DEPARTMENT OF TRANSPORTATION

Investigating Inductive Loop Signature Technology for Statewide Vehicle Classification Counts

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October 2018

Research Project
Final Report 2018-31

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16. Abstract (Limit: 250 words)

An inductive loop signature technology was previously developed by a US Department of Transportation (DOT) Small Business Innovation Research (SBIR) program to classify vehicles along a section of the roadway using existing inductive loop detectors installed under the pavement. It was tested and demonstrated in California that the loop signature system could obtain more accurate, reliable and comprehensive traffic performance measures for transportation agencies. Results from the studies in California indicated that inductive loop signature technology was able to re-identify and classify vehicles along a section of roadway and provide reliable performance measures for assessing progress, at the local, State, or national level. This study aimed to take advantage of the outcomes from the loop signature development to validate the performance with ground truth vehicle classification data in the Twin Cities Metropolitan Area (TCMA). Based on the results from individual vehicle class verification, class 2 vehicles had the highest match rate of 90%. Possible causes of classification accuracy for other vehicle classes may include types of loops, sensitivity of inductive loops that generates a shadow loop signal on neighboring lanes, and classification library that was built based on California data. To further understand the causes of loop signature performance and improve the classification accuracy, the author suggests performing additional data verification at a permanent Automatic Traffic Recorder (ATR) site. There is also an opportunity to investigate the classification algorithm and develop an enhanced pattern recognition methodology based on the raw loop signature profile of various types of vehicles in Minnesota.

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Investigating Inductive Loop Signature Technology for Statewide Vehicle Classification Counts

FINAL REPORT

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Special thanks to Jordan Supper Club & Tap Room restaurant for allowing us to deploy the video data collection system on its property.

Finally, the author would like to thank the Center for Transportation (CTS) for providing administrative assistance for this project.

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LIST OF ABBREVIATIONS

ATR	Automatic Traffic Recorder
AADT	Annual Average Daily Traffic
CEGE	Civil Environmental and Geo Engineering
CMR	Correctly Matched Ratio
CSAH	County State-Aid Highways
CTS	Center for Transportation Studies
DOT	Department of Transportation
FAST	Fixing America's Surface Transportation
FHWA	Federal Highway Administration
HCAADT	Heavy Commercial Annual Average Daily Traffic
ILD	Inductive Loop Detector
KNN	K Nearest Neighbors
MAP-21	Moving Ahead for Progress in the 21st Century
MnDOT	Minnesota Department of Transportation
MR	Match Ratio
MTO	Minnesota Traffic Observatory
NEMA	National Electrical Manufacturers Association
RTMC	Regional Traffic Management Center
ROW	Right of Way
SBIR	Small Business Innovation Research
SQL	Structured Query Language
TAP	Technical Advisory Panel
TCMA	Twin Cities Metropolitan Area
TH	Trunk Highway

TIMS	Traffic Information Monitoring System
UMN	University of Minnesota
USDOT	United States Department of Transportation
WIM	Weigh-In-Motion

EXECUTIVE SUMMARY

An inductive loop signature technology was previously developed by a US Department of Transportation (USDOT) Small Business Innovation Research (SBIR) program to classify vehicles along a section of the roadway using existing inductive loop detectors installed under the pavement. It was tested and demonstrated in California that the loop signature system could obtain more accurate, reliable and comprehensive traffic performance measures for transportation agencies. Results from the studies in California indicated that inductive loop signature technology was able to re-identify and classify vehicles along a section of roadway and provide reliable performance measures for assessing progress, at the local, State, or national level. This study aimed to take advantage of the outcomes from the loop signature development to validate the performance with ground truth vehicle classification data in the Twin Cities Metropolitan Area (TCMA).

The research team installed loop signature cards and video data collection systems at 5 test sites (2 locations on interstate highways, 2 sites at signalized intersections, and the other site on a major highway) to evaluate the system performance. We collected and processed over 807,000 vehicles from more than 400 hours of video and vehicle loop signature data among the 5 test sites.

Two methods were used to perform vehicle class verification for each individual vehicle and using 15-minute aggregation interval. The individual vehicle verification process was laborious and time-consuming. The per vehicle approach was performed using data from 24 periods at the different test site. The other 400-plus hours of data were analyzed using the aggregated method.

Using the verification approach at an individual vehicle level from the 24 periods, the match rate for all 13 Federal Highway Administration (FHWA) categories of vehicle types ranges from 65% to 90%, with an average matching rate of 75% and a standard deviation (SD) of 8%. The overall match rate is biased toward class 2 and 3 vehicles due to the higher percentage of passenger vehicles. Modern vehicles such as sedans, pickup truck, and SUVs share similar vehicle chassis with very close inductive loop signature pattern.

Results from the aggregated approach indicated that the loop signature system has a tendency to averagely undercount class 2 vehicles by about 13% of total traffic and overcount class 3 vehicles by about 13% of all traffic.

The research team also used the Highway Performance Monitoring System (HPMS) scheme for vehicle classification. The HPMS classification bin 1 to 4 matches the FHWA classification scheme 1 to 4. Overall, HPMS group 5 count error was within 1% of total traffic count and traffic count error in bin #6 was less than 2% of the total volume. On average, the loop signature system tended to overcount HPMS class 5 vehicles and undercount HPMS class 6 vehicle.

Based on the results from individual vehicle class verification, class 2 vehicles had the highest match rate of 81% with 17% of passenger vehicles being misclassified as class 3 vehicles. All the other vehicle classes had a relatively lower matching rate, i.e., less than 50%. The matching rate was lower than the results from the California Department of Transportation (Caltrans). After further investigation of a

sample set of data at site #3, we found that the signature data collected from this location were not typical. It was found that more abnormal loop signatures occurred at Lane 2 as compared to the abnormalities that occurred at Lane 1. The causes are not clear, but are probably due to damaged loops, broken loop sealant, crosstalk, or lead-in cable not twisted properly. The abnormality of the signature data also affected the overall performance. For this particular sample dataset (517 vehicles), if only data from Lane 1 were considered, the performance could have been improved from 84.5% to 90.8%, which is similar to the performance observed in southern California, according to the vendor.

We suspect the possible causes of poor classification accuracy may include the followings:

- Types of loops (circular loops in CA vs. rectangular loops in MN)
- Sensitivity of inductive loops that generates a shadow loop signal on a neighboring lane
- Classification template library prepared based on California data
- Inappropriate parameter setup. (We learned that each loop channel of detector card needed to be configured properly to remove possible cross-talks and achieve good signature data quality. Main parameters that need to be customized including loop frequency, noise suppression filter, and detects-in-a-row. The loop frequency was very site specific.)

After discussing this with the vendors as well as the current practices in California, we feel a field deployment procedure would be helpful to set up a loop card by measuring inductance for each loop and checking check vehicle signatures in the field to ensure there is no noise or interference from all loops.

To further understand the causes of loop signature performance and improve the classification accuracy, we suggest installing the 4 loop signature cards at a couple of permanent ATR locations and performing additional data verification with a video camera and pneumatic tube counter. We believe there is also an opportunity to investigate the classification algorithm and develop a better pattern recognition methodology based on the raw loop signature profile of various types of vehicles in Minnesota.

CHAPTER 1: INTRODUCTION

1.1 BACKGROUND

In 2013, USDOT sponsored a study that uses inductive loop signatures from existing Inductive Loop Detectors (ILD) installed under the pavement to obtain more accurate, reliable and comprehensive traffic performance measures for transportation agencies. Results from the study indicated that inductive loop signature technology is able to re-identify and classify vehicles along a section of roadway and provide reliable performance measures for assessing progress, at the local, state, or national level. We would like to take advantage of the outcomes from the loop signature development to validate the performance with ground truth vehicle classification data. Our goal is to evaluate the accuracy and reliability of using the single loop detector signature for vehicle classification under different traffic conditions. We believe, there are opportunities to convert current traffic volume counters (ATR/volume) into volume and classification stations using existing inductive loop detectors. The technology has the potential to save lots of time and money, and could provide MnDOT more data especially in the metro area where loop detectors are already installed on freeways, ramps, and at traffic signals.

1.2 OBJECTIVE

The loop signature technology could be a huge innovation addition to existing data collection methods for MnDOT and could save the state a large amount of resources. Adding benefit to existing infrastructure is preferred over adding new technology and benefits a wider audience. The objectives of this study are to (1) leverage existing loop detectors for vehicle classification counts, (2) and if successful, save time and money while providing state, county or city more data especially in the metro area where loop detectors are already installed.

1.3 LITERATURE REVIEW

Transportation agencies in the U.S. monitor and evaluate their existing traffic systems using devices such as loop detectors, automatic traffic recorders (ATR), and Weigh-In-Motion (WIM) sensors to collect traffic volume, speed, vehicle classification, and weight information for safety evaluation, pavement design, funding decisions, forecasting, modeling, and much more. The traffic management center and traffic forecasting and analysis division of MnDOT have been using collected traffic data to generate performance measures to support decision making and planning [1].

In Minnesota, vehicle classification is collected from WIM sensors at 22 locations, continuous classifiers using ATR at over 70 locations, or manually on high-volume roadways. Double tubes are used to get axle-based vehicle classification counts on roadways with less traffic. Currently, it takes a significant amount of time and effort to collect vehicle classification data annually.

Sun et al. [2] developed a vehicle re-identification algorithm based on freeway inductive loop data and demonstrated the robustness of its algorithm under different traffic-flow conditions. Kwon & Parsekar

[3] developed two deconvolution approaches to measure travel time from two sets of spatially separated loop detectors using re-identification of vehicle inductance signatures generated by the inductive loops. In addition, Sun et al. [4] and Ki & Baik [5] developed vehicle classification algorithms using artificial intelligent and neural networks, respectively. The classification rates for 7 vehicle categories using inductive classifying artificial network [4] were 87% and 82% for two datasets. The neural network approach [5] has a recognition rate of 91.5% for 5 vehicle categories.

Tok [6] developed a high-fidelity inductive loop sensing system for commercial vehicle classification. Axle and body classification models were developed to accurately classify the axle configuration of commercial vehicles and examine the function and unique impacts of the drive and trailer units of each commercial vehicle. In 2012, Minge et al. [7] analyzed several length-based vehicle classification schemes and conducted field tests of loop and non-loop sensors for evaluating their performance. The research recommended a 5-bin based vehicle classification scheme.

In 2013, the USDOT Small Business Innovation Research (SBIR) program [8] sponsored research to use existing Inductive Loop Detectors (ILD) under the pavement to obtain more accurate, reliable and comprehensive traffic performance measures for transportation agencies. CLR Analytics Inc. developed an ILD signature technology using wavelet transformation and K Nearest Neighbors (KNN) technique to re-identify and classify vehicles along a section of roadway [9]. The average classification rate was 92.2% for Highway Performance Monitoring System (HPMS) scheme (6 classes) [10]. Based on the SBIR study, CLR and Diamond traffic designed and developed a cost-effective loop signature card to collect loop signature data and enhance the vehicle re-identification and classification algorithms [9, 10 & 11]. In addition, a high-definition traffic performance monitoring system for both freeway and arterial applications was also developed as part of the SBIR study [11, 12 & 13]. The traffic monitoring system provides functionalities to monitor traffic in real-time, analyze historical performance, and generate reports [14].

Resulting from the SBIR sponsored study, commercially available products (detector card, data collection system, and data analysis software) to record high-resolution loop signature pattern and perform vehicle identification and classification were tested on several highway locations in California and 4 arterial intersections on Highway 55 in Minnesota.

This project takes advantage of the development of the loop signature technology and validates the performance with ground true video data. The goal is to convert current traffic volume counters (ATR/volume) into volume and classification stations using existing inductive loop detectors. The technology has the potential to save lots of time and money and could provide MnDOT more data especially in the metro area where loop detectors are installed on freeways and ramps, and at traffic signals.

1.4 REPORT ORGANIZATION

This report is organized as follows. Five test site in the Twin Cities Metropolitan Area (TCMA) are identified and presented in Chapter 2. Chapter 3 describes the data collection plan and the installation of the loop signature system. Results from data analysis and vehicle class verification are presented and discussed in Chapter 4. Finally, a summary and discussion of this study are presented in Chapter 5. The FHWA 13 vehicle classification categories are illustrated in Appendix A. A selected number of comparisons of loop signature profile and video data is included in Appendix B. Vehicle classification accuracy and comparison of classification performance in rush-hour and mid-day periods are presented in Appendix D.

CHAPTER 2: IDENTIFY DATA COLLECTION SITES

The research team worked with the member of the Technical Advisory Panel (TAP) to select 5 test sites (see Table 1) in the Twin Cities metro area. These locations were evaluated to ensure each location meets the minimum hardware requirements to install the new loop signature cards in the existing controller cabinets.

Table 2.1 List of Test Sites

Site	Type	Station ID	Description	# of Lanes	City	County
1	ATR	ATR353	Highway 169, W of CSAH 59 (Delaware Ave), W of Jordan	4	Jordan	Scott
2	Loop	21479	Highway 169 & TH 282/CSAH 9 (Quaker Ave), Jordan	4	Jordan	Scott
3	Loop	20290	TH 13 at CSAH 31 (Lynn Ave)	4	Savage	Scott
4	Loop	S872, S903	I-35E, South of McAndrews Road	4	Burnsville	Dakota
5	ATR/Loop	ATR301 (S778, S788)	I-94, West of N Victoria St in St Paul	8	St. Paul	Ramsey

The Minnesota Traffic Observatory (MTO) has developed custom traffic information monitoring systems (called TIMS). The video-based traffic data collection systems have been deployed for a wide variety of projects and on all types of roadways. These self-contained systems include a high-resolution camera mounted to an extendable mast (up to 28 ft) or directly to existing infrastructure via non-invasive steel bands. A weatherproof steel container houses recording equipment and independent battery power. The entire system attaches non-invasively to any conveniently placed pole or tree. Images of the system deployed are included in Figure 2.1. The TIMS will be used to collect ground-truth vehicle classification information.

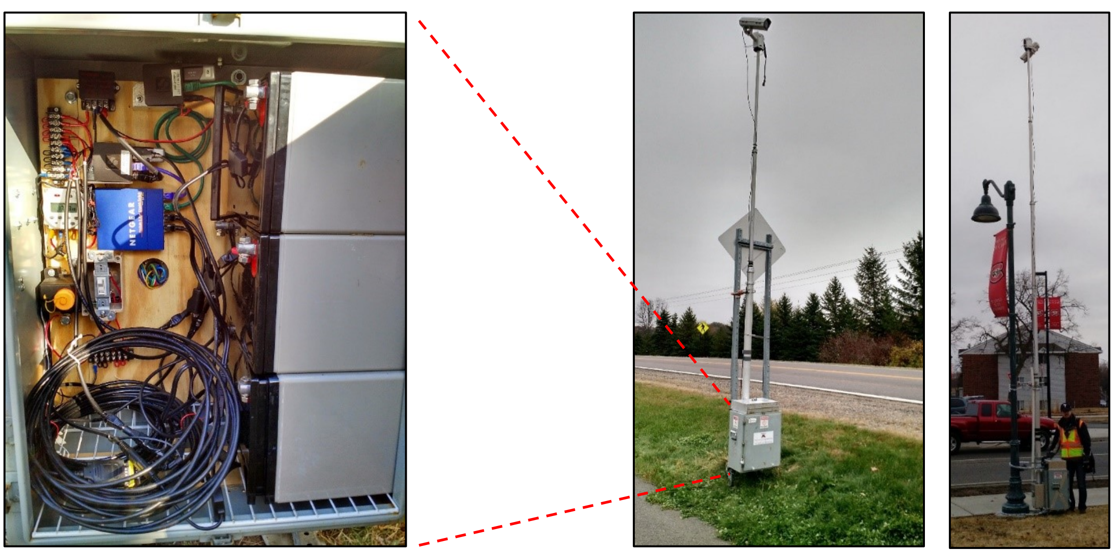
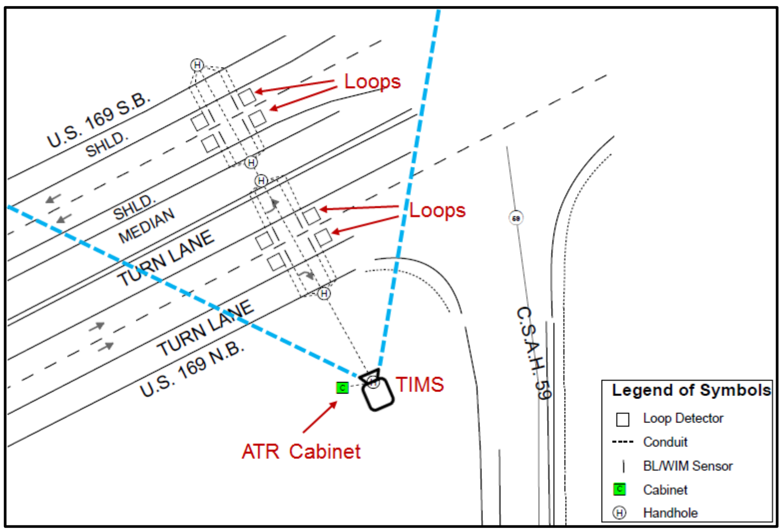


Figure 2.1 Inside of the TIMS Cabinet and Deployment of the TIMS.

The research team recently met with MnDOT ATR/WIM equipment engineer at site #1 and traffic signal technician in the metro distract at site #2 & #3 to better understand the equipment in the traffic control cabinet and identify suitable locations for the TIMS deployment. The research team is working with engineers from the RTMC to schedule a cabinet visit to site #4 & #5, Additional information about each selected test site is discussed as follows.

2.1 SITE #1: ATR353 – TH169 & CSAH 59

Figure 2.2 illustrates the installation location of the inductive loop detectors and the ATR353 controller cabinet located on the SW corner of highway 169 and CSAH50. A photo of the ATR353 site is displayed in Figure 2.3.



ATR 353

Figure 2.2 Drawing of Existing ATR353 Cabinet, Loop Detectors and TIMS Installation.

Figure 2.3 Photo of ATR353 Cabinet and Loop Detector Location.

Figure 2.4(a) illustrates the PEEK ADR3000[1] controller inside the cabinet. As illustrated in Figure 2.4(b), it is suggested to place the TIMS right next to a lamp post own by the Jordan Supper Club & Tap Room restaurant near the ATR353 controller cabinet to collect ground truth vehicle classification information during our experiments.

Figure 2.4 **PEEK ADR3000 Controller and TIMS Deployment.**

2.2 SITE #2: SIGNALIZED INTERSECTION – TH169 & TH282

Figure 2.5 shows an aerial view of the intersection at Highway 169 and TH282 in Jordan. It is suggested to place the TIMS in the NE and SW corners of the intersection to collect video data. Traffic controller at this intersection is housed in a NEMA TS-1 cabinet (see Figure 2.5 & 2.6) in the SE corner of the intersection. A mix of EDI LM604[2] and Sarasota[3] 224N GP5 loop detection cards are used at this location.

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[1] PEEK ADR-3000 Traffic Counter/Classifier, http://www.ustraffic.net/adr_3000.php
[2] Eberle Design Inc. (EDI) Traffic Detector, https://www.editraffic.com/products-page/lmd604/
[3] Sarasota is the former name of Peek Traffic Corp., https://www.peektraffic.com/index.php

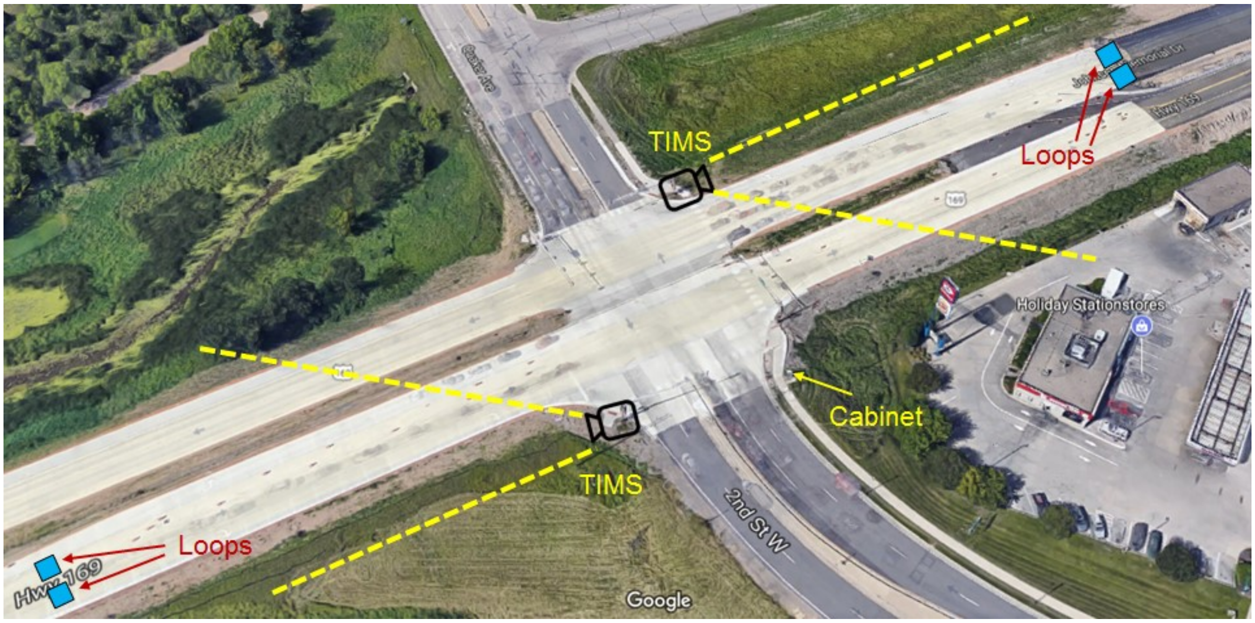

Figure 2.5 **Loop Detector Locations and TIMS deployment at TH169 & TH282 Intersection.**

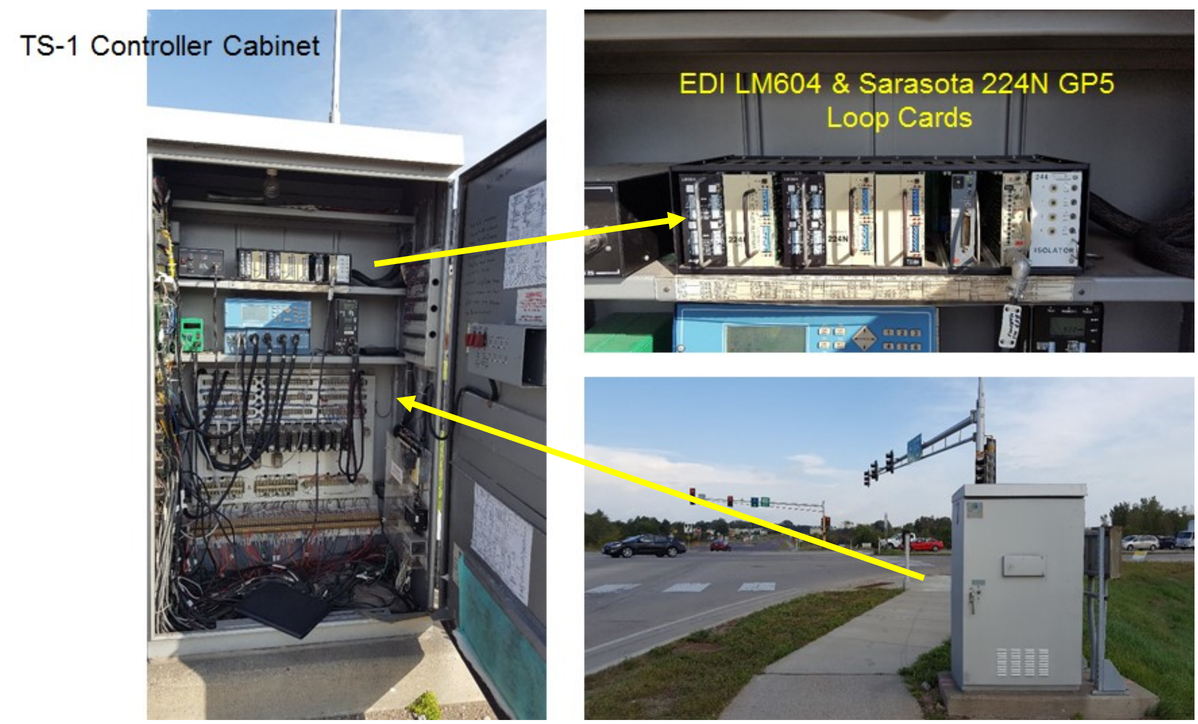

Figure 2.6 **Controller Cabinet and Loop Detector Cards at TH169 & TH282 Intersection.**

2.3 SITE #3: SIGNALIZED INTERSECTION – TH13 & LYNN AVE

Figure 2.7 shows an aerial view of the intersection at Highway 13 and Lynn Ave in Savage. It is suggested to place the TIMS in the NE and SW corners of the intersection to collect video data. Traffic controller at this intersection is housed in a NEMA TS-2 cabinet (see Figure 2.8) in the NW corner of the intersection. EDI LM624 loop detection cards are used at this location.

