DEPARTMENT OF TRANSPORTATION

Refining Inductive Loop Signature Technology for Statewide Vehicle Classification Counts

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Transportation agencies in the U.S. use devices such as loop detectors, automatic traffic recorders (ATR), or weigh-in-motion (WIM) sensors to monitor the performance of traffic network for planning, forecasting, and traffic operations. With a limited number of ATR and WIM sensors deployed throughout the state roadways, temporary double tubes are often deployed to get axle-based vehicle classification counts. An inductive loop signature technology previously developed by a Small Business Innovation Research (SBIR) program sponsored by the US Department of Transportation is used to classify vehicles using existing loops. This technology has the potential to save time and money while providing the state, counties or cities more data especially in the metro area where loop detectors have already been installed.

This research leveraged the outcomes from previous development to validate the classification accuracy with video data. A loop signature system was initially installed at a traffic station in Jordan, MN, to evaluate its performance. The system was later moved to another location on US-52 near Coates, MN, to validate its classification accuracy with more heavy-vehicle traffic. Individual vehicle records were manually verified and validated with ground-truth video data using both the 13 and 7-bin classification schemes from the Federal Highway Administration (FHWA) and the Highway Performance Monitoring System (HPMS). The combined results from both test sites indicated that the loop signature technology had an overall classification accuracy of 93% and 96% using the FHWA and HPMS schemes, respectively. The classification performance can be further improved by including additional vehicle signatures from the state to the classification library.

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Refining Inductive Loop Signature Technology for Statewide Vehicle Classification Counts

FINAL REPORT

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LIST OF ABBREVIATIONS

AI	Artificial Intelligent
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 Study
DOT	Department of Transportation
FAST	Fixing America's Surface Transportation
FHWA	Federal Highway Administration
HCAADT	Heavy Commercial Annual Average Daily Traffic
HPMS	Highway Performance Monitoring System
ILD	Inductive Loop Detector
KNN	K Nearest Neighbors
MAP-21	Moving Ahead for Progress in the 21st Century
MnDOT	Minnesota Department of Transportation
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
TMG	Traffic Monitoring Guide
UMN	University of Minnesota
USDOT	United States Department of Transportation
WIM	Weigh-In-Motion

EXECUTIVE SUMMARY

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, decision making, traffic forecasting, modeling, and much more. In Minnesota, vehicle classification information is typically collected from WIM sensors, ATR stations, or manually on high-volume roadways. With a limited number of ATR and WIM stations permanently installed throughout the state highway network, temporary double tubes are often deployed to get axle-based vehicle classification counts on roadways with less traffic. It takes a significant amount of time and effort to collect vehicle classification data annually.

An inductive loop signature technology was previously developed by a Small Business Innovation Research (SBIR) program sponsored by the US Department of Transportation (USDOT) to classify vehicles along a section of roadway using existing inductive loop detectors. In the past decade, the loop signature technology has been installed and tested at locations in California, Alaska, Alabama, Washington, Colorado, and other states. The loop signature system can obtain more accurate, reliable, and comprehensive traffic performance measures for transportation agencies. Results from studies in California indicated that the 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 previous loop signature development and validate the system performance with ground-truth vehicle class data extracted from video in the Twin Cities Metropolitan Area (TCMA).

Leveraging the effort from the previous study, the research team installed a loop signature-based vehicle classification system at 2 test sites to evaluate the system performance. The loop signature system was initially installed at a location in Jordan, MN, (ATR353 station) for about 5 months to evaluate the classification accuracy. The system was later moved to another location (ATR382) on US-52 near Coates, MN, to measure and validate its performance with more heavy-vehicle traffic.

Individual vehicle records were manually verified and validated with video ground-truth data using the 13-bin vehicle classification scheme from the Federal Highway Administration (FHWA) and the 7-bin Highway Performance Monitoring System (HPMS) classification categories described in the Federal Highway Administration (FHWA) *Traffic Monitoring Guide* (TMG).

The combined validation results from both test sites indicated that the loop signature technology can identify class 2 and 3 vehicles with an accuracy of 99% and 92.5%, respectively. Class 5 and 9 vehicles have a correct classification rate of 86.8% and 85.9%, respectively. Class 6 vehicles have a much lower classification rate of around 51.6%, with 36.7% of vehicles misclassified as class 5. The combined traffic volume (190, less than 1.8%) of the other vehicle classes (i.e., 1, 4, 7, 8, 10-13) observed at these 2 locations was relatively low with inconclusive classification performance. The overall classification accuracy at ATR353 and ATR382 sites was 92.9% and 93.8%, respectively.

To further refine the system performance, the research team, in collaboration with the vendor, adopted an updated vehicle library that includes the signature profiles of 2,000 vehicles from the ATR382 site. Another round of validation was conducted after incorporating the updated vehicle library. The validation results using the updated library indicted that the loop signature system can identify class 1, 2 and 3 vehicles with an accuracy of 90% or higher. When pulling a trailer, 4.4%, 4.9% and 4.4% of class 3 pickup trucks, and class 5 and 6 trucks were misclassified as class 8 vehicles. The research team observed twice as many pickup trucks pulling a trailer in the summer than in the January 2021 observation period. Class 5 and 9 vehicles had a correct classification rate of 80% and 88%, respectively. However, class 6 vehicles had a relatively lower accuracy rate of 57% with 30% of vehicles misclassified as class 5. The combined traffic count (263, less than 1.9%) of vehicle classes 1, 4, 7, 8, and 10-13 observed during the observed period was relatively low with inconclusive classification performance.

The research team further compared the classification accuracy of the two datasets before and after adapting the updated vehicle library. With the updated vehicle library, the classification accuracy of vehicles in class 6 increased by 5% (from 52% to 57%). However, the classification accuracy of class 5 vehicles dropped by about 6%. The percentage of class 6 vehicles misclassified as 5 decreased by 7% (from 36.7% to 29.7%), while the number of class 5 vehicles misclassified as 6 increased from 3.9% to 6.3%.

Trucks with lift axles could be challenging for the loop signature algorithm to distinguish whether the lift axles were raised or on the road. In general, the refined vehicle library helped improve the class 6 classification performance by reducing the misclassified vehicles in class 5. However, it also impacted the classification accuracy in the class 5 bin. The overall classification accuracy using the FHWA classification scheme did not change significantly (around 93-94%) when incorporating the updated vehicle library. The overall accuracy of the loop signature system using the HPMS classification scheme remained at around 96%.

Further classification accuracy can be achieved by adding validated signature profiles (at least 2,000 signature profiles in each bin) to the classification library for the heavy commercial vehicles in Minnesota.

CHAPTER 1: INTRODUCTION

1.1 BACKGROUND

In 2013, the US Department of Transportation (USDOT) sponsored a research study that used 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 the 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.

In recent years, the loop signature technology has been deployed in several US states, such as California, Alaska, Alabama, Washington, Colorado, Delaware, and New Hampshire. There is an opportunity for Minnesota to take advantage of the outcomes from the loop signature development and leverage the technology to collect statewide vehicle classification data to support transportation planning and forecasts using the existing loop detectors. For example, transportation agencies can potentially convert current traffic volume counters (ATR/volume) into volume and classification stations using existing detectors. The loop signature technology has the potential to save 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 objectives of this study are to (1) leverage existing loop detectors for vehicle classification counts, (2) refine the loop signature classification library by including additional vehicle profiles from Minnesota, (3) and if successful, save time and money while providing the state, counties or cities more data especially in the metro area where loop detectors are already installed. 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.

1.3 LITERATURE REVIEW

Transportation agencies in the US 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 data are collected from WIM sensors at 23 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 and 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 an 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 the 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 the Highway Performance Monitoring System (HPMS) scheme (6 classes) [10]. Based on the SBIR study, CLR and Diamond Traffic Products (https://diamondtraffic.com/) 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 provided 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 builds on our previous research [15] to perform further evaluation and validation of the loop signature technology at 2 ATR test sites in Minnesota. The research team will also collect video data at each test site to validate the performance. The technology could potentially save time and money and 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. Chapter 2 includes the system setup and installation of the loop signature technology at 2 ATR locations in the metro area. Chapter 3 describes the vehicle classification and validation methodology. Chapter 4 discusses the data collection and analysis results from both test sites. Chapter 5 describes the system refinement by including an updated library to compare the validation classification performance. And, Chapter 6 summarizes the research findings and overall system performance of the loop signature technology.

The FHWA 13 vehicle classification categories are illustrated in Appendix A. Specifications of the solar-powered camera is included in Appendix B.

CHAPTER 2: SYETEM SETUP AND INSTALLATION

With the assistance from the MnDOT staff, the research team installed and tested the loop signature system at 2 existing ATR stations (as listed in Table 1) in the Twin Cities metro area.

The loop signature vehicle classification system consists of 4 I-Loop Duo cards, a data collection master computer, a cell modem and an industrial Ethernet switch. Each loop card can handle up to 2 loop detectors. The research team upgraded the firmware of I-Loop Duo detector cards to the latest version 3.11 using a software tool (called *UniFlash*) provided by the Texas Instrument (TI). The data collection master gateway (called Vsign mater) was sent back to the vendor for upgrading firmware (to version 3.0.11) and adding a desktop enclosure as shown on the right in Figure 2.1. According to the vendor, the latest firmware includes several vehicle templates to the Artificial Intelligent (AI) library to boost the classification performance. The vendor has also updated classification decision tree and classification related thresholds in the firmware. In addition, they also improve the system health monitoring system that detects and reports system and sensor issues on a web dashboard.

Table 2.1 List of Test Sites

Site	Station ID	Description	# of Lanes	Configuration
1	ATR353	Highway 169, W of CSAH 59, Jordan, MN	7	Single Loop
2	ATR382	US-52 & 180th ST E, Vermillion Township, MN	4	Dual-Loop

Figure 2.1 A I-Loop Duo card (left) and the loop signature data collection computer (right).

2.1 ATR353 – TH 169 & CSAH 59

The upgraded loop signature system was first installed in the ATR353 cabinet to collect traffic data from 8/24/2020 to 12/3/2020. A solar-powered Wi-Fi camera was mounted on a trailer to collect ground-truth vehicle class data.

2.1.1 Loop Signature System

Four loop signature cards were installed in a card file powered by a 12 VDC power supply placed inside the cabinet. Each loop card can handle up to 2 loop detectors. Loop detector wires were directly connected to the backplane of the card file for each corresponding channel as illustrated in Figure 2.2.

The front loop detector in each lane at this station was connected to a corresponding channel on the loop cards for vehicle classification. Figure 2.3 illustrates the loop assignments in each lane at the ATR353 station. Odd number (front) loops were connected to the backplane of the card file.

Inductive loop #1 and #3 (as illustrated in Figure 2.3) were connected to the first loop signature card for 2 NB through traffic lanes. Similarly, loop #5 & #7 were connected to loop signature card #2 for SB through traffic lanes. The detector loops in the NB right-turn (#9) and left-turn (#11) lanes were connected to loop card #3 channel #1 and #2, respectively. And, finally, loop #13 in the SB left-turning lane was connected to the 4th loop card channel #1.

A digital signature profile is generated by the loop card processor sampling at 1,000 Hz when a vehicle traveling over the inductive loop in each lane. Loop signature profiles captured by each loop card are simultaneously transmitted to the Vsign master through Ethernet cables connected to the network switch or though USB cables directly connected to the Vsign master computer as illustrated in Figure 2.4. The Vsign mater device was connected to a cell modem through the network switch to transmit the real-time data to a cloud server. In addition, a solar-powered camera can be connected to the cell model through the local Wi-Fi network to transmit the video data to the cloud server.

Figure 2.5 displays an image of the integrated loop signature system installed in the ATR 353 cabinet in Jordan, MN.

