OR 15-187
April 30, 2018

An Evaluation of Michigan's Continuous Count Station (CCS) Distribution

FINAL REPORT

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Transportation Research Center for Livable Communities
Western Michigan University

Technical Report Documentation Page

<table>
<tr><td>1. Report No.
OR 15-187</td><td>2. Government Accession No.
N/A</td><td>3. MDOT Project Manager
Kevin Krzeminski</td></tr>
<tr><td colspan="2" rowspan="2">4. Title and Subtitle
An Evaluation of Michigan’s Continuous Count Station (CCS) Distribution</td><td>5. Report Date
April 30, 2018</td></tr>
<tr><td>6. Performing Organization Code
N/A</td></tr>
<tr><td colspan="2">7. Author(s)
Jun-Seok Oh, Valerian Kwigizile, Md Mehedi Hasan and Sepideh Mohammadi</td><td>8. Performing Org. Report No.
N/A</td></tr>
<tr><td colspan="2" rowspan="3">9. Performing Organization Name and Address
Western Michigan University
1903 West Michigan Avenue
Kalamazoo, MI 49008</td><td>10. Work Unit No. (TRAIS)
N/A</td></tr>
<tr><td>11. Contract No.
2016-0069 Z2</td></tr>
<tr><td>11(a). Authorization No.
Z2</td></tr>
<tr><td colspan="2" rowspan="2">12. Sponsoring Agency Name and Address
Michigan Department of Transportation
Research Administration
8885 Ricks Rd.
P.O. Box 30049
Lansing MI 48909</td><td>13. Type of Report & Period Covered
Final Report
04/01/2016 – 04/30/2018</td></tr>
<tr><td>14. Sponsoring Agency Code
N/A</td></tr>
<tr><td colspan="3">15. Supplementary Notes</td></tr>
<tr><td colspan="3">16. Abstract
This report evaluated Michigan’s current continuous counting program and proposed a program combining traffic data from Intelligent Transportation Systems (ITS) sites and continuous counting stations (CCS) sites. A web-based survey was conducted to understand other states’ experience in maintaining their statewide traffic monitoring program. Information on sensor type, coverage, number, class, satisfaction rate and use was sought. A detailed evaluation of current ITS sensors was performed by comparing them with adjacent CCS sensors for volume, speed, and vehicle classification data. An analysis for sufficiency and redundancy of current CCS sites was performed. In this study, CCS sites were evaluated by geographical classification, functional classification, and MDOT’s locational clusters. The evaluation revealed that 37 ITS sensors can be added to the Michigan’s Traffic Management Program (TMP) while two CCS sites can be removed. In addition, 12 CCS sites are suitable for replacement with ITS sites A cost saving analysis was performed for the proposed TMP sensors. For missing data imputation, a DNN based deep learning approach was proposed along with routine sensor calibration and a maintenance plan.</td></tr>
<tr><td colspan="2">17. Key Words
Continuous Count Stations (CCS), ITS Site Evaluation, Traffic Monitoring Program</td><td>18. Distribution Statement
No restrictions. This document is available to the public through the Michigan Department of Transportation.</td></tr>
</table>

19. Security Classification - report	20. Security Classification - page	21. No. of Pages	22. Price
Unclassified	Unclassified	134	N/A

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Acknowledgments

We would like to thank Mr. Kevin Krzeminski, the project manager, and Mr. Mark Polsdofer, the research manager, for their continued support and technical guidance during this project. We also would like to thank Mr. Lawrence Whiteside, former project manager, for his initiation of this research and continued support on data communication. In addition, we would like to thank the Research Advisory Panel members for their comments and suggestions.

Ms. Wendi Burton, Michigan Department of Transportation
Ms. Melissa Carswell, Michigan Department of Transportation
Ms. Elise Feldpausch, Michigan Department of Transportation
Mr. Jason Firman, Michigan Department of Transportation
Mr. Laurent Fournier, Michigan Department of Transportation
Mr. Joseph Gorman, Michigan Department of Transportation
Mr. Ron Katch, Michigan Department of Transportation

Their comments and suggestions greatly helped the research team in improving the final product of this research. This report is based upon work supported by the Michigan Department of Transportation under the contract number 2016-0069 Z2.

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List of Acronyms and Definitions

AADT	Average Annual Daily Traffic (the number of vehicles passing a site in a year divided by 365 days)
AASHTO	American Association of State Highway and Transportation Officials
ADT	Average Daily Traffic (the average 24-hr volume at a given location over a defined time period less than one year)
ATMS	Advanced Traffic Management System (It is an internal management system to coordinate with TOCs to represent real-time traffic data from cameras, speed sensors, etc.)
AVC	Automatic Vehicle Classifier (a high speed device which records the side profile of the vehicle and classifies it as defined vehicle class, typically used at toll and ramp metering)
CAVC	Continuous Automatic Vehicle Classification (Type of permanent automatic vehicle classification)
CCS/ATR	Continuous Count Stations/Automatic Traffic Recorders (permanent device in the pavement surface that continuously and automatically collects traffic data)
DDHV	Directional Design Hour Volume (Typically the 30th highest hour of the year)
DNN	Deep Neural Network (Typically constitutes with multiple hidden layers in a neural network)
FHWA	Federal Highway Administration
GIS	Geographic Information System
HF	Hourly Factors (assess the degree of hourly variation of a day that exists in the area for a given year)
HPMS	Highway Performance Monitoring System (a systematic measure encompassing the scope, condition, performance, use and operating characteristics of the Nation's highways)
ILD	Inductive Loop detectors (Typically detects vehicle by generating an inductive (magnetic) field through a set of embedded wires under the pavement)

IRD	International Roadway Dynamics (Portable road tube classifier/counter equipment for collecting axle and classification data)
ITS	Intelligent Transportation Systems (A system that applies a broad range of diverse modern electronic and communications technologies for traffic)
LSTM	Long Short Term Memory (A specific type of deep learning architecture)
LTPP	Long-Term Pavement Performance (Typically collect pavement performance data as one of the major research areas)
MAPE	Mean Absolute Percentage Error
MDOT	Michigan Department of Transportation
MF	Monthly Factors (assess the degree of monthly variation of traffic that exists in the area for a given year)
MPO	Metropolitan Planning Organizations
MS2	Midwestern Software Solutions vs.2 (Cloud-based transportation data management software)
MVDS	Microwave Vehicle Detection System (a noninvasive vehicle detection system installed above ground on the side of the road to support ITS communication network
MWF	Monthly Weekday Factors (assess the degree of weekday variation over a month that exists in the area)
O&M	Operation and Maintenance
PTR	Portable Traffic Recorders (Temporary device that counts traffic for a short period of time)
QA/QC	Quality Assurance (the process used to measure and assure the quality of a product)
RWIS	Road Weather Information System (Process weather data from environmental sensor stations)
SEMTOC	South-East Michigan Transportation Operations Center (Operated and maintained by MDOT, which covers southeast region of Michigan including all Metro Detroit Area)

STOC	Statewide Transportation Operations Center (Operated and maintained by MDOT, which covers Southwest, University, Bay, North, and Superior Regions, and also provides overnight operations for Grand Region)
TMG	Traffic Monitoring Guideline
TMP	Traffic Monitoring Program
TOC	Transportation Operation Centers (Responsible for traffic operations for a particular area)
TRADAS	TRAfficDAta System (implemented and used by Idaho department of Transportation)
TTMS	Telemetered Traffic Monitoring Sites (Typically the locations that are polled via modem daily by the TOC's central office computers)
VIP	Video Image Processors (Automatically analyze the scene of interest and extract information for traffic surveillance and management)
WF	Weekly Factors (assess the degree of daily variation of a week that exists in the area for a given year)
WIM	Weigh in Motion (Special type of sensor that weighs vehicles)
WMTOC	West Michigan Transportation Operations Center (Operated and maintained by MDOT, which covers west region of Michigan including 13 counties of MDOT’s Grand Region)

Executive Summary

Traffic data plays an important role in establishing traffic characteristics of roadways, such as average annual daily traffic (AADT), average daily traffic (ADT), and directional design hourly volume (DDHV). Accurate and reliable measurements of traffic counts, speed, and vehicle classification are critical for traffic monitoring, planning, and traffic design. According to the Federal Highway Administration (FHWA)'s Traffic Monitoring Guide (FHWA, 2016), the primary objective of a statewide continuous count program is to develop hour of day (HOD), day of week (DOW), and month of year (MOY) factors from volume data in addition to collecting speed and vehicle classification data. The above time varying factors help to compute short duration counts, such as ADT and area wide coverage counts. Moreover, those factors are used to determine the appropriate number of statewide continuous count stations as part of the traffic monitoring program (TMP) evaluation process. Currently, the Michigan's TMP needs to be evaluated for appropriateness of site locations of MDOT's continuous count stations and to develop recommendations on whether they should be relocated. In this research, an extensive evaluation of Michigan's traffic monitoring program, including CCS site appropriateness, site redundancy, and incorporating count sites from other sources (e.g. Intelligent Transportation Systems), was performed.