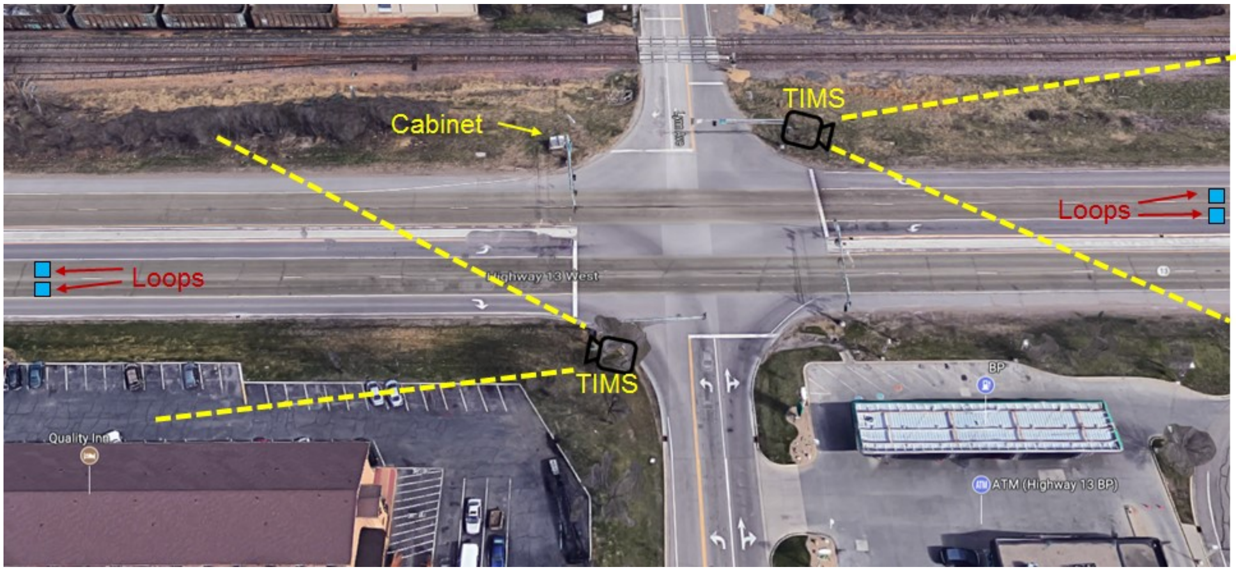

Figure 2.7 Loop Detector Locations and TIMS deployment at TH13 & Lynn Ave Intersection.

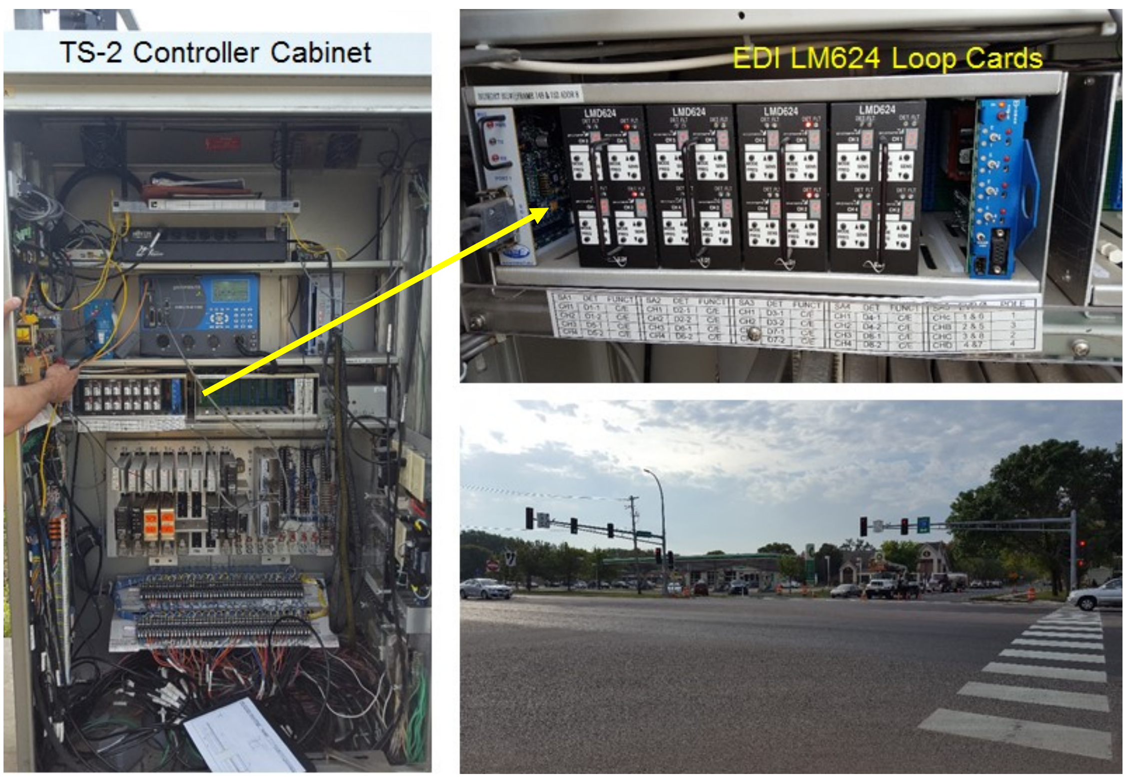

Figure 2.8 Controller Cabinet and Loop Detector Cards at TH13 & Lynn Ave Intersection.

2.4 SITE #4: FREEWAY – I-35E SOUTH OF MCANDREWS ROAD

Test site #4 is located on I-35E south of McAndrews Road in Burnsville as illustrated in Figure 2.9 & 2.10.

Figure 2.9 Loop Detector Locations on I-35E South of McAndrews Road.

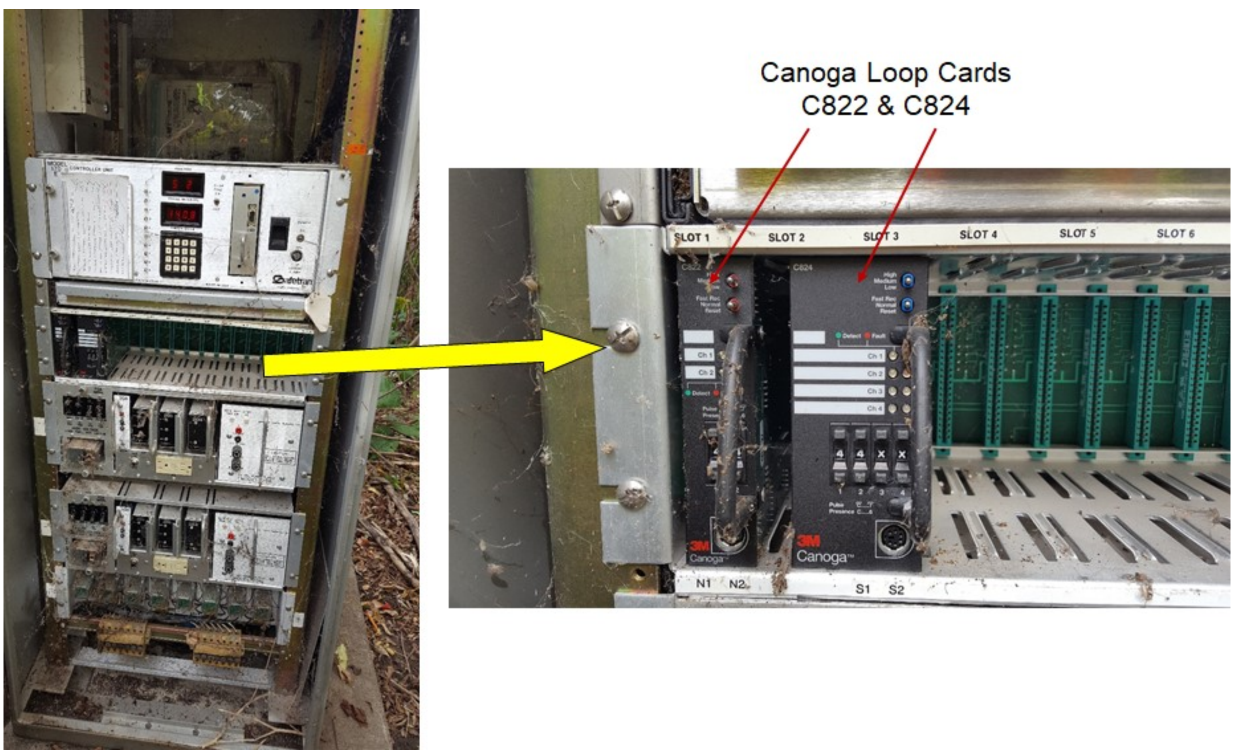

Figure 2.10 Controller Cabinet and Loop Detector Cards at I-35E South of McAndrews Road.

2.5 SITE #5: FREEWAY – I-94 WEST OF N. VICTORIA STREET

Test site #5 is located on I-94 west of Vitoria Street in St. Paul (see Figure 2.11 & 2.12).

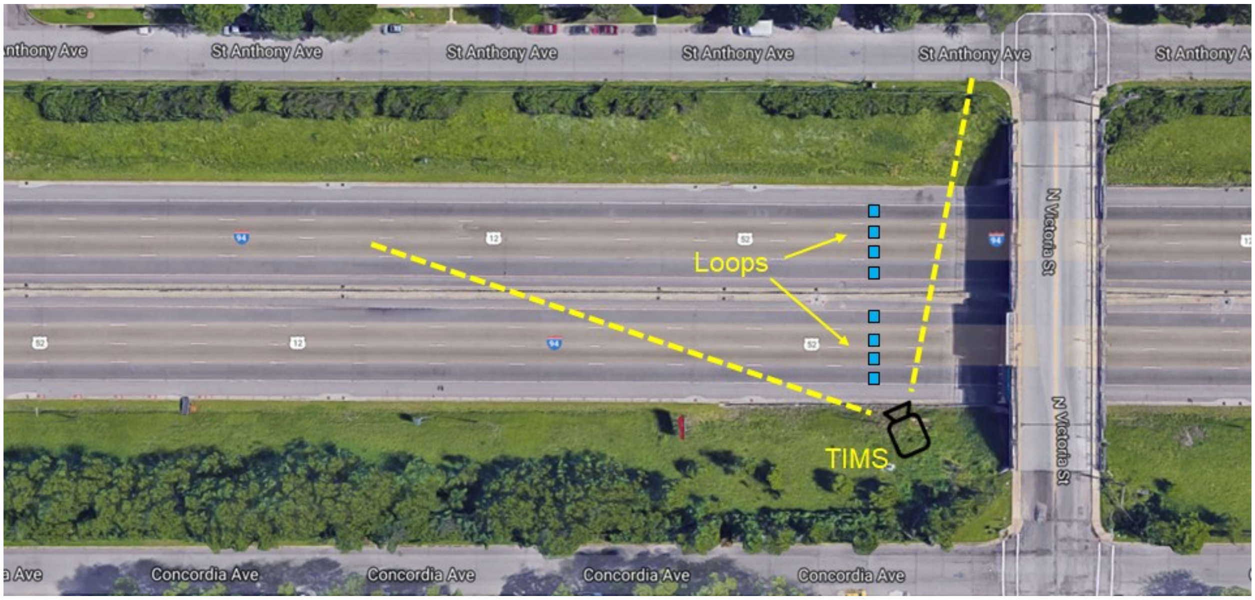

Figure 2.11 **Loop Detector Locations on I-94 West of N. Victoria Street.**

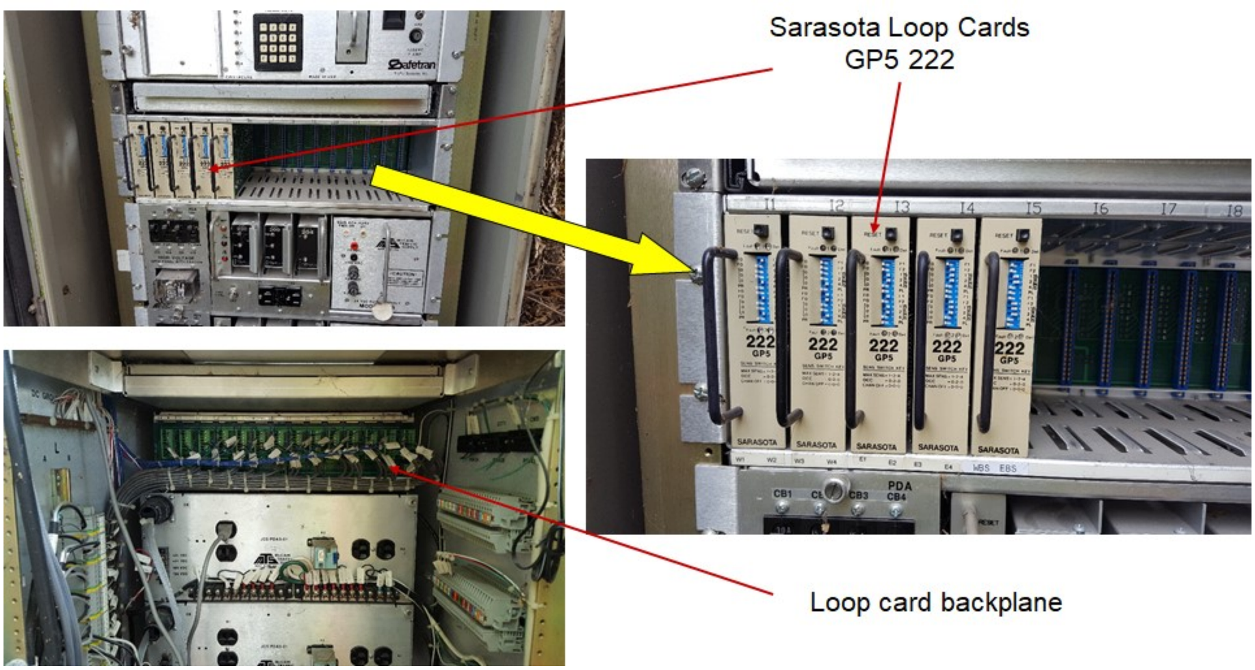

Figure 2.12 **Controller Cabinet and Loop Detector Cards at on I-94 West of N. Victoria Street.**

CHAPTER 3: METHODOLOGY AND SYSTEM INSTALLATION

3.1 METHODOLOGY

In Minnesota, vehicle classification is collected from Weigh-In-Motion (WIM) sensors at 22 stations, continuous classifiers using ATR at over 70 locations, or manually on high volume roadways. Double tubes are often used to get axle-based vehicle classification counts on roadways with less traffic. There is a need to collect vehicle classification data effectively and efficiently to support statewide transportation planning and operation.

An inductive loop signature technology was recently developed using existing loop infrastructure for vehicle classification. High resolution inductive loop signatures (as illustrated in Figure 3.1) were used to analyze unique attributes of vehicles and improve classification count accuracy. Sponsored by the USDOT SBIR program, CLR Analytics Inc. has developed a single loop signature technology using wavelet transformation and K-Nearest Neighbors (KNN) technique to re-identify and classify vehicles along a section of roadway. We would like to investigate and evaluate the performance of the single loop signature based vehicle classification technology at locations where loop detectors are installed on freeways and ramps, and at traffic signals.

Loop signature detector cards (as illustrated in Figure 3.2) and field data collection hardware and software were acquired and installed at test sites to collect vehicle classification information.

Figure 3.1 Loop Signatures for Different Type of Vehicles (Image from CLR Analytics Inc.).

Figure 3.2 Inductive Loop Signature Cards for Vehicle Classification (Image from CLR Analytics Inc.).

During the data collection period (about 1-2 week for each site), we will also collect ground-truth video data using a rapid-deployable, low-cost traffic data and video collection system (as illustrated in Figure 3.3) to validate the accuracy and reliability of vehicle classification results from the inductive loop signature cards at each test site.

The transportable video data collection was previously developed by researchers from the Minnesota Traffic Observatory (MTO)[4]. The video data collection system has an extensible mast and customized base to elevate the camera to a maximum height of 28 feet above ground. The system can be secured by clamps to sign, light, or traffic signal poles. An interface was developed to configure daily recording schedules and other hardware in order to utilize battery power as efficiently as possible. Approximately 40 hours of traffic video can be stored before battery swapping/recharging is necessary[5].

Match Ratio (MR) and Correctly Matched Ratio (CMR) measures will be used to validate the accuracy of vehicle classification results from the loop signature based vehicle classification technology. Match Ratio (MR) by vehicle class and time period is defined as the number of matched vehicle divided by the total number of vehicle observed in a time period for a vehicle class group. The Correctly Matched Ratio (CMR) measure is computed as the number of corrected matched vehicle divided by the total number of matched vehicle.

Figure 3.3 A Rapid-Deployable, Low-Cost Traffic Video Data Collection System.

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[4] "Transportable Low Cost Traffic Data Collection Device for Rapid Deployment for Intersections and Arterials" http://www.mto.umn.edu/research/ProjectDetail.html?id=2008011
[5] MTO TIMS, http://www.mto.umn.edu/research/technologies/featured/

3.2 INSTALLATION OF LOOP SIGNATURE SYSTEM

Data collection hardware, including 4 loop cards (firmware 1.76) and 2 vehicle classification master boards (firmware 1.11.0), and software were purchased to instrument the loop signature technology at each test site. The acquired hardware allows us to collect loop signature data up to 2 locations concurrently. The research team applied permits to work on MnDOT right of way (ROW) and installed loop signature and deployed video data collection system at test sites.

Inductive loop signature cards and signature data collection gateway (called *SigMaster*) were configured and installed at each site for a few weeks to collect vehicle class data. The detector card is designed to be installed into a standard rack of 170/2070 and NEMA TS-1/TS-2 controller cabinets. It is fully compatible with the conventional loop detector card. Each loop signature card is capable of collecting data from 2 independent loop channels. Each channel can be selected to operate from 16 programmable loop frequencies. The loop cards, scanning at 1,000 Hz in class mode, were configured to handle one loop detector per lane in our experiments. Local system time on both loop signature and video data collection systems was synchronized to satellite clock during each data collection period. This section describes the installation of the loop cards at each location.

3.2.1 Site #1 US-169 at CSAH 59

Two loop signature cards were installed inside the ATR353 data collection cabinet located at US169 & Delaware Ave. in Jordan MN, as illustrated in Figure 3.4. The first loop card collects loop signature data in the NB of US-169 and the other loop card collects data in the SB direction. The camera view of the video data collection system installed at this site is displayed in Figure 3.5.

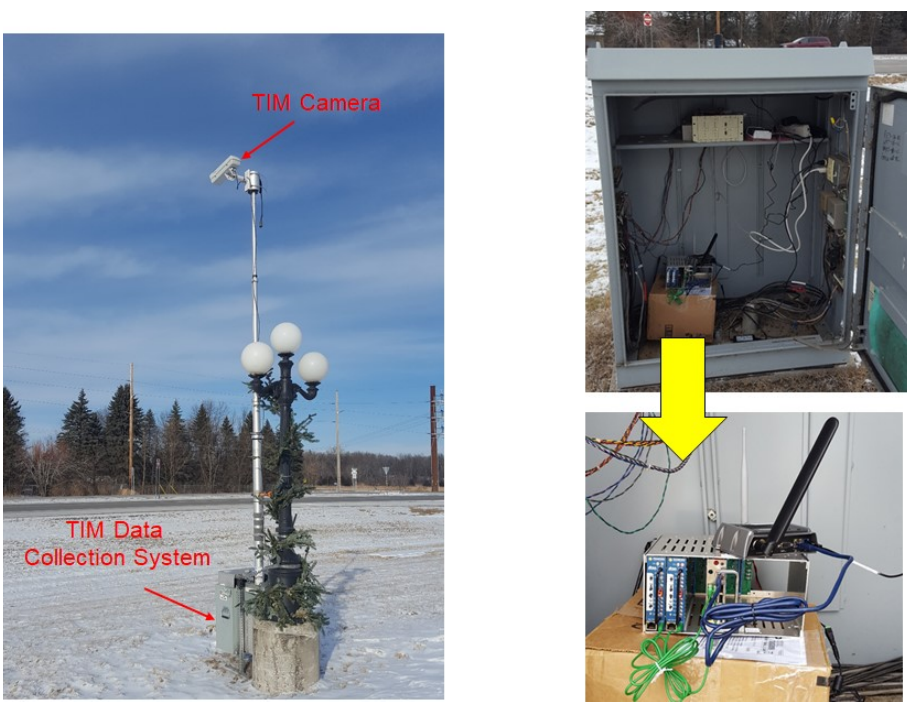


Figure 3.4 **Loop Cards and Data Collection Gateway Installed at US-169 and CR59 (Delaware Ave.).**

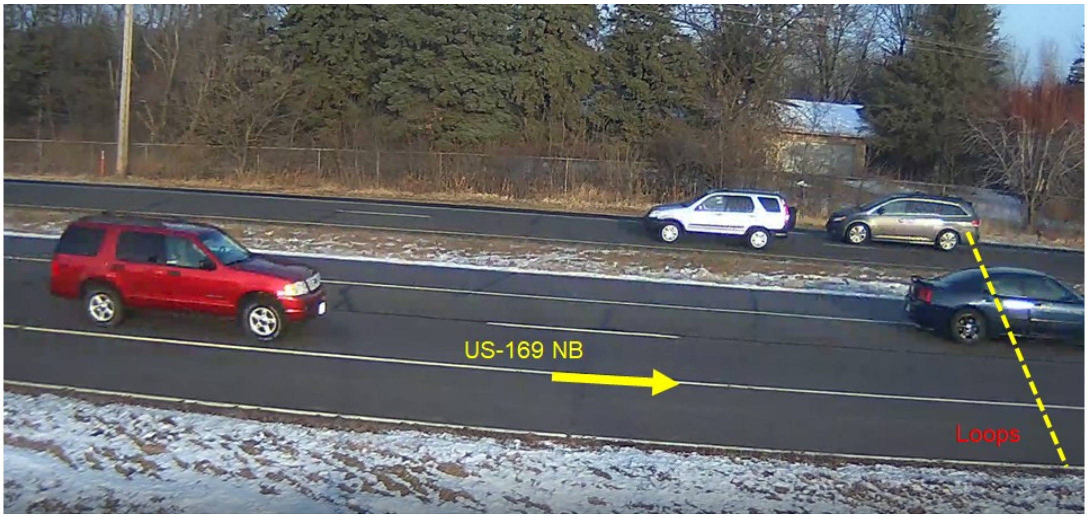


Figure 3.5 Camera View at Site #1 (US-169 at CR59/ Delaware Ave. in Jordan).

3.2.2 Site #2 US-169 at TH 282/CSAH 9

Two loop signature cards were installed inside the TS-1 signal controller cabinet at US169 & Quaker Ave. in Jordan MN, as illustrated in Figure 3.6. The first loop card covers the 2 through lane traffic on US-169 NB (signal phase 2) and the other loop card collects data from the 2 through lane traffic in the SB direction (signal phase 6). For signal control cabinet, each loop signature card requires 3 jumpers to be installed in order to provide detection output to the traffic controller. A software setting (BD1) was also adjusted to hold the detection output for 250 ms in order for the traffic controller to capture it. Installation of the data collection system at this site is illustrated in Figure 3.7. The camera views of the video data collection at this site in both NB & SB directions are displayed in Figure 3.8 and 3.9, respectively.

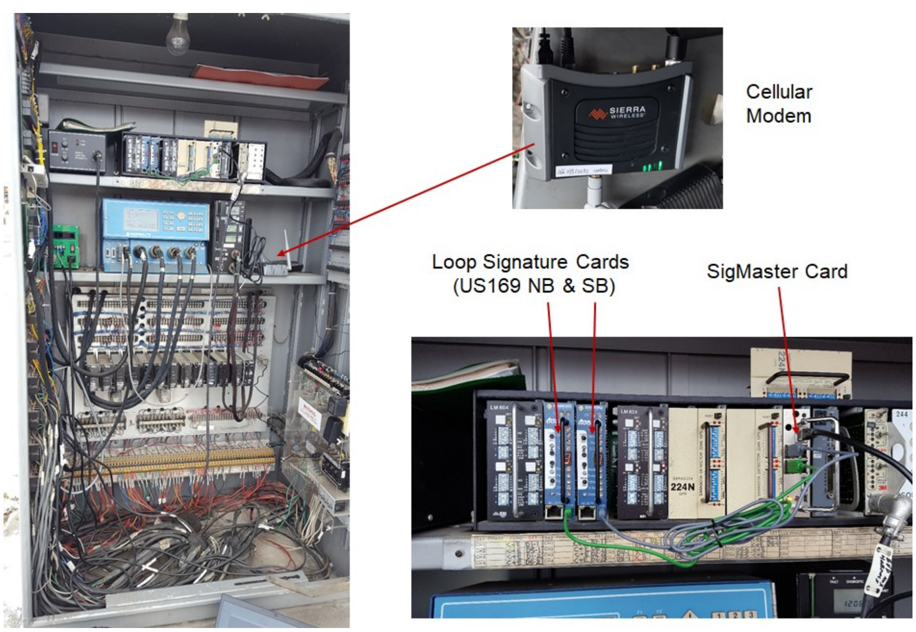


Figure 3.6 Loop Cards and Data Collection Gateway Installed at US-169 & TH-282/Quaker Ave.