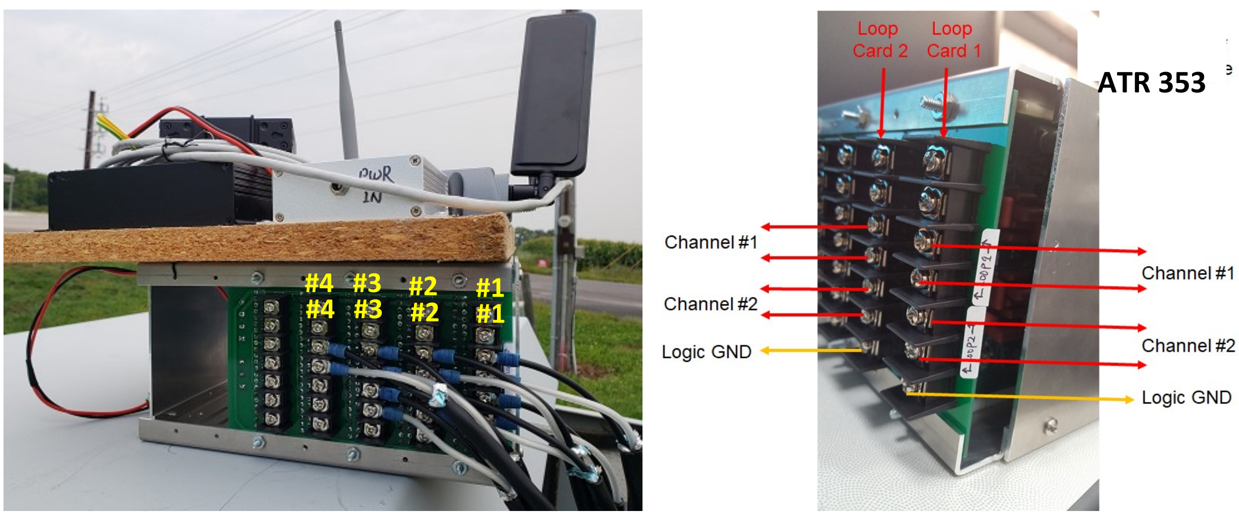


Figure 2.2 Loop detectors connected to the card file backplane at ATR353.

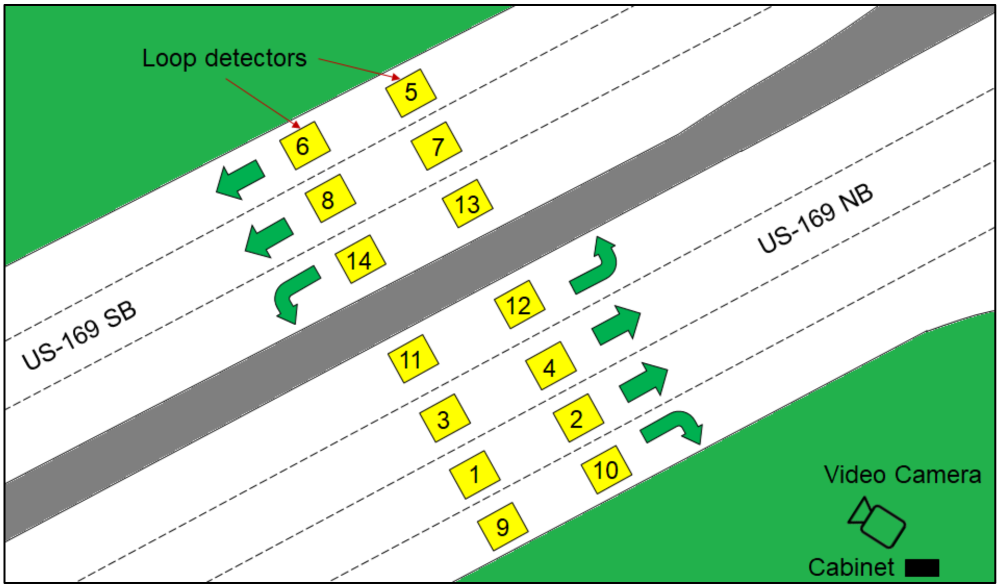


Figure 2.3 ATR353 station loop assignments.

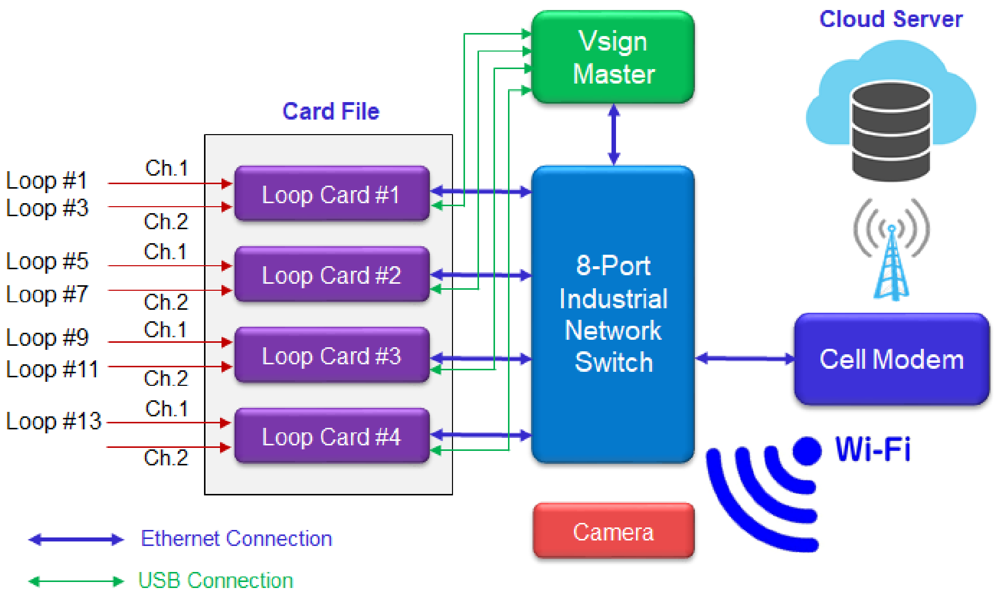


Figure 2.4 System Diagram of the loop signature cards installed inside ATR353 cabinet.

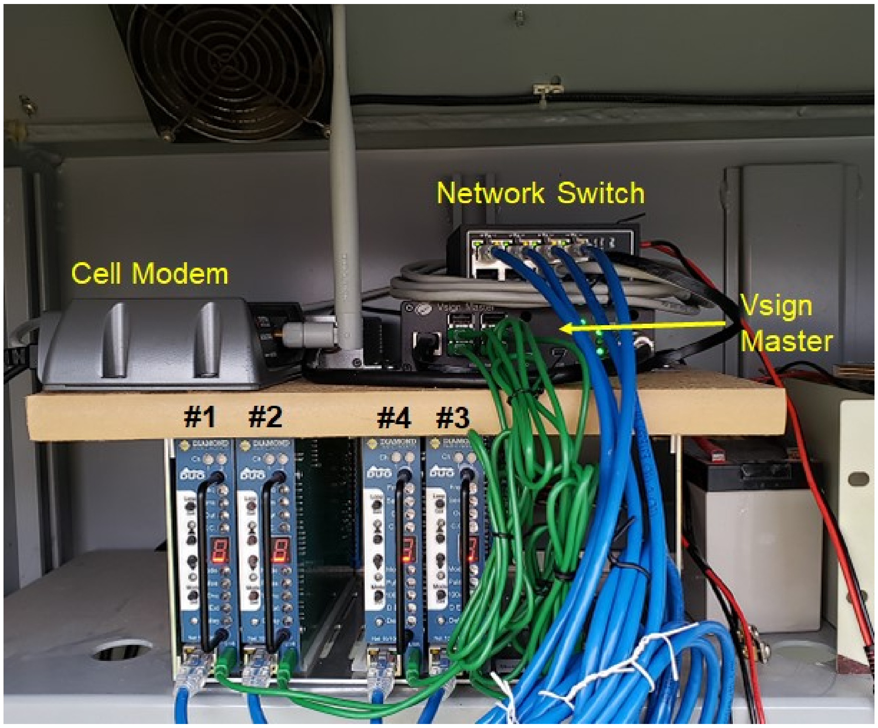


Figure 2.5 Image of the loop signature data collection system installed in the ATR 353 cabinet.

2.1.2 Video Data Collection System

With the assistance from MnDOT engineers, the research team installed a Wi-Fi camera and a solar panel (as displayed in Figure 2.6) mounted on top of an extendable arm of a traffic detection trailer to collect vehicle video data. The camera is powered by a solar panel with a small rechargeable battery and wirelessly connected to the cell modem placed inside the cabinet. This setup enables the research team to remotely monitor the traffic and collect video data for validation.

Figure 2.7 displays a snapshot of the recorded video from the wireless camera. Individual vehicle class information will be manually extracted from the video data. The extracted vehicle classification data will be used as ground truth to verify the results from the loop signature technology.

Figure 2.6 Image of a video data collection system mounted on a trailer next to ATR353 cabinet.

Figure 2.7 A snapshot of video recorded from the camera at ATR353 station.

2.2 ATR382 – US 52 & 180TH ST E

After a TAP meeting held on 11/19/2020, the TAP recommended us to move the loop signature system from ATR353 to ATR382 station located on US-52 south of Coates, MN, to collect additional data. ATR382 site historically has a higher number of heavy commercial vehicles than the truck volume at ATR353. With the permission from MnDOT RTMC and support from MnDOT staff, we attached the solar-power camera to a RTMC pole across the highway from the ATR382 cabinet to collect video data.

2.2.1 Loop Signature System

The ATR382 location has 2 lanes of through traffic in each direction. Both the front and rear loop sensors in each lane at this site were connected to the loop card. Figure 2.8 illustrates the loop assignments in each lane at the ATR382 station. Odd number loops were connected to the front loop channel of the card file.

Inductive loop #1 and #2 (as illustrated in Figure 2.9) were connected to the first loop signature card for the NB driving lane. Loop #3 & #4 were connected to loop signature card #2 for the NB passing lane. The detector loops in the SB passing and driving lanes were connected to loop card #3 and #4, respectively.

In addition to the setup at ATR353, the research team added an external antenna (a 4-in-1 LTE, GNSS, Wi-Fi antenna) and a web power switch in the ATR382 cabinet to improve data communication reliability. Figure 2.10 displays an image of the integrated loop signature system components installed inside the ATR382 cabinet.

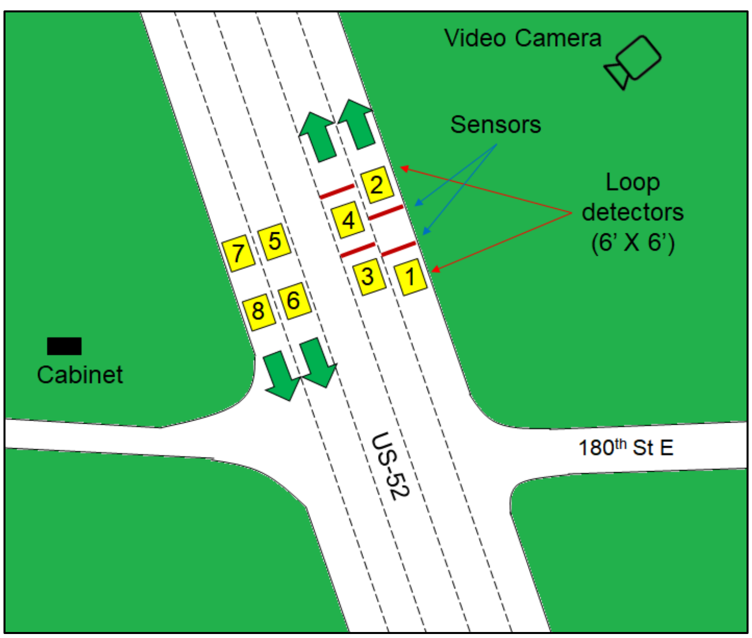


Figure 2.8 ATR382 station loop assignments.

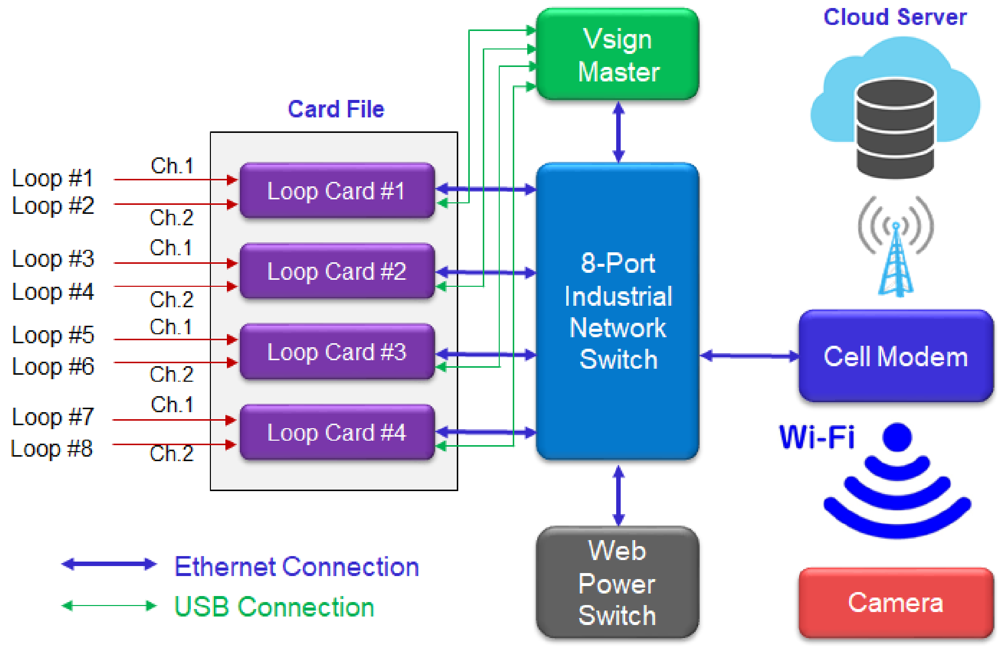


Figure 2.9 System Diagram of the loop signature cards installed inside ATR382 cabinet.