First, an in-depth literature review and a web-based survey were performed in relation to the current CCS program, other monitoring sources (Intelligent Transportation Systems and Weigh-in-motion sensors), state-of-the-art practice in managing traffic monitoring and management programs. Traffic count data from CCS and other sources were collected and stored in an integrated multisource GIS database to allow detailed comparisons between the CCS and other ITS data. Then, ITS data was evaluated in terms of volume, speed, and classification level in comparison to nearby CCS censors while assuming that CCS stations are the ground truth data. Next, the Michigan's CCS program was evaluated and analyzed to determine the appropriate CCS sites. Further, a comprehensive analysis for combining ITS sensors into TMP was conducted and its costs were evaluated. Finally, this research drew conclusions and recommendations. In order to ensure data quality, the research also provided an ITS sensor calibration and maintenance plan.

Literature Review and Survey Results:

FHWA's Traffic Monitoring Guideline (TMG) defines Continuous Counting Stations (CCS) as permanent traffic counting stations that collect vehicle volume through 24 hours a day, seven days a week, and 356 days a year. The statewide CCS program is usually used to develop different time varying seasonal factors. Different clustering approaches, including highway functional classification and computer-generated clusters, are widely used to determine the existing patterns of CCS distribution for evaluating the traffic monitoring program. Data from weigh-in-motion (WIM) sensors, ITS sensors and local agencies are typically incorporated into the traffic monitoring program for improving the data. Volume, speed, and vehicle class data are usually collected by the CCS sites from both intrusive and non-intrusive types of sensors. Inductive loop detectors (ILD) and WIM are the most common sensors for CCS. Microwave and ILD are commonly used for ITS. State DOTs are trying to improve the CCS program, but most of them are facing similar concerns about data quality and maintenance issues. Many states already use or plan to use cloud-based traffic data management software, such as MS2 or other kinds, for better data management and data quality control.

Data Collection:

In this study, data was collected from CCS, ITS microwave vehicle detection system (MVDS), and WIM sites in the state of Michigan. CCS data was collected for the past 5 years ranging from 2012 to 2016 on a total of 126 sites. ITS MVDS data was collected from a total of 575 sites in 2015 and 614 sites in 2016. WIM data was collected from a total of 54 sites in 2015. Data was processed for an hourly interval basis for 24 hours in a day for each of the individual devices of CCS, ITS-MVDS, and WIM sites. The data availability was assessed for each device by considering the yearly available hours over the total possible hours in a year ranging from January 1st to December 31st. The summary of the yearly CCS and ITS data availability is shown in Table E.1 and E.2 respectively.

Table E.1 Summary of Yearly CCS Data Availability by Devices

Criteria (% of available data)	2012		2013		2014		2015		2016		Total	
	# of devices	%	# of devices	%	# of devices	%	# of devices	%	# of devices	%	# of devices	%
>90	100	82.6	103	85.1	108	87.8	108	85.7	118	96.7	537	87.6
80-90	11	9.1	12	9.9	8	6.5	9	7.1	3	2.4	43	7
70-80	2	1.6	1	0.8	2	1.6	3	2.3	0	0.0	8	1.3
60-70	2	1.6	0	0.0	0	0.0	0	0.0	0	0.0	2	0.3
50-60	0	0.0	1	0.8	2	1.6	0	0.0	0	0.0	3	0.4
< 50	6	4.9	4	3.3	3	2.4	6	4.7	1	0.8	20	3.2
Total	121	100	121	100	123	100	126	100	122	100	613	100

Table E.2 Summary of Yearly ITS Data Availability by Devices[1]

Criteria (% of available data)	SEMTOC (# of Devices)		WMTOC (# of Devices)		STOC (# of Devices)		Overall (# of Devices and Percentage)			
	2015	2016	2015	2016	2015	2016	2015	%	2016	%
>90	164	220	41	0	0	12	205	47.1	232	42.4
80-90	23	30	22	0	0	30	45	10.3	60	10.9
70-80	7	10	8	32	0	14	15	3.4	56	10.2
60-70	19	6	11	20	0	14	30	6.8	40	7.3
50-60	3	7	7	24	0	3	10	2.4	34	6.2
< 50	9	2	21	25	101	98	131	30	125	22.8
Total	225	275	110	101	101	171	436	100	547	100

<u>ITS Data Evaluation:</u>

ITS MVDS sensor data for volume, speed, and vehicle classification were evaluated to examine if ITS data are usable in the CCS program. Data from ITS sites were compared with those from adjacent CCS sites by assuming that the data from CCS sites are ground truth data. In the volume data comparison, a total of 31 and 37 directional ITS sites were selected for the year of 2015 and 2016, respectively. For the comparable ITS sites, an individual model based on a scatter plot diagram was developed and analyzed for volume data evaluation. The Mean Absolute Percentage Error (MAPE) was used to check accuracy of volume data from ITS sensors.

[1] SEMTOC refers to Southeast Michigan TOC, WMTOC refers to West Michigan TOC, and STOC refers to Statewide TOC in Michigan.

Table E.3 Summary of ITS Volume Data Accuracy

MAPE	2015		2016	
	Number of Sites	%	Number of Sites	%
Less than 10%	11	35.5	12	32.4
11% - 20%	2	6.4	12	32.4
More than 20%	18	58.1	13	35.1
Total	31	100	37	100

Table E.3 summarizes ITS data accuracy. It should be noted the time frame of the study was during a transition to all ITS-MVDS reporting to the central ATMS software, which may have caused higher error rates. According to the Traffic Monitoring Guide (TMG) and other related resources, an MAPE of 10 percent or less is regarded as good and acceptable in its accuracy. As shown in Table E.3, approximately one third (35 percent in 2015 and 32 percent in 2016) of the comparable ITS sensors show acceptable accuracy with less than 10 percent of MAPE. That is, ITS sensors could provide high quality data when they are well maintained.

For speed data comparison, a total of 23 directional ITS sites nearby CCS sites were selected. The speed distribution of ITS speed data was compared in 16 different speed bins (FHWA, 2016). A chi-square test was performed to check the similarity of speed distribution between the ITS and CCS sites. The chi-square test statistic reveals that around 60 percent of ITS speed data yield similar speed distributions compared to the data from nearby CCS sites as shown in Table E.4.

Table E.4 Summary of ITS Speed Data Accuracy

ITS Speed Data Accuracy				
Chi-square goodness of fit test	2015		2016	
	No.	%	No.	%
Similar speed distribution between ITS and CCS	6	60	7	53
Non-similar speed distribution between ITS and CCS	4	40	6	47
Total	10	100	13	100

ITS sensors can classify vehicles into four types by length. A total of 7 directional ITS sites were available to compare the vehicle classification data. In this comparison, SEMTOC sites were not considered due to the unavailability of vehicle classification data. Thirteen vehicle classes in CCS classification were combined into 4 classes based on the length and axle size of vehicles. In the comparison, although ITS sensors tended to underestimate small vehicles, ITS sensors successfully classified vehicles into four types.