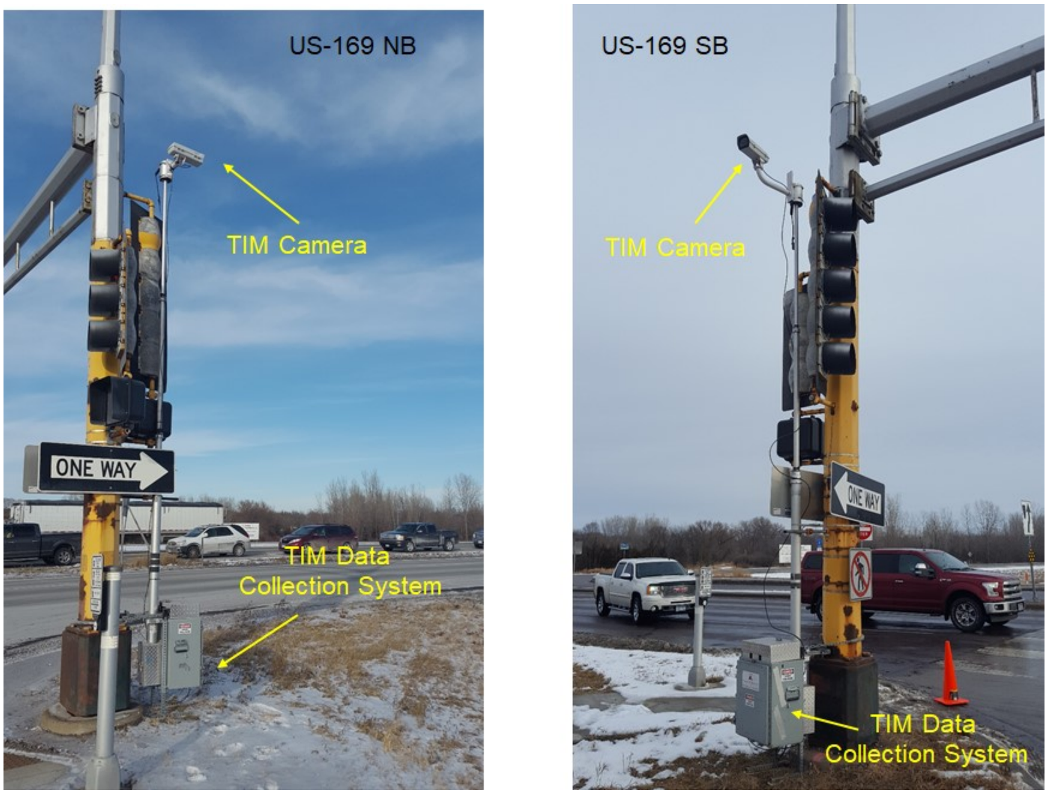


Figure 3.7 Installation of Video Data Collection System at US-169 & TH-282/Quaker Ave.

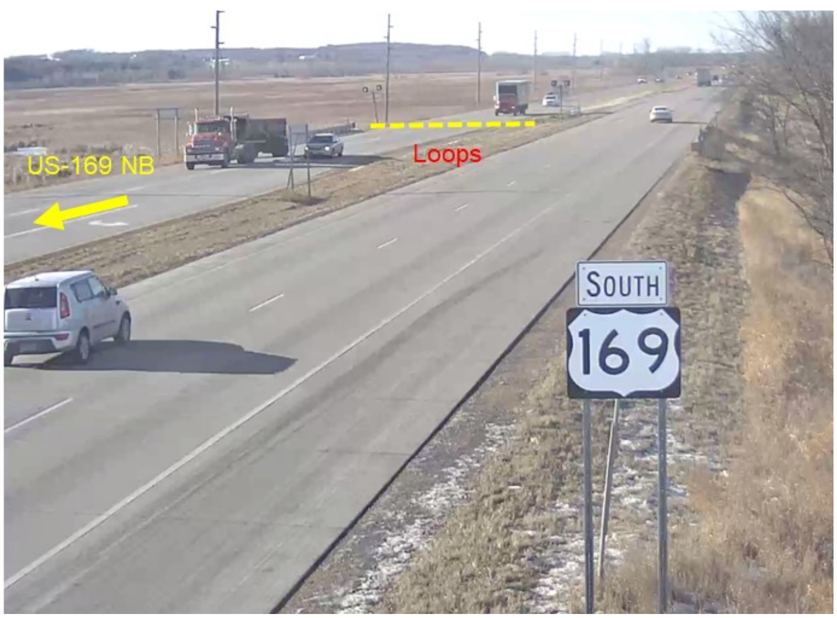


Figure 3.8 Camera View at Site #2 (US-169 NB Traffic at TH-282/Quaker Ave).

Figure 3.9 Camera View at Site #2 (US-169 SB Traffic at TH-282/Quaker Ave).

3.2.3 Site #3 TH 13 at CSAH 31 / Lynn Ave

Two loop signature cards were installed inside the TS-2 signal controller cabinet at Highway 13 and Lynn Ave. in Savage MN, as illustrated in Figure 3.10. The first loop card covers the 2 through lane traffic on TH-13 NB (signal phase 2) and the other loop card collects data from the 2 through lane traffic in the SB direction (signal phase 6). For this signal control cabinet, 3 jumpers were installed on each loop signature card in order to provide detection output to the traffic signal controller. A software setting (BD1) was also adjusted to hold the detection output for 120 ms in order for the traffic signal controller to recognize it. Installation of the data collection system at this site is illustrated in Figure 3.11. The camera views of the video data collection at this site in both NB & SB directions are displayed in Figure 3.12 and 3.13, respectively.

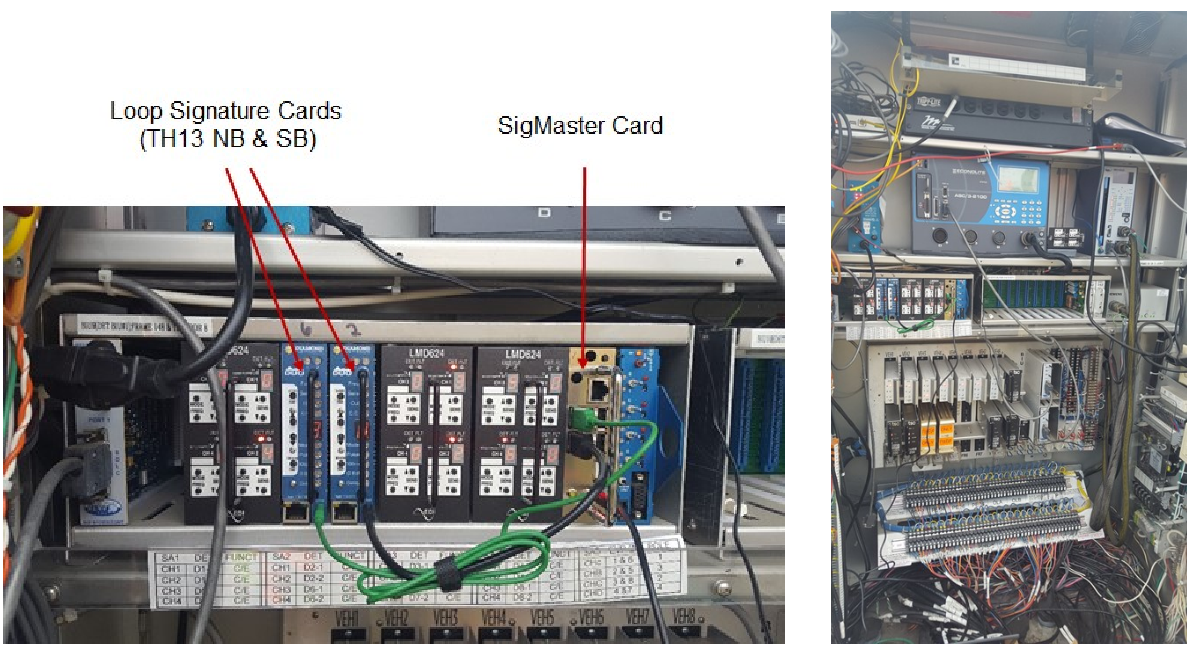


Figure 3.10 Loop Cards Installed at Site #3 (TH-13 at Lynn Ave).

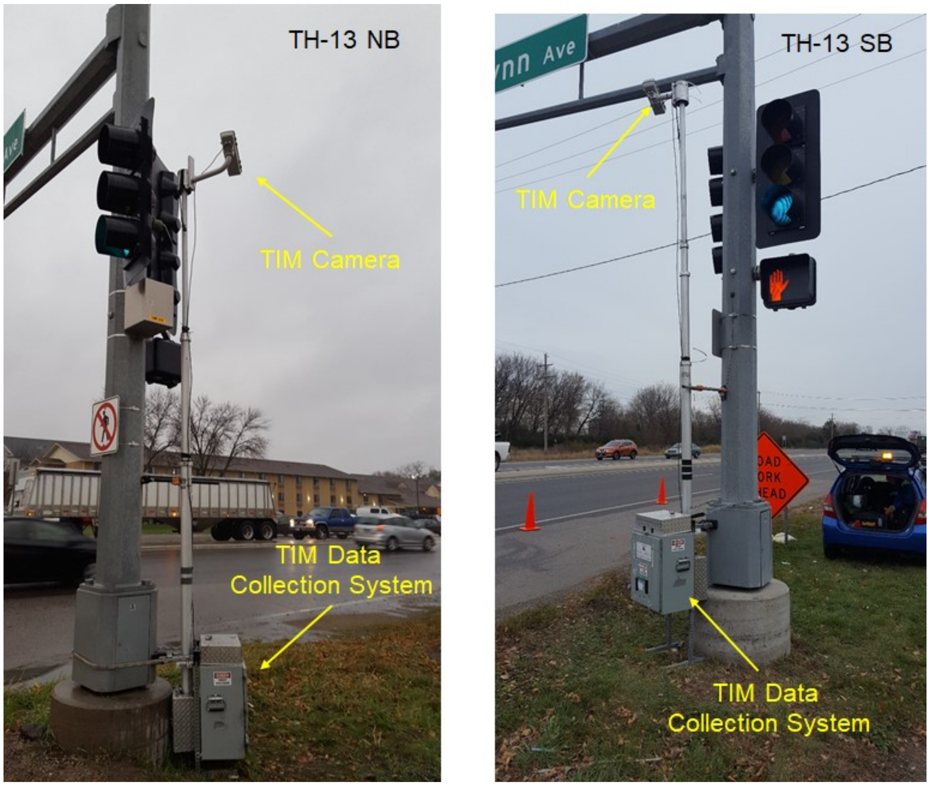


Figure 3.11 Installation of Video Data Collection System at Site #3 (TH-13 at Lynn Ave).

Figure 3.12 Camera View at Site #3 (TH-13 NB Traffic at Lynn Ave).

Figure 3.13 Camera View at Site #3 (TH-13 SB Traffic at Lynn Ave).

3.2.4 Site #4 I-35E at McAndrews Road

Two loop signature cards were installed inside the RTMC loop controller cabinet and our video data collection system was attached to the RTMC camera pole at I-35E & McAndrews Rd in Burnsville MN, as illustrated in Figure 3.14. The first loop card covers the 2-lane traffic on I-35E NB and the other loop card collects data from the 2-lane traffic in the SB direction. The camera view of the video data collection at this site is displayed in Figure 3.15.

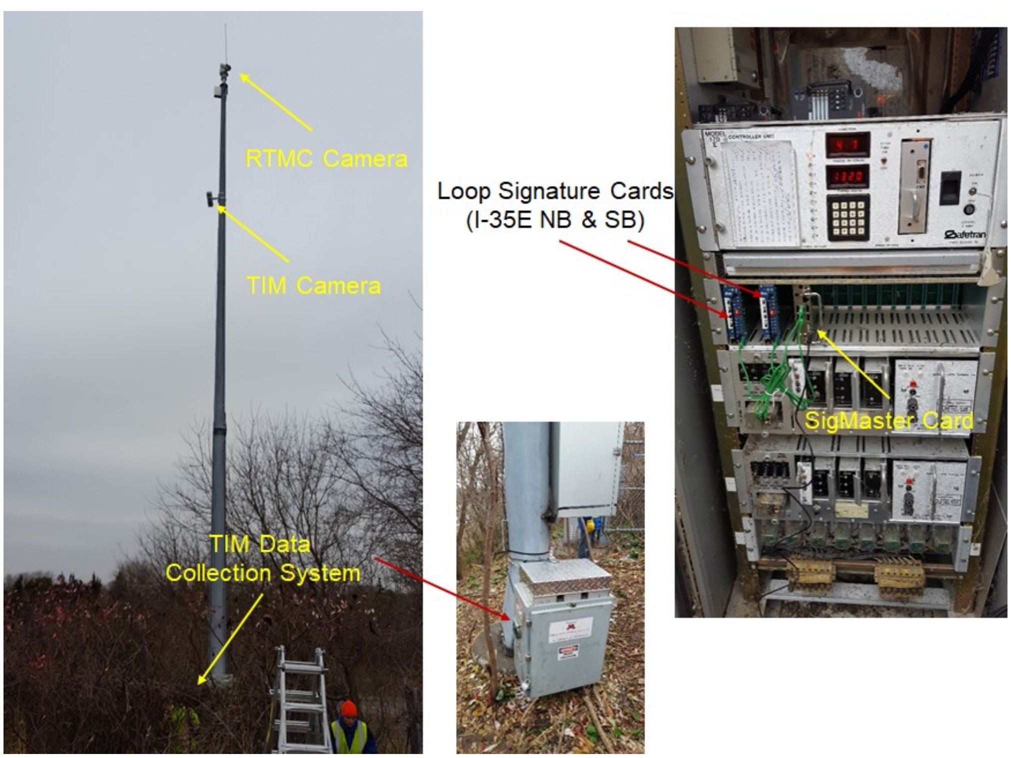


Figure 3.14 Loop Cards and Video Data Collection System Installed on I-35E at McAndrews Rd.

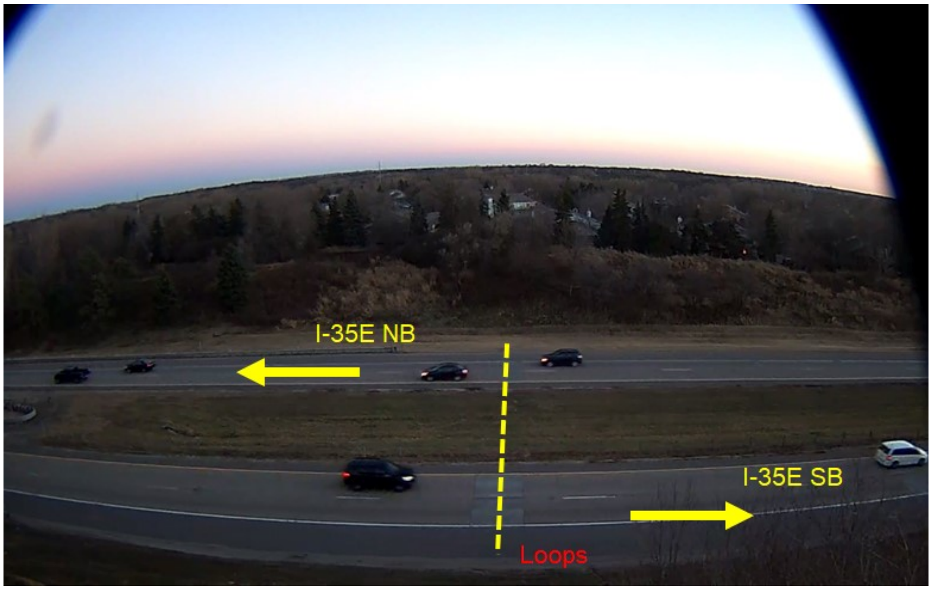


Figure 3.15 Camera View at Site #4 (I-35E at McAndrews Rd).

3.2.5 Site #5 I-94 at N Victoria St

Four loop signature cards and a data collection gateway (SigMaster card) were installed inside the RTMC loop controller cabinet at I-94 & N Victoria St. in St. Paul MN, as illustrated in Figure 3.16. The first and second loop cards cover the 4 lanes of traffic on I-94 WB and the other two loop cards collect data from the 4 lanes of traffic in the EB direction. Location of inductive loop sensors at this site is shown in Figure 3.17.

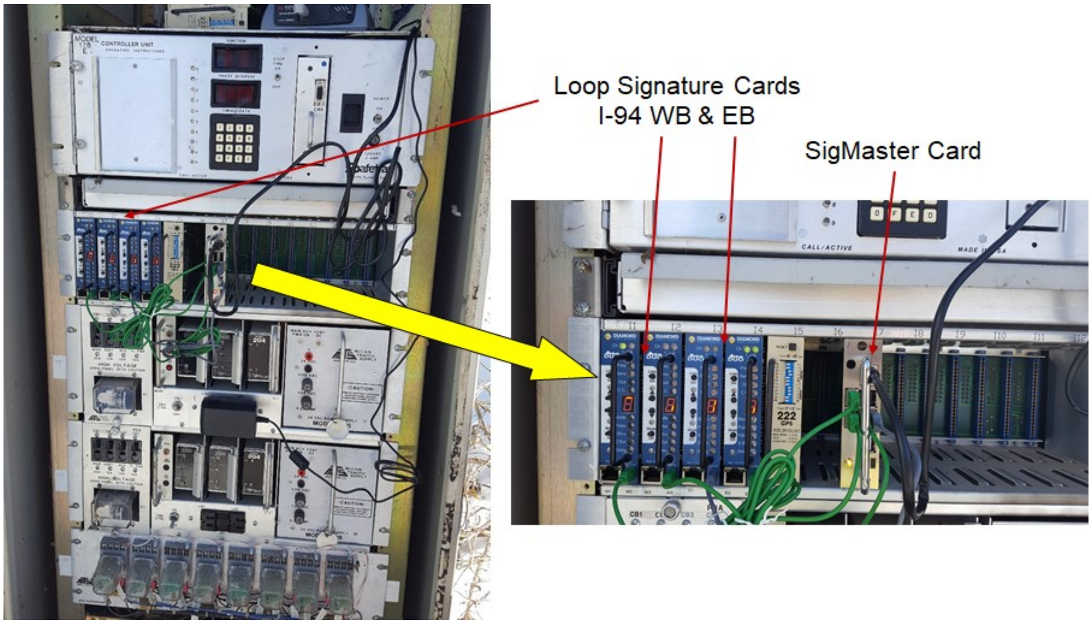


Figure 3.16 Loop Signature Cards Installed at Site #5 (I-94 at N. Victoria St. in St. Paul).

Figure 3.17 Location of Inductive Loop Sensors at Site #5 (I-94 at N Victoria St).

CHAPTER 4: DATA COLLECTION AND ANALYSIS

Loop signature data and video for ground truth data were collected at five test sites for vehicle class verification. Table 4.1 lists the data collection period for each site. Loop signature cards were installed inside the traffic signal control cabinets for two signalized intersections (site #2 and #3) and in the loop detection cabinets for an Automatic Traffic Recorder (ATR) station (site #1) and two highway sites (site #4 and #5). The loop signature cards are compatible with existing loop cards in the cabinets. A hot-swap was performed to temporarily replace the MnDOT loop cards during our data collection period.

Table 4.1 Data Collection Periods at Test Sites

Site #	Location	2016 AADT	Loop Signature Data Collection	Video Data Collection
1	ATR353, US-169 at CR59	23,000	12/14/2017 – 02/06/2018	12/15/2017 – 12/24/2017 & 12/27/2017 (Both Directions)
2	US-169 at TH-282	21,000	12/06/2017 – 01/18/2018	12/13/2017 – 12/29/2017 (SB) 12/19/2017, 12/22/2017 (NB)
3	TH-13 at Lynn Ave.	48,500	11/03/2017 – 12/06/2017	11/22/2017 – 12/05/2017 (EB) 11/20/2017 – 12/02/2017 (WB)
4	I-35E at McAndrews Rd.	55,000	11/01/2017 – 12/14/2017	11/02/2017 – 11/30/2017 (Both Directions)
5	I-94 at N. Victoria St.	154,000	02/14/2018 – 04/24/2018	03/15/2018 – 03/28/2018 (Both Directions)

A custom traffic surveillance system was previously deployed by the Minnesota Traffic Observatory (MTO) for a wide variety of projects and on many types of roadways. The self-contained system includes a high-resolution camera mounted to an extendable mast or directly to the existing infrastructure via non-invasive steel bands. A weatherproof steel container houses recording equipment and independent battery power. The entire system attaches non-invasively to any conveniently placed pole or tree.

Data collection of vehicle loop signatures and video data recording are presented in the following sections.

4.1 LOOP SIGNATURE DATA COLLECTION

The loop signature data stored locally on each data collection card were compressed into two zipped files for each day as illustrated in Figure 4.1. For example, the 'I94_Victoria-usb-I102-2018-03-29-00-00-00.zip' file contains loop signature records from a dual-loop card (configured for loop #1 & #2 at the I-94 & Victoria test site) on 3/29/2018 from 00:00:00 to 11:59:59. And, the 'I94_Victoria-usb-I102-2018-03-29-12-00-00.zip' file contains loop signature data from12:00:00 to 23:59:59 on 3/29/2018. The zipped data files can be stored locally on a SD card or automatically uploaded to a cloud server remotely if the data collection gateway is connected to the internet. We used a data modem to monitor the status of loop data collection system and retrieve the recorded loop signature data remotely.

Name	Type
I94_Victoria-usb-I102-2018-03-29-00-00-00	Compressed (zipped) Fol...
I94_Victoria-usb-I102-2018-03-29-12-00-00	Compressed (zipped) Fol...
I94_Victoria-usb-I304-2018-03-29-00-00-01	Compressed (zipped) Fol...
I94_Victoria-usb-I304-2018-03-29-12-00-03	Compressed (zipped) Fol...
I94_Victoria-usb-I506-2018-03-29-00-00-06	Compressed (zipped) Fol...
I94_Victoria-usb-I506-2018-03-29-12-00-00	Compressed (zipped) Fol...
I94_Victoria-usb-I708-2018-03-29-00-00-01	Compressed (zipped) Fol...
I94_Victoria-usb-I708-2018-03-29-12-00-01	Compressed (zipped) Fol...

Figure 4.1 Sample Loop Signature Data from Compressed in Zip Files.

Each of the zipped data files can be imported into a MySQL database, which is an open-source relational database management system (RDBMS), using a customized software tool (called *SignScope*) provided by the loop signature card vendor (CLR Analytics, Inc.). A sample of the loop signature card stored in the MySQL database is displayed in Figure 4.2. Each loop signature record includes the following data components.

- *timestamp* is the local system time when a loop card is activated by a vehicle and the signature of the inductive loop signal was captured.
- *lane* is the assigned lane number based on existing label from the traffic signal cabinet
- *loopid* is the identification of each loop assigned in the loop card to match the existing lane labels
- *seq* is the sequential number assigned by the loop card
- *classLabel* is the vehicle class determined by the vehicle classification algorithm
- *sampleCount* is the number of data samples from a loop signature profile
- *psr* data field contains the raw digital signature of a vehicle traveling over the loop detector

In addition, the *SignScope* software tool can also generate graphical loop signature profiles as displayed in Figure 4.3 for each vehicle. The vendor's software uses proprietary vehicle classification algorithm to determine the vehicle class based on the loop signature profile.

timestamp	lane	loopid	seq	classLabel	sampleCount	psr
2018-02-18 09:00:00.419	7	Loop 7S	2430	2	257	+0.025613+0.062121+0.058219+0.053751+0...
2018-02-18 09:00:01.324	5	Loop 5S	978933	2	245	+0.021704+0.041161+0.044207+0.037312+0...
2018-02-18 09:00:01.885	8	Loop 8S	755293	2	226	+0.011568+0.03444+0.049773+0.050038+0....
2018-02-18 09:00:02.794	6	Loop 6S	530195	2	265	+0.024449+0.057473+0.055878+0.043055+0...
2018-02-18 09:00:04.091	5	Loop 5S	978934	2	249	+0.023355+0.036183+0.036279+0.046477+0...
2018-02-18 09:00:07.949	7	Loop 7S	2431	2	303	+0.016905+0.051394+0.058086+0.034507+0...
2018-02-18 09:00:09.215	6	Loop 6S	530196	2	236	+0.033604+0.063015+0.055248+0.035179+0...
2018-02-18 09:00:10.586	5	Loop 5S	978935	2	235	+0.022926+0.044721+0.041532+0.040352+0...
2018-02-18 09:00:11.131	1	loop 1S	142378	2	202	+0.019367+0.041279+0.044763+0.044923+0...
2018-02-18 09:00:11.750	3	Loop 3S	578761	2	221	+0.0213+0.049091+0.050606+0.047209+0.0...
NULL	NULL	NULL	NULL	NULL	NULL	NULL

Figure 4.2 Sample Loop Signature Data Imported to a MySQL Database.