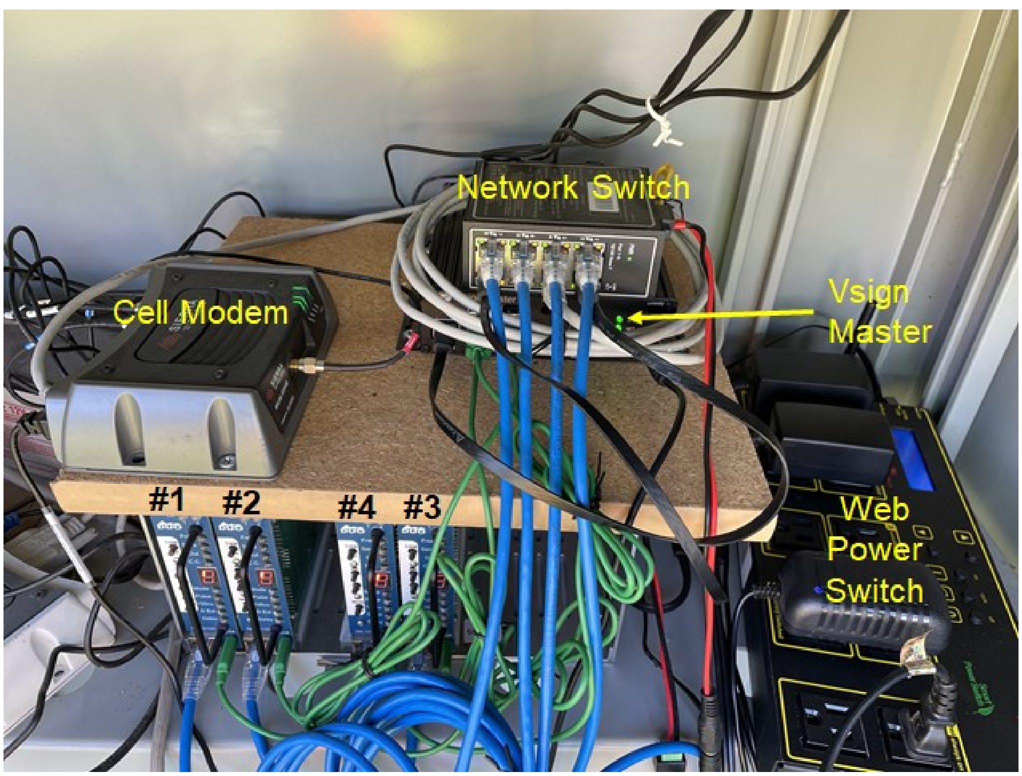


Figure 2.10 Image of the loop signature data collection system installed in the ATR 382 cabinet.

2.2.2 Video Data Collection System

With the assistance from MnDOT engineers, the research team attached a Wi-Fi camera and a solar panel (as displayed in Figure 2.11) to a RTMC camera pole on the east side of US-52. Figure 2.12 displays a snapshot of the recorded video from the wireless camera. Individual vehicle class information will be later extracted from the video data manually. The extracted vehicle classification data will be used as ground truth to verify the results from the loop signature technology.

Figure 2.11 Image of a video data collection system mounted on a RTMC pole near ATR382.

Figure 2.12 A snapshot of video recorded from the camera at ATR382 station.

CHAPTER 3: METHODOLOGY

3.1 VEHICLE CLASSIFICATION

In Minnesota, vehicle classification is usually collected from Weigh-In-Motion (WIM) sensors at 23 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 operations.

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 previously acquired and can be installed at selected test sites to collect vehicle classification information using existing loop detectors under the pavement.

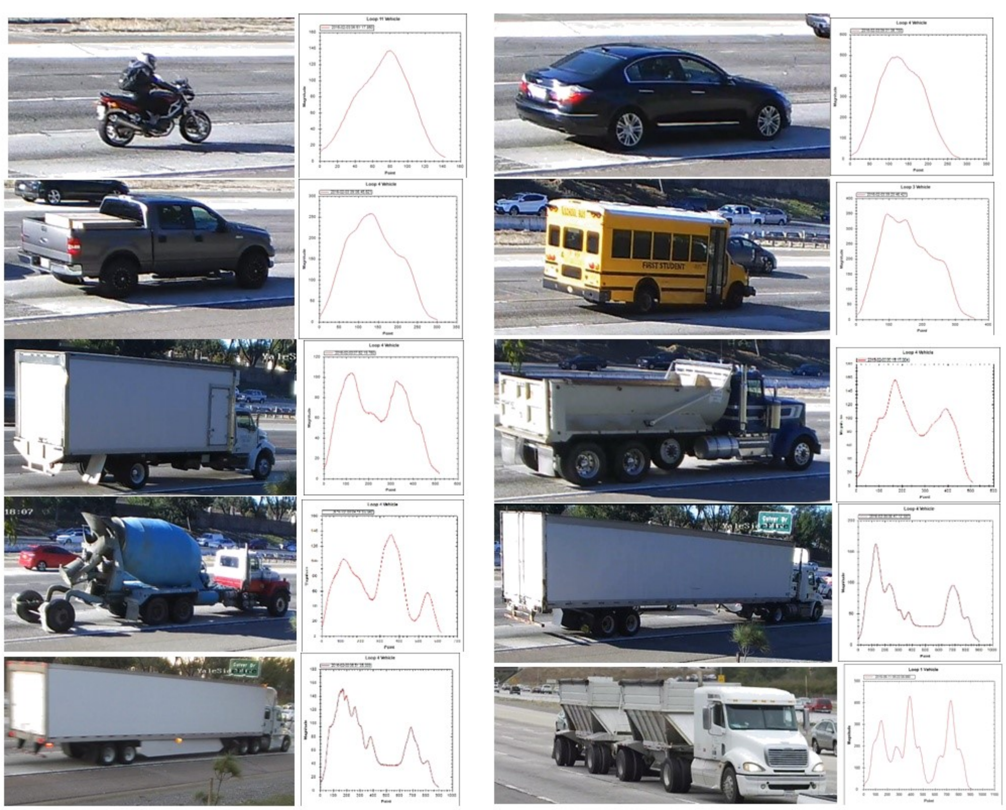


Figure 3.1 Loop Signatures for Different Type of Vehicles (Image from CLR Analytics Inc.).

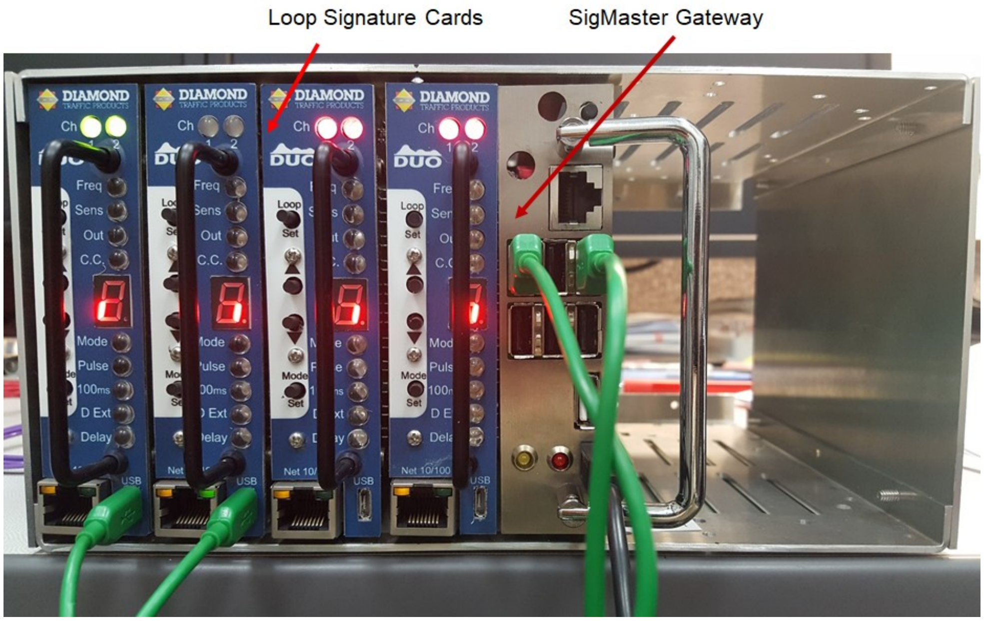


Figure 3.2 Inductive Loop Signature Cards for Vehicle Classification.

3.2 VALIDATION PROCESS

Raw loop signature data were initially processed and stored locally as zip files. These zip files were uploaded to a cloud server daily. The research team downloaded the raw zipped files from the cloud server and generated individual vehicle record using a customized software, called *SignScope* (See Figure 3.3), for data processing and analysis. For example, “site250-usb-l203-2020-11-20-12-00-03_mag.zip” is a compressed file containing the raw signature data for lane 2 and 3 on 11/20/2020 downloaded from the server. A text file with individual vehicle information (see Table 3.1) and a loop signature image (see Figure 3.4) for each vehicle were generated by the SignScope tool.

Table 3.1 listed a sample of individual vehicle classification data and timestamp from the loop signature system. Figure 3.4 displayed two loop signature profiles of vehicle #534866 and #534867 identified as FHWA vehicle class 5 and 9, respectively.

Figure 3.5 illustrated a flowchart to process loop data. The compressed raw loop data files were first downloaded from the cloud server then the customized SignScope tool was used to generate vehicle signature profiles and convert the raw data into text files that contain vehicle classification, lane, and timestamp information for data validation.

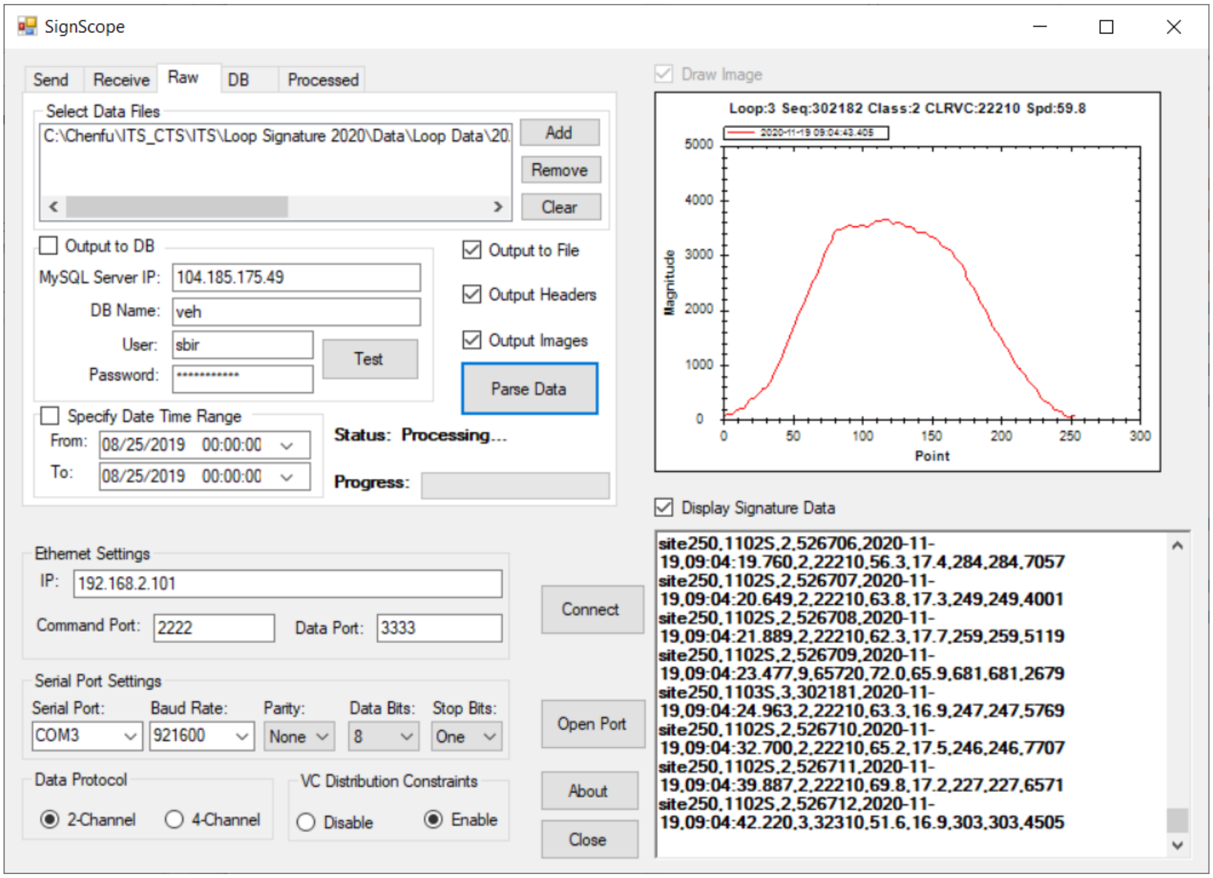


Figure 3.3 Screenshot of the SignScope tool.

