21. No. of Pages 229	22. Price

ACKNOWLEDGEMENTS

The author thanks the Florida Department of Transportation for sponsoring this research project.

EXECUTIVE SUMMARY

Origin and destination (O–D) include the start and endpoints and times of any vehicular trip. These data are valuable to traffic modelers and transportation planners. The collection of O–D data usually comes from surveys, visual counts, classifier counts, or other methods. These methods of collection tend to be expensive and time consuming. This research project aims to develop a novel method of automated real-time O–D data collection that is reliable, inexpensive, and portable using a mix of commercial off-the-shelf hardware and custom software. As such, the researchers conducted an automated license plate reading methodology.

The objective of this research was to understand the correlation between travel time and diversion and thus, assist integrated corridor management efforts in the area.

The researchers have accomplished this objective by two primary and complementary steps:

1) Development of a real-time system for data collection of cars and trucks
2) Development of a framework which uses the data from step 1 to develop and then to quantify the benefits of the diversion.

The researchers designed and implemented a microcontroller-based system for counting cars and trucks. The system is solar-powered and includes the ability to both collect data and communicate these data to the cloud, thereby offering real-time counts and traffic assessment.

Collected data via the system design, hardware, and software were extensively evaluated. Data collected from the two test sites were compared with the loop detector counts under the supervision of FDOT District 5. As a result of the data analysis from test site 1, data collected during weekdays, results showed that the accuracy relative to loop counts varies from +/- 5% to +5/-10%. Furthermore, data analysis based on the test site 2 has shown that the UCF

fast lane counts are within 1% - 4% of the FDOT loop counts, with an average of 1.8% using data from 3 days. UCF fast lane counts are within 2% of manual counts. UCF middle lane counts are within 2% of manual counts (based on a 1-hour manual count comparison). Finally, when FDOT loops counts were compared with UCF middle lane counts, differences reached up to approximately 10%. In some cases, variations up to 8% were due to sensor issues

A diversion decision-making framework for selecting alternative truck routes to circumvent congested highway segments was developed. To achieve this objective, data were collected, prepared, and utilized to design and build a dynamic routable network dataset for the state of Florida. Additionally, the ArcGIS platform was utilized to generate an alternative route that accommodates truck characteristics and constraints. Predefined alternative route selection criteria were developed, taking into consideration road conditions, truck weight and height restrictions, and neighborhood impact.

The application of appropriate diversion criteria utilizing truck VOT analysis, fuel consumption aspects, safety studies, and environmental impact analysis can lead to the selection of alternative routes that reduce travel time, meet the restrictions for truck operations, and sustain an acceptable level of service on the alternative route. This framework provides a decision-support tool for decision makers and traffic management centers that can enable them to cope more efficiently and effectively with nonrecurrent congestion on highway networks.

TABLE OF CONTENTS

LIST OF TABLES xii

LIST OF FIGURES xiii

CHAPTER 1: Introduction 1

1.1 Background 1

1.2 Project Objectives 2

1.3 Project Progress 3

CHAPTER 2: Literature Review 5

2.1 Traffic Data Collection Methods 7

2.2 On-Site Detectors (In Situ Technologies) 8

2.2.1 Intrusive (In-Roadway) Technologies 9

2.2.1.1 Magnetometers 10

2.2.1.2 Inductive Detector Loops 11

2.2.2 Pneumatic Tube Detectors 13

2.2.3 Weigh-in-Motion (WIM) Sensors 15

2.2.3.1 Bending Plate WIM Sensors 15

2.2.3.2 Piezoelectric WIM Sensors 16

2.3 Non-Intrusive Technologies 18

2.3.1 Video Vehicle Detection System 18

2.3.2 Microwave Detection System (MVDS) 20

2.3.3 Infrared Sensors 21

2.3.3.1 Active Infrared 21

2.3.3.2 Passive Infrared 23

2.3.4 Ultrasonic Sensors 23

2.4 In-Vehicle Technologies 25

2.5 Probe Vehicles 25

2.6 Global Positioning System (GPS) 26

2.6.1 Mobile Phone 28

2.6.2 Bluetooth Device 29

2.6.3 Automatic Vehicle Identification (AVI) 30

2.6.3.1 License Plate Readers 30

2.6.3.2 Transponder Readers 30

2.6.3.3 Radio Frequency Identification (RFID) 31

2.7 Remote Sensing 32

2.8 Truck Re-routing Strategies 32

2.9 Conclusions 35

CHAPTER 3: System Description and Data Collection 37

3.1 Installation at Test Site 1 37

3.2 Hardware 38

3.3 Sensor Technology Evaluation 40

3.3.1 Sensor 1 (Benewake TFmini) 40

3.3.2 Sensor 2 (Benewake TF02) 41

3.3.3 Sensor 3 (Garmin) 41

3.3.4 Sensor 4 (Garmin HP) 41

3.4 Communications 42

3.5 Summary of Results 44

3.6 Installation at Test Site 2 61

3.7 Power Wiring Diagram 62

3.8 Communications Diagram 63

3.9 Data Validation for Test Site 2 64

3.10 Laser Testing 67

3.11 Lessons Learned 68

CHAPTER 4: Truck Diversion Model- Case Studies 70

4.1 Data Collection 70

4.2 Study Area 73

4.3 Data Preparation 75

4.3.1 Network Dataset and Historical Traffic Data 75

4.3.2 Criteria for Alternative Route Selection 79

4.3.2.1 Height and Weight Restrictions 80

4.3.2.2 Pavement Conditions 80

4.3.2.3 Geometry and Road Characteristics 81
4.3.2.4 Existence of Schools and Hospitals 81
4.3.2.5 The Intensity of Commercial Development 81
4.3.2.6 Level of Service 81
4.3.2.7 Truck Weight and Size Restrictions Data 82
4.3.3 Data for Cost-Benefit Analysis 82
4.4 Methodology 83
4.5 Crash Hotspot Analysis 83
4.6 Space-Time Cube Analysis 86
4.7 Global Spatial Autocorrelation Analysis 87
4.8 Emerging Hotspot Analysis 88
4.9 Network Building 88
4.10 Alternative Route Selection Criteria 90
4.10.1 Roadway Geometry 91
4.10.2 Traffic Conditions 91
4.10.3 Neighborhood Impacts 92
4.10.4 Heavy Vehicle Restrictions 92
4.11 Benefit Estimation 93
4.12 Summary 93
4.13 Model Development 94

4.13.1 Crash Hotspots Analysis 94

4.13.2 Incident Clearance Prediction Model Development 97

4.14 Sensitivity Analysis 99

4.15 Diversion Model 103

4.16 Results and Discussion 106

4.17 Case Studies Overview 106

4.18 Case Study 1 114

4.19 Case Study 2 115

4.20 Case Study 3 116

4.21 Benefit Estimation 117

4.22 Conclusion and Future Research 119

4.23 Model Scalability 120

4.24 Recommendations for Future Research 120

CHAPTER 5: Conclusion 122

5.1 Real-Time Data Collection System 122

5.2 Quantification of Truck Diversion 123

REFERENCES 124

APPENDIX A- Report Figures 127

APPENDIX B- User Manual for Excel Macro 181

APPENDIX C- 24-Hour Profile Charts 192

LIST OF TABLES

Table 1: A Summary of a Literature Review of Related Studies 32

Table 2: Right Lane vs. Left Lane Comparison 45

Table 3: Car vs. Truck Counts Comparison 48

Table 4: Cars vs. Trucks on Left Lane vs. Right Lane Comparison 52

Table 5: Data Collection 12/06 for three hours (2:00pm to 5:00pm)............................... 65

Table 6: Data Collection 12/07 All-day 65

Table 7: Data Collection 12/08 All-day 65

Table 8: Data Collection 12/09 All-day 66

Table 9: Data Collection 12/13 for One Hour (2:00pm to 3:00pm)................................. 66

Table 10: Network Dataset Description and Sources 78

Table 11: Incident Data Categories for Sensitivity Analysis 101

Table 12: Results of Sensitivity Analysis Scenarios 102

Table 13: Details Information for Case Study 1... 108

Table 14: Detailed Information Related to Case Study 2 110

Table 15: Detailed Information Related to Case Study 3 111

Table 16: A Summary of Benefit Estimation of Three Case Studies.............................. 118

LIST OF FIGURES

Figure 1: Traffic Data Collection Technologies 8

Figure 2: Wireless Magnometer and the Installation Process 11

Figure 3: Inductive Loops 12

Figure 4: Vehicle Classifications 13

Figure 5: Fixed and Embedded Types of Pneumatic Detectors 14

Figure 6: WIM Sensor 15

Figure 7: Bending Plate Sensor 16

Figure 8: Full Lane Width WIM Sensor 17

Figure 9: Video Detection 19

Figure 10: Microwave Detection System 21

Figure 11: Active Infrared Sensor 22

Figure 12: Passive Infrared Sensor [7] 23

Figure 13: Acoustic Sensor 24

Figure 14: GPS Data Collection 27

Figure 15: Bluetooth Data Collection 29

Figure 16: Workflow for an RFID System 31

Figure 17: Test Site 1 37

Figure 18: Mesh Architecture 38

Figure 19: Gateway 39

Figure 20: Bracket with Sensor 40

Figure 21: Sensor 1 (Benewake TFmini) 40

Figure 22: Sensor 2 (Benewake TF02) 41

Figure 23: Sensor 3 (Garmin) 41
Figure 24: Sensor 4 (Garmin HP) 41
Figure 25: Traffic Data June 1-3, 2019 43
Figure 26: Accuracy Comparison (Left Lane vs. Right Lane) 46
Figure 27: Error Percentage (Left Lane vs. Right Lane) 47
Figure 28: Accuracy Comparison (Cars vs. Trucks) 49
Figure 29: Error Percentage (Cars vs. Trucks) 50
Figure 30: Trucks vs. Cars on Left Lane 53
Figure 31: 5-Day Moving Average Error Percentage for Left-Lane Counts 54
Figure 32: Trucks vs. Cars Comparison on Right Lane 55
Figure 33: 5-Day Moving Average Error Percentage for Right-Lane Counts 56
Figure 34: Error Percentage on Weekdays: Left Lane 58
Figure 35: 5-Day Moving Average Error Percentage on Weekdays: Left Lane 58
Figure 36: Error Percentage on Weekdays: Right Lane 59
Figure 37: 5-Day Moving Average Error Percentage on Weekdays: Right Lane 60
Figure 38: Test Site 2 61
Figure 39: Solar System Configuration 62
Figure 40: Communications Flowchart 63
Figure 41: Overall Structure of the Research 72
Figure 42: Study Area: Counties along the I-75 Corridor 74
Figure 43: Flowchart of Data Categories and Related Sources 75
Figure 44: Workflow to Build Network Dataset 77
Figure 45: Study Alternative Route Selection Criteria 80

Figure 46: Flowchart of Hotspot Analysis 84

Figure 47: Crash Data Distribution over the Study Area 85

Figure 48: Crash Data by Month for the Years of 2014 to 2017...................................... 86

Figure 49: Space-Time Cube Structure (ArcGIS Tool Reference) 87

Figure 50: Emerging Hotspot Analysis 96

Figure 51: Space-Time Crash Trends 3D Analysis... 97

Figure 52: Impact of Input Parameters on Model Accuracy 103

Figure 53: Incident Location: Case Study 1 109

Figure 54: Incident Location: Case Study 2 110

Figure 55: Incident Location: Case Study 3 112

Figure 56: Case Study 1: Base Scenario Route on I-75 114

Figure 57: Truck Alternative Route to Bypass the Congested Segment: Case Study 1.. 114

Figure 58: Case Study 2: Base Scenario Route on I-75 115

Figure 59: Truck Alternative Route to Bypass the Congested Segment: Case Study 2.. 115

Figure 60: Case Study 3: Base Scenario Route on I-75 116

Figure 61: Truck Alternative Route to Bypass the Congested Segment: Case Study 3.. 116

Figure 62: Internal Board Data Capture 128

Figure 63: Internal Board Data Capture 129

Figure 64: Capture Unit with Bracket 130

Figure 65: Connection Bracket to Guard Rail 131

Figure 66: Connection to Simple Bracket 132

Figure 67: Shows Bracket along with Safety Tether... 133

Figure 68: Capture Unit above the Highway... 134

Figure 69: Wired and Tethered Unit 135

Figure 70: Sensor Looking Down on Traffic 136

Figure 71: Sensor Looking Down on Traffic 137

Figure 72: New Laser Sensor (High Frequency).. 138

Figure 73: Complete Capture Unit with Bracket.. 139

Figure 74: Gateway Board: Site 1 140

Figure 75: Gateway Board: Site 1 141

Figure 76: Gateway Showing Modern and Relay Units.. 142

Figure 77: Close-up of Gateway Unit 143

Figure 78: Screen Showing Traffic Counts.. 144

Figure 79: Solar Power Unit for Sits 1.. 145

Figure 80: Solar Power Unit for Site 1 with Battery Box 146

Figure 81: Solar Power Unit for Site 1 with Battery Box 147

Figure 82: Site 1 Battery Unit Showing the Solar Controller 148

Figure 83: Slight Voltage Drop from 15V 149

Figure 84: Solar Unit for Site 2 (24V) 150

Figure 85: Solar Unit for Site 2 (6 Traffic Lanes).. 151

Figure 86: Solar Unit: Site 2.. 152

Figure 87: Solar Unit: Site 2.. 153

Figure 88: Capture Unit above Traffic.. 154

Figure 89: Capture Unit above Traffic.. 155

Figure 90: Capture Units on Southbound.. 156

Figure 91: Site 2: Gateway Unit and Capture Unit 157

Figure 92: Bracket Ready for Capture Units 158

Figure 93: Capture Unit During Installation 159

Figure 94: Site 2: Gateway Unit with Voltage Regulator 160

Figure 95: Site 2: Gateway Unit 161

Figure 96: Site 2: Gateway Unite and Capture Unit on One Bracket 162

Figure 97: Site 2: Gateway Unit and Capture Unit on One Bracket 163

Figure 98: Site 2: Gateway Unit 164

Figure 99: Site 2: Gateway Unit 165

Figure 100: Site 2: Gateway Unit 166

Figure 101: Three Complete Capture Units 167

Figure 102: Capture Unit with Three Different Sensors 168

Figure 103: Capture Unit with Two Different Sensors 169

Figure 104: Tethered Bracket before Installation 170

Figure 105: Batteries for Solar Panels (24V) 171

Figure 106: Solar Controller and Power Relay 172

Figure 107: Electrical Connections 173

Figure 108: Power Relay 174

Figure 109: Site 2: Solar Controller 175

Figure 110: Solar Controller Display via Bluetooth 176

Figure 111: Solar Controller Display via Bluetooth 177

Figure 112: Solar Controller Display via Bluetooth 178

Figure 113: Solar Controller Display via Bluetooth 179

Figure 114: Distance from Sensor to Highway below 180

CHAPTER 1: INTRODUCTION

1.1 Background

This research project's primary objective was to assess the benefits of diverting truck traffic around accident locations on freeways. To accomplish this objective, one needs a means for continuous data collection AND communication of traffic counts for both cars and trucks. Then the system needs to sense a reduction of traffic flow indicating an incident. Incidents are communicated to a central location where diversion scenarios are developed then communicated to interested parties.

For such a system to function efficiently in the real world and multiple locations (rural and urban), it needs to be powered by solar (or wind), have ULTRA low power consumption, be easy to install, and provide real-time updates using cell technology. Cost is always an important consideration.

The development of Intelligent Transportation Systems (ITS) requires high-quality information in real time. Over the years, the expense in both time and cost related to the collection of such data has been a challenge. Freight traffic Origin and Destination (O–D) data collection rely primarily on either traditional methods, which are manual counts and interviews, or on expensive ITS technologies that require excessive MOT and lane stoppages for installation. The collection of reliable O–D data for freight has profound consequences for a broad range of applications in both planning and operations. The demand for such data is also expected to increase with the modernization of the Panama Canal and the implications on freight in United States ports.

In a previous project, the research team has developed an automated O–D data development system for commercial vehicles. That research project was aimed at collecting truck-related data to support O–D studies. However, during the implementation of the research, the team realized that the hardware and system could be further expanded without an increase in system cost to the collection of comprehensive traffic data, including personal and commercial vehicles.

According to the extensive literature review performed in this study, the cost of loop detectors, pull and junction boxes, fiber optic cables, conduit, control cabinets, maintenance of traffic (MOT), and miscellaneous costs are about $5,500 for two lanes of traffic (excluding power). The system cost in the earlier project was about $2,000 per lane. With less than half of the cost, the system provides a superior architecture as well as captures truck license plate images which can be used for O/D studies.

In this research, the technology proposed has a substantially lower cost for roads with a few lanes. As compared to the side-fire radar method, this methodology requires much lower installation costs, integrates camera systems which enable to produce average speed between locations, provides height information, and less probability of having occlusion problems due to its installation architecture.

The I-75 corridor is a significant route for visitors to Florida by their vehicles, bus, or motor homes. Also, 60 million tons of freight is moved via I-75, annually on 12,000 trucks per day. By 2040, the numbers are projected to double. (I-75 Florida's Regional Advanced Mobility Elements (FRAME)).

1.2 Project Objectives

This deliverable report on 1) Installation at Test Site 1, 2) Installation at Test Site 2, 3) Preliminary Data Analysis, and 4) testing additional sensors.

This research aims to use O/D approaches in conjunction with the ATIS to determine and inform truckers of the benefits of alternative routes and collect data to dynamically capture the rate of divergence off I-75 before and after the information is provided. The objective is to understand the correlation between travel time and divergence and provide mutual support to the Integrated Corridor Management efforts in the area. Selected sites are equipped with cameras and traffic detectors to collect truck data and total volume counts around the Ocala area.

1.3 Project Progress

In the previous report, to improve the system, increase its range, and increase the number of nodes supported by each Gateway, the researchers decided to change the architecture to a mesh-based communications architecture. This required new hardware and multiple changes in the code. The code running on the microcontrollers has gone through numerous enhancements, including the transition to a mesh architecture. The system has been collecting data since early December 2018 with an almost 99.9% uptime.

A preliminary data analysis is provided in this report. Data has been continuously collected since December 20, 2018. The system has sent over 27000 updates to the cloud since that time. Data is sent to the cloud via cell communications with a monthly cost (2 sensors) of $7. In this report, we have included an extensive display of data belonging to March 2019. For an unknown reason, data collected by our sensors on weekends differ from loop counts.

Additionally, three case studies demonstrating the efficiency of the developed truck routing framework during incident-induced congestion on a segment of I-75 in Florida are presented. The proposed framework first performed a space-time cube hotspot analysis to identify statistically significant hotspots and classify hotspot trends over space and time to identify high-crash segments. A statistical regression model was applied to identify the explanatory variables that influence incident clearance duration. Finally, a regression model was developed to estimate incident clearance duration times in the I-75 corridor.

CHAPTER 2: LITERATURE REVIEW

This literature review includes two main sections: First, a review of the latest automated traffic data collection technologies is presented. Next, studies of the traffic incident management process and various diversion strategies are reviewed.

Due to the dramatic increase in vehicular traffic in today's world, congestion is becoming more problematic. To manage traffic and to prevent congestion, the options are either expanding the transportation systems or utilizing the existing infrastructure more efficiently by increasing the capacity [1]. The second option is being achieved by implementing Intelligent Transportation Systems, which requires data generated by surveillance, including sensor, communication, and traffic control technologies. Deployment of ITS technologies enables decision-makers to enhance public safety, reduce congestion, improve access to travel information, assess cost savings, and reduce harmful environmental impacts.

Moreover, traffic data is demanded design, operations, maintenance, programming, forecasting, and other functions. Personnel involved in actual data collection require specific guidance in collection methodology and data handling. The main goal of traffic data collection is to provide the basis for identifying problems, quantifying the impact of changes, and determining the nature or magnitude of needed improvements. To ensure valid interpretation and comparability, reliable and adequate data are essential. The primary traffic data measurements collected with ITS devices can be listed as follows; volume count, vehicle classification, vehicle occupancy, travel time, spot speed, average speed, and travel delay [2].

Volume counts obtain the estimation of traffic flow and volume. Volume counts are conducted in two methods depending on the length of the sampling period. For small sample size studies where the effort and cost of automated equipment are not warranted, manual counts can be performed typically for less than a day. Traffic counts obtained via automated equipment that would generate large amounts of traffic data are generally taken in 1-hour intervals every 24 hours. In addition to total traffic counts, directional, lane, pedestrian, or freeway segment counts are collected as traffic volume data. This information also helps to identify peak (critical flow) periods, and by adding classification level, the influence of large vehicles or pedestrians on traffic flow will be determined.

Vehicle classification information provides prediction and planning for commercial vehicles and freight movement, development of weight enforcement facilities, crash record analysis, environmental impact analysis, and alternative infrastructure investment policies. Further, the use of vehicle classification data includes establishing pavement, structural, and geometric design criteria, management, and maintenance.

Vehicle occupancy is another measurement that is a function of speed and length of the vehicle and can be considered a substitute for density. It is primarily used in congestion management to evaluate the efficiency of the roadway system and High Occupancy Vehicle (HOV) lanes.

The travel time, defined as the period to complete a route between two points of interest, is a fundamental transportation measurement for a variety of transportation analyses, including planning, congestion management, and traveler information, etc. In today's world, real-time travel time information and predictions are widely available via advanced traveler information systems (ATIS). Travel delay measurement is derived by computing the difference between free-flow travel time and detected actual travel time [3].

2.1 Traffic Data Collection Methods

Based on their functionalities, traffic data collection methods can be categorized into two main groups. In Figure-1, a category tree of technologies is provided. On-site detectors, also known as in-situ technologies and in-vehicle technologies which generate Floating Car Data (FCD). On-site detectors are also divided into two groups, such as intrusive (a.k.a. in the roadway) detectors and non-intrusive (a.k.a. on-roadway) detectors. An intrusive sensor is one that is embedded in the subgrade of the roadway or attached to the roadway surface [4]. Commonly used intrusive technologies include inductive loop detectors, weigh-in-motion (WIM) sensors, embedded magnetometers, pneumatic detectors, and piezoelectric detectors. Non-intrusive technologies are mounted either above or alongside the roadways. Existing non-intrusive sensors can be listed as Automatic Vehicle Identification (i.e., license plate readers, Bluetooth readers, transponder readers, radio-frequency ID, light detection and ranging (LIDAR)), Video Vehicle Detection Sensors (VVDS) (i.e., CCTV or video image processing), Microwave Detection Sensors (MVDS) (i.e., continuous-wave (CW, Doppler) and frequency-modulated continuous-wave (FMCW)), aerial photography, and infrared systems (i.e., active and passive infrared systems).

In-vehicle technologies, which are relatively new traffic data sources, are considered in two groups in this report: probe vehicles and remote sensing. Probe vehicles could be further broken down into five different methods based on their technologies: GPS, mobile phone, Bluetooth device, Automatic Vehicle Location (AVL), and AVL systems [5].

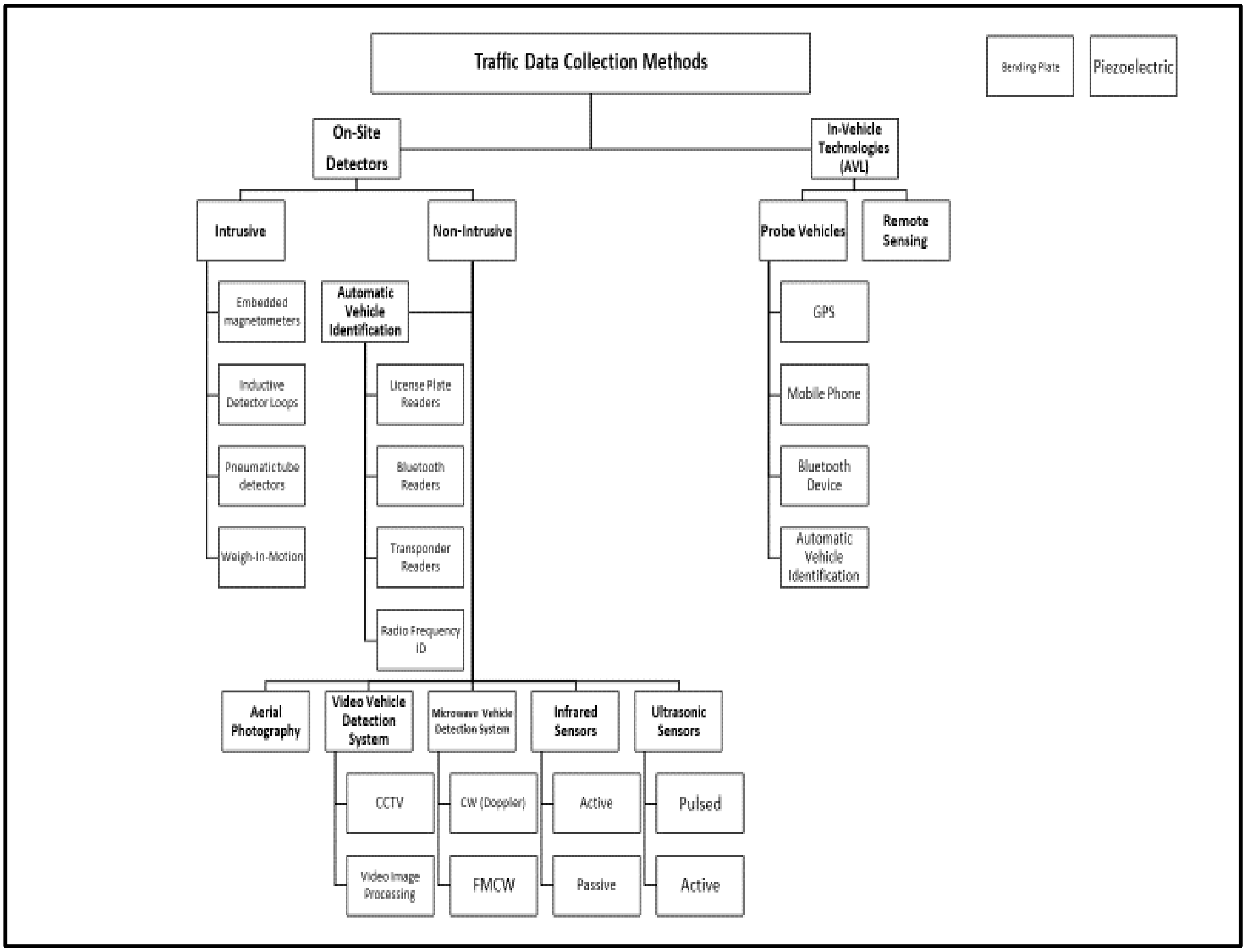


Figure 1: Traffic Data Collection Technologies

2.2 On-Site Detectors (In Situ Technologies)

The first group of on-site detectors is intrusive technologies. These sensors/detectors are mounted at or below the road surface, which potentially disrupts traffic if not installed on a new roadway facility. However, non-intrusive technologies generally are less disruptive in terms of maintenance of traffic and have lower rates of failure as compared to intrusive detectors. Intrusive technologies are required to be permanent, while non-intrusive sensors/cameras could be either temporary (portable) or permanent (fixed). Further, in another way of categorizing in-situ technologies based on their functionalities, three groups are considered: point sensors, point-to-point sensors, and area-wide sensors. Point sensors are the most widely used category among traffic data collection methods in current use.

These are inductive loop detectors, radar, infrared, MVDS, acoustic, ultrasonic sensors, video image detection systems, and WIM sensors where the data collection is performed at one single site/point. Examples of technologies in point-to-point sensors are AVI, AVL, license plate matching with optical character recognition algorithms. This type of data collection can be performed at multiple locations as vehicles move among the network. With this type of detection, tracking and re-identification are achieved, which may provide average speeds, travel times/delay, Origin-Destination (OD) information, and route choices [6].

Last but not least, area-wide sensors are essential sources of real-time traffic monitoring. The traffic information collected using aerial photography, LiDAR technology, and VVDS systems can be considered area-wide sensors where the data requires a telecommunication connection for transferring to the Traffic Management Center (TMC). Recently, the Floating Car Data concept is widely used in real-time traffic data collection. In this method, data is obtained from GPS equipped vehicles that provide higher coverage travel speeds in such high resolution (as low as 1-minute intervals). Therefore, FCD could inform the TMC to focus on recurrent congestion areas and is also capable of detecting non-recurrent congestion, which possibly enabling drivers to avoid longer delays [7].

2.2.1 Intrusive (In-Roadway) Technologies

The five types of intrusive detectors mentioned on page 5 of this report are discussed below.

2.2.1.1 Magnetometers

Magnetometers, also known as passive magnetic sensors, are embedded in roadway surfaces. The sensors require either wired or wireless communication with a nearby base station. The unit has a circular or elliptical offset zone of detection. In Figure-2, an example of a wireless magnetometer and an image from the installation process is provided [6].

Magnetometers monitor for fluctuations in the relative strength of the Earth's magnetic field, which is changed by the presence of a moving vehicle with metal parts. A single passive magnetic system collects flow and occupancy. Thus, to collect flow, occupancy, vehicle length, and speed dual magnetometer system is used. There are two types of magnetic sensors used for traffic flow parameter measurement. The first type detects changes in the x and y-axis of the magnetic field by a metal content of a moving vehicle, while the other type of magnetic field sensor is the magnetic detector that detects the vehicle signature by measuring the change in the magnetic lines of flux caused by the change in field values produced by a moving metal content of the vehicle [7].

Magnetometers are usually mounted in a small hole in the road surface and hard wired to the processing unit, and they're suitable for deployment on bridges. On the other hand, they can easily get damaged by utility maintenance activities [8].

Figure 2: Wireless Magnometer and the Installation Process

2.2.1.2 <u>Inductive Detector Loops</u>

The most widely deployed sensor technology, loop detectors, are typically low-cost sensors, but the most crucial downside is the installation and maintenance, which interrupts traffic, and there are potentially severe reliability and accuracy issues. In this method, the oscillating electrical signal is applied to the loop. The metal content of a moving vehicle changes the electrical properties of the circuit, and these changes are detected at a roadside unit. A single loop system collects flow and occupancy, and two-loop systems collect flow, occupancy, vehicle length, and speed. Due to their ubiquity, researchers have developed ways to use them for vehicle classification and vehicle reidentification [2]. Vehicle classes considered are presented in Figure 4. Recently, devices that can perform similar functions with higher accuracy and reliability, easier installation, lower maintenance, and longer life span have been introduced (e.g., sensysnetworks.com). Another disadvantage is some radio interference can occur between loops near to each other.

Figure 3: Inductive Loops

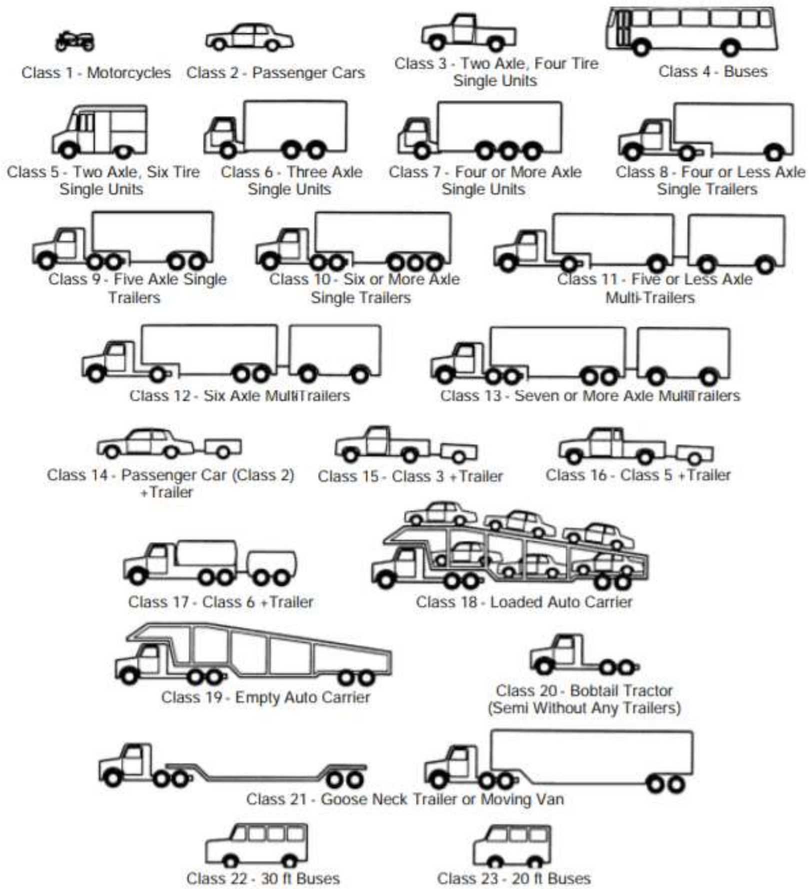


Figure 4: Vehicle Classifications

2.2.2 Pneumatic Tube Detectors

The pneumatic tube is one of the oldest traffic data collection methods. With technological advances, there has been a tendency for substitution by inductive loops. However, they are still widely used because of their reliability regarding temporary counting. A pneumatic road tube sensor is presented in a rubber tube attached to the pavement surface using appropriated spikes. These sensors send a burst of air pressure along the tube when a vehicle's tire passes over. This variation pressure is propagated to the extremities of the tube and the end, connected to an air pressure-sensitive element that triggers an electrical contact. Thus, it can count the number of axles that pass over the sensor. The pneumatic road tube sensor is portable and installed perpendicular to the traffic flow direction, as shown in Figure 5. It is commonly used for short-term traffic counting, vehicle classification by axle count and spacing. Some data to calculate vehicle gaps, intersection stop delay, stop sign delay, saturation flow rate, spot speed as a function of classification, and travel time when the counter is utilized together with a vehicle transmission sensor. However, the life of the tubes is usually less than one month. The tube detectors are not suitable for high flow and high-speed roads. Parking spots should be avoided for tube locations. Also, it is not capable of detecting two-wheelers [9].

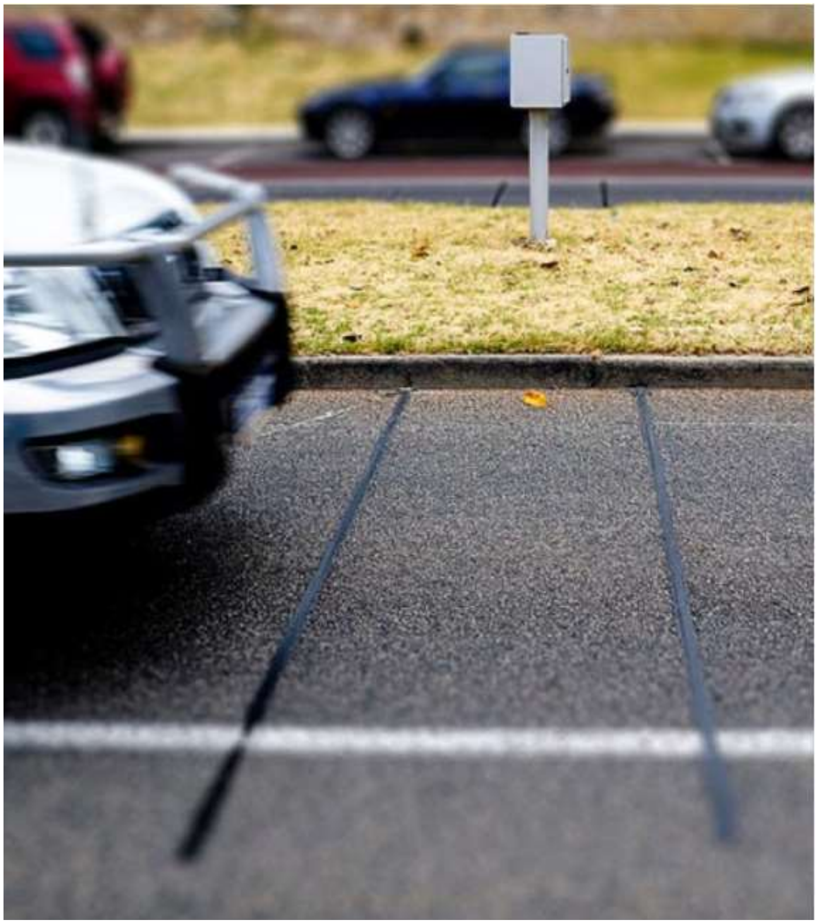


Figure 5: Fixed and Embedded Types of Pneumatic Detectors

2.2.3 Weigh-in-Motion (WIM) Sensors

WIM systems allow for the unremarkable and non-disruptive collection of vehicle weight information [64]. Two commonly used types are covered in this report: bending plate WIM sensors and piezoelectric WIM sensors.

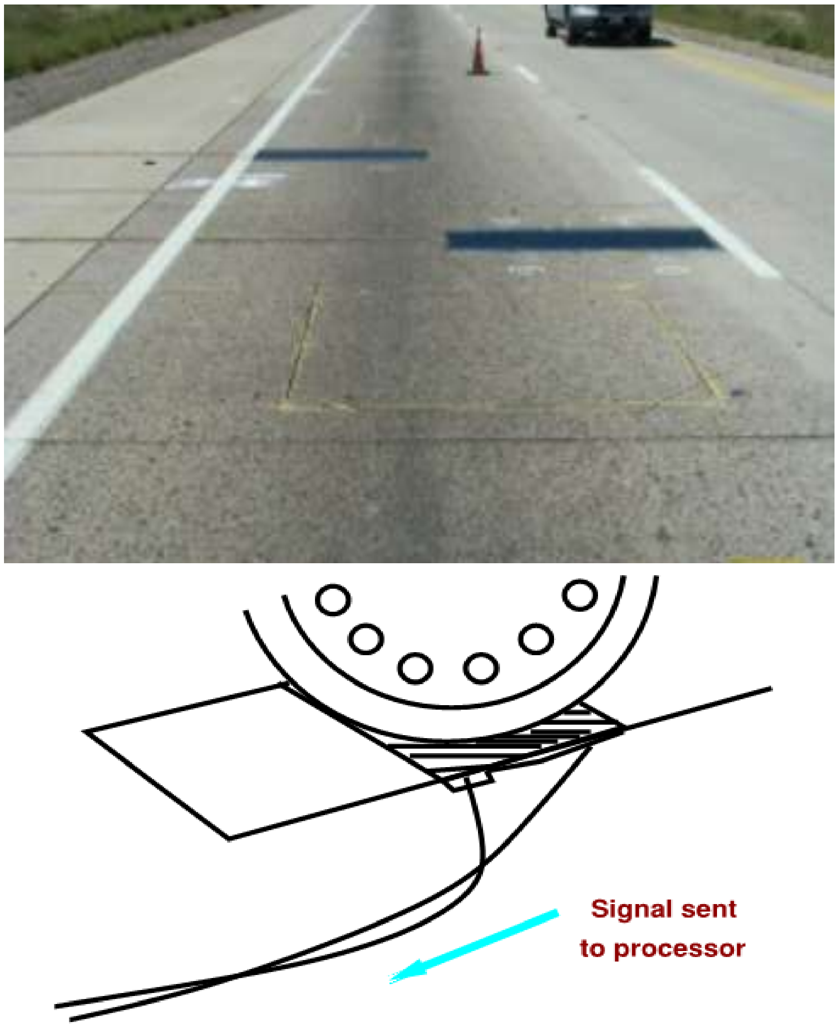


Figure 6: WIM Sensor

2.2.3.1 <u>Bending Plate WIM Sensors</u>

Bending plate WIM systems is used for traffic data collection as well as for weight enforcement purposes. It utilizes plates with strain gauges bonded below the roadway surface. The system records the strain measured by strain gauges and thereby calculates the dynamic load. The static load is estimated using the measured dynamic load and calibration parameters. Calibration parameters account for factors, such as vehicle speed and pavement or suspension dynamics that influence estimates of the static weight. The accuracy of bending plate WIM systems can be expressed as a function of the vehicle speed traversed over the plates, assuming the system is installed in a sound road structure and subject to normal traffic conditions. The accuracy of these systems is higher than piezoelectric systems but are considerably more expensive than piezoelectric systems. Their cost is lower than, however, are not as accurate as load cell systems [10]. Bending plate WIM systems do not require complete replacement of the sensor (see Figures 6 - 7)

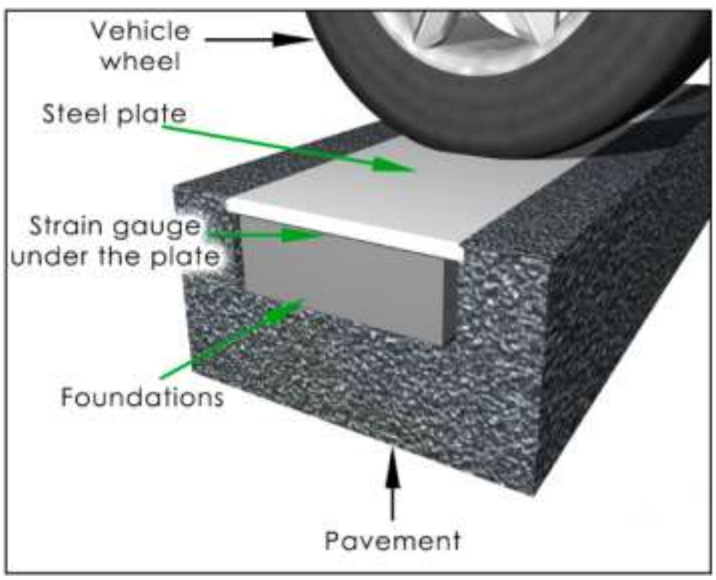


Figure 7: Bending Plate Sensor

2.2.3.2 Piezoelectric WIM Sensors

Typical piezoelectric WIM systems are among the least expensive systems in use today in terms of initial capital costs and life cycle maintenance costs. They can be used at higher speed ranges (16 to 112 mph) than bending plate systems, and they can be used to monitor up to four lanes. Piezoelectric WIM systems contain one or more piezoelectric sensors that detect a change in voltage caused by pressure on the sensor by an axle and thereby measure the weight of axles. As a vehicle passes over the piezoelectric sensor, the system records the sensor output voltage and calculates the dynamic load. With bending plate systems, the dynamic load provides an estimate of the static load when the WIM system is calibrated correctly. The piezoelectric sensor is placed in the travel lane perpendicular to the travel direction. They are generally used in conjunction with inductive loops, which are placed upstream and downstream of the piezoelectric sensor. The upstream loop detects vehicles and alerts the system to an approaching vehicle while the downstream loop provides data to determine vehicle speed and axle spacing based on the time it takes the vehicle to traverse the distance between the loops. Figure 8 shows a full-lane width piezoelectric WIM system installation. Piezoelectric sensors for WIM systems must be replaced at least once every 3 years [7].

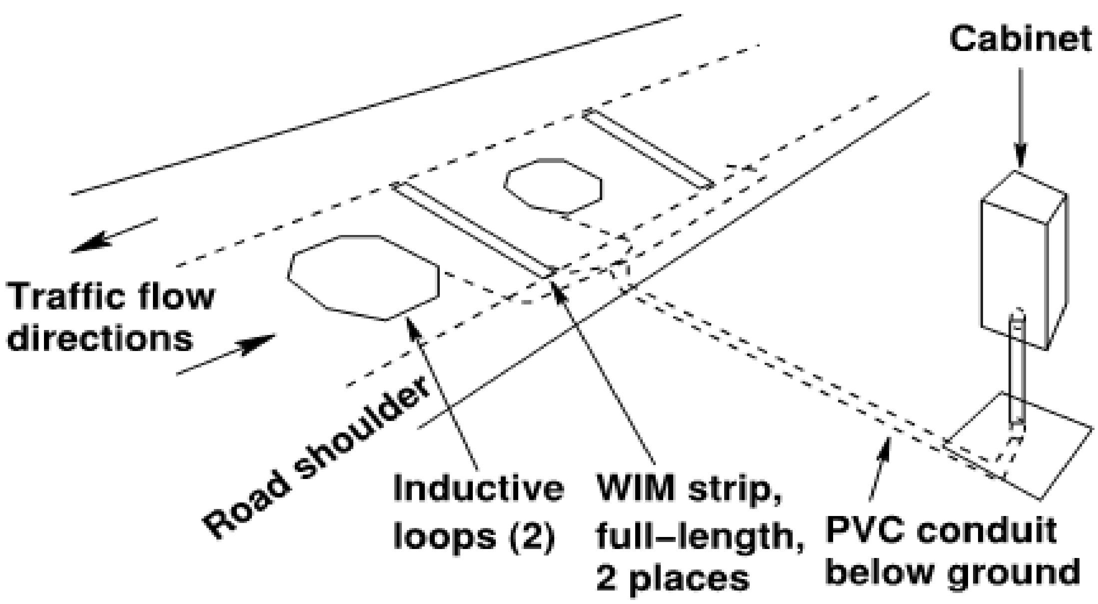


Figure 8: Full Lane Width WIM Sensor

2.3 Non-Intrusive Technologies

Non-intrusive (over-roadway) methods of traffic data collection are alternative reliable, and cost-effective vehicle detection and tracking systems, which can be installed and maintained with safety and slight disruption of traffic and can provide accurate traffic data, has been in use for some time. Recent evaluations have shown that modern over-roadway sensors produce data that meet the requirements of many current freeways and local road applications. Over-roadway sensors can be mounted above the lane of traffic they are monitoring or on the roadway side at a certain height where multiple lanes of traffic can be viewed at angles perpendicular to or at a tilted angle the flow direction. Existing technologies currently used in over-roadway sensors are Video Vehicle Detection System (VVDS), Microwave Detection System (MVDS), infrared sensors, ultrasonic sensors, and combinations sensor technologies such as passive infrared and microwave Doppler or passive infrared and ultrasonic. Like the intrusive sensors, the non-intrusive sensors measure vehicle count, presence, and passage. However, many also provide vehicle speed, vehicle classification, and multiple-lane—multiple-detection zone coverage. There are also multiple zones of detection defined within the overall field of regard, or the zone of detection as the field of regard, depending on the detector type and technology[2].

2.3.1 Video Vehicle Detection System

The development of video sensors for traffic analysis is a relatively recent technology, intended for automatic detection of incidents and the development of traffic studies. Despite the technological diversity of cameras, video sensors require models specially adapted to the concerned applications [11]. Necessarily, a video system follows the scheme in Figure 9.

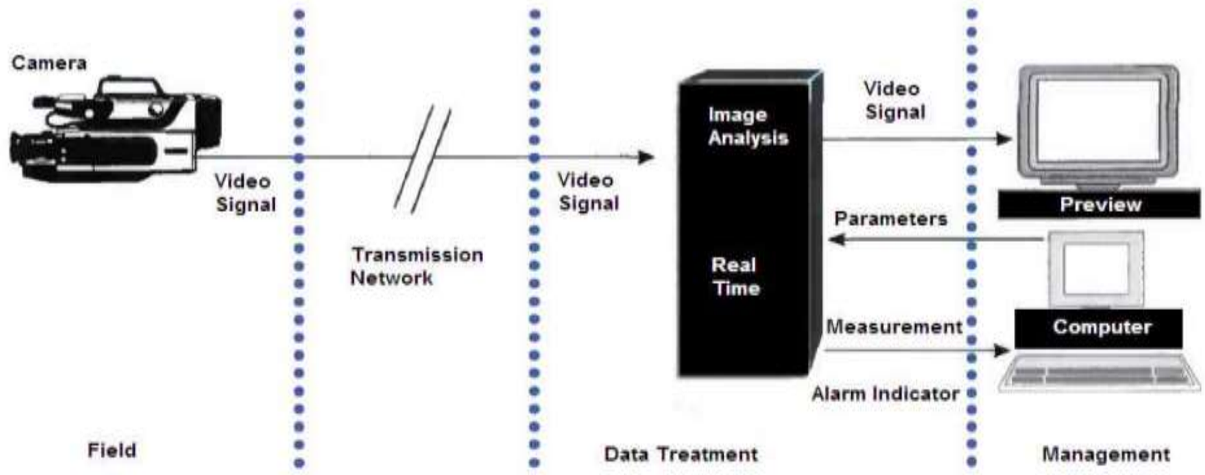


Figure 9: Video Detection

The most common video systems can be listed as follows;

- CCTV
- Video Image Processing

The traffic parameters are collected by frame-by-frame analysis of video images captured by roadside cameras. The following parameters are collected: Depending on the processing methodology, almost all traffic parameters are captured from video analysis. Simple video systems often collect flow volume and occupancy. More sophisticated systems allow the extraction of additional parameters. VVDS's are capable of capturing all desired traffic information, including some parameters that are not readily obtainable using other types of detectors. Possibility of a permanent visual record of the traffic flow that was reviewed and analyzed manually by a human operator. As with other non-intrusive detectors, VVDS systems are also susceptible to obscure performance issues as they are sometimes affected by severe weather or low light conditions [2].

2.3.2 Microwave Detection System (MVDS)

The microwave detection system is another widely used traffic data collection method that includes small sensors that are light in weight and easy to install. They are low in cost alternative to detect vehicle presence when compared to inductive loops. Also, low energy consumption makes them ideal for detecting moving vehicles at intersections with traffic lights and roads in construction. In this method, the detection of a vehicle is made with the spread of low-level microwave energy along the section of a road. While the vehicle approaches, a portion of the microwave energy is blocked and reflected by the sender allowing to refer to speed and direction of vehicle movement. It can't detect stationary objects. At installation, their potential tendency to suffer interference should be considered [2]. The frequency shift of the return is used to calculate the speed at doppler units (see Figure 10).

There are three types of radar systems in use:

- *Continuous Wave Doppler*
- *Frequency-Modulated Continuous Wave (FMCW)*
- *Microwave*

Doppler units collect flow volume and speed. In FMCW, flow volume, speed, and presence are collected. In a microwave, flow volume, speed, presence, and possibly classification are collected.

The accuracy in radar systems is very high. They're easy to install, non-stop day and night operation is possible. Multiple detection zones can be detected. However, some restrictions may be on use due to electromagnetic interference with other electronics [7].

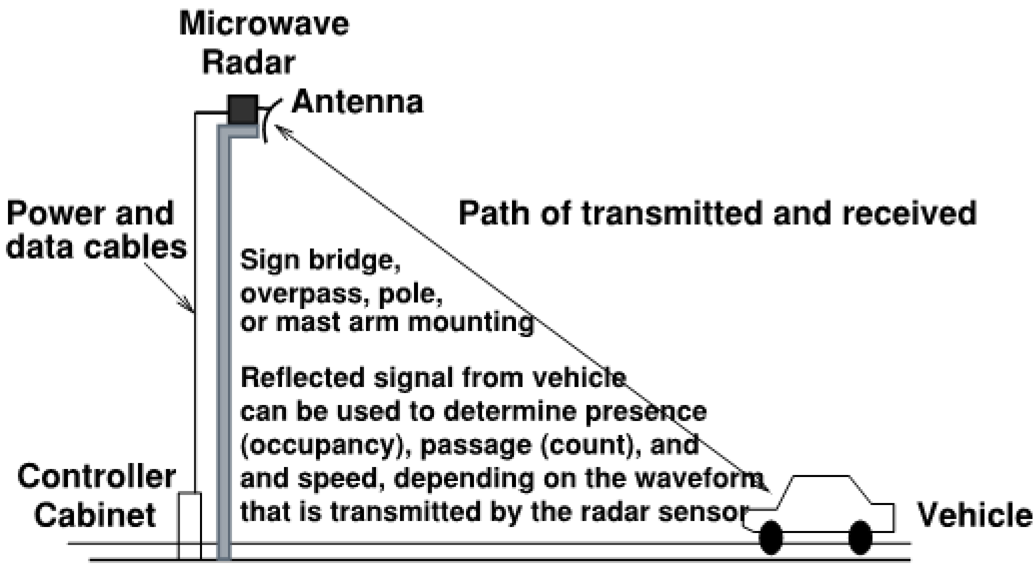


Figure 10: Microwave Detection System

2.3.3 Infrared Sensors

Infrared sensors are widely used in many ITS applications. The sensors are mounted overhead to view approaching or departing traffic or traffic from a side-looking configuration. Infrared sensors are used for signal control, volume, speed, and class measurement, as well as detecting pedestrians in crosswalks. With infrared sensors, the word detector takes on another meaning, namely the light-sensitive element that converts the reflected or emitted energy into electrical signals. Real-time signal processing is used to analyze the received signals for the presence of a vehicle. Infrared sensors can be classified into two prominent families, passive infrared and active infrared, both used for traffic purposes [6].

2.3.3.1 <u>Active Infrared</u>

Active infrared work by the principle of emission/reception of an infrared ray (wavelength from 0.9 to 1 µm).

Depending on the mode of reflection of the ray, the whole emitter/receiver can be used in three different ways based on how the transmitter and receiver are located. In barrier mode, the transmitter and receiver are placed face to face to allow the detection of the vehicle in motion cutting the infrared ray. The range may exceed 200 meters. When the transmitter and receiver are placed in the same box and the ray is reflected by a surface consisting of a prismatic reflector or glass microspheres, it is in reflection mode. The range can be more than 30 m in this mode. Finally, in proximity mode, the transmitter and receiver are also placed in the same box as reflection mode. In this method, the vehicle ensures reflection. The proximity mode setting is more straightforward than other methods. However, it has some disadvantages, such as difficulty detecting dark-colored vehicles and range limited to approximately 3 m.

The active infrared system is capable of collecting flow volume, speed, classification, vehicle presence, and traffic density. It also works in day and night conditions. However, it could be affected by weather conditions, and it is slightly higher in cost than other units [12].