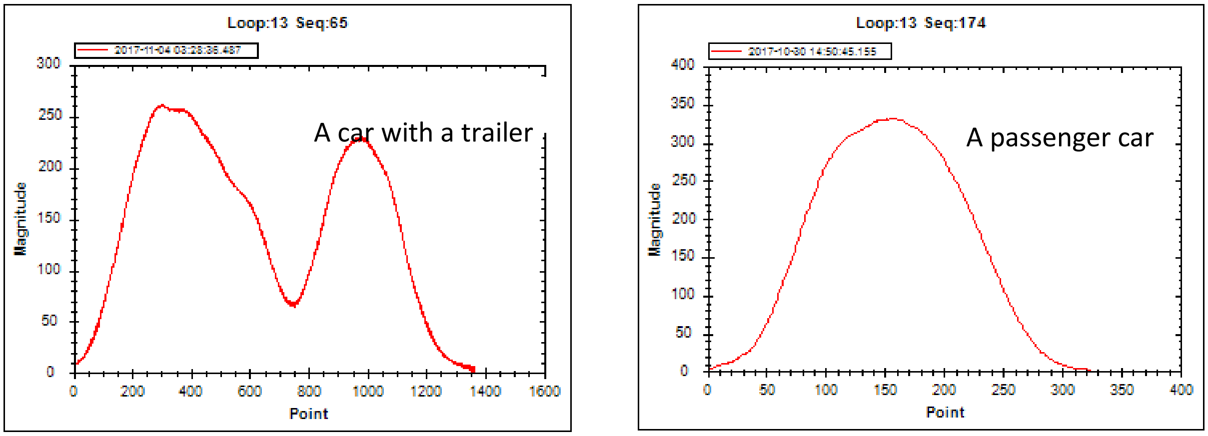


Figure 4.3 **Sample Loop Signature Profiles of Two Vehicles.**

Figure 4.4 illustrates the process of uploading the loop signature data to a cloud server and making the data available for data analysis. The cloud server is managed by the loop card vendor. Raw vehicle signature data collected from the loop detector cards were processed and stored locally on the gateway card. Daily loop data were compressed and uploaded to a cloud server via a data modem. The web-based analysis tool on the cloud server allows clients to analyze or visualize the data on a web interface. Users can also download the raw data and import the data to an open source database (MySQL) for further analysis.

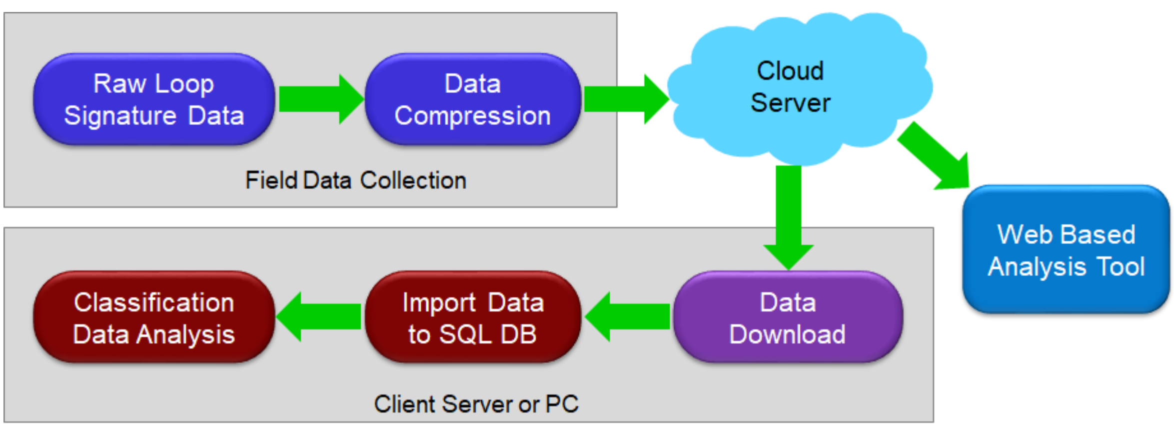


Figure 4.4 **Flowchart of Loop Data Processing and Analysis.**

4.2 VIDEO DATA COLLECTION

In the past, the Minnesota Traffic Observatory (MTO) has developed several custom traffic surveillance systems for a wide variety of projects and on all types of roadways. The system includes a high-definition camera (1080p) mounted to a mast (extendable up to 30 feet) or directly to an existing infrastructure using non-invasive steel bands. A weatherproof steel container houses recording equipment and independent battery power. The entire system can non-invasively be attached to any conveniently placed pole or tree. Figure 4.5 illustrates the attachment of the system to a traffic signal mast and the inside of the container. An inexpensive Raspberry Pi processor was used to record and store the video data on USB drives. A timer was also integrated into the system to collect video data within a desired time period (for example, 8am to 7pm) and preserve battery power. The entire system, powered by 4 deep-cycle batteries (75AH@12V), is capable of automatically recording video for about 2 weeks in the winter weather.

After obtaining permits from MnDOT, the research team deployed the video data collection equipment next to a lamp post at site #1, signal poles at signalized intersections at site #2 and #3, and RTMC light/camera poles at site #4 and #5. All 5 video data collection stations were secured to the poles at the test locations in a minimally invasive way. Deployment of the video data collection system at each test site was presented as follows.

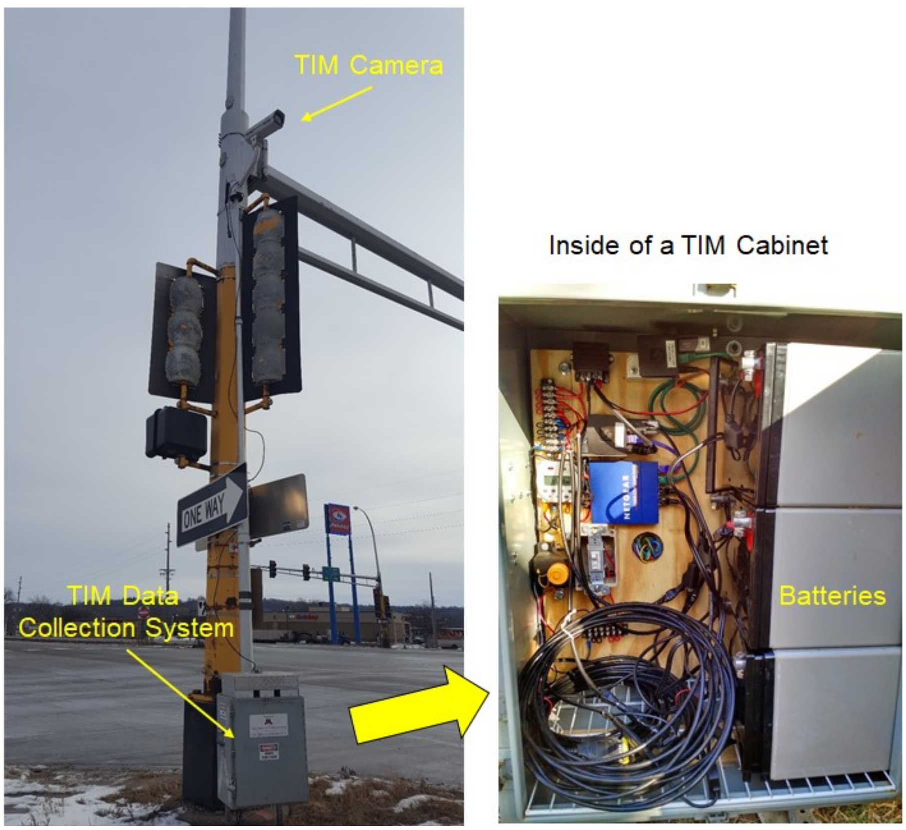


Figure 4.5 TIM Video Data Collection System Installed at Site #2

4.2.1 Site #1

A video data collection system was deployed next to a light post next to the parking lot of the Jordan Supper Club & Tap Room restaurant from 12/15/2017 to 12/17/2017. A camera (named *Ganz_India*) with 1920x1080 resolution and aspect ratio of 16:9 was used at this test site. A sample camera view of the video data collection system installed at this site is shown in Figure 4.6.

Figure 4.6 **Camera View of TIMS at Test Site #1 (Camera Facing North)**

4.2.2 Site #2

Two video data collection systems were deployed next to traffic signal poles in the NW and SE corners of the US-169 & TH-282 intersection in Jordan from 12/13/2017 to 12/29/2017. A camera (named *Axis_Hotel*) with 1280x960 resolution and aspect ratio of 4:3 was used at this location. A sample camera view of the video data collection system installed in the SE corner at this site is shown in Figure 4.7.

Figure 4.7 **Camera View of TIMS at Test Site #2 (Camera Facing Northeast)**

4.2.3 Site #3

Two video data collection systems were deployed next to traffic signal poles in the NW and SE corners of the TH-13 and Lynn Ave intersection in Savage from 11/20/2017 to 12/5/2017. A camera (named *Ganz_India*) with 1920x1080 resolution and aspect ratio of 16:9 was used at this location. A sample camera view of the video data collection system installed in the SE corner at this site is shown in Figure 4.8.

Figure 4.8 Camera View of TIMS at Test Site #3 (Camera Facing East)

4.2.4 Site #4

A video data collection systems was deployed next to the RTMC camera pole on McAndrews Road in Burnsville from 11/2/2017 to 11/30/2017. A camera (named *Ganz_Foxtrot*) with 1920x1080 resolution and aspect ratio of 16:9 was used at this location. Our camera was attached to the RTMC camera pole at this location. A sample camera view of the video data collection system installed at this site is shown in Figure 4.9.

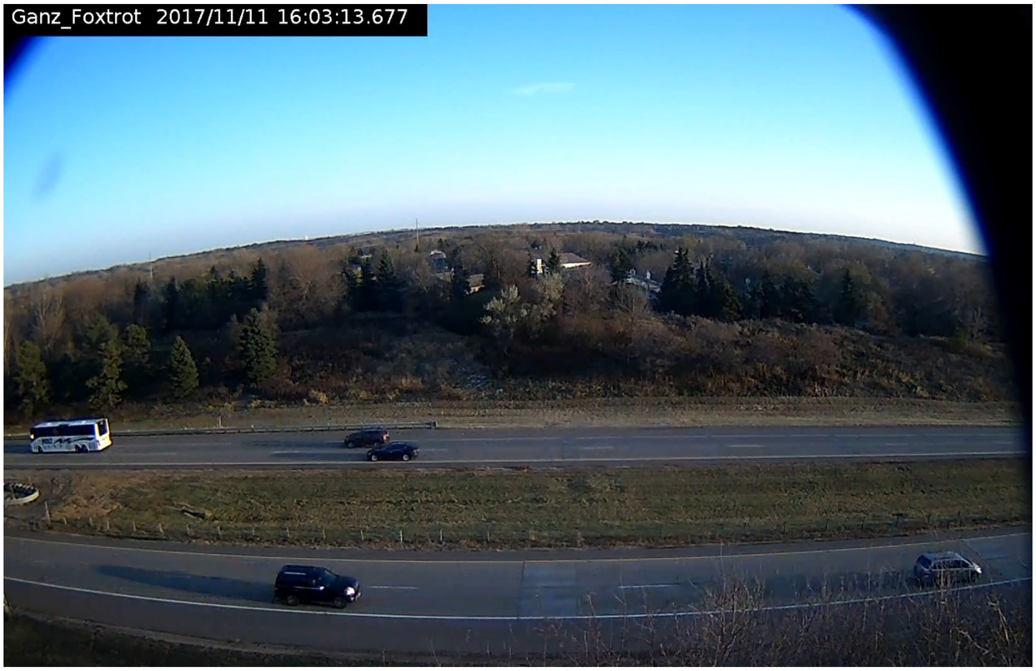


Figure 4.9 Camera View of TIMS at Test Site #4 (Camera Facing South)

4.2.5 Site #5

A video data collection systems was deployed next to the RTMC light pole on I-94 EB at N Victoria St in St. Paul from 3/15/2018 to 4/10/2018. A camera (named *Axis_Hotel*) with 1280x960 resolution and aspect ratio of 4:3 was used at this location. camera was attached to a light pole at this location. A sample camera view of the video data collection system installed at this site is shown in Figure 4.10.

Figure 4.10 Camera View of TIMS at Test Site #5 (Camera Facing East)

4.3 DATA ANALYSIS AND VERIFICATION

Traffic volume collected from loop signature system was examined and analysis. The research team also analyzed over 400 hours of loop signature data and obtained vehicle class information of over 800,000 vehicles from the recorded video data among the five test sites. Vehicle verification methodology and analysis results were discussed in this section. Table 4.2 summarizes the processed video and loop signature data.

Table 4.2 Summary of Processed Data

Site No.	1	2	3	4	5
City	**Jordan**	**Jordan**	**Savage**	**Burnsville**	**St. Paul**
Description	US169 at CSAH59	US169 at TH282	TH13 at Lynn	I-35E at McAndrew's	I-94 at Victoria
Type	ATR Loops	Intersection Loops	Intersection Loops	Highway Loops	Highway Loops
Hours of Video Processed	80	17	167.25	86	64
Total # of Vehicles Processed from Video	58,586	14,791	211,512	165,338	356,937

4.3.1 Volume Analysis

Figure 4.11 displays the hourly traffic volume at site #1 (US169 at CR59/Delaware Ave. in Jordan, MN) in the NB direction using one week of data from 12/15/2017 to 12/21/2017. The bar chart indicates the average hourly traffic count over the entire week. Throughout the entire data collection period (12/15/2017 – 2/5/2018) at this location, the average daily traffic volume in the NB direction on weekdays is 10,268, and the average daily traffic count in the NB direction on weekends is 8,919. The Annual Average Daily Traffic (AADT) count at this location in 2016 for both directions is 23,000 [15].

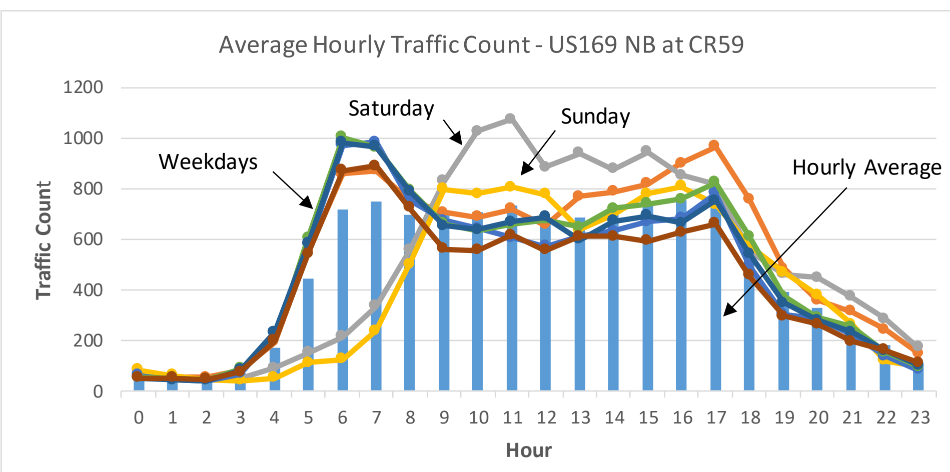


Figure 4.11 One Week of Traffic Volume by Hour at the Site #1.

Figure 4.12 shows the distribution of vehicle classification based on the Highway Performance Monitoring System (HPMS) vehicle class groups [16] at the site #1 in the NB direction using one week of loop data. Based on the loop data, class 2 or 3 vehicles averagely make up over 90% of the traffic at this location.

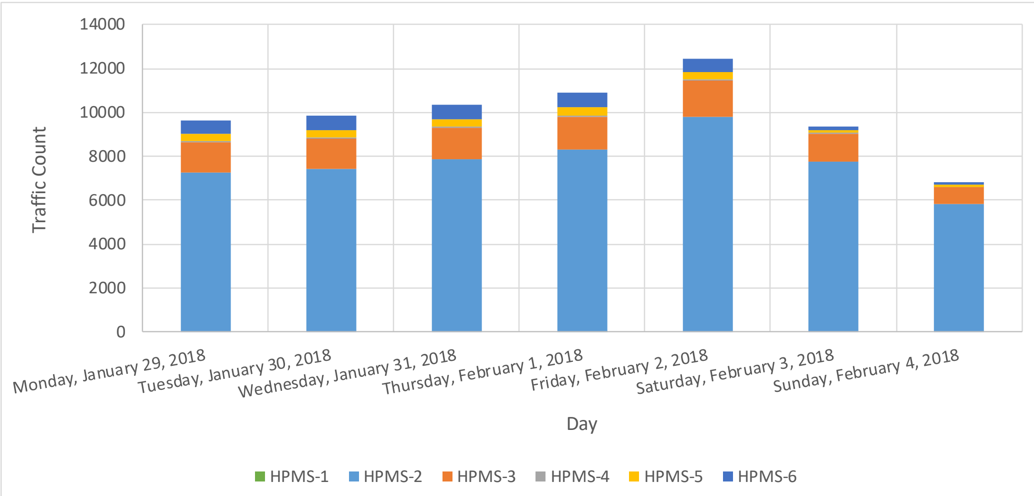


Figure 4.12 One Week of Traffic Count by HPMS Vehicle Classification at the Site #1.

Figure 4.13 displays the hourly traffic volume at site #4 (I-35E at McAndrews Road in Burnsville, MN) in the NB direction using one week of data from 12/3/2017 to 12/9/2017. The bar chart indicates the average hourly traffic count over the entire week. Throughout the entire data collection period (11/2/2017 – 12/13/2017) at this location, the average daily traffic volume in the NB direction on weekdays is 28,628, and the average daily traffic count in the NB direction on weekends is 22,556. The AADT count at this location in 2016 for both directions is 55,000.

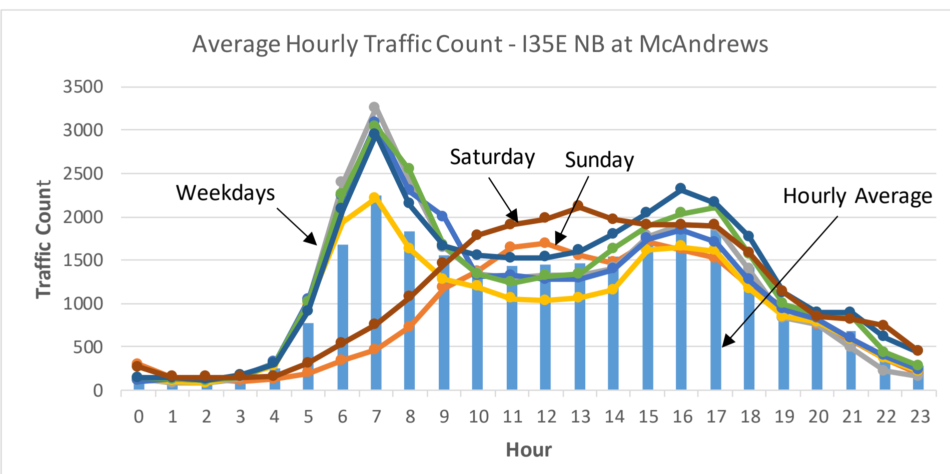


Figure 4.13 One Week of Traffic Volume by Hour at the Site #4.

Figure 4.14 shows the distribution of vehicle classification based on the HPMS vehicle class groups at the site #4 in the NB direction using one week of loop data. Based on the loop signature data, class 2 or 3 vehicles averagely make up over 94% of the traffic at this location.

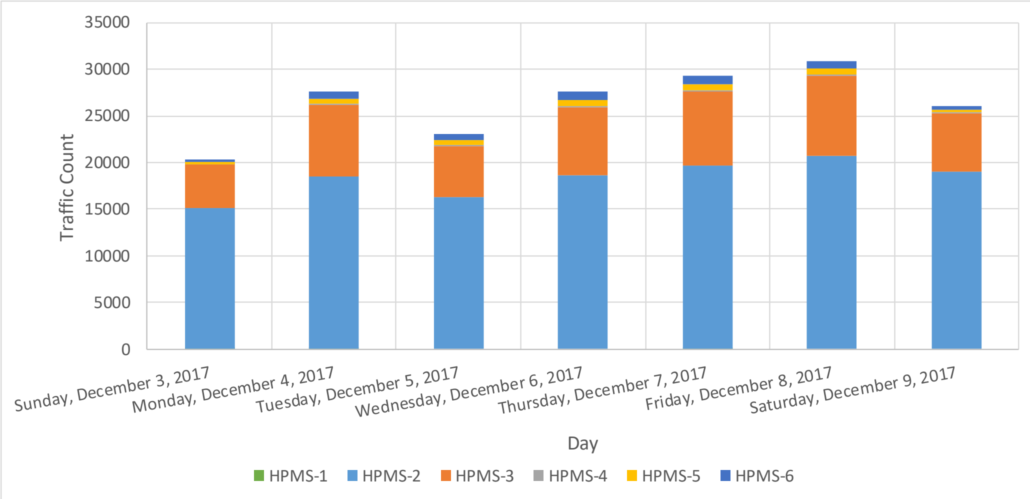


Figure 4.14 One Week of Traffic Counts by HPMS Vehicle Classification at the Site #4.

Figure 4.15 displays the hourly traffic volume at site #5 (I-94 at N Victoria Street in St. Paul, MN) in the WB direction using one week of data from 3/18/2018 to 3/24/2018. The bar chart indicates the average hourly traffic count over the entire week. Throughout the entire data collection period this location, the average daily traffic volume in the WB direction on weekdays is 87,030, and the average daily traffic count in the WB direction on weekends is 68,013. The AADT count at this location in 2016 for both directions is 154,000.

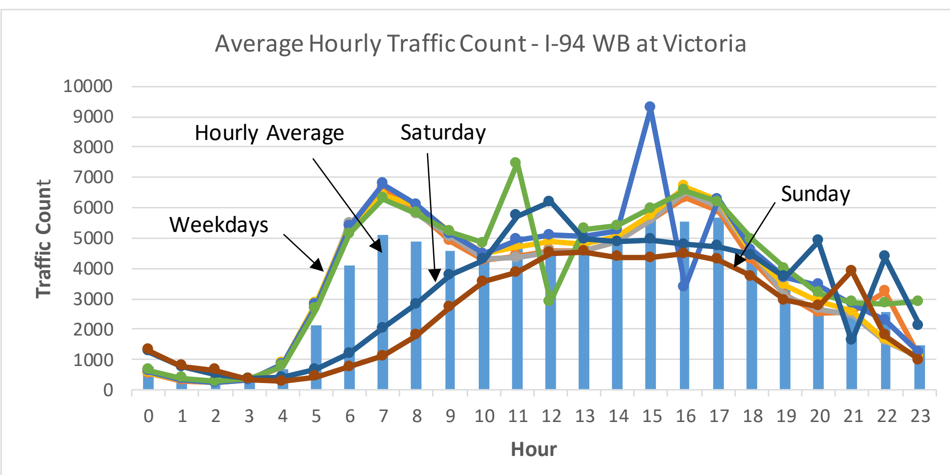


Figure 4.15 One Week of Traffic Volume by Hour at the Site #5.

Figure 4.16 shows the distribution of vehicle classification based on the HPMS vehicle class groups at the site #5 in the WB direction using one week of loop data. Based on the loop signature data, class 2 or 3 vehicles averagely make up over 96% of the traffic at this location.

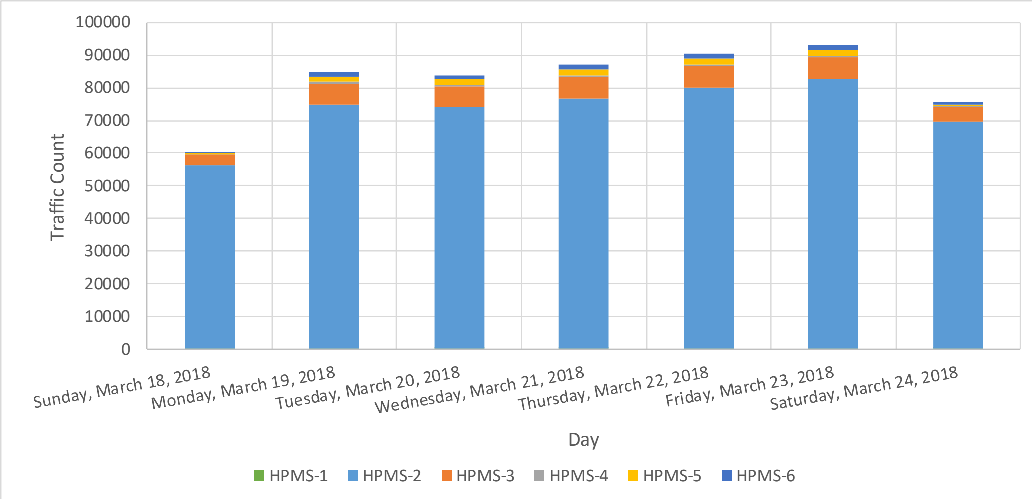


Figure 4.16 One Week of Traffic Counts by HPMS Vehicle Classification at the Site #5.

4.3.2 Verification Methodology

Vehicle classification verification was performed using two different methods: per individual vehicle and a 15-min aggregation interval. The individual vehicle verification process was time-consuming. It was analyzed using a selected set of samples (24) at difference test site. The other 400+ hours of data were analyzed using the aggregated method.

4.3.2.1 Vehicle Class Verification at Individual Vehicle Level

In order to match a vehicle from the video to the classification output from the loop signature card, the research team needs to first ensure the clock on both the video data collection and the loop signature systems are synchronized. The clock on the camera was synchronized to the internet clock prior to the deployment to each test site. The video data collection system uses the timestamp from the GPS signal when storing the hourly video data. The system clock on the loop signature card was periodically synchronized to the internet time through a data modem connected to the cellular network. Through our data analysis and verification process, we learned that the system clock on both the video and loop signature system could drift slightly over time or an offset exists due to the difference between the actual location of loops under the pavement and the perceived loop location from the camera view.