Table 3.1 Sample raw individual vehicle data from loop signature system.

Site	Loop ID	Lane	Sequence Number	Date	Time	Vehicle Class	Class Codes
site250	1103S	3	306207	11/20/2020	12:01:36.36	2	22210
site250	1103S	3	306208	11/20/2020	12:01:41.41	3	32310
site250	1102S	2	534866	11/20/2020	12:01:42.42	5	52110
site250	1103S	3	306209	11/20/2020	12:01:56.56	2	22210
site250	1102S	2	534867	11/20/2020	12:01:59.59	9	65110

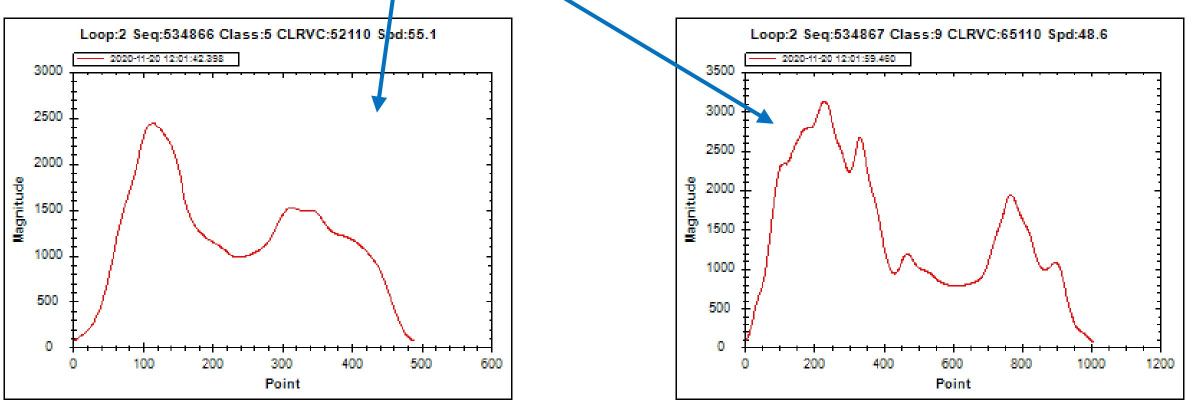


Figure 3.4 Sample loop signature profiles of two vehicles (class 5 & 9).

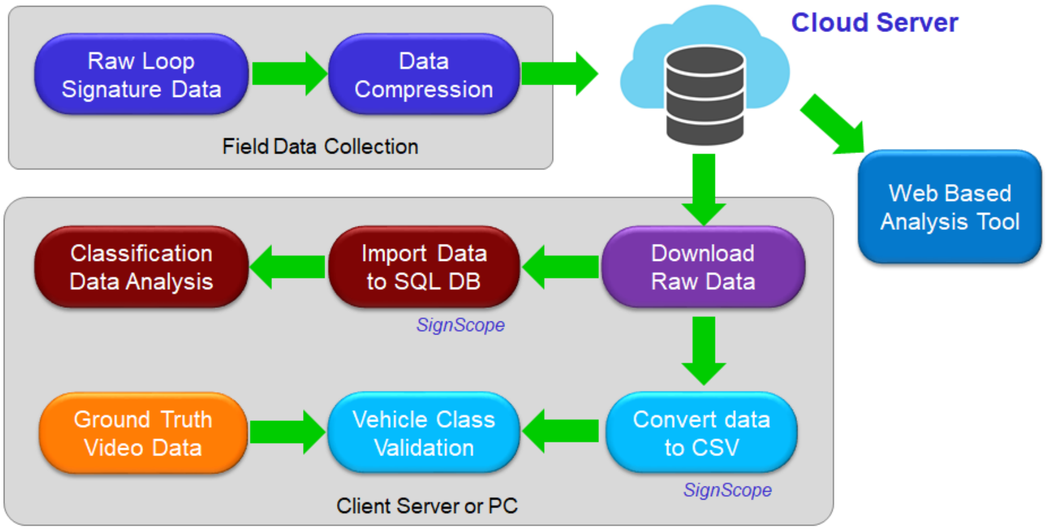


Figure 3.5 Data analysis flowchart for individual vehicle class validation.

Recorded video data were used as ground-truth references to validate the vehicle classification accuracy of the loop signature system. In order to reduce battery power consumption, the solar-powered camera was configured with a passive infrared (PIR) setting to stop video recording when there is no vehicle activity. In addition, the research team used a Windows-based freeware video player software (VSPlayer) to review the video data and validate the vehicle class results from the loop signature system.

The research team first identified the time offset between the video timestamp and the loop signature data timestamp. Then, the research team visually observed each vehicle on a particular lane and manually recorded the vehicle class using the FHWA 13-category scheme (See Appendix A). For example, Figure 3.6 displays a screenshot of video image and the corresponding loop signature profile of a class 6 vehicle on 9/22/2020 in the SB driving lane of HWY 169 at ATR353 site.

Validation results were imported to a SQL database for statistical analysis.

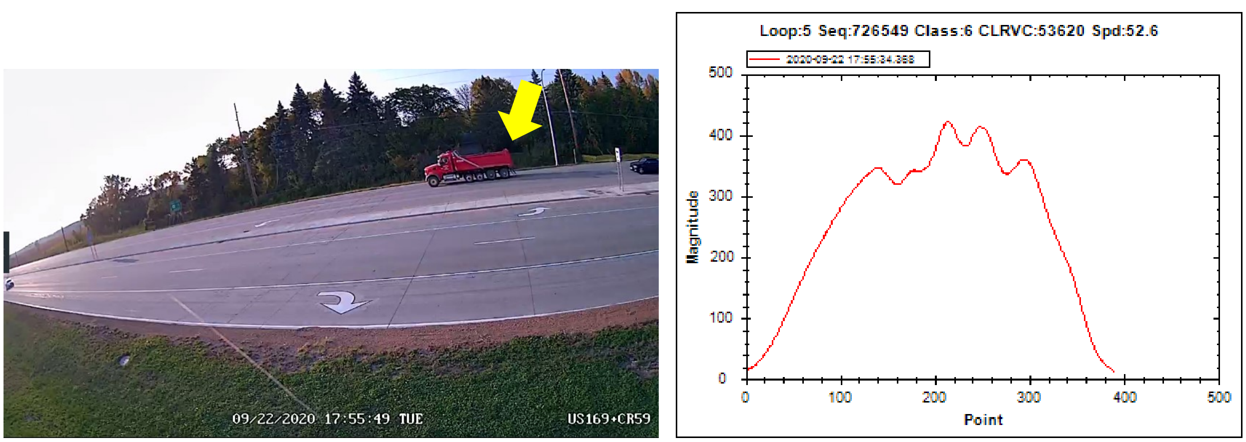


Figure 3.6 Vehicle #726549 – Class 6.

CHAPTER 4: DATA COLLECTION AND ANALYSIS

Loop signature data were collected at ATR353 station from 8/24/2020 to 12/3/2020 and at ATR382 location (ongoing since 12/3/2020). A week of video data (9/15/2020 to 9/23/2020 for ATR353 and 1/25/2021 to 1/31/2021 for ATR382) were recorded at each site for validation.

4.1 VOLUME DATA FROM LOOP SIGNATURE SYSTEM

Daily loop signature data stored locally on each data collection card were compressed into two zipped files. The zipped data files were automatically uploaded to a remote cloud server when the data collection gateway is connected to the internet. The research team used a data modem to monitor the status of loop data collection system and retrieve the recorded loop signature data remotely.

4.1.1 ATR353

Figure 4.1 and 4.2 display the daily traffic volume by FHWA vehicle class at the ATR353 site processed from the loop signature data on weekday and weekend, respectively. On weekdays, 64% of the traffic are class 2 vehicle and 20% of the traffic are class 3 vehicles. Nearly 9% of the traffic are class 9 truck at the ATR353 site on weekdays. All the other vehicle types consist of less than 7% of traffic at ATR353 site on weekdays.

Weekday	Percentage
Class1	0.11%
Class2	64.09%
Class3	20.00%
Class4	0.12%
Class5	3.10%
Class6	0.89%
Class7	0.11%
Class8	1.19%
Class9	8.93%
Class10	0.99%
Class11	0.15%
Class12	0.23%
Class13	0.00%
Others	0.08%
Total	100.00%

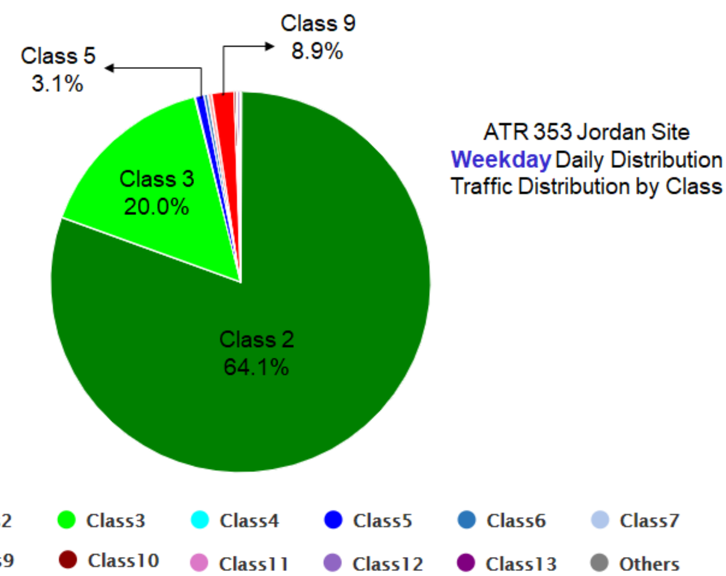
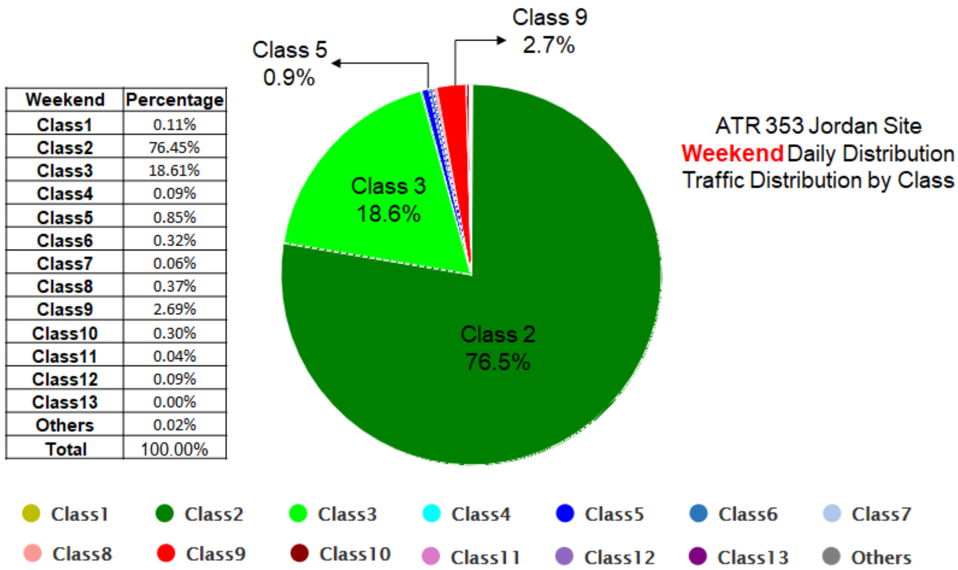


Figure 4.1 ATR353 Weekday traffic distribution by FHWA vehicle class.