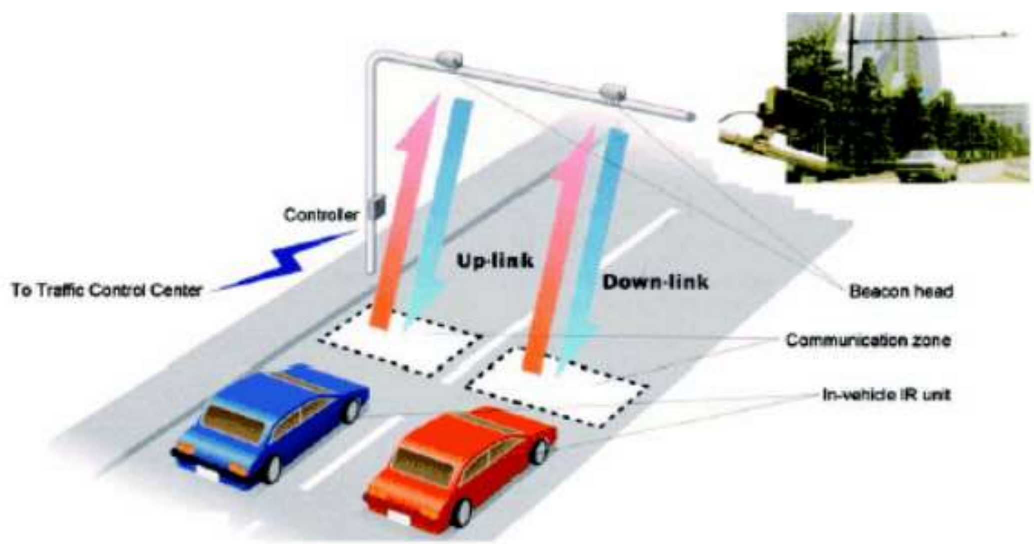


Figure 11: Active Infrared Sensor

2.3.3.2 Passive Infrared

The passive infrared works by detecting the heat emitted or reflected by an object (electromagnetic radiation of frequency 1011− 1014Hz) and is commonly used in lighting controls, opening doors, or entrance control security. The primary use of this type of sensor is to detect the presence of vehicles or pedestrians, reaching up to 100 meters range. This detection can be operated primarily in urban areas, with the traffic lights to detect, for example, the presence of pedestrians on a crosswalk or approaching vehicles. The passive infrared system can collect the following parameters: Flow volume, vehicle presence, and occupation in the detection zone. Also, speed can be calculated via units at multiple detection zones [7].

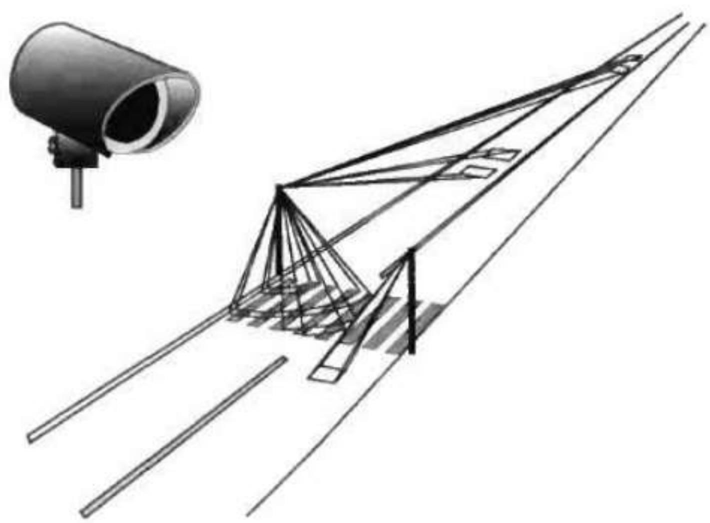


Figure 12: Passive Infrared Sensor [7]

2.3.4 Ultrasonic Sensors

In non-intrusive data collection methods, ultrasonic sensors are presented as an alternative to the inductive loops. The ultrasonic sensor consists of a directed antenna that emits ultrasonic sound waves between 25 and 50 KHz. Pulse waveforms measure distances to the road surface and vehicle surface by detecting the portion of the transmitted energy that is reflected towards the sensor from an area defined by the transmitter's beam width. While there is no obstruction, the detection radius corresponds to a disk whose diameter depends on the direction and antenna height. When a vehicle passes, the reflected wave will be captured by the receiver after a specific time. The sensor will send a signal for the count of vehicles and calculate the occupation rate. The measurement of time between emission and reception allows the measurement of the distance between the transmitter of ultrasound and the vehicle. From this distance, vehicle classification information can be captured. With the small size of ultrasonic sensors, they can be either permanently mounted or portable units can be used, both on the side and the overpasses/gantries. This equipment is reliable, durable, and requires minimal maintenance. The range can reach to approximately 10 to 12 meters, allowing. The vehicle classification is possible via the vertical sight or horizontal sight. The occupation rate is also obtained. In Europe, generally, these sensors are not permanently installed, being used for temporary measurements. Despite being usually highly accurate, these sensors are sometimes impacted by environmental impacts that affect sound propagation and therefore degrade performance [1].

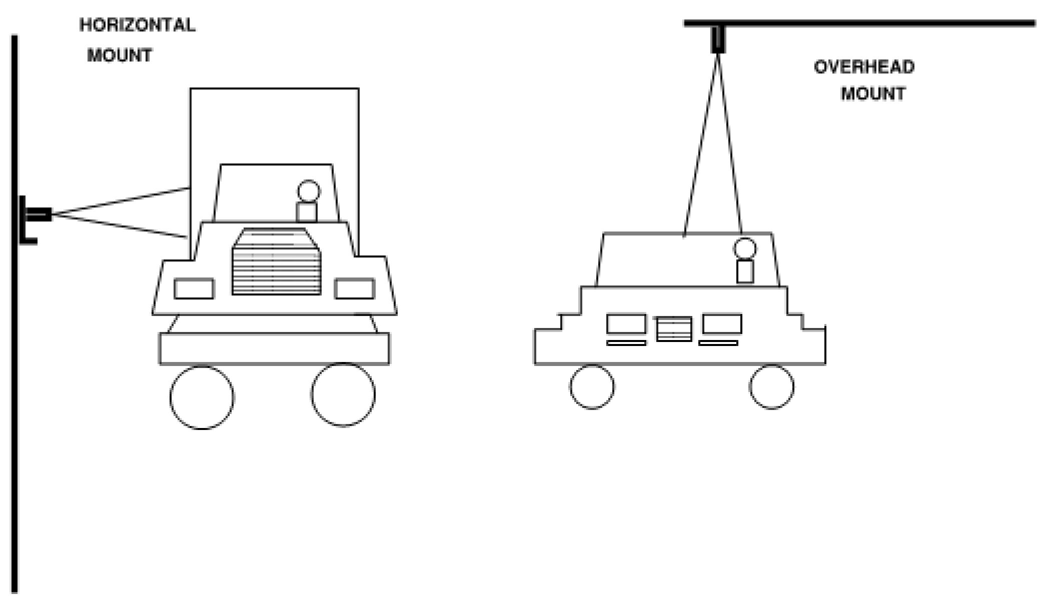


Figure 13: Acoustic Sensor

2.4 In-Vehicle Technologies

In addition to using on-site (in-situ) technologies for traffic data collection, many network management applications use in-vehicle technologies, also named Automatic Vehicle Location (AVL) systems. AVL devices can either provide spatial information whenever a suitably equipped vehicle passes a certain point in the network or continuous information as the vehicle travels through a network. In earlier stages, the system typically relies on appropriate vehicles equipped with transponders that transmit and receive information from roadside units. Later, vehicles equipped with Global Positioning System (GPS) technologies that generate FCD were used. The principle of FCD is to collect real-time traffic data by locating the vehicle via GPS or cellular phones over the entire road network. It represents that all vehicles are equipped with a mobile phone or GPS, which will act as a sensor for the road network. The location of vehicles, speed, and direction of travel data is sent anonymously to a processing center. After collecting and extracting useful information such as the status of traffic and alternative routes in real-time, the information can be distributed to the drivers on the road again via the same smart devices. FCD is an alternative or instead serves as a complement source of high-quality real-time data to existing technologies to improve the safety, efficiency, and reliability of the transportation system. These technologies are becoming crucial in the development of ITS. In this report, vehicle technologies are divided into two groups: probe vehicles and remote sensing [1].

2.5 Probe Vehicles

Probe vehicle technologies include GPS, mobile phones, Bluetooth, and AVI. They collect real-time traffic data for operation monitoring, incident detection, and route guidance. Probe vehicle systems usually require relatively higher implementation costs and fixed infrastructure; however, they have the advantages of continuous data collection and no disruption to traffic.

2.6 Global Positioning System (GPS)

GPS is becoming increasingly useful and inexpensive; in-vehicle navigation devices with GPS are becoming most of the network systems. The vehicle location precision was found to be relatively high, usually less than 30 m. Generally, traffic data obtained from personal vehicles or commercial trucks are more suitable for motorways and rural areas. Currently, GPS probe data are widely used as a source of real-time information by many service providers [13].

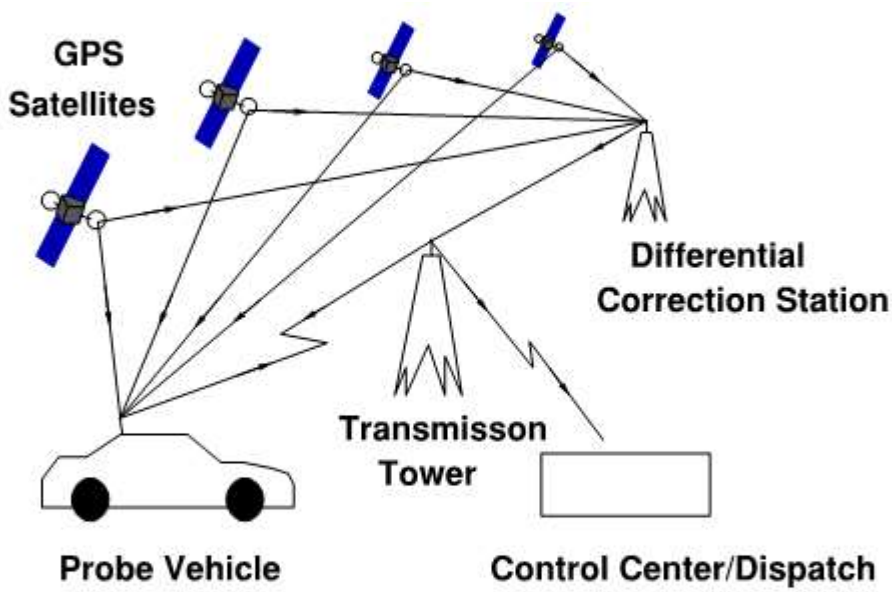


Figure 14: GPS Data Collection

2.6.1 Mobile Phone

Cellular reporting requires volunteer drivers to call a central facility when they pass checkpoints along the freeway. The cellular geolocating methodology discreetly tracks cellular telephone calls to collect travel time data and monitor freeway conditions. An operator at the central control facility records each driver's identification, location, and time. By monitoring the time between successive telephone calls, the travel time or travel speed between reporting locations may be determined [14]. The technique is useful for reporting a qualitative assessment of current traffic conditions and collecting travel time data during delays or accidents since the incident can be visually confirmed. However, probe vehicle drivers often miss checkpoints or fail to report locations at proper times. Travel times can be skewed by one or two minutes and can vary between individual probe vehicle reports. The mobile phone reporting method is recommended for short-term studies with low accuracy requirements.

The cellular geolocating methodology discreetly tracks cellular telephone calls to collect travel time data and monitor freeway conditions. This experimental technology can collect travel time data by discretely tracking mobile phone call transmissions. Mobile phones are also useful for collecting travel time data. All vehicles equipped with mobile phones are potential probe vehicles. The system automatically detects mobile phone call initiations and locates the particular probe vehicle in a brief period. Mobile phone data processing usually would need big data analytics due to the large potential sample [14].

2.6.2 Bluetooth Device

Recently, travel time measurements using Bluetooth have become popular due to the widespread use of Bluetooth devices in our daily lives. Bluetooth-based travel time collection is a new technique that utilizes enabled Bluetooth portable devices such as mobile phones, computers, personal digital assistants, and car radios to identify specific vehicles at downstream and upstream locations by tracking their unique 48-bit Machine Access Control (MAC) addresses. Figure 2-1 shows how the travel time can be "calculated" by matching Bluetooth MAC addresses at following detection locations along the road according to the timestamps associated with those MAC addresses. Bluetooth-based travel time data was used in this project to provide the ground truth travel times [15][16].

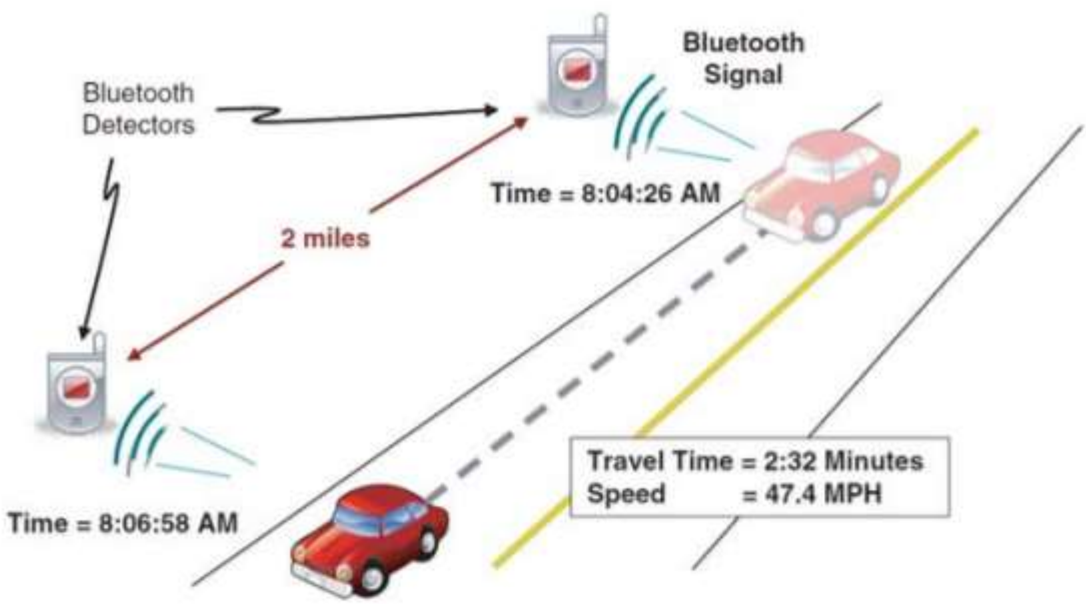


Figure 15: Bluetooth Data Collection

2.6.3 Automatic Vehicle Identification (AVI)

In automatic vehicle identification, probe vehicles are equipped with electronic tags. These tags communicate with roadside transceivers to identify unique vehicles shown and collect travel times between transceivers. In this report, four categories of AVI have listed: License plate readers, Bluetooth readers, transponder readers, and Radio Frequency Identification (RFID).

2.6.3.1 License Plate Readers

Travel times by matching vehicle license plates between consecutive checkpoints with varying levels of instrumentation: tape recorders, video cameras, portable computers, or automatic license plate optical character recognition (OCR). The advantages of license plate readers are the travel times are obtained from a large sample of motorists and provides a continuum of travel times during the data collection period. On the other hand, the disadvantages are, travel time data limited to locations where video cameras can be positioned, limited geographic coverage on a single day, and accuracy of license plate reading can be an issue for a manual and portable computer. Travel time between points can be calculated. It can be used almost universally since every vehicle is required to have license plates [3].

2.6.3.2 Transponder Readers

Probe vehicles may be equipped with several different types of electronic transponders or receivers. A signpost-based system, typically used by transit agencies for tracking bus locations, relies on transponders attached to roadside signposts. AVI transponders are located inside a vehicle and are used in electronic toll collection applications. Ground-based radio navigation systems use triangulation techniques to locate radio transponders on vehicles and are used in route guidance and personal communication systems [2].

2.6.3.3 <u>Radio Frequency Identification (RFID)</u>

RFID is another automatic identification method that relies on storing and retrieving data from remote areas using devices called RFID tags or transponders. The technology requires some extent of cooperation of an RFID reader and an RFID tag. An RFID tag is a unit that can be incorporated into a product, or even a person for identification and tracking using radio waves. Some tags can be read from several meters away and beyond the line of sight of the reader. A simple RFID system consists of an antenna, a transceiver with a decoder, and a transponder, also known as a radio-frequency tag. An RFID tag is comprised of a microchip to collect information and an antenna that transmits this data wirelessly to a reader. Generally, processed data would be used to provide revised scheduling and arrival time information to the public, via variable information signs. RFID's are also are widely used in parking management. They can be read through materials without a line of sight. However, reader collision may occur when the signals from two or more readers overlap, or many tags are present in a small area [15].

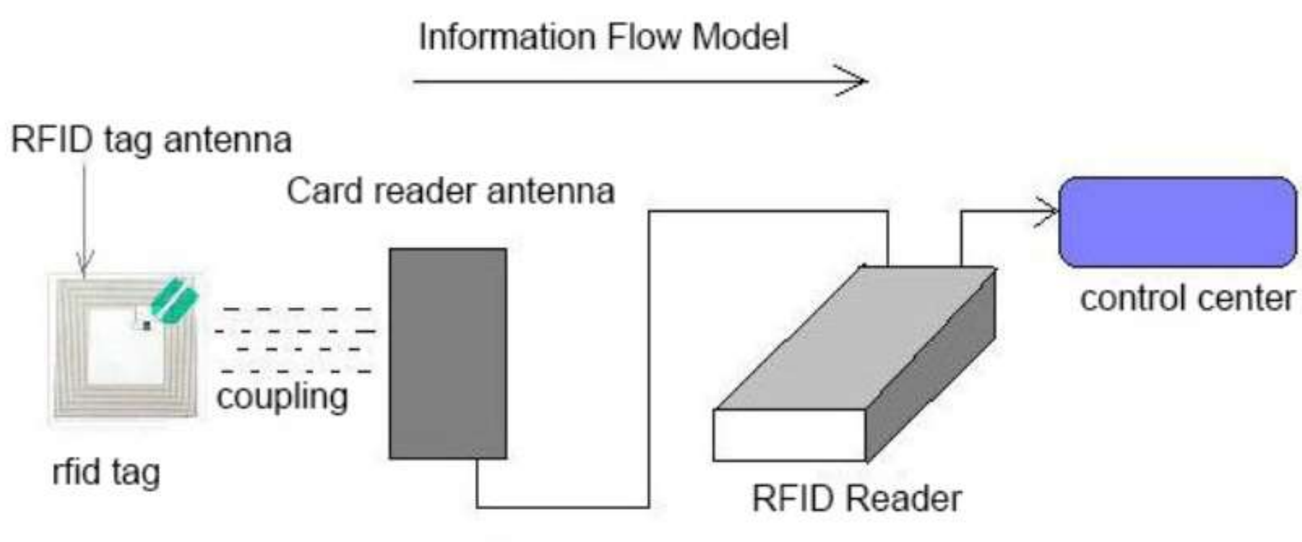


Figure 16: Workflow for an RFID System

2.7 Remote Sensing

Remote sensing is the measurement of information of some property of an object by examining electromagnetic radiation reflected or emitted from the Earth's surface or subsurface and stream the information to users. Remote sensing is commonly used at aircraft or satellites. This technology applies aircraft or satellite images to analyze and extract traffic information. However, for real-time traffic monitoring, remote sensing utilization is relatively limited [17].

2.8 Truck Re-routing Strategies

This literature review includes four sections: First, traffic congestion types are presented, including recurrent and nonrecurrent congestion. Next, studies of the traffic incident management process are reviewed; this section helps lay the foundation for examining the relevant congestion mitigation studies. The third section of this chapter first explores various diversion strategies and then summarizes the criteria for selecting an alternative route. In the fourth section, various network simulation tools are reviewed, with a focus on the application of a geographic information system (GIS) in transportation. Table 1 summarizes the reviewed literature on truck diversion studies.

Table 1: A Summary of a Literature Review of Related Studies

Study	**Evaluation Method**	**Findings**
Cragg and Demetsky, 1995	Corridor Simulation Software Package (CORSIM)	While traffic diversion might reduce travel time on the freeways, it can increase delays on the detour route by 64%. The inclusion of ramps and weaving sections with sufficient capacity to accommodate diverted traffic is crucial.

Aden and Nageli, 1999	Corridor Simulation Software Package (CORSIM)	The authors stressed the importance of testing signal-timing plans for alternate routes to relieve bottlenecks and reduce network delays.
Backfrieder, 2014	Traffic Simulator Platform (TraffSim)	The authors presented a microscopic simulation platform with the capability of integrating OpenStreetMap to generate a better simulation scenario and to simulate real traffic in a real environment.
Güner et al., 2012	Stochastic dynamic programming	The results confirmed that travel time savings were higher during peak times and lower when the traffic tended to be static.
Lin and Kou, 2003	Microscopic simulation	The modeling results of the case study offered several advantages for drivers using an alternate route. The findings evaluated the effectiveness of alternative route operations in reaction to a major highway accident.
Huaguo, 2008	CORSIM	Road diversion strategies could significantly reduce network delays—by an estimated 21%. A 10% redirected traffic volume has a significant effect on the average delay of the entire system.

Dia et al., 2008	Large-scale micro-simulation	The optimum diversion rate reached was 30%. This decreased the delay of 9%, the number of stops by 22%, and travel times by 3%.
Cuneo et al., 2014	Microscopic traffic simulation	The optimal diversion rate depends on the current traffic demand. This suggests the need to carry out a thorough assessment to determine the impacts of diversion techniques before they are introduced in the field.
Fries et al., 2007	Paramics	Only specific configurations of incident duration and simulation precision fulfilled the decision-time constraints for supporting real-time decision-making.
Luo et al. (2016)	Support vector regression	The study found a 15% difference between the model forecasts and the simulation, indicating the efficiency of the decision support system.
Li and Khattak (2018)	TransModeler	Their study assessed the impact of different Advanced Travel Management System(ATMS) technologies on en route diversion and investigated the delay decrease and cost savings for passenger vehicles and trucks.
Aleksandr et al. (2018)	Conceptual diagram	The authors presented and explained all the dynamic traffic rerouting (DTR) using a conceptual diagram. They determined a traffic flow threshold condition that can be used as a start for DTR.

2.9 Conclusions

This report lists the various technologies used for traffic data collection. The research team plans to use this knowledge to select the best technologies for our project. The major takeaways are:

1) As a significant (and often neglected component) is installed cost, noninvasive technologies will be selected to reduce or eliminate the need to stop traffic from installing and maintaining sensors.
2) Since the significant application of this project will be on busy highways, extensive consideration of reducing or eliminating MOT will be addressed.
3) As the benefits of this project are substantially magnified by increasing the number of locations that are instrumented, extensive consideration will be given to BOTH reducing power consumption (leading to smaller and less costly solar plants), and also simplifying installation by using simple wiring and very light sensors.

This chapter reviewed various studies on traffic management and truck rerouting to identify and analyze truck traffic rerouting strategies to avoid nonrecurrent congestion. Strategies that divert truck traffic to an alternative route can be used as congestion mitigation strategies. The alternative route consequently carries both the diverted traffic and its regular traffic load. Therefore, the alternative route should be carefully selected, and the safety and efficiency of the overall network should be considered when evaluating truck traffic diversion options. While traffic diversion strategies are deployed in many regions, there is minimal consideration of alternative route requirements when the optimal diversion route for trucks is chosen.

Nonetheless, the criteria for choosing alternative truck routes should be carefully defined to consider truck characteristics and to select routes that can efficiently accommodate truck traffic. Most previous studies of this issue focused more on enhancing traffic conditions for passenger vehicles than on conditions for trucks. Hence, little consideration has been given to evaluating the economic, social, and environmental impacts of truck traffic diversion on the performance of the selected alternative routes. The rapid growth of truck traffic has raised safety and operational concerns. Truck diversion strategies have been executed throughout the U.S. to diminish the impact of incident-induced congestion. Proper truck rerouting strategies can improve the operational efficiency of freeways and enhance traffic safety on these roadways.

This research proposes enhancing current frameworks with empirical data and conceptual supplements to improve traffic diversion strategies by incorporating uncertainties such as nonrecurrent congestion to assist decision-makers in strategy planning.

CHAPTER 3: SYSTEM DESCRIPTION AND DATA COLLECTION

3.1 Installation at Test Site 1

The first site is located at the overpass on Warm Springs Ave. And the Florida Turnpike (28.799611, -81.998932). Two northbound traffic lanes are instrumented.

The distance from the solar plant to the first sensor (and the Gateway) is 120 feet. The distance from the Solar plant to the farthest sensor is 135 feet.

Figure 17: Test Site 1

3.2 Hardware

To improve the system, increase its range and increase the number of nodes supported by each Gateway, the researchers decided to change the architecture to a mesh-based communications architecture. This required new hardware and changes in the code.

The hardware selected consists of a "Gateway" microcontroller, which receives wirelessly, via BLE (low-power Bluetooth), data from several laser sensors. The communication utilizes a mesh-architecture that enables one Collector to communicate to a large number of sensors that may be a reasonable distance away from the Gateway.

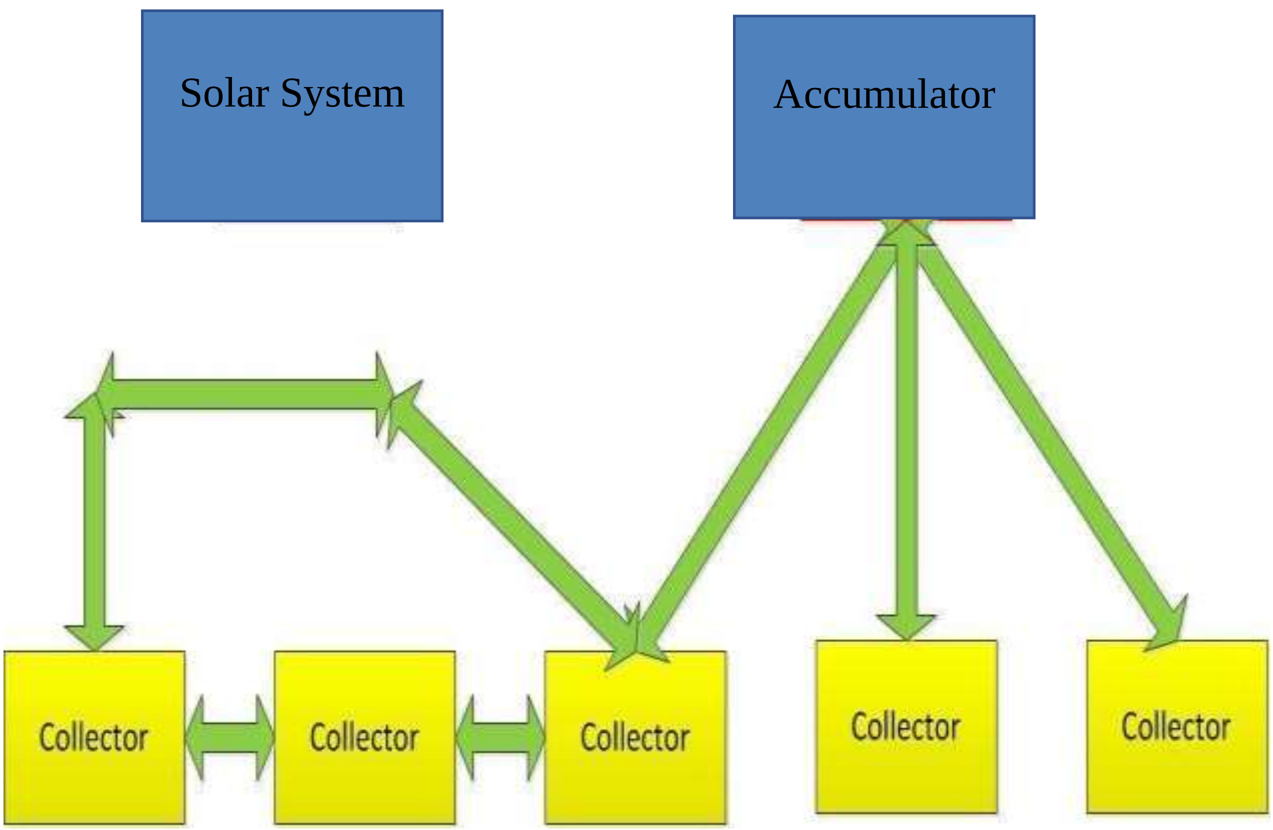


Figure 18: Mesh Architecture

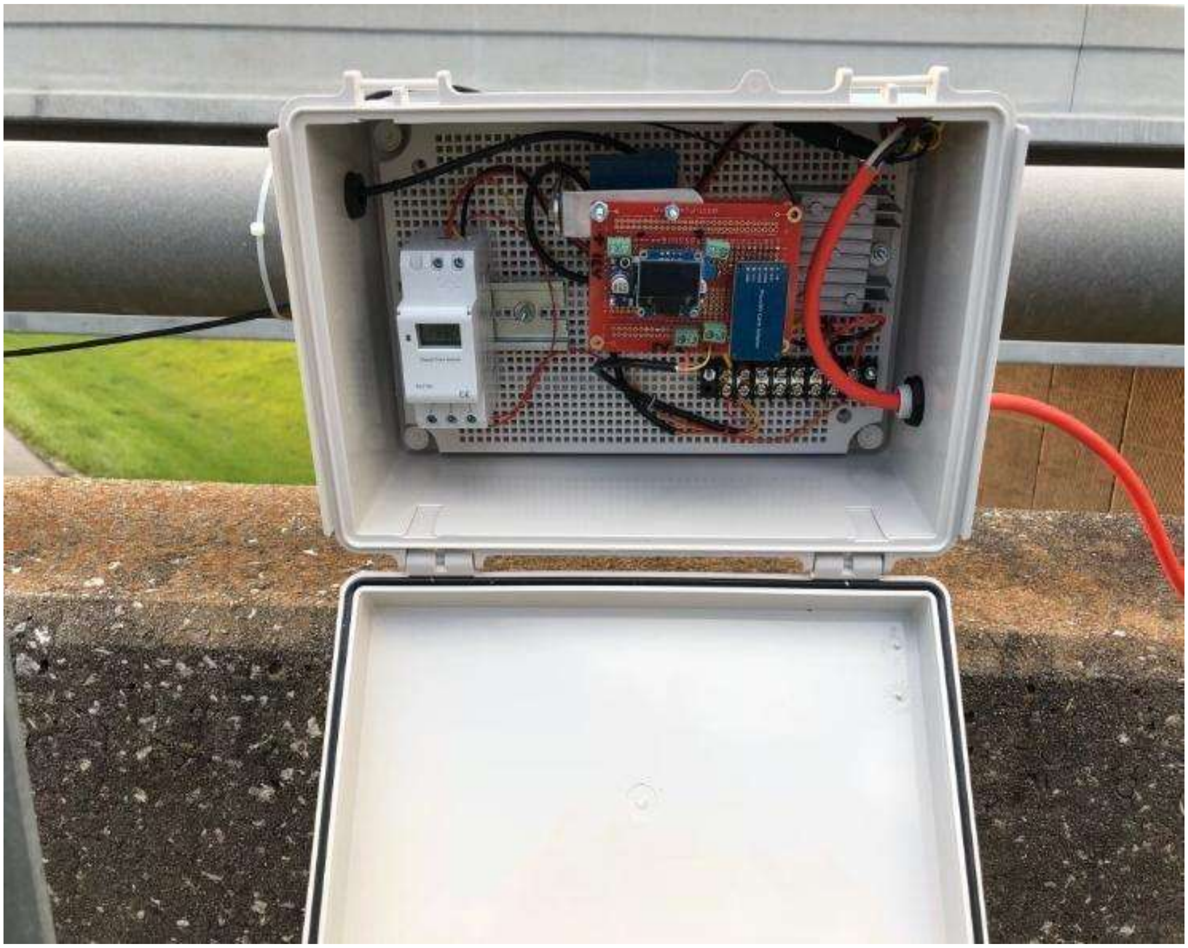


Figure 19: Gateway

Each traffic lane has a laser sensor that is connected to its microcontroller, "Collector." The Collector processes the data from the sensor then communicated to the Gateway. Using cell communications, the Collector aggregates the data and then sends it to cloud storage. The system can be monitored, and the data collected can be viewed as live 24/7.

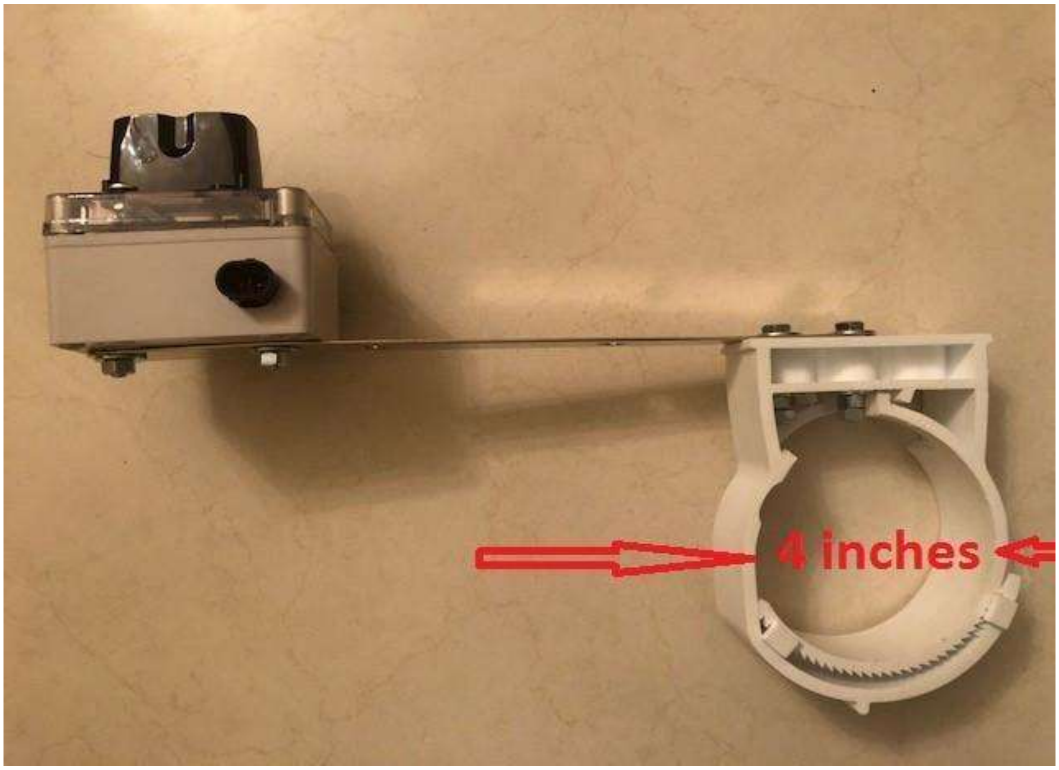


Figure 20: Bracket with Sensor

3.3 Sensor Technology Evaluation

This is the single most expensive component ($40-$500). The researchers evaluated multiple sensors, as described below:

3.3.1 Sensor 1 (Benewake TFmini)

This sensor was evaluated due to its low cost ($40).

Figure 21: Sensor 1 (Benewake TFmini)

3.3.2 Sensor 2 (Benewake TF02)

This sensor was evaluated due to its relatively low cost ($100).

Figure 22: Sensor 2 (Benewake TF02)

3.3.3 Sensor 3 (Garmin)

This sensor was evaluated due to its relatively low cost ($130).

Figure 23: Sensor 3 (Garmin)

3.3.4 Sensor 4 (Garmin HP)

This sensor was evaluated due to its relatively low cost ($150).

Figure 24: Sensor 4 (Garmin HP)

3.4 Communications

The Gateway aggregates the data in batches (200 data points each representing a vehicle). The number of vehicles in a batch is configurable and has an impact on the number of batches communicated and, therefore, on the amount of data transferred, which in turn, impacts communication costs. The data is transferred to the cloud and stored on a Thingspeak website. https://thingspeak.com/channels/632152. Data is graphed live, and an example is below. (system restarts every new day at 12:01 am). Thingspeak is a website owned by MATLAB and supports data analysis. A screenshot of the website's dashboard is presented in figure 21.

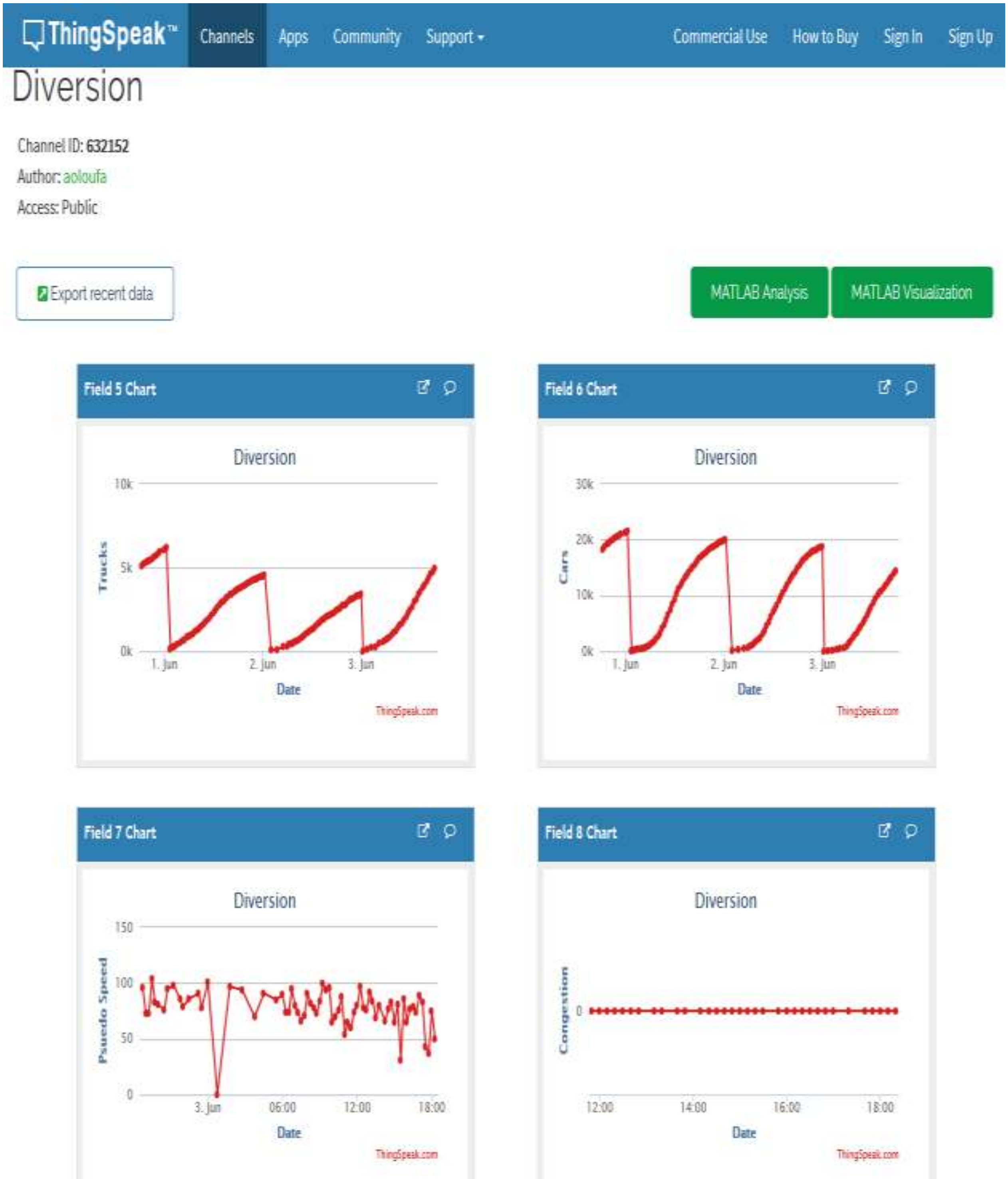


Figure 25: Traffic Data June 1-3, 2019

3.5 Summary of Results

In this section, traffic count data collected in March 2019 were processed. To conduct a comparative analysis, FDOT Telemetered Traffic Monitoring Site (TTMS) data were utilized as a benchmark. Summary results included counts from UCF detectors versus TTMS detectors, per lane and vehicle type, and presented by calendar days as well as weekdays-only charts. Metrics used in this summary include +/- error ratio and accuracy of UCF counts as compared to TTMS counts.

In Table 3-1, daily counts in March 2019 from UCF detectors and TTMSs are summarized per direction along with error percentages and accuracies for left lane, right lane, and total counts. In Figure 3-1, the accuracy profile for March 2019 is shown – on left lane (blue line), accuracy was maintained at or above 90% for the entire month except for the 21st and 23rd of March, where it drops to 87.2% and 83.3%, respectively. Right lane (red line) and overall (grey-dashed line) accuracies are found to be lower on weekends. Error percentages are also presented in Figure 3-2.

In Table 3-2, count data were summarized by dividing in-vehicle type categories. In Figure 3-3 and Figure 3-4, accuracies and error percentages were presented by vehicle types, including total counts. Similar trends are captured in these comparisons. UCF counts differ significantly compared to TTMS counts on weekends, while on weekdays, accuracy ranges from 85% to 100%.

Table 2: Right Lane vs. Left Lane Comparison

	Right Lane				Left Lane				Total			
Date	UCF	TTMS	RL ERROR	RL Accuracy	UCF	TTMS	LL ERROR	LL Accuracy	UCF RL+LL	TTMS RL+LL	ERROR %	Total Accuracy
3/1/2019	12,600	13,540	6.9%	93.1%	15,800	14,322	-10.3%	89.7%	28,400	27,862	-1.9%	98.1%
3/2/2019	9,200	12,610	27.0%	73.0%	11,200	10,819	-3.5%	96.5%	20,400	23,429	12.9%	87.1%
3/3/2019	9,000	12,616	28.7%	71.3%	13,200	13,026	-1.3%	98.7%	22,200	25,642	13.4%	86.6%
3/4/2019	12,600	11,613	-8.5%	91.5%	11,400	11,245	-1.4%	98.6%	24,000	22,858	-5.0%	95.0%
3/5/2019	12,600	11,564	-9.0%	91.0%	10,800	10,513	-2.7%	97.3%	23,400	22,077	-6.0%	94.0%
3/6/2019	12,800	11,731	-9.1%	90.9%	11,200	10,958	-2.2%	97.8%	24,000	22,689	-5.8%	94.2%
3/7/2019	12,800	12,123	-5.6%	94.4%	13,000	12,501	-4.0%	96.0%	25,800	24,624	-4.8%	95.2%
3/8/2019	12,800	12,631	-1.3%	98.7%	17,800	18,699	4.8%	95.2%	30,600	31,330	2.3%	97.7%
3/9/2019	10,200	14,148	27.9%	72.1%	15,200	15,795	3.8%	96.2%	25,400	29,943	15.2%	84.8%
3/10/2019	9,600	14,738	34.9%	65.1%	18,600	18,932	1.8%	98.2%	28,200	33,670	16.2%	83.8%
3/11/2019	12,200	12,405	1.7%	98.3%	13,200	13,943	5.3%	94.7%	25,400	26,348	3.6%	96.4%
3/12/2019	13,000	11,739	-10.7%	89.3%	11,000	11,195	1.7%	98.3%	24,000	22,934	-4.6%	95.4%
3/13/2019	13,000	11,421	-13.8%	86.2%	12,000	11,011	-9.0%	91.0%	25,000	22,432	-11.4%	88.6%
3/14/2019	13,600	13,275	-2.4%	97.6%	15,000	14,785	-1.5%	98.5%	28,600	28,060	-1.9%	98.1%
3/15/2019	14,800	15,576	5.0%	95.0%	19,200	19,162	-0.2%	99.8%	34,000	34,738	2.1%	97.9%
3/16/2019	11,400	15,560	26.7%	73.3%	18,200	18,910	3.8%	96.2%	29,600	34,470	14.1%	85.9%
3/17/2019	9,200	14,514	36.6%	63.4%	17,400	18,125	4.0%	96.0%	26,600	32,639	18.5%	81.5%
3/18/2019	12,600	12,871	2.1%	97.9%	14,200	14,007	-1.4%	98.6%	26,800	26,878	0.3%	99.7%
3/19/2019	13,000	12,057	-7.8%	92.2%	12,200	12,056	-1.2%	98.8%	25,200	24,113	-4.5%	95.5%
3/20/2019	13,000	12,271	-5.9%	94.1%	12,600	12,662	0.5%	99.5%	25,600	24,933	-2.7%	97.3%
3/21/2019	11,800	13,243	10.9%	89.1%	12,800	14,683	12.8%	87.2%	24,600	27,926	11.9%	88.1%
3/22/2019	14,200	15,385	7.7%	92.3%	19,600	19,477	-0.6%	99.4%	33,800	34,862	3.0%	97.0%
3/23/2019	8,800	15,339	42.6%	57.4%	15,200	18,253	16.7%	83.3%	24,000	33,592	28.6%	71.4%
3/24/2019	10,000	16,020	37.6%	62.4%	20,400	20,929	2.5%	97.5%	30,400	36,949	17.7%	82.3%
3/25/2019	20,200	12,716	-58.9%	41.1%	14,600	14,032	-4.0%	96.0%	34,800	26,748	-30.1%	69.9%
3/26/2019	13,200	11,871	-11.2%	88.8%	11,200	11,157	-0.4%	99.6%	24,400	23,028	-6.0%	94.0%
3/27/2019	13,800	11,609	-18.9%	81.1%	11,400	11,590	1.6%	98.4%	25,200	23,199	-8.6%	91.4%
3/28/2019	13,400	13,303	-0.7%	99.3%	14,200	14,179	-0.1%	99.9%	27,600	27,482	-0.4%	99.6%
3/29/2019	16,200	14,835	-9.2%	90.8%	20,800	18,968	-9.7%	90.3%	37,000	33,803	-9.5%	90.5%
3/30/2019	11,000	15,074	27.0%	73.0%	17,200	17,636	2.5%	97.5%	28,200	32,710	13.8%	86.2%
3/31/2019	10,400	14,164	26.6%	73.4%	16,000	16,514	3.1%	96.9%	26,400	30,678	13.9%	86.1%

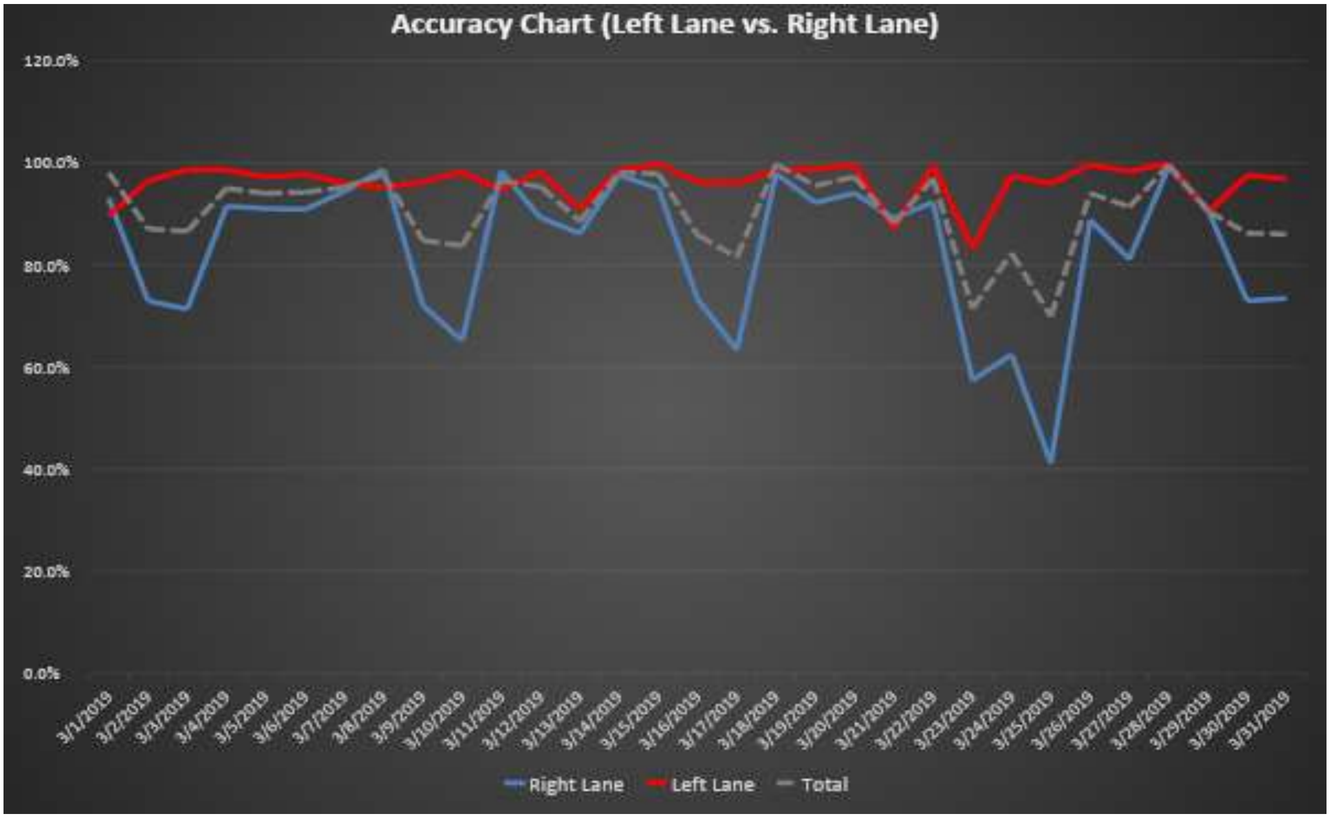


Figure 26: Accuracy Comparison (Left Lane vs. Right Lane)

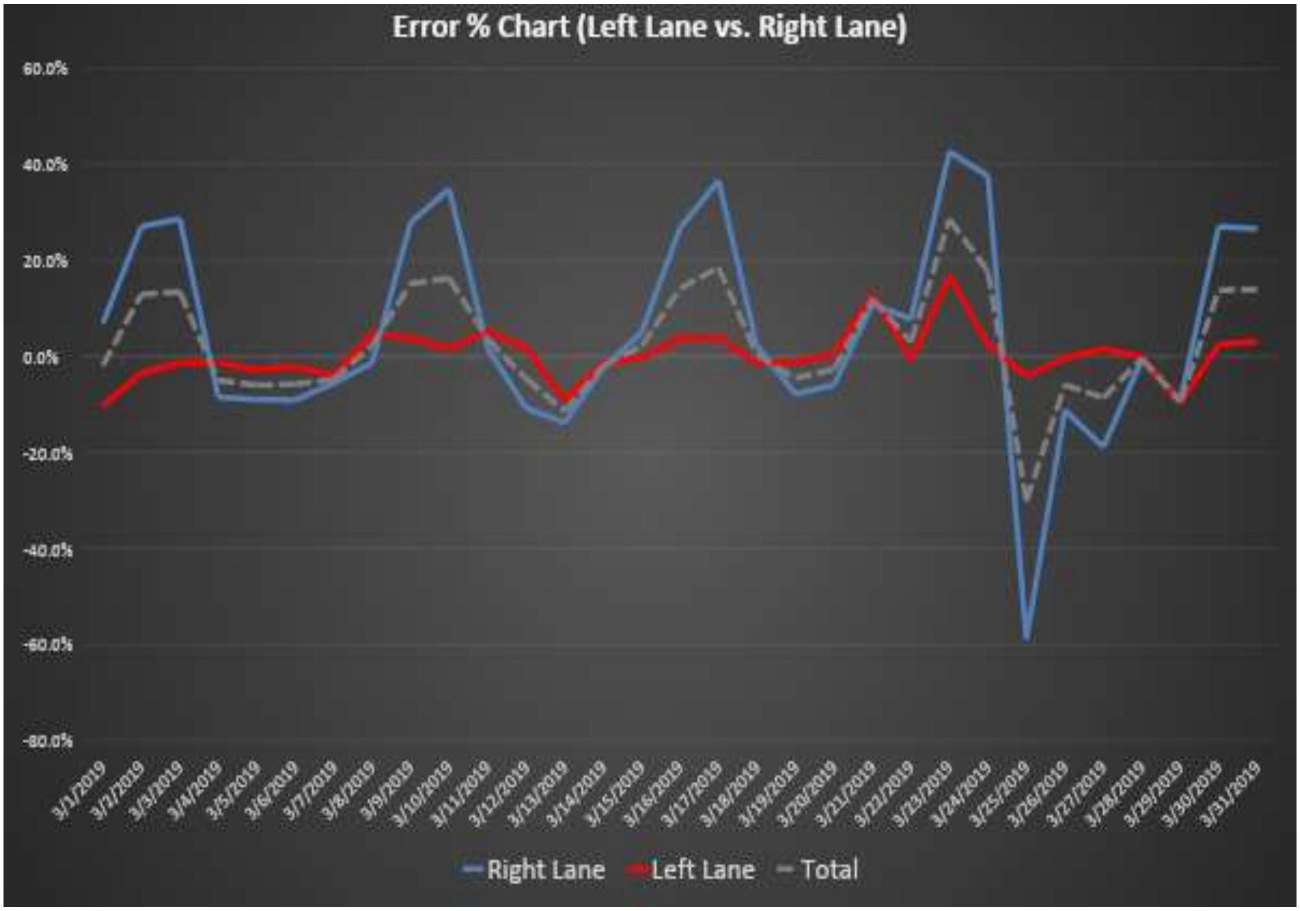


Figure 27: Error Percentage (Left Lane vs. Right Lane)