To determine the time offset between the video data and the loop signature records, the research team processed a 15-minute video by recording the lane, vehicle class, and arrival time at the loop detector for each vehicle. The pattern of the time interval between two consecutive vehicles was computed and compared with the time interval pattern from the loop signature data. For example, Figure 4.17 illustrates a pattern of time intervals between two consecutive vehicles at site #3 (TH13 SB) on 12/1/2017. The X-axis represents time in seconds from 3:00 pm and the Y-axis represents the time interval of vehicles going over loop detectors. The blue line with circle mark is the time interval manually processed from the video data. The red line with square marker represents the time intervals from the loop signature card. The time interval pattern from both datasets does not match with each other.

By examining the lane number of each vehicle and corresponding lane pattern, the researcher was able to identify the timestamp on the loop signature system was about 25.5 sec faster than the video records. After adjusting the time offset, the gap pattern from both datasets was closely matched to each other as displayed in Figure 4.18.

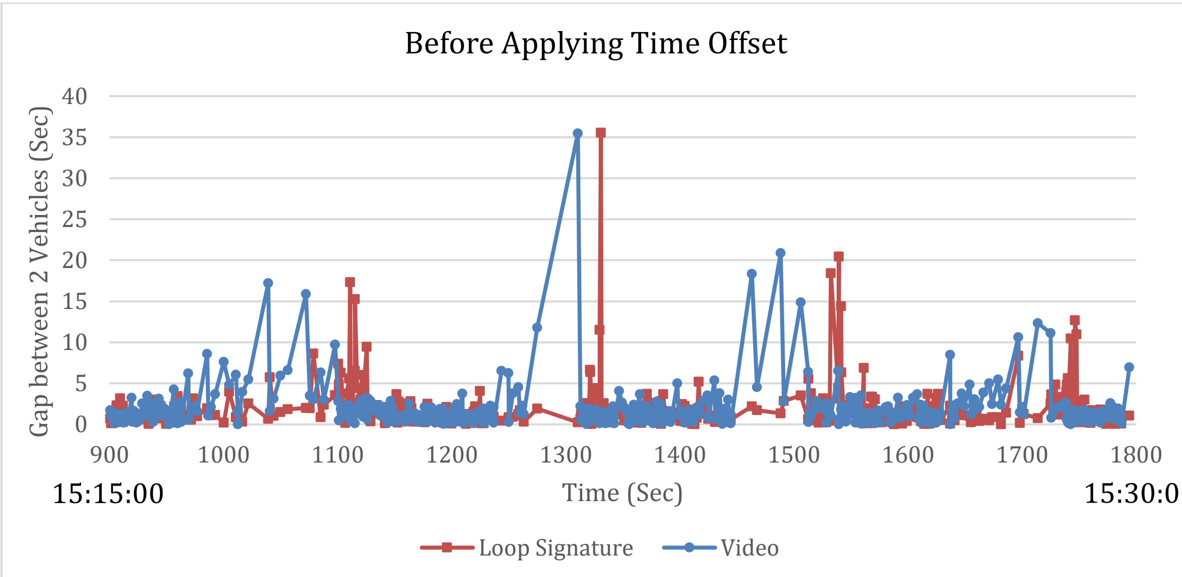


Figure 4.17 Pattern of Time Interval between Two Consecutive vehicles at Site #3 (12/1/2017 3PM).

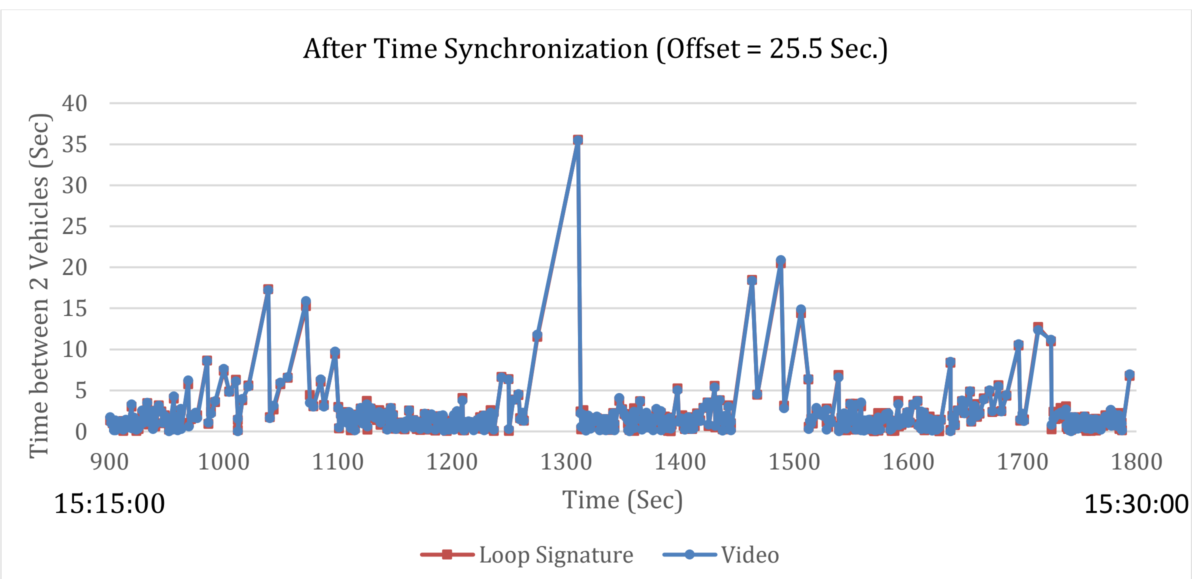


Figure 4.18 Gap Pattern of Two Consecutive Vehicles at Site #3 After Applying Clock Offset.

After applying the clock offset between the video and the loop signature data, validation of vehicle classification for each loop signature record was performed to evaluate the performance of the loop signature system. For example, Table 4.3 lists the results of matched vehicle type using the 13 Federal

Highway Administration (FHWA) vehicle classification categories (see Appendix A). Among the 516 vehicles in the 15-min interval (from 15:15:00 to 15:30:00) at site #3 in the SB of TH13 on 12/1/2017, 395 vehicles (76.6%) were matched and classified as the exact same type of vehicle as identified from the video data. Most of the vehicles were cars and the class 2 vehicles have a slightly higher matched classification rate of 80.6%.

Table 4.3 Matched Vehicle Classification Counts from Site #3

Vehicle Class	1	2	3	4	5	6	7	8	9	10	11	12	13	Total
Matched	0	370	8	1	7	1	1	0	6	1	0	0	0	395
Count from video	1	459	20	3	17	1	3	1	10	1	0	0	0	516
Match Rate	0%	81%	40%	33%	41%	100%	33%	0%	60%	100%	NA	NA	NA	77%

Table 4.4 lists the classification results of vehicles in the same 15-minute interval at site #3 by including the unmatched but classified vehicles in the corresponding bins. The loop signature card at this location tends to undercount class 2 and over count class 3 vehicles.

The approach described above was used to synchronize the timestamp between the video and loop signature data. It is time-consuming to record the time and lane number of each individual vehicle going over the loop detectors. 24 15-min time periods of video data from a selected number of days were processed to identify the clock offset and perform vehicle class validation at the individual vehicle level. Comparison of loop signatures of a few vehicles and their corresponding images from the video data were displayed in Appendix B.

Table 4.4 Vehicle Classification Counts from Site #3

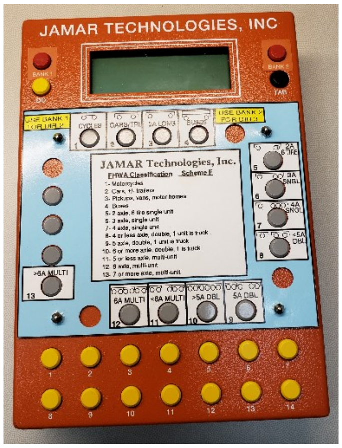
Vehicle Class	1	2	3	4	5	6	7	8	9	10	11	12	13	Total
Count from loop	0	377	103	9	12	6	1	1	6	1	0	0	0	516
Count from video	1	459	20	3	17	1	3	1	10	1	0	0	0	516
Error %	-100%	-18%	415%	200%	-29%	500%	-67%	0%	-40%	0%	NA	NA	NA	0%

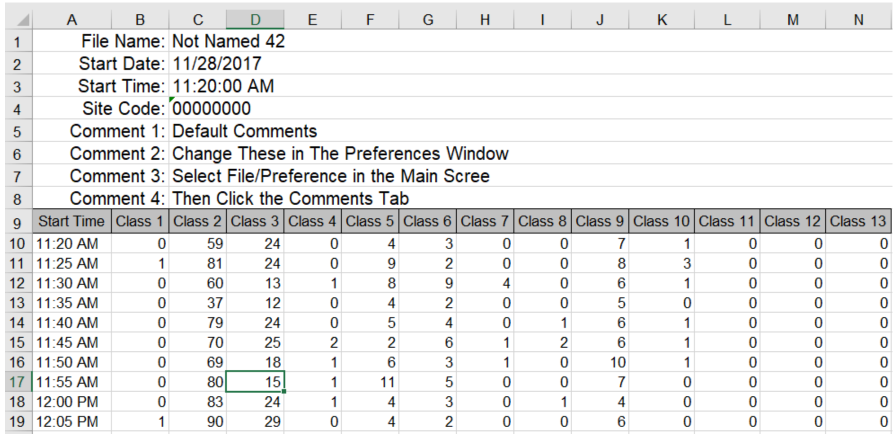
4.3.2.2 Vehicle Class Verification Using 15-min Aggregation

The research team initially used the Jamar traffic data collector[6] to manually obtain vehicle class information. Undergraduate student assistants were asked to observe the recorded video and press the corresponding button on the Jamar counter for each vehicle. The Jamar data recorder and a sample of exported vehicle classification output are shown in Figure 4.19. The Jamar counter allows users to set the starting time of the counter to the video timestamp. However, this counter is designed for counting

[6] JAMAR Technologies, https://www.jamartech.com/index.html

traffic on the street in real-time. There is no time synchronization between the Jamar counter and the video. Students will need to reinitiate a new counting task after pausing the video observation.





	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	File Name:	Not Named 42												
2	Start Date:	11/28/2017												
3	Start Time:	11:20:00 AM												
4	Site Code:	00000000												
5	Comment 1:	Default Comments												
6	Comment 2:	Change These in The Preferences Window												
7	Comment 3:	Select File/Preference in the Main Scree												
8	Comment 4:	Then Click the Comments Tab												
9	Start Time	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12	Class 13
10	11:20 AM	0	59	24	0	4	3	0	0	7	1	0	0	0
11	11:25 AM	1	81	24	0	9	2	0	0	8	3	0	0	0
12	11:30 AM	0	60	13	1	8	9	4	0	6	1	0	0	0
13	11:35 AM	0	37	12	0	4	2	0	0	5	0	0	0	0
14	11:40 AM	0	79	24	0	5	4	0	1	6	1	0	0	0
15	11:45 AM	0	70	25	2	2	6	1	2	6	1	0	0	0
16	11:50 AM	0	69	18	1	6	3	1	0	10	1	0	0	0
17	11:55 AM	0	80	15	1	11	5	0	0	7	0	0	0	0
18	12:00 PM	0	83	24	1	4	3	0	1	4	0	0	0	0
19	12:05 PM	1	90	29	0	4	2	0	0	6	0	0	0	0

Figure 4.19 JAMAR Traffic Data Collector and a Sample Output.

The research team later used a vehicle counting software (*CountPro*) and a keypad (*CountPad2*) from countingCar.com [17] to better facilitate the video data reduction process. The *CountPro* tool allows users to load a video and synchronize the system time to the timestamp on the video. The video control options allow the user to zoom into the video and select a different playback speed. As illustrated in Figure 4.20, the software tool can automatically generate vehicle counts in corresponding bins in a selectable time interval (e.g., 1, 5, or 15-min, etc.). In order to facilitate the classification counting process for this project, we created a customized template on the Count Pad and only use 14 keys around the template for our classification counts. In addition, the red pause key in the middle of the Count Pad allows users to pause the video and resume the vehicle count at any time. After finishing the data reduction on a video, the *CountPro* software can export the results to an Excel file for additional analysis with the loop signature data.

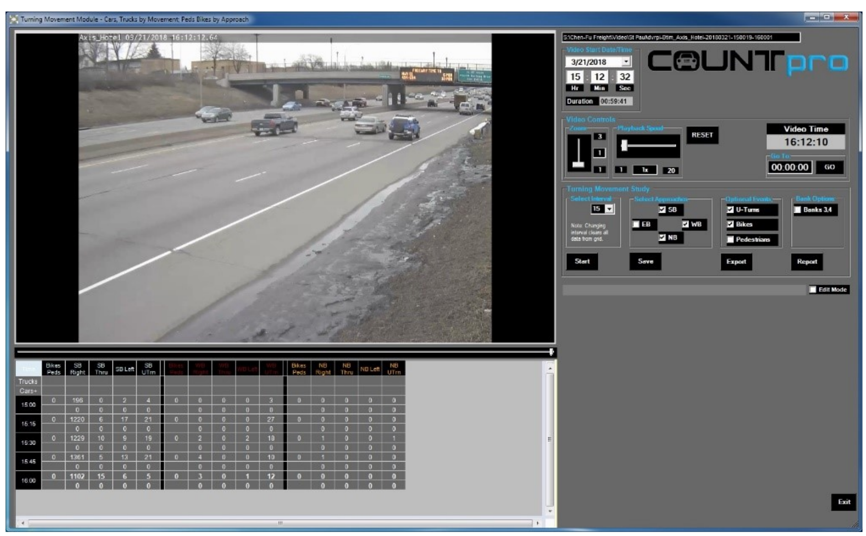


Figure 4.20 CountPad (left) and a Screenshot of the CountPro Software Tool.

4.4 VERIFICATION OF VEHICLE CLASSIFICATION

Verification results from the vehicle classification process using both methods as described in the previous section were discussed and presented as follows.

4.4.1 Individual Vehicle Verification

The research team performed 24 rounds of vehicle class verification (over 8,000 vehicles) at the individual vehicle level. As listed in Table 4.5, the exact match rate for all 13 types of vehicles ranges from 65% to 90%, with an average matching rate of 75.1% and a standard deviation (SD) of 7.7%. Modern vehicles such as sedans, pickup truck, and SUVs share similar vehicle chassis. The classification distinctions between type 2 and 3 vehicles are less obvious. If we include the miscount error between class 2 and 3 for the classification analysis, the average matching rate (column "Match Rate 23" in Table 4.5) improves to 88.9% with an SD of 6.7%. Additional results by vehicle class are summarized in Appendix C.

Table 4.5 Summarized Results of Individual Vehicle Classification Match

ID	Site	Date	Time	Match Rate	Match Rate 23	Number of Vehicles
1	1	20171220	10:00 AM	78.8%	83.2%	139
2	1	20171220	3:00 PM	79.7%	85.7%	182
3	1	20171222	10:00 AM	70.3%	85.5%	165
4	1	20171227	3:00 PM	83.8%	92.7%	180
5	3	20171121	10:00 AM	70.2%	81.4%	258
6	3	20171121	3:00 PM	67.7%	85.0%	397
7	3	20171123	10:00 AM	78.5%	98.1%	260
8	3	20171123	3:00 PM	84.4%	97.6%	212
9	3	20171125	10:00 AM	76.0%	95.9%	221
10	3	20171125	3:00 PM	79.5%	96.2%	292
11	3	20171127	10:00 AM	65.9%	79.3%	261
12	3	20171127	3:00 PM	65.0%	85.0%	320
13	3	20171129	10:00 AM	66.4%	74.9%	235
14	3	20171129	3:00 PM	66.5%	84.4%	352
15	3	20171201	10:00 AM	66.1%	77.1%	271
16	3	20171201	3:00 PM	76.6%	92.2%	516
17	4	20171128	10:00 AM	65.2%	90.5%	316
18	4	20171128	3:00 PM	69.3%	89.8%	449
19	4	20171129	10:00 AM	70.3%	88.2%	340
20	4	20171129	3:00 PM	89.3%	93.9%	413
21	5	20180321	10:00 AM	81.2%	96.1%	549
22	5	20180321	3:00 PM	82.8%	93.8%	664
23	5	20180322	10:00 AM	84.8%	91.3%	448
24	5	20180322	3:00 PM	84.0%	95.5%	733
Average Match Rate				**75.1%**	**88.9%**	**Total: 8,173 Vehicles**
Standard Deviation (SD)				**7.7%**	**6.7%**	

4.4.1.1 Site 1: US-169 at CR59 (Jordan)

Table 4.6 summaries the vehicle classification results by FHWA vehicle class from site #1. Class 2 vehicle has the highest matching rate (85%) with a large amount of class 2 vehicles (12%) being misclassified as class 3. Similarly, class 3 has a relatively lower matching rate of 35% with a significant number of class 3 vehicles (35%) being misclassified as class 2. Class 5 has a relatively lower matching rate of 50% with 10%, 20%, and 20% of class 5 trucks being respectively misclassified as class 2, 3, and 4 vehicles. In addition, Class 9 has a relatively lower matching rate of 29% with a significant number of class 9 trucks (17%) being misclassified as class 2 vehicles.

Table 4.6 Vehicle Classification Results by Class at Site #1 (662 Vehicles)

Class		Vehicle Classified by Loop Signature System													Sum	Percent
		1	2	3	4	5	6	7	8	9	10	11	12	13		
Vehicle Class from Video Data	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	NA
	2	0	493	68	4	5	0	0	2	6	3	1	0	0	582	84.7%
	3	0	7	7	2	1	2	0	0	0	0	1	0	0	20	35.0%
	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	NA
	5	0	1	2	2	5	0	0	0	0	0	0	0	0	10	50.0%
	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	NA
	7	0	1	0	0	0	2	0	0	0	0	0	0	0	3	0.0%
	8	0	0	0	0	0	1	0	1	0	0	0	0	0	2	50.0%
	9	0	7	1	1	4	3	0	10	12	0	3	1	0	42	28.6%
	10	0	0	0	0	0	1	0	1	0	1	0	0	0	3	33.3%
	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	NA
	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	NA
	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	NA

4.4.1.2 Site 3: TH-13 at Lynn Ave (Savage)

Table 4.7 summaries the vehicle classification results by FHWA vehicle class from site #3. Class 2 vehicle has the highest matching rate (77%) with a large amount of class 2 vehicles (20%) being misclassified as class 3. Similarly, class 3 has a relatively lower matching rate of 40% with a significant number of class 3 vehicles (33%) being misclassified as class 2. Class 5 has a relatively lower matching rate of 50% with 9%, 13%, and 18% of class 5 trucks being respectively misclassified as class 2, 3, and 4 vehicles. In addition, Class 9 has a relatively lower matching rate of 48% with a significant number of class 9 trucks (20%) being misclassified as class 2 vehicles.

Table 4.7 Vehicle Classification Results by Class at Site #3 (3,572 Vehicles)

Class		Vehicle Classified by Loop Signature System													Sum	Percent
		1	2	3	4	5	6	7	8	9	10	11	12	13		
Vehicle Class from Video Data	1	0	3	1	0	1	0	0	0	0	0	0	0	0	5	0.0%
	2	0	2365	613	23	42	5	1	5	6	0	2	1	0	3063	77.2%
	3	0	58	69	27	11	3	2	2	0	0	0	0	0	172	40.1%
	4	0	3	3	2	3	0	0	0	0	0	0	0	0	11	18.2%
	5	0	11	16	22	59	6	3	2	0	0	0	0	0	119	49.6%
	6	0	2	6	1	10	12	1	1	0	1	0	0	0	34	35.3%
	7	0	3	6	1	5	4	7	0	0	0	0	0	0	26	26.9%
	8	0	1	0	0	1	0	0	1	3	0	0	0	0	6	16.7%
	9	0	23	11	2	6	1	0	6	54	7	3	0	0	113	47.8%
	10	0	4	4	0	0	0	0	1	6	6	1	0	0	22	27.3%
	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	NA
	12	0	0	0	0	0	0	0	0	0	0	0	1	0	1	100.0%
	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	NA

4.4.1.3 Site 4: I-35E at McAndrews Rd (Burnsville)

Table 4.8 summaries the vehicle classification results by FHWA vehicle class from site #4. Class 2 vehicle has the highest matching rate (79%) with a large amount of class 2 vehicles (20%) being misclassified as class 3. Similarly, class 3 has a relatively lower matching rate of 36% with a significant number of class 3 vehicles (46%) being misclassified as class 2. Class 5 has a relatively lower matching rate of 33% with 47% and 7% of class 5 trucks being respectively misclassified as class 2 and 3 vehicles. In addition, Class 9 has a relatively lower matching rate of 44% with a significant number of class 9 trucks (28%) being misclassified as class 2 vehicles.

Table 4.8 Vehicle Classification Results by Class at Site #4 (1,518 Vehicles)

Class		Vehicle Classified by Loop Signature System													Sum	Percent
		1	2	3	4	5	6	7	8	9	10	11	12	13		
Vehicle Class from Video Data	1	0	2	0	0	0	0	0	0	0	0	0	0	0	2	0.0%
	2	0	1055	271	1	4	0	0	2	0	0	0	0	0	1333	79.1%
	3	0	36	28	0	6	4	0	3	0	1	0	0	0	78	35.9%
	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	NA
	5	0	7	1	0	5	1	1	0	0	0	0	0	0	15	33.3%
	6	0	3	0	0	3	1	0	0	0	0	0	0	0	7	14.3%
	7	0	1	0	0	0	1	0	1	0	0	0	0	0	3	0.0%
	8	0	0	0	0	1	0	0	2	0	0	0	0	0	3	66.7%
	9	0	21	2	0	2	0	0	8	33	8	1	0	0	75	44.0%
	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	NA
	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	NA
	12	0	0	0	0	0	0	0	0	1	0	0	1	0	2	50.0%
	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	NA

4.4.1.4 Site 5: I-94 at N. Victoria Street (St. Paul)

Table 4.9 summaries the vehicle classification results by FHWA vehicle class from site #5. Class 2 vehicle has the highest matching rate (88%) with a large amount of class 2 vehicles (11%) being misclassified as class 3. Similarly, class 3 has a relatively lower matching rate of 34% with a significant number of class 3 vehicles (45%) being misclassified as class 2. Class 5 has a relatively lower matching rate of 50% with 14%, 9%, and 5% of class 5 trucks being respectively misclassified as class 2, 3, and 4 vehicles. In addition, Class 9 has a relatively lower matching rate of 53% with a significant number of class 9 trucks (15%) being misclassified as class 2 vehicles.

Table 4.9 Vehicle Classification Results by Class at Site #5 (2,381 Vehicles)

Class		Vehicle Classified by Loop Signature System													Sum	Percent
		1	2	3	4	5	6	7	8	9	10	11	12	13		
Vehicle Class from Video Data	1	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0.0%
	2	0	1901	232	4	17	3	1	1	4	0	1	0	0	2164	87.8%
	3	0	47	35	5	10	4	0	3	0	0	0	0	0	104	33.7%
	4	0	2	1	7	2	3	0	0	0	0	0	0	0	15	46.7%
	5	0	3	2	1	11	4	1	0	0	0	0	0	0	22	50.0%
	6	0	1	1	0	1	2	0	0	0	0	0	0	0	5	40.0%
	7	0	1	0	0	3	2	0	1	0	0	0	0	0	7	0.0%
	8	0	0	0	0	0	0	0	1	0	0	0	0	0	1	100.0%
	9	0	9	3	0	2	1	0	10	32	4	0	0	0	61	52.5%
	10	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0.0%
	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	NA
	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	NA
	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	NA

4.4.1.5 Combined 24 Samples

Table 4.10 summaries the vehicle classification results by FHWA vehicle class from all sites. Class 2 vehicle has the highest matching rate (81%) with a large amount of class 2 vehicles (17%) being misclassified as class 3. Similarly, class 3 has a relatively lower matching rate of 37% with a significant number of class 3 vehicles (40%) being misclassified as class 2. Class 5 has a relatively lower matching rate of 48% with 13%, 13%, and 15% of class 5 trucks being respectively misclassified as class 2, 3, and 4 vehicles. In addition, Class 9 has a relatively lower matching rate of 45% with a significant number of class 9 trucks (21%) being misclassified as class 2 vehicles. The traffic volume in the other class categories is relatively low among all the test sites.