On weekends, 77% and 19% of the traffic are class 2 and 3 vehicles, respectively. The class 9 truck consist of almost 3% of the traffic on weekends. All the other vehicle types consist of less than 3% of traffic at ATR353 site on weekends.

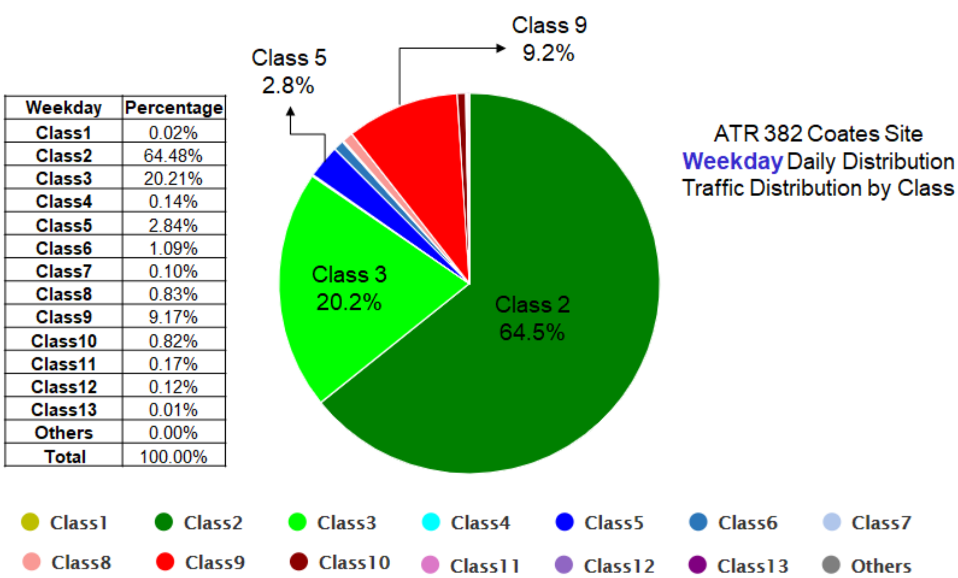


Weekend	Percentage
Class1	0.11%
Class2	76.45%
Class3	18.61%
Class4	0.09%
Class5	0.85%
Class6	0.32%
Class7	0.06%
Class8	0.37%
Class9	2.69%
Class10	0.30%
Class11	0.04%
Class12	0.09%
Class13	0.00%
Others	0.02%
Total	100.00%

Figure 4.2 ATR353 Weekend traffic distribution by FHWA vehicle class.

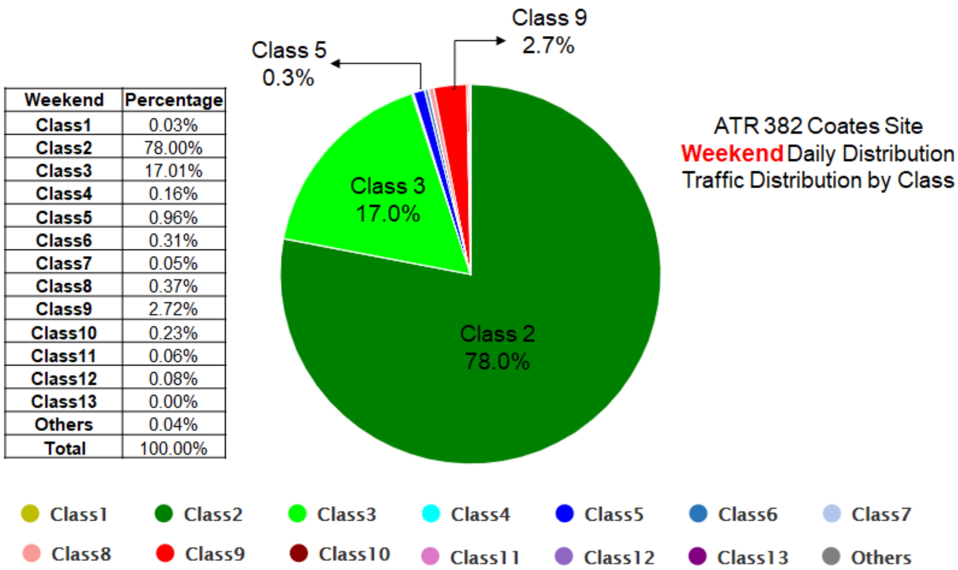
4.1.2 ATR382

Vehicle loop signature data at this location has been collected since the installation on 12/3/2020. The daily vehicle volume distribution by FHWA class on weekdays and weekends were displayed in Figure 4.3 and 4.4, respectively. On average, 65% of the traffic at the ATR382 site are class 2 cars and 20% of the traffic are class 3 vehicles on weekdays. Class 5 and 9 vehicles consist of 3% and 9% of the overall traffic, respectively.



Weekday	Percentage
Class1	0.02%
Class2	64.48%
Class3	20.21%
Class4	0.14%
Class5	2.84%
Class6	1.09%
Class7	0.10%
Class8	0.83%
Class9	9.17%
Class10	0.82%
Class11	0.17%
Class12	0.12%
Class13	0.01%
Others	0.00%
Total	100.00%

Figure 4.3 ATR382 Weekday traffic distribution by FHWA vehicle class.



Weekend	Percentage
Class1	0.03%
Class2	78.00%
Class3	17.01%
Class4	0.16%
Class5	0.96%
Class6	0.31%
Class7	0.05%
Class8	0.37%
Class9	2.72%
Class10	0.23%
Class11	0.06%
Class12	0.08%
Class13	0.00%
Others	0.04%
Total	100.00%

Figure 4.4 ATR382 Weekend traffic distribution by FHWA vehicle class.

4.2 VALIDATION RESULTS

Validation results from the vehicle classification process using methodologies described in the previous chapter for both test sites were discussed as follows.

4.2.1 ATR353

The research team obtained vehicle class information from the video data and validated vehicle class with the results from loop signature system. Table 4.1 listed the validation results of 4,607 vehicles using FHWA class scheme at the ATR353 site. Passenger vehicles (class 2) consisted of over 60% of the traffic at this location. The classification accuracy for class 1, 2 and 3 were above 90%. We observed 22 class 2 vehicles (0.8%) being misclassified as class 3 vehicles and 35 class 3 vehicles (4%) being misclassified as class 2 passenger vehicles. We also noticed that 21 pickup trucks (class 3) pulling a trailer were misclassified as class 8 trucks.

The results indicated that 46 (37%) of class 6 trucks were misclassified as class 5 vehicles. For class 9 heavy commercial vehicles, 37 (6%) and 47 (8%) of semi-trucks were misclassified as class 8 and 10, respectively. The loop signature system correctly identified class 5 and 9 vehicles over 83% of the time. However, the classification accuracy for the other vehicle classes were lower than 80% with a relatively small sample size.

Overall, the combined vehicle count (191) for class 4, 6, 7, 8, and 10 to 13 during the observation period is less than 5% of the entire traffic volume. The overall classification accuracy, i.e., sum of correctly classified vehicles (4,278) divided by the total vehicle count (4,607), is about 93%.

Table 4.1 Vehicle classification result – ATR353 site (9/22/2020).

Vehicle Class		Classification from Loop Signature													Total	Vehicle Class		Classification Accuracy %
		1	2	3	4	5	6	7	8	9	10	11	12	13				
FHWA Class	1	28	3												31	FHWA Class	1	90.3%
	2	2	2777	22		3	1		2						2807		2	98.9%
	3		35	796	2	16			21	2					872		3	91.3%
	4			1	2	2									5		4	40.0%
	5		1	2	1	92	4		9						109		5	84.4%
	6		1	4		46	68	2		2	2				125		6	54.4%
	7			4	5	3	9	1	2						24		7	4.2%
	8								6	5					11		8	54.5%
	9			7	1	4	3		37	498	47				597		9	83.4%
	10					3			1	11	9				24		10	37.5%
	11											0			0		11	NA
	12												1		1		12	100.0%
	13									1				0	1		13	0.0%
Total		30	2817	836	11	169	85	3	78	519	58	0	1	0	4607	Overall		**92.9%**

4.2.2 ATR382

Table 4.2 listed the validation results of 3,111 vehicles using FHWA class scheme at the ATR382 site on 1/26/2021. Passenger vehicles (class 2) consisted of over 59% of the traffic at this location. The classification accuracy for class 2, 3, 5 and 9 are above 89%. We observed 16 class 2 vehicles (0.87%) being misclassified as class 3 vehicles and 17 class 3 vehicles (3.7%) being misclassified as class 2 passenger vehicles. We also noticed that 8 pickup trucks (class 3) pulling a trailer were misclassified as class 8 trucks (1.5%).

In addition, the results indicated that 29 (41%) of class 6 trucks were misclassified as class 5 vehicles. For class 9 heavy commercial vehicles, 15 (3%) and 31 (6.5%) of semi-trucks were misclassified as class 8 and 10, respectively. The loop signature system correctly identified class 5 and 9 vehicles about 89% of the time. However, the classification accuracy for the other vehicle classes are lower than 80% with a relatively small sample size. That is, the combined vehicle count (101) for class 6, 7, 10 and 13 during the observation period is less than 3% of the entire traffic volume. The overall classification accuracy, i.e., sum of correctly classified vehicles (2,928) divided by the total vehicle count (3,111), is about 94%.

Table 4.3 listed the validation results of 3,119 vehicles using FHWA class scheme at the ATR382 site on 1/27/2021. Passenger vehicles (class 2) consists of over 59% of the traffic at this location. The classification accuracy for class 2, 3, 5 and 9 are above 86%. We observed 16 class 2 vehicles (0.9%) being misclassified as class 3 vehicles and 18 class 3 vehicles (3.2%) being misclassified as class 2 passenger vehicles. We also observed 14 pickup trucks (class 3) pulling a trailer were misclassified as class 8 trucks (2.5%).

We also found that 26 (33%) of class 6 trucks were misclassified as class 5 vehicles. For class 9 heavy commercial vehicles, 21 (4.4%) and 37 (7.7%) of semi-trucks were misclassified as class 8 and 10, respectively. The loop signature system correctly identified class 5 and 9 vehicles over 86% of the time. However, the classification accuracy for the other vehicle classes are lower than 80% with a relatively small sample size. That is, the combined vehicle count (124) for class 4, 6, 7, 8, 10 and 11 during the observation period is less than 4% of the entire traffic volume. The overall classification accuracy, i.e., sum of correctly classified vehicles (2,914) divided by the total vehicle count (3,119), is about 93%.

Table 4.2 Vehicle classification result – ATR382 site (1/26/2021).

Vehicle Class		Classification from Loop Signature													Total	Vehicle Class		Classification Accuracy %
		1	2	3	4	5	6	7	8	9	10	11	12	13				
FHWA Class	1	0	0												0	FHWA Class	1	NA
	2	1	1818	16		1									1836		2	99.0%
	3		17	520	1	5			8	2					553		3	94.0%
	4			0	1										1		4	100.0%
	5		2	2	1	112	5		3						125		5	89.6%
	6			1	1	29	34	6							71		6	47.9%
	7			4		3	7	0	3	1					18		7	0.0%
	8								9	2					11		8	81.8%
	9			3	1	2	2		15	426	31				480		9	88.8%
	10					1			2	5	4				12		10	33.3%
	11											2			2		11	100.0%
	12												2		2		12	100.0%
	13													0	0		13	NA
Total		1	1837	546	5	153	48	6	40	436	35	2	2	0	3111	Overall		**94.1%**

Table 4.3 Vehicle classification result – ATR382 site (1/27/2021).