Table 3: Car vs. Truck Counts Comparison

	Cars				Trucks				Total			
Date	**UCF**	**TTMS**	**Cars ERROR**	**Cars Accuracy**	**UCF**	**TTMS**	**Trucks ERROR**	**Trucks Accuracy**	**UCF RL+LL**	**TTMS RL+LL**	**ERROR %**	**Total Accuracy**
3/1/2019	19986	16606	-20.4%	79.6%	8414	11256	25.2%	74.8%	28400	27862	-1.9%	98.1%
3/2/2019	13937	11836	-17.8%	82.2%	6463	11593	44.3%	55.7%	20400	23429	12.9%	87.1%
3/3/2019	15848	14338	-10.5%	89.5%	6352	11304	43.8%	56.2%	22200	25642	13.4%	86.6%
3/4/2019	16150	14412	-12.1%	87.9%	7850	8446	7.1%	92.9%	24000	22858	-5.0%	95.0%
3/5/2019	15679	13966	-12.3%	87.7%	7721	8111	4.8%	95.2%	23400	22077	-6.0%	94.0%
3/6/2019	16399	14452	-13.5%	86.5%	7601	8237	7.7%	92.3%	24000	22689	-5.8%	94.2%
3/7/2019	17736	15876	-11.7%	88.3%	8064	8748	7.8%	92.2%	25800	24624	-4.8%	95.2%
3/8/2019	22053	20991	-5.1%	94.9%	8547	10339	17.3%	82.7%	30600	31330	2.3%	97.7%
3/9/2019	18102	18010	-0.5%	99.5%	7298	11933	38.8%	61.2%	25400	29943	15.2%	84.8%
3/10/2019	21234	20605	-3.1%	96.9%	6966	13065	46.7%	53.3%	28200	33670	16.2%	83.8%
3/11/2019	17783	17185	-3.5%	96.5%	7617	9163	16.9%	83.1%	25400	26348	3.6%	96.4%
3/12/2019	16248	14687	-10.6%	89.4%	7752	8247	6.0%	94.0%	24000	22934	-4.6%	95.4%
3/13/2019	17082	14357	-19.0%	81.0%	7918	8075	1.9%	98.1%	25000	22432	-11.4%	88.6%
3/14/2019	19864	18275	-8.7%	91.3%	8736	9785	10.7%	89.3%	28600	28060	-1.9%	98.1%
3/15/2019	24095	22462	-7.3%	92.7%	9905	12276	19.3%	80.7%	34000	34738	2.1%	97.9%
3/16/2019	21606	21073	-2.5%	97.5%	7994	13397	40.3%	59.7%	29600	34470	14.1%	85.9%
3/17/2019	19513	19622	0.6%	99.4%	7087	13017	45.6%	54.4%	26600	32639	18.5%	81.5%
3/18/2019	18798	17353	-8.3%	91.7%	8002	9525	16.0%	84.0%	26800	26878	0.3%	99.7%
3/19/2019	17351	15560	-11.5%	88.5%	7849	8553	8.2%	91.8%	25200	24113	-4.5%	95.5%
3/20/2019	17745	16116	-10.1%	89.9%	7855	8817	10.9%	89.1%	25600	24933	-2.7%	97.3%
3/21/2019	17004	18127	6.2%	93.8%	7596	9799	22.5%	77.5%	24600	27926	11.9%	88.1%
3/22/2019	24073	22721	-6.0%	94.0%	9727	12141	19.9%	80.1%	33800	34862	3.0%	97.0%
3/23/2019	17649	20527	14.0%	86.0%	6351	13065	51.4%	48.6%	24000	33592	28.6%	71.4%
3/24/2019	22955	22657	-1.3%	98.7%	7445	14292	47.9%	52.1%	30400	36949	17.7%	82.3%
3/25/2019	26502	17436	-52.0%	48.0%	8298	9312	10.9%	89.1%	34800	26748	-30.1%	69.9%
3/26/2019	16642	14779	-12.6%	87.4%	7758	8249	6.0%	94.0%	24400	23028	-6.0%	94.0%
3/27/2019	17320	14868	-16.5%	83.5%	7880	8331	5.4%	94.6%	25200	23199	-8.6%	91.4%
3/28/2019	18885	17479	-8.0%	92.0%	8715	10003	12.9%	87.1%	27600	27482	-0.4%	99.6%
3/29/2019	25336	22079	-14.8%	85.2%	11664	11724	0.5%	99.5%	37000	33803	-9.5%	90.5%
3/30/2019	20140	19878	-1.3%	98.7%	8060	12832	37.2%	62.8%	28200	32710	13.8%	86.2%
3/31/2019	18972	18138	-4.6%	95.4%	7428	12540	40.8%	59.2%	26400	30678	13.9%	86.1%

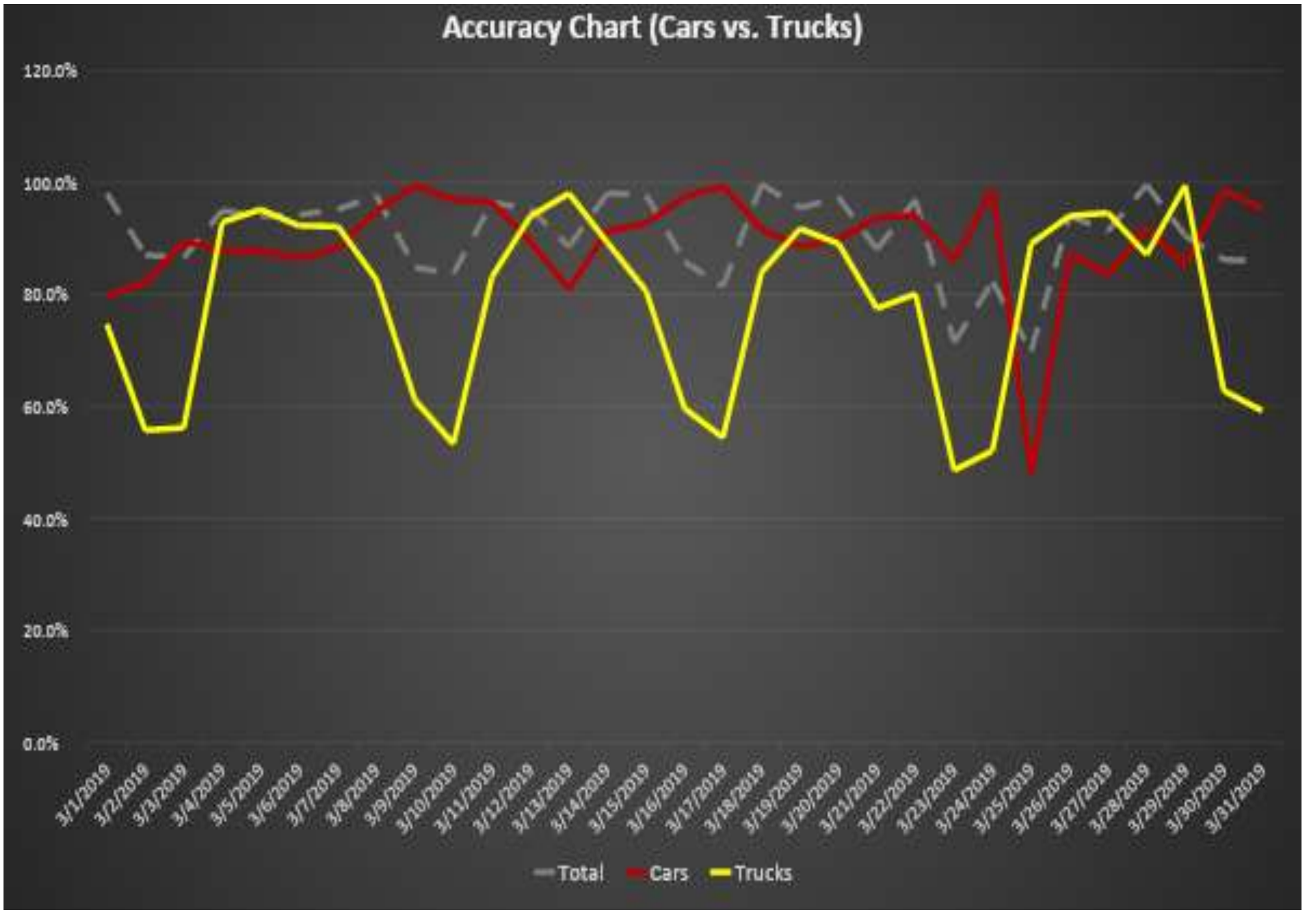


Figure 28: Accuracy Comparison (Cars vs. Trucks)

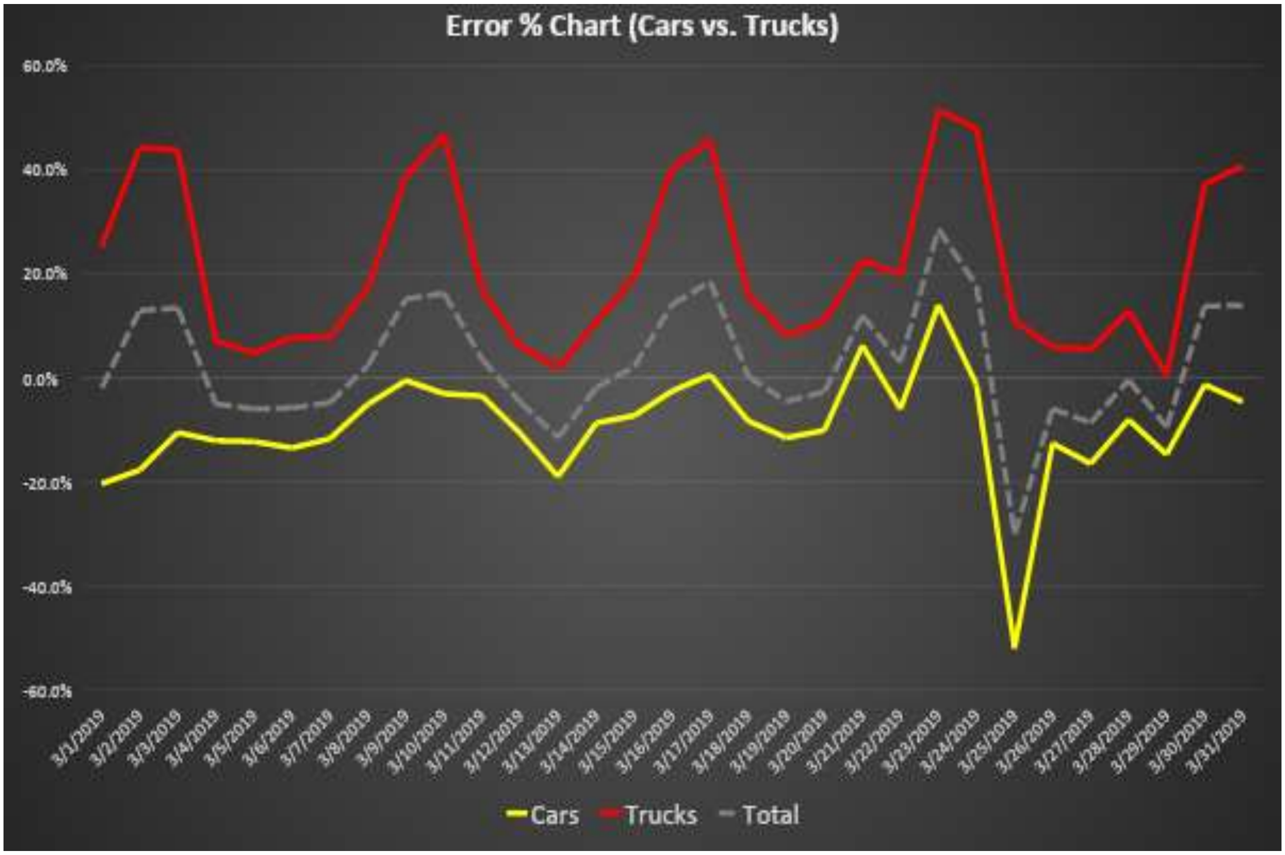


Figure 29: Error Percentage (Cars vs. Trucks)

To compare each vehicle type counts on each lane, Table 3-3 summarizes passenger car and truck counts on the left lane, and passenger car and truck counts on the right lane. Figure 3-5 represents counts from left lane only where trucks (Yellow line) and Cars (Redline) are compared utilizing error percentages. Total counts comparisons indicate low error percentages within 10% while in truck counts, much higher errors were captured, especially on weekends.

To illustrate the overall trend with less noise in comparison charts, a 5-day moving average chart on the left lane is presented in Figure 3-6. Total counts are mostly within a 5% error range for the entire month.

Figure 3-7 shows the trucks and cars' error percentage profile for the entire month on the right lane. Overall, the errors are found to be much higher on the right lane as compared to left lane errors. The 5-day moving average chart in Figure 3-8 indicates that moving average errors of total counts on the right lane reach up to 20%. On the right lane, the 25th day of the month has a significant drop in UCF counts than TTMS's.

Table 4: Cars vs. Trucks on Left Lane vs. Right Lane Comparison

Date	Left Lane						Right Lane					
	UCF TRUCK	TTMS TRUCK	Error %	UCF CAR	TTMS CAR	Error %	UCF TRUCK	TTMS TRUCK	Error %	UCF CAR	TTMS CAR	Error %
3/1/2019	1012	2205	54.1%	14788	12117	-22.0%	7402	9051	18.2%	5198	4489	-15.8%
3/2/2019	334	1663	79.9%	10866	9156	-18.7%	6129	9930	38.3%	3071	2680	-14.6%
3/3/2019	305	768	60.3%	12895	12258	-5.2%	6047	10536	42.6%	2953	2080	-42.0%
3/4/2019	885	1166	24.1%	10515	10079	-4.3%	6965	7280	4.3%	5635	4333	-30.0%
3/5/2019	1099	1229	10.6%	9701	9284	-4.5%	6622	6882	3.8%	5978	4682	-27.7%
3/6/2019	939	1111	15.5%	10261	9847	-4.2%	6662	7126	6.5%	6138	4605	-33.3%
3/7/2019	1098	1235	11.1%	11902	11266	-5.6%	6966	7513	7.3%	5834	4610	-26.6%
3/8/2019	964	1793	46.2%	16836	16906	0.4%	7583	8546	11.3%	5217	4085	-27.7%
3/9/2019	355	658	46.0%	14845	15137	1.9%	6943	11275	38.4%	3257	2873	-13.4%
3/10/2019	344	488	29.5%	18256	18444	1.0%	6622	12577	47.3%	2978	2161	-37.8%
3/11/2019	881	1156	23.8%	12319	12787	3.7%	6736	8007	15.9%	5464	4398	-24.2%
3/12/2019	1025	1201	14.7%	9975	9994	0.2%	6727	7046	4.5%	6273	4693	-33.7%
3/13/2019	1049	1175	10.7%	10951	9836	-11.3%	6869	6900	0.4%	6131	4521	-35.6%
3/14/2019	1065	1317	19.1%	13935	13468	-3.5%	7671	8468	9.4%	5929	4807	-23.3%
3/15/2019	793	1184	33.0%	18407	17978	-2.4%	9112	11092	17.9%	5688	4484	-26.9%
3/16/2019	443	760	41.7%	17757	18150	2.2%	7551	12637	40.2%	3849	2923	-31.7%
3/17/2019	365	630	42.1%	17035	17495	2.6%	6722	12387	45.7%	2478	2127	-16.5%
3/18/2019	956	1136	15.8%	13244	12871	-2.9%	7046	8389	16.0%	5554	4482	-23.9%
3/19/2019	1096	1169	6.2%	11104	10887	-2.0%	6753	7384	8.5%	6247	4673	-33.7%
3/20/2019	948	1180	19.7%	11652	11482	-1.5%	6907	7637	9.6%	6093	4634	-31.5%
3/21/2019	903	1237	27.0%	11897	13446	11.5%	6693	8562	21.8%	5107	4681	-9.1%
3/22/2019	863	1292	33.2%	18737	18185	-3.0%	8864	10849	18.3%	5336	4536	-17.6%
3/23/2019	324	718	54.9%	14876	17535	15.2%	6027	12347	51.2%	2773	2992	7.3%
3/24/2019	328	500	34.4%	20072	20429	1.7%	7117	13792	48.4%	2883	2228	-29.4%
3/25/2019	1303	1202	-8.4%	13297	12830	-3.6%	6995	8110	13.7%	13205	4606	-186.7%
3/26/2019	984	1174	16.2%	10216	9983	-2.3%	6774	7075	4.3%	6426	4796	-34.0%
3/27/2019	1272	1307	2.7%	10128	10283	1.5%	6608	7024	5.9%	7192	4585	-56.9%
3/28/2019	1192	1355	12.0%	13008	12824	-1.4%	7523	8648	13.0%	5877	4655	-26.3%
3/29/2019	1169	1743	32.9%	19631	17225	-14.0%	10495	9981	-5.1%	5705	4854	-17.5%
3/30/2019	449	747	39.9%	16751	16889	0.8%	7611	12085	37.0%	3389	2989	-13.4%
3/31/2019	290	565	48.7%	15710	15949	1.5%	7138	11975	40.4%	3262	2189	-49.0%

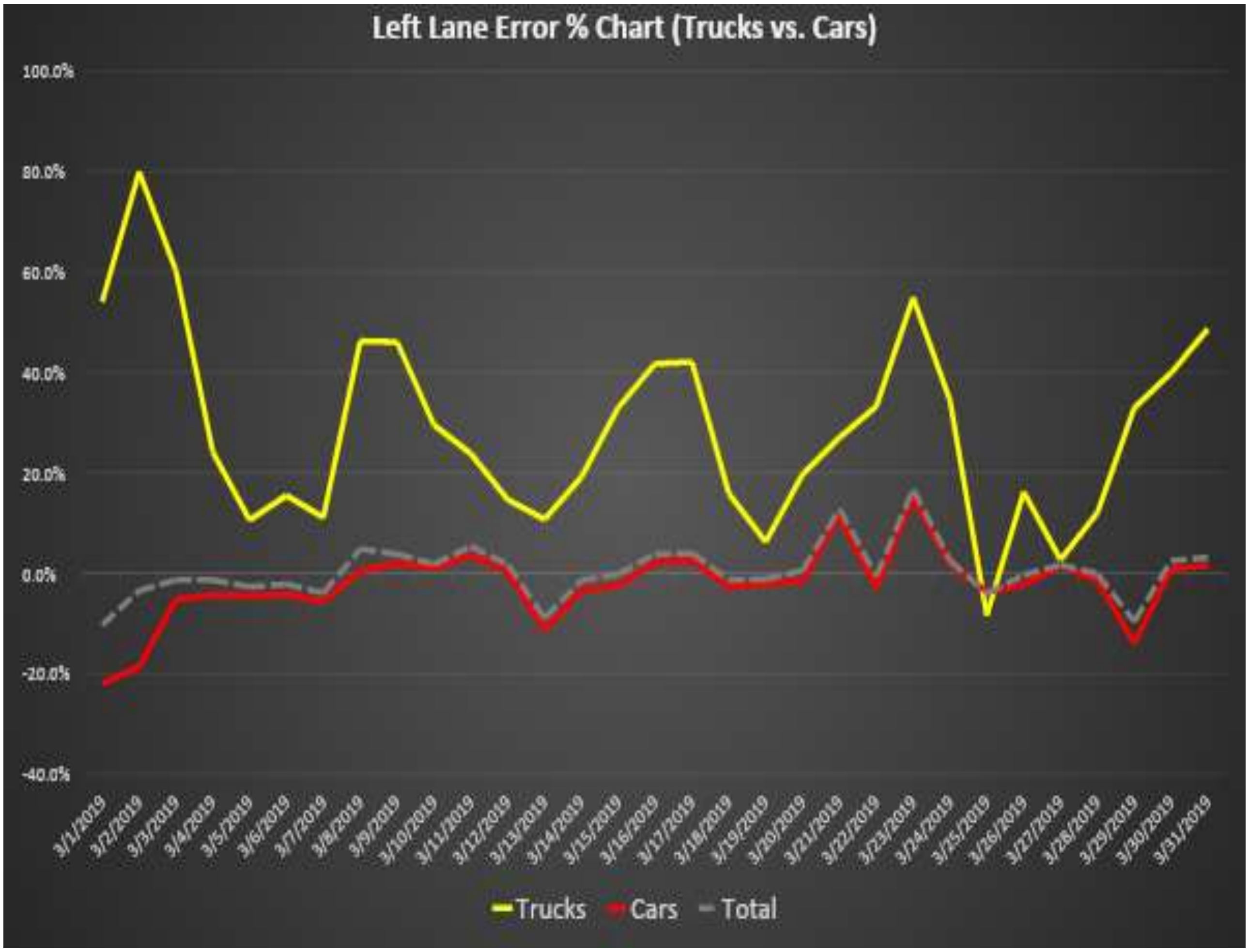


Figure 30: Trucks vs. Cars on Left Lane

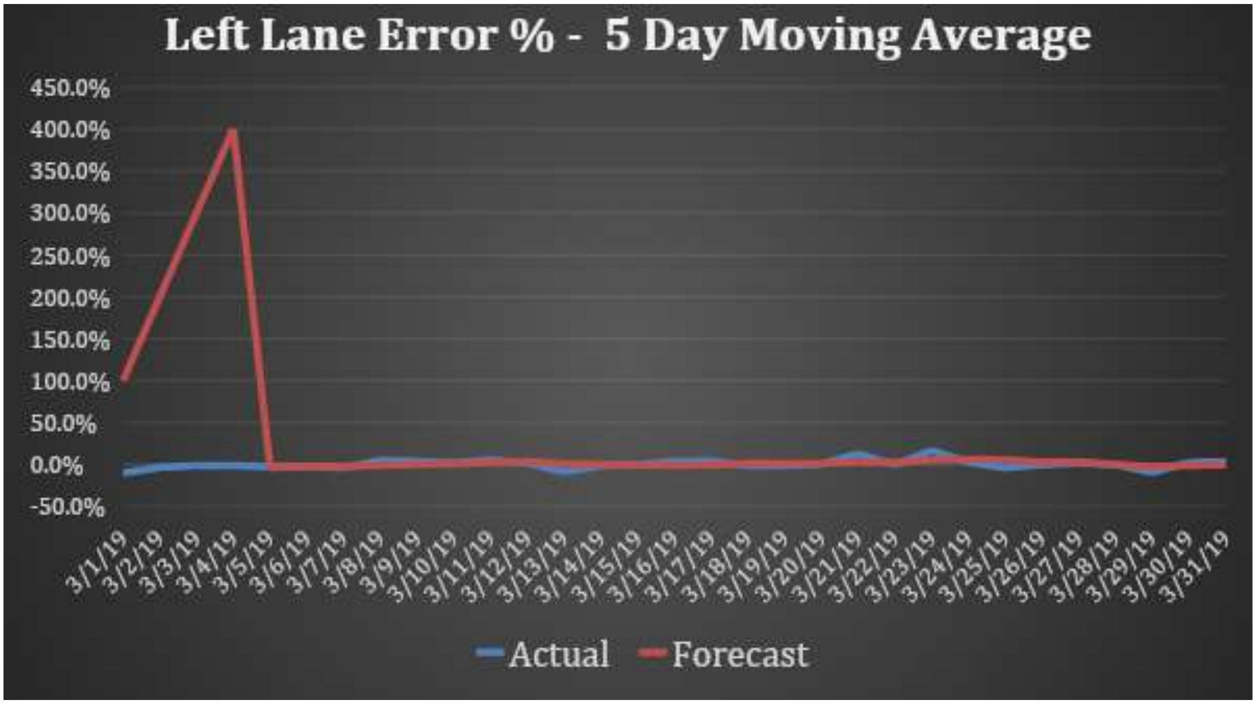


Figure 31: 5-Day Moving Average Error Percentage for Left-Lane Counts

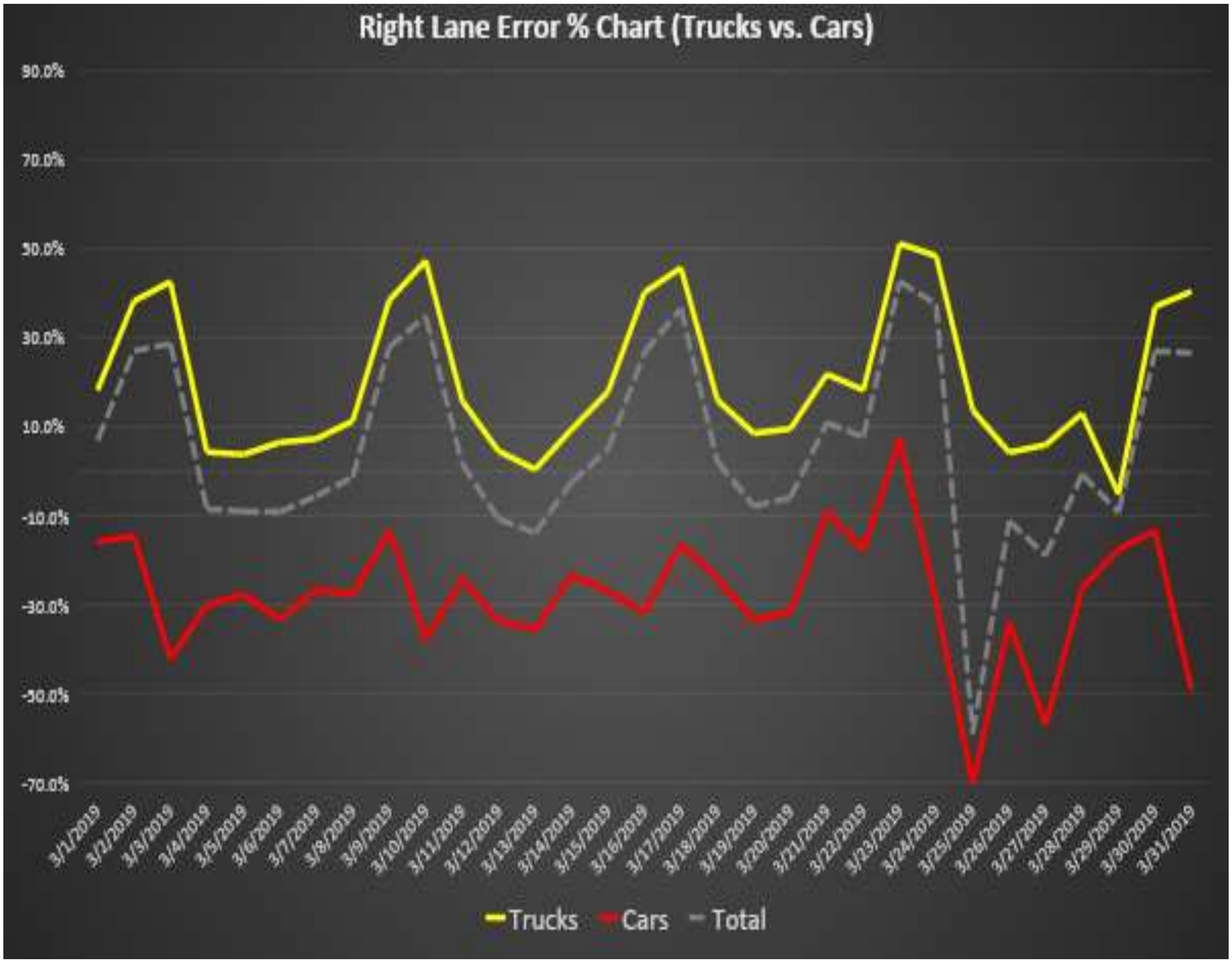


Figure 32: Trucks vs. Cars Comparison on Right Lane

Figure 33: 5-Day Moving Average Error Percentage for Right-Lane Counts

Due to higher error rates and lower accuracies seen on weekends via overall month profile charts shown earlier, summary statistics of only weekdays are also provided in this section.

Figure 3-9 shows a left lane weekday error profile of March 2019 for cars and truck counts, while Figure 3-11 shows a right lane weekday error profile. 5-day moving average chart for total counts on the left lane (Figure 3-10) and right lane (Figure 3-12) are also presented. As can be seen in these figures, by removing weekend counts, trendlines become smoother with less variation.

Finally, to have a more detailed comparison and investigate the underlying causes of variations from TTMS counts, the 24-hour profile of each day in March 2019 has been provided for UCF, and TTMS counts for left-lane truck counts, left lane car counts, and right lane truck counts, right lane car counts, separately. Thus, four charts are presented for each day of the month. 24-hour profile charts are presented in the "APPENDIX" section.

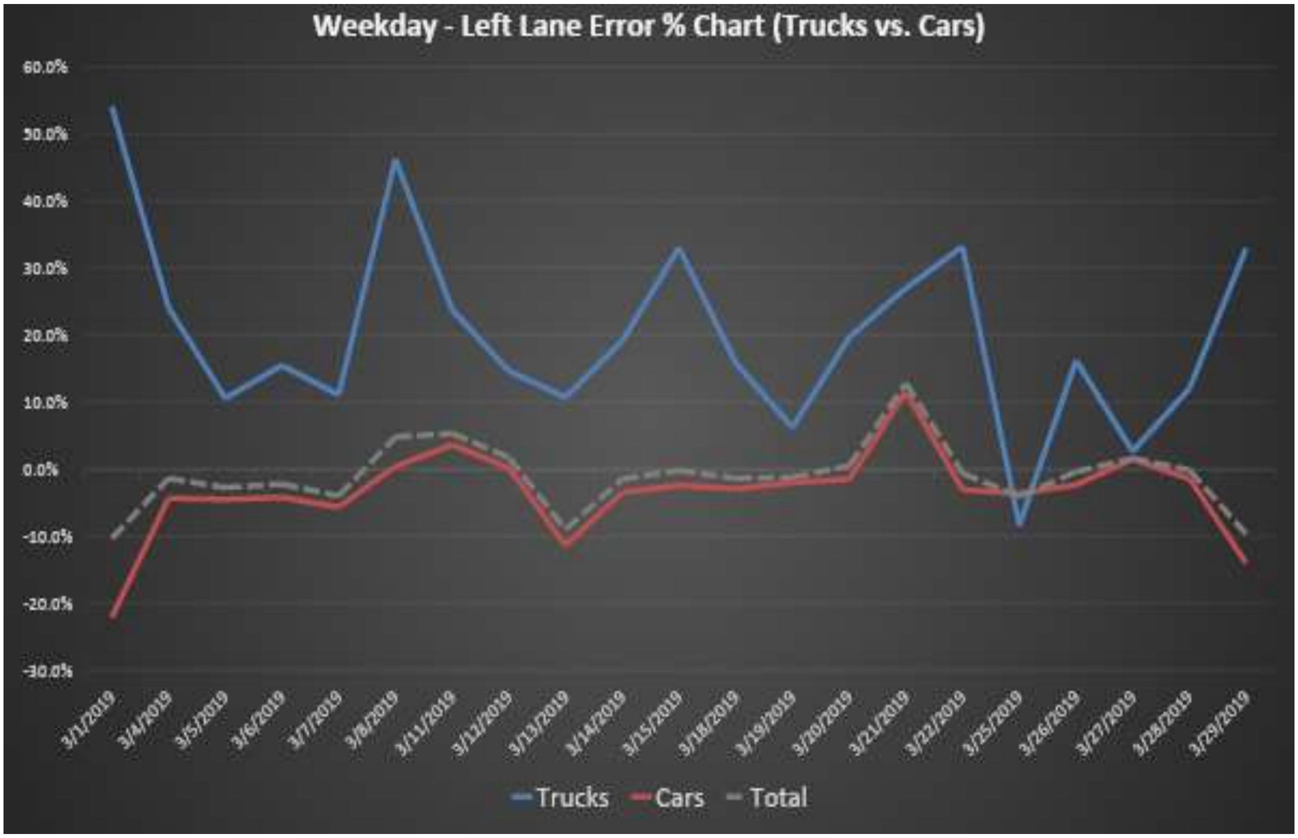


Figure 34: Error Percentage on Weekdays: Left Lane

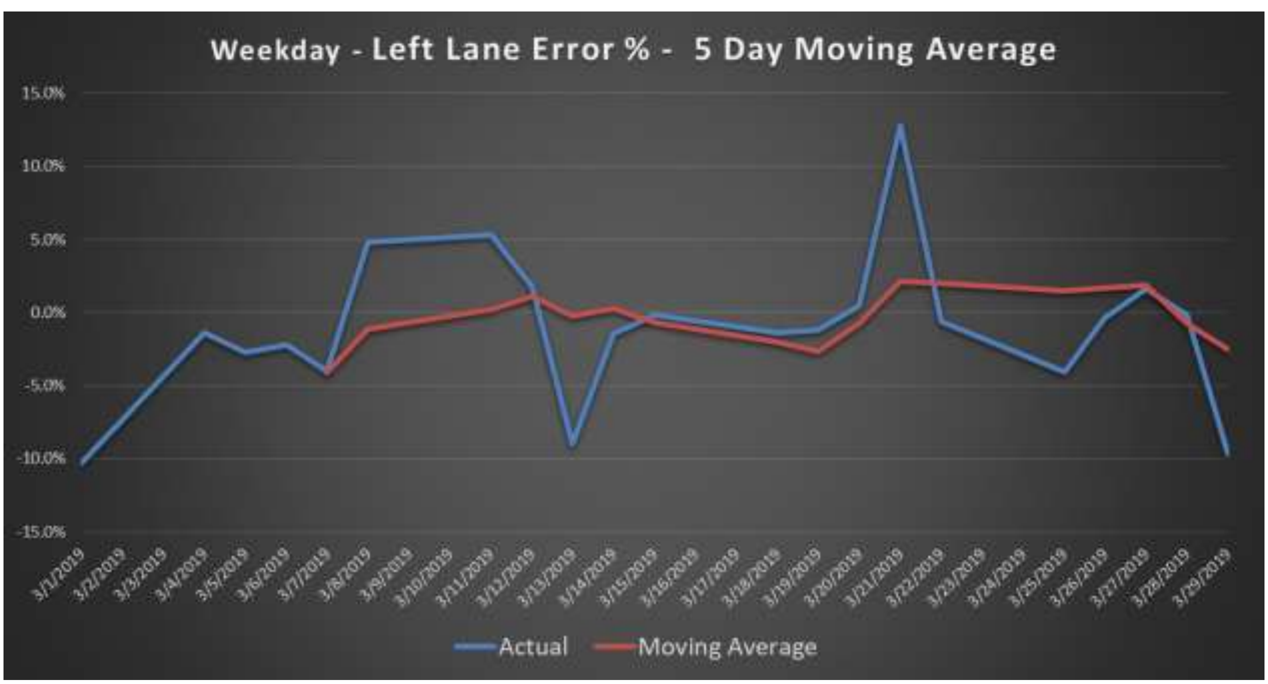


Figure 35: 5-Day Moving Average Error Percentage on Weekdays: Left Lane

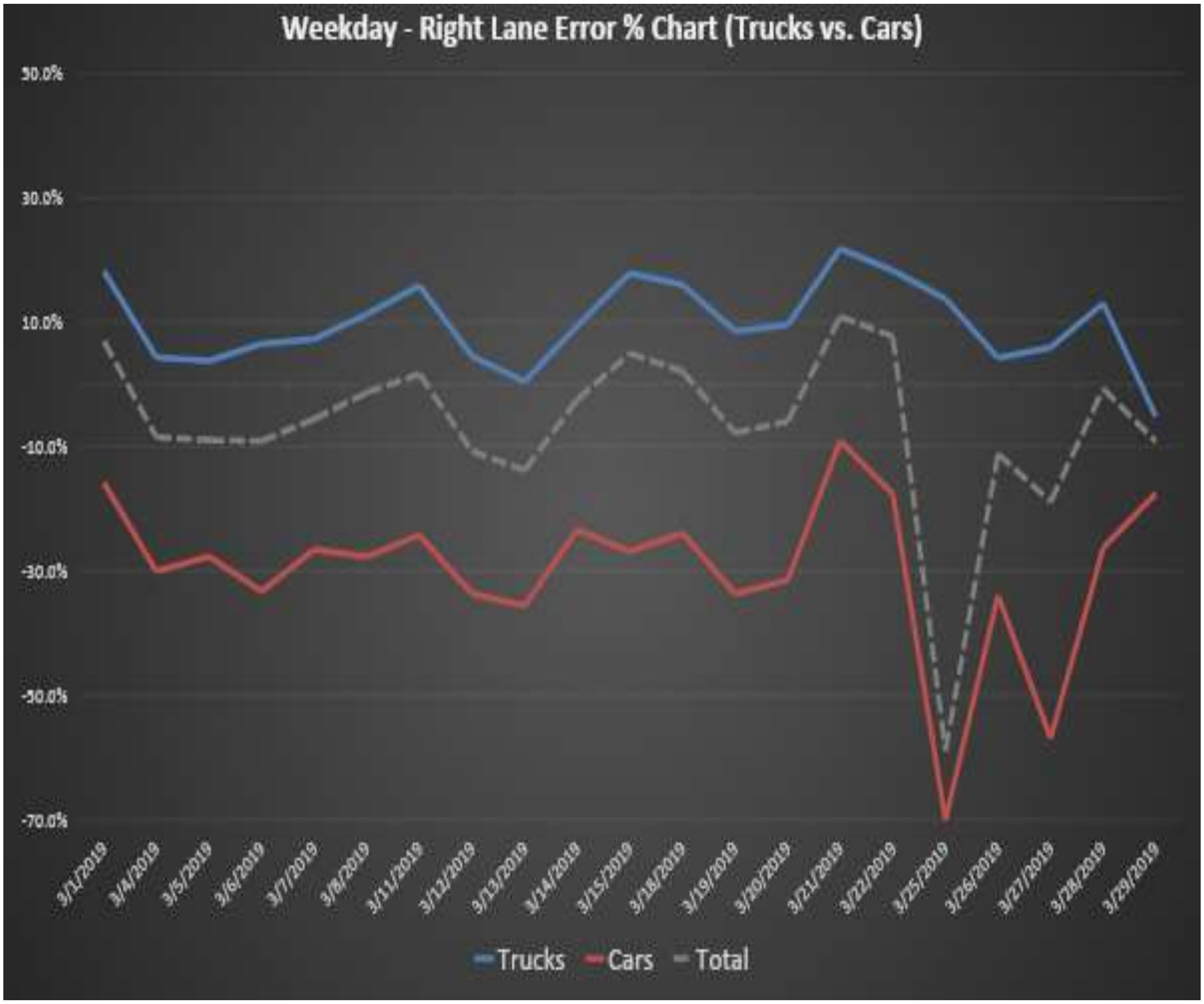


Figure 36: Error Percentage on Weekdays: Right Lane

Figure 37: 5-Day Moving Average Error Percentage on Weekdays: Right Lane

3.6 Installation at Test Site 2

The second test site is located at the overpass on I75 (28.799864, -82.088359) and Warm Springs Ave. in Coleman, FL. Six traffic lanes will be instrumented. Currently, 3 lanes have been completed in the southbound direction. Due to long distances, the researchers have increased the voltage to 24V (two 12-VDC batteries wired in series). An additional solar cell has been added to cope with the increased power demands from 3 additional sensors. Distance from the solar plant to the first sensor (and the new Gateway) is 75 feet. Distance from the Solar plant to the farthest sensor is 185 feet.

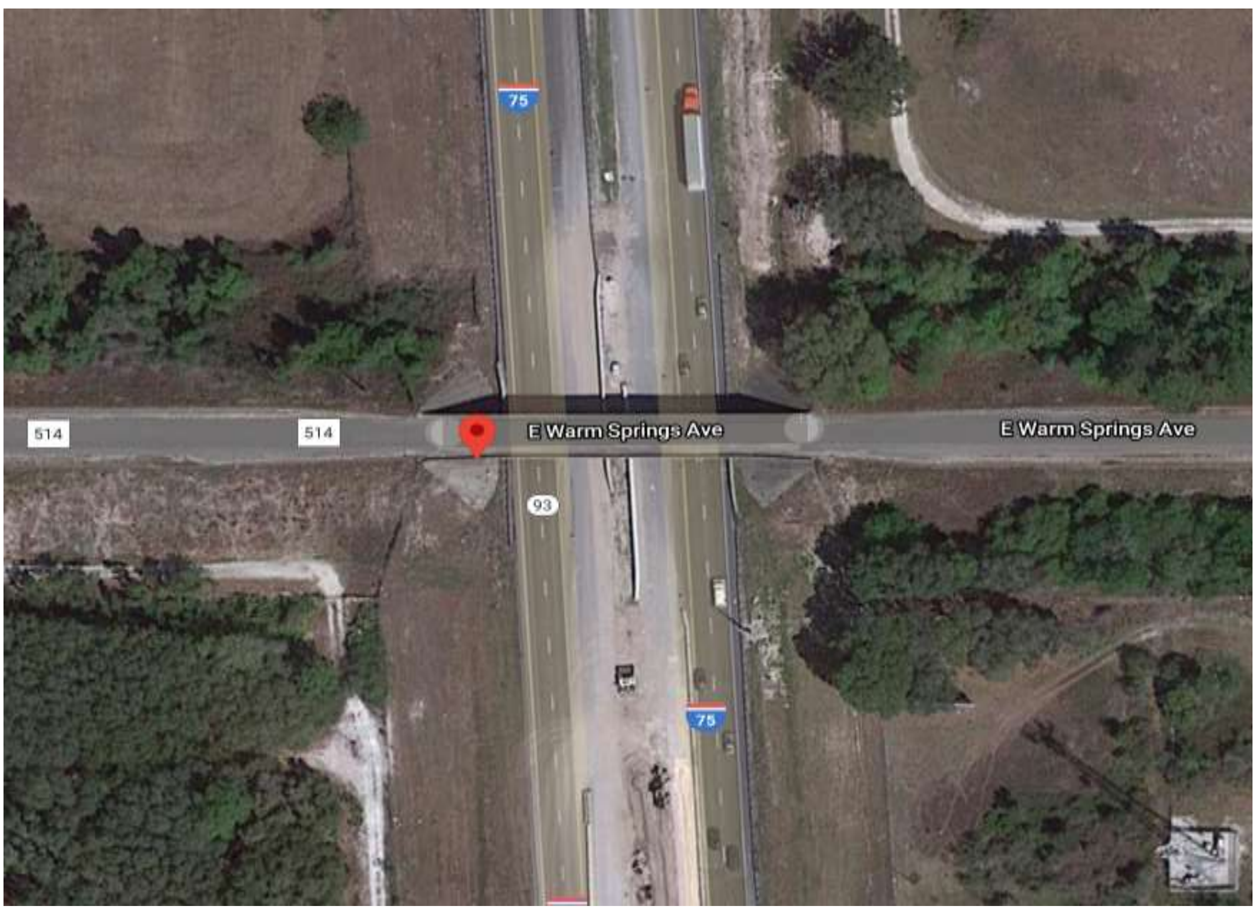


Figure 38: Test Site 2

3.7 Power Wiring Diagram

24VDC powers the system. Power comes from two 12VDC batteries that are wired in series. Additionally, a timer was added to recycle power to the system every 24 hours. From our experience, this clears potential memory problems that may disable the system or impact its operation. The batteries are recharged using the solar panels and a solar charge controller. The wiring is shown below.

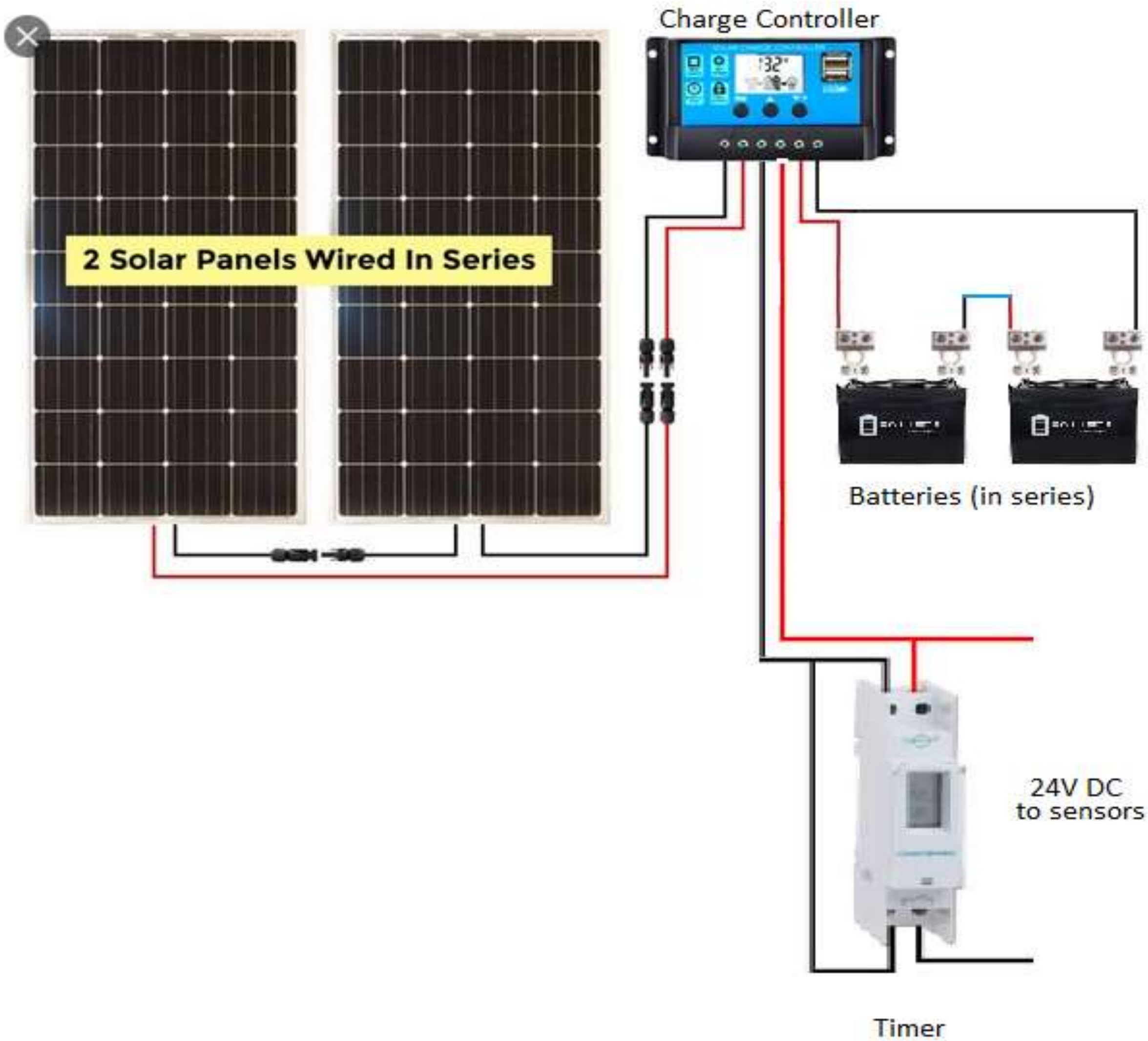


Figure 39: Solar System Configuration

3.8 Communications Diagram

The individual sensors communicate their information to the accumulator using Bluetooth. Every 25 vehicles are communicated as a batch. The accumulator then aggregates 100 records from each sensor (lane) and communicates this information to the cloud. This is shown below.

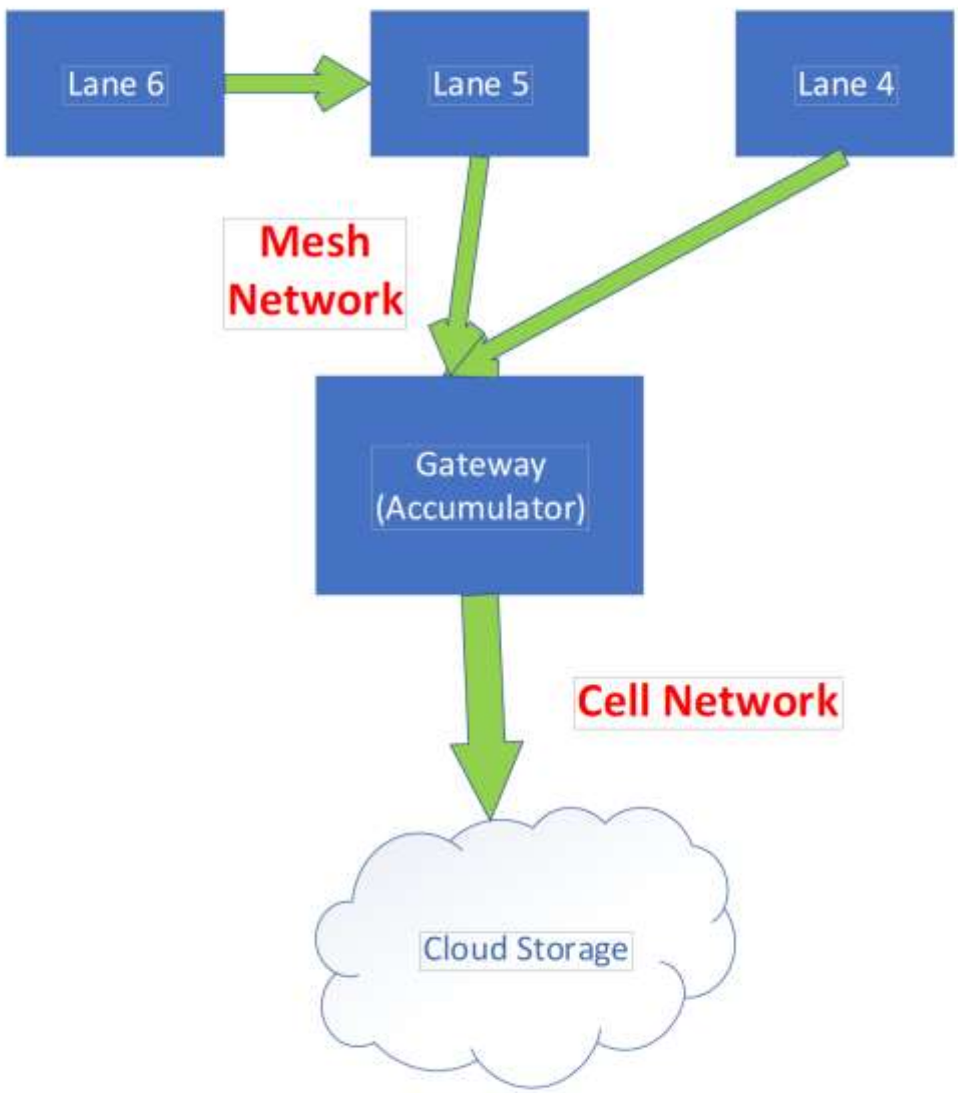


Figure 40: Communications Flowchart

3.9 Data Validation for Test Site 2

To validate the accuracy of the collected data, the researchers compared the traffic counts for cars and trucks collected by the sensors and compared to loop counts from the Florida DOT. Also, the researchers conducted manual counts via the FDOT camera. The results are summarized next page and are followed by an analysis. It is worth noting that sometimes, the video feed from the camera was interrupted, which has an impact on the count's accuracy. The researchers will address this issue at a later date using the following strategies:

- If video feed continues to be unreliable, the researchers will use a manual count at the site.
- Using the latest version of the Garmin sensor after the vendor mentioned that earlier versions of the sensor (up to January 2020) had stability issues due to temperature and humidity.
- Use two new sensors and validate their performance.

In Tables 1-4, Lane 5 refers to the center lane of the southbound direction of travel. The "Fast Lane" refers to the leftmost lane of travel. Lane 4 (not shown) is the rightmost travel lane in the southbound direction. Some differences in cars vs. trucks may be attributed to the way that FDPT classifies various smaller trucks.

Table 5: Data Collection 12/06 for three hours (2:00pm to 5:00pm)

	Fast Lane		Lane 5			
	Cars	Trucks	Cars	Trucks	Fast	Middle
FDOT	1908	100	2272	353	2008	2625
Manual	1949	29	2627	387	1978	3014
UCF	1961	24	N/A	N/A	1985	N/A
FDOT/Manual	2%	71%	14%	9%	2%	-13%
FDOT/UCF	3%	76%	N/A	N/A	1%	N/A
Manual/UCF	1%	17%	N/A	N/A	0%	N/A

Table 6: Data Collection 12/07 All-day

	Fast Lane		Lane 5			
	Cars	Trucks	Cars	Trucks	Fast	Middle
FDOT	5659	262	9493	1384	5921	10877
UCF	5835	49	10587	1222	5884	11809
FDOT/UCF	0%	81%	10%	12%	1%	-8%

Table 7: Data Collection 12/08 All-day

	Fast Lane		Lane 5			
	Cars	Trucks	Cars	Trucks	Fast	Middle
FDOT	6648	281	9961	1382	6929	11343
UCF	6608	49	10184	1166	6657	11350
FDOT/UCF	0%	83%	2%	16%	4%	0%

Table 8: Data Collection 12/09 All-day

	Fast Lane		Lane 5			
	Cars	Trucks	Cars	Trucks	Fast	Middle
FDOT	4987	286	8012	2131	5273	10143
UCF	5235	83	9178	2095	5318	11273
FDOT/UCF	5%	71%	13%	2%	-1%	-10%

Table 9: Data Collection 12/13 for One Hour (2:00pm to 3:00pm)

	Lane 5		
	Cars	Trucks	**Total**
FDOT	703	130	833
Manual	814	105	919
UCF	821	112	933
FDOT/Manual	14%	19%	-9%
FDOT/UCF	14%	14%	-11%
Manual/UCF	1%	5%	-2%

UCF fast lane counts are within 1% - 4% of the FDOT loop counts, with an average of 1.8% using data from 3 days.

- UCF fast lane counts are within 2% of manual counts.
- UCF middle lane counts are within 2% of manual counts (based on a 1-hour manual count comparison). However, in comparison with FDOT loops counts, it varies by up to 10%.

The research team continues to assess the reason for the discrepancy by making code revisions and by trying new sensors.

3.10 Laser Testing

Before a sensor is installed at the sites, the researchers have done an extensive evaluation of its fitness for use and integration within both the hardware and software architectures that were used. As the results from manual and DOT counts have shown some discrepancies, the researchers decided to evaluate more sensors, and the results are discussed below.