Table E.5 Summary of ITS Vehicle Classification Data Accuracy

2015			2016		
Class	CCS	ITS	Class	CCS	ITS
1	64.25%	59.65%	1	73.02%	61.78%
2	27.20%	27.30%	2	19.42%	21.64%
3	7.95%	6.90%	3	7.00%	13.86%
4	0.55%	6.05%	4	0.58%	2.70%

Evaluation of CCS Sites:

Existing CCS sites were evaluated by two approaches: redundancy analysis and sufficiency analysis. Correlation and proximity analyses were performed to identify redundant CCS sites. Through the redundant analysis, four CCS sites were identified as possibly redundant and potentially removable. Among those four, two on interstate freeways were highly possible to remove while the other two on urban arterials were possible but recommended to be kept as potential relocation sites when they fail due to the insufficient number of CCS sites on urban arterials.

The number of CCS sites needed was evaluated by quantifying the numbers in each category by geographical and functional classifications. The analysis results show that more CCS sites are needed in the North region and on rural freeways and urban arterials. More specifically, the Rural-North (cluster 4 in MDOT's classification) needs at least four more CCS sites to meet the requirement for monthly factors (MF). When applying the requirement for hourly factors (HF), four more sites are needed for cluster 3 and 5, and 10 more sites for cluster 6. Table E.6 and E.7 show a summary of the findings for CCS site appropriateness by geographical, functional types, and MDOT clusters.

Table E.6 Summary of CCS Site Appropriateness by Geographical and Functional types

Geographical Cluster	Cluster-1 (Superior)				Cluster-2 (North)				Cluster-3 (West)				Cluster-4 (East)			
	MF	WF	MWF	HF	MF	WF	MWF	HF	MF	WF	MWF	HF	MF	WF	MWF	HF
Required as 95th Percentile	11	4	2	56	11	21	5	34	19	21	4	30	34	13	12	42
# of Current CCS	16				10				30				66			
Functional Cluster	Cluster-1 (Urban Freeway)				Cluster-2 (Rural Freeway)				Cluster-3 (Urban Arterial)				Cluster-4 (Rural Arterial)			
	MF	WF	MWF	HF	MF	WF	MWF	HF	MF	WF	MWF	HF	MF	WF	MWF	HF
Required as 95th Percentile	36	5	9	23	28	8	2	29	37	16	28	25	19	13	6	62
# of Current CCS	42				22				15				43			

Table E.7 Summary of CCS site appropriateness by MDOT Clusters

MDOT Cluster	Cluster-1 (Urban)				Cluster-2 (Urban Rural)				Cluster-3 (Rural)				Cluster-4 (Rural North)				Cluster-5 (Recreational)				Cluster-6 (Recreational Corridor)			
	MF	WF	MWF	HF	MF	WF	MWF	HF	MF	WF	MWF	HF	MF	WF	MWF	HF	HF	WF	MWF	HF	MF	WF	MWF	HF
Required as 95th Percentile	37	8	3	35	25	5	2	31	5	4	2	17	15	8	4	62	9	13	6	22	5	4	4	18
# of Current CCS	41				27				19				11				18				8			

<u>Combining ITS Sensors into Traffic Monitoring Program:</u>

As shown in Table E.6 and E.7, MDOT's traffic monitoring program needs more sensors to meet the FHWA's TMG requirements. The gap could be fulfilled by using existing ITS sensors. In this research, both CCS sites and ITS sites were analyzed in order to identify ITS sensors that could replace existing CCS sites or be added into MDOT's traffic monitoring program. Those replaceable CCS sites and addable ITS sensors were analyzed by the MDOT's cluster. After combining all existing CCS and ITS sensor sites, the study proposes to have a total of 159 sensors in MDOT's traffic monitoring program (TMP) as summarized in Table E.8.

Table E.8 Summary of CCS Sites in the Proposed Traffic Monitoring Program

	Cluster-1 (Urban)	Cluster-2 (Urban Rural)	Cluster-3 (Rural)	Cluster-4 (Rural North)	Cluster-5 (Recreational)	Cluster-6 (Recreational Corridor)	Total
Number of existing CCS sites	41	27	19	11	18	8	124
Number of CCS sites required by MF	37	25	5	15	9	5	96
Number of CCS sites required by HF	35	31	17	62	22	18	185
Number of CCS sites removable	2	0	0	0	0	0	2
Number of CCS sites replaceable with ITS	11	1	0	0	0	0	12
Number of ITS sites addable to TMP	14	7	2	5	3	6	37
Total number of sites in proposed TMP	53	34	21	16	21	14	159
Number of CCS sites	28	26	19	11	18	8	110
Number of ITS sites	25	8	2	5	3	6	49

As summarized in Table E.9, the proposed MDOT's TMP includes: 1) removing 2 CCS sites; 2) replacing 12 CCS sites with ITS sensors; and 3) adding 37 ITS sensors. Annual equivalent cost savings from these changes can be estimated as follows:

- Annual cost saving from removing 2 CCS sites = $4,771.8 x 2 = $9,544
- Annual cost saving from replacing 12 CCS sites with ITS = $3,285 x 12 = $39,416
- Annual cost saving from adding 37 ITS sensors instead of CCS = $4,136 x 37 = $153,031

The total cost saving from the proposed TMP was estimated to be $201,990 annually for next 20 years.

Data Maintenance and Implementation Plan:

Compared to the conventional inductive loop detectors, ITS MVDS are easy to maintain without interruption of traffic. However, in order to continue obtaining high quality data, ITS MVDS sensors need routine maintenance and management including checking setup position, on-site calibration, data communication, and data management. The research team proposes to conduct routine on-site calibration and maintenance at least twice a year (spring and fall) for those ITS sensors to be used in the traffic monitoring program.

This research recommends five implementable items including 1) removal of two CCS sites, 2) replacing 12 CCS sites with existing ITS sensors, 3) adding 37 ITS sensors into MDOT TMP, 4) utilizing a comprehensive sensor testbed, and 5) incorporating a deep learning-based data imputation method. In order to ensure data quality, the research also provided an ITS sensor calibration and maintenance plan and presented a case example of data imputation method using a deep learning approach.

Chapter 1 Introduction

1.1 Problem Statement and Background

Peter Ferdinand Drucker, a social ecologist, has emphasized the importance of performance measures by stating that "*You cannot manage what you cannot measure*," and the transportation bill, Moving Ahead for Progress in the 21st Century (MAP-21), emphasized the importance of performance measures. Traffic count stations play a key role in measuring highway performances. Accurate and reliable measurements of traffic counts, speed, and vehicle classification are critical for traffic monitoring, planning, and traffic design. Traffic counts measure the number of vehicles passing through a point (or a data collection site) during a specified time period. They are usually conducted to monitor and describe traffic characteristics (Garber & Hoel, 1999) such as average annual daily traffic (AADT), average daily traffic (ADT), and directional design hourly volume (DDHV). They can be further used to infer hourly factors, daily factors, and seasonal factors. The reliability and accuracy of this data is greatly dependent on the allocation of data collection sites (e.g., CCS, ITS, weigh states, etc.) throughout the system. Generally speaking, as the density of data collection sites increases, the coverage of the sampling pool and the accuracy of the estimated seasonal factors tend to improve. In reality, however, as data collection sites are limited resources, the deployment needs to be optimized given the locational and budgetary restrictions.

According to the Federal Highway Administration's Traffic Monitoring Guide (FHWA, 2013), the primary objective of a statewide continuous count program is to develop hour of day (HOD), day of week (DOW), month of year (MOY) and yearly factors to expand short-duration counts, such as ADT to AADT. This objective is the basis for determining and evaluating the number and location of continuous count sites operated by the state highway agency. In particular, the Monthly and DOW patterns are of much greater interest in the refinement of the continuous count program since the effectiveness of the seasonal factoring process (and consequently the accuracy of most AADT counts) is a function of the seasonal patterns observed around the state. Understanding what patterns exist, how those patterns are distributed, and how they can be cost-effectively monitored is a major portion of the evaluation process.

The measurements of vehicle speeds are a byproduct of some continuous counting stations. For traffic monitoring purposes, the speed information of all the vehicles passing through a single point in a roadway can be directly collected or estimated, depending on the type and configuration of traffic monitoring devices (Treiber & Kesting, 2013). The collected speeds are then reported as individual vehicle speeds or aggregated during a specific time period (1 minute, 5 minutes, 15 minutes, 1 hour). Linking speed information with weather information collected from Road Weather Information System (RWIS) can be further used to assess the traffic system performance under adverse traffic conditions. Relevant research can be found in Shah *et al.* (2003), and Souleyrette *et al.* (2006).