Table 4.10 Vehicle Classification Results by Class (Combining all 24 Samples, 8,133 Vehicles)

Class		Vehicle Classified by Loop Signature System													Sum	Percent
		1	2	3	4	5	6	7	8	9	10	11	12	13		
Vehicle Class from Video Data	1	0	6	1	0	1	0	0	0	0	0	0	0	0	8	0.0%
	2	0	5814	1184	32	68	8	2	10	16	3	4	1	0	7142	81.4%
	3	0	148	139	34	28	13	2	8	0	1	1	0	0	374	37.2%
	4	0	5	4	9	5	3	0	0	0	0	0	0	0	26	34.6%
	5	0	22	21	25	80	11	5	2	0	0	0	0	0	166	48.2%
	6	0	6	7	1	14	15	1	1	0	1	0	0	0	46	32.6%
	7	0	6	6	1	8	9	7	2	0	0	0	0	0	39	17.9%
	8	0	1	0	0	2	1	0	5	3	0	0	0	0	12	41.7%
	9	0	60	17	3	14	5	0	34	131	19	7	1	0	291	45.0%
	10	0	5	4	0	0	1	0	2	6	7	1	0	0	26	26.9%
	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	NA
	12	0	0	0	0	0	0	0	0	1	0	0	2	0	3	66.7%
	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	NA

4.4.2 Aggregated Analysis

In addition, the research team also analyzed over 400 hours of video data from five test sites with a total number of vehicles over 807,000 in 15-min aggregation. Analysis results from each test site are discussed as follows.

4.4.2.1 Site 1: US-169 at CR59 (Jordan)

The research team observed 80 hours (9am-5pm for 11 days) of video data and processed over 58,450 vehicles at this location. As illustrated in Figure 4.21, 91.1% of vehicles at this location are class 2 passenger cars and 4.7% of the traffic is class 9 trucks. The other vehicles combined consist of less than 5% of the total traffic at this site. Figure 4.22 illustrates the daily traffic volume percentage error when comparing the vehicle counts from the loop signature system to the video data. On average, the traffic volume error is within ±1% except on 12/27/2017 which has an error of 2.16%. Comparisons of traffic count in peak and off-peak periods are also displayed in Figure 4.22. There is no significant traffic count error between peak and mid-day hours. The reason for the spike of volume count error is unknown, however, we noticed that the average temperature on 12/27/2017 is relatively lower than the average temperature from previous days as listed in Table 4.11.

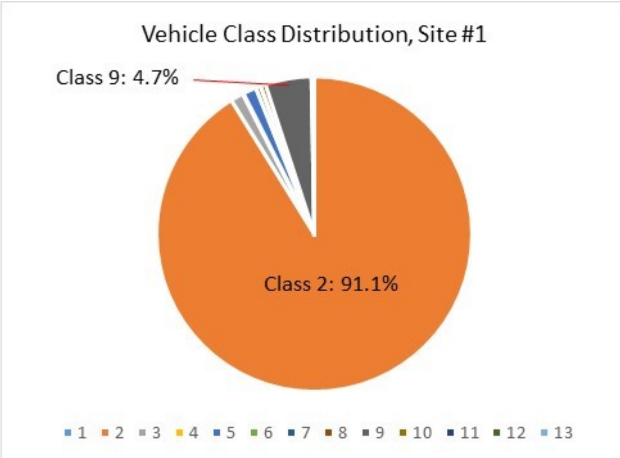


Figure 4.21 Distribution of Vehicle Classification at Site #1.

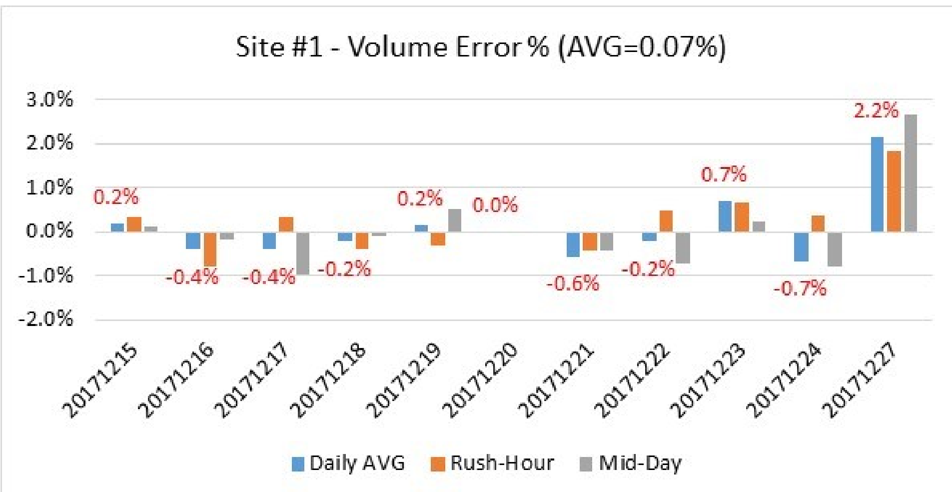


Figure 4.22 Traffic Volume Error Percentage at Site #1.

Table 4.11 Historical Temperature in TCMA 12/15/2017 – 12/27/2017.

2017	Temp. (°F)			Events
Dec	High	Average	Low	
15	30	26	22	Snow
16	31	27	23	
17	28	23	18	
18	42	33	24	
19	38	31	24	
20	24	21	18	Snow
21	24	22	19	
22	27	23	18	
23	23	17	11	
24	22	13	4	Snow
25	4	-1	-6	Snow
26	1	-4	-9	
27	5	-1	-8	

Table 4.12 summarizes the classification results using the FHWA classification scheme. On average, the loop signature card undercounts 11% of total traffic in class 2 and over counts 12% of total traffic in class 3. For class 4 to 12, the loop signature system tends to undercount class 6 and class 9 vehicles and over count traffic in the other vehicle types.

Table 4.12 Vehicle Classification Results from Site #1 Using FHWA Classification Scheme.

Vehicle Class	1	2	3	4	5	6	7	8	9	10	11	12	13	?	Total
Video Count	0	53233	769	57	792	306	7	296	2761	149	16	2	1	62	58451
Loop Count	2	47038	7487	303	1046	288	44	560	1360	220	86	18	2	1	58455
Difference	2	-6195	6718	246	254	-18	37	264	-1401	71	70	16	1	-61	4
Error %	NA	-12%	874%	432%	32%	-6%	529%	89%	-51%	48%	438%	800%	100%	-98%	0.01%
Diff / Vol (%)	0.0%	-10.6%	11.5%	0.4%	0.4%	0.0%	0.1%	0.5%	-2.4%	0.1%	0.1%	0.0%	0.0%	-0.1%	0.01%

? – Unknown class

Table 4.13 summarizes the classification results using the Highway Performance Monitoring System (HPMS) classification categories. The HPMS classification group 1 to 4 matches the FHWA classification scheme 1 to 4. HPMS vehicle group 5 includes vehicles in FHWA class 5 to 7 and group 6 includes vehicles FHWA class 8 to 13. Using the HPMS scheme, the loop signature system over counts 0.5% of overall traffic in group 5 and undercounts 1.7% of the traffic in group 6. Additional classification results comparing rush-hour and non-rush hour at this site are included in Appendix D-1.

Table 4.13 Vehicle Classification Results from Site #1 Using HPMS Classification Group.

Vehicle Class	1	2	3	4	5	6	?	Total
Video Count	0	53233	769	57	1105	3225	62	58451
Loop Count	2	47038	7487	303	1378	2246	1	58455
Difference	2	-6195	6718	246	237	-979	-61	4
Error %	NA	-12%	874%	432%	21%	-30%	-98%	0.01%
Diff / Vol (%)	0.0%	-10.6%	11.5%	0.4%	0.47%	-1.67%	-0.1%	0.01%

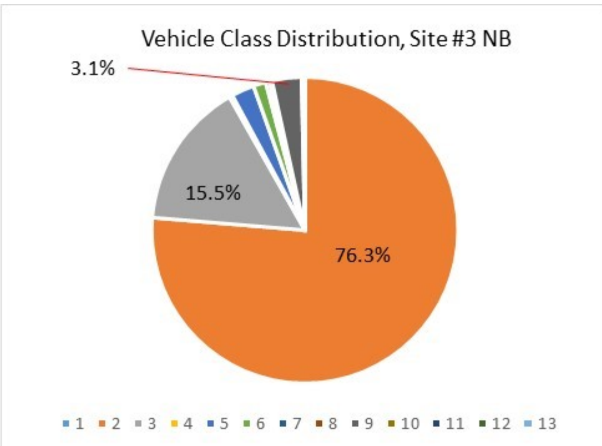
? – Unknown class

4.4.2.2 Site 2: US-169 at TH-282 (Jordan)

The research team observed 17 hours of video data and processed over 14,000 vehicles at the US-169 and TH-282 signalized intersection. We noticed the loop signature system has an average 24% to 38% of traffic volume less than the vehicle counts from the video data. The loop cards installed in the traffic signal control cabinet require 3 jumpers to enable vehicle detection outputs to the signal controller. In addition, a software setting was configured in the loop signature card (operating in pulse mode) to hold the detection output for 200 ms (typical range between 100 and 150 ms) in order for the signal controller to register the vehicle detection for actuated signal control. We are not sure if this setting causes the loop signature card to miss vehicles.

4.4.2.3 Site 3: TH-13 at Lynn Ave (Savage)

We observed and analyzed 167 hours (9am-5pm for respectively 9 and 13 days in both the NB and SB directions) of video data and processed over 211,500 vehicles at this location. As illustrated in Figure 4.23, 76.3% and 15.5% of NB traffic at this location is respectively class 2 and 3 vehicles and 3.1% of the traffic is class 9 trucks. The other vehicles combined consist of about 5% of the total NB traffic. In the SB direction, 87.7% and 4.6% of NB traffic at this location is respectively class 2 and 3 vehicles and 2.8% of the traffic is class 9 trucks. The other vehicles combined consist of less than 5% of the total SB traffic.



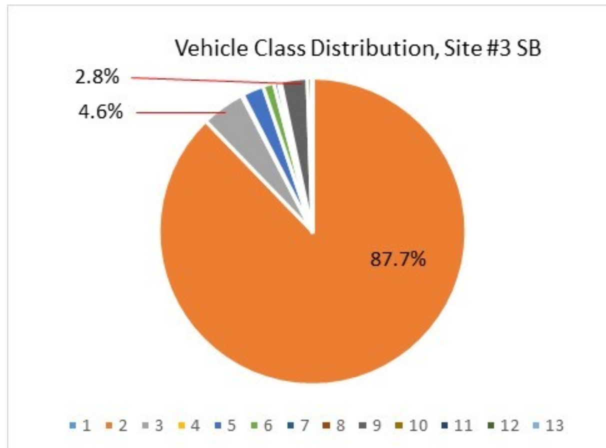


Figure 4.23 Distribution of Vehicle Classification at Site #3.

Figure 4.24 illustrates the daily traffic volume percentage error in the NB traffic and Figure 4.25 displays the traffic volume percentage error in the SB direction. On average, the traffic volume errors in the NB direction are within ±5% except on 11/27/2017 which has an error of -12.76%. Comparisons of traffic count in peak and off-peak periods in both directions are also displayed in Figure 4.24 and 4.25, respectively. The reason for the spike of volume count error is not sure. The average temperatures from 11/20/2017 to 12/2/2017, as listed in Table 4.14, are pretty consistent. The average traffic volume errors in the SB direction are within ±4%. This test location is the other signalized intersection site in our study. The software setting on the loop card to hold the detection output for the signal controller was set at 125 ms. We did not notice any significant undercount issue as occurred at site #2.

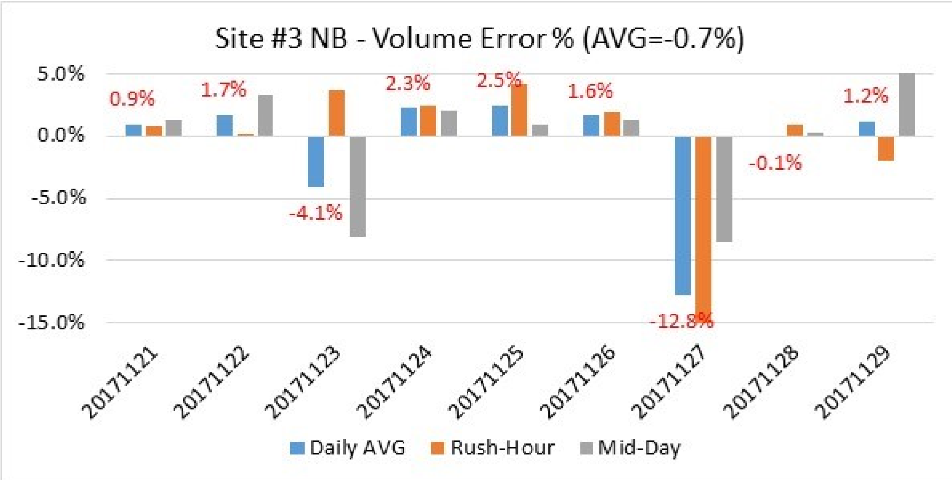


Figure 4.24 Traffic Volume Error Percentage at Site #3 NB.

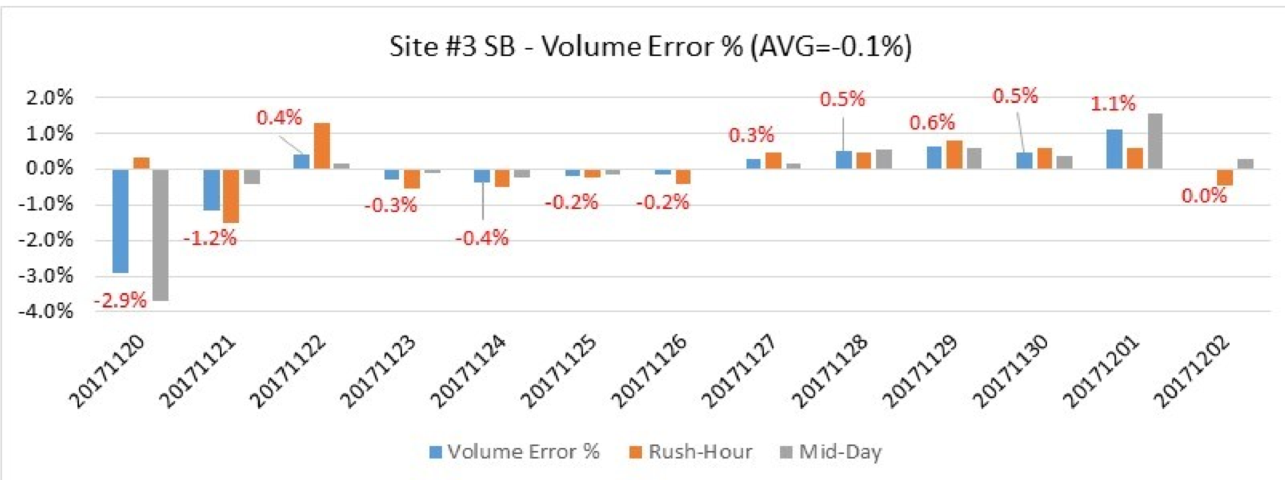


Figure 4.25 Traffic Volume Error Percentage at Site #3 SB.

Table 4.14 Historical Temperature in TCMA 11/20/2017 – 12/2/2017.

2017	Temp. (°F)			Events
Nov	High	Average	Low	
20	48	38	28	
21	42	30	18	Snow
22	33	24	15	
23	49	36	23	
24	60	50	40	
25	41	35	29	
26	51	38	24	
27	60	46	32	
28	53	43	33	
29	46	36	25	
30	48	40	31	
1	51	40	28	
2	47	39	30	

Table 4.15 summarizes 9 days of classification results using the FHWA classification scheme. On average, the loop signature card at site #3 in the NB direction undercounts 2.1% and 1.6% of total traffic in class 2 and 9, respectively. The overall traffic count error is within 1%. The loop signature system was not able to classify nearly 2% of the NB traffic, probably due to incomplete, insufficient, or noisy inductive signals.

Table 4.15 Vehicle Classification Results from Site #3 NB Using FHWA Classification Scheme.

Vehicle Class	1	2	3	4	5	6	7	8	9	10	11	12	13	?	Total
Video Count	53	75781	15382	349	2383	1317	421	249	3089	315	11	12	4	0	99366
Loop Count	3	73741	15733	1050	2695	694	276	567	1533	198	77	22	1	1922	98512
Difference	-50	-2040	351	701	312	-623	-145	318	-1556	-117	66	10	-3	1922	-854
Error %	-94%	-3%	2%	201%	13%	-47%	-34%	128%	-50%	-37%	600%	83%	-75%	NA	-0.9%
Diff / Vol (%)	-0.1%	-2.1%	0.4%	0.7%	0.3%	-0.6%	-0.1%	0.3%	-1.6%	-0.1%	0.1%	0.0%	0.0%	1.9%	-0.9%

? – Unknown class

Table 4.16 summarizes the classification results at site #3 in the NB direction using the HPMS classification bins. The HPMS classification group 1 to 4 matches the FHWA classification scheme 1 to 4. HPMS vehicle group 5 includes vehicles in FHWA class 5 to 7 and group 6 includes vehicles FHWA class 8 to 13. Using the HPMS scheme, the loop signature system undercounts 1.3% of the traffic in group 6. Additional classification results comparing rush-hour and non-rush hour at this site are included in Appendix D-2.

Table 4.16 Vehicle Classification Results from Site #3 NB Using HPMS Classification Group.

Vehicle Class	1	2	3	4	5	6	?	Total
Video Count	53	75781	15382	349	4121	3680	0	99366
Loop Count	3	73741	15733	1050	3665	2398	1922	98512
Difference	-50	-2040	351	701	-456	-1282	1922	-854
Error %	-94%	-3%	2%	201%	-11%	-35%	NA	-0.9%
Diff / Vol (%)	-0.1%	-2.1%	0.4%	0.7%	-0.46%	-1.29%	1.9%	-0.9%

? – Unknown class

Table 4.17 summarizes 13 days of classification results using the FHWA classification scheme. On average, the loop signature card in the SB direction undercounts 16.4% of total traffic in class 2 and over counts 15.4% of total traffic in class 3. The overall traffic count error is within 1%. For class 4 to 11, the loop signature system tends to undercount class 6, 7, 9 and class 10 vehicles and over count traffic in the other vehicle categories (4, 5, 8, 11). The loop signature system has a perfect count of the class 12 vehicles in the SB direction. The loop signature system was unable to classify 0.5% of the traffic in the SB direction, probably due to incomplete, insufficient, or noisy inductive signals.

Table 4.18 summarizes the classification results using the HPMS classification categories. The HPMS classification group 1 to 4 matches the FHWA classification scheme 1 to 4. HPMS vehicle group 5 includes vehicles in FHWA class 5 to 7 and group 6 includes vehicles FHWA class 8 to 13. Using the HPMS scheme, the loop signature system undercounts 0.9 % of the traffic in group 6.

Table 4.17 Vehicle Classification Results from Site #3 SB Using FHWA Classification Scheme.

Vehicle Class	1	2	3	4	5	6	7	8	9	10	11	12	13	?	Total
Video Count	67	98384	5118	184	2534	1301	541	285	3137	559	13	22	1	0	112146
Loop Count	13	79902	22346	1758	3327	700	336	763	1865	241	113	22	3	554	111943
Difference	-54	-18482	17228	1574	793	-601	-205	478	-1272	-318	100	0	2	554	-203
Error %	-81%	-19%	337%	855%	31%	-46%	-38%	168%	-41%	-57%	769%	0%	200%	NA	-0.2%
Diff / Vol (%)	0.0%	-16.4%	15.4%	1.4%	0.7%	-0.5%	-0.2%	0.4%	-1.1%	-0.3%	0.1%	0.0%	0.0%	0.5%	-0.2%

? – Unknown class

Table 4.18 Vehicle Classification Results from Site #3 SB Using HPMS Classification Group.

Vehicle Class	1	2	3	4	5	6	?	Total
Video Count	67	98384	5118	184	4376	4017	0	112146
Loop Count	13	79902	22346	1758	4363	3007	554	111943
Difference	-54	-18482	17228	1574	-13	-1010	554	-203
Error %	-81%	-19%	337%	855%	-0.3%	-25%	NA	-0.2%
Diff / Vol (%)	0.0%	-16.4%	15.4%	1.4%	-0.01%	-0.90%	0.5%	-0.2%

? – Unknown class

4.4.2.4 Site 4: I-35E at McAndrews Rd (Burnsville)

The research team observed and analyzed 86 hours (9am-5pm for 11 days) of video data and processed over 165,000 vehicles at this location. As illustrated in Figure 4.26, 82.1% and 12.4% of traffic at this location are respectively class 2 and 3 vehicles, and 3.1% of the traffic is class 9 trucks. The other vehicles combined consist of less than 3% of the total traffic at this site. Figure 4.27 illustrates the daily traffic volume percentage error of the loop signature system. On average, the traffic volume error of the loop signature card at site #4 is about 1.1% with a standard deviation of 3.7%. Comparisons of traffic count in peak and off-peak periods are also displayed in Figure 4.27.

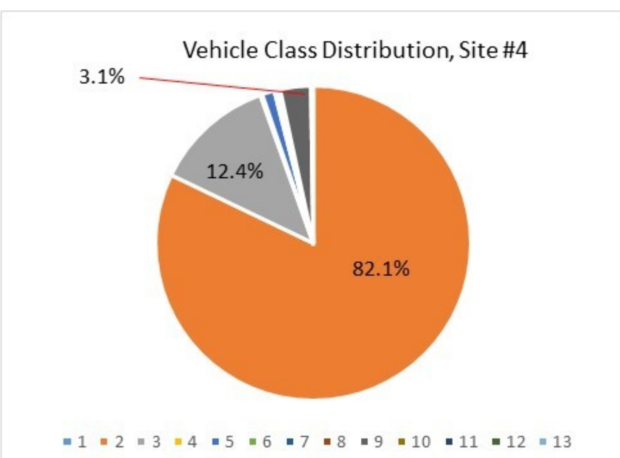


Figure 4.26 Distribution of Vehicle Classification at Site #4.

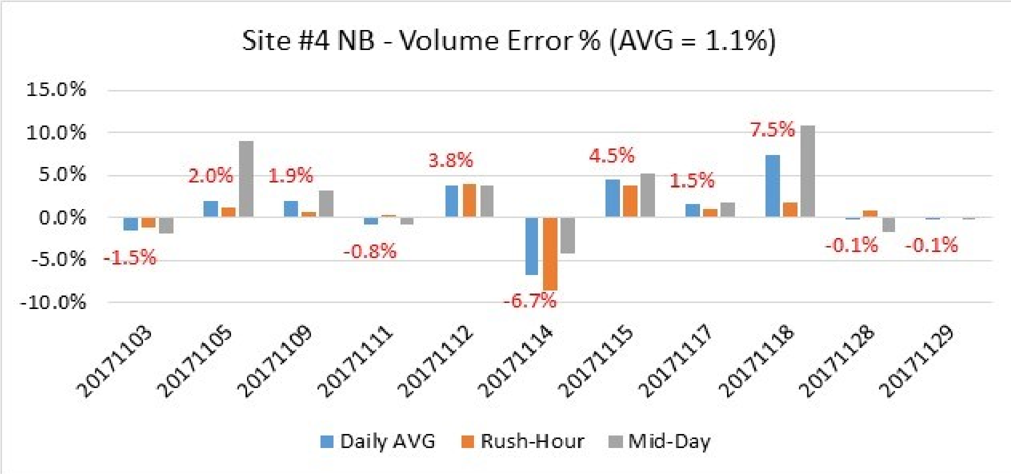


Figure 4.27 Traffic Volume Error Percentage at Site #4 NB.

Table 4.19 summarizes the classification results using the FHWA classification scheme. On average, the loop signature card has an undercount of 12% of total traffic in class 2 and an overcount of 13% of total traffic in class 3. For class 4 to 12, the loop signature system tends to undercount class 7, 9 and 11 vehicles and over count traffic in the other vehicle types. The loop signature system was unable to classify 0.1% of the traffic at this test site, probably due to incomplete, insufficient, or noisy inductive signals.

Table 4.20 summarizes the classification results using the HPMS classification categories. The HPMS classification group 1 to 4 matches the FHWA classification scheme 1 to 4. HPMS vehicle group 5 includes vehicles in FHWA class 5 to 7 and group 6 includes vehicles FHWA class 8 to 13. Using the HPMS scheme, the loop signature system has an overcount of 0.42% of total traffic in group 5 and an undercount of 0.96% of the traffic in group 6. Additional classification results comparing rush-hour and non-rush hour at this site are included in Appendix D-3.

Table 4.19 Vehicle Classification Results from Site #4 NB Using FHWA Classification Scheme.

Vehicle Class	1	2	3	4	5	6	7	8	9	10	11	12	13	?	Total
Video Count	15	125036	18872	342	1916	369	398	177	4770	159	188	6	1	1	165338
Loop Count	6	105603	40172	626	2513	603	257	1195	1970	328	163	53	2	233	166595
Difference	-9	-19433	21300	284	597	234	-141	1018	-2800	169	-25	47	1	232	1257
Error %	-60%	-16%	113%	83%	31%	81%	-61%	520%	-55%	116%	-4%	983%	100%	23200%	0.76%
Diff / Vol (%)	0.0%	-11.8%	12.9%	0.2%	0.4%	0.1%	-0.1%	0.6%	-1.7%	0.1%	0.0%	0.0%	0.0%	0.2%	0.76%

? – Unknown class

Table 4.20 Vehicle Classification Results from Site #4 NB Using HPMS Classification Group.