Vehicle Class		Classification from Loop Signature													Total	Vehicle Class		Classification Accuracy %
		1	2	3	4	5	6	7	8	9	10	11	12	13				
FHWA Class	1	0													0	FHWA Class	1	NA
	2		1820	16											1836		2	99.1%
	3		18	517	1	5			14	1					556		3	93.0%
	4				0				1						1		4	0.0%
	5		1	3	0	104	5		7	1					121		5	86.0%
	6		1	1	2	26	40	5	3	1					79		6	50.6%
	7				1	1	4	3	1						10		7	30.0%
	8								6	7					13		8	46.2%
	9			5	0	3			21	413	37	1			480		9	86.0%
	10					1			3	6	8				18		10	44.4%
	11								1			1	1		3		11	33.3%
	12												2		2		12	100.0%
	13													0	0		13	NA
Total		0	1840	542	4	140	49	8	57	429	45	2	3	0	3119	Overall		**93.4%**

4.2.3 Combined Results

The research team evaluated the loop signature based vehicle classification system at 2 ATR stations (ATR353 and ATR 382) in the metro area. In total, 10,837 vehicles were validated by comparing the vehicle classification output from the loop signature system with recorded video data. The overall classification accuracy at ATR353 and ATR382 sites is 92.9% and 93.8%, respectively.

Based on the validation results from the 2 ATR sites, it is confident to say that the loop signature system can identify class 2 and 3 vehicles with a respective accuracy of 99% and 92.5%, as listed in Table 4.4. Class 5 and 9 vehicles have a correct classification rate of 86.8% and 85.9%, respectively. Class 6 vehicles have a much lower classification rate around of 51.6% with 36.7% of vehicles were misclassified as class 5. The combined traffic volume (190, less than 1.8%) of the other vehicle classes (i.e., 1, 4, 7, 8, 10-13) observed at these 2 locations was relatively low with inconclusive classification performance.

Table 4.4 Combined vehicle classification results – ATR353 and ATR382.

Vehicle Class		Classification from Loop Signature													Total	Vehicle Class		Classification Accuracy %
		1	2	3	4	5	6	7	8	9	10	11	12	13				
FHWA Class	1	28	3												31	FHWA Class	1	90.3%
	2	3	6415	54		4	1		2						6479		2	99.0%
	3		70	1833	4	26			43	5					1981		3	92.5%
	4			1	3	2			1						7		4	42.9%
	5		4	7	2	308	14		19	1					355		5	86.8%
	6		2	6	3	101	142	13	3	3	2				275		6	51.6%
	7			8	6	7	20	4	6	1					52		7	7.7%
	8								21	14					35		8	60.0%
	9			15	2	9	5		73	1337	115	1			1557		9	85.9%
	10					5			6	22	21				54		10	38.9%
	11								1			3	1		5		11	60.0%
	12												5		5		12	100.0%
	13									1				0	1		13	0.0%
Total		31	6494	1924	20	462	182	17	175	1384	138	4	6	0	**10837**	Overall		**93.4%**

4.2.4 Misclassification

Among the 13 vehicle class bins the research team analyzed, five of them have a vehicle sample size over 100 and achieve a classification accuracy of over 85% except for the class 6 bin (see Table 4.5). The research team further analyzed the class 6 vehicle data and learned that 36.7% of the class 6 vehicles, on average, were misclassified as class 5 trucks. As listed in Table 4.6, the misclassification rate of class 6 vehicles as class 5 ranges from 33% to 41% between the 2 sites. The research team further examined the loop signature profiles of a sample of misclassified vehicles and compared them with the video data to investigate the possible causes of misclassification. Our findings indicated that many misclassified trucks have retractable axles.

Figure 4.5 to 4.10 display images and corresponding signature profiles of 6 class 6 trucks that were misidentified as class 5 trucks. The loop signature profiles vary quite significantly depending on the truck body type and the materials they carry. The loop signature profiles of two similar trucks as shown in Figure 4.6 & 4.7 are quite different. Additional refinement is needed to improve the performance of class 6 vehicles by including the loop signature of class 6 vehicles in the classification algorithm.

Table 4.5 Classification accuracy for binned vehicle count over 100.

Vehicle Class	2	3	5	6	9
Accuracy	99.0%	92.5%	86.8%	51.6%	85.9%

Table 4.6 Class 6 vehicles misclassified as class 5 trucks.

Site	ATR 353	ATR 382		Combined
Data Collection Date	9/22/2020	1/26/2021	1/27/2021	Combined
Vehicle Classification Accuracy, %	54.4%	47.9%	50.6%	51.6%
Misclassified as Class 5 Vehicles	46 (36.8%)	29 (40.8%)	26 (32.9%)	101 (36.7%)
Number of Actual Class 6 Vehicles, N	125	71	79	275

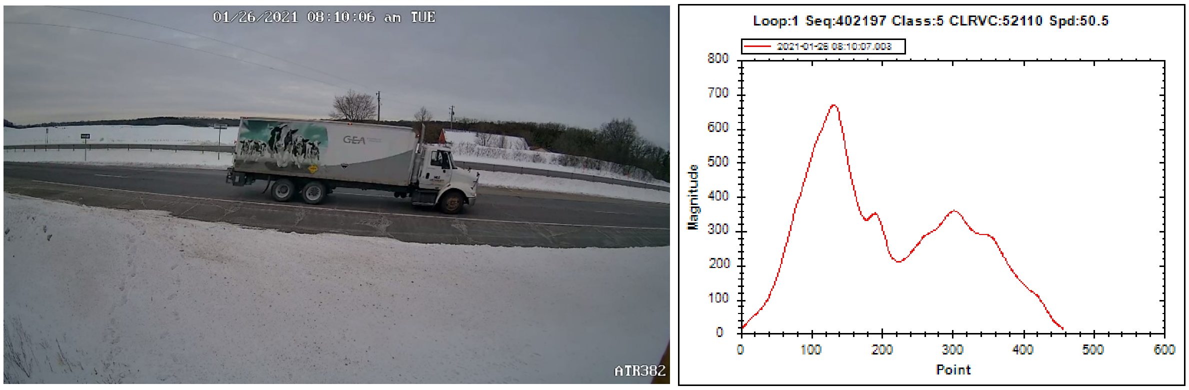


Figure 4.5 Vehicle #402197 – Class 6 (1/26/2021) Misclassified as Class 5.

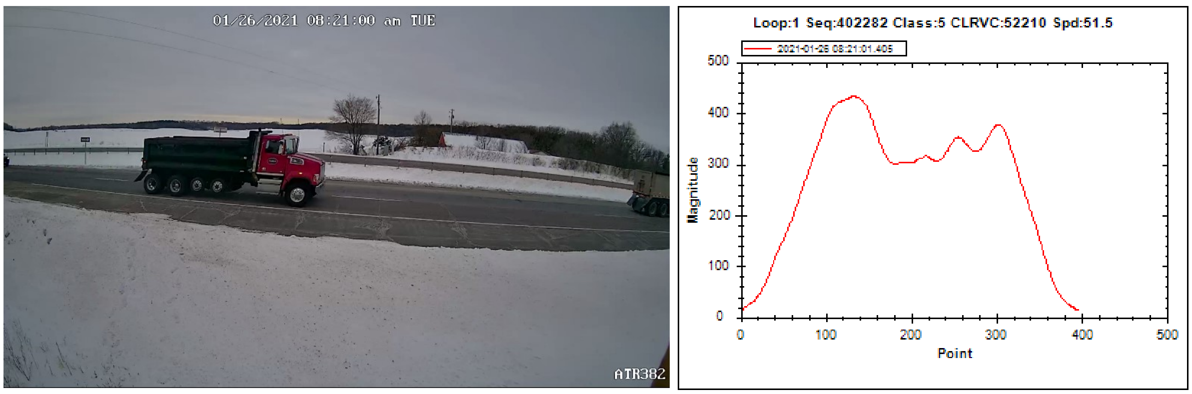


Figure 4.6 Vehicle #402282 – Class 6 (1/26/2021) Misclassified as Class 5.

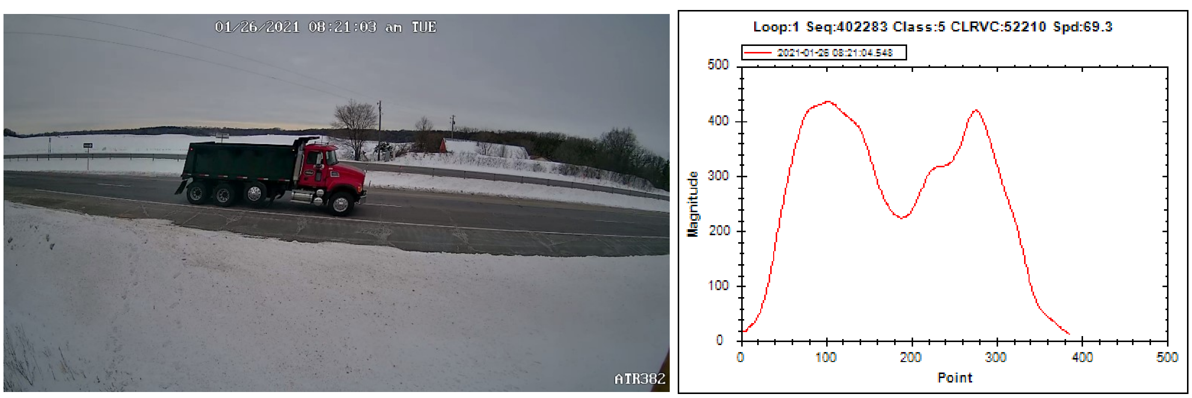


Figure 4.7 Vehicle #402283 – Class 6 (1/26/2021) Misclassified as Class 5.

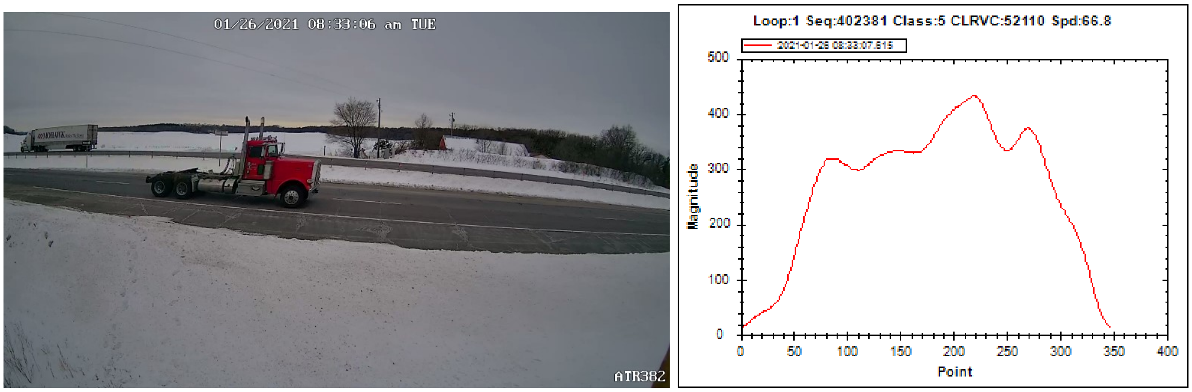


Figure 4.8 Vehicle #402381 – Class 6 (1/26/2021) Misclassified as Class 5.

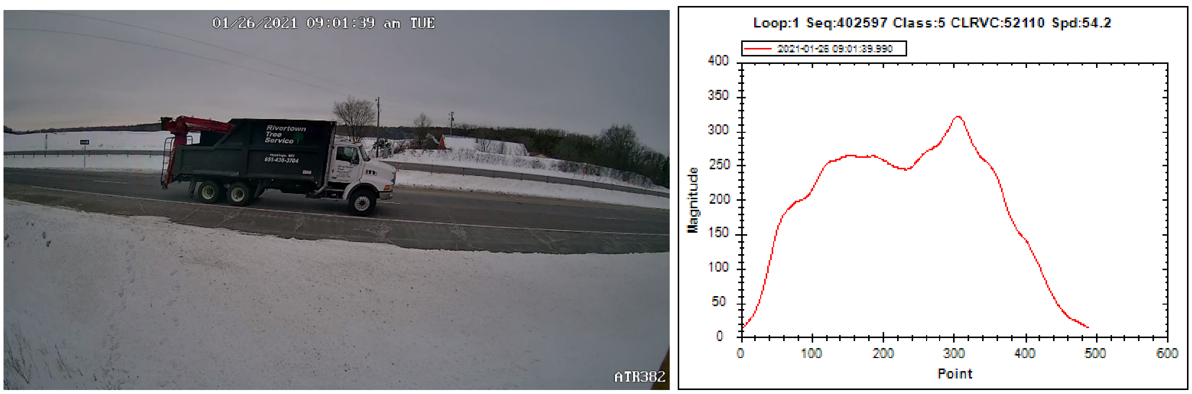


Figure 4.9 Vehicle #402597 – Class 6 (1/26/2021) Misclassified as Class 5.