In addition to traffic volume and speed, vehicle classification data are also collected at some CCS. The current state-of-the-practice vehicle classification methods rely on fixed-location sensors such as pneumatic tubes, inductive loop detectors, piezoelectric sensors, and Weigh-in-motion (WIM) systems, besides manual observation and classification. Depending on the type of sensors and classification techniques, the collected vehicle class information may be available for the FHWA's 13-vehicle class scheme, or for regrouped vehicle classes such as 3 classes, 6 classes, etc. A comprehensive review of vehicle classification methods can be found in Sun and Ban (2013). Since traffic data collected at continuous count stations are subject to discontinuities due to equipment malfunctions and errors, data adjustment and imputation methods may need to be applied. Obtaining data from other sources (volume, speed and classification) and integrating the data with existing sources can be beneficial in this regard.

Currently, the Michigan's traffic monitoring program needs evaluation of site location appropriateness and develop recommendations on MDOT's continuous count station locations and adequacy. This evaluation needs to consider the new traffic volume data from the ITS system sites, RWIS sites and other available sources including private sector sources. Strategic plans are needed to allow the monitoring program to enhance the pool of traffic information, reducing any possible data collection redundancy, and expanding the sampling on roads.

1.2 Research Objectives

The objectives of this research include the following:

1. Evaluate site placement appropriateness and develop recommendations on if they should be relocated (126 locations throughout Michigan); and consider traffic volume data from the 614 ITS-MVDS system sites, 54 WIM sites and other available sources.

2. Provide a strategic implementation plan on how the recommended monitoring sites should be located to enhance the pool of traffic information, reducing any possible data collection redundancy; and expand the sampling on roads, while considering pavement condition.
3. Confirm that MDOT's CCS sites are located on road segments, which benefit the monitoring program and meet the 2016 Traffic Monitoring Guide recommendations for site selection and distributions.
4. Ensure that the recommended sites are placed in locations most beneficial to the department for traffic reporting and other uses; provide a strategy for the development of seasonal factors for all roads considering the proposed new traffic devices location.
5. This research will address the continuous count program network of sites in relation to other MDOT traffic volume sources.

Chapter 2 Literature Review

2.1 Introduction

Continuous Counting Stations (CCS) are permanent traffic counting stations that collect vehicle volume through 24 hours a day, seven days a week, and 356 days a year (FHWA, 2014). Some of CCSs also collect vehicle speed, classification and weight continuously throughout the year. Traffic count stations play a key role in measuring highways' performance, traffic monitoring, planning, and traffic design. Data from the CCS are used to describe the Average Annual Delay Traffic (AADT), Average Daily Traffic (ADT), and Directional Design Hourly Volume (DDHV). CCS and other traffic count (ITS, WIM etc.) help to determine the number of expected road users and the expected loads for designing a safe and adequate road in the future (FHWA, 2014).

2.2 Continuous Counting Stations (CCS)

2.2.1 Review of Traffic Monitoring Guide (TMG)

The main objective of a statewide CCS program is to develop hour of day (HOD), day of week (DOW), and month of year (MOY). The DOW and the MOY are of much greater concern. The other secondary objectives include the collection of traffic peak hour data and volume with directional distribution used by traffic forecasters and roadway designers. The CCS also collects an anchor point for using ramp-balancing methods and gathers data to understand geographic differences in travel trends. Another secondary objective for CCS is to collect data on roadway sections in proxy of portable counters (FHWA, 2014).

Vehicle volume data is collected by CCS as the part of the state's Continuous Counting Program (FHWA, 2014). Traffic Monitoring Program (TMG) suggests several steps to monitor and evaluate a CCS program to determine the improvements needed. The first step is to review the existing continuous count program by checking traffic patterns, data adjustment, and quality control. The next step is to develop an inventory of the available and needed continuous count locations and equipment by using existing and other data sources. After that, the traffic patterns are examined by analyzing time patterns, monthly factors, hour of day adjustments and day of week adjustments. Then, monthly pattern groups are established by using the traditional approach, cluster analysis, and volume factor groups. Next, the appropriate number of continuous counting stations are determined by specific locations and, finally, temporal factors are computed to complete the evaluation for the CCS (FHWA, 2014).

Speed data is also frequently collected by many states as part of their CCS program. The speed data is used for determining travel time reliability and planning for constructing new lanes. TMG suggests collecting the speed data by CCS to address safety issues (FHWA, 2014). CCSs are also used for collecting vehicle classification data with determining axle and length of the vehicle. The vehicle classification program by CCS could be different from the traditional CCS program (FHWA, 2014). The vehicle classification program used by CCS could be maintained in a fashion similar to CCS's volume data collection program. Vehicle weight data is also primarily collected by most of the state's CCS programs. Collection of weight data is difficult and costly in comparison to gathering other data by CCS (FHWA, 2014). Traffic performance statistics could be derived from most of the CCS, and these statistics are widely used for important analytical tasks. Lane occupancy characteristics, which are important for determining congestion scenarios on the roadway, are obtained by the CCSs.

2.2.2 Review of Different CCS Sensors

Types of sensors vary by size, accuracy, cost, and ease of installation (Oh *et al.*, 2009). Inductive loop detectors, pneumatic road tubes, magnetic sensors, non-invasive microloops, and Sensys systems are generally used as the in-roadway (intrusive) sensors for CCS. Microwave Radar, Active/Passive Infrared, Ultrasonic, Acoustic array, and Video Image Processing (VIP) are generally used as non-intrusive sensors for CCS (Leduc 2008).

Inductive loop detectors, magnetic sensors, microwave radars, and video image processing sensors can collect volume, speed, classification, occupancy, and presence of vehicles in roadways. However, the pneumatic road tube and active-infrared sensors only collect volume, classification, and speed data for the vehicles (Martin 2003).

2.2.3 Review of CCS Site Management and Evaluation

Highway functional classification from FHWA is important for grouping CCSs and for calculating seasonal factors from the groups. Albright *et al.* (1989) conducted a study to develop and monitor the Automatic Traffic Recorders (ATR) for the state of New Mexico, USA. The traditional highway functional classes from the FHWA were considered to group the ATR volume counts and seasonal variation. Traffic data that they obtained from ATR counts were drafted, refined, and adopted in terms of standardization. There was a high correlation between functional classification and seasonal variation that was obtained from volume counts and corresponding seasonal factors. Therefore, annual and monthly factors were calculated from the same highway functional classification, and the individual ATRs were used to compute the factor coverage counts throughout the state for missing data. The study concluded that the procedures in the TMG were very helpful in developing the statewide traffic monitoring standards.

In another study, Ledbetter *et al.* (1991) evaluated the existing Automatic Traffic Recorders (ATR) stations in Oregon and provided some recommendations to improve the site selection of ATR stations with alternative methods for calculating seasonal adjustment factors. The volume count data from 115 permanent counters for the years of 1984 through 1988 was considered for the analysis. A computer-based cluster analysis was performed to segment the ATRs into different groups. Several variables were included to form the cluster analysis. These variables included the natural log of AADT of each ATR station, urban or rural classification of each ATR station, functional classification of the ATR station that is recommended by TMG, latitude and longitude of the ATR station, percent of heavy vehicles in each recorder, design hour (highest 30^{th} hour) volume, and a factor index for controlling the range of volume between January and August. The optimal number of ATR groups was counted by comparing the coefficient of variation for each group. The seasonal adjustment factors were calculated by using four different methods including cluster means, cluster specific regression coefficients, triangulation, and ATR specific regional adjustment factors. The accuracy of each method was observed by calculating the absolute error between "ground truth data" and "point estimation data." The ATR volumes were then compared with the coverage count data for the same groups and revealed large variances between permanent count data and coverage volumes in some specific areas. For those specific areas, the study suggested to consider a new class of highway called "small urban" for the higher volume counts. Moreover, the study suggested to replicate the average count data for the ATR counters, which were being recorded by the coverage count locations in the same areas.

Ritchie *et al.* (1990) also conducted a study to assess the statewide data collection program for the State of Washington including the evaluation of permanent traffic stations. This study evaluated volume counts, factoring and data manipulation, vehicle classification, truck weighting, and speed data in detail using statistical analysis methods. Seven factor groups were considered for analyzing volume data based on highway functional classification and geographical variation.