The researchers have tried three additional sensors, and results are summarized:

- Lightware LW20 Provisional success, but the firmware is currently being updated after numerous crashes by the microcontroller.

  https://lightware.co.za/products/lw20-c-100-m

- Benewake TF03 Numerous crashes are caused by the microcontroller. Sensor returned.

  http://en.benewake.com/product/detail/5c345cc2e5b3a844c472329a

- Teraranger Evo: Laser was too weak despite specs indicating 60 m operation. The device maker admitted that the range is effectively about 4m, and the reseller accepted return. https://www.terabee.com/shop/lidar-tof-range-finders/teraranger-evo-60m/

3.11 Lessons Learned

This project has encompassed a large variety of tasks, including hardware, software, sensor selection, system installation, testing, and data validation. Below are some lessons learned:

1. Technologies for IoT are changing rapidly. The selection of technology needs to have a reasonable chance of succeeding in the marketplace, so adhering to standards is essential.
2. Sensor communications to the Gateway remain the major challenge in such installations.
3. Environmental conditions impact laser sensors. These impacts are often not disclosed by vendors (or at best not readily available). So, long-term testing is essential.
4. Both Communications and Power have to be integral in system design.
5. The ability to view and change sensor software, parameters, and viewing results are a significant improvement over older technologies.
6. A means for comparison to reliable counts is essential.

7. Tethering of the sensor bracket AND installation tools such as wrenches, screwdrivers, etc. allows for an extremely safe installation over live traffic. The only risk remaining is the unlikely (albeit possible) scenario of dropping a nut or a washer on the traffic below. Some sort of a "catchment device" is needed. This cable is as simple as a net carried by a second person.

CHAPTER 4: TRUCK DIVERSION MODEL- CASE STUDIES

4.1 Data Collection

This chapter presents the development of a framework that can be used to assist traffic control centers in evaluating truck diversion strategies during nonrecurrent congestion. When an incident occurs and is detected, the duration of the incident is predicted based on the available incident characteristics. The delay caused by the incident is then compared with a threshold. If it is found to be higher than the threshold, the diversion algorithm is initiated to divert the truck traffic to an alternative route based on predefined alternative route selection criteria.

The process of developing the framework was segmented into four main phases. First, a hotspot analysis was conducted to define the spatial incident distribution. Second, an incident clearance prediction model was developed, and the variables impacting the incident clearance time were statistically tested. Third, a truck route selection model was developed to select alternative routes that accommodate truck characteristics and restrictions. Finally, a cost-benefit analysis was performed to estimate economic and environmental benefits engendered by implementing the diversion decision model.

Extensive data collection was required for each step of this research. This chapter describes the methods for collecting and cleaning the data and for preparing them for analysis. Suitable statistical approaches and techniques used for analyzing the performance of the developed framework based on the available data are also discussed.

The overall process used to achieve the objectives of this study is summarized in the in Figure 37.

Figure 37 shows the data analysis approach and the techniques used in addressing each objective. It is important to note that this section offers an overview of the process; the details of each analysis are provided in the relevant chapter.

Phase		Input Data	Tool	Output
Phase 1	**Spatial-Temporal Crash Analysis**	Crash Data for the years of (2014 to 2017) including crash location, date, and time Roadway Segments	ArcGIS Pro 2.5, Geographic Information System (GIS) Spatial Analyst	Statistically significant space-time crash trends, Description of hotspot and crash trends categories over time, High-rate crash segments, 3D visualization of crash clusters locations over time
Phase 2	**Incident Clearance Prediction Model**	Incident data for the year of (2018-2019), including: **Temporal characteristics** (Incident date, incident time, day of week, month of year, incident notification, verification, and response time) **Incident characteristics** (Incident type, incident location, number of blocked lanes, incident severity) **Road characteristics** (median type, median width, functional classification, number of lanes) **Traffic characteristics** (AADT, maximum speed, capacity reduction, truck percentage)	Multiple Linear Regression Statistical Package of Social Science (SPSS)	Prediction of incident clearance duration, Significant explanatory variables were identified
Phase 3	**GIS network Analysis and Truck Diversion Feasibility Analysis**	**Street dataset**, elevation, turn restrictions, one-way restrictions **Traffic data**: Historical traffic data, Live traffic data, Time one table, TMC table, Speed profiles table, Street profiles table **Alternative route selection criteria including**: **Roadway geometry** (lane width, number of lanes) **Traffic conditions** (Level of Service, speed limit) **Heavy vehicle restrictions** (vertical clearance, bridge design load) **Neighborhood impact** (Proximity to schools and hospitals)	ArcGIS Network Analyst, Python for ArcGIS, Arcpy for Geoprocessing	Dynamic routable network, All potential alternative routes (base scenario) , Optimal truck alternative routes, turn by turn direction on each route, travel time, route length
Phase 4	**Diversion Decision-Making**	Predicted incident clearance duration Travel time and route length on both base scenario and alternative route AADT, truck volume, speed limit	National Highway Traffic Safety Administration (NHTSA), Commercial Medium and Heavy-Duty Truck Fuel Efficiency Technology Report	Benefits in terms of delay savings, fuel consumption savings Monetary equivalents of time and fuel consumption Decision-making tool to select optimal alternative route for truck diversion

Figure 41: Overall Structure of the Research

4.2 Study Area

The Interstate 75 (I-75) corridor is a limited access facility and is one of the most critical transportation facilities in the state of Florida. It facilitates freight movement to, from, and within the state, starting from the south in Miami south to north in approximately 272 miles of I-75 cross through the Florida Department of Transportation (FDOT) Districts 6, 1, 7, 5, and 2.

Interstate 75 is mostly a four-lane highway, but there is a six-lane section with 12-foot lane widths and a minimum 40-foot median. I-75 is an integral part of the strategic intermodal system (SIS), a system of significant roadways intended to provide high-speed travel connections between major population centers throughout the states.

Due to the growth in freight miles traveled, I-75 has experienced a significant increase in traffic volume, which has resulted in operational deficiencies and additional congestion. Given the importance of the I-75 corridor, it was selected as a study area for this research with the purpose of congestion mitigation. Figure 2 shows the spatial extent of the study area selected for this research, which includes 20 counties through the north, central, and southeast Florida.

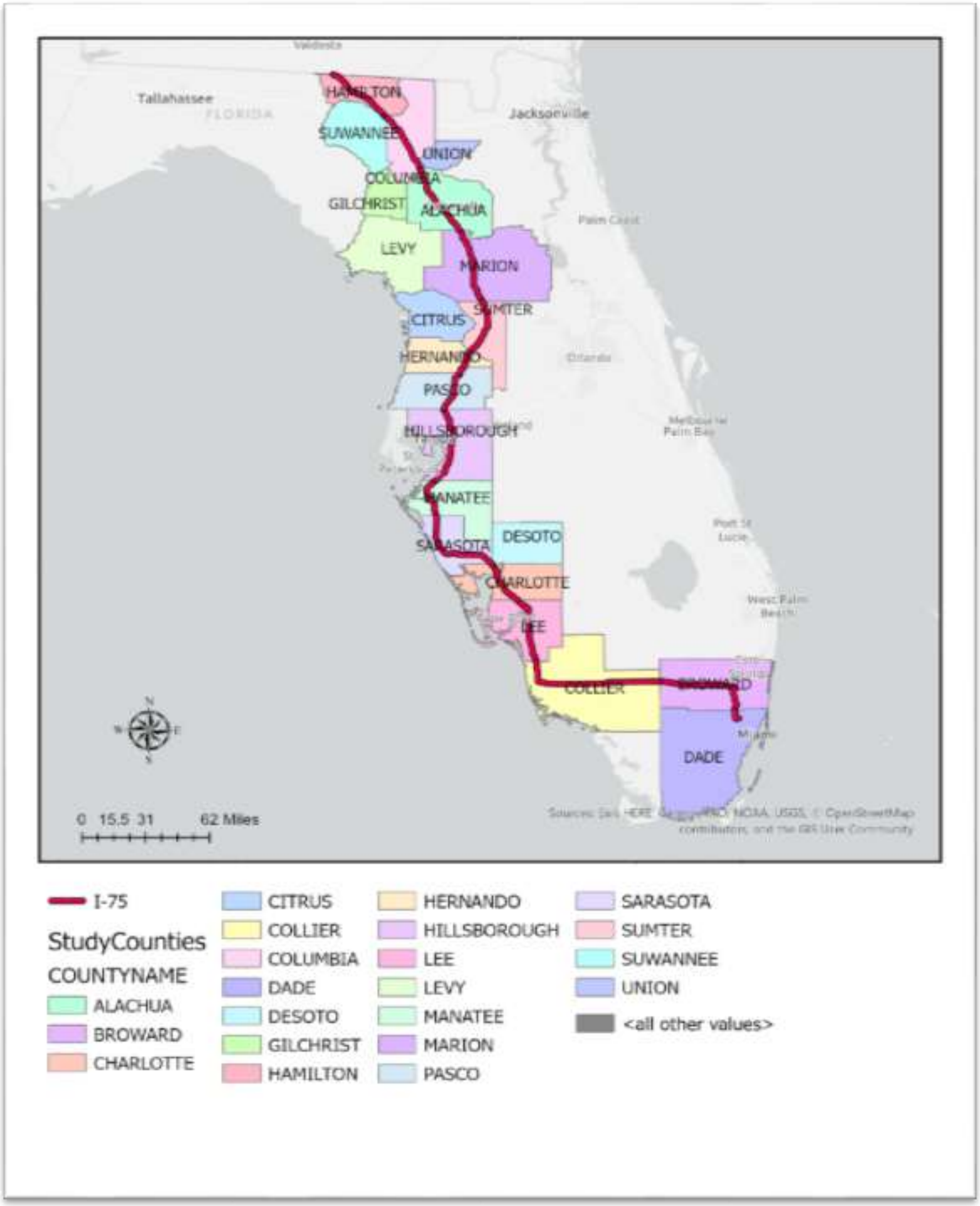


Figure 42: Study Area: Counties along the I-75 Corridor

4.3 Data Preparation

Data were collected for each phase of this research. The following sections provide details of the data collection and preparation processes. Four sets of data were used: crash data, incident data, a street network and historical traffic dataset, and GIS data. A list of the sources of these data is presented in Figure 3.

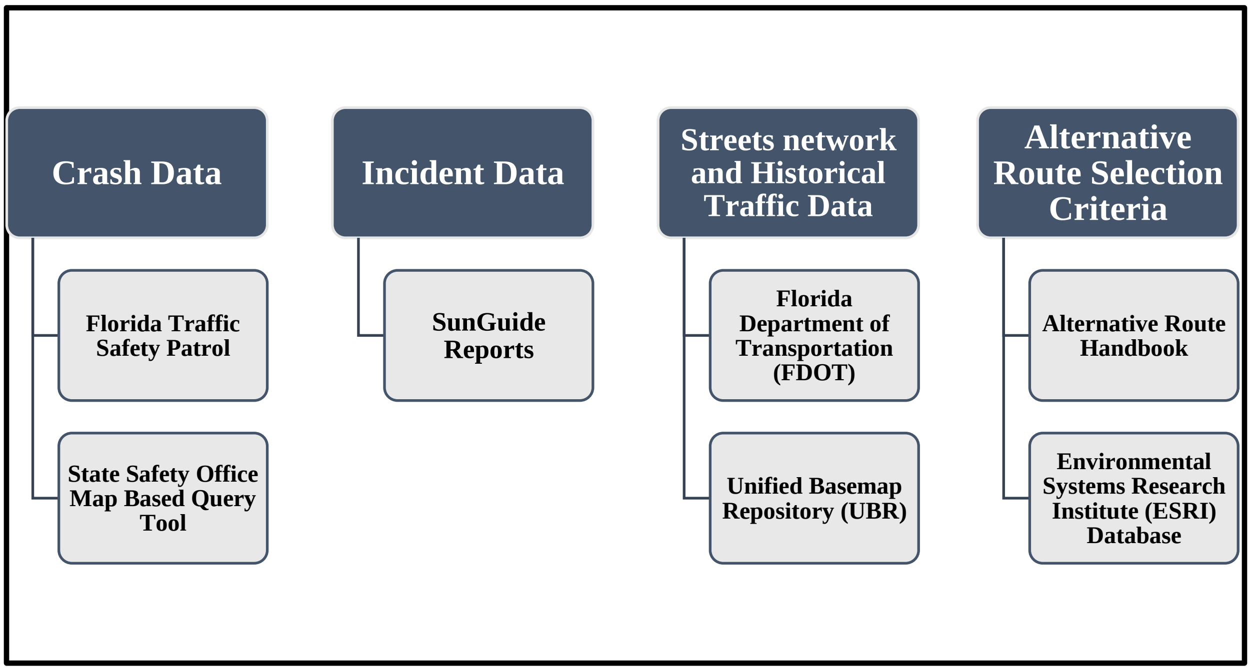


Figure 43: Flowchart of Data Categories and Related Sources

4.3.1 Network Dataset and Historical Traffic Data

For the third phase of this research, a network analysis was performed. The objective of this phase was to develop an alternative route selection model to determine the route most suitable for truck traffic. Data for this analysis were collected from various sources. First, street and traffic data were collected and processed to build a dynamic routable network dataset that stored road edges and junctions and their attributes for all segments of the road network. Second, historical traffic profiles were incorporated into road edges. This allowed time-dependent variables to be assigned to road edges and junctions to reflect actual traffic conditions throughout the day. Finally, truck alternative route selection criteria were defined to evaluate the network in terms of suitability for trucks.

The ArcGIS Network Analyst extension was utilized to design, create, and build a transportation network dataset. The network dataset is a series of synchronized network components, including the edges, junctions, and turns of the road network model. Network databases are well suited for the simulation of transportation networks. They are designed based on a source feature class, which may include features such as lines, points, one-way restrictions, and turns. For this research, a file geodatabase network was created. Streets and turn feature classes were created in one feature dataset and stored in this file geodatabase. Figure 40 presents the workflow used to build the network dataset.

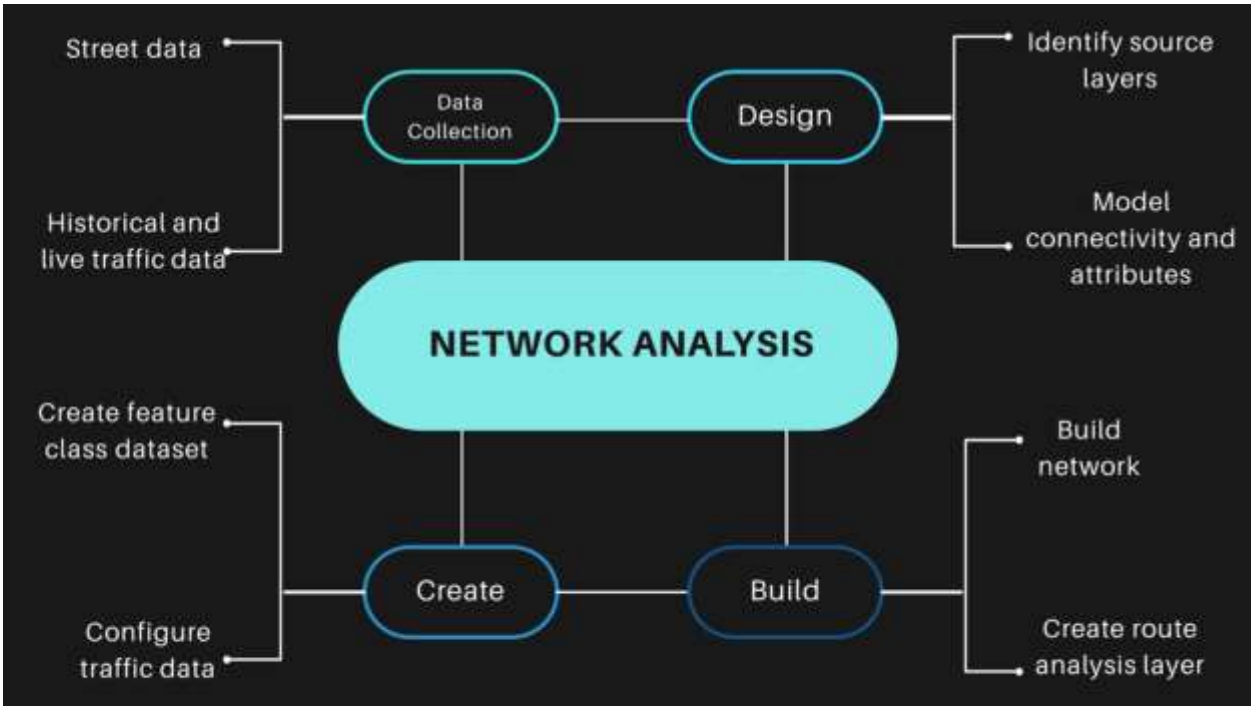


Figure 44: Workflow to Build Network Dataset

This section describes the data sources and explains how the data were collected and prepared to build a routable network incorporating traffic data. Most of the geographic datasets used in this analysis were collected from the FDOT's Unified Basemap Repository (UBR) database. The UBR provides quarterly street and traffic datasets from the network provider NAVSTREET's street data by HERE Technologies. Additionally, the UBR database contains data suitable for routing applications with a complete navigable road network. Data were extracted in the format of a file geodatabase for the GIS platform. The Z-level layer was used to create roadway connectivity. The quality of the collected data was evaluated, and data were preprocessed for integration into the Network Analyst extension. The related dataset descriptions and sources are listed in Table 10.

Table 10: Network Dataset Description and Sources

Data Description		Data Source
Streets Dataset	Street database including street shapefile, one-way restriction, U-turn, prohibited street, toll road, hierarchy, and shape-length	FDOT, Unified Base Repository, HERE
Traffic Dataset	Historical traffic data and live traffic data	FDOT, Unified Base Repository, HERE
School Zones	Private and public-school information including school address, zip code, and county	Florida Geographic Data Library
Hospital Locations	Hospital facility information, address, zip code, and county	Florida Geographic Data Library
National Bridge Inventory	Data on more than 600,000 bridges in the US; includes information about design load, vertical clearance, and efficiency ranks	Bureau of Transportation Statistics
Interstate Exits	The dataset contains roadway ID, exit number, county, and district	FDOT Transportation Data and Analytics Office GIS Data

To perform routing analysis, a file geodatabase network was created to support historical and live traffic data. This research used the ArcGIS Network Analyst extension to incorporate traffic data in the routing analysis. Properties of the network layer were set to include travel time and impedance attributes.

4.3.2 Criteria for Alternative Route Selection

When an incident occurs and causes road closures, state agencies consult guidelines for determining when to divert traffic to circumvent the congested facility. The Federal Highway Administration *Alternative Route Handbook* (2006) provides a comprehensive guideline on how to execute diversion strategies considering key factors, including incident duration, the number of lanes blocked, the observed traffic condition, and the capacity of the candidate alternative route.

Truck diversion strategies should be based on a collection of specifications to determine the effect of the rerouted traffic. In this research, alternative selection criteria were defined based on four key considerations:

1. Roadway characteristics.
2. Heavy vehicle restrictions.
3. Traffic conditions.
4. Neighborhood impacts.

Data collection was required for each selection criterion. In this study, alternative route selection criteria were defined based on the Federal Highway Administration (FHWA) handbook. These criteria can be defined as truck restrictions used for assessing alternative route candidates. They serve as measures of how effectively a route is being utilized for diversion. Data for selection criteria were collected as variable indicators, processed to create input layers for network analysis, and finally applied to evaluate potential alternative routes to select the optimal route for truck traffic. Generally, the alternative route is the shortest route, but some increase in distance can be allowed to avoid specific road characteristics that are not suitable for trucks. Multiple sets of data were collected for each selection criterion. Data were separated into several feature classes and projected into the same coordinate system for the analysis. Figure 41 presents the selection criteria that were considered in this research.

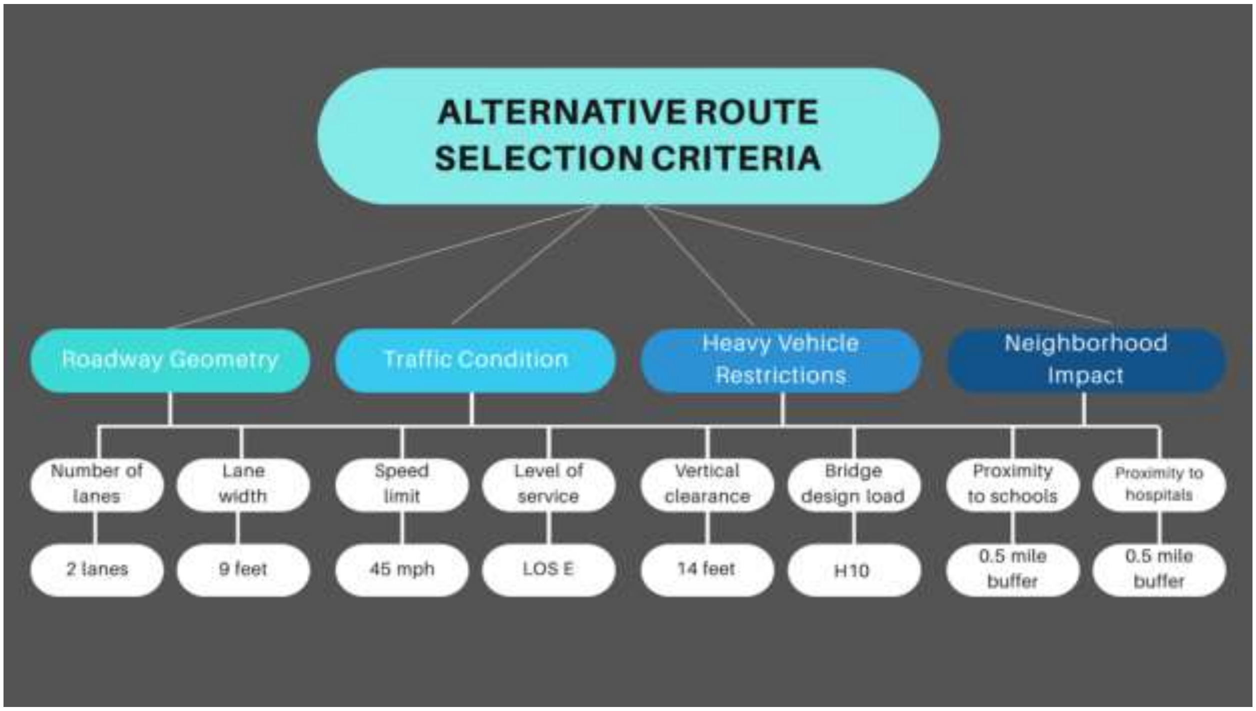


Figure 45: Study Alternative Route Selection Criteria

4.3.2.1 Height and Weight Restrictions

From the National Bridge Inventory database of 600,000 bridges, Florida bridges with low clearance, restriction design loads, and poor performance were selected.

4.3.2.2 Pavement Conditions

It is essential to ensure that the appropriate pavement conditions are available on the selected alternative route. Poor pavement conditions can be hazardous for heavy vehicles, which can cause safety issues. If the pavement condition on the alternative route is already poor, the redirected truck traffic can cause further damage.

4.3.2.3 Geometry and Road Characteristics

It is essential to investigate roadway characteristics and geometry to select an alternative route that can accommodate truck restrictions. Vertical clearance, turn restrictions, and steep roadway grades should be evaluated prior to the diversion operation.

4.3.2.4 Existence of Schools and Hospitals

Roadways near schools and hospitals should be avoided to ensure these facilities remain accessible for public service. The locations of Florida schools and hospitals were collected from the Environmental System Research Institute (ESRI) database for the study area. A new layer was created with this information and incorporated into the network model as a scaled factor barrier. Additionally, parks and public recreational areas should be safely accessible to the public and should also be avoided.

4.3.2.5 The Intensity of Commercial Development

A potential alternative route that is near substantial commercial development should be avoided, as diverted traffic increases traffic demand and therefore affects roadway capacity.

4.3.2.6 Level of Service

When traffic is diverted from the main roadway to an alternative route, the alternative route then carries both its traffic and the rerouted traffic. Therefore, it is essential to evaluate the level of service of the potential alternative route before diverting traffic. In this research, alternative route selection criteria were predefined and implemented in the rerouting model as restoration or scaled costs.

4.3.2.7 Truck Weight and Size Restrictions Data

According to the FHWA's and Florida's weight and height restrictions on heavy vehicles, the maximum width for a truck is 102 inches, and the maximum height is 13 feet, 6 inches. Additionally, the maximum weight limit for a single axle is 22,000 lbs. And for a tandem axle is 34,000 lbs.

4.3.3 Data for Cost-Benefit Analysis

This study developed diversion decision-support tools to assist transportation personal in making the best diversion decisions. The developed model quantified the resulting benefits by comparing diversion scenarios to scenarios without diversion. This section presents the procedure followed to collect the data needed to estimate the benefits of traffic diversion during nonrecurrent congestion.

This study used the total travel time along the alternative route, taken from the output of the developed model, to compute the reduction in delay due to the diversion. Moreover, as reducing delays can also decrease fuel consumption, both delay reduction and fuel consumption savings were converted to monetary values using conversion factors obtained from the U.S. Census Bureau.

4.4 Methodology

All data of interest collected and prepared for this study were utilized to develop a framework for evaluating truck diversion strategies. The following sections present the approaches used to achieve the objectives for each stage of the study. This chapter starts with a crash hotspot analysis of the collected data, including a descriptive analysis of the distribution of crash records over the study area. The statistical regression approach used to assess the impacts of various explanatory variables on incident clearance duration is then described, as is the methodology of the incident clearance prediction model. Finally, the process of the design of the network dataset is presented.

4.5 Crash Hotspot Analysis

It is essential to understand, interpret, and forecast the trends in road safety and then implement appropriate countermeasures to prevent crashes and reduce injury severity. For this purpose, traffic safety indicators, such as fatality risk, the number of crashes with injuries, and the numbers of victims, are regularly collected to monitor the safety trends of specific sites (Bergel-Hayat et al., 2013). Because of the complexity of identifying the causes of crashes, the role of the crash location, recognizing high-crash and low-crash road segments, is a challenging problem. In this section, the first phase of the research methodology is presented. The main objective of this phase was to understand crash patterns and to examine the distribution of crashes utilizing hotspot and spatial statistics analysis. This section presents the methodology used to conduct a spatiotemporal analysis utilizing a space-time cube, spatial autocorrelation, and emerging hotspot analysis to identify high-crash-rate locations in the study area. Twenty counties in Florida along the I-75 corridor were selected as a case study. The crash analysis was performed utilizing ArcGIS Pro 2.5. Crash data for the years 2014–2017 were investigated to identify statistically significant crash trends over space and time. The structure of the first phase of this research is diagrammed in Figure 42.

First, road segment data were collected and clipped to the study area. Crash data were obtained from the SSOGIS Crash Query Tool web application for the years 2014–2017. Crash data included location, date, and time. Subsequently, crash data points were aggregated using the space-time cube tool. Spatial autocorrelation analysis was then performed to investigate spatial hotspot trends. Finally, emerging hotspot analysis was utilized to classify the hotspots and analyze their spatiotemporal patterns.

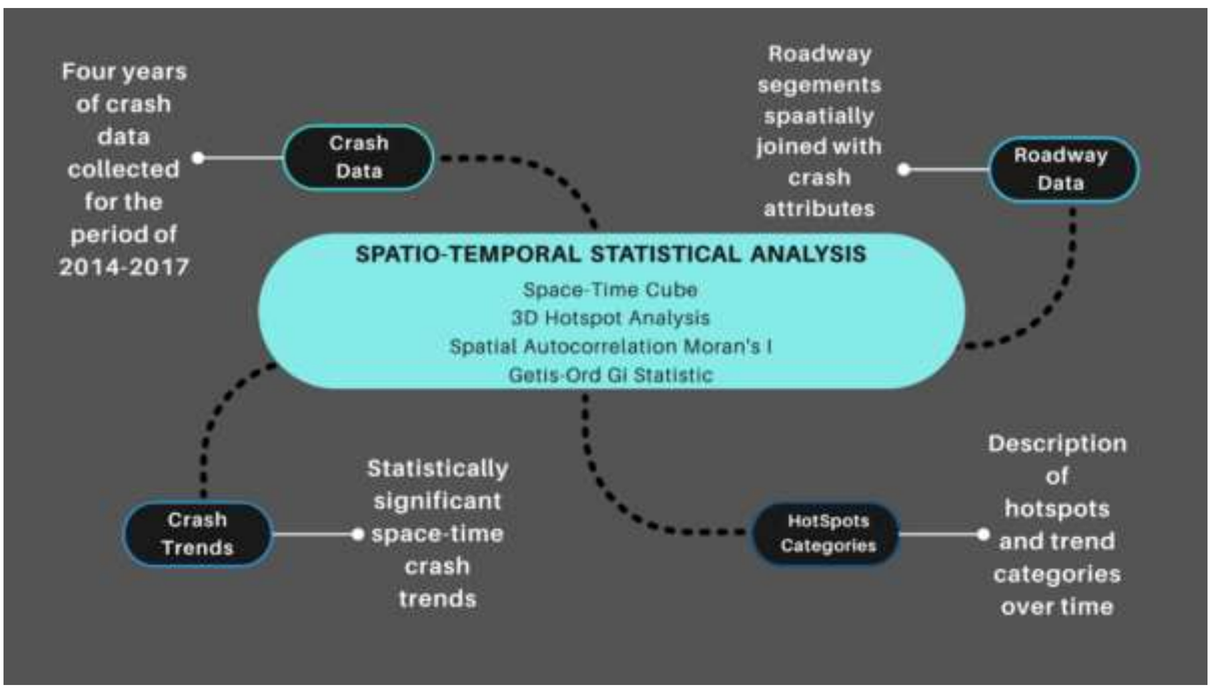


Figure 46: Flowchart of Hotspot Analysis

The aim of the spatiotemporal crash analysis was to analyze the characteristics of crashes and classify hotspot trends over time to identify the location with the highest rate of crashes. Descriptive analysis was performed to investigate the distribution of crash frequencies over the study area. Graphs of these distributions and summaries of observations from these figures are provided in the following sections. Crash data were plotted into ArcMap by using the longitude and latitude of each crash data point. The distribution of four years of crashes over the study area is illustrated in Figure 43.

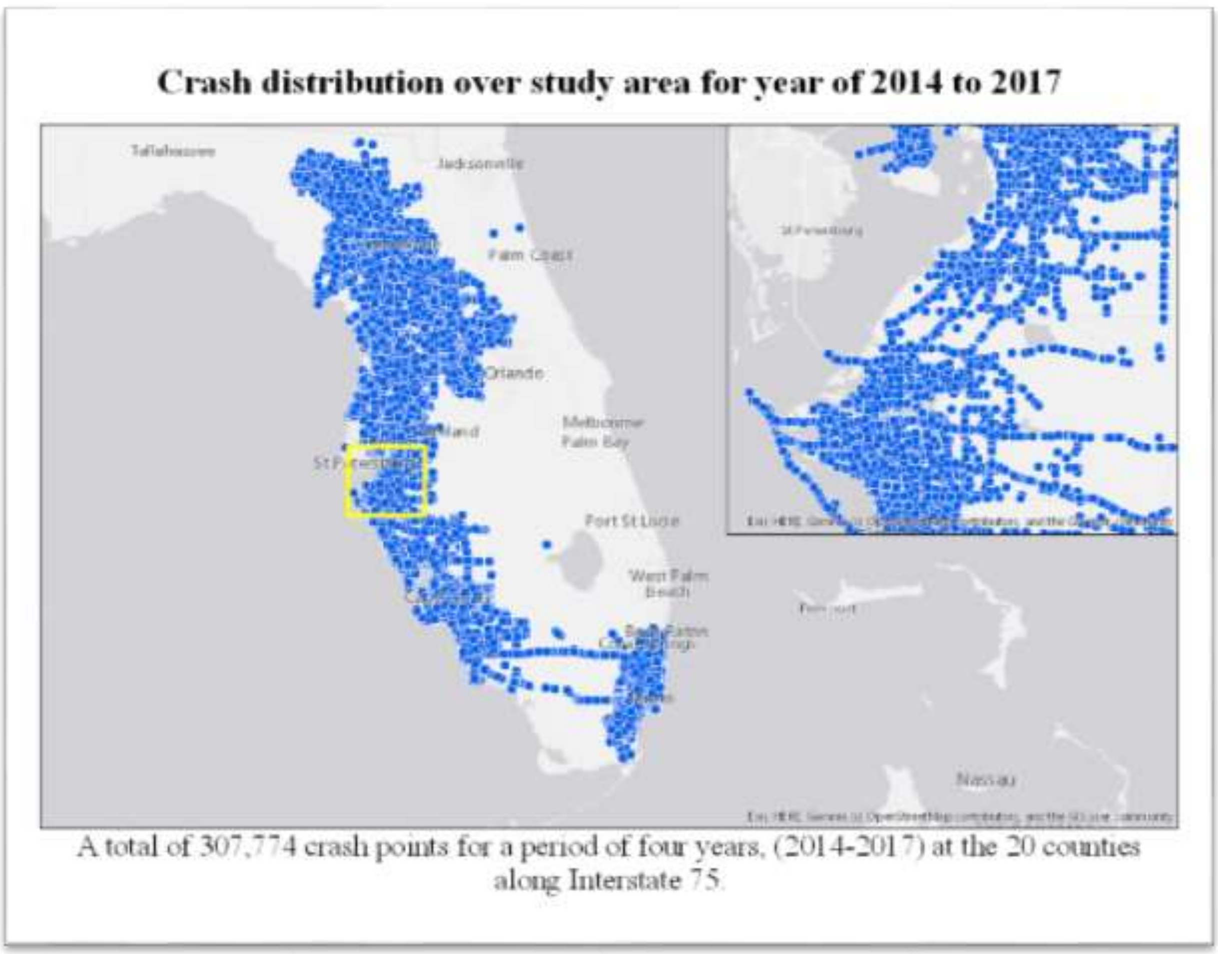


Figure 47: Crash Data Distribution over the Study Area

To investigate the temporal distribution of the crash data, the crash counts were plotted by month for the years 2014 to 2017. Figure 44 presents a monthly crash time clock over the study period.

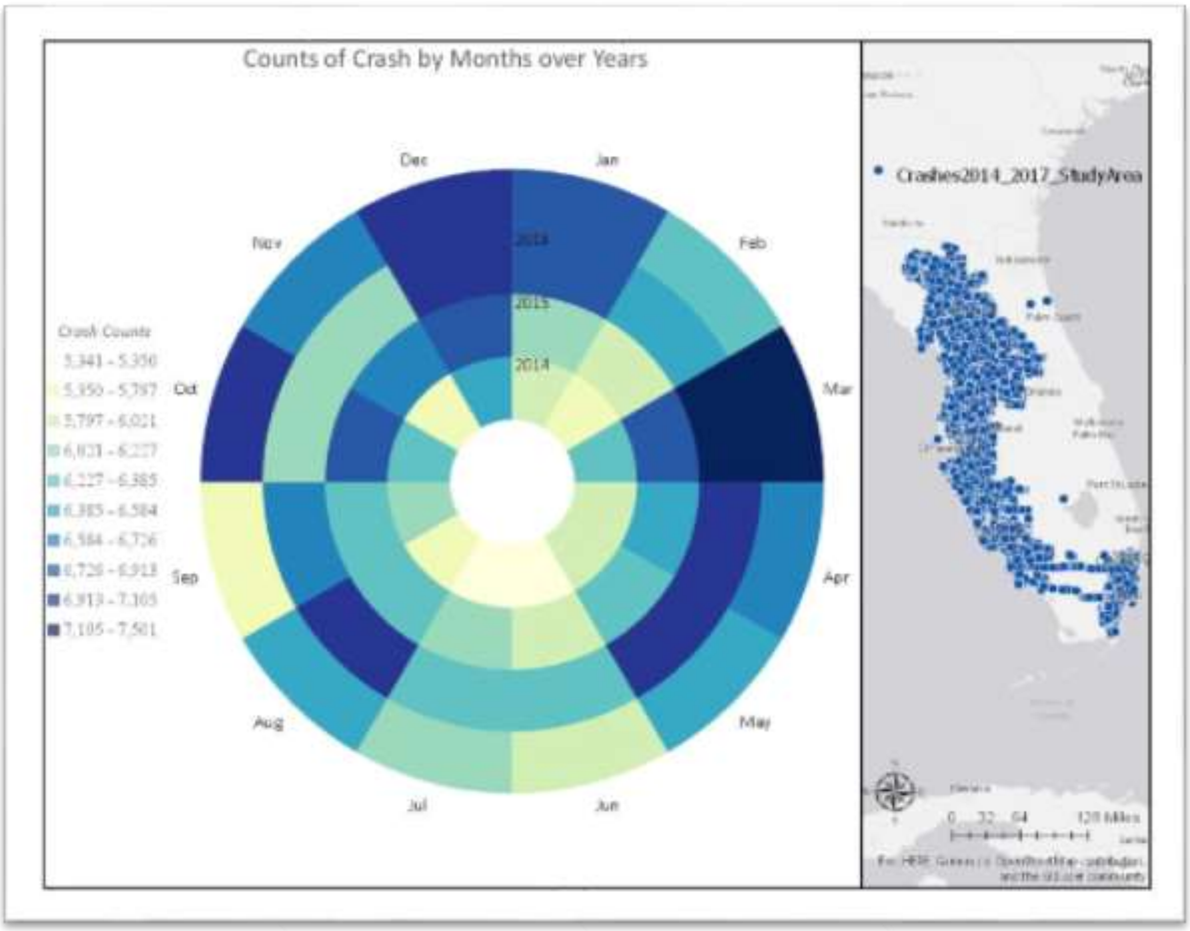


Figure 48: Crash Data by Month for the Years of 2014 to 2017

4.6 Space-Time Cube Analysis

A space-time cube model was utilized on the ArcGIS platform to analyze the temporal characteristics of the crash points along with roadway segments. A space-time cube is a tool that provides 3D visualization of crash data in spatial and temporal dimensions. The Space-time cube tool aggregates data points into space-time bins. The timestep interval defines the time period for each bin. In space-time cube analysis, time is denoted along the *z*-axis, and the spatial locations of the crash records are represented using the *x*-axis and *y*-axis. Figure 45 depicts the structure of the space-time cube analysis. A timestep of one month was defined; thus, the *z*-axis included 48 time steps that represented the 48 months of the study period. In the crash dataset, a field with type "date" was created in the attribute table. This field was populated based on crash occurrence date and time and aggregated the data points into 1-month bins by time.

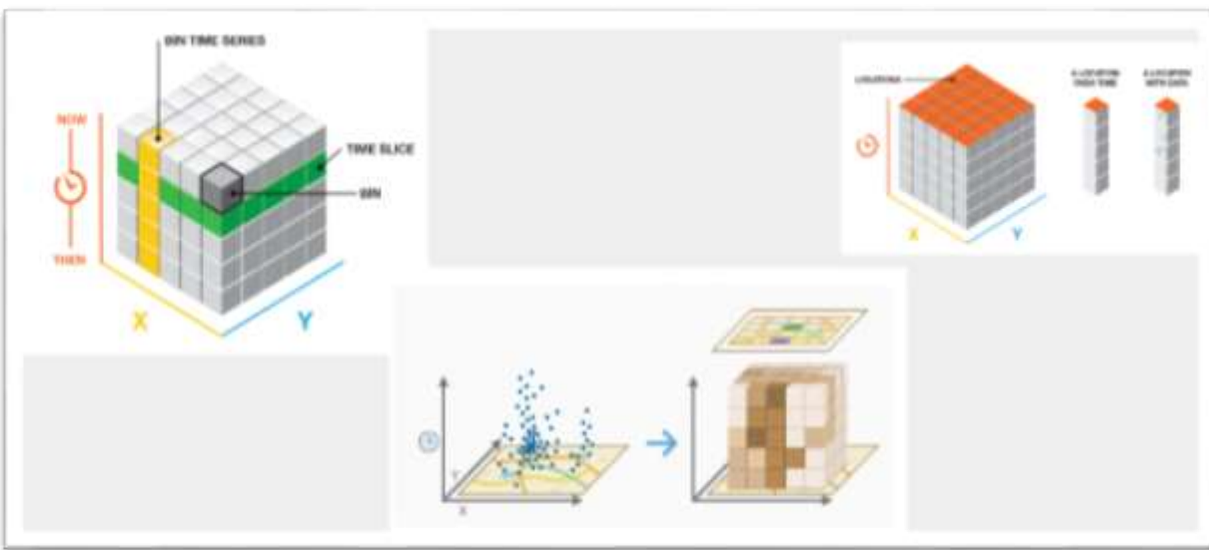


Figure 49: Space-Time Cube Structure (ArcGIS Tool Reference)

4.7 Global Spatial Autocorrelation Analysis

The previous section described the space-time cube analysis. To further explore the spatial aggregation characteristics and to identify statistically significant crash locations, autocorrelation analyses were also conducted. Generally, spatial autocorrelation analysis can be classified as global spatial autocorrelation or local spatial autocorrelation.

The space-time cube analysis identified the spatiotemporal aspects of crash location but did not explore the spatial aggregation characteristics of the statistical significance of the crash distribution. To determine statistically significantly high spatial autocorrelation locations, a spatial autocorrelation analysis was conducted on crash data for the years 2014–2017 in the selected counties using Moran's index (Moran's I). First, the crash attributes were spatially joined with road segments based on their longitude and latitude. Second, a road network was built using the joined crash–road segment attribute. Finally, a spatial weights matrix for the network arcs was generated, and a global Moran's I was computed.

4.8 Emerging Hotspot Analysis

As explained in the previous section, autocorrelation analysis was conducted to identify crash hotspots. This section describes a detailed interpretation and classification of crash hotspots and the analysis of emerging hotspots. After crash data had been aggregated into space-time cube bins, the emerging hotspot analysis tool was used to statistically analyze each bin. Subsequently, crash trends were identified by the Getis-Ord Gi statistic. Hotspots were classified in 17 different categories to present a detailed explanation of hot and cold spots and their locations and changes over time.

4.9 Network Building

This section presents the procedure used to design and create a dynamic network dataset and to develop an alternative route selection tool that can identify optimal routes that accommodate truck traffic. First, street and traffic data were collected and processed, and a dynamic routable network dataset was built to store road edges and junctions and their attributes for all segments of the road network. Second, historical traffic profiles were incorporated into road edges; this allowed time-dependent variables to be assigned to road edges and junctions to reflect actual traffic conditions throughout the day. Finally, truck alternative route selection criteria were defined to evaluate the network in terms of suitability for tucks.

The network dataset is a roadway network segmented at intersecting roadways. These segments are called edges, and the intersection points are called junctions. The ArcGIS platform and its Network Analyst extension were utilized to design and build a network dataset that incorporates traffic data and facilitates navigation from one edge to another.

The first step in creating a network dataset was to create a file geodatabase to store and manage spatial and nonspatial data. Then, a line feature class and two historical traffic data tables were created and stored in the file geodatabase. The line feature class represents the road segments, while the two historical traffic tables were used to store the change in travel time throughout the day. These tables are a speed-profiles table used to store speed profiles and a street-profiles table used to store the relationships between streets and speed profiles. The times of day were grouped into 15-minute intervals. Each record in the traffic profiles table has a scale factor that is multiplied by free-flow speed for each time slice. Historical traffic data (with 15-minute time slices) and real-time data were incorporated in the network dataset. Time-dependent variables were assigned to road edges and junctions to reflect actual traffic conditions throughout the day. Finally, a network dataset was built to develop network elements and to assign values to the network attributes. Additionally, connectivity was established with *z*-elevation to simulate overpass and underpass scenarios. After the network was built and traffic data were incorporated, all potential alternative routes were identified and evaluated using alternative route selection criteria. The selection criteria were defined based on the FHWA's alternate route handbook. Routing restrictions and attributes can also be incorporated into the network analysis. Network attributes, including travel time, restricted turns, posted speeds, and one-way streets, were assigned to network elements.

4.10 Alternative Route Selection Criteria

To select an alternative route that can accommodate heavy vehicle characteristics and restrictions, selection criteria were defined. The main characteristics for assessing whether a candidate route is feasible for truck traffic were specified as follows:

1. Roadway geometry, including lane width and number of lanes
2. Roadway conditions, including the level of service and speed limit
3. Heavy vehicle restriction, including vertical clearance restrictions and insufficient bride design loads
4. Neighborhood impacts, including proximity to schools and hospitals

After identifying the alternative route criteria, relevant data were collected from various sources. Data were extracted in shapefile format, and additional data processing was done utilizing data management tools in the ArcGIS platform.

This section presents the methodology used for developing requirements for evaluating whether alternative routes are suitable for heavy vehicles. Collected data relevant to alternative route selection considerations were used as restrictions or scaled-cost barriers in the network analysis. Restrictions indicate that the selected road segment is restricted for heavy vehicles and is not feasible for truck traffic diversion. Scaled cost barriers penalize a route by increasing the travel time based on predefined factors.

Barriers raise the cost of transport along edges and junctions of the linked network dataset. Barriers can be classified as points, lines, or polygons, and they can be modeled as preferred or avoided features within the Network Analyst extension to represent temporary changes to the network. When point barriers are added to a roadway segment, travel in the segment is prohibited. Added cost point barriers, however, still allow movement through them but may add costs to that movement. Line barriers are the second type of barrier within ArcGIS. Line barriers can restrict road segments entirely or can multiply travel costs by a given factor. The third type of barrier is the polygon barrier. A scaled cost can be added to roads that pass through a polygon barrier.

4.10.1 Roadway Geometry

Roadway capacity is related to the number of lanes on the roadway. Additionally, lane width is an essential factor for maneuverability. In this study, the threshold for truck diversion was identified as lanes with a width of 9 feet. Roads with lane widths of 9 feet or less were added to the network as restrictions.

4.10.2 Traffic Conditions

To ensure that diversion does not increase congestion on an alternative route, the available level of service on the route was determined and added to the network as a scaled cost.

Roads operating near capacity or having a low level of service were assigned a cost factor of 2, which doubles the travel cost

4.10.3 Neighborhood Impacts

It is essential to eliminate truck traffic from suburban areas with high population densities to preserve the health and quality of life of the neighborhood. Areas near schools are overcrowded during morning and afternoon hours, and a heavy vehicle redirected to the vicinity of a school would present a risk to schoolchildren.

Data were collected from the ESRI database and extracted as a shapefile then clipped to the study area. A 0.5-mile buffer was created around school locations, and a polygon barrier was added to network analysis as a scaled cost. Segments that intersect with school polygon barriers were assigned a scaled cost value of 2. Hospital locations data were collected from the ESRI library and extracted as a point shapefile. Data were clipped to the study area, and a 0.5-mile buffer was created around each hospital location. A polygon barrier was added to the network analysis as a scaled cost barrier.

4.10.4 Heavy Vehicle Restrictions

The National Bridge Inventory data were inspected to identify criteria that could be used as restrictions on the network. Bridges with insufficient design loads (less than H1) were added to the network in a new layer as restrictions to prevent the diversion of truck traffic to these locations. Bridges with vertical clearance less than 14 feet were also added to the network as restrictions.

Bridge inventory data was extracted as a CSV file and converted to a shapefile, and the layer was projected and plotted to ArcGIS. The bridge points were clipped to the study area. Bridges with a design load less than H1 or with low vertical clearance were selected, and a new layer with the selection was created. This feature class was buffered by 0.5 miles. These buffers were added as scaled-cost polygon barriers in Network Analyst.

4.11 Benefit Estimation

The model benefits allowed for the following:

1. Calculations of the travel time with and without diversion.
2. Estimates of the difference in total travel time between two scenarios.
3. A reduction in delays due to truck diversion.
4. Reduced fuel consumption due to the diversion strategy, using conversion factors obtained from the National Highway Traffic Safety Administration's *Commercial Medium- and Heavy-Duty Truck Fuel Efficiency Technology Study* (June 2015).
5. Conversion of savings in delay time and fuel consumption to monetary values using conversion factors obtained from Texas A&M Transportation Institute's *Urban Mobility Report*.

4.12 Summary

A research methodology was developed to improve truck travel efficiency and assess the impacts of truck diversion strategies. This chapter described the details of the methodology and the criteria used for the methodology and for data collection. It also described the various data sources used in this research and the primary methods of analysis employed for different phases of the study. The following chapter details the development of a model that uses the analysis approaches described above.

4.13 Model Development

4.13.1 Crash Hotspots Analysis

Traffic crashes are a significant public safety concern and are one of the leading causes of death around the world (World Health Organization, 2015). For this reason, traffic safety indicators, such as fatality risk, the number of crashes with injuries, and the number of victims, are regularly collected to monitor the safety trends of specific sites (Bergel-Hayat et al., 2013). Identifying high-crash-rate road segments provides safety professionals with insight into crash patterns to improve road safety management. Due to the increasing number of crashes and insufficient financial resources, it is imperative to identify priorities for future investments in road safety to ensure more efficient resource distribution. Identifying crash-prone segments can help decision-makers to prioritize financial resources and to plan the proper actions to improve the problematic segments.

This study presents a methodology for prioritizing and classifying roadway segments by employing a comprehensive 3D hotspot analysis based on crash data, including crash severity and crash spatial and temporal characteristics. Evaluation and classification of road networks based on safety performance and crash rates can be used to identify the most critical segments in terms of crash severity and crash type.

A macroscopic spatial analysis was conducted using traffic crashes to identify statistically significant crash trends and locations on the I-75 corridor from 2014–2017. The proposed model was incorporated into the diversion decision-making tool to more efficiently support the planning and improvement of road safety.

The hotspot crash analysis investigated crash trends over time and space. The findings are symbolized by 17 distinct categories defining the statistical importance of hot or cold spots and the pattern of locations over time. Crash patterns were identified in the study area between 2014 and 2017.

The emerging hotspot analysis revealed that four types of hotspots—consecutive hotspots, intensifying hotspots, sporadic hotspots, and for the years 2014–2017, new hotspots are statistically distributed at various locations in the study area. Figure 46 shows seven new hotspot locations. These locations need more attention, and more traffic management needs to be applied in line with the particular temporal and spatial patterns of these hotspots. In conclusion, the results determined the locations where different types of hotspots are concentrated.

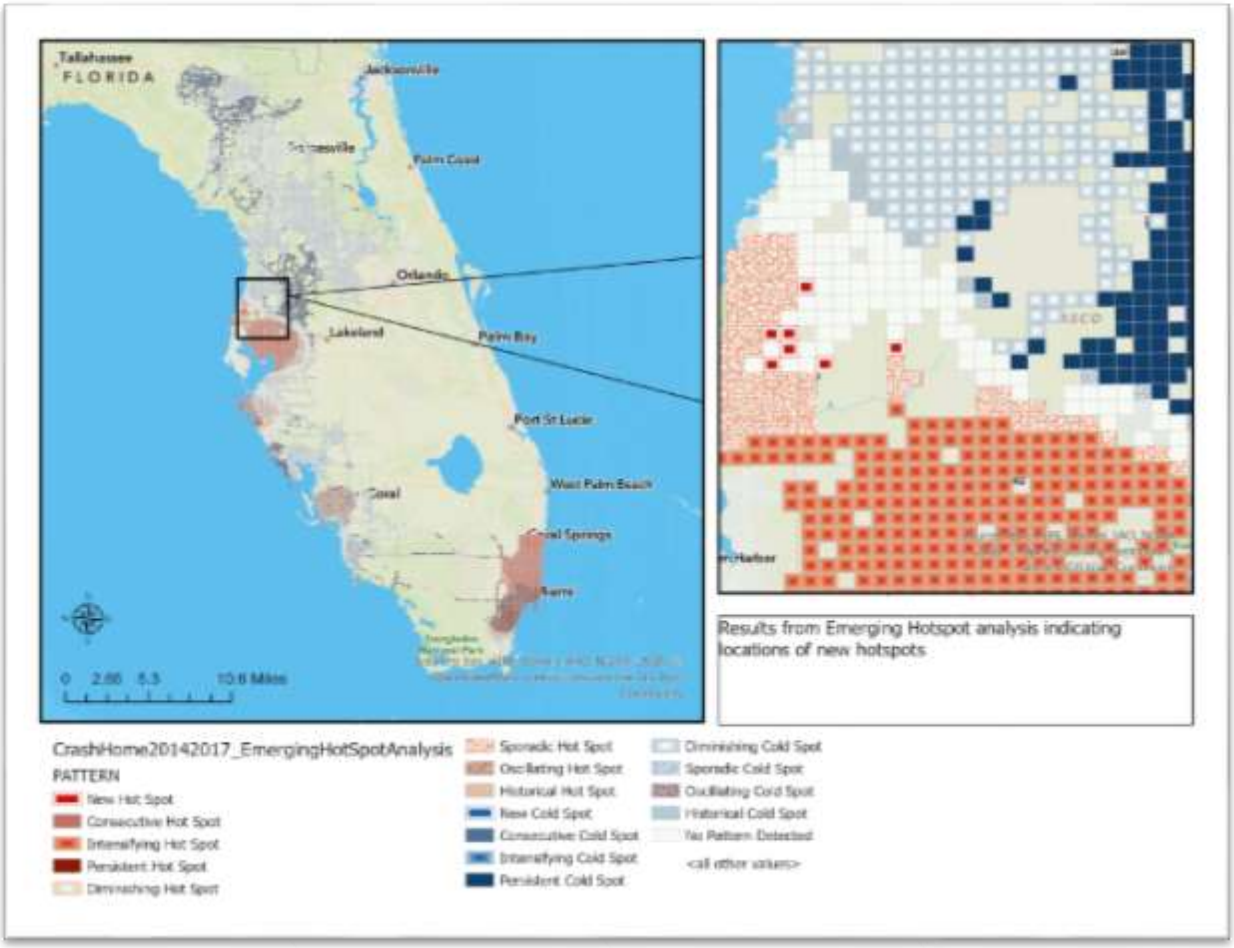


Figure 50: Emerging Hotspot Analysis

In this research, Space-Time Cube analysis was performed to identify the statistically significant locations of the crashes between the years 2014 and 2017. Additionally, the crash trends were investigated and visualized in three dimensions to present crash spatiotemporal patterns over the study area during the years of 2014 to 2017. As shown in Figure 47, hexagons in 3D are shown as columns of slanted bins. Each bin represents one month time period. The top of the column represents the most recent time. The red bins are statistically significant crash clusters with high crash rates, while the blue bins are statistically significant clusters of low crash rates.