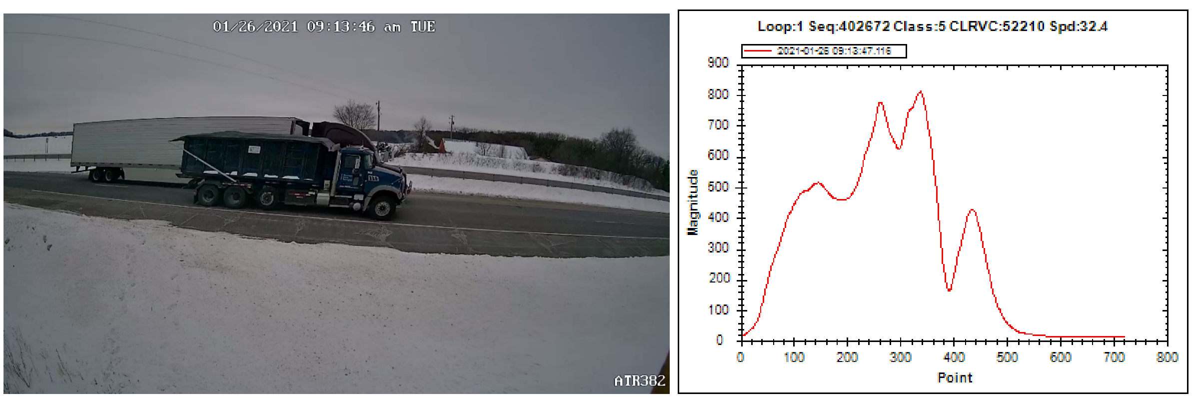


Figure 4.10 Vehicle #402672 – Class 6 (1/26/2021) Misclassified as Class 5.

4.3 HPMS CLASSIFICATION

The research team also analyzed the classification results from both ATR stations using the HPMS classification scheme for 7 aggregate classes of vehicles: motorcycles (MC), passenger cars (PC), light duty trucks (LT), buses (BS), single unit trucks (SU), trucks with single trailer (ST), and trucks with multi-unit trailers (MT). As listed in Table 4.7, the loop signature system has over 81% of classification accuracy for all HPMS class bins except for bus class which has only 43% of accuracy (N=7). The overall accuracy of the loop signature system using the HPMS classification scheme is 96.9%.

Table 4.7 Combined vehicle classification results using HPMS classification scheme.

Vehicle Class		Classification from Loop Signature HPMS Class							Total (N)	Vehicle Class		Classification Accuracy %
HPMS	FHWA	1	2	3	4	5	6	7		HPMS	FHWA	
MC (Bin 1)	1	28	3						31	MC (Bin 1)	1	90.3%
PC (Bin 2)	2	3	6415	54		5	2		6479	PC (Bin 2)	2	99.0%
LT (Bin 3)	3		70	1833	4	26	48		1981	LT (Bin 3)	3	92.5%
BS (Bin 4)	4			1	3	2	1		7	BS (Bin 4)	4	42.9%
SU (Bin 5)	5, 6, 7		6	21	11	609	35		682	SU (Bin 5)	5, 6, 7	89.3%
ST (Bin 6)	8, 9 10			15	2	19	1609	1	1646	ST (Bin 6)	8, 9 10	97.8%
MT (Bin 7)	11, 12, 13						2	9	11	MT (Bin 7)	11, 12, 13	81.8%
Total		31	6494	1924	20	661	1697	10	**10837**	Total		**96.9%**

4.4 ESAL COMPARISONS

As suggested by the Technical Advisory Panel (TAP), the research team also compared the combined Equivalent Single Axle Load (ESAL) for each vehicle class using the Equivalent Axle Load Factor (EALF) derived from MnDOT's WIM data. As listed in Table 4.8, the total ESALs for each vehicle class was determined by taking the median EALF and multiplying with the total number of vehicle counts in each class bin from the loop signature system and the ground-truth dataset, respectively.

Among the 13 vehicle class bins we validated, five (class 2, 3, 5, 6, and 9) of them have vehicle count over 100. The ESALS differences between the loop signature and the   for class 2 and 3 vehicles are less than 3% as shown in Table 4.8. The ESALs difference for Class 9 vehicles (N=1,557) is about 11%. We observed 355 and 275 vehicles in class 5 and 6, respectively. The EALF value for class 6 vehicle (0.272) is about 10 times larger than the EALF for class 5 trucks (0.0276). Both classes have a ESALs absolute difference percentage around 30-34% that 14 (4%) class 5 vehicles were misclassified as class 6 and 101 (37%) class 6 vehicles were misclassified as class 5 as shown in Table 4.6.

Table 4.8 ESAL Comparison by Class for both ATR353 and ATR382 stations.

Vehicle Class		Median EALF	ESALs from Loop Signature	ESALs from Ground Truth	Count (N)	Diff. (%)
FHWA Class	1	0.00	0.00	0.00	31	NA
	2	0.0004	2.60	2.59	6479	0.23%
	3	0.0013	2.50	2.58	1981	2.88%
	4	0.214	4.28	1.50	7	185.71%
	5	0.0276	12.75	9.80	355	30.14%
	6	0.272	49.50	74.80	275	33.82%
	7	0.924	15.71	48.05	52	67.31%
	8	0.205	35.88	7.18	35	400.00%
	9	0.509	704.46	792.51	1557	11.11%
	10	0.706	97.43	38.12	54	155.56%
	11	1.34	5.36	6.70	5	20.00%
	12	0.737	4.42	3.69	5	20.00%
	13	1.00	0.00	1.00	1	100.00%
Total			**934.88**	**988.51**	**10837**	**5.42%**

CHAPTER 5: SYSTEM REFINEMENT

To further investigate the opportunity to improve classification accuracy, the research team worked closely with the vendor in this task to (1) install a web power switch in the cabinet to improve system reliability, (2) adjusted signature filter parameters to reduce smoothing effects and increase signature resolution, and (3) adopted a revised classification library, which was generated by adding the sample vehicle from ATR382 station in January 2021, into the dataset. The research team then re-evaluated vehicle classification accuracy by collecting additional video data to validate the system performance with the modified parameter settings and updated vehicle libraries.

5.1 UPDATE VEHICLE CLASS LIBRARY

Loop signature profile of 2,000 vehicles (800 trucks and 1,200 the other vehicle types) from the video data collected on 1/26/2021 were reviewed, analyzed, and included in the classification library. In addition, the vendor adjusted a loop signature filter parameter to reduce smoothing effects and modified another signature resolution parameter to provide a 3X higher signature resolution than the previous setting. The objective is to extract more distinctive features from the higher resolution loop signature profiles.

5.2 RE-VALIDATION RESULTS

Table 5.1 listed the validation results of 7,861 vehicles using FHWA class scheme at the ATR382 site on 7/20/2021. Passenger vehicles (class 2) consisted of over 66% of the traffic in this dataset. The classification accuracy for class 1, 2, 3, 4, 5, 9, 11, and 12 were above 80%. We observed that 64 class 2 vehicles (1.2%) were misclassified as class 3 vehicles and 30 class 3 vehicles (2.0%) were misclassified as class 2 passenger vehicles. We noticed that class 3 pickup trucks pulling a trailer have a high tendency of being misclassified as trucks (7.1%).

In addition, the results indicated that 26 (29%) of class 6 trucks were misclassified as class 5 vehicles, and 16 (7%) of class 5 trucks were misclassified as class 6 vehicles. For class 9 heavy commercial vehicles, 36 (5%) and 30 (4%) of semi-trucks were misclassified as class 8 and 10, respectively. The loop signature system correctly identified class 5 and 9 vehicles about 81% of the time. The overall classification accuracy on the 7/20/2021 dataset is 94% (7,390/7,861),

Table 5.2 listed the validation results of 5,878 vehicles on 7/21/2021. Passenger vehicles (class 2) consisted of over 50% of the traffic in this dataset. The classification accuracy for class 1, 2, 3 and 9 were above 88%. We observed 55 class 2 vehicles (1.6%) being misclassified as class 3 vehicles and 27 class 3 vehicles (8.6%) being misclassified as class 2 passenger vehicles. We also noticed that 86 (8.7%) pickup trucks (class 3) pulling a trailer were misclassified as trucks.

For the 7/21/2021 dataset, the results indicated that 21 (31%) of class 6 trucks were misclassified as class 5 vehicles, and 10 (5%) of class 5 trucks were misclassified as class 6 vehicles. For class 9 heavy commercial vehicles, 30 (5%) and 31 (5%) of semi-trucks were misclassified as class 8 and 10, respectively. The loop signature system correctly identified class 5 and 9 vehicles over 80% of the time. The overall classification accuracy, i.e., sum of correctly classified vehicles (5,471) divided by the total vehicle count (5,878), for 7/21/2021 dataset is 93%. The combined (7/20 & 7/21) validation results are listed in Table 5.3 with an overall classification accuracy of 93.6%.

Table 5.1 Vehicle classification result – ATR382 site (7/20/2021).

Vehicle Class		Classification from Loop Signature													Total	Vehicle Class		Classification Accuracy %
		1	2	3	4	5	6	7	8	9	10	11	12	13				
FHWA Class	1	34													34	FHWA Class	1	100.0%
	2	7	5132	64		10	4		1						5218		2	98.4%
	3		30	1325	3	19	13	1	58	12					1461		3	90.7%
	4				5	1									6		4	83.3%
	5		2	8	3	188	16	1	9	3					230		5	81.7%
	6			2	2	26	47	3	6	3	1				90		6	52.2%
	7					8	16	8		1					33		7	24.2%
	8			1			1		0	6					8		8	0.0%
	9		2		1	12	2	2	36	638	30	2			725		9	88.0%
	10			5	1				7	30	9				52		10	17.3%
	11											1			1		11	100.0%
	12												3		3		12	100.0%
	13														0		13	NA
Total		41	5166	1405	15	264	99	15	117	693	40	3	3	0	7861	Overall		**94.0%**

Table 5.2 Vehicle classification result – ATR382 site (7/21/2021).

Vehicle Class		Classification from Loop Signature													Total	Vehicle Class		Classification Accuracy %
		1	2	3	4	5	6	7	8	9	10	11	12	13				
FHWA Class	1	22	1	1											24	FHWA Class	1	91.7%
	2	3	3836	55		7	4		1	1					3907		2	98.2%
	3		27	874	2	19	10		51	6					989		3	88.4%
	4			2	8	1	1								12		4	66.7%
	5		3	7	5	145	10	1	11						182		5	79.7%
	6			1		21	43		1	1	1				68		6	63.2%
	7				1	8	29	2							40		7	5.0%
	8			1			1	1	0	14					17		8	0.0%
	9			1	2	8	1		30	530	31	1	2		606		9	87.5%
	10						1	2	1	18	6				28		10	21.4%
	11											1			1		11	100.0%
	12												4		4		12	100.0%
	13													0	0		13	NA
Total		25	3867	942	18	209	100	6	95	570	38	2	6	0	5878	Overall		**93.1%**

Table 5.3 Combined vehicle classification results – ATR382 site (7/20 & 7/21).

Vehicle Class		Classification from Loop Signature													Total	Vehicle Class		Classification Accuracy %
		1	2	3	4	5	6	7	8	9	10	11	12	13				
FHWA Class	1	56	1	1											58	FHWA Class	1	96.6%
	2	10	8968	119		17	8		2	1					9125		2	98.3%
	3		57	2199	5	38	23	1	109	18					2450		3	89.8%
	4			2	13	2	1								18		4	72.2%
	5		5	15	8	333	26	2	20	3					412		5	80.8%
	6			3	2	47	90	3	7	4	2				158		6	57.0%
	7				1	16	45	10		1					73		7	13.7%
	8			2			2	1	0	20					25		8	0.0%
	9		2	1	3	20	3	2	66	1168	61	3	2		1331		9	87.8%
	10			5	1		1	2	8	48	15				80		10	18.8%
	11											2			2		11	100.0%
	12												7		7		12	100.0%
	13													0	0		13	NA
Total		66	9033	2347	33	473	199	21	212	1263	78	5	9	0	**13739**	Overall		**93.6%**

5.3 HPMS CLASSIFICATION

The research team also analyzed the classification results using the HPMS classification scheme. As listed in Table 5.4, the loop signature system has an over 89% of classification accuracy for all HPMS class bins except for vehicle class 4 (bus) which has only 72% of accuracy (N=18). The overall accuracy of the loop signature system using the HPMS classification scheme is 96% (N=13,739).