Vehicle Class	1	2	3	4	5	6	?	Total
Video Count	15	125036	18872	342	2683	5301	1	165338
Loop Count	6	105603	40172	626	3373	3711	233	166595
Difference	-9	-19433	21300	284	690	-1590	232	1257
Error %	-60%	-16%	113%	83%	26%	-30%	23200%	0.76%
Diff / Vol (%)	0.0%	-11.8%	12.9%	0.2%	0.42%	-0.96%	0.2%	0.76%

? – Unknown class

4.4.2.5 Site 5: I-94 at N. Victoria Street (St. Paul)

We observed and analyzed 64 hours (9am-5pm for 8 days) of video data and processed over 356,000 vehicles at this location. As illustrated in Figure 4.28, 93.4% of traffic in the EB direction is class 2 passenger cars and 1.9% of the EB traffic is class 9 trucks. The other vehicles combined consist of less than 5% of the total EB traffic at this site. In the WB direction, 92.9% of traffic is class 2 passenger cars, 2.7% of traffic is class 3 vehicles, and 1.7% of the traffic is class 9 trucks. The other vehicles combined consist of less than 3% of the total WB traffic at this site.

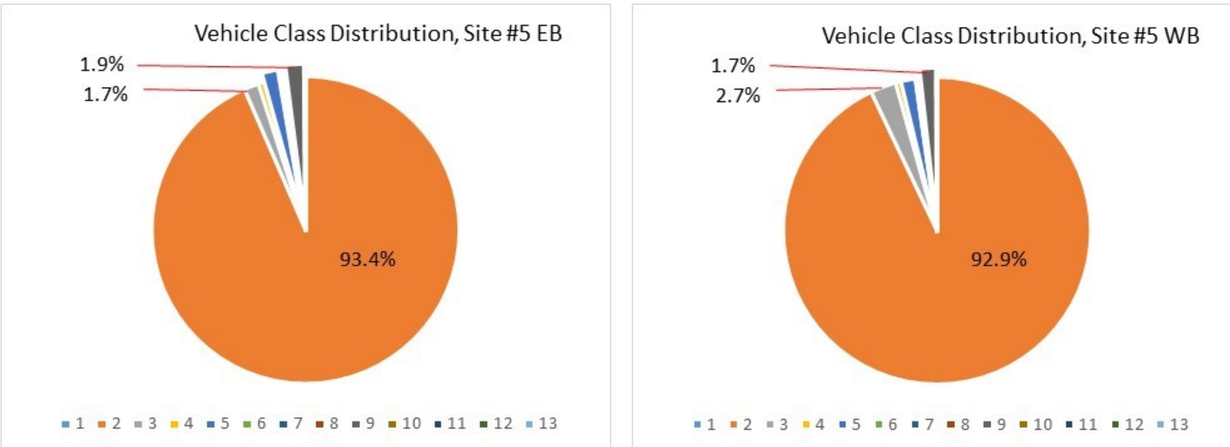


Figure 4.28 Distribution of Vehicle Classification at Site #5.

Figure 4.29 illustrates the daily traffic volume percentage error of the loop signature system. The loop signature cards at this location tend to overcount traffic. On average, the traffic volume error of the loop signature system at site #5 is about 6.2% with a standard deviation of 5%. Comparisons of traffic count in peak and off-peak periods are also displayed in Figure 4.29.

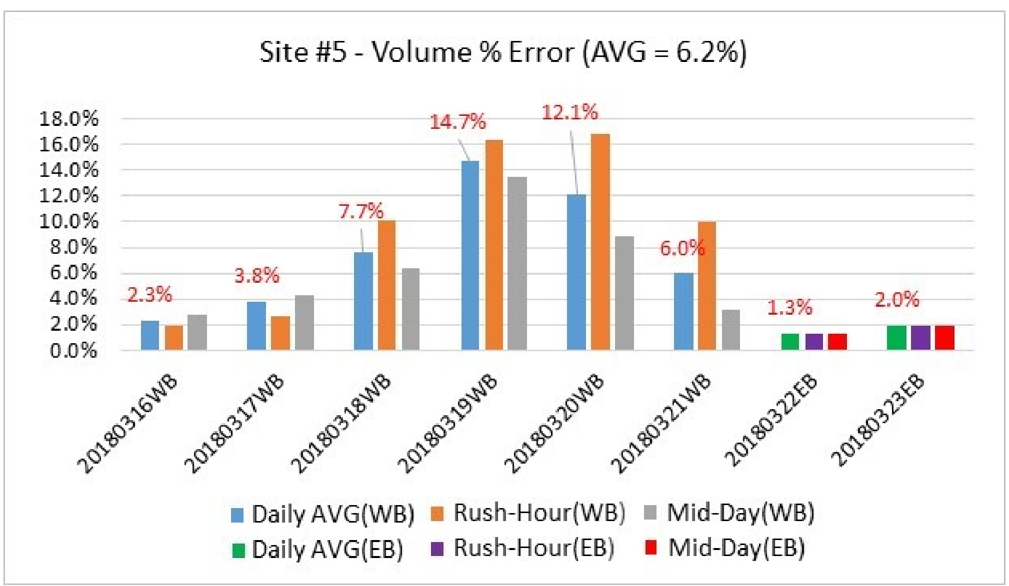


Figure 4.29 Traffic Volume Error Percentage at Site #5.

Table 4.21 summarizes the classification results using the FHWA classification scheme. On average, the loop signature card has an overcount of 5.4% of total traffic in class 3. The loop signature system tends to undercount class 9 vehicles. The loop signature system was unable to classify 0.2% of the traffic at this test site, probably due to incomplete, insufficient, or noisy inductive signals.

Table 4.21 Vehicle Classification Results from Site #5 Using FHWA Classification Scheme.

Vehicle Class	1	2	3	4	5	6	7	8	9	10	11	12	13	?	Total
Video Count	34	253798	7388	1560	4118	890	22	501	4573	155	45	2	3	120	273209
Loop Count	20	254662	23474	1733	4800	1190	379	1175	2301	354	160	16	4	65	290333
Difference	-14	864	16086	173	682	300	357	674	-2272	199	115	14	1	-55	17124
Error %	-41%	0%	218%	11%	17%	34%	1623%	135%	-50%	128%	256%	700%	33%	-46%	6.27%
Diff / Vol (%)	0.0%	0.3%	5.4%	0.1%	0.2%	0.1%	0.1%	0.2%	-0.8%	0.1%	0.0%	0.0%	0.0%	0.0%	6.27%

? – Unknown class

Table 4.22 summarizes the classification results using the HPMS classification categories. The HPMS classification group 1 to 4 matches the FHWA classification scheme 1 to 4. HPMS vehicle group 5 includes vehicles in FHWA class 5 to 7 and group 6 includes vehicles FHWA class 8 to 13. Using the HPMS scheme, the loop signature system has an overcount of 0.45% of the total traffic in group 5 and an undercount of 0.43% of the traffic in group 6. Additional classification results comparing rush-hour and non-rush hour at this site are included in Appendix D-4.

Table 4.22 Vehicle Classification Results from Site #5 Using HPMS Classification Group.

Vehicle Class	1	2	3	4	5	6	?	Total
Video Count	34	253798	7388	1560	5030	5279	120	273209
Loop Count	20	254662	23474	1733	6369	4010	65	290333
Difference	-14	864	16086	173	1339	-1269	-55	17124
Error %	-41%	0%	218%	11%	27%	-24%	-46%	6.27%
Diff / Vol (%)	0.0%	0.3%	5.4%	0.1%	0.45%	-0.43%	0.0%	6.27%

? – Unknown class

4.4.3 Investigation of Misclassification

Vehicle classification rate from our results is relatively lower than the performance from the loop signature systems installed in CA. The research team worked with the vendor to better understand and investigate the possible causes.

Data of sample #16 from Table 4.5 at site #3 were reprocessed and analyzed. 15-min of video data was observed carefully to create ground-truth reference and a newer version of the classification algorithm was used for the investigation. We found the existing vehicle classification algorithm (implemented in the *SignScope* software tool) provided by the vendor has a small bug that may classify a class 9 vehicle to a class 3 vehicle. In addition, inconsistent video ground-truth data and signature sequences could affect the classification rate. For example, when a truck is traveling in Lane 1 ahead of a closely following car in Lane 2 before both vehicles passing over the loop detectors from the camera's field of view. The ground-truth data may record the truck in Lane 1 with a timestamp slightly earlier than the car in Lane 2.

However, there were about 20 occurrences in sample #16 that the car in Lane 2 actually hit the loop detector a few milliseconds earlier than the truck in Lane 1.

After carefully reviewing the ground-truth data and accounted for the signature sequence difference, the classification rate for sample #16 has improved from 77% to 85% for all classes. Table 4.23 summaries the vehicle classification results by FHWA vehicle class from sample #16 at site #3. Class 2 vehicle has a matching rate of 89% with 5% of class 2 vehicles being misclassified as class 3. Similarly, class 3 has a relatively lower matching rate of 72% with 10% of class 3 vehicles being misclassified as class 2. Class 5 has a relatively lower matching rate of 50%. In addition, Class 9 has a matching rate of 55% with 45% of class 9 trucks being misclassified as class 8 vehicles.

Table 4.23 Vehicle Classification Results from Sample #16 (517 Vehicles)

Class		Vehicle Classified by Loop Signature System													Sum	Percent
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**		
Vehicle Class from Video Data	**1**														-	-
	2	3	353	20		19									395	89.4%
	3	4	8	59	6	1	1		3						82	72.0%
	4				2			1							3	66.7%
	5			4	2	8	2								16	50.0%
	6						3								3	100.0%
	7						1								1	-
	8								5						5	100.0%
	9								5	6					11	54.5%
	10										1				1	100.0%
	11														-	-
	12														-	-
	13														-	-

We also found that the signature data collected from this location are not typical. More signatures at Lane 2 are abnormal than those at Lane 1. The causes are not clear but it is possible due to damaged loops, broken loop sealant, crosstalk, cross-wired loops/loops wired together, rectangular loops (vs. circular loops in CA), or leads in cable not twisted properly. Further investigation is needed to determine the causes. According to the vendor, if only data from Lane 1 are considered, the performance could be improved from 84.5% to 90.8%, which is similar to the performance observed in southern California.

CHAPTER 5: SUMMARY AND DISCUSSION

In 2013, USDOT sponsored the SBIR project that used inductive loop signatures from existing inductive loop detectors installed under the pavement to obtain more accurate, reliable and comprehensive traffic performance measures for transportation agencies. Results from the study indicated that inductive loop signature technology was able to re-identify and classify vehicles along a section of roadway and provide reliable performance measures for assessing progress, at the local, state, or national level. This study aimed to take advantage of the outcomes from the loop signature development to validate the performance with ground truth vehicle classification data in the Twin Cities Metropolitan Area (TCMA).

5.1 SUMMARY

The research team worked with members of the technical advisory panel to select 5 test sites including 2 locations on interstate highways, 2 sites at signalized intersections, and the other site on a major highway. Four loop signature cards with firmware 1.76 and 2 vehicle classification master cards with firmware 1.11.0 were used in the experiments. Loop signature cards and video cameras were deployed at test sites to collect vehicle signature profile and ground truth video data for vehicle classification verification. Over 400 hours of video and vehicle loop signature data were collected from the selected test sites.

The research team analyzed loop signature data and extracted vehicle class information from each test site. The loop signature data were loaded into an open source SQL database for vehicle classification and verification analysis. A Jamar traffic counter and a *CountPro/CountPad*2 tool were used to obtain individual vehicle class information by undergraduate students. In total, the research team processed vehicle class information for over 807,000 vehicles among all the test sites.

The research team first conducted traffic count analysis and learned that the loop signature cards at site #2 had an average of 24% to 38% fewer vehicle counts than the counts from the video. We are not exactly sure about the possible causes of the significant undercount by the loop signature system. However, we suspect the cause is likely to be related to a software setting on the loop cards for holding the detection output in order for the signal controller to register the vehicle detection for actuated signal control. We would not recommend using the loop signature cards for vehicle classification and vehicle detection/actuation at signalized intersections.

On average, sites #1, #3, and #4 had an average volume count error of less than 1%. However, site #5 (I-94 & Victoria in St. Paul) had a significantly larger average error of traffic volume count (6%). This could have been caused by noisy loop signals and/or the higher number of vehicles changing lanes during AM & PM rush hours in a congested traffic flow. In each test site, more than 90% of the traffic was either class 2 or 3 vehicles.

Two methods were used to perform vehicle class verification for each individual vehicle using 15-minute aggregation intervals. The individual vehicle verification process was laborious and time-consuming. The per vehicle approach was performed using data from 24 periods at the different test sites. The other 400-plus hours of data were analyzed using the aggregated method.

Using the verification approach at an individual vehicle level from the 24 periods, the match rate for all 13 FHWA categories of vehicle types ranged from 65% to 90%, with an average matching rate of 75% and a standard deviation (SD) of 8%. The overall match rate was biased toward class 2 and 3 vehicles due to the higher percentage of passenger vehicles. Modern vehicles, such as sedans, pickup truck, and SUVs, share similar vehicle chassis with very close inductive loop signature patterns. The classification distinctions between type 2 and 3 vehicles were less obvious. When including the miscount error between class 2 and 3 for additional classification analysis, the average matching rate of all traffic improved to 89% with an SD of 7%.

Results from the aggregated approach indicated that the loop signature system had a tendency to, on average, undercount class 2 vehicles by about 13% of total traffic and overcount class 3 vehicles by about 13% of all traffic.

When using the Highway Performance Monitoring System (HPMS) scheme for vehicle classification, the HPMS classification bin 1 to 4 matches the FHWA classification scheme 1 to 4. HPMS vehicle group 5 includes vehicles in FHWA class 5 to 7 and group 6 includes vehicles FHWA class 8 to 13. Overall, the HPMS group 5 count error is within 1% of total traffic count, and traffic count error in bin #6 is less than 2% of the total volume. On average, the loop signature system tends to overcount HPMS class 5 vehicles and undercount HPMS class 6 vehicles.

5.2 DISCUSSION

Based on the results from individual vehicle class verification, class 2 vehicles have the highest match rate of 81% with a 17% of passenger vehicles being misclassified as class 3 vehicles. All the other vehicle classes have a relatively lower matching rate, i.e., less than 50%. The matching rate is lower than the results from California Department of Transportation (Caltrans). After further investigation of a sample set of data at site #3, we found that the signature data collected from this location were not "typical." It was obvious at Lane 2, but the abnormality was not easily observable at Lane 1. The causes were not clear, but the abnormality was possible due to damaged loops, broken loop sealant, crosstalk, or lead-in cable not twisted properly. The abnormality of the signature data also affected the overall performance. For this particular sample dataset (517 vehicles), if only data from Lane 1 were considered, the performance could be improved from 84.5% to 90.8%, which is similar to the performance observed in southern California, according to the vendor.

We suspect the possible causes of poor classification accuracy may include the followings:

- Types of loops (circular loops in CA vs. rectangular loops in MN)
- Sensitivity of inductive loops that generate a shadow loop signal on a neighboring lane
- Classification template library prepared based on California data
- Inappropriate parameter setup (We learned that each loop channel of detector card needed to be configured properly to remove possible cross-talks and achieve good signature data quality.

Main parameters that needed to be customized including loop frequency, noise suppression filter, and detects-in-a-row. The loop frequency was very site specific.)

After discussing this with the vendor as well as the current practices in California, we feel a field deployment procedure would be helpful to set up a loop card by measuring inductance for each loop and checking check vehicle signatures in the field to ensure there is no noise or interference from all loops.

To further understand the causes of loop signature performance and improve the classification accuracy, we suggest installing the 4 loop signature cards at a couple of permanent ATR locations and performing additional data verification with a video camera and a pneumatic tube counter. The vehicle classification mater card will be upgraded to the latest firmware version 1.14.5. We believe there is also an opportunity to investigate the classification algorithm and develop a better pattern recognition methodology based on the raw loop signature profile of various types of vehicles.

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APPENDIX A
FHWA VEHICLE CLASSIFICATIONS

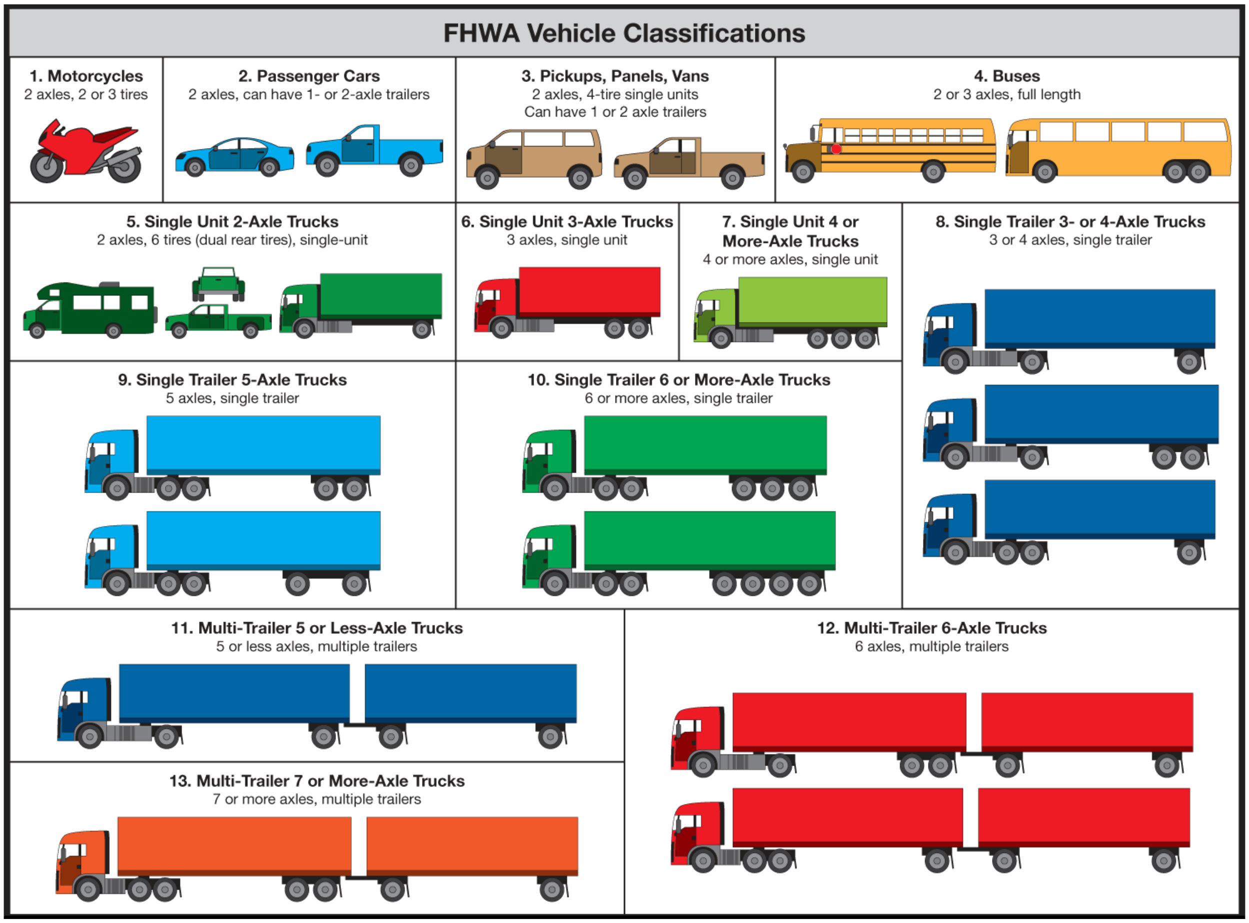


Figure A-1. Vehicle Classification Using FHWA 13-Category

APPENDIX B

COMPARISON OF VEHICLE SIGNATURES AND VEHICLE TYPE

The loop signatures of a selected number of vehicles are illustrated and compared with the corresponding vehicle images captured from the video data.

B.1 Site #1 US169 @ CR59 NB (Jordan)

Vehicle Class (loop signature): 4 Vehicle Class (video): 9

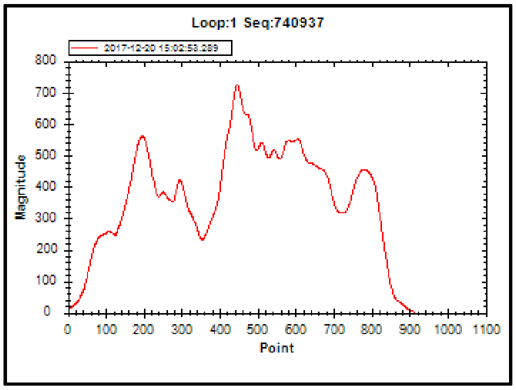


Figure B-1. 12/20/2017, 15:01:49.6, Lane 1

Vehicle Class (loop signature): 2 Vehicle Class (video): 2

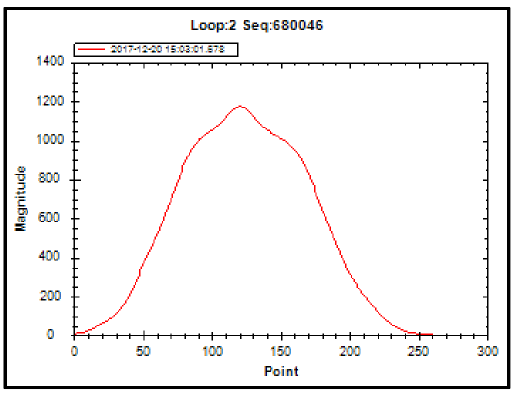


Figure B-2. 12/20/2017, 15:01:57.9, Lane 2

Vehicle Class (loop signature): 9 Vehicle Class (video): 9

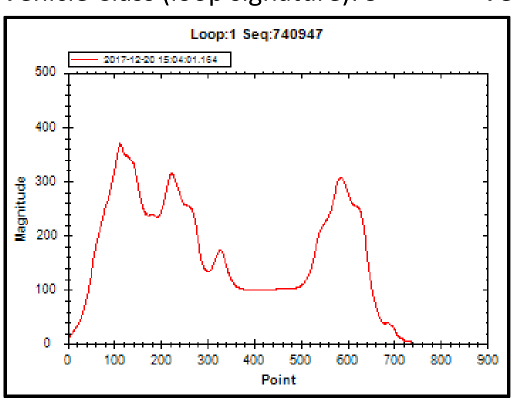


Figure B-3. 12/20/2017, 15:02:57.5, Lane 1

Vehicle Class (loop signature): 4 Vehicle Class (video): 5

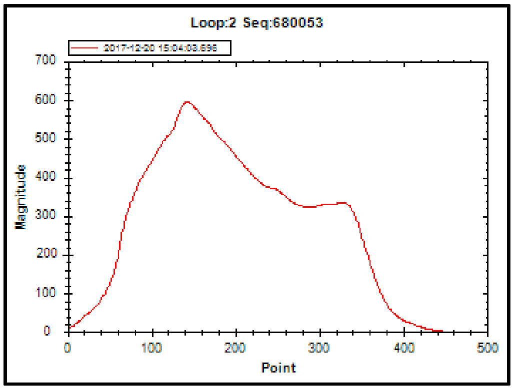


Figure B-4. 12/20/2017, 15:02:59.9, Lane 2

Vehicle Class (loop signature): 2 Vehicle Class (video): 3

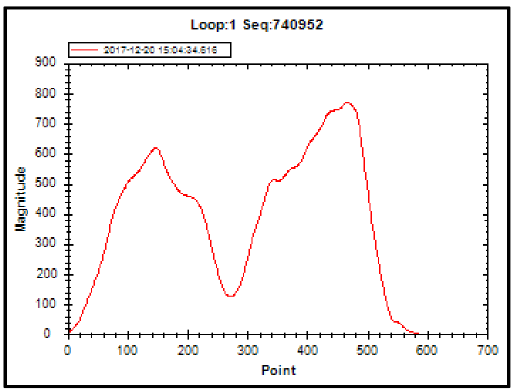


Figure B-5. 12/20/2017, 15:03:30.8, Lane 1

Vehicle Class (loop signature): 4 Vehicle Class (video): 5

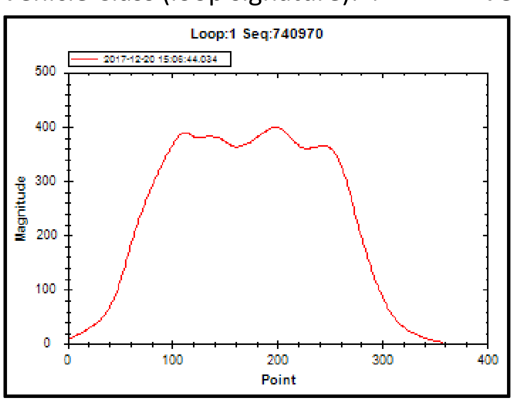


Figure B-6. 12/20/2017, 15:05:40.2, Lane 1

Vehicle Class (loop signature): 10 Vehicle Class (video): 10

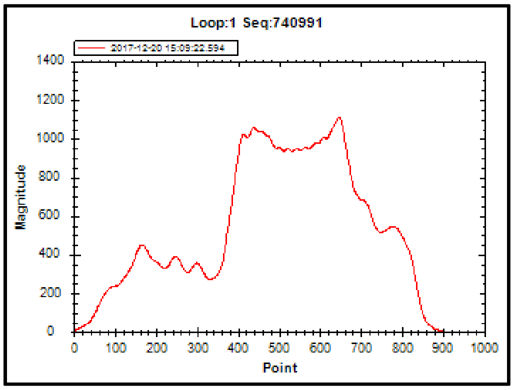


Figure B-7. 12/20/2017, 15:08:18.9, Lane 1

Vehicle Class (loop signature): 8 Vehicle Class (video): 8

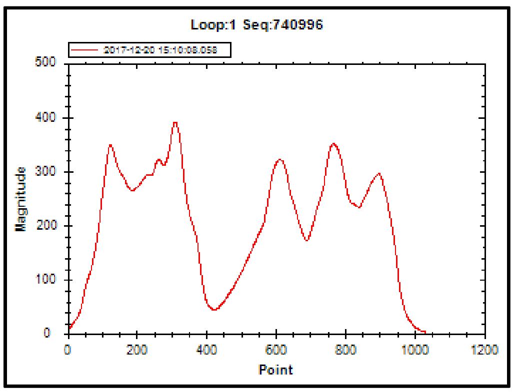


Figure B-8. 12/20/2017, 15:09:4.4, Lane 1

Vehicle Class (loop signature): 8 Vehicle Class (video): 10

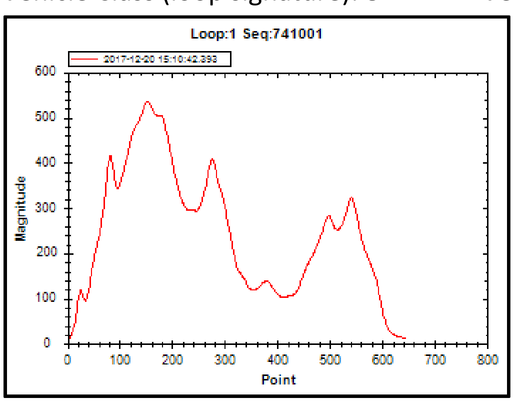


Figure B-9. 12/20/2017, 15:09:38.7, Lane 1

Vehicle Class (loop signature): 4 Vehicle Class (video): 2

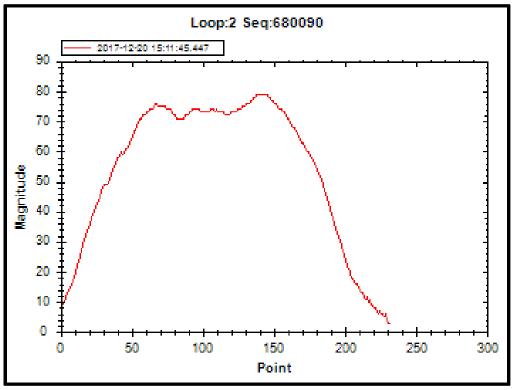


Figure B-10. 12/20/2017, 15:10:41.6, Lane changing from 2 to 1

B.2 Site #3 TH13 @ Lynn SB (Savage)