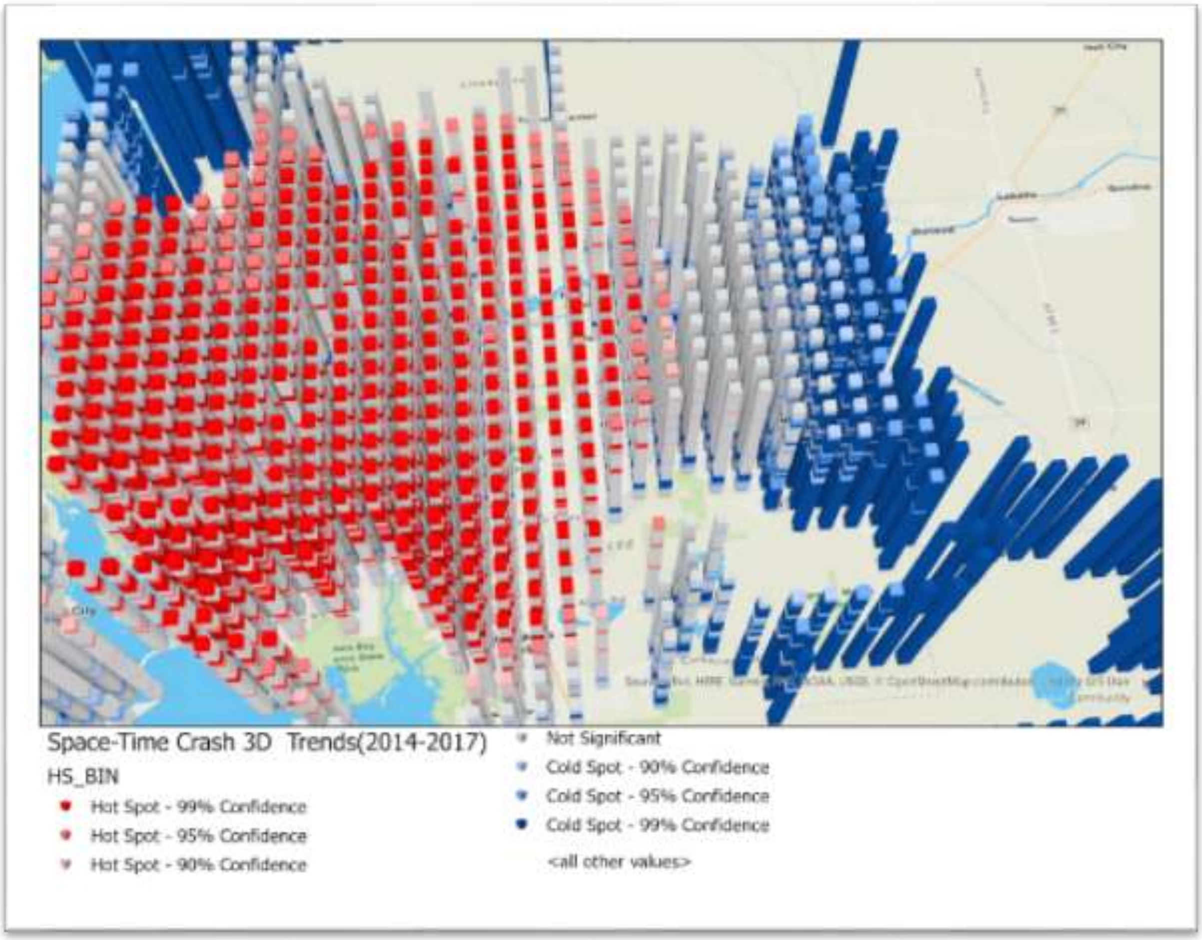


Figure 51: Space-Time Crash Trends 3D Analysis

4.13.2 Incident Clearance Prediction Model Development

To validate the linear regression model, data were tested to determine whether they met the regression model assumptions. Several approaches could be used to investigate the assumptions of linear regression, such as collinearity and normality. In this research, the criteria used were skewness of the histogram, normal probability plots, variance, and scatterplots between the dependent variable and independent variables.

Scatterplots were constructed between the dependent and the explanatory variables to test the linearity assumption. To evaluate the normality assumption, the histogram skewness was measured. To evaluate multicollinearity between independent variables, the correlation coefficient and variance inflation factor (VIF) was determined by applying multiple linear regressions. Tolerance values less than 0.3 and a VIF greater than 10 indicate a multicollinearity problem. The dependent variable (incident duration, or *dur5*) was transformed using the log function for improved symmetry and stable variance with the purpose of improving normality.

To demonstrate how independent variables relate to each other and to evaluate the strength of correlations among these variables, the relationships between all pairs of variables were plotted. The overall pattern of these relationships appears regular and shows typical trends.

This section presents the development of the incident clearance duration prediction model. Prediction of incident clearance time is essential in the management of nonrecurrent congestion due to incidents on freeways. A statistical model was developed to predict incident clearance duration. Findings from this model were implemented in the incident management process to reduce the impact of congestion on the network. To improve the operational efficiency of urban freeways and to minimize the impact of congestion, several strategies were implemented. To make these strategies operate efficiently, the prediction of incident clearance duration is necessary. In chapter 3, a description of incident data and an overview of the study area were presented. In this section, the development of the incident clearance prediction model is presented, followed by a discussion of how the results of this model are integrated with a diversion decision algorithm.

In this study, regression analysis was used to develop a model for predicting incident clearance duration as a function of relevant variables. The goal is to develop a prediction model that can easily be used by a practitioner in incident management. The multiple regression analysis options of SPSS software were utilized in developing this prediction model. The first step was to regress the dependent variable (incident clearance duration) with all the independent variables to examine the effect of each variable. Determining which variables are significant at $\alpha = 0.05$ was the second step. The third step was to regress the dependent variable individually with all possible combinations of independent variables to select the best functional form. Next, each two-factor interaction term was introduced. The final step was to employ the stepwise procedure one more time using the variables resulting from the previous three steps.

4.14 Sensitivity Analysis

The statistical approach used in this study to predict incident clearance time is Multiple Linear Regression. Multiple linear regression attempts to model the relationship between two or more independent or explanatory variables and a dependent variable by fitting a linear equation to observed data. Based on the normality tests, trials, and errors during the model calibration efforts, explanatory variables were modified to assess the effect of each variable on the incident clearance; all categorical attributes were transformed into binary representations (i.e., 0 or 1). The Statistical Package for Social Science (SPSS) software was utilized for model development.

A set of the incident, traffic, and road characteristics were examined for possible inclusion as independent variables in the developed prediction model. Several approaches could be used to investigate the assumptions of linear regression, such as collinearity and normality. In this research, the criteria that were used to validate these assumptions were skewness of the histogram, normal probability plots, variance, and scatterplots between the dependent variable and independent variables. Scatter plots were performed between the dependent and the explanatory variables to test the linearity assumption. In order to evaluate the normality assumption, the value of Histogram skewness was identified. In evaluating multicollinearity between independent variables, an inspection of the correlation coefficient and Variance Inflation Factor (VIF) was performed by applying multiple linear regressions. Values of tolerance less than 0.3 and VIF greater than 10 indicate the problem of multicollinearity.

The dependent variable (Incident duration dur5) was transformed using the log function for improved symmetry and stable variance with the purpose of improving normality. The incident duration was transformed into its natural log and included in the model as the dependent variable. The model summary output revealed that the model could predict 31.4 % of the incident clearance duration using the selected independent variables. Sensitivity analysis was used to indicate which parameters have more influence on the prediction of the dependent variable.

Therefore, Sensitivity Analysis was performed by varying the input parameters one by one while keeping the other inputs fixed at the baseline and monitor changes in the output. Regression analysis was utilized for sensitivity analysis. The importance of inputs was indicated by the changes in R squared with the change of each input in the regression model. The sensitivity analysis steps of this study are as follows:

- First, the base scenario output was defined. The base scenario includes all the independent variable in the prediction model, and all the input are kept constant.
- Then, the value of the output after removing one of the input parameters while keeping other inputs constant was calculated.
- The percentage change in the output was obtained by comparing the model accuracy of each scenario with the base scenario.

Incident data were divided into six categories; Incident type, road closure, time of day, month, day of the week, road characteristics. Table 11 shows the parameters included in each category.

Table 11: Incident Data Categories for Sensitivity Analysis

Data Category	**Incident type**	**Time of Day**	**Month**	**Road Closure**	**Day of Week**	**Road Characteristics**
	Crash	12:00am-6:00am	January	Right lane blocked	Sunday	Lane Width
	Disabled Vehicle	6:00am-9:00am	February	Center lane blocked	Monday	Number of Lanes
	Debris on road	9:00am-11:00am	March	Left lane blocked	Tuesday	Median Type
	Fire	11:00am-2:00pm	April	Shoulder closed	Wednesday	Median Width
	Wildlife	2:00pm-4:00pm	May	Exit ramp	Thursday	Functional Classification
	Police Activity	4:00pm-7:00pm	June	Entry Ramp	Friday	Speed Limit
Parameter	Emergency Vehicle	7:00pm-12:00am	July	Ramp Shoulder	Saturday	AADT
	Other		August	One lane blocked		Truck Percentage
			September	Two lanes blocked		
			October	Three lanes blocked		
			November			
			December			

By removing one of the input parameters while keeping other inputs constant, model accuracy was calculated and compared with the model accuracy of the base scenario. As shown in Table 12, six scenarios were performed, and model accuracy was compared to the base scenario.

Table 12: Results of Sensitivity Analysis Scenarios

Variables	Model Accuracy
Road Characteristics	3.6%
Road Closure	8.0%
Incident Type	11.5%
Time of Day	1.3%
Day of Week	0.6%
Month	1.0%

The results of the six scenarios were plotted. As shown in Figure 48, the incident type has a significant impact on model accuracy, followed by road closure parameters.

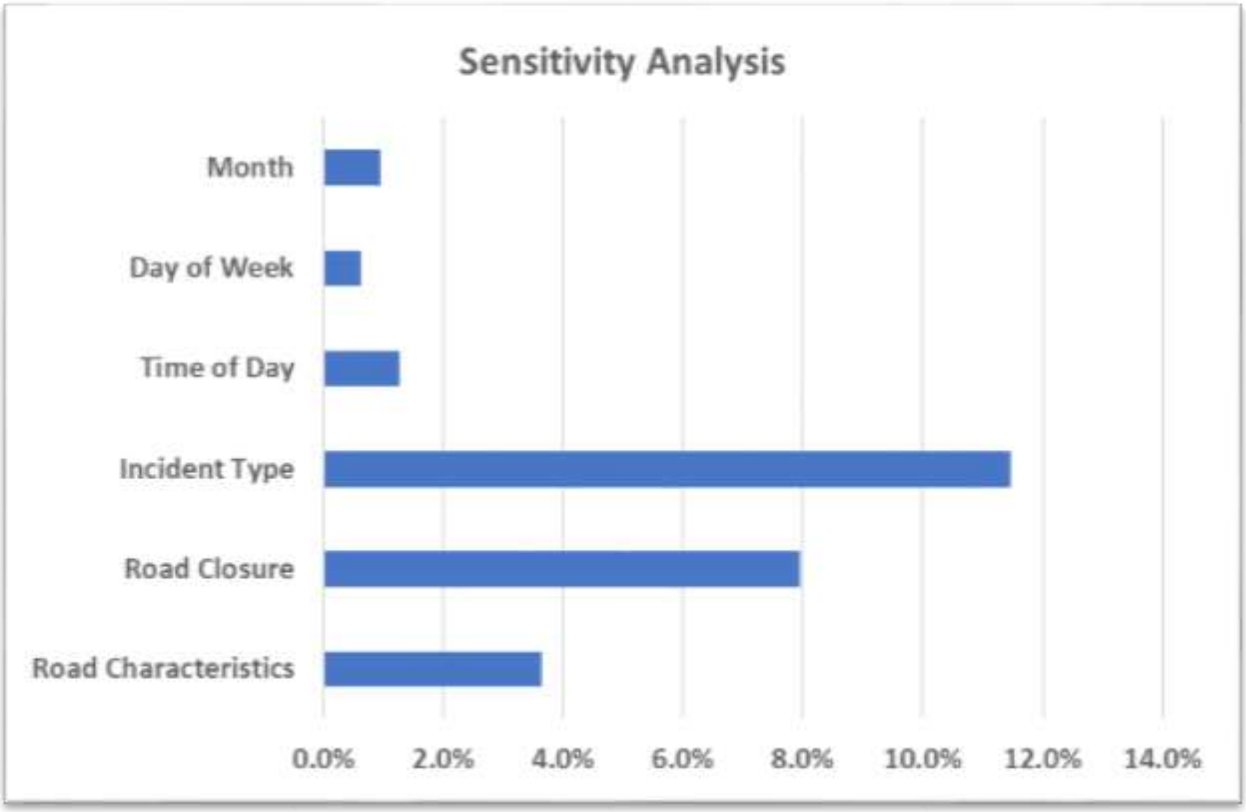


Figure 52: Impact of Input Parameters on Model Accuracy

4.15 Diversion Model

A network analysis model of I-75 in Florida was developed. The developed model finds all potential alternative routes throughout the study area, taking into consideration heavy vehicle restrictions and the impacts of traffic diversion on neighborhood and traffic conditions. Predefined alternative route selection criteria were incorporated in the network dataset. Based on the criteria for lane width, capacity, and vertical clearance, those routes with features that made them unacceptable as alternate routes were excluded from consideration. A penalty factor (scaled cost) was also applied to roads within a defined distance of schools or hospitals.

The main objective of this research was to develop a framework to evaluate the impact on the overall road network operation of truck diversion strategies to mitigate nonrecurrent congestion due to incidents. As explained previously, a network analysis dataset was designed and created, and the ArcGIS platform was utilized with it to develop alternative routes that consider truck restrictions such as vertical clearance limitations, road characteristics, and traffic conditions. The entire corridor of I-75 was analyzed using this approach.

The next process was to establish criteria that made it possible to test alternative routes in terms of appropriateness for trucks. A threshold was identified for each criterion. Alternative route selection criteria were added to the network as restrictions or scaling factors to assign penalties to each segment that intersected a specified criterion. Additionally, estimated travel time, restrictions, and barriers such as low-clearance bridges and school zones were considered.

The algorithm was designed to find the shortest path, excluding scalable costs and constraints; this would be the base scenario. Another scenario was also considered that added cost factors and restriction barriers. This scenario simulates the truck diversion route. The Network Analyst extension produces turn-by-turn instructions for each simulation scenario to define alternative routes to avoid high-risk interstate closures.

The criteria used to evaluate potential truck routes are summarized as follows:

1. Neighborhood impact
2. Traffic conditions
3. Roadway geometries
4. Heavy vehicle restrictions
5. Cost

Neighborhood impacts consider the properties of nearby land use along the proposed truck path. Truck intrusions into residential areas and near other critical facilities, such as schools or parks, are not desirable. Truck restrictions can be introduced to prevent truck drivers from driving on roads near these land uses. Also, road conditions selection criteria consider both the level of traffic congestion along the proposed road route and its capacity. Roads carrying traffic volumes approaching capacity are less attractive as potential truck routes, as traffic congestion would have a detrimental effect on freight movements. Different case studies were developed to evaluate the potential alternative route and validate the proposed model. These scenarios were compared with the base scenario, which is travel on the main route during incident conditions.

4.16 Results and Discussion

Traffic diversion strategies can be utilized as congestion mitigation strategies by diverting truck traffic to an alternative route. The alternative route then carries both the diverted traffic and its regular traffic load. Therefore, the selection of an alternative truck route should consider the safety and efficiency of the overall network system. Although traffic diversion strategies are implemented in many regions, there has been only limited study of the criteria used in deciding on optimal truck traffic diversion routes.

The criteria for selecting alternative truck routes should be carefully defined to consider truck characteristics so that only optimal routes that can efficiently accommodate truck traffic are selected. Limited work has been done evaluating the economic, social, and environmental impacts of truck traffic diversion on the performance of the selected alternative routes.

This chapter details three case studies to demonstrate the efficiency of the developed truck routing framework during incident-induced congestion on a segment of I-75 in Florida. The proposed framework first performed a space-time cube hotspot analysis to identify statistically significant hotspots and classify hotspot trends over space and time to identify high-crash segments. Additionally, a statistical regression model was applied to identify the explanatory variables that influence incident clearance duration. Finally, a regression model was developed to estimate incident clearance duration times in the I-75 corridor.

4.17 Case Studies Overview

The proposed truck rerouting framework was applied to three case studies using suitable alternative route selection criteria. The selected truck routes helped to reduce delays and satisfy truck maneuverability restrictions while maintaining satisfactory road conditions on the selected route. The scenario sites were determined by investigating high-crash trends and statistically analyzing incident clearance results. A stretch of I-75 was identified as a study site for applying the developed framework for each case.

The first case study was of an incident on I-75 Northbound, beyond mile marker 258, that occurred on September 3, 2018. The incident type was a crash with severity level 3, which is defined as causing an incapacitating injury. The incident blocked two out of three lanes. Incident information was collected from the FDOT SunGuide report. The roadway characteristics and simulation variables used in the model and the details of the incident characteristics are listed in Table 13. Additionally, Figure 49 shows the incident location of the first case study.

Table 13: Details Information for Case Study 1

Category	Data details
Date and time	2018/09/03 13:15:17
Location	I-75 Northbound, Beyond MM 258
Severity	3
Number of blocked lanes	2 Right Lanes (of 3 Lanes) Blocked
First responder arrival time	2018/09/03 13:23:09
Incident clearance duration (minutes)	52.7
County	Hillsborough
Notifier Agency	TBRCC
Incident type	Crash
maximum speed	70
AADT	151500
Truck %	6.50%

Figure 53: Incident Location: Case Study 1

A second case study selected for model application simulated an incident that occurred on I-75 Northbound on December 25, 2018. The incident type was a crash with severity level 2, which is defined as a possible injury. The incident caused the blockage of the exit ramp as well as the left lane. Incident information was again collected from the FDOT SunGuide report. The roadway characteristics and simulation variables used in the model and the details of the incident characteristics are given in Table 14. Additionally, Figure 50 shows the incident location of the second case study.

Table 14: Detailed Information Related to Case Study 2

Category	Data details
Date and time	2018/12/25 02:00:33
Location	I-75 Northbound, Ramp to Big Bend Rd
Severity	2
Number of blocked lanes	Exit Ramp Left Lane Blocked
First responder arrival time	2018/12/25 02:08:06
Incident clearance duration (minutes)	92.4
County	Hillsborough
Notifier Agency	FHP
Incident type	Crash
maximum speed	70
AADT	89000
Truck %	10.50%

Figure 54: Incident Location: Case Study 2

The third case study assessed an incident that occurred on July 07, 2018 and closed all lanes on I-75 Northbound at mile marker 91. Incident information was collected from the FDOT SunGuide report. The roadway characteristics and simulation variables used in the model and the details of the incident characteristics are shown in Table 15. Additionally, Figure 51 maps the incident location of the third case study.

Table 15: Detailed Information Related to Case Study 3

Category	Data details
Date and time	2018/07/011 15:00:27
Location	I-75 Northbound, At Mile Marker 91
Severity	3
Number of blocked lanes	Road closed
First responder arrival time	2018/11/15 04:23:15
Incident clearance duration (minutes)	65.68
County	Collier
Notifier Agency	FHP
Incident type	Vehicle fire
maximum speed	70
AADT	41500
Truck %	11.20%

Figure 55: Incident Location: Case Study 3

The three case studies were simulated using the developed algorithm. The appropriate height restriction was identified as follows: descriptor attributes specified the height limit for each road, and a restriction attribute stored the vehicle height parameter. Following this, a script evaluator was created so that selection of a street was prohibited when the actual vehicle height exceeded the maximum vertical clearance. By applying height restrictions, the developed model diverted trucks to avoid low vertical clearances. Additionally, a scaled factor was used as a polygon barrier to avoid school zones.

When constraints and scaling factors were applied to the network, the resulting algorithm was used to classify two sets of alternate routes. To compare travel times and estimate benefits from the model application, two simulation scenarios were performed for each case study: a base scenario and an optimized alternative route scenario. The base scenario route was estimated without consideration of the limitations and the scaled factors, resulting in the shortest path between origin and destination. The optimized route scenario was estimated with consideration of scaled costs and limitations; this route provided an optimized diversion path for trucks. Additionally, turn-by-turn directions were generated for each route scenario.

The results of the three case studies are presented below. As shown in Figures 52 to 57, for each case study, two routes were generated with driving directions.

4.18 Case Study 1

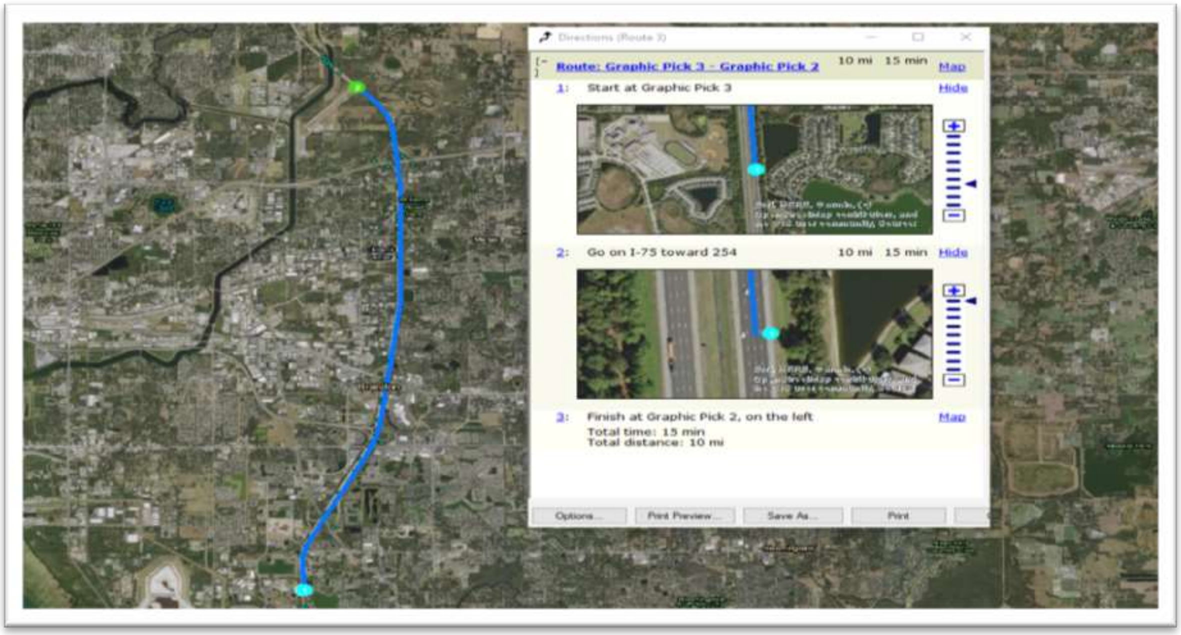


Figure 56: Case Study 1: Base Scenario Route on I-75

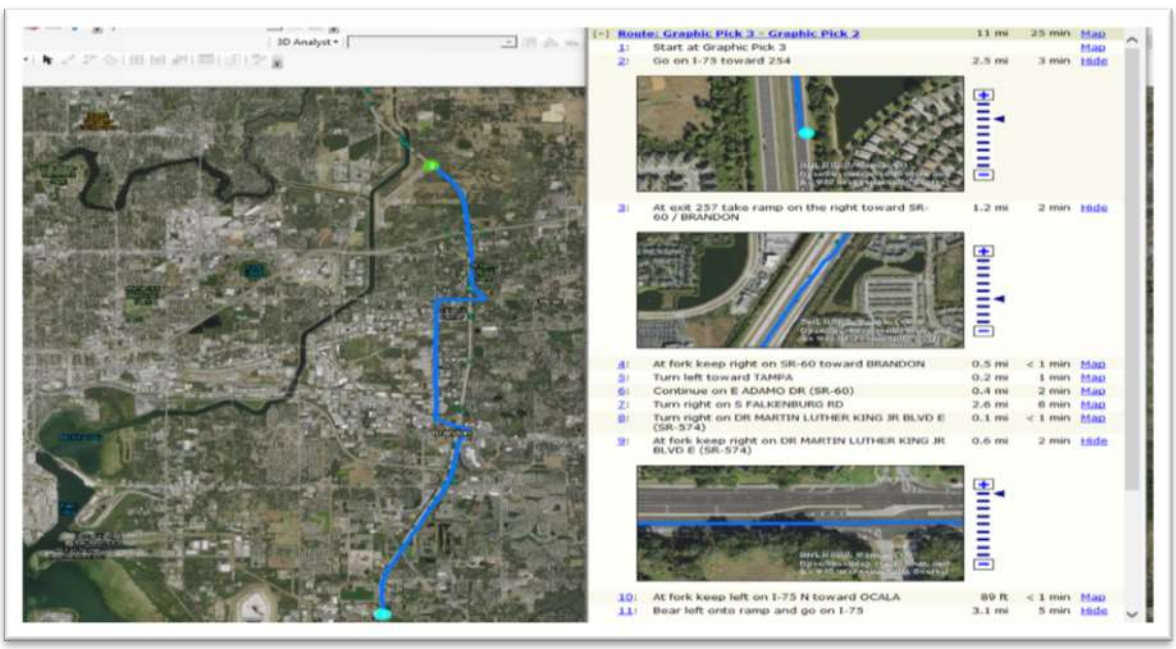


Figure 57: Truck Alternative Route to Bypass the Congested Segment: Case Study 1

4.19 <u>Case Study 2</u>

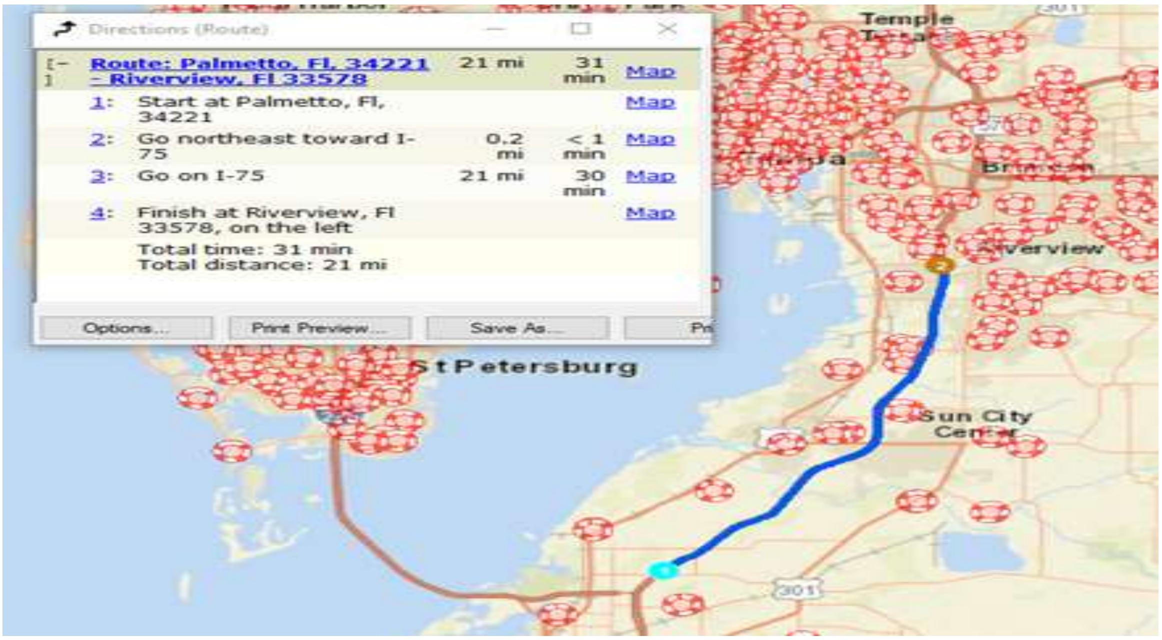


Figure 58: Case Study 2: Base Scenario Route on I-75

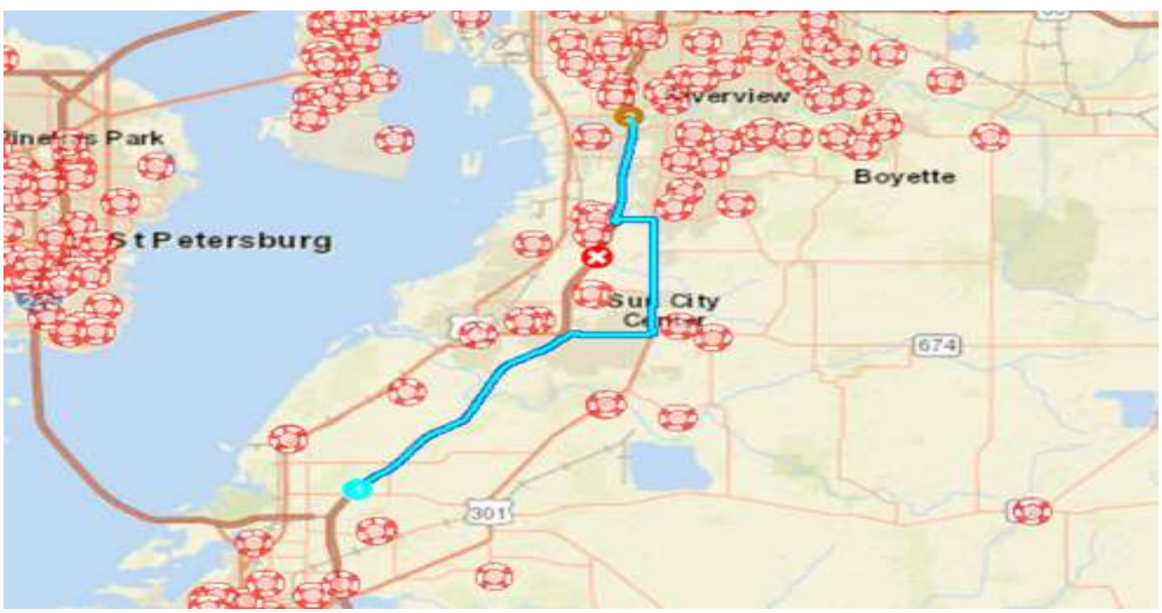


Figure 59: Truck Alternative Route to Bypass the Congested Segment: Case Study 2

4.20 Case Study 3

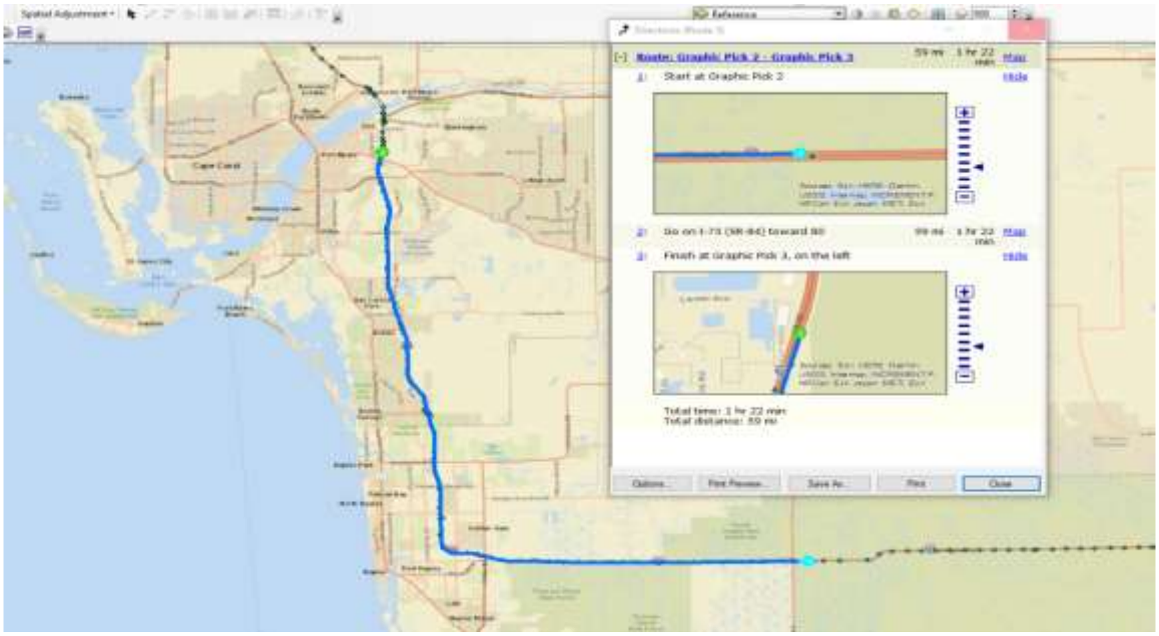


Figure 60: Case Study 3: Base Scenario Route on I-75

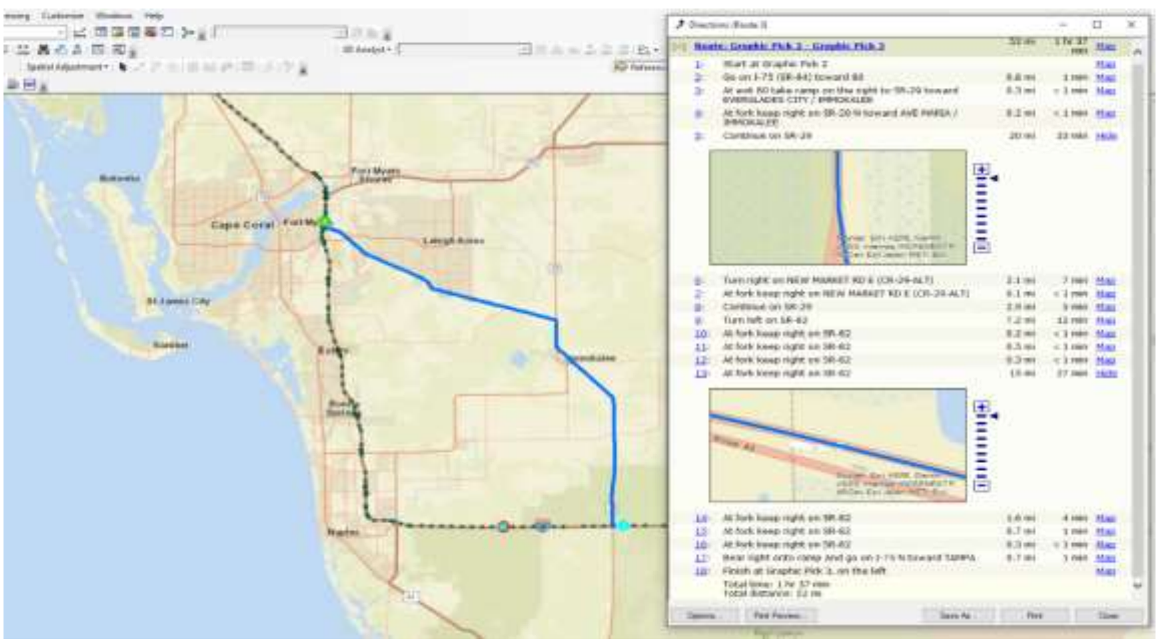


Figure 61: Truck Alternative Route to Bypass the Congested Segment: Case Study 3

4.21 Benefit Estimation

The primary purpose of incorporating diversion strategies is to alleviate congestion and the potential delay caused by an unforeseen interruption of the road. Therefore, it is essential to quantify the advantages resulting from diversion strategies as a basis for comparing operational costs. This section explains how the benefits of diversion strategies were quantified to validate the proposed diversion decision-making framework. Moreover, it demonstrates whether the diversion strategy implemented is genuinely advantageous for the overall network.

To explore how the advantages of diversion strategies can vary depending on the traffic situation and incident impacts, three case studies were chosen for incorporating diversion strategies based on this diversion-decision framework.

The model benefits were estimated with the following procedure:

1. Calculation of the travel time on the shortest route (without diversion) and the travel time on the optimized truck route (with diversion).
2. Estimation of the difference in total travel time between the two scenarios.
3. Calculation of the reduction in delays due to the implementation of the diversion operation.
4. Quantification of the reduction in fuel consumption due to the implementation of the diversion strategy, using conversion factors obtained from the National Highway Traffic Safety Administration *Commercial Medium- and Heavy-Duty Truck Fuel Efficiency Technology Study* (June 2015). The following conversion factors were used in this step:
    a. For idle, a value of 6.515 miles per gallon
    b. For stop and go, a value of 3.78 miles per gallon
    c. For the alternative route, a value of 5.13 miles per gallon (The World Harmonized Vehicle Cycle) (WHVC)
5. Conversion of the savings from reduced delays and fuel consumption to monetary value using the following values:
    a. Truck VOT = $96/hour
    b. Price of diesel = $2.55/gallon

Table 16 presents a summary of the benefit estimation from the three case studies.

Table 16: A Summary of Benefit Estimation of Three Case Studies

	Case Study 1		**Case Study 2**		**Case Study 3**	
	Base Route	Alternative Route	Base Route	Alternative Route	Base Route	Alternative Route
Travel Time (minutes)	16	26	31	49	82	97
Route Length (miles)	9.7	11	21	25	59	52
Incident Duration/additional time (minutes)	52.75	10	92.4	18	65.7	15
AADT	151,500	38,000	89,000	15,400	41,500	3,100
I-75 Diverted one-way AADT Trucks	4,924		4,673		2,531	
Speed limit (mph)	70	45	70	55	70	60
Delay Reduction (minute)	42.75		74.4		50.7	
Delay Cost $	$17,315	$3,283	$28,783	$ 5,607	$11,088	$ 2,531
Delay Saving $	$ 14,033		$23,176		$ 8,556	
Total Fuel Consumption	$ 1,147	$ 485	$4,229	$ 1,973	$7,663	$ 4,401
Fuel Saving $	$ 662		$ 2,256		$ 3,263	
Total	$ 14,695		$ 25,432		$ 11,819	
Median	$ 14,695					
Total for a year per Corridor	$ 52,165,570					

4.22 Conclusion and Future Research

In this research, the main objective was to develop a diversion decision-making framework for selecting alternative truck routes to circumvent congested highway segments. To achieve this objective, data were collected, prepared, and utilized to design and build a dynamic routable network dataset for the state of Florida. Additionally, the ArcGIS platform was utilized to generate an alternative route that accommodates truck characteristics and constraints. Predefined alternative route selection criteria were developed, taking into consideration road conditions, truck weight and height restrictions, and neighborhood impact. Truck diversion strategies are fundamental as an approach to congestion mitigation. Previous comprehensive analysis has been undertaken to understand various congestion mitigation strategies. Overall, the findings of this study shed considerable light on the impact of truck diversion on the performance of a road network. The systematic approach used in this study included alternative route selection criteria, such as truck characteristics of weight and size, to ensure that the alternative route could accommodate the diverted truck traffic.

The purpose of this research was to develop a truck-routing framework to improve the process of selecting alternative truck routes and to measure the effectiveness of rerouting approaches on travel time, and to determine the resulting effects on the economy and the environment. The study showed that truck rerouting strategies for relieving traffic congestion have substantial economic and environmental impacts. The framework methodology developed in this study can be used to measure these impacts on any segment of limited access highway with an alternative route. The use of an efficient traffic diversion strategy during incident-induced congestion provides safety and mobility benefits to highway users. The application of appropriate diversion criteria utilizing truck VOT analysis, fuel consumption aspects, safety studies, and environmental impact analysis can lead to the selection of alternative routes that reduce travel time, meet the restrictions for truck operations, and sustain an acceptable level of service on the alternative route. This framework provides a decision-support tool for decision-makers and traffic management centers that can enable them to cope more efficiently and effectively with nonrecurrent congestion on highway networks.

4.23 Model Scalability

The methodology described in this study can be applied to roadway networks in other locations in order to facilitate diversion decisions. The presented framework can also be used as a basis for making more efficient rerouting decisions while maintaining operational safety.

While this study was conducted into the Interstate 75 in Florida, the developed framework can be generalized to all of the Florida interstate corridors. By following the same procedure developed in this study, Decision makers would be able to:

- Predicting incident clearance duration at the study area of interest.
- Building a dynamic routable network
- Implementing alternative route selection criteria into the network to select the optimal route that suitable to divert truck traffic
- Quantifying the benefits resulting from diverting truck traffic to the selected alternative route

The effects of incident data for other highways would be different depending on different road characteristics, different traffic conditions; therefore, a different incident timeline could be predicted. However, the developed framework could be applied to other regions in the U.S. interstates

4.24 Recommendations for Future Research

The rapid growth of truck traffic has raised safety and operational concerns. Truck diversion strategies have been executed throughout the U.S. to diminish the impact of incident-induced congestion. The execution of optimized truck rerouting strategies can improve the operational efficiency of freeways and enhance traffic safety in these facilities.

Although trucks need to support trade and business productivity, their movements do not have to lead to a deterioration in the quality of life or public safety. The impact of freight on the transportation system is further exacerbated by the fact that trucks occupy a greater proportion of the road capacity and thus trigger more severe problems, particularly traffic congestion, delays, secondary incidents, air pollution, fuel consumption, and pavement damage.

This study reviewed research related to traffic management and truck rerouting to identify and analyze truck traffic rerouting strategies meant to avoid nonrecurrent congestion. This section presents an overview of the limitations in the development and deployment of diversion strategies, such as a lack of comprehensive evaluation of the impact of truck drivers' behavior on route preference. These limitations suggest a direction for future research to advance the congestion management process and create more efficient traffic flows. Given the limitations noted above, together with the investment gap in infrastructure expansion in the U.S., there is a need to embrace alternative strategies to detect, manage, and efficiently mitigate traffic congestion.

CHAPTER 5: CONCLUSION

The objective of this research is to understand the correlation between travel time and diversion, thus, assist integrated corridor management efforts in the area.

The researchers have accomplished this objective by two primary and complementary steps:

1. Development of a real-time system for data collection of cars and trucks.
2. Development of a framework which uses the data from step 1 to develop, and then to quantify the benefits of the diversion.

5.1 Real-Time Data Collection System

The researchers designed and implemented a microcontroller-based system for counting cars and trucks. The system is solar-powered and includes the ability to both collect data and communicate this data to the cloud, thereby offering real-time counts and traffic assessment.

Installing this system, which consists of a solar plant, data collection nodes, and a cloud-communication aggregator can be installed on overpasses without the need for any MOT, greatly simplifying its installation. This architecture also simplifies system maintenance and reduces costs. Perhaps the biggest benefit is the substantial reduction of overall cost relative t invasive methods such as loops. Additionally, for the same number of lanes, the cost of the entire system is less than one-tenth of the cost of RTMS radar (although the current system does not output speed). Collected data via the system design, hardware, and software is extensively evaluated. Data collected from the two test sites were compared with the loop detector counts under the supervision of FDOT District 5. As a result of the data analysis from test site-1, data collected during weekdays, results show that the accuracy relative to loop counts varies from +/-

5% to +5/-10%. Furthermore, data analysis based on the test site-2 has shown that the UCF fast lane counts are within 1% - 4% of the FDOT loop counts, with an average of 1.8% using data from 3 days. UCF fast lane counts are within 2% of manual counts. UCF middle lane counts are within 2% of manual counts (based on a 1-hour manual count comparison). Finally, in comparison with FDOT loops counts, UCF middle lane counts, differences reach up to approximately 10%. In some counts, variations were higher (8%) due to sensor issues. The team also has videos of installation and system operations, which can be accessed from this link: https://drive.google.com/open?id=138IU1lYqJ3pkWGOLbNX3wa89d5MscipY

5.2 Quantification of Truck Diversion

A diversion decision-making framework for selecting alternative truck routes to circumvent congested highway segments was developed. To achieve this objective, data were collected, prepared, and utilized to design and build a dynamic routable network dataset for the state of Florida. Additionally, the ArcGIS platform was utilized to generate an alternative route that accommodates truck characteristics and constraints. Predefined alternative route selection criteria were developed, taking into consideration road conditions, truck weight and height restrictions, and neighborhood impact.

The application of appropriate diversion criteria utilizing truck VOT analysis, fuel consumption aspects, safety studies, and environmental impact analysis can lead to the selection of alternative routes that reduce travel time, meet the restrictions for truck operations, and sustain an acceptable level of service on the alternative route. This framework provides a decision-support tool for decision-makers and traffic management centers that can enable them to cope more efficiently and effectively with nonrecurrent congestion on highway networks.

REFERENCES

1. Traffic Monitoring Guide. FHWA, U.S. Department of Transportation, Washington, D.C., 2001.
2. Gordon, R. L., Tighe, W., & Siemens, I. T. S. (2005). *Traffic control systems handbook* (No. FHWA-HOP-06-006). United States. Federal Highway Administration. Office of Transportation Management.
3. Turner, S. M., Eisele, W. L., Benz, R. J., & Holdener, D. J. (1998). Travel time data collection handbook (No. FHWA-PL-98-035). United States. Federal Highway Administration.
4. Shi, Q., Wu, Y., Radwan, E., & Zhang, B. (2016). Integration of microscopic big traffic data in simulation-based safety analysis. Final Report of University Transportation Centers Program.
5. L. E. Y. Mimbela and L. A. Klein, (2000). “A Summary of Vehicle Detection and Surveillance Technologies used in Intelligent Transportation Systems”, Southwest Technology Development Institute (SWTDI) at New Mexico State University (NMSU).
6. Antoniou, C., Balakrishna, R., & Koutsopoulos, H. N. (2011). A synthesis of emerging data collection technologies and their impact on traffic management applications. European Transport Research Review, 3(3), 139-148.
7. Selezneva, O., & Wolf, D. J. (2017). Successful Practices in Weigh-in-Motion Data Quality with WIM Guidebook [Volumes 1 & 2] (No. FHWA-AZ-17-731). Arizona. Dept. of Transportation.
8. Silva, H. A. V. (2012). Methods, techniques and instruments of data collection in European Countries. Master’s In civil engineering, Specialization in Transport Infrastructures.
9. Hobbs, F. D. (2016). Traffic planning and engineering: Pergamon international library of science, technology, engineering and social studies. Elsevier..
10. Leduc, G. (2008). Road traffic data: Collection methods and applications. Working Papers on Energy, Transport and Climate Change, 1(55), 1-55.
11. D. Rosenbaum, J. Leitloff, F. Kurz, O. Meynberg and T. Reize, (2010). "Real-time image processing for road traffic data extraction from aerial images", Proc. ISPRS Commission VII Symp., pp. 372-388,
12. Burnos, P., & Gajda, J. (2016). Thermal property analysis of axle load sensors for weighing vehicles in weigh-in-motion system. Sensors, 16(12), 2143.
13. Sun, Z., & Ban, X. J. (2013). Vehicle classification using GPS data. Transportation Research Part C: Emerging Technologies, 37, 102-117.
14. O. Altintasi, H. Tuydes-Yaman, and K. Tuncay, (2017). "Detection of urban traffic patterns from Floating Car Data (FCD)," *Transp. Res. Procedia*, vol. 22, pp. 382–391.
15. Yatskiv, A. Grakovski, and E. Yurshevich, (2010). "An Overview of Different Methods Available to Observe Traffic Flows Using New Technologies " Survey Harmonisation with New Technologies Improvement (SHANTI) " and ERDF funding project " Fiber Optic Sensor Applications for Automatic Measurement of the Weight," Res. Dev.
16. Morgul, E. F., Yang, H., Kurkcu, A., Ozbay, K., Bartin, B., Kamga, C., & Salloum, R. (2014). Virtual sensors: Web-based real-time data collection methodology for transportation operation performance analysis. Transportation Research Record, 2442(1), 106-116.
17. Armstrong, S. K. (1999). U.S. Patent No. 5,986,576. Washington, DC: U.S. Patent and Trademark Office.
18. Aden, D., & Nageli, n. (1999). Corsim evaluation of incident diversion signal timing plans. *In proceedings of 6th world congress on intelligent transport systems (ITS)*
19. Aleksandr, N., Vladimir, Z., & Anastasiya, F. lova. (2018). Dynamic traffic re-routing as a method of reducing the congestion level of road network elements, 1, 70–74.

https://doi.org/10.5937/jaes16-15289
20. Antoniou, C., Koutsopoulos, H. N., Ben-Akiva, M., & Chauhan, A. S. (2011). Evaluation of diversion strategies using dynamic traffic assignment. *Transportation Planning and Technology*, *34*(3), 199–216. https://doi.org/10.1080/03081060.2011.565168
21. Aved, A., Do, T., Hamza-Lup, G., Hua Ho, A., Hoang, L., Hsia, L., Peng, R. (2007). A Real-Time route diversion Management System. *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*, 1131–1136. https://doi.org/10.1109/ITSC.2007.4357659
22. Backfrieder, C., Ostermayer, G., & Mecklenbräuker, C. F. (2014). TraffSim-A Traffic Simulator for Investigations of Congestion Minimization through Dynamic Vehicle Rerouting. *International Journal of Simulation -- Systems, Science & Technology EBSCO*. https://doi.org/10.5013/IJSSST.a.15.04.05
23. Braekers, K., Ramaekers, K., & Van Nieuwenhuyse, I. (2016). The vehicle routing problem: State of the art classification and review. https://doi.org/10.1016/j.cie.2015.12.007
24. Cragg, C. A., & Demetsky, M. J. (1995). Simulation analysis of route diversion strategies for freeway incident management: final report. *Council, Virginia Transportation Research*. Retrieved from https://rosap.ntl.bts.gov/view/dot/12575
25. Dunn, W. M., & Jr. , Robert A. Reiss, and S. P. L. (1999). *Synthesis of Highway Practice Roadway Incident Diversion Practices*. *Transportation Research Board*.
26. Eksioglu, B., Volkan Vural, A., & Reisman, A. (2009). The vehicle routing problem: A taxonomic review. *Computers & Industrial Engineering*, *57*, 1472–1483. https://doi.org/10.1016/j.cie.2009.05.009
27. Dunn Engineering Associates. (2006). Alternate Route Handbook. Report FHWA-HOP-06-092. FHWA, U.S. Department of Transportation.
28. Güner, A. R., Murat, A., & Chinnam, R. B. (2012). Dynamic routing under recurrent and non-recurrent congestion using real-time ITS information. *Computers and Operations Research*, *39*(2), 358–373. https://doi.org/10.1016/j.cor.2011.04.012
29. Hu, , Wang, Chu, Lee. (2005). Value of traffic information for route diversion control scheme under traffic incidents. *Journal of the Eastern Asia Society for Transportation Studies*. Retrieved from https://www.jstage.jst.go.jp/article/easts/6/0/6_0_2487/_pdf
30. Juan Pan, S., Sandu Popa, I., Borcea, C., Juan, S., & Pan, J. (2017). DIVERT: A Distributed Vehicular Traffic Re-Routing System for Congestion Avoidance. *IEEE Transactions on Mobile Computing*, *16*(1). https://doi.org/10.1109/TMC.2016.2538226ï
31. Li, X., & Khattak, A. J. (2018). Large-scale incident-induced congestion: en-route diversions of commercial and non-commercial traffic under connected and automated vehicles. *Proceedings of the 2018 Winter Simulation Conference*. Retrieved from https://www.informs-sim.org/wsc18papers/includes/files/094.pdf
32. Liu, Y., Kim, W., & Chang, G.-L. (2013). Decision Model for Justifying the Benefits of Detour Operation under Non-Recurrent Congestion. *Journal of Transportation Engineering*, *139*(1), 40–49. https://doi.org/10.1061/(asce)te.1943-5436.0000474
33. Luo, L., Ge, Y.-E., Zhang, F., & Ban, X. (Jeff). (2016). Real-time route diversion control in a model predictive control framework with multiple objectives: Traffic efficiency, emission reduction and fuel economy. *Transportation Research Part D: Transport and Environment*, *48*, 332–356. https://doi.org/10.1016/J.TRD.2016.08.013
34. Hooper, A., Murray, D. (2017). An Analysis of the Operational Costs of Trucking: 2017 Update. https://atri-online.org/wp-content/uploads/2017/10/ATRI-Operational-Costs-of-Trucking-2017-10-2017.pdf
35. Pan, J., Popa, I. S., Zeitouni, K., & Borcea, C. (2013). Proactive Vehicular Traffic Rerouting for Lower Travel Time. *IEEE Transactions on Vehicular Technology*, *62*(8), 3551–3568. https://doi.org/10.1109/TVT.2013.2260422
36. Pell, A., Meingast, A., & Schauer, O. (2017). Trends in Real-time Traffic Simulation. *Transportation Research Procedia*, *25*, 1477–1484.

https://doi.org/10.1016/j.trpro.2017.05.175

37. Schrank, D., Lomax, T., Fellow, R., Bak, J., & Analyst, R. (2015). *2015 URBAN MOBILITY SCORECARD*. Retrieved from https://static.tti.tamu.edu/tti.tamu.edu/documents/mobility-scorecard-2015.pdf
38. Spiliopoulou, A., Kontorinaki, M., Papamichail, I., & Papageorgiou, M. (2013). Real-time route diversion control at congested motorway off-ramp areas - Part I: User-optimum route guidance. In *16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013)* (pp. 2119–2125). IEEE. https://doi.org/10.1109/ITSC.2013.6728542
39. Wang, Y., Szeto, W. Y., Han, K., & Friesz, T. L. (2018). Dynamic traffic assignment: A review of the methodological advances for environmentally sustainable road transportation applications. *Transportation Research Part B: Methodological*

APPENDIX A- REPORT FIGURES

Site 1

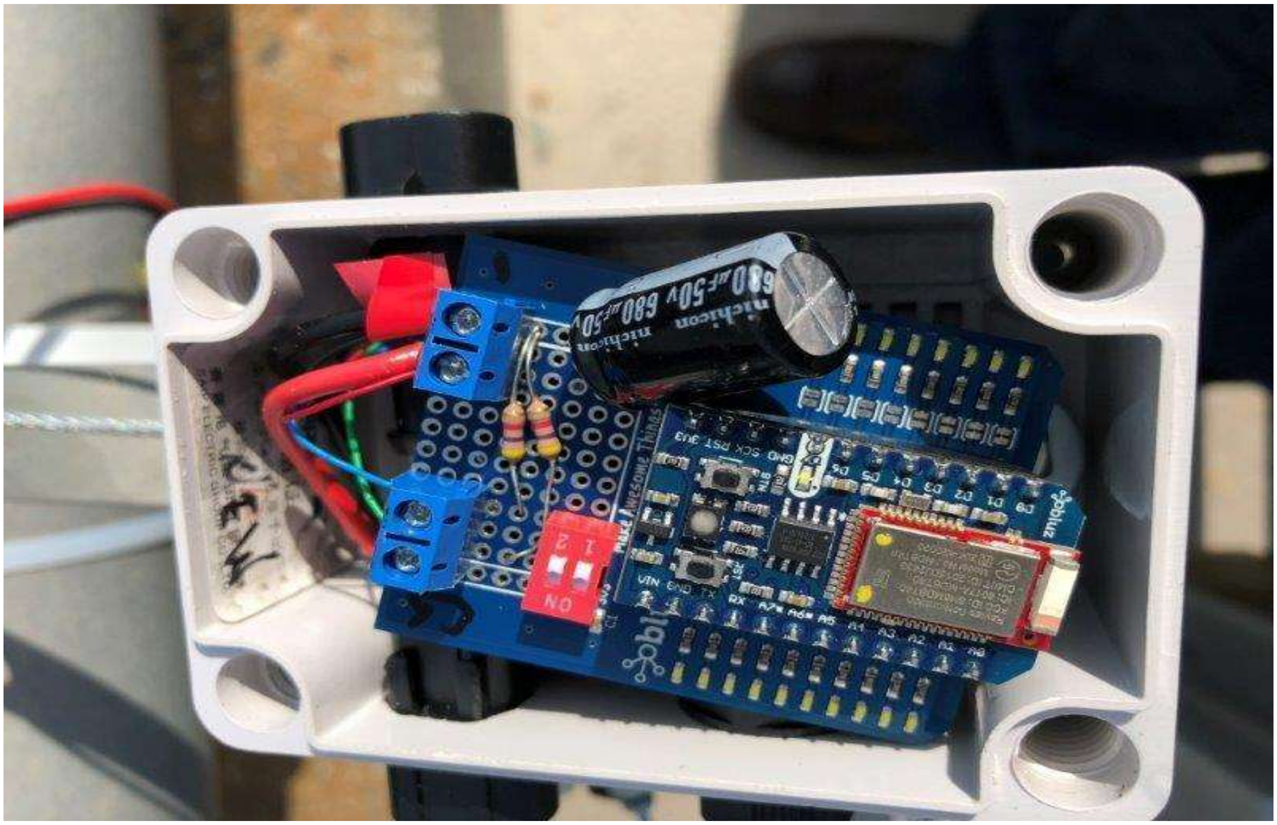


Figure 62: Internal Board Data Capture

This board was later replaced with mesh technology components.