Table 5.4 Combined vehicle classification results using HPMS classification scheme.

Vehicle Class		Classification from Loop Signature HPMS Class							Total (N)	Vehicle Class		Classification Accuracy %
HPMS	FHWA	1	2	3	4	5	6	7		HPMS	FHWA	
MC (Bin 1)	1	56	1	1					58	MC (Bin 1)	1	96.6%
PC (Bin 2)	2	10	8968	119		25	3		9125	PC (Bin 2)	2	98.3%
LT (Bin 3)	3		57	2199	5	62	127		2450	LT (Bin 3)	3	89.8%
BS (Bin 4)	4			2	13	3	0		18	BS (Bin 4)	4	72.2%
SU (Bin 5)	5, 6, 7		5	18	11	572	37		643	SU (Bin 5)	5, 6, 7	89.0%
ST (Bin 6)	8, 9 10		2	8	4	31	1386	5	1436	ST (Bin 6)	8, 9 10	96.5%
MT (Bin 7)	11, 12, 13						0	9	9	MT (Bin 7)	11, 12, 13	100.0%
Total		66	9033	2347	33	693	1553	14	**13739**	**Total**		**96.1%**

5.4 ESAL COMPARISONS

The combined Equivalent Single Axle Load (ESAL) was also analyzed for each vehicle class using the Equivalent Axle Load Factor (EALF) derived from MnDOT's WIM data. As listed in Table 5.5, the total ESALs for each vehicle class was determined by taking the median EALF and multiplying with the total number of vehicle counts in each class bin from the loop signature system and the ground-truth dataset, respectively.

Among the 13 vehicle class bins we validated, five (class 2, 3, 5, 6, and 9) of them have vehicle count over 100. The ESALS differences between the loop signature and the ground truth for class 2 and 3 vehicles were less than 5% as shown in Table 5.5. The ESALs difference for Class 9 vehicles (N=1,331) was about 5.1%. We observed 412 and 158 vehicles in class 5 and 6, respectively. The EALF value for class 6 vehicle (0.272) was about 10 times larger than the EALF for class 5 trucks (0.0276). Both class 5 and 6 had a ESALs absolute difference percentage around 14-26% that 26 (5%) class 5 vehicles were misclassified as class 6 and 47 (30%) class 6 vehicles were misclassified as class 5 as shown in Table 5.3.

Table 5.5 ESAL Comparison by Class for 7/20 & 7/21 at ATR382 station.

Vehicle Class		Median EALF	ESALs from Loop Signature	ESALs from Ground Truth	Count (N)	Diff. (%)
FHWA Class	1	0.00	0.00	0.00	58	NA
	2	0.0004	3.61	3.65	9125	1.01%
	3	0.0013	3.05	3.19	2450	4.20%
	4	0.214	7.06	3.85	18	83.33%
	5	0.0276	13.05	11.37	412	14.81%
	6	0.272	54.13	42.98	158	25.95%
	7	0.924	19.40	67.45	73	71.23%
	8	0.205	43.46	5.13	25	748.00%
	9	0.509	642.87	677.48	1331	5.11%
	10	0.706	55.07	56.48	80	2.50%
	11	1.34	6.70	2.68	2	150.00%
	12	0.737	6.63	5.16	7	28.57%
	13	1.00	0.00	0.00	0	NA
Total			**855.04**	**879.41**	**13739**	**2.77%**

CHAPTER 6: CONCLUSIONS

This study aimed to take advantage of the outcomes from the loop signature development and leverage our previous study to validate vehicle classification performance with ground-truth video data. The loop signature technology was initially installed at the ATR353 station in Jordan, MN, from 8/24/2020 to 12/3/2020 to validate system performance. The system was then moved to ATR382 station on US-52 to observe more truck traffic and conduct additional validations.

The combined validation results from the 2 ATR sites indicated that the loop signature technology can identify class 2 and 3 vehicles with an accuracy of 99% and 92.5%, respectively. Class 5 and 9 vehicles have a correct classification rate of 86.8% and 85.9%, respectively. Class 6 vehicles have a much lower classification rate of around 51.6%, with 36.7% of vehicles misclassified as class 5. The combined traffic volume (190, less than 1.8%) of the other vehicle classes (i.e., 1, 4, 7, 8, 10-13) observed at these 2 locations was relatively low with inconclusive classification performance.

To further refine the system performance, the research team in collaboration with the vendor adopted an updated vehicle library that includes the signature profiles of 2,000 Minnesota vehicles from the ATR382 station. After incorporating the updated library, another round of validation was conducted by using 2 additional days of video data (13,739 vehicles on 7/20/2021 and 7/21/2021).

The validation results with the updated vehicle library indicted that the loop signature system can successfully identify class 1, 2 and 3 vehicles with an accuracy of 90% or higher. When pulling a trailer (see Figure 6.1), 4.4%, 4.9% and 4.4% of class 3 pickup trucks, and class 5 and 6 trucks were misclassified as class 8 vehicles. The research team observed twice as many pickup trucks pulling a trailer in the summer than during the January 2021 observation. Class 5 and 9 vehicles have a correct classification rate of 80% and 88%, respectively. However, class 6 vehicles have a relatively lower accuracy rate of 57%, with 30% of vehicles misclassified as class 5. The combined traffic count (263, less than 1.9%) of vehicle classes 1, 4, 7, 8, and 10-13 observed during the observation period was relatively low with inconclusive classification performance.

Table 6.1 compares the classification accuracy of the two datasets in January 2021 (using original vehicle library) and July 2021 (using updated vehicle library) for class 2, 3, 5, 6, and 9 vehicles. The classification accuracy of vehicle class 6 increases by 5% (from 52% to 57%) with the updated vehicle library. However, the accuracy of class 5 vehicles decreases by about 6%. As shown in Table 6.2, the percentage of class 6 vehicles misclassified as 5 decreases by 7% (from 36.7% to 29.7%) while the number of class 5 vehicles misclassified as 6 increases from 3.9% to 6.3%.

Trucks with lift axles (see examples in Figures 6.2 and 6.3) could be challenging for the loop signature algorithm to distinguish whether the lift axles are raised or on the road. In general, the updated vehicle library helps improve the class 6 classification performance by reducing the misclassified vehicles in class 5. However, it also impacts the classification accuracy in the class 5 bin. The overall classification accuracy does not change significantly (around 93-94%) when using the FHWA classification scheme.

The overall accuracy of the loop signature system using the HPMS classification scheme remains around 96%.

We believe, further classification accuracy can be achieved by adding validated signature profiles (at least 2,000 signature profiles in each bin) to the classification library for heavy commercial vehicles in Minnesota.

Table 6.1 Comparison of classification accuracy for two validation datasets.

Dataset	Vehicle Class	2	3	5	6	9	All
7/20 & 7/21/2021	N	9125	2450	412	158	1331	13739
	Accuracy	98.3%	89.8%	80.8%	57.0%	87.8%	93.6%
	ESAL Diff. (%)	1.0%	4.2%	14.8%	25.9%	5.1%	2.8%
1/26 & 1/27/2021	N	6479	1981	355	275	1557	10837
	Accuracy	99.0%	92.5%	86.8%	51.6%	85.9%	93.4%
	ESAL Diff. (%)	0.2%	2.9%	30.1%	33.8%	11.1%	5.4%
Change of Accuracy with Updated Library		**-0.7%**	**-2.8%**	**-5.9%**	**5.3%**	**1.9%**	**0.2%**

Table 6.2 Misclassification rate between class 5 and 6 vehicles.

Dataset	Type	5 misclassified as 6	6 misclassified as 5
7/20 & 7/21/2021	N	26	47
	Misclassification	6.3%	29.7%
1/26 & 1/27/2021	N	14	101
	Misclassification	3.9%	36.7%
Change of Misclassification Rate with Updated Library		**2.4%**	**-7.0%**

Figure 6.1 A class 3 pickup truck pulling a camping trailer.

Figure 6.2 A dump truck with 2 raised lift axles pulling a trailer.

Figure 6.3 A tanker truck with lift axles on the road.

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APPENDIX A
FHWA VEHICLE CLASSIFICATIONS

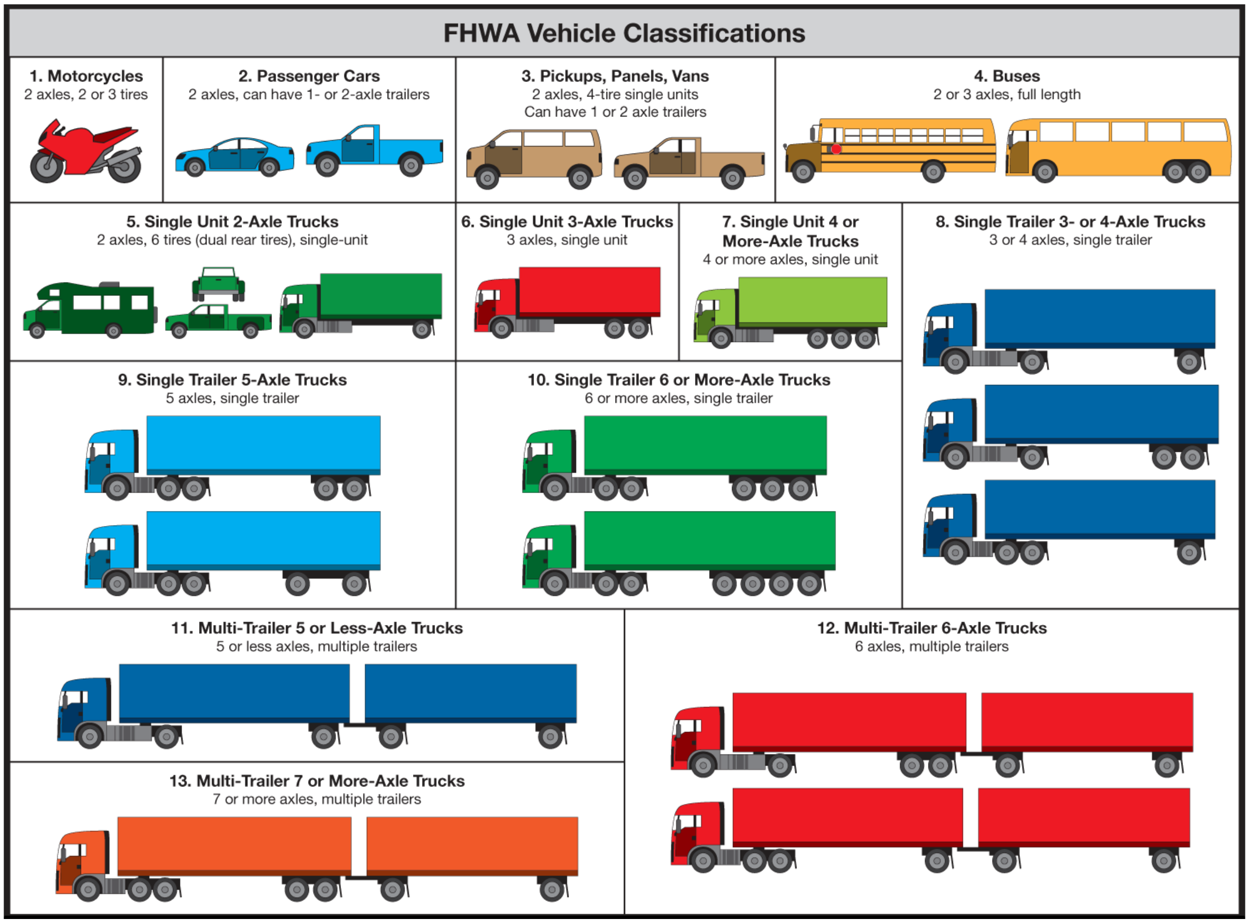

Figure A-1. Vehicle Classification Using FHWA 13-Category

APPENDIX B

SOLAR PANEL AND VIDEO CAMERA SPECIFICATIONS

Solar panel Specifications:

- Max voltage: 6.0V
- Max current: 530 mA
- Max power: 3.2 W
- IP65 waterproof
- Dimensions: 18 x 11.5 x 2.7 cm

Wi-Fi camera specifications:

- Video resolution: 1080p HD at 15 frames/sec
- Field of view: 130 degrees
- IP65 certified weatherproof
- Rechargeable battery
- Solar powered
- Digital zoom: 6x
- Wi-Fi standard: IEEE 802.11b/g/n, 2.4 GHz