The four-year's PTR data from 1980 to 1984 was used to analyze the factor groups. Several alternative procedures were evaluated for estimating seasonal factors including cluster analysis and regression analysis. The study found the cluster analysis was inappropriate in terms of using it in different years since the seasonal factors vary from year to year. During the evaluation process, regression analysis was used to derive the seasonal factors for each month of the year for all of the seven groups.

In terms of regression analysis, the AADT for each group for each month was used as the dependent variable, while the 24-hours short count was used as the independent variable of that particular group. The coefficient for the independent variable was considered as the seasonal factor for that particular month of the particular group. The outcome of the regression analysis for some groups was heteroscedasticity in nature, and therefore a standard transformation was applied to make it homogeneous. The study also calculated the precision level of estimated AADT and found that it varies as a function of number of PTRs in each group, whereas the number of PTRs beyond six to eight in each group produced better results.

For evaluating the vehicle classification, about 248 manual short counters were used to assess the database for 1980-1981 in the State of Washington. About eight factor groups were considered along with six vehicle classifications for evaluating vehicle class and determining seasonal factors to the groups. A two-stage (weekdays and weekends) cluster sampling approach was used to determine the seasonal factors. The evaluation of truck weight was conducted in different manner rather than volume and classification data. The data analysis for vehicle weight was performed by using the available axle weights in terms of Equivalent Axle Loadings (EALs) for flexible and rigid pavement (Richie *et al.*, 1990).

A computerized cluster approach was used by the Wisconsin DOT (WSDOT 1987) to group their statewide permanent traffic stations for factor analysis. The traditional approach with manual functional classification was found to be somewhat difficult (e.g. time constraints) in terms of determining factor groups. Consequently, existing volume counts from permanent stations were used for cluster analysis to calculate monthly and weekly factors. The results showed that the monthly factors were more accurate to estimate AADT instead of weekly factors. It was also found that the traditional six factor groups were providing some instability in terms of estimating AADT. Therefore, three optimal factor groups were selected as urban highways, rural highways, and recreational area highways. The study found that the result of estimating AADT was correct up to

9 percent for urban highways, 16 percent for rural highways, and 27 percent for recreational highways group.

Gur and Hocherman (1989) also conducted a study to estimate the AADT by using different methods, and found the cluster analysis was more accurate in terms estimating seasonal adjustment and growth factors. In another study, Esteve (1987) applied a cluster analysis to examine seasonal patterns and to estimate grouping variables by using the data obtained from a state's permanent traffic stations. The mean seasonal factors and coefficient of variations for different cluster groups were calculated to compare with the groups that are proposed by traffic monitoring guide (TMG). The findings showed that the both groups were statistically reliable in terms of estimating seasonal factors. Another cluster analysis was performed to group the rural highways in Virginia based on homogeneous characteristics (e.g. AADT and seasonal variations in traffic patterns) (Ledbetter *et al.*, 1991). The candidate variables were included with the FHWA functional class, functional use, land use and population of the associated link highways, and the terrain types. As a result, the new classification for estimating AADT was statistically accurate and tested for group factors.

GDOT (2012) conducted a study to evaluate the traffic monitoring system by selecting the criterion for siting the location of a new continuous count station. One primary and several secondary criteria were designated in the study for selecting the location of a new CCS site. The primary criteria was to select the minimum of five to eight CCS sites per traffic factor group depending upon the traffic patterns and precision desired. The other secondary criterion for siting the CCS station were to select the critical nodes on high volume roads, to verify adequate coverage by satisfying the geographic differences in travel trends, to provide a minimum of one operational CCS site per interstate route and other major arterials, and to select an area of particular interest to meet specific federal requirements.

Cheng *et al.* (1992) conducted a study to optimize the CCSs based on computer-based statistical methods by using an exchange algorithm and a two-stage sampling algorithm. CCS sites were sequentially added to and deleted from the site design based on the exchange algorithm, while optimal weight was being calculated for each cluster based on the sampling algorithm. The random sampling was performed to select the optimal CCSs from each cluster based on the weight for the two-stage sampling algorithm.

2.3 Intelligent Transport Systems (ITS) and Weigh-in-Motion (WIM)

Different traffic data were obtained from various sources in addition to continuous counting stations. FHWA (2013) suggested to incorporate those data to evaluate and compare with the continuous counting programs. Among the existing data sources, Intelligent Transport Systems (ITS) and Weigh-in-Motion (WIM) have been quintessential in collecting different traffic data sets in addition to continuous counting programs.

2.3.1 Review of Intelligent Transport Systems (ITS) Sensors

The data from Intelligent Transport Systems (ITS) sensors are designed to improve the existing transportation system by improving safety, efficiency, comfort, and adverse environmental effects. ITS applications are effective in advanced traffic management systems, vehicle control systems, traveler information systems, and advanced commercial vehicle or public transport systems (Newman-Askins 2003).

Different ITS sensors have been used for collecting data in roadways including inductive loop surveillance, machine vision sensors, passive acoustic sensors, remote traffic microwave sensors, infrared sensors, and CCTV video camera etc. (USDOT 2007). Different data sets, including vehicle volume, classification, and speed data, are collected by the ITS sensors.

Evaluation of ITS data is important in assessing and improving the efficiency of sensors as well as determining their suitability for adoption in other counting programs. Therefore, a comprehensive evaluation technique is imperative to examine the empirical impact of the ITS data (Kulmala, and Pajunen-Muhonen 1999). In order to effectively plan and implement ITS data, conventional roadway project evaluation methods could be implemented to assist the evaluation and comparison of ITS alternatives (e.g. permanent traffic counters or short-term traffic counters etc.). However, the nature of some ITS data is different from traditional roadway projects (e.g. travel time reliability, travel choices, environmental factors etc.). Therefore, it needs an alternative project evaluation process that differs from conventional roadway counting systems (Bristow *et al.*, 1997).

Different methods have been suggested by different studies for evaluating ITS data. Turner *et al.* (1998) suggested that the capacity (volume, road network, signal etc.) of ITS data could be evaluated by examining the level of service of the roadways. In terms of volume dataset, ITS sensors achieve less improvement in comparison to traditional traffic counting systems, and therefore temporal fluctuations of traffic impacts should be incorporated into ITS evaluation (Underwood and Gehring 1994). Other approaches of evaluating ITS data could be cost-effectiveness analysis where monetary values are available (Baum and Schultz 1997), and multi-criteria analysis where monetary values are not available for major impacts (Bristow *et al.*, 1997).

2.3.2 Review of Weigh-in-Motion (WIM) Sensors

Weigh-in-Motion (WIM) sensors are critical not only for overweight commercial vehicle enforcement but also for effective transportation infrastructure design, pavement design, and overload estimation of roadways (Faruk *et al.*, 2016). Piezoelectric, Bending Plate, and Capacitance Mat, which are considered as an on-pavement sensors, are usually used for a Weigh-in-Motion system.

As guided by FHWA (2013), the state roadways should be grouped in terms of similar characteristics for analyzing WIM data to identify the seasonal pattern of vehicle classification in each group. The characteristics for grouping roadways could be based on the combination of known geographic, industrial, agricultural, and commercial patterns (FHWA 2013). Moreover, the percentage of through trucks and the geographic region based on economic activity could be used to group the roadways for analyzing WIM data, where more detailed information is not available. From the available WIM sites, at least one permanent WIM station should be available in each group to predict the seasonal pattern for all of the roadways in that group.

WIM data can be also evaluated by comparing with other counting approaches (e.g. CCSs, short-term counters etc.) in terms of vehicle volumes, class, and speed data sets. Faghri *et al.* (1996) conducted a study to monitor and evaluate the traffic data obtained by CCSs and WIM stations for the State of Delaware. Through a descriptive statistical analysis, seasonal factors were calculated to determine and compare the number and location of CCS and WIM stations. Another study by Qi *et al.* (2013) compared the CCS and WIM program by evaluating data collection technologies, transmission and management, users and uses, and collection site selection/prioritization. The study was performed to evaluate the statewide CCS and WIM stations for the State of Montana. A comprehensive survey was performed from the current practices of selected states (ND, SD and ME) for traffic data collection, processing and use. The study provided a series of concluding remarks on sensor systems, technological costs, and siting criteria for both CCS and WIM stations. The study suggested an optimization approach for selecting sites for WIM and CCS stations with prioritization. This allowed more efficient weight enforcement based on identification of problem areas, and provides adequate data, independent of absolute volume of traffic for planning purposes throughout the state (Qi *et al.*, 2013).