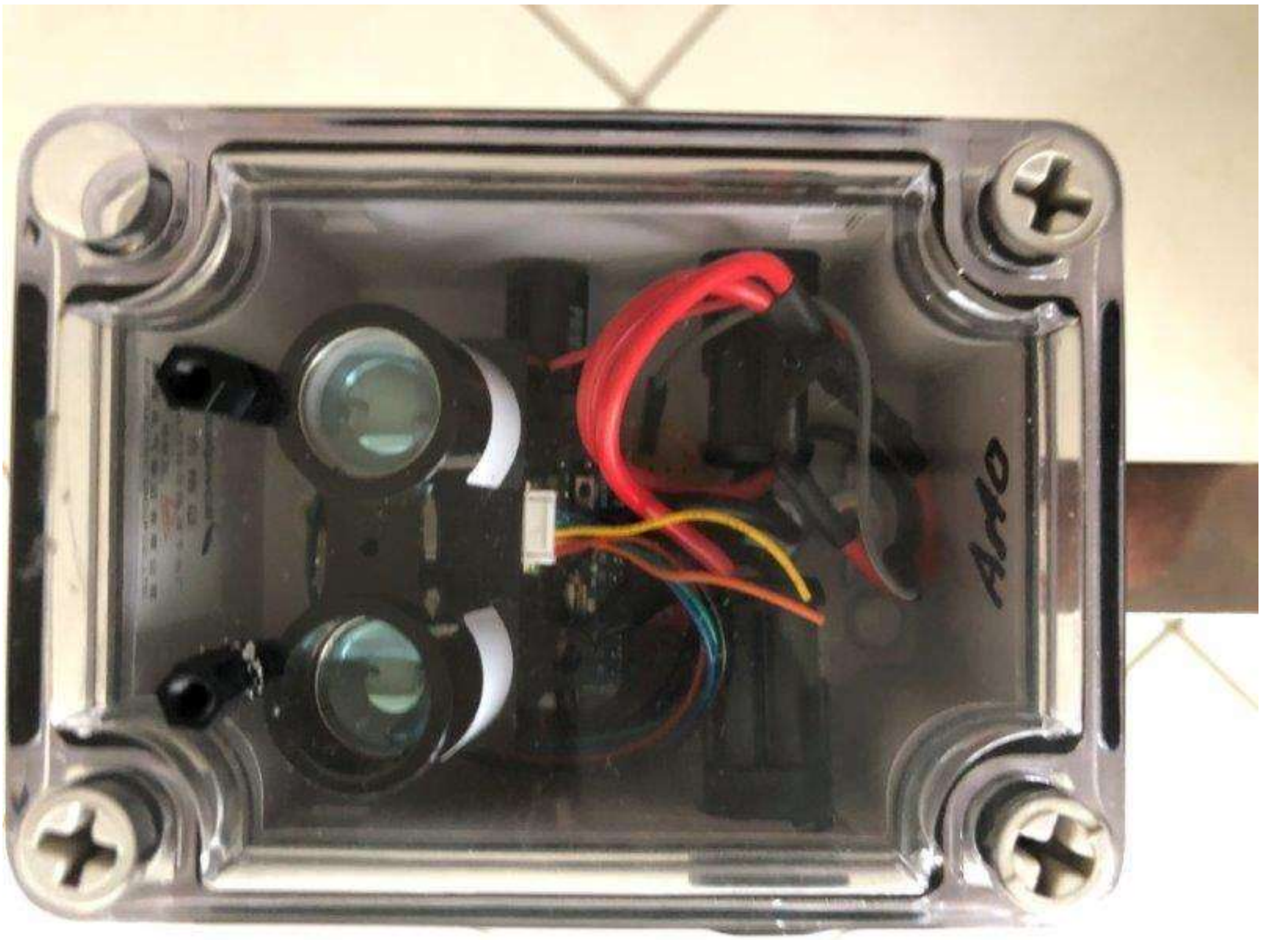


Figure 63: Internal Board Data Capture

Shows sealed unit with sensor.

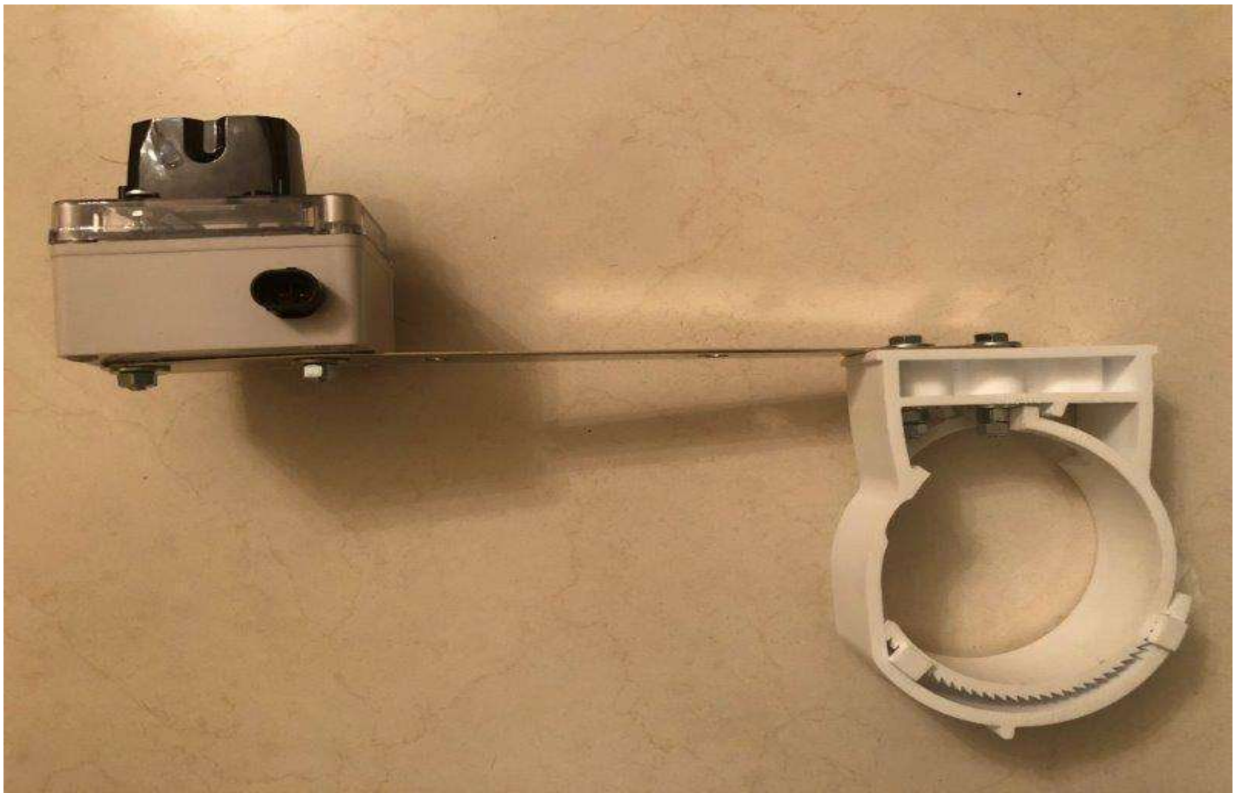


Figure 64: Capture Unit with Bracket


Figure 65: Connection Bracket to Guard Rail

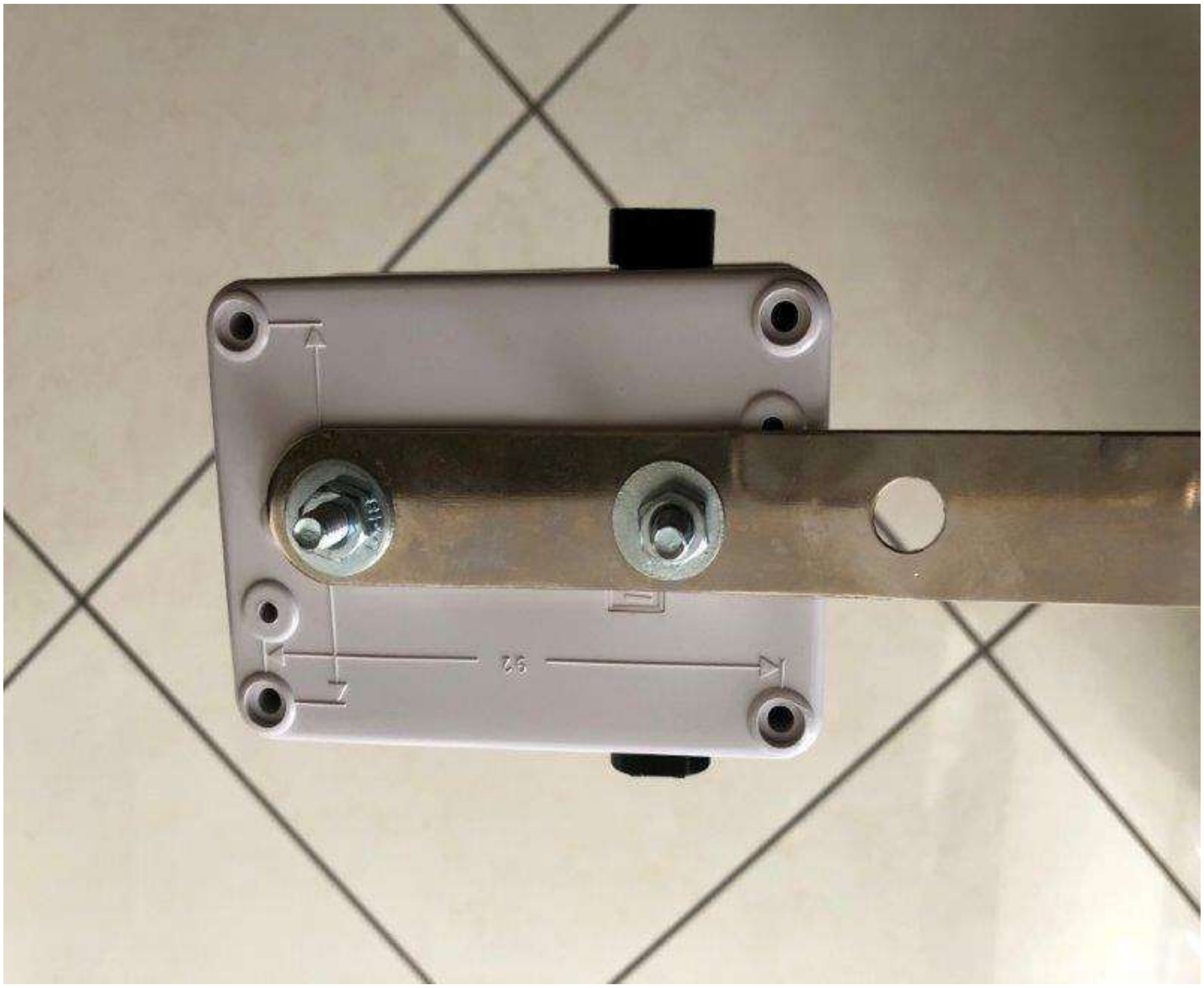


Figure 66: Connection to Simple Bracket

Figure 67: Bracket along with Safety Tether

Figure 68: Capture Unit above the Highway

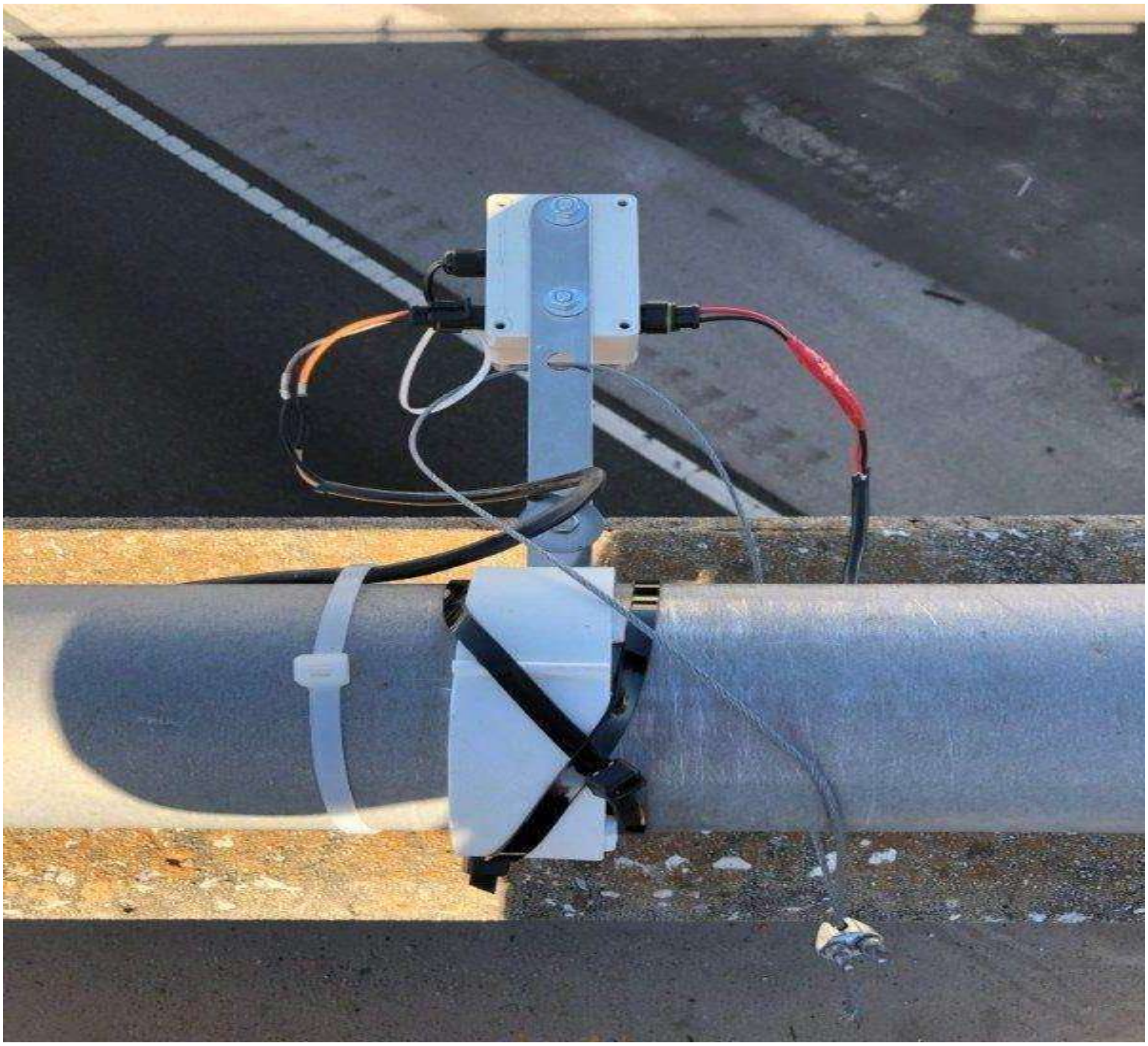


Figure 69: Wired and Tethered Unit

Figure 70: Sensor Looking Down on Traffic

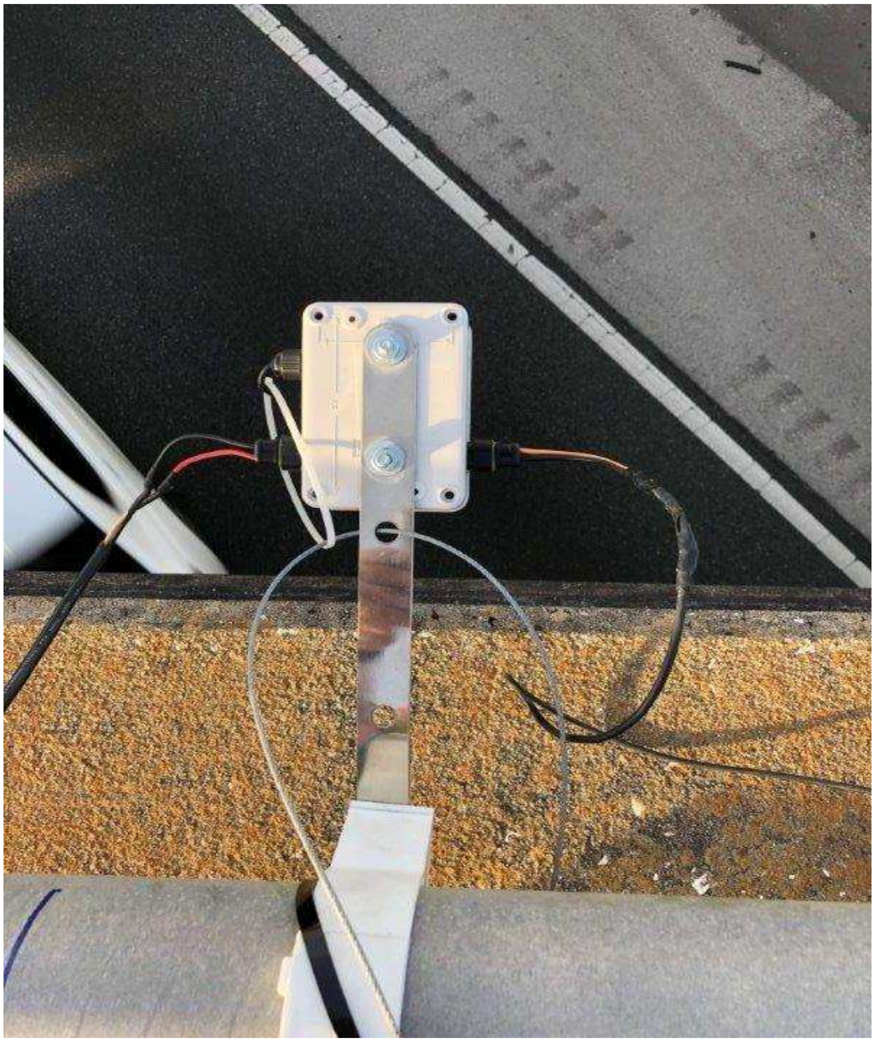


Figure 71: Sensor Looking Down on Traffic


Figure 72: New Laser Sensor (High Frequency)

Figure 73: Complete Capture Unit with Bracket

Figure 74: Gateway Board: Site 1

Figure 75: Gateway Board: Site 1

Figure 76: Gateway Showing Modern and Relay Units

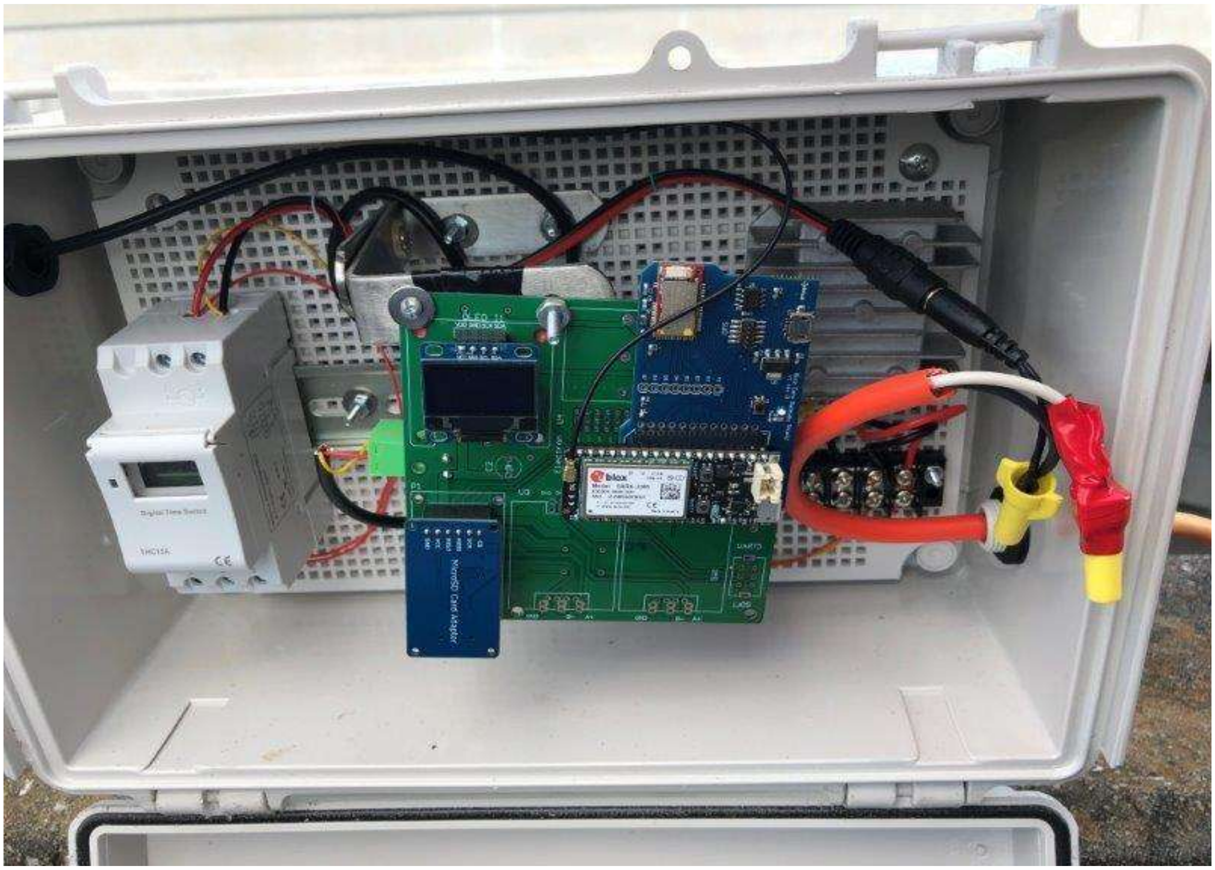


Figure 77: Close-up of Gateway Unit

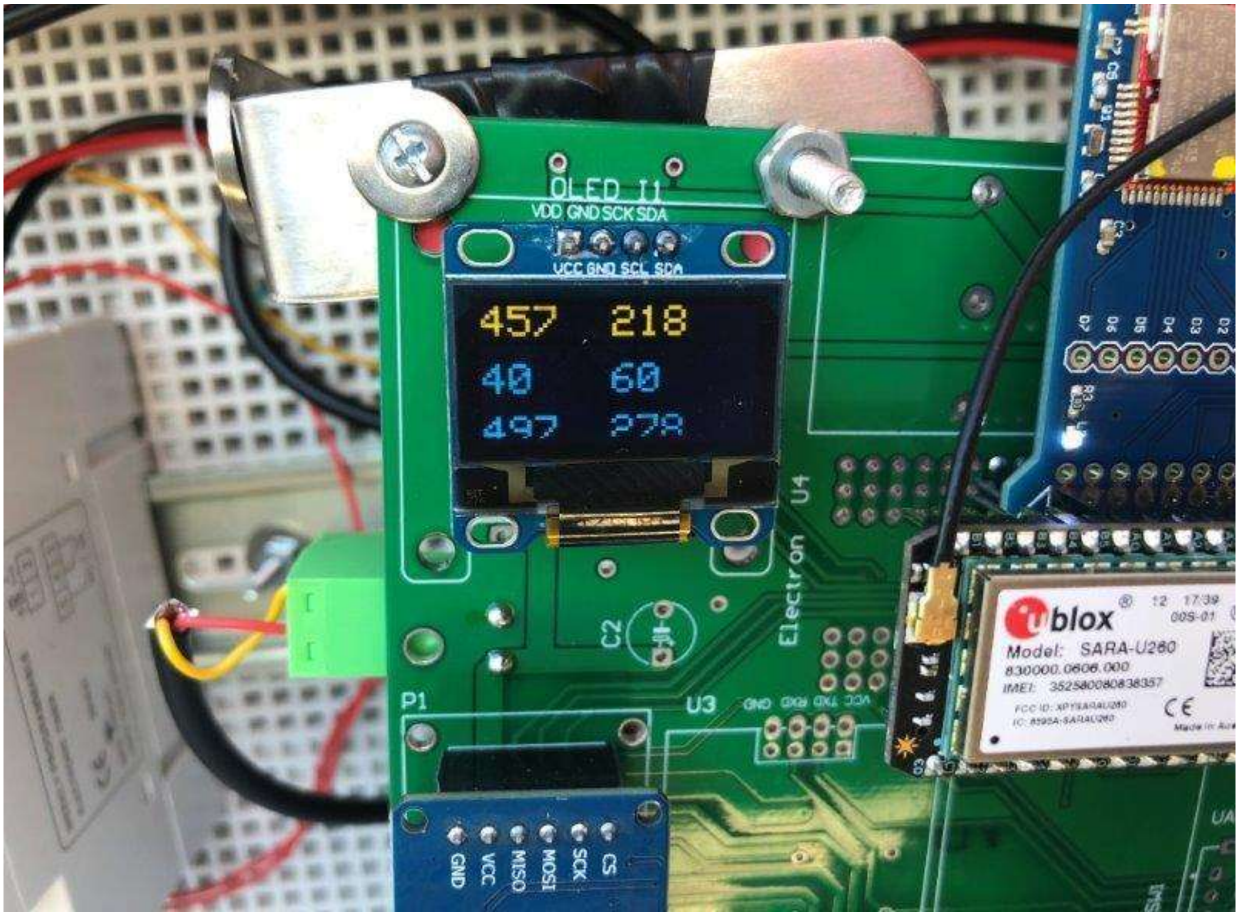


Figure 78: Screen Showing Traffic Counts

Figure 79: Solar Power Unit for Sits 1


Figure 80: Solar Power Unit for Site 1 with Battery Box


Figure 81: Solar Power Unit for Site 1 with Battery Box

Figure 82: Site 1 Battery Unit Showing the Solar Controller

Figure 83: Slight Voltage Drop from 15V

Site 2

Figure 84: Solar Unit for Site 2 (24V)

Figure 85: Solar Unit for Site 2 (6 Traffic Lanes)

Figure 86: Solar Unit: Site 2

Figure 87: Solar Unit: Site 2

Figure 88: Capture Unit above Traffic

Figure 89: Capture Unit above Traffic

Figure 90: Capture Units on Southbound

Figure 91: Site 2: Gateway Unit and Capture Unit

Figure 92: Bracket Ready for Capture Units

Figure 93: Capture Unit During Installation

Shows tether used for safety during installation.

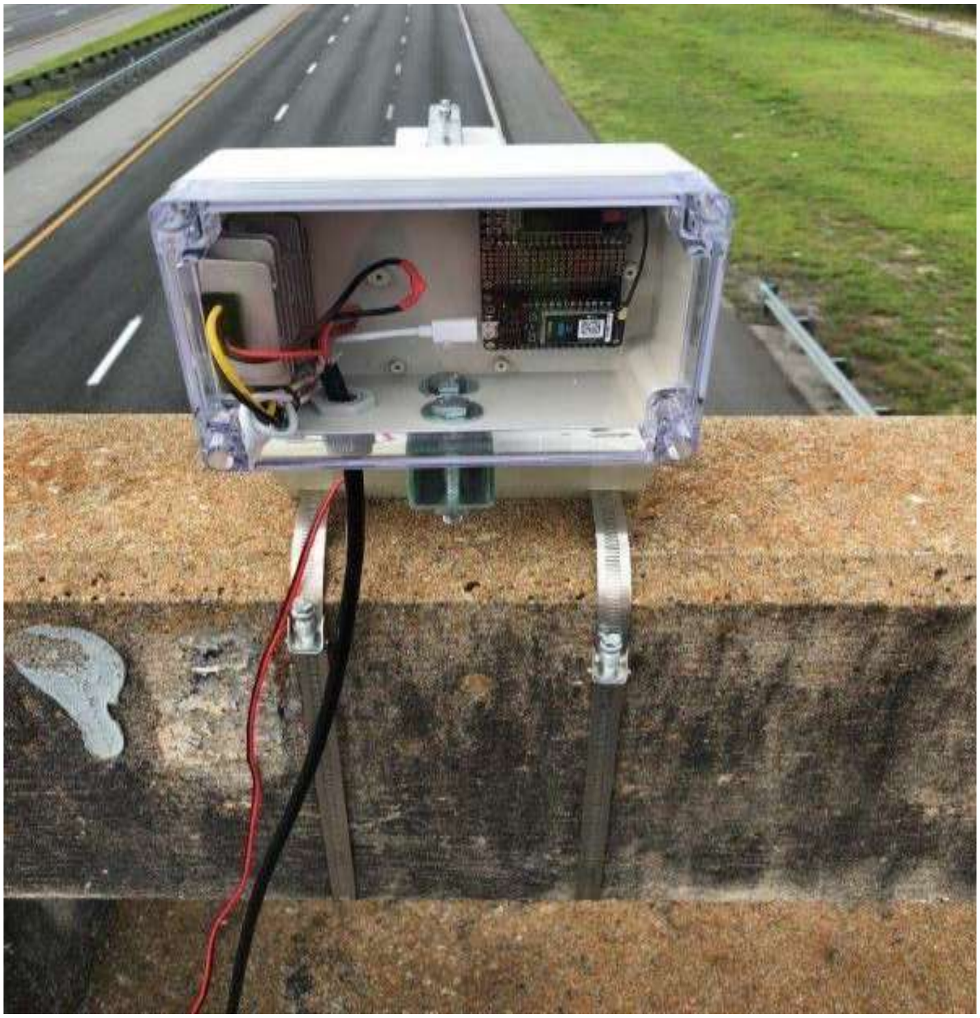


Figure 94: Site 2: Gateway Unit with Voltage Regulator

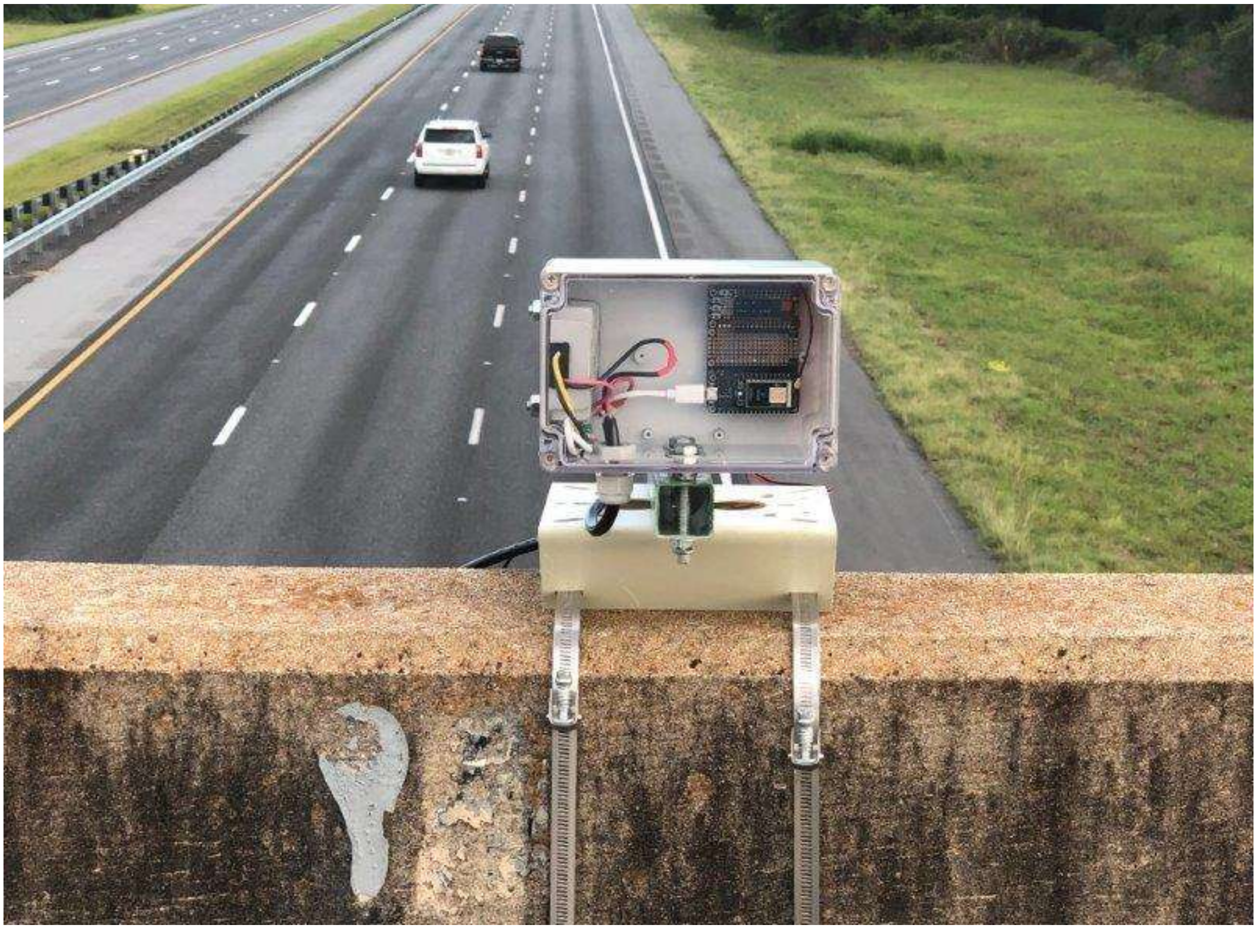


Figure 95: Site 2: Gateway Unit

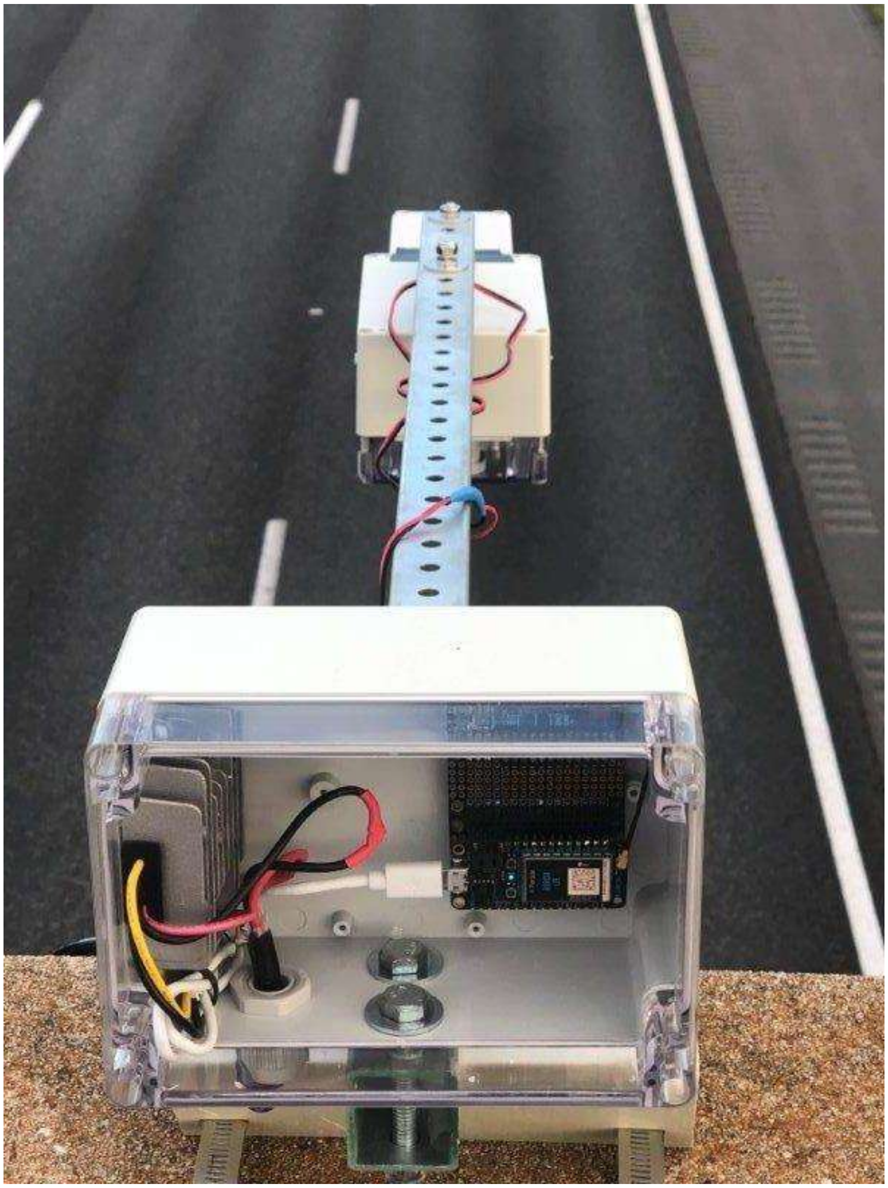


Figure 96: Site 2: Gateway Unite and Capture Unit on One Bracket


Figure 97: Site 2: Gateway Unit and Capture Unit on One Bracket

Figure 98: Site 2: Gateway Unit

Figure 99: Site 2: Gateway Unit

Figure 100: Site 2: Gateway Unit

Figure 101: Three Complete Capture Units

Figure 102: Capture Unit with Three Different Sensors

Figure 103: Capture Unit with Two Different Sensors

Figure 104: Tethered Bracket before Installation

Figure 105: Batteries for Solar Panels (24V)

Two batteries (12V) connected in serial.

Figure 106: Solar Controller and Power Relay

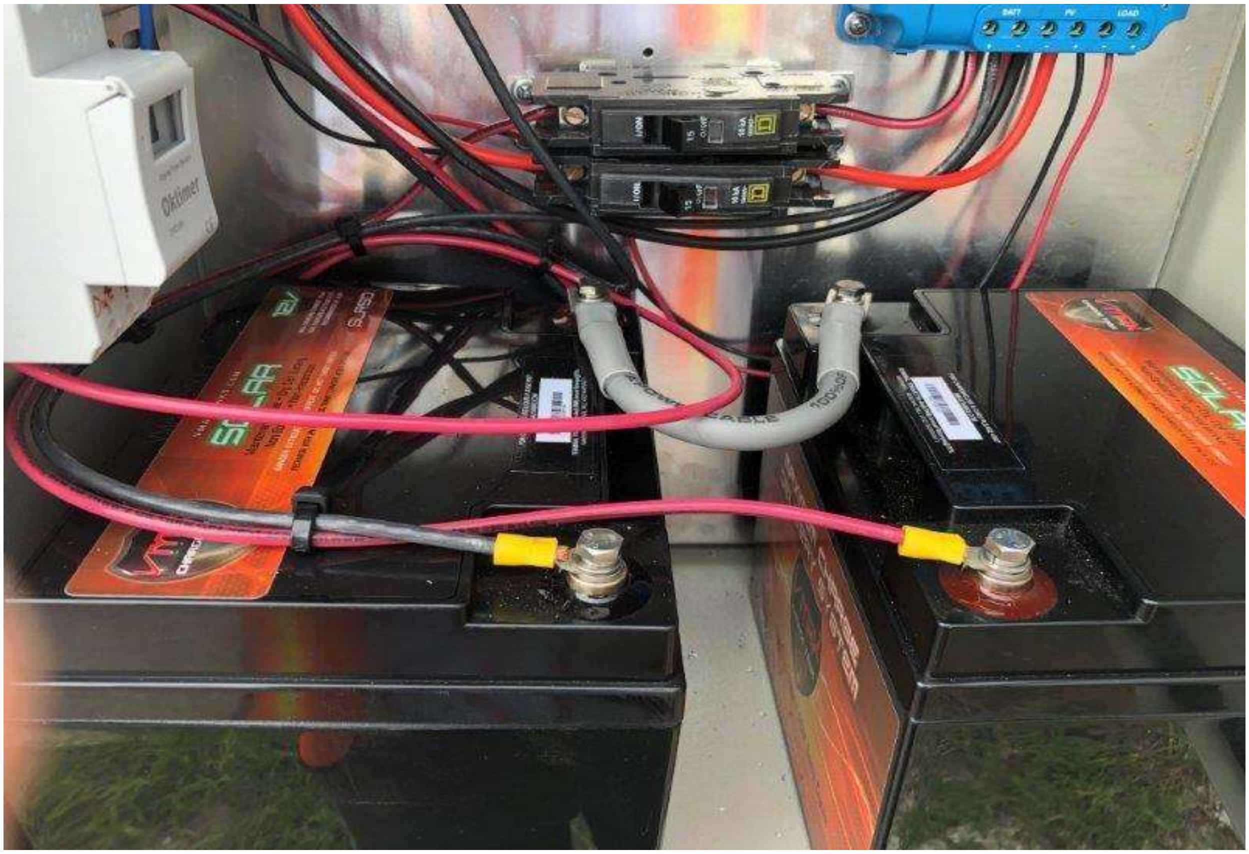


Figure 107: Electrical Connections

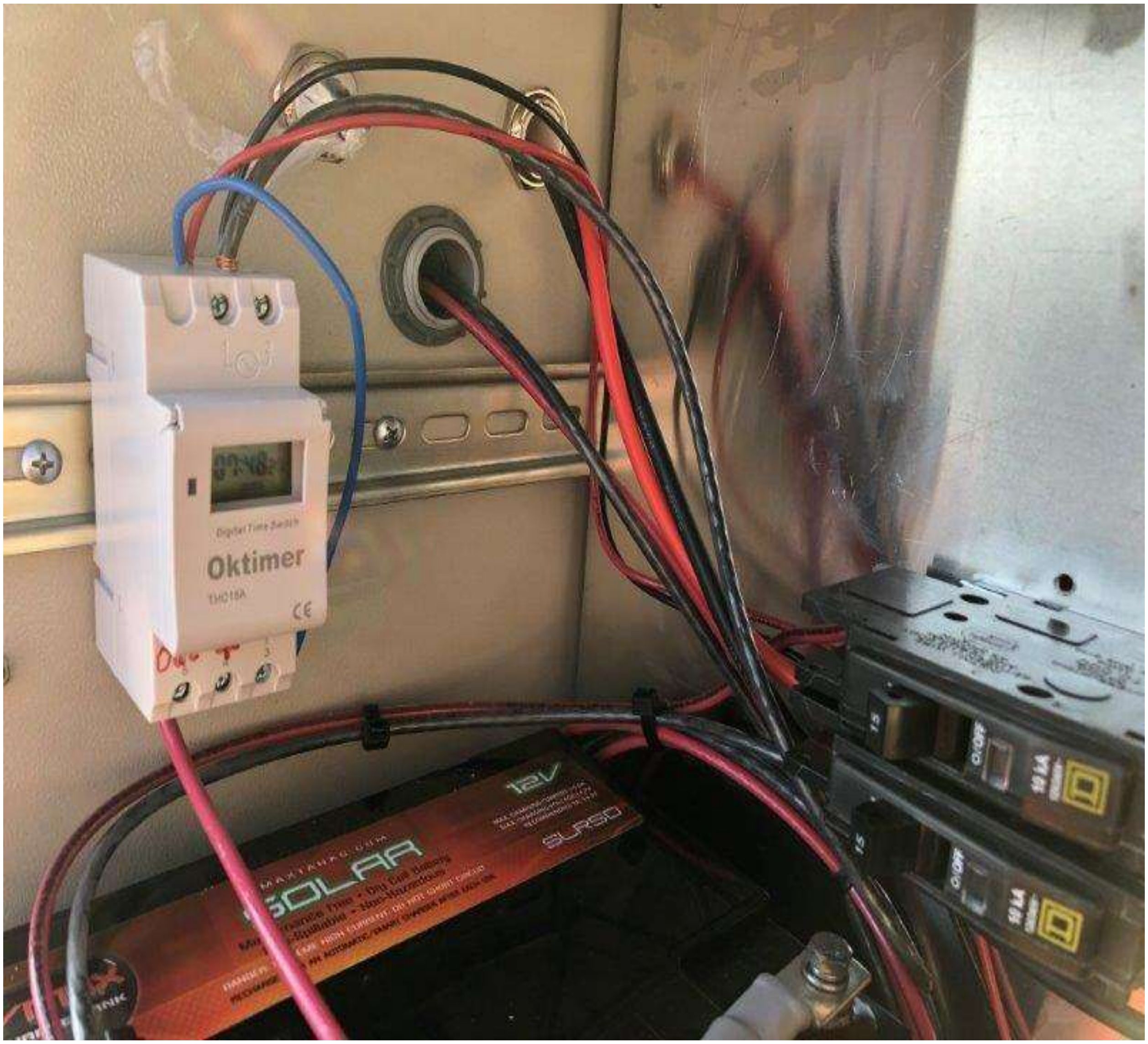


Figure 108: Power Relay

Circulates power every 24 hours.

Figure 109: Site 2: Solar Controller

Figure 110: Solar Controller Display via Bluetooth

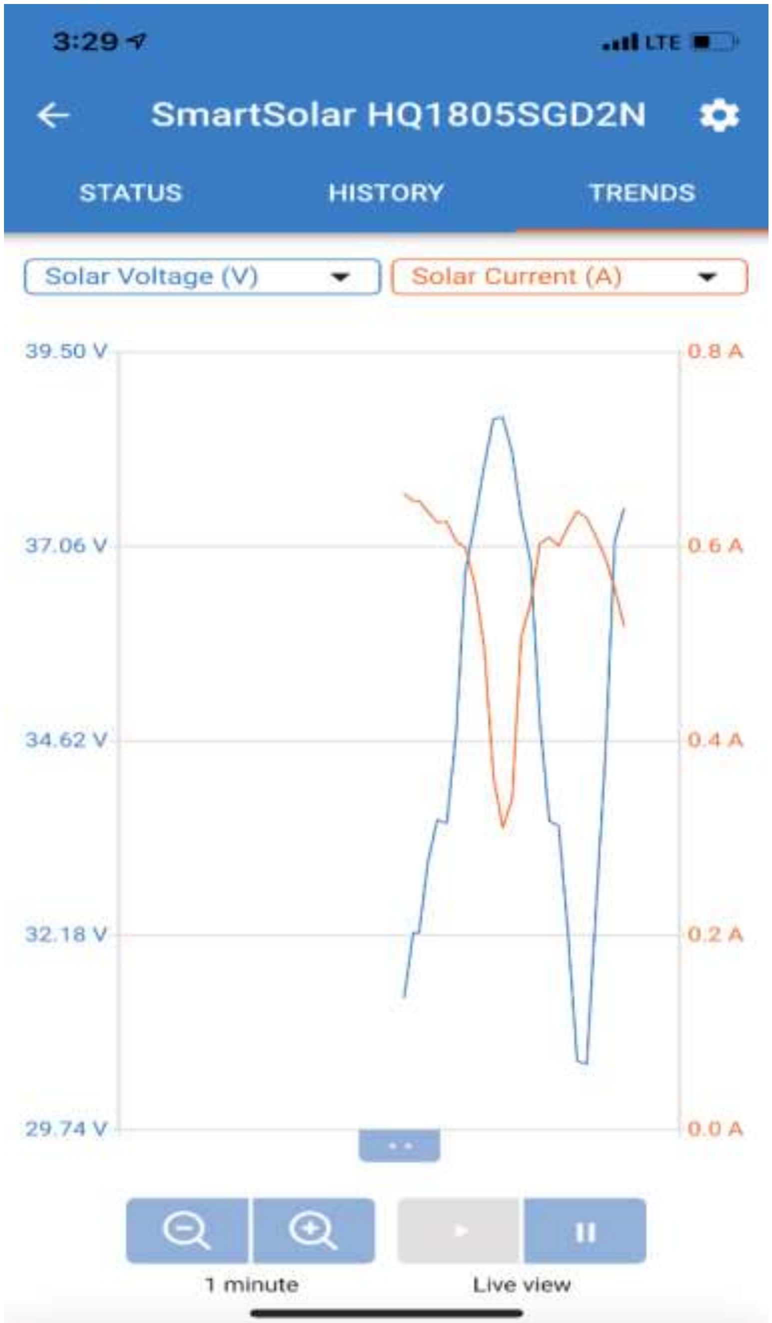


Figure 111: Solar Controller Display via Bluetooth

Figure 112: Solar Controller Display via Bluetooth

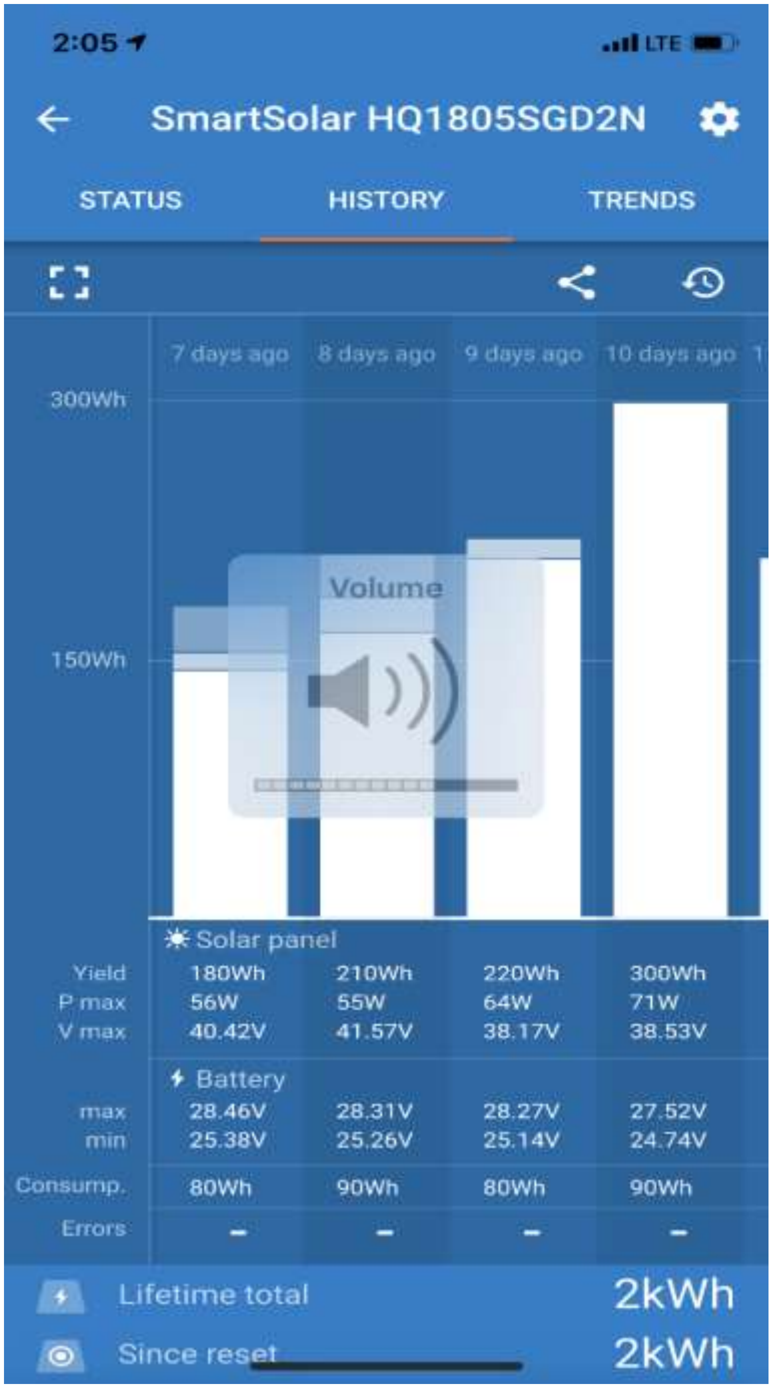


Figure 113: Solar Controller Display via Bluetooth

Figure 114: Distance from Sensor to Highway below

APPENDIX B- USER MANUAL FOR EXCEL MACRO

User manual for the Excel Macro:

1. The excel workbook file consists of three worksheets. Ensure that Worksheet names are not amended and are named as "Master," "Data," "filter."