Vehicle Class (loop signature): 4 Vehicle Class (video): 5

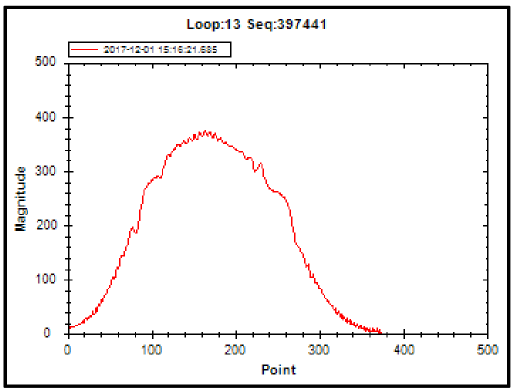


Figure B-11. 12/01/2017, 15:15:56.4, Lane 2

Vehicle Class (loop signature): 7 Vehicle Class (video): 7

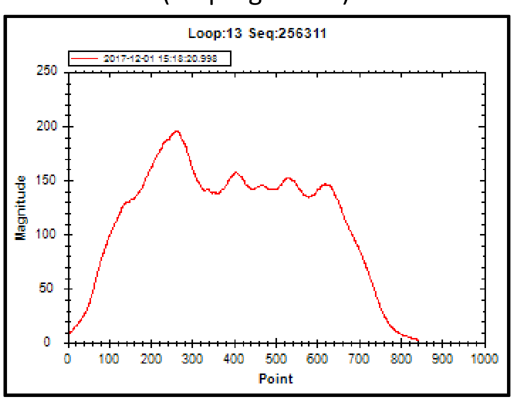
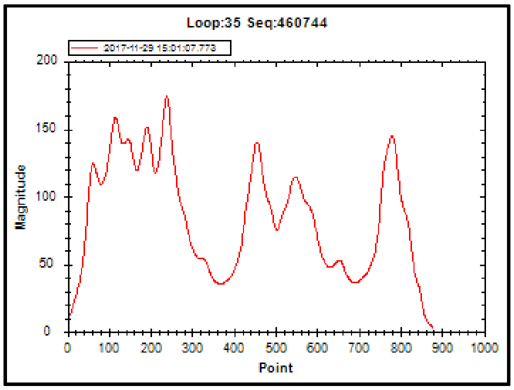


Figure B-12. 12/01/2017, 15:17:55.4, Lane 1

B.3 Site #4 I-35E @ McAndrews NB (Burnsville)

Vehicle Class (loop signature): 12



Vehicle Class (video): 12

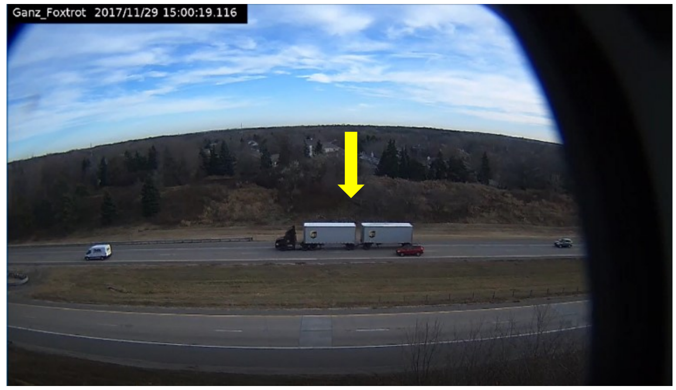
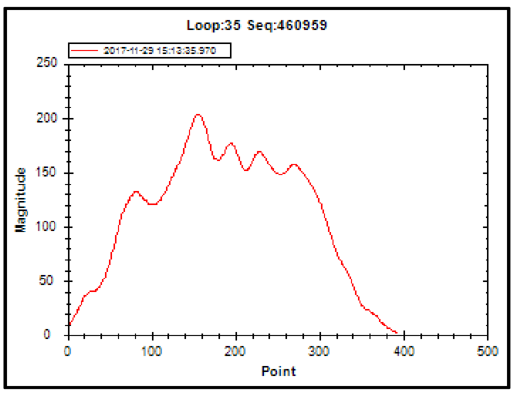


Figure B-13. 11/29/2017, 15:00:19.1, Lane 1

Vehicle Class (loop signature): 3



Vehicle Class (video): 6

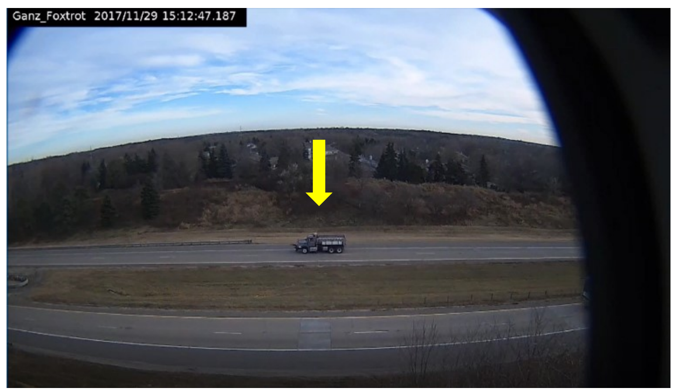
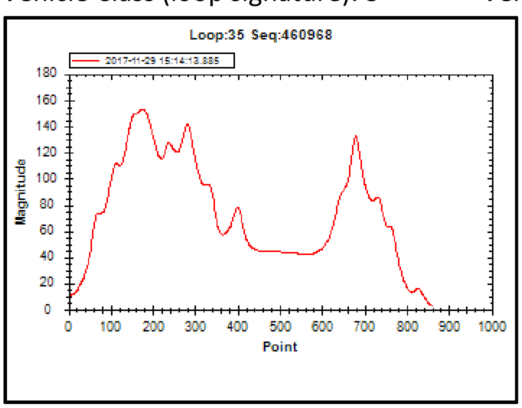


Figure B-14. 11/29/2017, 15:12:47.2, Lane 1

Vehicle Class (loop signature): 3



Vehicle Class (video): 9

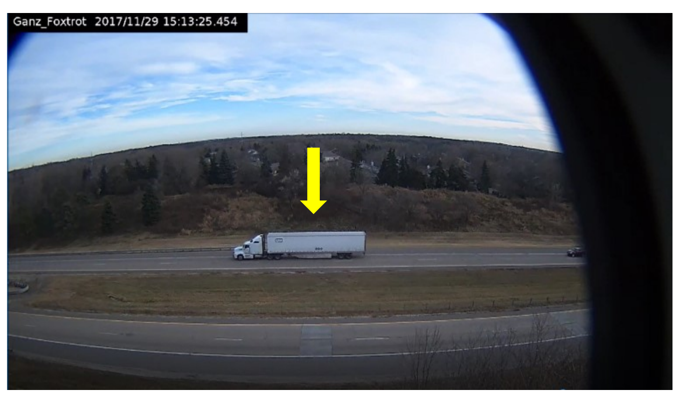


Figure B-15. 11/29/2017, 15:13:25.5, Lane 1

APPENDIX C

SUMMARY OF CLASSIFICATION ACCURACY BY VEHICLE CLASS

Table C-1 summaries the vehicle classification results by FHWA vehicle class from the highway sites (site #4 and #5). Class 2 vehicle has the highest matching rate (85%) with a large amount of class 2 vehicles (14%) being misclassified as class 3. Similarly, class 3 has a relatively lower matching rate of 35% with a significant number of class 3 vehicles (46%) being misclassified as class 2. Class 5 has a relatively lower matching rate of 43% with 27%, 8%, and 3% of class 5 trucks being respectively misclassified as class 2, 3, and 4 vehicles. In addition, Class 9 has a relatively lower matching rate of 48% with a significant number of class 9 trucks (22%) being misclassified as class 2 vehicles.

Table C-1. Vehicle Classification Results by Class (Highway Only, Sample #17 - #24)

Class		**Vehicle Classified by Loop Signature System**													**Sum**	**Percent**
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**		
Vehicle Class from Video Data	**1**	0	3	0	0	0	0	0	0	0	0	0	0	0	3	0.0%
	2	0	2956	503	5	21	3	1	3	4	0	1	0	0	3497	84.5%
	3	0	83	63	5	16	8	0	6	0	1	0	0	0	182	34.6%
	4	0	2	1	7	2	3	0	0	0	0	0	0	0	15	46.7%
	5	0	10	3	1	16	5	2	0	0	0	0	0	0	37	43.2%
	6	0	4	1	0	4	3	0	0	0	0	0	0	0	12	25.0%
	7	0	2	0	0	3	3	0	2	0	0	0	0	0	10	0.0%
	8	0	0	0	0	1	0	0	3	0	0	0	0	0	4	75.0%
	9	0	30	5	0	4	1	0	18	65	12	1	0	0	136	47.8%
	10	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0.0%
	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	NA
	12	0	0	0	0	0	0	0	0	1	0	0	1	0	2	50.0%
	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	NA

APPENDIX D

COMPARISON OF AGGREGATED CLASSIFICATION RESULTS

Comparison of aggregated classification results during rush-hour and mid-day periods at each site was discussed as follows.

D.1 Site #1

We observed 31 hours of video data and processed 22,850 vehicles at this location in rush hours. 92.5% of vehicles at this location are class 2 passenger cars and 4% of the traffic is class 9 trucks. Table D-1 summarizes the classification results at site #1 in peak period using the FHWA classification scheme. On average, the loop signature card undercounts 11% of total traffic in class 2 and over counts 11% of total traffic in class 3. For class 4 to 12, the loop signature system tends to undercount class 6 and class 9 vehicles and over count traffic in the other vehicle types.

Table D-1. Vehicle Classification Results from Site #1 During Rush Hours

Vehicle Class	1	2	3	4	5	6	7	8	9	10	11	12	13	?	Total
Video Count	0	21141	255	33	271	85	1	99	908	38	2	0	0	17	22850
Loop Count	1	18738	2810	107	353	89	12	209	448	81	20	3	1	0	22872
Difference	1	-2403	2555	74	82	4	11	110	-460	43	18	3	1	-17	22
Error %	NA	-11%	1002%	224%	30%	5%	1100%	111%	-51%	113%	900%	NA	NA	-100%	0.10%
Diff / Vol (%)	0.0%	-10.5%	11.2%	0.3%	0.4%	0.0%	0.0%	0.5%	-2.0%	0.2%	0.1%	0.0%	0.0%	-0.1%	0.10%

? – Unknown class

We observed 49 hours of video data and processed 36,040 vehicles at this location in rush hours. 90.2% of vehicles at this location are class 2 passenger cars and 5.2% of the traffic is class 9 trucks. Table D-2 summarizes the classification results at site #1 in mid-day using the FHWA classification scheme. On average, the loop signature card undercounts 11% of total traffic in class 2 and over counts 12% of total traffic in class 3. For class 4 to 12, the loop signature system tends to undercount class 6 and class 9 vehicles and over count traffic in the other vehicle types.

Table D-2. Vehicle Classification Results from Site #1 in Mid-Day

Vehicle Class	1	2	3	4	5	6	7	8	9	10	11	12	13	?	Total
Video Count	0	32507	516	24	524	220	6	198	1872	111	14	2	1	45	36040
Loop Count	1	28672	4740	197	701	199	32	353	916	141	67	15	1	1	36036
Difference	1	-3835	4224	173	177	-21	26	155	-956	30	53	13	0	-44	-4
Error %	NA	-12%	819%	721%	34%	-10%	433%	78%	-51%	27%	379%	650%	0%	-98%	-0.01%
Diff / Vol (%)	0.0%	-10.6%	11.7%	0.5%	0.5%	-0.1%	0.1%	0.4%	-2.7%	0.1%	0.1%	0.0%	0.0%	-0.1%	-0.01%

? – Unknown class

D.2 Site #3

We processed 52,620 vehicles at this location in rush hours. 92% of vehicles at this location are class 2 or 3 vehicles and 3% of the traffic is class 9 trucks. Table D-3 summarizes 9 days of classification results at site #3 NB in peak period using the FHWA classification scheme. On average, the loop signature card at site #3 in the NB direction in rush hours undercounts 2.7% and 1.4% of total traffic in class 2 and 9, respectively. The overall traffic count error is within 2%. The loop signature system was not able to classify nearly 2% of the NB traffic, probably due to incomplete, insufficient, or noisy inductive signals.

Table D-3. Vehicle Classification Results from Site #3 NB during Rush Hours

Vehicle Class	1	2	3	4	5	6	7	8	9	10	11	12	13	?	Total
Video Count	26	40535	7904	195	1314	609	218	149	1506	151	6	6	2	0	52621
Loop Count	3	39140	8041	554	1352	338	139	280	757	95	40	12	1	945	51697
Difference	-23	-1395	137	359	38	-271	-79	131	-749	-56	34	6	-1	945	-924
Error %	-88%	-3%	2%	184%	3%	-44%	-36%	88%	-50%	-37%	567%	100%	-50%	NA	-2%
Diff / Vol (%)	0.0%	-2.7%	0.3%	0.7%	0.1%	-0.5%	-0.2%	0.2%	-1.4%	-0.1%	0.1%	0.0%	0.0%	1.8%	-2%

? – Unknown class

We processed 46,745 vehicles at this location during mid-day period. 91.4% of vehicles at this location are class 2 or 3 vehicles and 3.4% of the traffic is class 9 trucks. Table D-4 summarizes the classification results at site #3 NB in mid-day using the FHWA classification scheme. On average, the loop signature card at site #3 in the NB direction in mid-day undercounts 1.3% and 1.7% of total traffic in class 2 and 9, respectively. The overall traffic count error is within 0.1%. The loop signature system was not able to classify nearly 2% of the NB traffic.

Table D-4. Vehicle Classification Results from Site #3 NB in Mid-Day

Vehicle Class	1	2	3	4	5	6	7	8	9	10	11	12	13	?	Total
Video Count	27	35246	7478	154	1069	708	203	100	1583	164	5	6	2	0	46745
Loop Count	0	34601	7692	496	1343	356	137	287	776	103	37	10	0	882	46720
Difference	-27	-645	214	342	274	-352	-66	187	-807	-61	32	4	-2	882	-25
Error %	-100%	-2%	3%	222%	26%	-50%	-33%	187%	-51%	-37%	640%	67%	-100%	NA	-0.1%
Diff / Vol (%)	-0.1%	-1.3%	0.5%	0.7%	0.6%	-0.8%	-0.1%	0.4%	-1.7%	-0.1%	0.1%	0.0%	0.0%	1.9%	-0.1%

? – Unknown class

We processed 47,906 vehicles at this location in rush hours. 91% of vehicles at this location are class 2 vehicles and 2% of the traffic is class 9 trucks. Table D-5 summarizes 13 days of classification results using the FHWA classification scheme. On average, the loop signature card in the SB direction undercounts 16.3% of total traffic in class 2 and over counts 15.2% of total traffic in class 3. The overall traffic count error is within 1%. For class 4 to 11, the loop signature system tends to undercount class 6, 7, 9 and class 10 vehicles and over count traffic in the other vehicle categories (4, 5, 8, 11). The loop signature system was unable to classify 0.7% of the traffic in the SB direction in peak period.

Table D-5. Vehicle Classification Results from Site #3 SB during Rush Hours

Vehicle Class	1	2	3	4	5	6	7	8	9	10	11	12	13	?	Total
Video Count	22	43353	1725	82	886	383	147	93	1052	147	7	9	0	0	47906
Loop Count	3	35557	9027	621	1106	225	106	246	612	57	33	7	0	342	47942
Difference	-19	-7796	7302	539	220	-158	-41	153	-440	-90	26	-2	0	342	36
Error %	-86%	-18%	423%	657%	25%	-41%	-28%	165%	-42%	-61%	371%	-22%	NA	NA	0.1%
Diff / Vol (%)	0.0%	-16.3%	15.2%	1.1%	0.5%	-0.3%	-0.1%	0.3%	-0.9%	-0.2%	0.1%	0.0%	0.0%	0.7%	0.1%

? – Unknown class

We processed 65,026 vehicles at this location in mid-day period. 91% of vehicles at this location are class 2 or 3 vehicles and 3% of the traffic is class 9 trucks. Table D-6 summarizes 13 days of classification results using the FHWA classification scheme. On average, the loop signature card in the SB direction in mid-day undercounts 16.6% of total traffic in class 2 and over counts 15.6% of total traffic in class 3. The overall traffic count error is within 0.1%. For class 4 to 11, the loop signature system tends to undercount class 6, 7, 9 and class 10 vehicles and over count traffic in the other vehicle categories (4, 5, 8, 11). The loop signature system was unable to classify 0.4% of the traffic in the SB direction in mid-day period.

Table D-6. Vehicle Classification Results from Site #3 SB during Mid-Day

Vehicle Class	1	2	3	4	5	6	7	8	9	10	11	12	13	?	Total
Video Count	46	55971	3304	108	1620	926	394	183	2056	397	7	13	1	0	65026
Loop Count	10	45135	13468	1123	2204	481	231	516	1246	182	77	16	3	278	64970
Difference	-36	-10836	10164	1015	584	-445	-163	333	-810	-215	70	3	2	278	-56
Error %	-78%	-19%	308%	940%	36%	-48%	-41%	182%	-39%	-54%	1000%	23%	200%	NA	-0.1%
Diff / Vol (%)	-0.1%	-16.6%	15.6%	1.6%	0.9%	-0.7%	-0.3%	0.5%	-1.2%	-0.3%	0.1%	0.0%	0.0%	0.4%	-0.1%

? – Unknown class

D.3 Site #4

We processed 71,353 vehicles at this location in peak period. 95% of vehicles at this location are class 2 or 3 vehicles and 3% of the traffic is class 9 trucks. Table D-7 summarizes the classification results using the FHWA classification scheme. On average, the loop signature card has an undercount of 15% of total traffic in class 2 and an overcount of 15% of total traffic in class 3. For class 4 to 12, the loop signature system tends to undercount class 7, 9 and 11 vehicles and over count traffic in the other vehicle types. The loop signature system was unable to classify 0.3% of the traffic at this test site.

Table D-7. Vehicle Classification Results from Site #4 NB during Rush Hours

Vehicle Class	1	2	3	4	5	6	7	8	9	10	11	12	13	?	Total
Video Count	3	59107	8787	166	788	137	139	79	1967	85	94	1	0	0	71353
Loop Count	0	48310	19659	253	1074	289	66	450	858	159	87	28	1	192	71426
Difference	-3	-10797	10872	87	286	152	-73	371	-1109	74	-7	27	1	192	73
Error %	-100%	-18%	124%	52%	36%	111%	-53%	470%	-56%	87%	-7%	2700%	NA	NA	0.1%
Diff / Vol (%)	0.0%	-15.1%	15.2%	0.1%	0.4%	0.2%	-0.1%	0.5%	-1.6%	0.1%	0.0%	0.0%	0.0%	0.3%	0.1%

? – Unknown class

We processed 83,299 vehicles at this location during mid-day period. 94% of vehicles at this location are class 2 or 3 vehicles and 4% of the traffic is class 9 trucks. Table D-8 summarizes the classification results using the FHWA classification scheme. On average, the loop signature card has an undercount of 11% of total traffic in class 2 and an overcount of 13% of total traffic in class 3. For class 4 to 12, the loop signature system tends to undercount class 7 and 9 vehicles and over count traffic in the other vehicle types. The loop signature system was unable to classify 0.1% of the traffic at this test site.

Table D-8. Vehicle Classification Results from Site #4 NB during Mid-Day

Vehicle Class	1	2	3	4	5	6	7	8	9	10	11	12	13	?	Total
Video Count	12	67145	11123	184	1162	242	261	101	2882	82	98	5	1	1	83299
Loop Count	6	58411	22186	392	1526	392	93	671	1320	194	101	37	1	117	85447
Difference	-6	-8734	11063	208	364	150	-168	570	-1562	112	3	32	0	116	2148
Error %	-50%	-13%	99%	113%	31%	62%	-64%	564%	-54%	137%	3%	640%	0%	11600%	3%
Diff / Vol (%)	0.0%	-10.5%	13.3%	0.2%	0.4%	0.2%	-0.2%	0.7%	-1.9%	0.1%	0.0%	0.0%	0.0%	11600.0%	3%

? – Unknown class

D.4 Site #5

We processed 115,221 vehicles at this location during peak period. 94% of vehicles at this location are class 2 vehicles and 1.2% of the traffic is class 9 trucks. Table D-9 summarizes the classification results using the FHWA classification scheme. On average, the loop signature card has an overcount of 2.3% and 5.3% of total traffic in class 2 & 3, respectively. The loop signature system tends to undercount class 9 vehicles by 0.6%.

Table D-9. Vehicle Classification Results from Site #5 during Rush Hours

Vehicle Class	1	2	3	4	5	6	7	8	9	10	11	12	13	?	Total
Video Count	16	108265	2854	732	1372	236	5	184	1425	46	39	2	1	44	115221
Loop Count	6	110869	9008	639	1606	468	102	386	699	110	67	2	3	65	124030
Difference	-10	2604	6154	-93	234	232	97	202	-726	64	28	0	2	21	8809
Error %	-63%	2%	216%	-13%	17%	98%	1940%	110%	-51%	139%	72%	0%	200%	48%	8%
Diff / Vol (%)	0.0%	2.3%	5.3%	-0.1%	0.2%	0.2%	0.1%	0.2%	-0.6%	0.1%	0.0%	0.0%	0.0%	0.0%	8%

? – Unknown class

We processed 170,217 vehicles at this location during mid-day. 92% of vehicles at this location are class 2 vehicles and 1.9% of the traffic is class 9 trucks. Table D-10 summarizes the classification results using the FHWA classification scheme. On average, the loop signature card has an undercount of 1.4% of overall traffic for class 2 cars and an overcount of 6.5% of total traffic in class 3. The loop signature system tends to undercount class 9 vehicles by 0.9%.

Table D-10. Vehicle Classification Results from Site #5 during Mid-Day

Vehicle Class	1	2	3	4	5	6	7	8	9	10	11	12	13	?	Total
Video Count	20	157293	4668	893	2849	670	17	349	3248	121	6	0	2	81	170217
Loop Count	14	154912	15771	1161	3369	775	284	820	1664	250	97	14	1	0	179132
Difference	-6	-2381	11103	268	520	105	267	471	-1584	129	91	14	-1	-81	8915
Error %	-30%	-2%	238%	30%	18%	16%	1571%	135%	-49%	107%	1517%	NA	-50%	-100%	5%
Diff / Vol (%)	0.0%	-1.4%	6.5%	0.2%	0.3%	0.1%	0.2%	0.3%	-0.9%	0.1%	0.1%	0.0%	0.0%	0.0%	5%

? – Unknown class