2.4 Review of Traffic Management and Monitoring Systems in Other States

The state of Arizona has almost 14,000 locations for vehicle counting stations on 6,700 miles of highways. There are about 175 continuous counting stations throughout the Arizona highway system (ADOT, 2011). The overall AADT is obtained by combining the data from CCS with other data obtained from short-term counting stations (up to 48 hours). Magnetic induction loops are used as the sensors to collect data by all of the 175 CCS in Arizona. The data from the sensors is directly monitored by the remote software and available for off-site ADOT employees (ADOT, 2011). Arizona is currently using the *MS2* Transportation Data Management System for its traffic count data. This software automatically calculates AADTs, filters count data through numerous QA/QC routines, and processes and stores short count and continuous count data including volume, classification, weigh-in-motion, speed, gap and vehicle length data.

The Texas Department of Transportation (TxDOT)'s Traffic Monitoring System consists of continuous counter operations as well as short-term traffic monitoring, including pneumatic tube counts and manual classification counts. TxDOT has installed and maintains about 350 permanent continuous traffic data collection sites that include collection of volume, classification, speed, and weight data. The 350 CCS sites include an automatic traffic recorder (ATR), automatic vehicle classification (AVC), long-term pavement performance (LTPP), weight in motion (WIM), and speed data collection sites (TxDOT, 2013). The traffic data is collected remotely via telemetry from permanent traffic data collection sites statewide. For continuous counter operations, TxDOT currently uses IRD Model ITC rack mount equipment to collect volume and classification data with loops and Measurement Specialties Brass Linguini (BL) Sensors. TxDOT also replaced landline modems with internet protocol modems at more than 95% of the permanent sites. This new idea is more expensive than the former one, but it would pay off within the first six months of operation. A secondary benefit of using the IP instead of the landline is that it increased the reliability by reducing the number of connection failures. TxDOT also found that changing the configuration from the detection array to a loop piezo loop configuration greatly reduced the sensor failure, and it also decreases the disruption of traffic flow when repairs are made. On the other hand, to improve the pneumatic tube's short-term operation, TxDOT developed a new software program in three phases to improve the pneumatic tube short-term count program. Regarding the short-term operational improvement (manual classification), it was proposed to use video technology to record the 24-hour count period. The recourse provided by video analysis can help to solve any problem when it rises (FHWA, 2013).

In Idaho, there are 225 permanent data collection sites. The majority of these sites collect a variety of classification, volume, and count data, while 26 sites specifically collect WIM data. In addition, Idaho Transportation Department (IDT) lays down over 2,200 portable counts at more than 600 stations. The department also works with other states and highway districts for comprehensive and consistent information sharing. The traffic monitoring program process begins with equipment maintenance before each collection season, followed by scheduling and collection. The process continues with data processing, analysis, and results in reporting. ITD has developed a specialized tool to schedule, collect, analyze, and report data. Some software has been around for many years (such as IDASITE and a host of SAS programs) while other systems have come online much more recently (such as ITD's customized version of TRADAS). In addition, there are two main areas where ITD has learned important lessons in maintaining an effective traffic data collection and reporting business model. The first involves strong cooperation and coordination of work, and the second involves a strong business process around testing.

Florida has more than 300 CCS that count data for vehicle volume, speed, classification, and weight. Single inductive loop and microwave radar sensors are used in Florida for counting volume. Loop-piezo-loop array sensors are used for collecting vehicle classification data. Truck weight data are collected through the weigh-in-motion equipment. Bending plates, piezoelectric axel sensors and quartz piezoelectric sensors are used for measuring weight data through weigh-in-motion equipment (TMH, 2007). FDOT use Florida Traffic Online, a web-based mapping application, that provides traffic count site locations and historical traffic count data. FDOT also provides real time traffic information through a web-based mapping application.

In Georgia, traffic count data is collected by 230 Continuous Count Station (CCS) sites as of January 2016 as part of Georgia's Traffic Monitoring Program. Georgia Department of Transportation's (GDOT's) Office of Transportation Data (OTD) is currently monitoring and retrieving the data from the CCS sites. About 20 percent of CCS stations are not in operation due to construction and other external factors throughout the state.

In California, *PeMS* is used as an Internet based data archive system that collects historical and real-time traffic data in California to compute freeway performance measures (Baucer *et al.*, 2016). It collects traffic data, such as counts and occupancies, from freeway detectors, and automatically computes speeds, vehicle miles travelled (VMT), vehicle hours traveled (VHT), delay, travel time index, and productivity for every detector location every 5 min. The *MTC 511 system* is a one-stop source for traffic, transit, ridesharing, along with parking and bicycling data for the nine-counties in the San Francisco Bay Area. The traffic section ingests real-time traffic speed and travel time information on highways and major arterials from a private data provider. The *HICOMP report* is produced annually and contains a compilation of measured congestion data reflecting conditions on urban freeways in California. *TASAS* is a traffic records system containing an accident database linked to a highway database. *TEMS* is a central database and equipment management system for the San Francisco Bay area's ITS and traffic operational devices. It includes a database mapping of ITS inventory along with traffic operation equipment, such as changeable message signs, highway advisory radios, control cabins, and associated communication.

In Michigan, *Mi Drive* is used as an Internet interactive map that can provide real time traffic information including freeway incidents, construction, camera feeds, road closure, speed data etc. This *Mi Drive* is regarded as an Advanced Traffic Management System (ATMS) that is used by all Traffic Operation Centers (TOCs) in Michigan.

VDOT (2016) runs a traffic-monitoring program where traffic count data are gathered from sensors in or along streets, highways and other sources. This data calculates the average number of vehicles that traveled each segment of road. Traffic volume estimates are statistically conducted county by county within the State of Virginia.

Indiana operates two traffic-monitoring systems (INDOT 2016). The first one is a statewide traffic monitoring system consisting of over 100 permanent continuous count stations that collect volume, speed, and vehicle classification data 24 hours a day, 365 days a year. The second system is the Statewide Coverage Count Program that utilizes portable traffic counters to collect 48-hour traffic counts on all state highway traffic sections, in rural and small urban areas, and on all highway performance-monitoring sections (HPMS).

The Ohio department of Transportation (ODOT, 2016) maintains about 200 permanent count stations and manages a web application tool (TMMS) that holds and delivers traffic monitoring data throughout the state. The TMMS system can provide traffic monitoring data, including ODOT's permanent traffic counts, short term counts, AADT data, and traffic count location maps, etc.

In Illinois, a cloud-based MS2 software automatically calculates AADTs and filters count data through numerous QA/QC routines. It also processes and stores short count data and continuous count data, including volume, classification, weigh-in-motion, speed, gap and vehicle length data (IDOT 2016).

The New Jersey Department of Transportation (NJDOT) maintains a traffic-monitoring program consisting of continuous and short-term elements. The traffic counting program is used to produce AADT estimates. This traffic monitoring program consists of approximately 90 preeminent WIM sites, 95 traffic volume and speed system sites, and 50 major station sites throughout the state (NJDOT, 2014).

The New York Department of Transportation (NYSDOT, 2016) is currently using a Traffic Data Viewer (TDV) in order to manage its traffic count data. TDV is a GIS web application for viewing the AADT, location of the traffic count, and traffic reports for individual road segments or traffic counter. NYSDOT operates two traffic monitoring systems. The first one is a statewide traffic monitoring system currently consisting of a 177 permanent continuous count stations that collect volume, speed, vehicle classification, and weight in motion data for 24 hours a day. Information from this system is used to determine the AADT and its traffic growth factors. The second monitoring program is for short-term traffic counts.

The Wisconsin Department of Transportation (WisDOT) depends on a traffic monitoring system that collects continuous count data from 221 permanent data collection stations within the state. WisDOT uses an Interactive Traffic Count map that shows a traffic count anywhere in the state (WisDOT 2016).