In the "Master" sheet: No modification for this worksheet except logging in the information defined in dialog boxes. All input cells shaded in yellow color are defined and positioned as per below:

- Input options for “Time Interval” is at C3 of Master Sheet: Aggregate (sum up) counts at 5, 10, 15, 20, 30, 45, 50, and 1-hr time interval options.
- The input value for "Base number" is at C5 of Master Sheet.
- The input value for "Sensor Number" is at C7 of Master Sheet.
- Input option for whether to "ignore" or "don't ignore" sensor number input value is at D7 of Master Sheet.
- The input value for threshold is at C11 of Master Sheet, which corresponds to the sum of passenger car and truck frequencies chosen at the data collection setup. This is currently used for debugging.

Update the data in the worksheet "Data." Be sure not to overwrite/amend the headers as the macro relies on their cell numbers. Below are the essential row and columns to take note of and ensure that it contains the correct data. Also, ensure;

In "Data" Sheet,

Row#1: must contain all the headers

Column#1 = Local Date and Time

Column#4 = Base#

Column#5 = Sensor#

Column#6 = Number of trucks

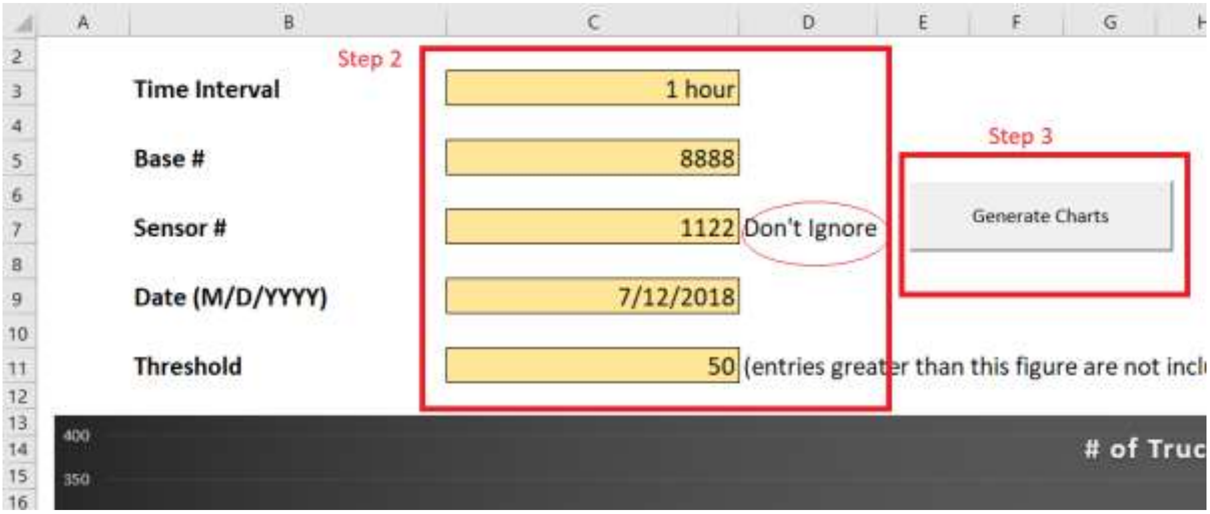
Column#7 = Number of cars

See below screenshot of the data worksheet:

	A	B	C	D	E	F	G	H	I	J	K
1	Local Time	created_at	entry_id	Base #	Sensor #	Trucks	Cars	total T	total C	field7	Congestion
2	7/2/2018 23:37:46	2018-07-03 03:37:46 UTC	1	8888	1122	24	0	148	44	99	0
3	7/2/2018 23:38:18	2018-07-03 03:38:18 UTC	2	8888	1122	5	19	153	63	76	0
4	7/2/2018 23:38:46	2018-07-03 03:38:46 UTC	3	8888	1122	0	24	153	87	75	0
5	7/2/2018 23:39:14	2018-07-03 03:39:14 UTC	4	8888	1122	6	18	159	105	43	0
6	7/2/2018 23:48:39	2018-07-03 03:48:39 UTC	5	8888	1122	22	2	181	107	89	0
7	7/2/2018 23:49:08	2018-07-03 03:49:08 UTC	6	8888	1122	24	0	205	107	99	0
8	7/2/2018 23:59:11	2018-07-03 03:59:11 UTC	7	8888	1122	21	3	226	110	86	0

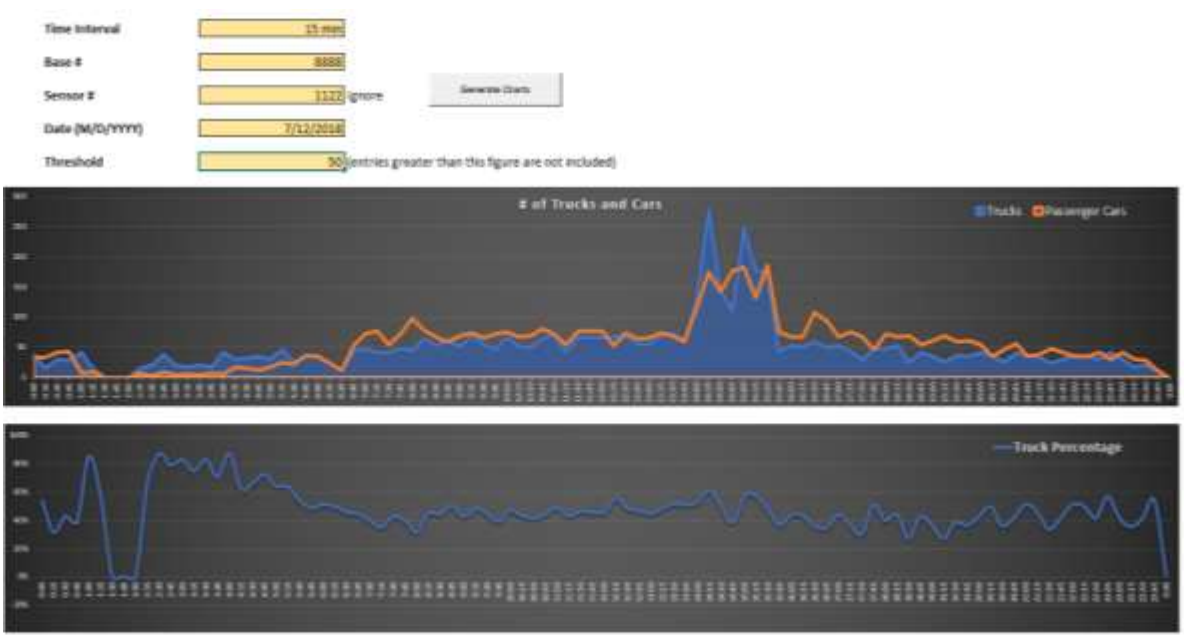
2. Go to the "Master" sheet. Update the values "Time interval", "Base #", "Sensor #", "Date (M/D/YYYY)" and the "Threshold". If you would like to ignore the sensor filter and sum all the sensor readings (except for 0, which is error readings), then fill up "Ignore" in Range "D7".

3. In this step, when the inputs are filled accordingly: Click "Generate Charts" to generate two charts. The first chart is a truck and car frequency graph in which the x-axis representing time (one-day) and the y-axis representing trucks/cars frequencies accordingly. The second chart is a truck percentage graph which x-axis representing time in one-day and the y-axis representing the corresponding truck percentages at time-of-the-day (see figure below).



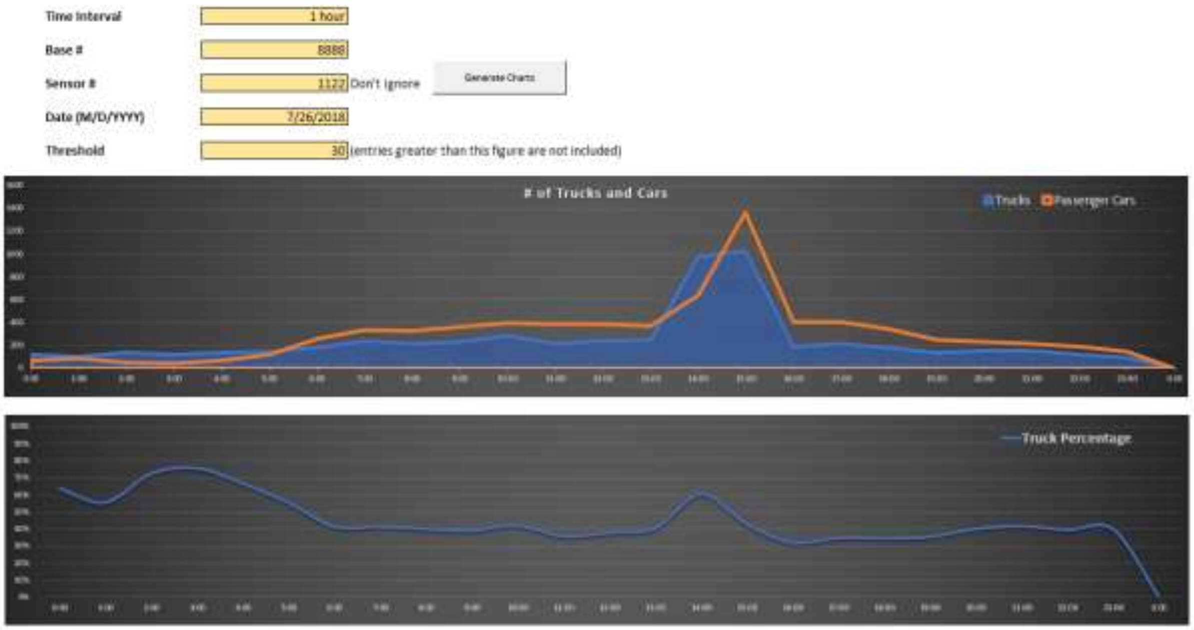
Example#1:

Date: 7/12/2018 with all sensors at Base#8888.
Time interval: 15 minutes.



Example#2:

Date: 7/26/2018 with Sensor# 1122 at Base# 8888.
Time interval: 1-hour.



Technical Documentation of the VBA (Visual Basic for Applications) Macro

The flow of macro (Upon clicking of "Generate Charts"):

1. **Reading the user-defined values in the "Master" Sheet.**

The macro starts by reading the user-defined values in the "Master" sheet and saving it into variables to determine which entry is selected.

2. **Determining the intervals or "floors" based on the Time interval selected.**

Intervals start from midnight and are incremented based on the "Time Interval" set by the user. For each entry, the macro will floor the time to the start of an interval. For instance, at a 20-minute time interval, 00:15 (HH: MM) will be floored to 00:00. Another example would be for a 50-minute time interval the time 01:10 will be floored to 00:50.

3. **Filtering the data entries in the "Data" sheet**

Entries are filtered based on the below list of criteria:

- Column#1 of entry must be equal to the "Date (M/D/YYYY)" selected by the user.
- Column#4 of a particular entry row in the "Data" sheet must be equal to "Base #" selected by the user.
- Column#5 of entry row.
- If the "Don't ignore" sensor option is selected, Column#5 of entry must be equal to "Sensor #" selected by the user.
- The number of trucks (Column#6).
- Aggregated number of passenger cars (Column#7) and the number of trucks (Column#6) must be less than the "Threshold" + 1.
- The number of passenger cars (Column#7).

4. **For each entry, a row in the "Filter" sheet will be populated.**

- Column#1 of "Filter" sheet = Local date and time (derived from original timestamp).
- Column#2 of "Filter" sheet = Number of trucks.
- Column#3 of "Filter" sheet = Number of cars
- Column#4 of "Filter" sheet = Number of trucks / (Number of cars + Number of trucks)
- Column#5 of "Filter" sheet = Floor of Column#6 to the time interval specified
- Column#6 of "Filter" sheet = Local Date and Time – Date of Local Time

*The reason column#6 is needed: MS Excel calculates the date and stores it as a number based on the 1900 date system. For example, at 50-min intervals, because 24 hrs is not divisible by 50 minutes without any remainders, some of the minutes are left to the next day, resulting in unintended consequences such as flooring ending in the first interval starting from 23:40 of the previous day instead of 00:00 of the current day.

Hence it is necessary to subtract the date before flooring the time. Thereby, the flooring will capture the first interval starting from 0:00 midnight.

5. **Binning the data into the intervals**

Intervals are calculated based on the "Time Interval" option selected by the user. For each entry row, data is being added to the corresponding interval if the floored time of data equals the start of interval time. Therefore, an entry with time 00:15 will be added to 00:00 bin for a 20-minute time interval, whereas the same time will be added to 00:15 bin for a 15-minute time interval.

Truck percentages are calculated based on the sum of all entries at the corresponding interval.

These data are populated into columns {H: K} of the "filter" worksheet.

6. **Refresh the chart**

Finally, the macro will refresh both the frequencies and truck percentage charts at the "Master" worksheet.

The VBA code for this tool is as follows:

```
Sub getFilteredData()

Application.ScreenUpdating = False
base = Sheets("master").Range("c5").Value
sensor = Sheets("master").Range("c7").Value
ignoreSensor = Sheets("master").Range("d7").Value
requiredDate = Sheets("master").Range("c9").Value
threshold = Sheets("master").Range("c11").Value

Select Case Sheets("master").Range("c3").Value
    Case "5 min":
        timeInterval = "0:05"
        incrementTime = 5
    Case "15 min":
        timeInterval = "0:15"
        incrementTime = 15
    Case "20 min":
        timeInterval = "0:20"
        incrementTime = 20
    Case "30 min":
        timeInterval = "0:30"
        incrementTime = 30
    Case "50 min":
        timeInterval = "0:50"
        incrementTime = 50
    Case "1 hour":
        timeInterval = "1:00"
        incrementTime = 60
    Case Else:
        End
End Select

RowIndex = 2
lastRow = Sheets("data").Range("a" & Rows.Count).End(xlUp).Row
' Clear contents
Sheets("filter").Range("a:k").ClearContents
Sheets("filter").Range("a1").Value = "Local time"
Sheets("filter").Range("b1").Value = "Trucks"
Sheets("filter").Range("c1").Value = "Passenger Cars"
Sheets("filter").Range("d1").Value = "Truck Percentage"
Sheets("filter").Range("e1").Value = "Floored time"
Sheets("filter").Range("f1").Value = "Intermediate Step"

For i = 2 To lastRow
    ' If base, sensor and date matches
        If Sheets("data").Cells(i, 4).Value = base And Not
Sheets("data").Cells(i, 5).Value = 0 And _
```

```
          ((ignoreSensor = "Don't Ignore" And Sheets("data").Cells(i,
5).Value = sensor) Or ignoreSensor = "Ignore") And
Int(Sheets("data").Cells(i, 1).Value) = requiredDate Then
            noTrucks = Sheets("data").Cells(i, 6).Value
            noCars = Sheets("data").Cells(i, 7).Value
            If noTrucks + noCars < threshold + 1 And Not (noCars < 0
Or noTrucks < 0) Then
                timeRequired = Sheets("data").Cells(i, 1).Value -
Int(requiredDate)
                Sheets("filter").Cells(RowIndex, 1).Value =
Sheets("data").Cells(i, 1).Value
                Sheets("filter").Cells(RowIndex, 2).Value = noTrucks
                Sheets("filter").Cells(RowIndex, 3).Value = noCars
                Sheets("filter").Cells(RowIndex, 4).Value = noTrucks /
(noTrucks + noCars)
                Sheets("filter").Cells(RowIndex, 6).Value =
timeRequired
                Sheets("filter").Cells(RowIndex, 5).Value = "=Floor(F"
& RowIndex & ", """ & timeInterval & """)"
                Sheets("filter").Cells(RowIndex, 5).Value =
Format(Sheets("filter").Cells(RowIndex, 5).Value, "HH:MM")
                RowIndex = RowIndex + 1
            End If
        End If
Next i

' Starting from requiredDate. increment 5 min time intervals and find
all rows that match and sum up the trucks and cars figure
Sheets("filter").Range("h1").Value = "Time"
Sheets("filter").Range("i1").Value = "Trucks"
Sheets("filter").Range("j1").Value = "Passenger Cars"
Sheets("filter").Range("k1").Value = "Truck Percentage"

lastRow = Sheets("filter").Range("a" & Rows.Count).End(xlUp).Row
incrementDate = 0
RowIndex = 2
Do While Int(incrementDate) = 0
    Sheets("filter").Cells(RowIndex, 8).Value = Format(incrementDate,
"HH:MM")
    noTrucks = 0
    noCars = 0
    For i = 2 To lastRow
        If Abs(Sheets("filter").Cells(i, 5).Value - incrementDate) <
0.000000116 Then
            noTrucks = noTrucks + Sheets("filter").Cells(i, 2).Value
            noCars = noCars + Sheets("filter").Cells(i, 3).Value
        End If
    Next i
    Sheets("filter").Cells(RowIndex, 9).Value = noTrucks
    Sheets("filter").Cells(RowIndex, 10).Value = noCars
    If Not noTrucks + noCars = 0 Then
```

```
        Sheets("filter").Cells(RowIndex, 11).Value = noTrucks /
(noTrucks + noCars)
        Sheets("filter").Cells(RowIndex, 11).Style = "Percent"

    Else
        Sheets("filter").Cells(RowIndex, 11).Value = 0
        Sheets("filter").Cells(RowIndex, 11).Style = "Percent"
    End If
    incrementDate = DateAdd("n", incrementTime, incrementDate)
    RowIndex = RowIndex + 1
Loop

' Change the data range of charts
lastRow = Sheets("filter").Range("j" & Rows.Count).End(xlUp).Row
Sheets("master").Shapes("Chart 1").Select
ActiveChart.SetSourceData Source:=Sheets("filter").Range("H1:J" &
lastRow)
Sheets("master").Shapes("Chart 2").Select
ActiveChart.SetSourceData Source:=Sheets("filter").Range("H1:H" &
lastRow & ",K1:K" & lastRow)
Application.ScreenUpdating = True
End Sub
```

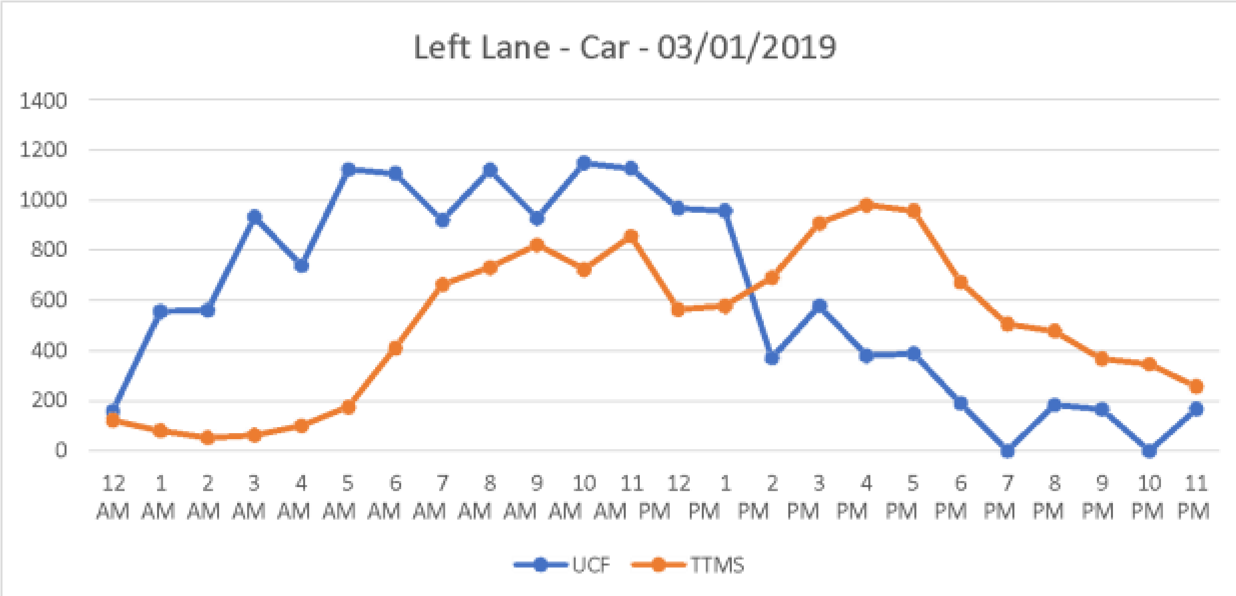
1) <u>Hardware issues</u>

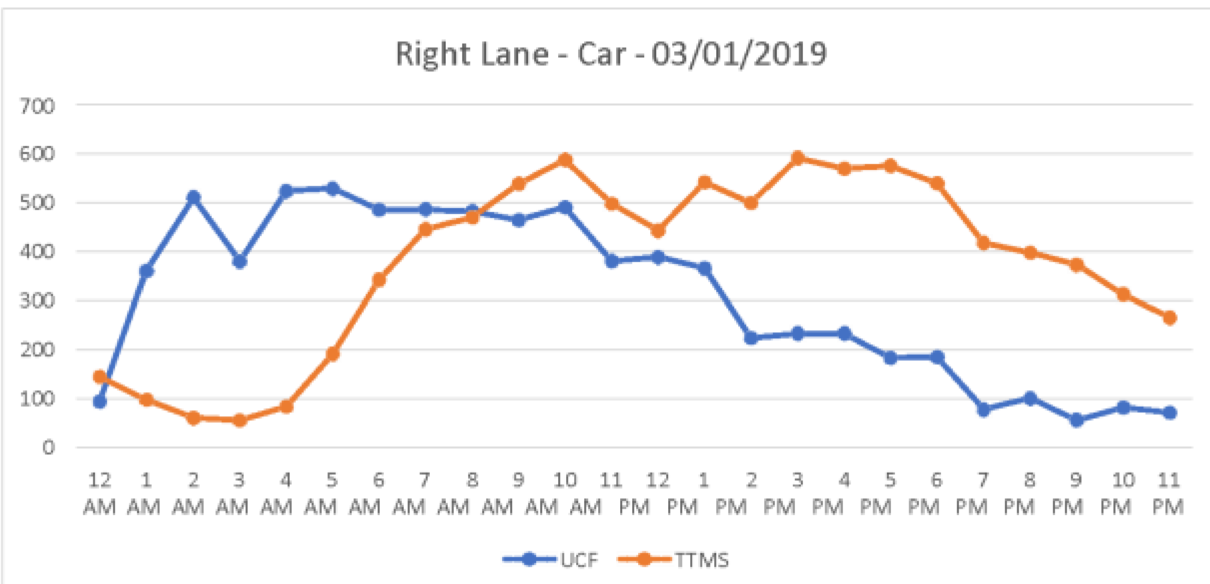
The hardware selected for this project worked well. However, the researchers recognized as a result of long term testing that the system can be substantially improved by expanding the number of lanes that can be handled by each accumulator (from the current limit of three).

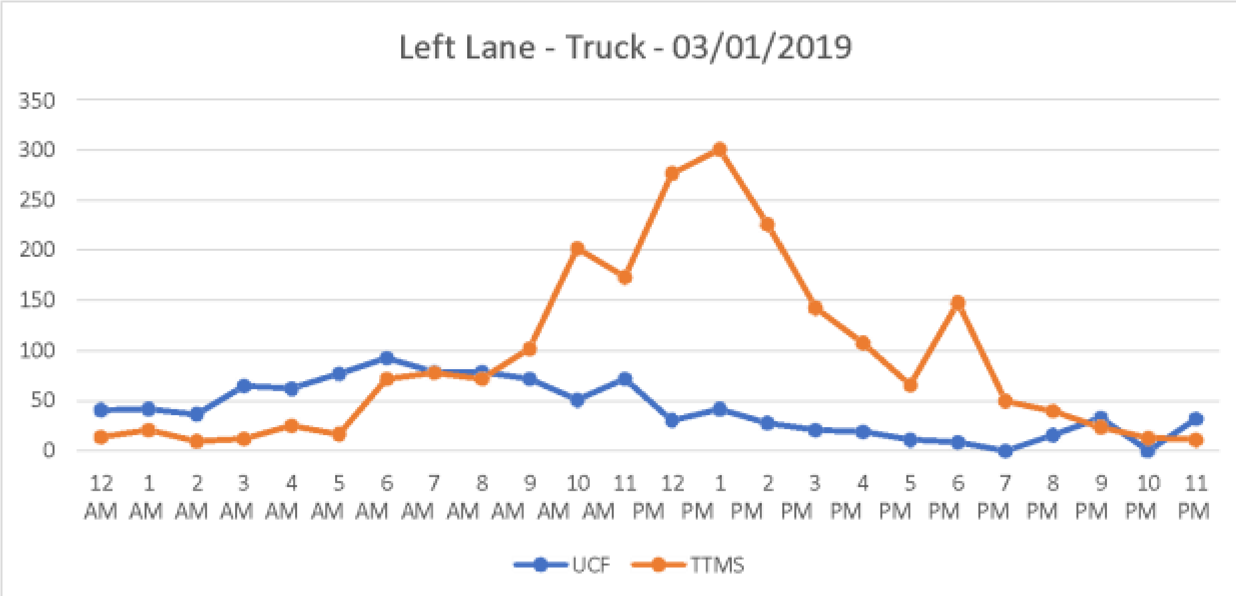
This modification will allow the use of a single accumulator to collect data from up to eight lanes (four lanes in each direction of travel) by selecting a mesh-based technology. This modification allows each sensor to act as a repeater for the next sensor, further expanding the local reach of the accumulator.

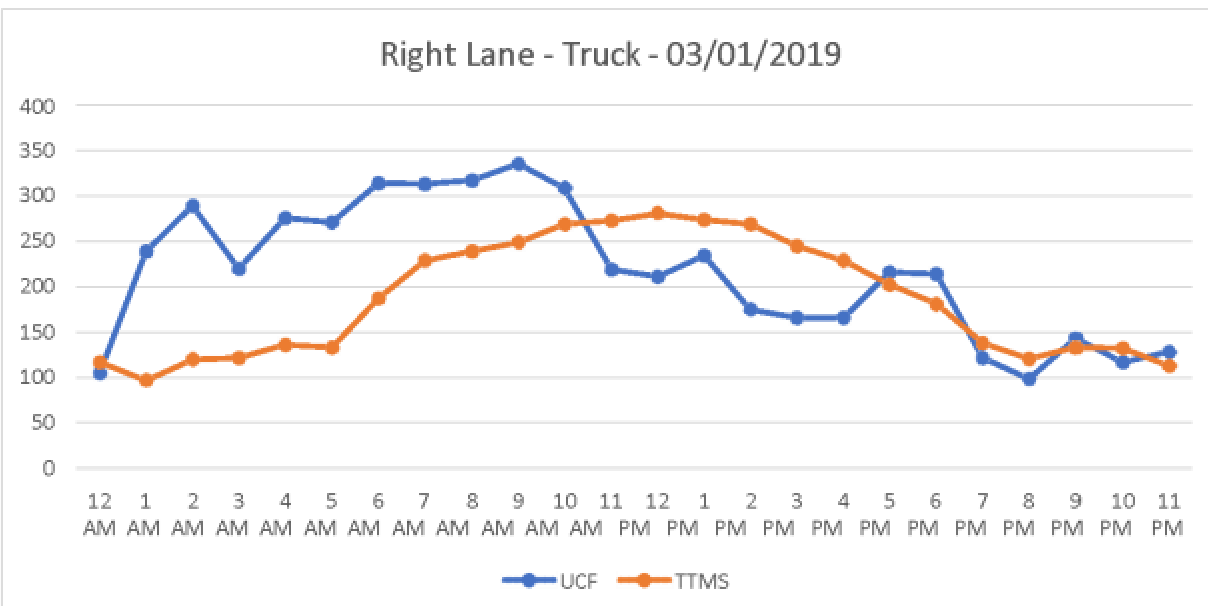
These changes will be implemented in the next period as soon as the hardware is available.

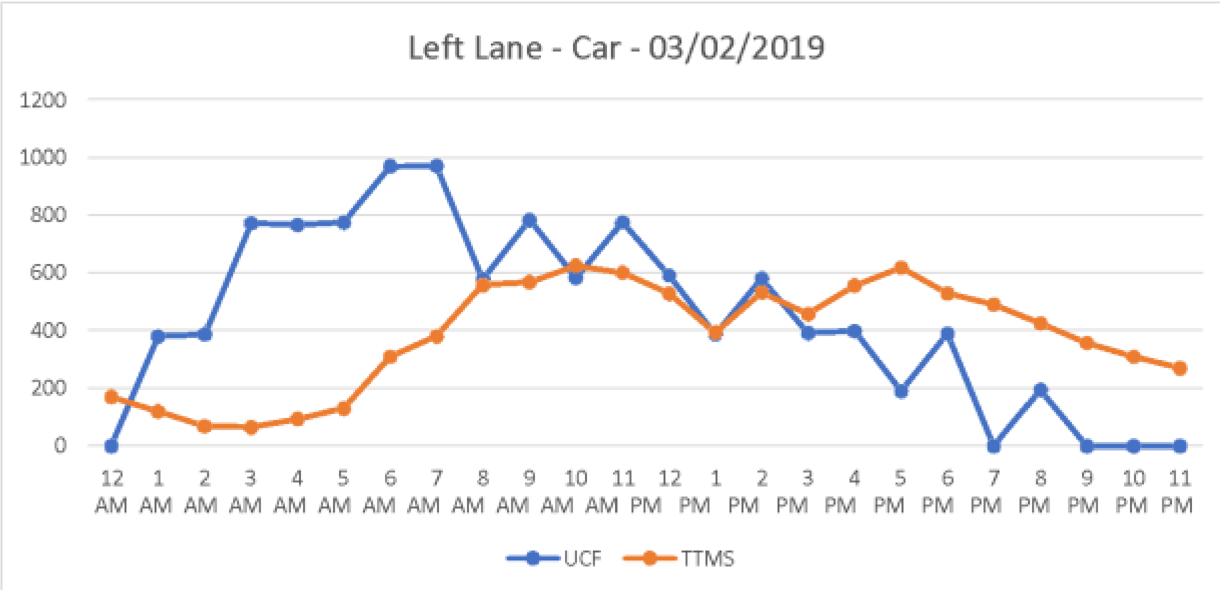
APPENDIX C- 24-HOUR PROFILE CHARTS

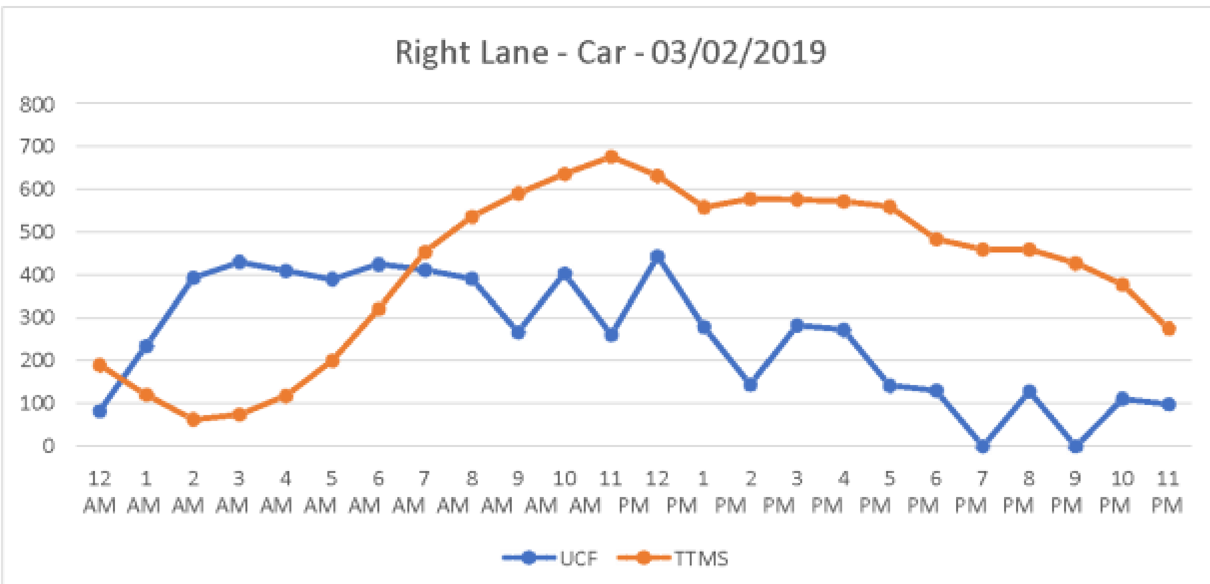

Left Lane - Car - 03/01/2019
1400
1200
1000
800
600
400
200
0
12 AM 1 AM 2 AM 3 AM 4 AM 5 AM 6 AM 7 AM 8 AM 9 AM 10 AM 11 AM 12 PM 1 PM 2 PM 3 PM 4 PM 5 PM 6 PM 7 PM 8 PM 9 PM 10 PM 11 PM
UCF
TTMS

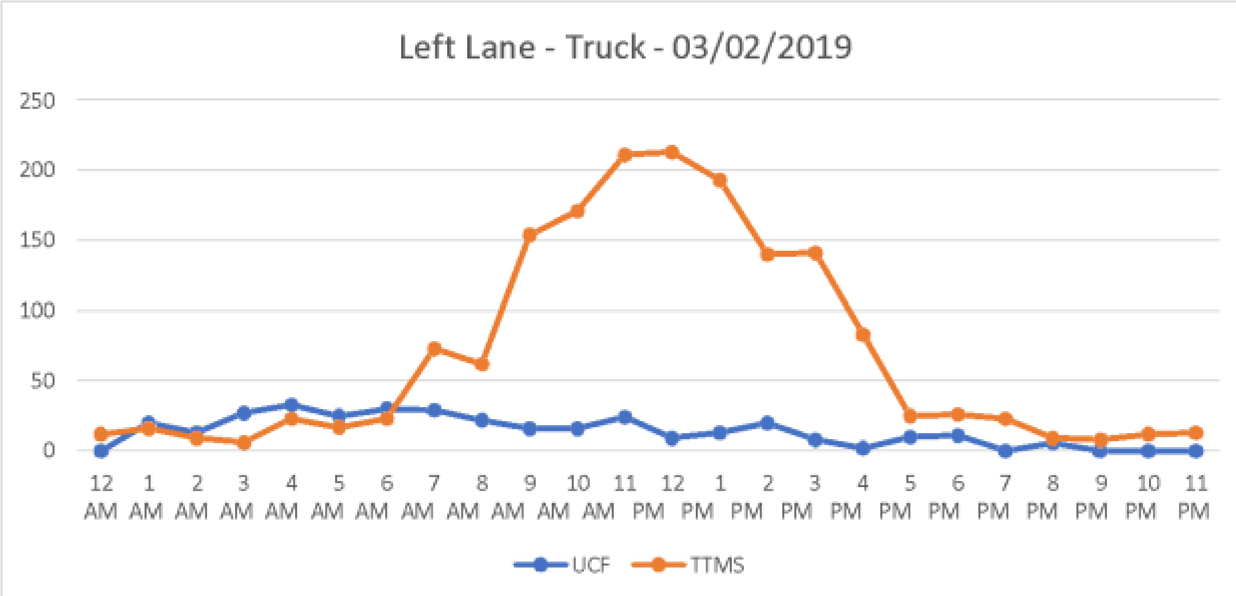

Right Lane - Car - 03/01/2019
700
600
500
400
300
200
100
0
12 AM 1 AM 2 AM 3 AM 4 AM 5 AM 6 AM 7 AM 8 AM 9 AM 10 AM 11 AM 12 PM 1 PM 2 PM 3 PM 4 PM 5 PM 6 PM 7 PM 8 PM 9 PM 10 PM 11 PM
UCF
TTMS

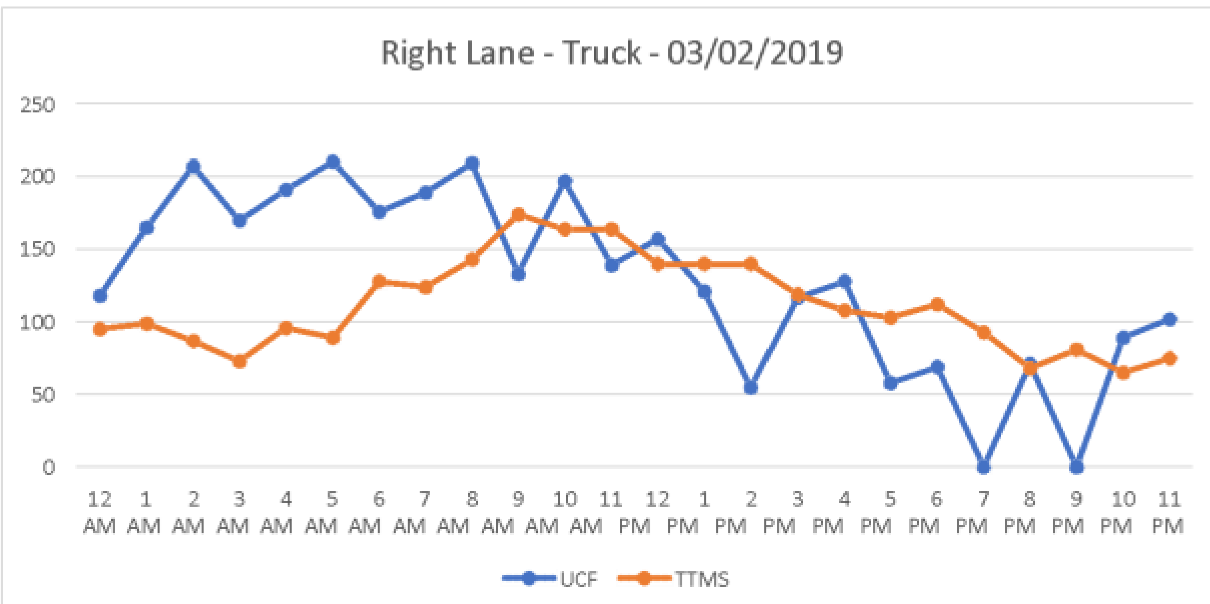

Left Lane - Truck - 03/01/2019
350
300
250
200
150
100
50
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

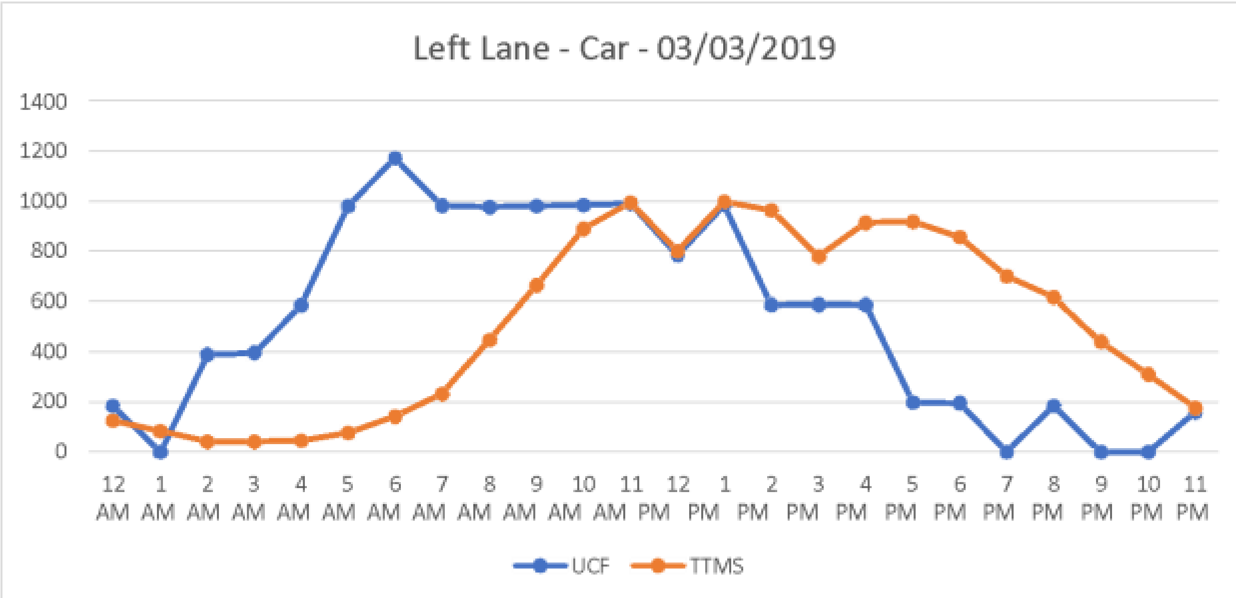

Right Lane - Truck - 03/01/2019
400
350
300
250
200
150
100
50
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

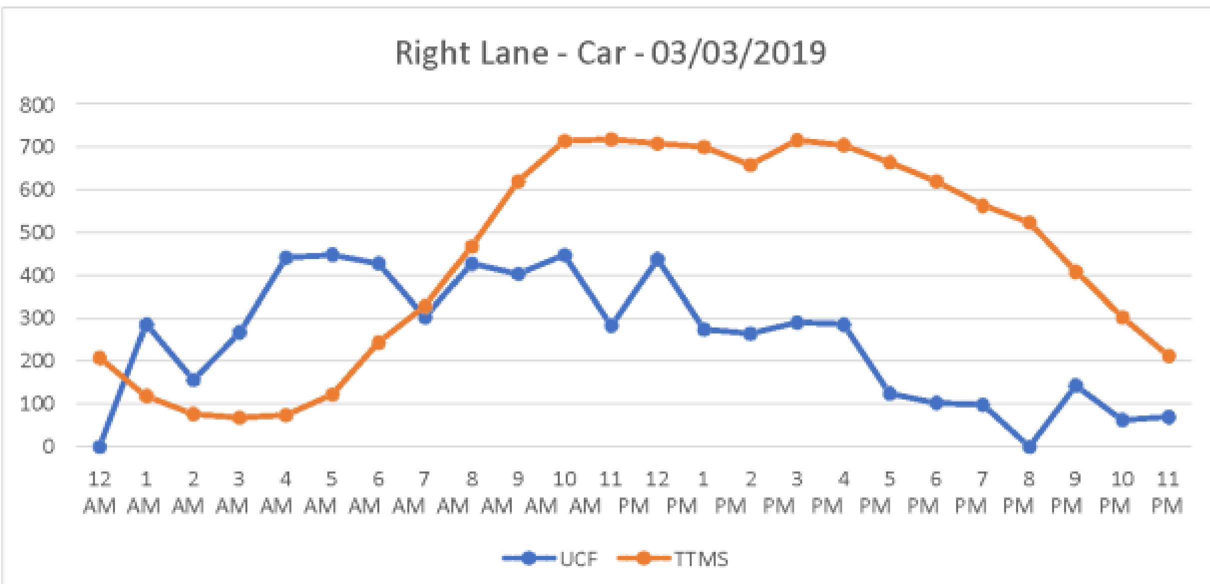

Left Lane - Car - 03/02/2019
1200
1000
800
600
400
200
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

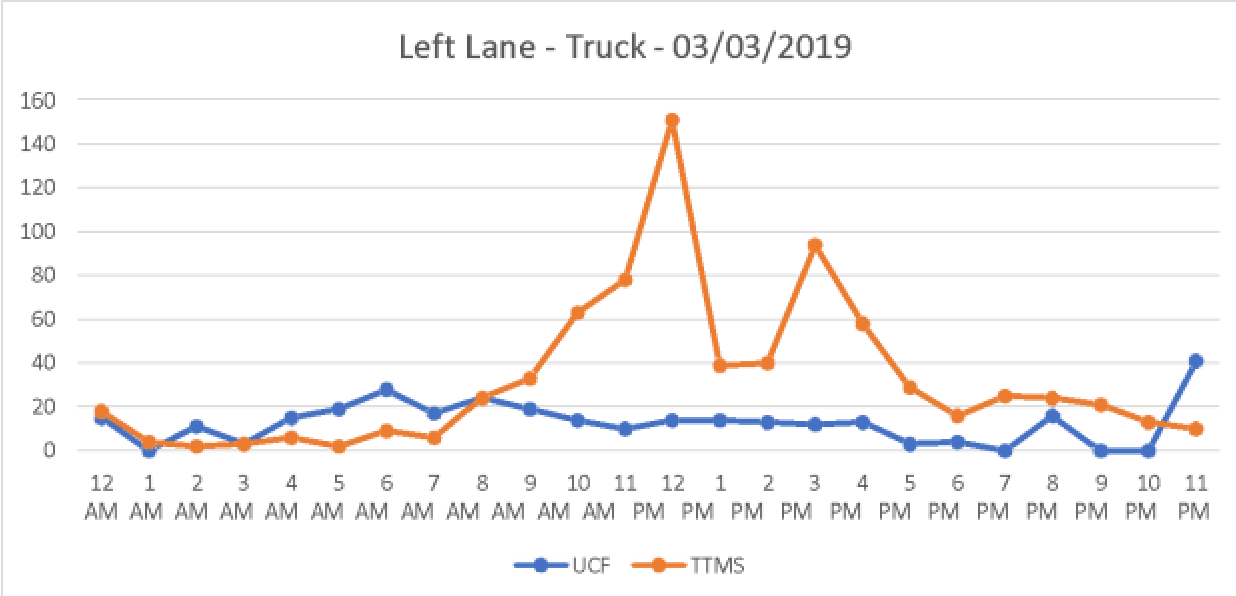

Right Lane - Car - 03/02/2019
800
700
600
500
400
300
200
100
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

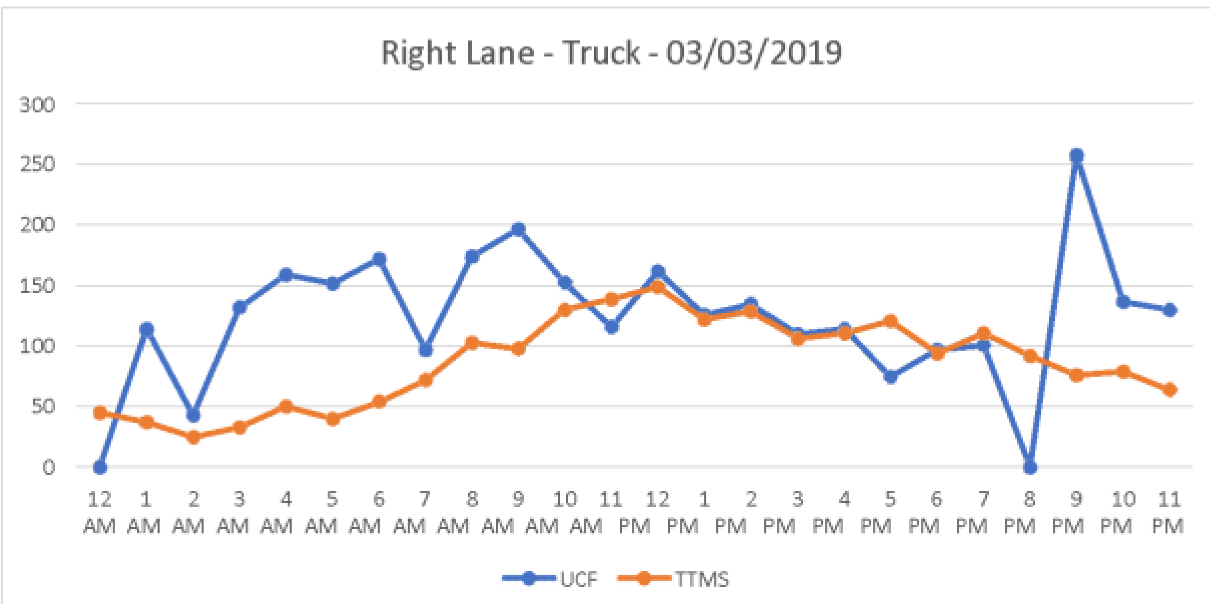

Left Lane - Truck - 03/02/2019
250
200
150
100
50
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

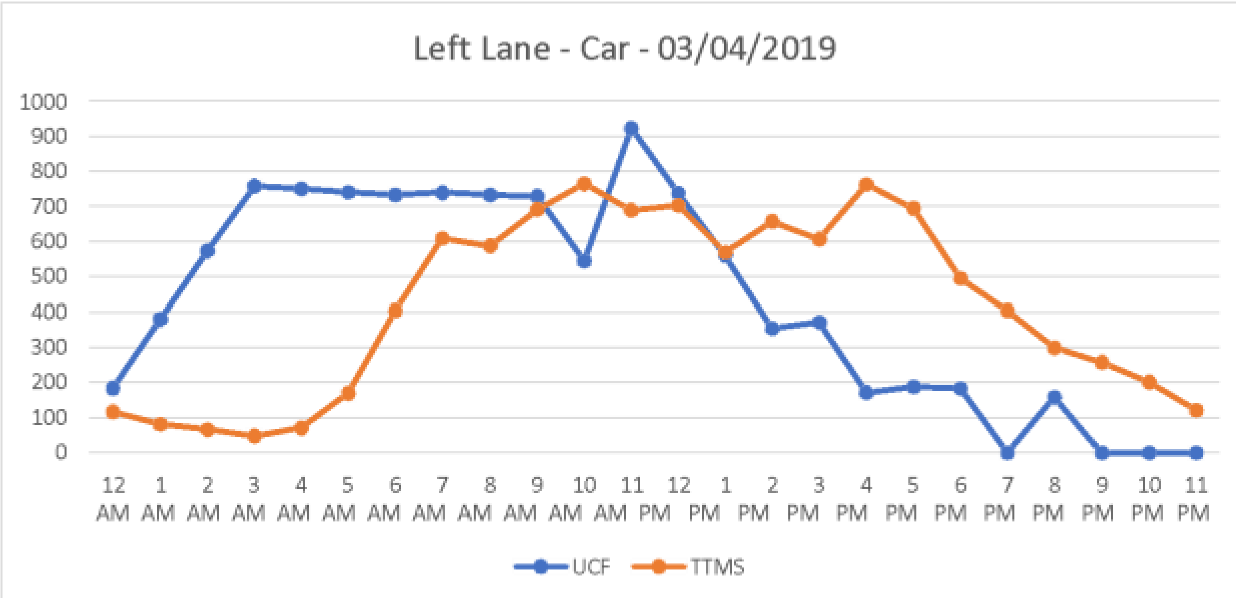

Right Lane - Truck - 03/02/2019
250
200
150
100
50
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

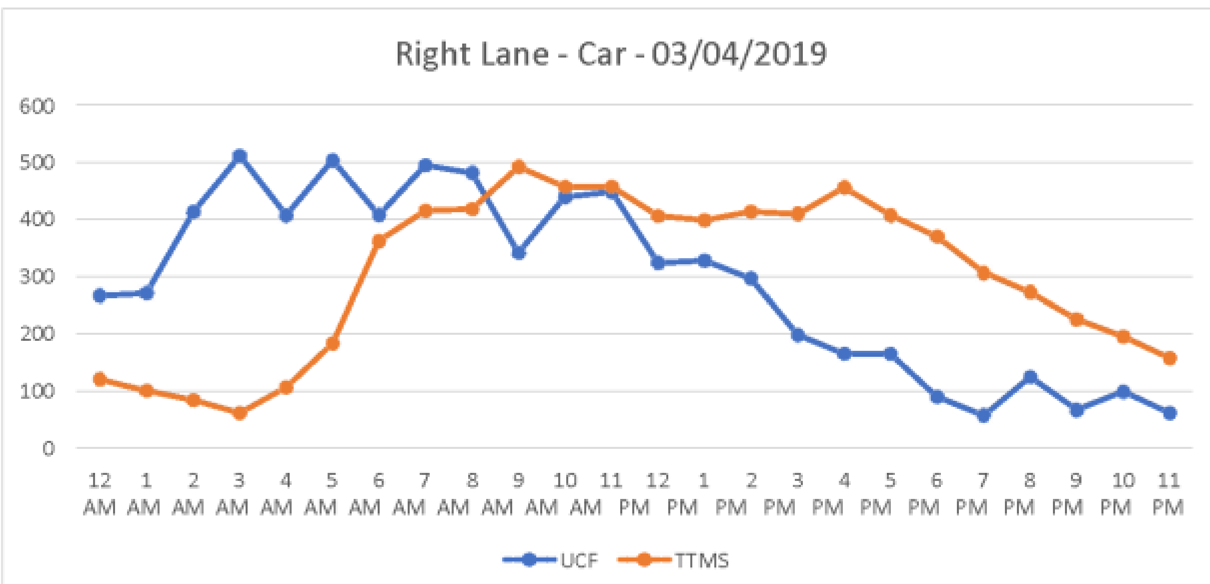

Left Lane - Car - 03/03/2019
1400
1200
1000
800
600
400
200
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