The Minnesota Department of Transportation (MnDOT) uses a traffic monitoring system that consists of a 33,000 portable short volume count sites, and 80 automatic traffic recorder sites. Additional 17 WIM sites and more than 240 counting sites are maintained by the regional traffic management center. MnDOT is currently using the Traffic Mapping Application to serve as a traffic management system. The Traffic Mapping Application is an interactive web tool that allows users to explore spatial traffic data (MnDOT 2016).

The Washington Department of Transportation (WSDOT 2016) uses a traffic data management system called *Traffic Data Geoportal*. This system allows users to view WSDOT annual average daily traffic volumes and truck percentages thought a map interface.

2.5 Data Maintenance and Calibration

2.5.1 Review of Data Imputation

Due to the need and diversity of application scenarios, a wide range of methods was applied for traffic data imputation purposes during the last decade (Duan *et al.*, 2016). According to previous literatures, traffic data was imputed mainly based on prediction, interpolation and statistical learning (Li *et al.*, 2014). The prediction model was used to forecast or predict the missing values based on the on-site historical data. Li *et al.* (2015) developed a prediction model based on principal component analysis (PCA) to observe abnormal data detection, data compression, missing data imputation, and traffic prediction by using temporal and spatial data patterns. Another prediction model was developed by Qu *et al.* (2009) based on probabilistic principal component analysis (PPCA) to impute the missing traffic volume data through a historical data mining algorithm. Moreover, Gan *et al.* (2015) developed a varying-coefficient autoregressive prediction model for non-linear and non-stationary time series data, which is based on a gradient radial basis function. According to Duan *et al.* (2016), the autoregressive integrated moving average (ARIMA) model is widely used for predicting missing traffic data in a sequential approach.

Traffic data imputation through the interpolation technique is slightly different from the prediction models, since missing values are replaced by an interpolation model through historical and neighboring data points. A history model was developed by Allison (2001) for imputing the missing values through same site and daily interval data for previous time periods. For data imputation with neighboring data points, the k-nearest neighbor (KNN) model was widely used to interpolate corrupted or missing data values. Chang *et al.* (2012) developed a model based on local least squares (LLS), which is an improved version of KNN and predicts the missing values based on weighted average of the neighboring data. In another study, Liu *et al.* (2008) conducted a study based on the KNN approach to interpolate the missing data during the holiday periods. This study found the output was fruitful for data imputation with consistent and reasonable results for different holidays and types of highways. The statistical learning approach is usually used to inference the missing values in an iterative fashion based on an observed learning scheme. The Markov Chain Monte Carlo (MCMC) method gas been widely used as a multiple imputation statistical approach, where missing values are treated as a combination of multiple imputed values instead of a single value. Farhan and Fwa (2013) conducted a study based on MCMC method for airport pavement missing data management and concluded with an outperformed success for missing values imputation.

In addition to aforementioned traditional imputation techniques, some researchers have used traffic simulation models (such as DynaMIT, DynaSmart, Paramics, etc.) to impute missing data (Duan *et al.*, 2016). A neural network was also considered as a promising approach to apply for missing data imputation and accuracy estimation. Researchers developed different models based on the neural network algorithm and found substantial improvement for missing data imputation. For example, Zhong *et al.* (2004) developed a model based on the neural network algorithm and found the algorithm outperformed with an error of 2 percent while traditional methods resulted in a 20 percent error.

In recent years, researchers have been using more advanced techniques for missing data imputation through a deep learning architecture. Due to the emerging traffic data, a big database is stored and managed through a new technique: the deep neural network. Lv *et al.* (2015) proposed a deep-learning-based traffic flow prediction method for big data analysis using auto-encoders as building blocks to represent traffic flow features for prediction. Moreover, Duan *et al.* (2016) conducted a study for missing traffic data imputation by using a deep learning model called de-noising stacked auto-encoders (DSCE) which treated normal data points and missing data points as corrupted vectors, while transforming data imputation into clean data recovering. In another study, Cui *et al.* (2017) proposed a deep-stacked bidirectional and unidirectional long-term short memory (LSTM) approach for traffic speed data imputation where both forward and backward time series data was used.

2.5.2 Review of Data Maintenance and Calibration

According to TMG, calibration and maintenance could occur on a regular basis (daily, monthly, and annually as needed) through on-site and in-office calibration processes. The calibration process could be initiated by implementing software tools that help to automate the process. In addition, checking data daily, along with collecting and storing it in a master database, could be performed as the data maintenance and calibration process (FHWA, 2016). Moreover, the, data validation process could be advanced by using monthly and yearly data patterns. A short-duration manual count could be performed and checked with sensor accuracy as an on-site calibration technique (TMG, 2016).

In addition, most of the states use both on-site and off-site calibration techniques. Some states developed their own software for data calibration, e.g. NYSDOT use Traffic Count Editor (TCE) software for calibration. Some other states usually contract to other agencies for processing sensor calibration, e.g. VDOT. In Washington, visual comparison and hand tally of vehicles for 5 minutes or 50 vehicles are checked for on-site calibration. In addition, automated validation procedures are checked from an office site location. In New York, sensor calibration is checked through consecutive zero hours, midnight/noon comparison, directional split daily/hourly, unchanging hours, peak hour zeros, and percent unclassified etc. In Alaska, manual two-hour counts are conducted at sites twice annually during the sensor calibration process.

In addition to state-of-the-practices, several studies were performed for developing new techniques on manual and automatic calibration processes. Lai *et al.* (2000) developed a method for a manual calibration technique that addresses vehicle classification and speed data through visual-based dimension estimation. In another study, Fung *et al.* (2003) developed a camera-based calibration technique through road lane marking. Videotaping data was also used as part of the manual calibration process to track vehicle class and speed in some other studies (Guido *et al.*, 2014).

Recently, Castro and Monzon (2014) conducted a study for manual sensor calibration through floating car data by associating GPS coordinates. To explore the automatic calibration technique, Kanhere and Sarasua (2008) conducted a study through automatic camera calibration using pattern detection for vision-based speed sensing. Moreover, Schoepflin and Dailey (2003) conducted an automatic sensor calibration based on a lane activity map and two vanishing points. In another study, Song *et al.* (2007) developed an image-based traffic sensor calibration system with a vehicle shadow suppression system.

2.6 Summary of Findings

CCS provides important data for determining Average Annual Daily Traffic (AADT), Average Daily Traffic (ADT), and Directional Design Hourly Volume (DDHV) in the traffic-monitoring program. Volume, speed, and vehicle classification data are typically collected from the CCS sites.

Both intrusive and non-intrusive sensors are used at CCS sites to collect vehicle data throughout the year. ITS and WIM data could be incorporated to improve the CCS program for better data management. Highway functional class and computer-generated clusters are used for clustering CCS. Most states follow similar practices for conducting a traffic monitoring program. Many states use traffic data management software, such as MS2 or other kinds, for better management. Many states use on-site, off-site and automatic sensor calibration systems for data maintenance and calibration. Data imputation for missing data values is also needed to maintain a complete data set.

Chapter 3 Survey Results

3.1 Introduction

A web-based survey was performed to understand other states' statewide traffic monitoring programs. Eleven other states participated in the survey: California, Florida, Idaho, Minnesota, New Jersey, New York, Ohio, Oregon, Pennsylvania, Virginia and Washington. Figure 3.1 shows the geographical distribution of these states. The survey contained 22 questions (see Appendix 1) about types of sensors used and data sources in their traffic monitoring programs, their experience with traffic sensors, the number of sensors managed, the coverage of statewide traffic monitoring program, the number of staff members for the program, etc. The survey also asked about statewide online traffic data management systems, methods of traffic data sharing and data users. Furthermore, the survey included questions on plans for improving their traffic monitoring program, strategic assessment for sensor location and methods for treating missing data. The survey results are presented in this chapter.