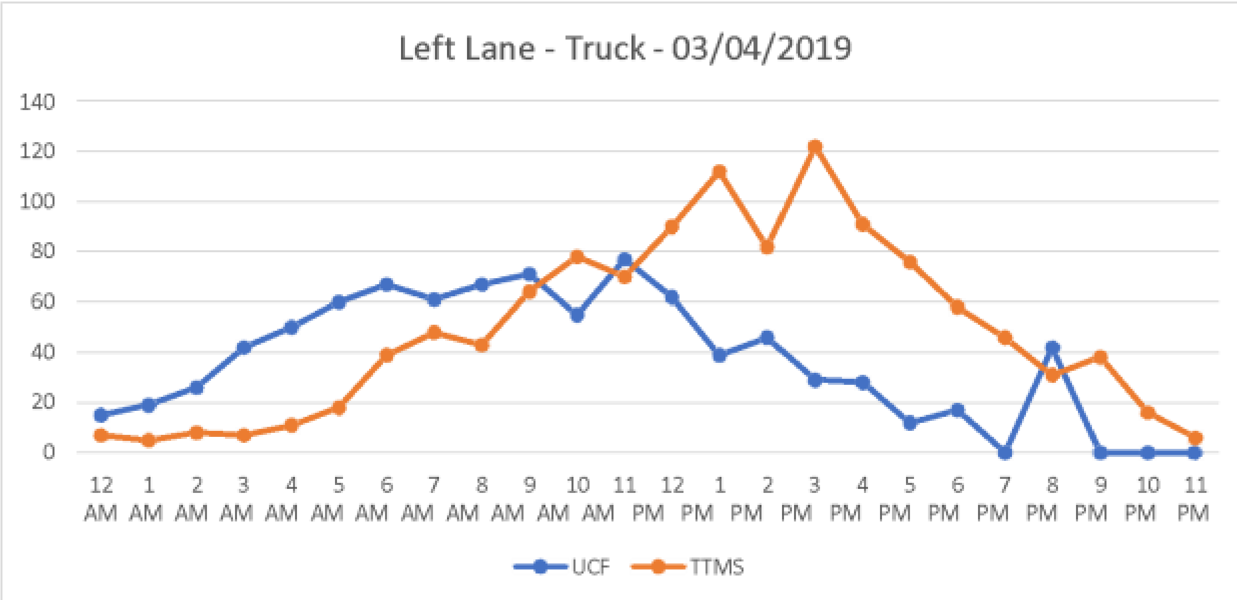

Right Lane - Car - 03/03/2019
800
700
600
500
400
300
200
100
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

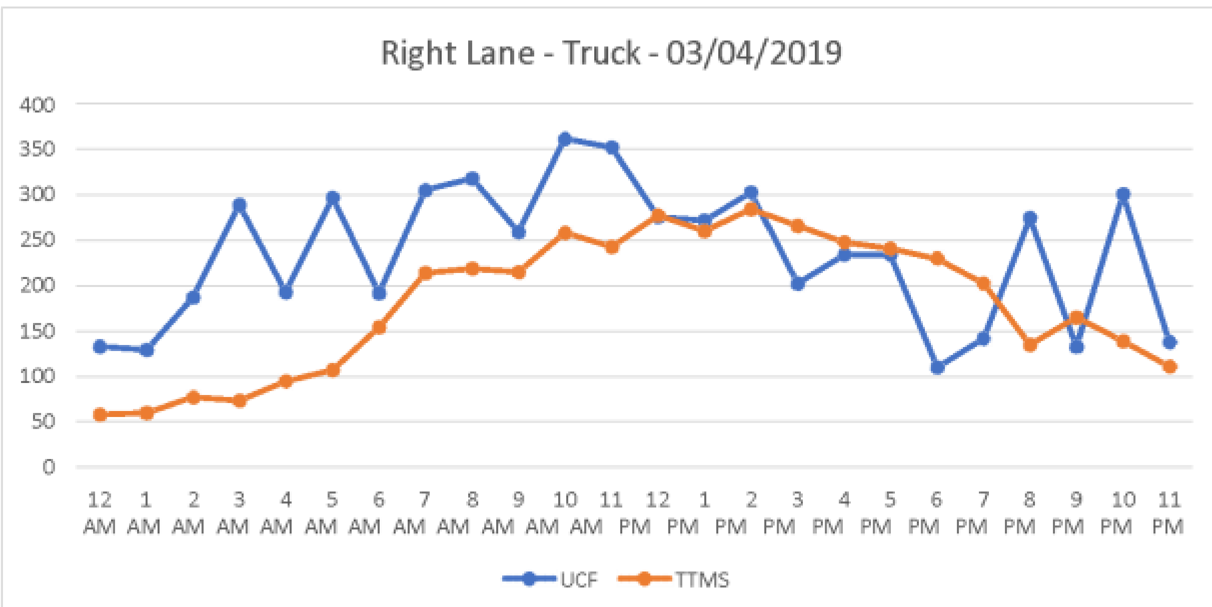

Left Lane - Truck - 03/03/2019
160
140
120
100
80
60
40
20
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 PM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

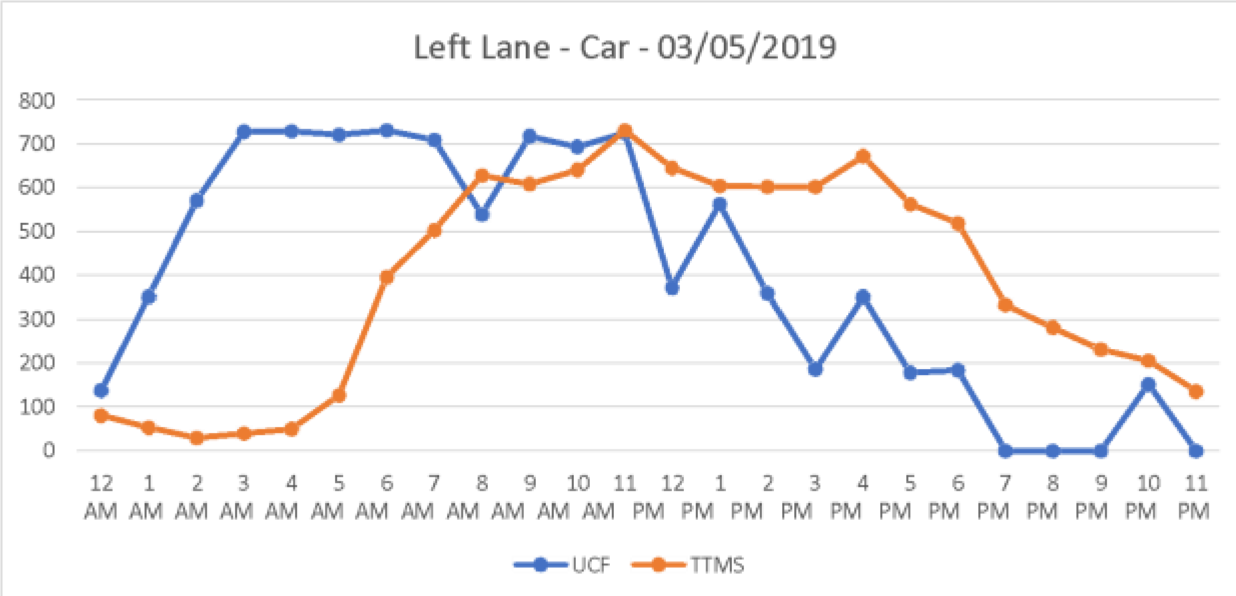

Right Lane - Truck - 03/03/2019
300
250
200
150
100
50
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 PM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

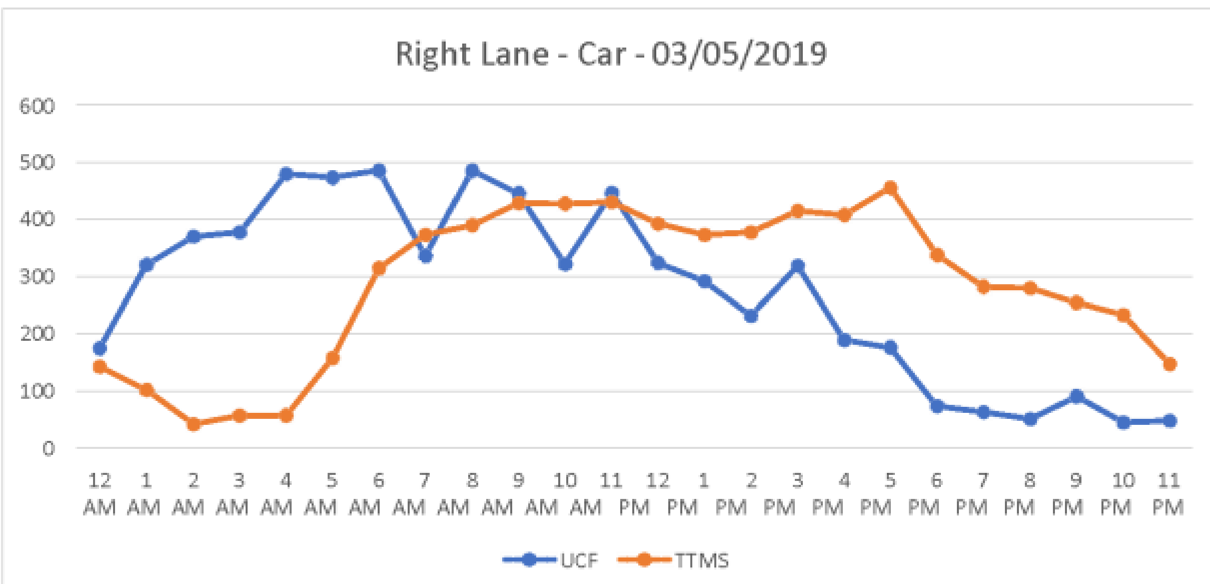

Left Lane - Car - 03/04/2019
1000
900
800
700
600
500
400
300
200
100
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

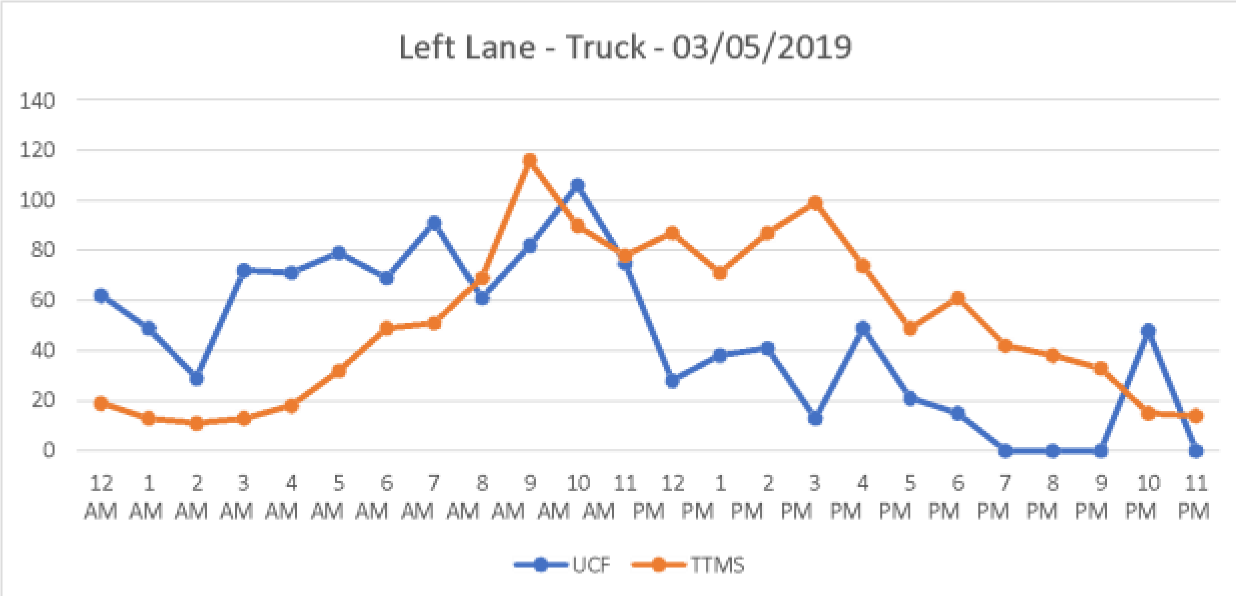

Right Lane - Car - 03/04/2019
600
500
400
300
200
100
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

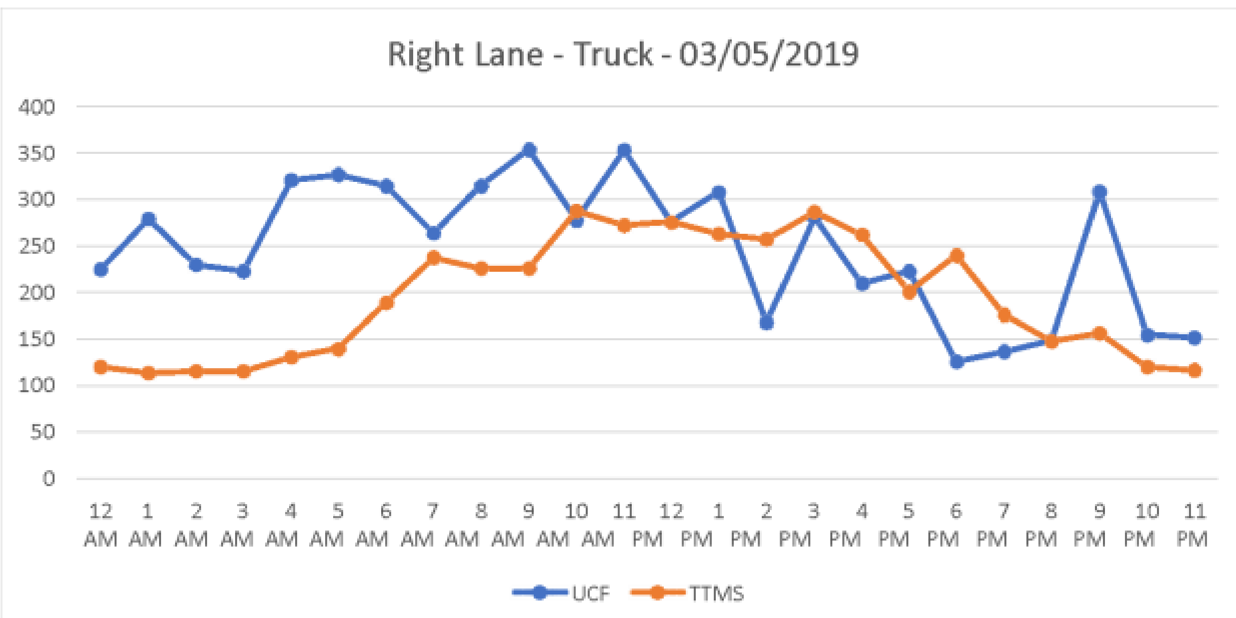

Left Lane - Truck - 03/04/2019
140
120
100
80
60
40
20
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

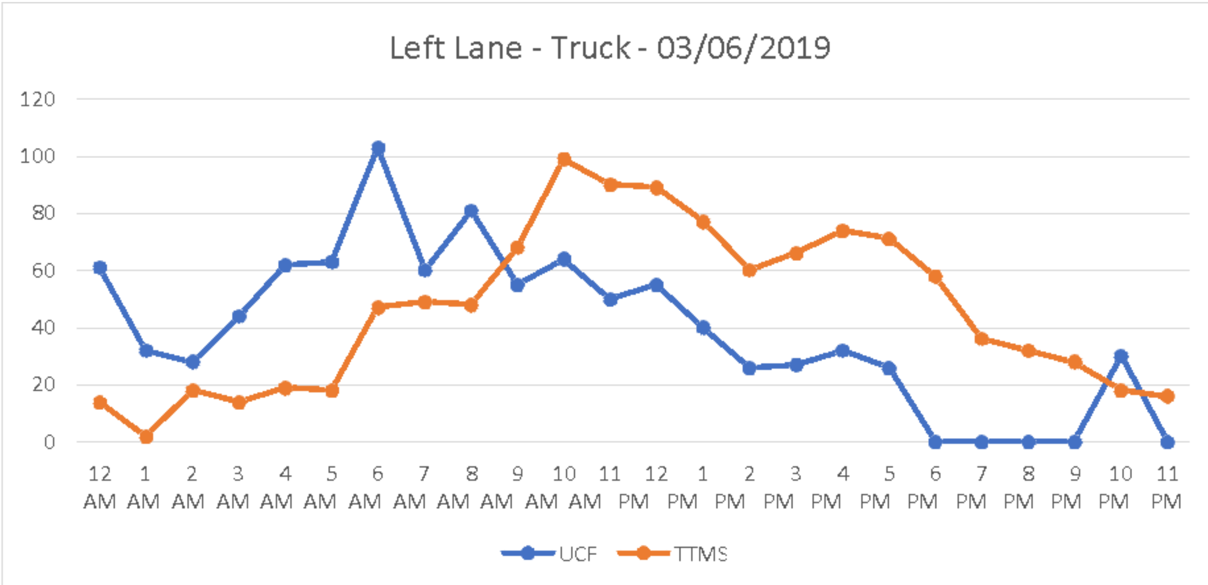

Right Lane - Truck - 03/04/2019
400
350
300
250
200
150
100
50
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

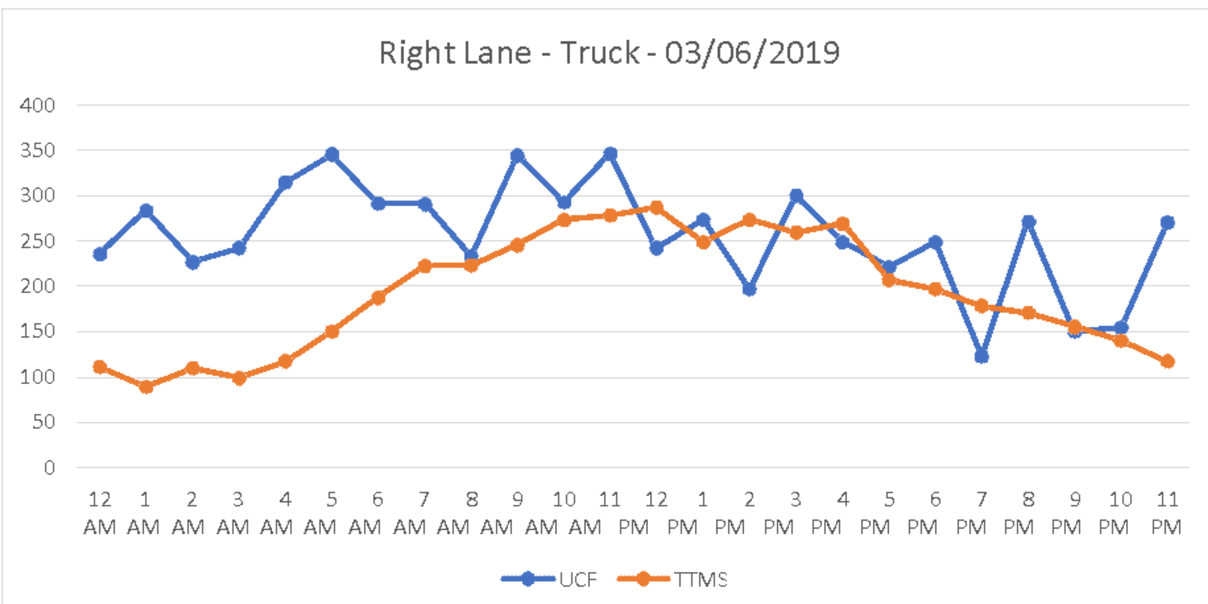

Left Lane - Car - 03/05/2019
800
700
600
500
400
300
200
100
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

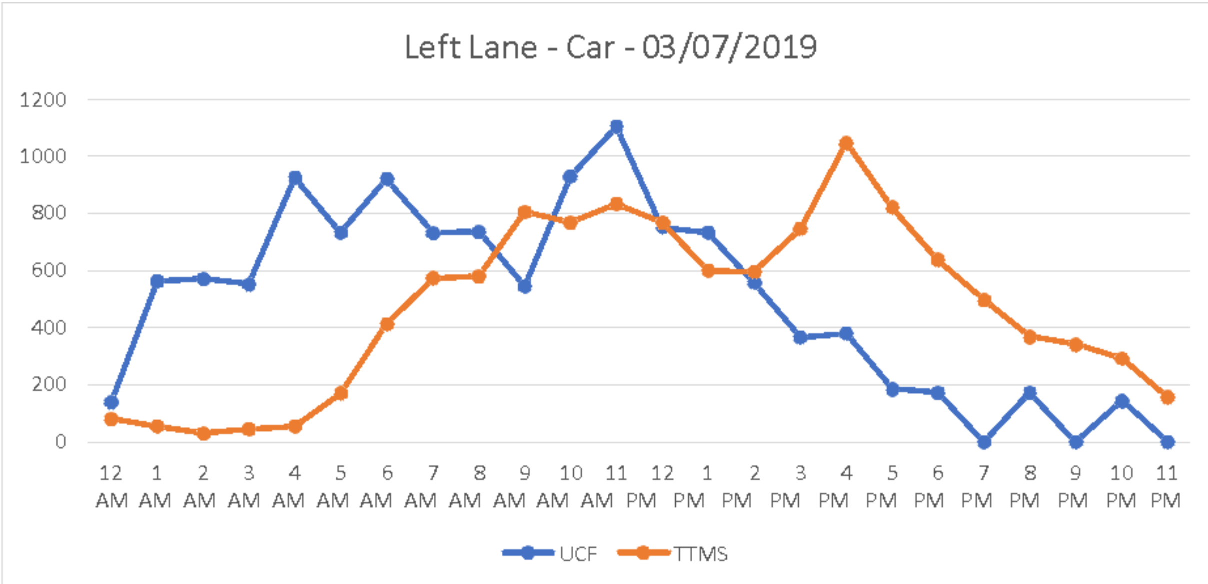

Right Lane - Car - 03/05/2019
600
500
400
300
200
100
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

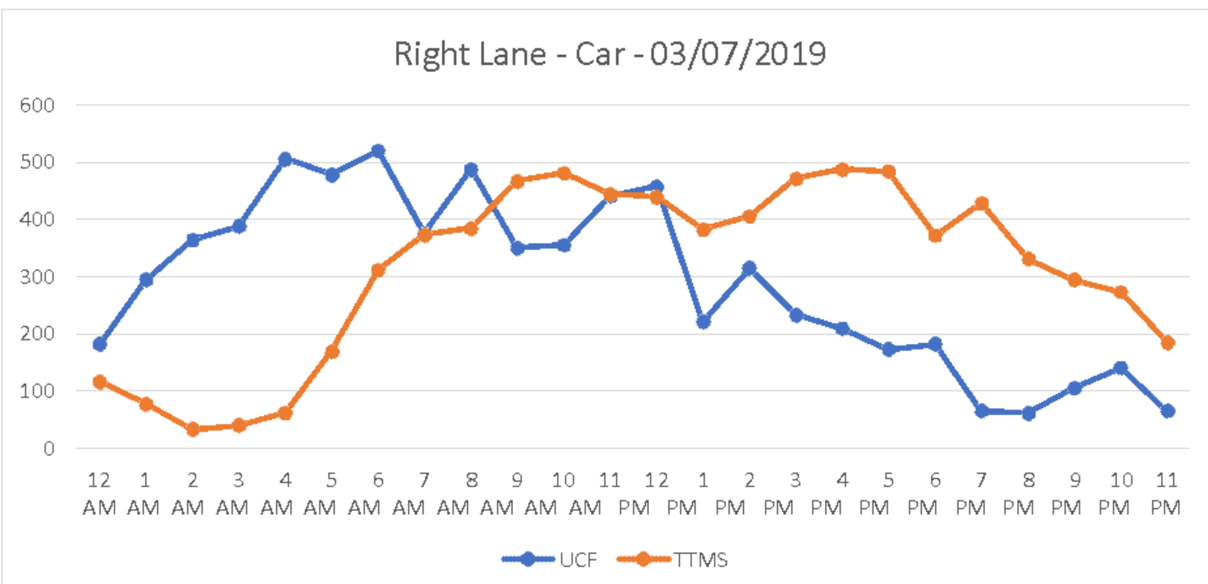

Left Lane - Truck - 03/05/2019
140
120
100
80
60
40
20
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

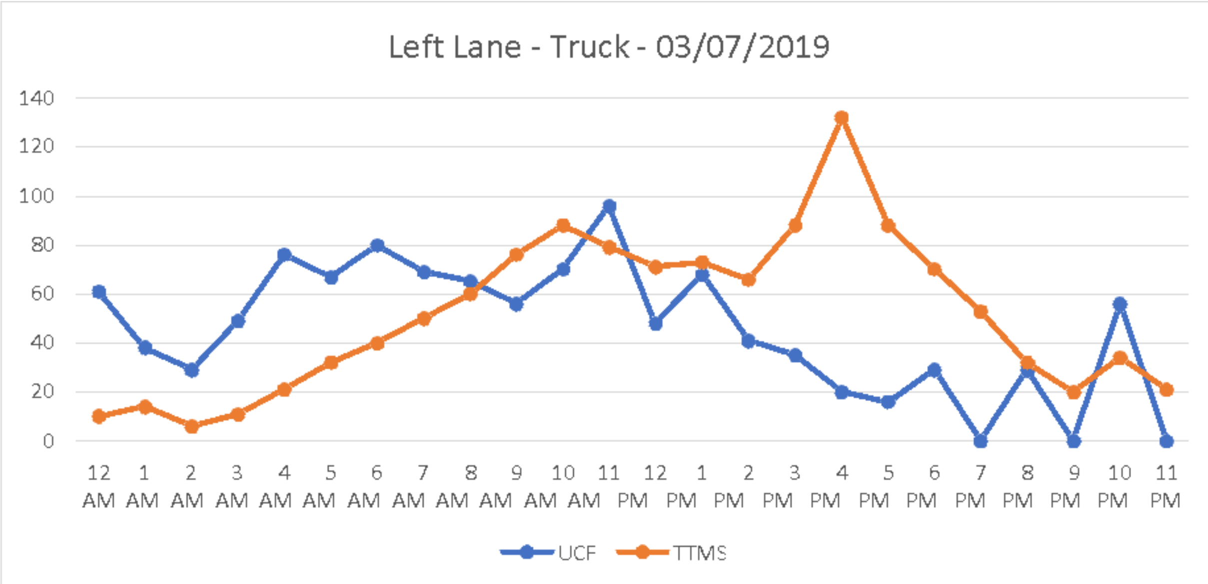

Right Lane - Truck - 03/05/2019
400
350
300
250
200
150
100
50
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

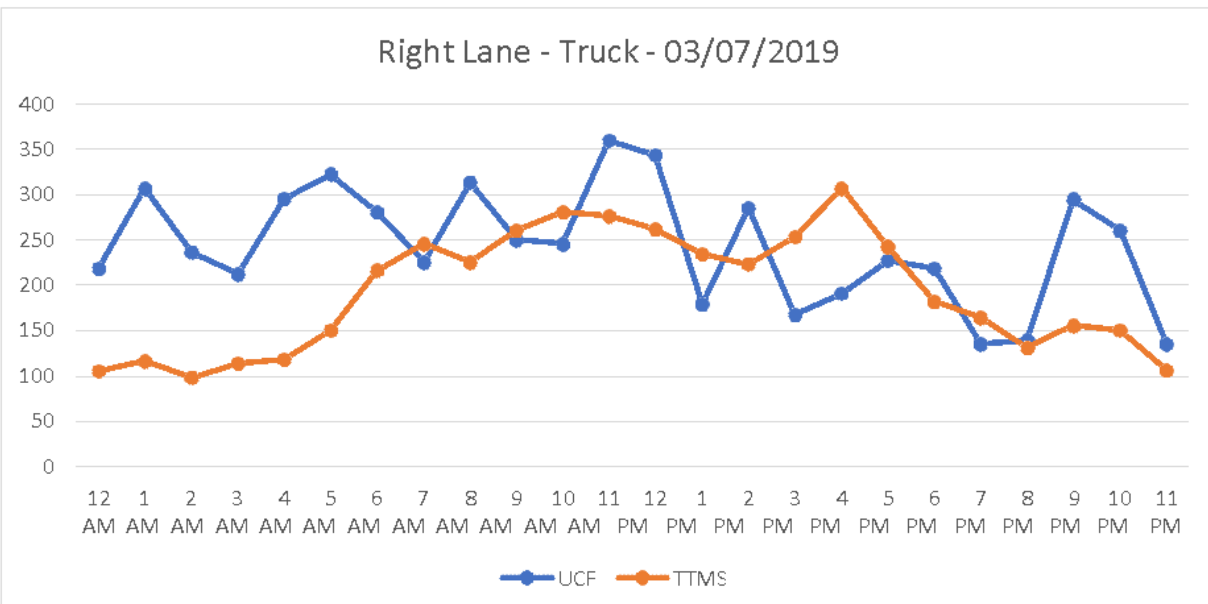

Left Lane - Truck - 03/06/2019
120
100
80
60
40
20
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

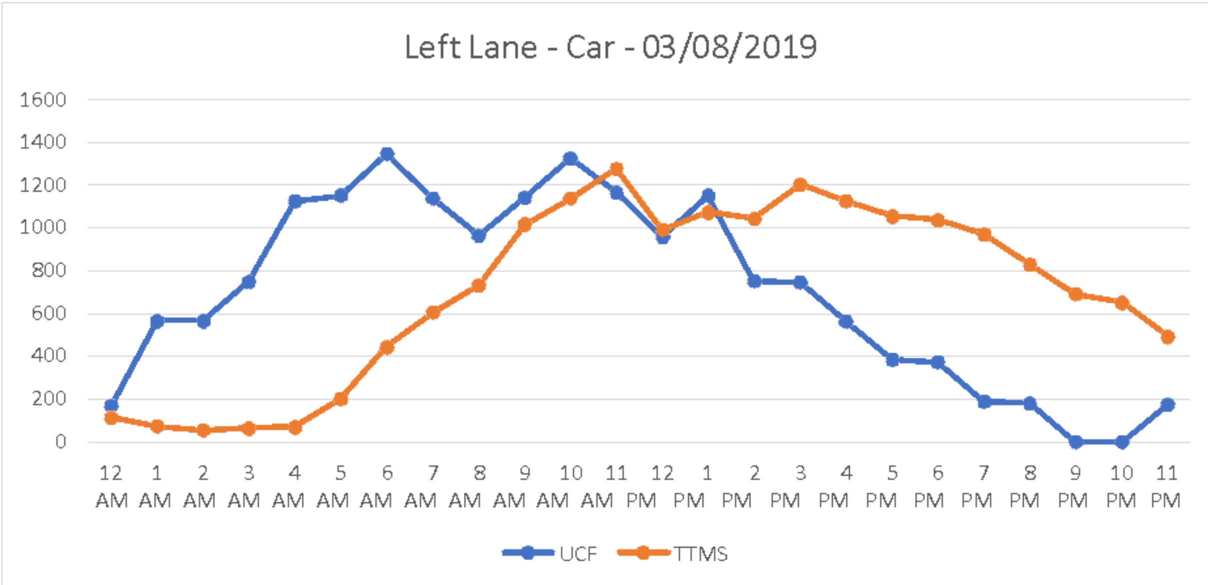

Right Lane - Truck - 03/06/2019
400
350
300
250
200
150
100
50
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

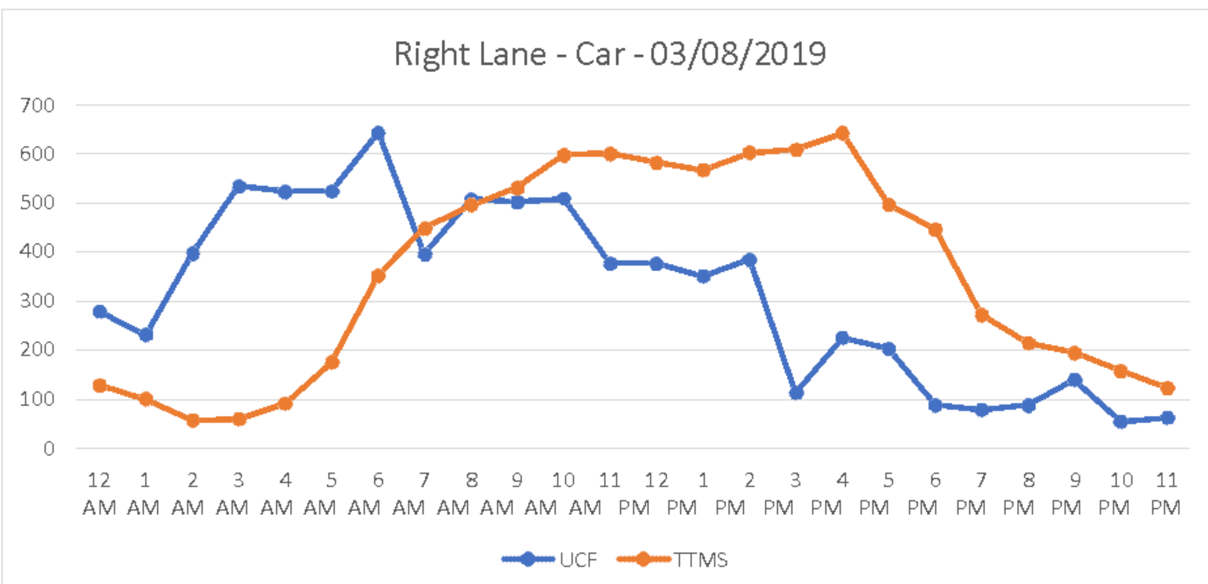

Left Lane - Car - 03/07/2019
1200
1000
800
600
400
200
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

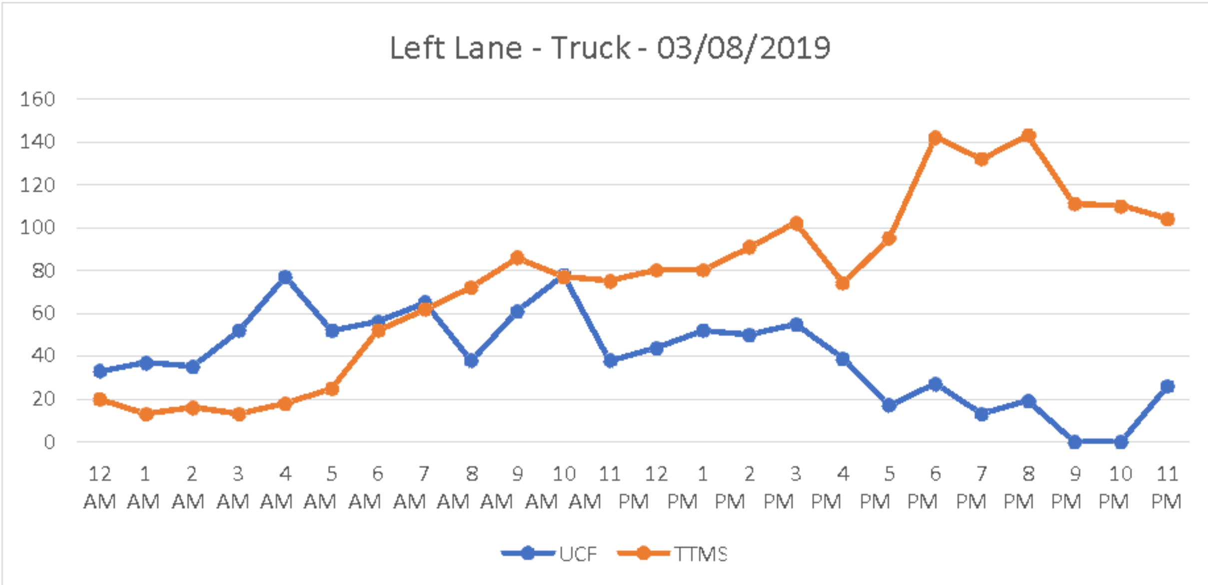

Right Lane - Car - 03/07/2019
600
500
400
300
200
100
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

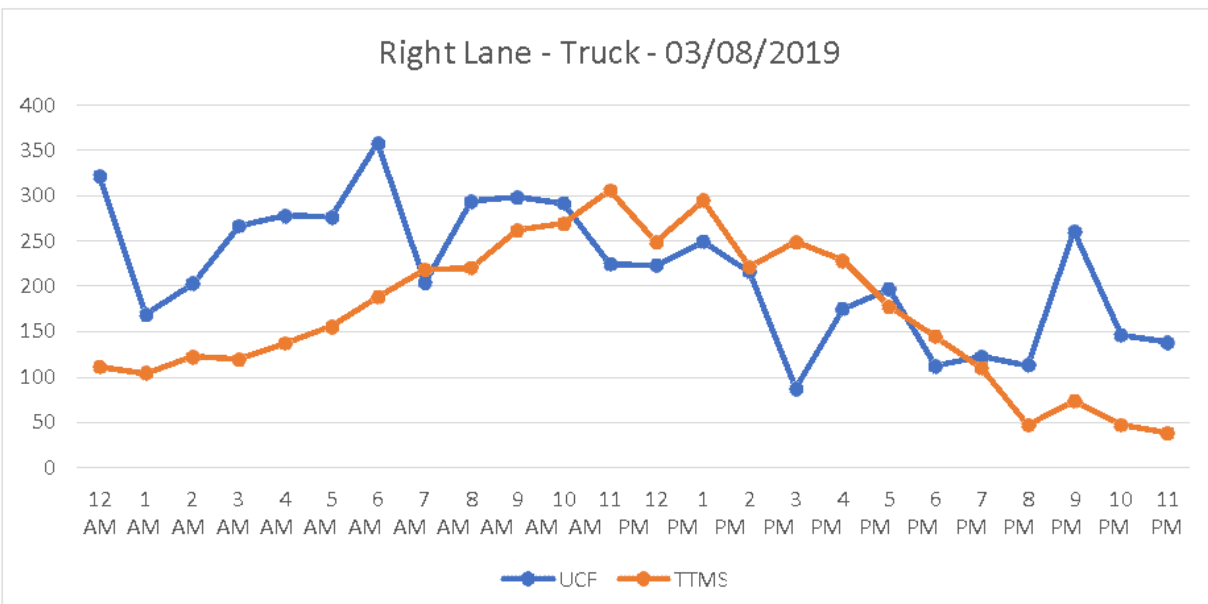

Left Lane - Truck - 03/07/2019
140
120
100
80
60
40
20
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

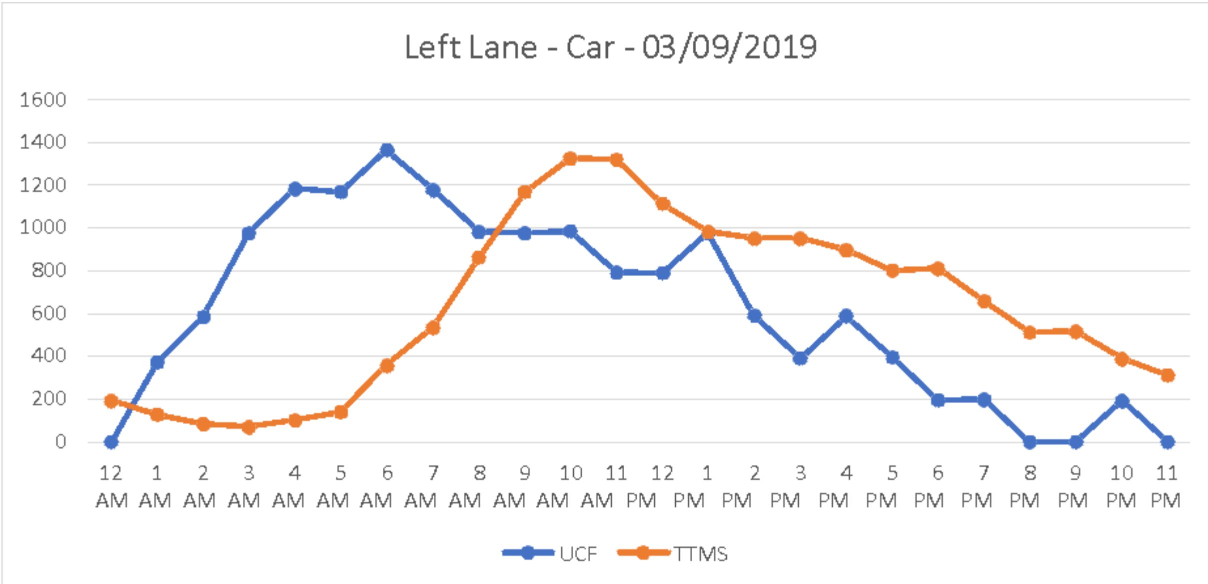

Right Lane - Truck - 03/07/2019
400
350
300
250
200
150
100
50
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

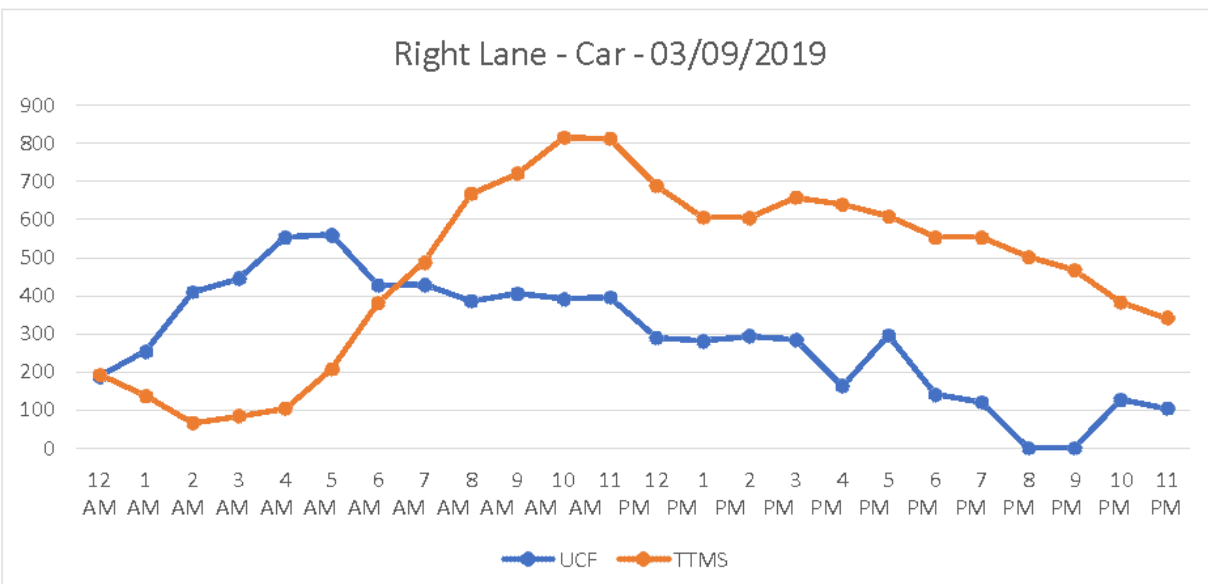

Left Lane - Car - 03/08/2019
1600
1400
1200
1000
800
600
400
200
0
12 AM 1 AM 2 AM 3 AM 4 AM 5 AM 6 AM 7 AM 8 AM 9 AM 10 AM 11 AM 12 PM 1 PM 2 PM 3 PM 4 PM 5 PM 6 PM 7 PM 8 PM 9 PM 10 PM 11 PM
UCF
TTMS

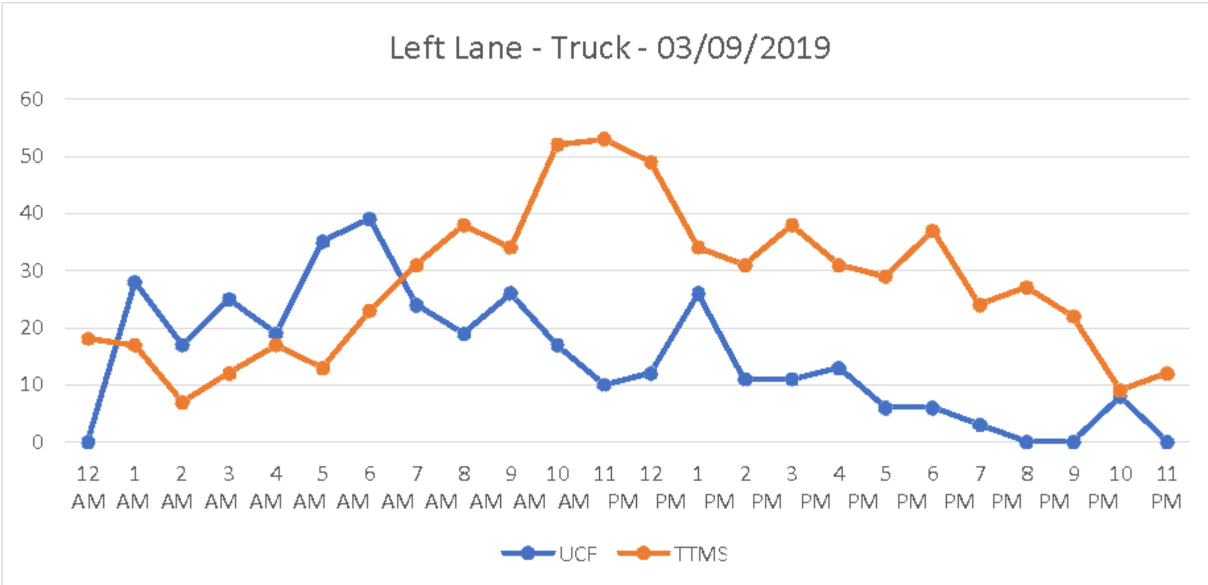

Right Lane - Car - 03/08/2019
700
600
500
400
300
200
100
0
12 AM 1 AM 2 AM 3 AM 4 AM 5 AM 6 AM 7 AM 8 AM 9 AM 10 AM 11 AM 12 PM 1 PM 2 PM 3 PM 4 PM 5 PM 6 PM 7 PM 8 PM 9 PM 10 PM 11 PM
UCF
TTMS

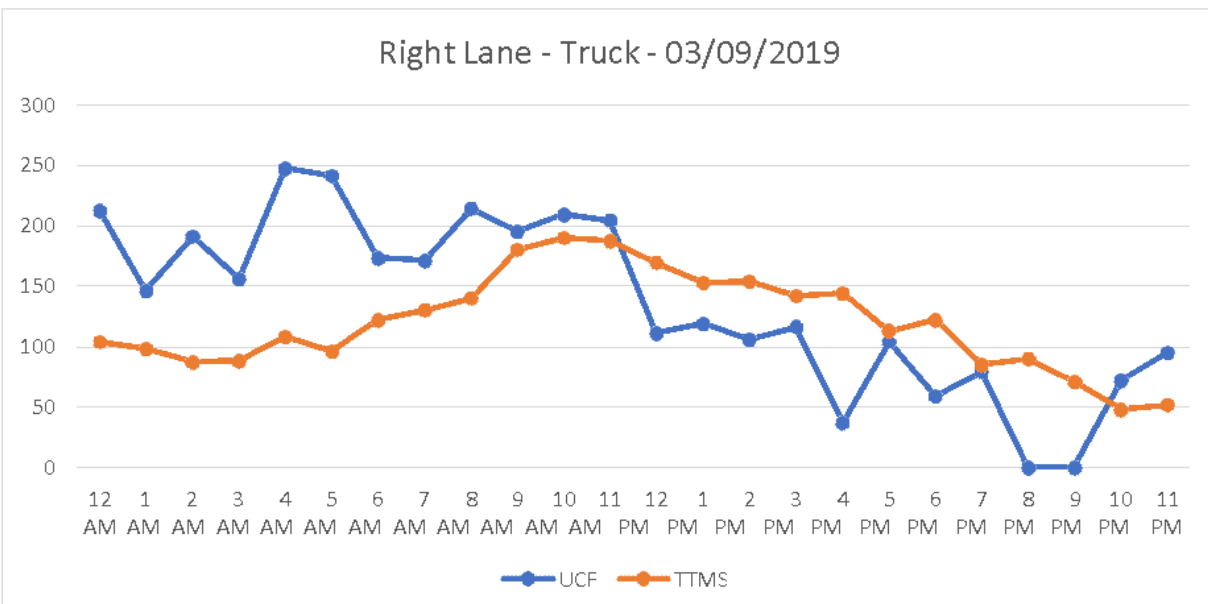

Left Lane - Truck - 03/08/2019
160
140
120
100
80
60
40
20
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

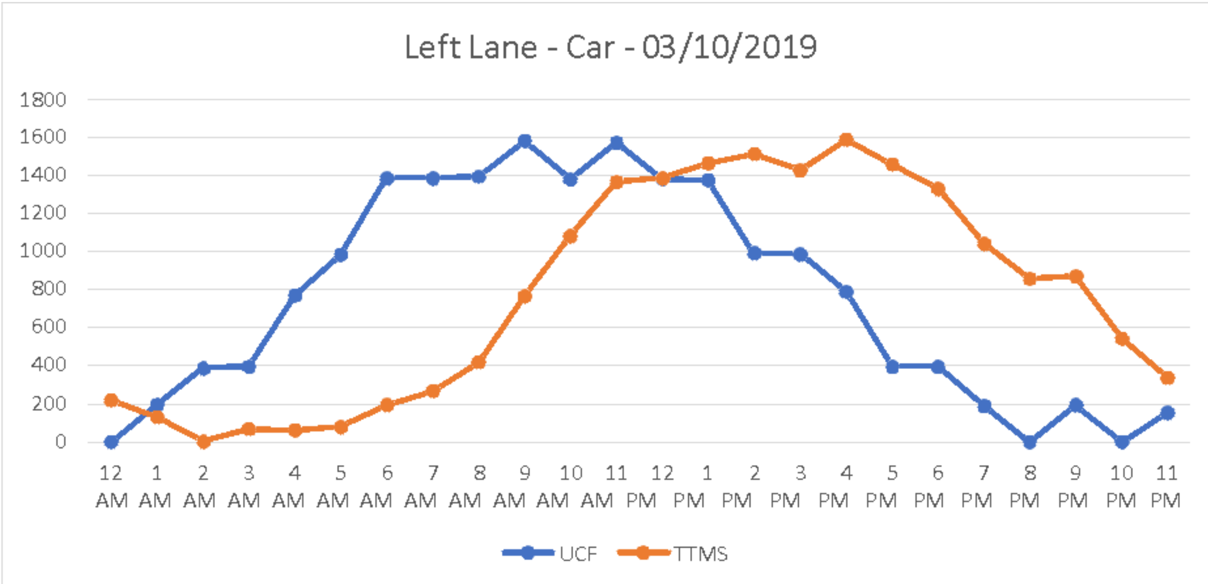

Right Lane - Truck - 03/08/2019
400
350
300
250
200
150
100
50
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

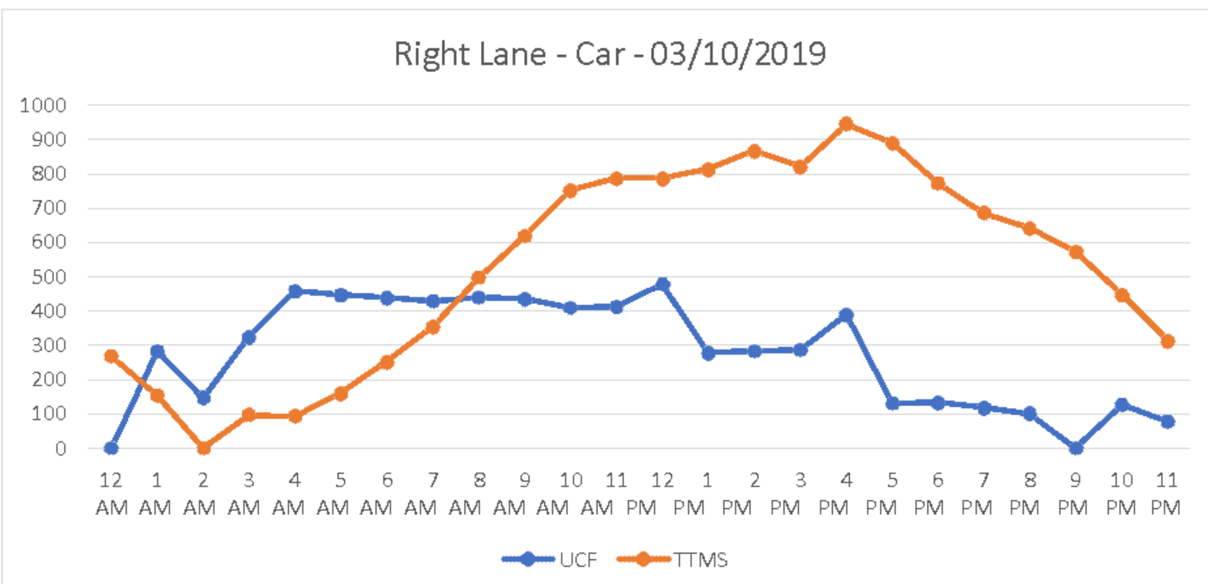

Left Lane - Car - 03/09/2019
1600
1400
1200
1000
800
600
400
200
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS


Right Lane - Car - 03/09/2019
900
800
700
600
500
400
300
200
100
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS


Left Lane - Truck - 03/09/2019
60
50
40
30
20
10
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS


Right Lane - Truck - 03/09/2019
300
250
200
150
100
50
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS


Left Lane - Car - 03/10/2019
1800
1600
1400
1200
1000
800
600
400
200
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS


Right Lane - Car - 03/10/2019
1000
900
800
700
600
500
400
300
200
100
0
12 AM
1 AM
2 AM
3 AM
4 AM
5 AM
6 AM
7 AM
8 AM
9 AM
10 AM
11 AM
12 PM
1 PM
2 PM
3 PM
4 PM
5 PM
6 PM
7 PM
8 PM
9 PM
10 PM
11 PM
UCF
TTMS

Videos Link:

https://drive.google.com/drive/u/1/folders/1PwLNFOer3uc0gp25qRsLs1UH_-AQwHjN

Video Filename	Description
IMG_2009.mov	Shows removal of the bracket over I75.
IMG_2011.mov	Shows installation of the bracket over I75.
IMG_2015.mov	Shows sensor brackets and traffic
IMG_2879.mov	Shows sensor brackets and traffic
IMG_3185.mov	Shows sensor brackets and traffic
IMG_3188.mov	Bracket with tether
IMG_7795.mov	Solar Plant for Site 2 – far shot
IMG_7796.mov	Solar Plant for Site 2
IMG_7797.mov	View of Capture Unit from the highway
IMG_7801.mov	Site 2 Solar Plant – view from the highway
IMG_8043.mov	Battery connections – Site 2
IMG_8044.mov	Battery connections – Site 2
IMG_8045.mov	Solar Controller – Site 2

University Transportation Center
Center for Advanced
Transportation Systems Simulation