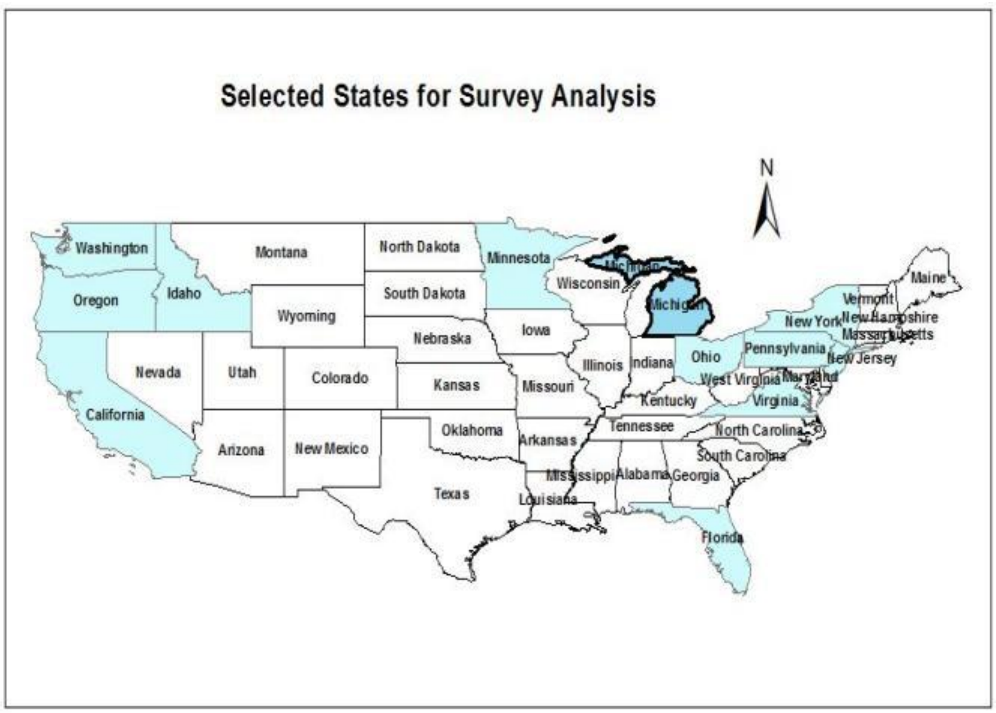


Figure 3.1 Selected states for survey

3.2 Sensors Used for CCS, ITS and Others

In the survey, inductive loop detectors and weigh-in-motion systems were two sensors used by all states for continuous counting purpose. Microwave radar sensors were also used by many states (9 out of 11 states) for the purpose. For ITS, microwave radar sensors and inductive loop detectors were most commonly used. Surveyed states have used various types of sensors, such as video image processing, active/passive sensors, Sensys system, non-intrusive microloops and magnetic sensors. Currently inductive loop detectors and weigh-in-motion systems are used for CCS and microwave radar detectors are for ITS in Michigan. The survey indicates that microwave radar sensors are usable for CCS.

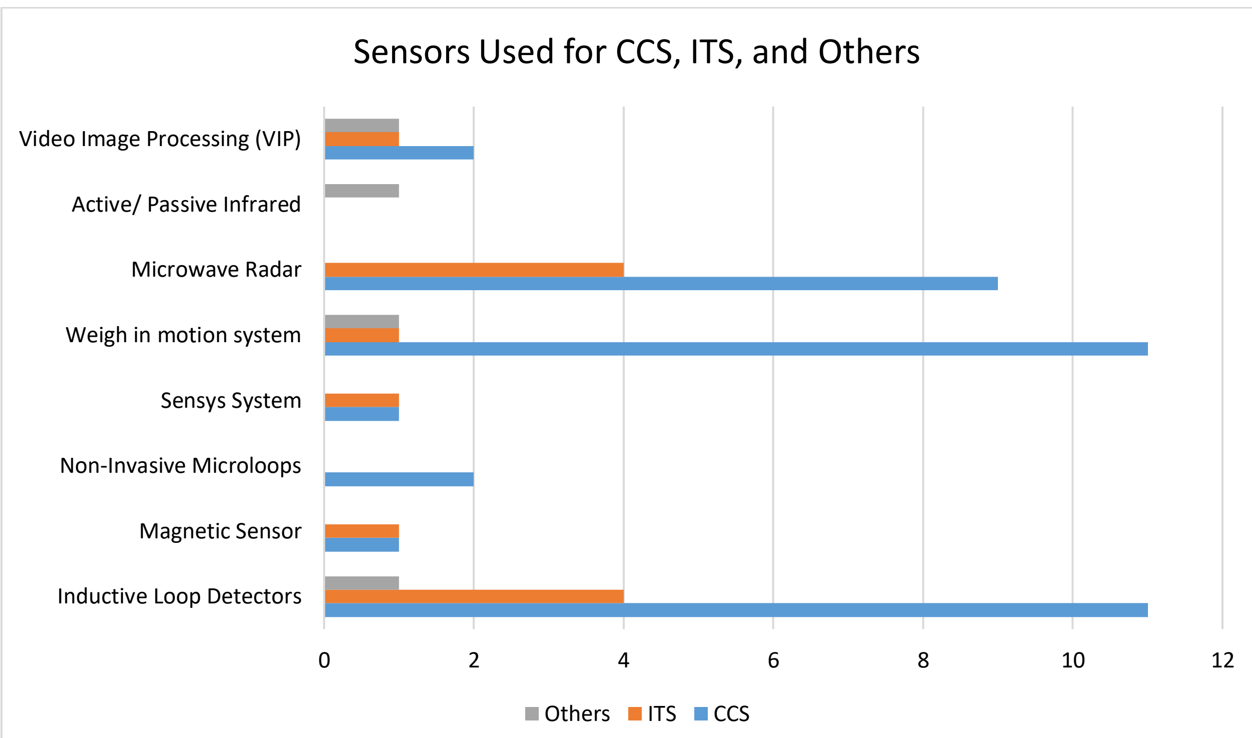


Figure 3.2 Sensors used for CCS, ITS, and others

3.3 The Number of Personnel, CCS Stations and Mileage Coverage

As shown in Table 3.1, the number of personnel for the state traffic-monitoring program was typically 3 - 6 members. California, being the state with the most number of CCS stations, had the most number of staff members (25 members) to maintain CCS programs. Pennsylvania and New York also had a considerable CCS program with 8 - 9 staff members. In Michigan, four staff members are currently assigned to maintain the CCS stations.

Table 3.1 Comparison of Staff Members and the Number of CCS by State

Name of State	Number of Staff Member	Number of CCS (Interstate)	Number of CCS (Highway)	Number of CCS (Local)
California	25	300	300	0
Florida	3	59	257	0
Idaho	3	0	250	0
Michigan	4	89	35	0
Minnesota	5	21	47	24
New Jersey	2	20	80	0
New York	8	176	0	0
Ohio	5	100	90	10
Oregon	5	45	135	0
Pennsylvania	9	34	72	0
Virginia	2	554	0	0
Washington	5	61	125	2

In regard to the number of CCS stations, California maintains the most number of CCS stations (about 600 in both interstate freeways and highways). Most of the surveyed states keep more CCS stations on their highways than interstate highways while Virginia (554 CCS stations) and New York (176 CCS Stations) have all CCS stations along their interstate highways. Only Minnesota, Ohio, and Washington maintain CCS stations along their local roadways as shown in Table 3.1. In Michigan, the traffic monitoring program manages 89 CCS stations on the interstate freeways and 35 CCS stations on other highways. There are no CCS stations on local roads in Michigan.

The survey also asked the miles covered by the CCS. Table 3.2 compares CCS coverage and density by state based on the coverage miles obtained from the survey. The freeway miles covered by CCS ranged from 10.8 percent (Ohio) to 77.9 percent (Virginia), and the distance between CCS sites within the coverage area ranged from 13 mile (Ohio) to 100 miles (New Jersey) as shown in Table 3.2. The distance between CCS sites in Michigan was 14.1 mile that is better than most states except Virginia (10.5 miles) or Ohio (13.0 miles), but the percentage of coverage was relatively low among the states surveyed.

Table 3.2 Comparison of CCS Coverage and Density by State

Name of State	# of CCS (A)	Total Freeway Miles (B)[1)]	Miles Covered by CCS (C)[2)]	% of CCS Coverage (C/B)	Freeway Miles per CCS (B/A)	Average Distance between CCS (C/A)
California	300	25,716	15,208	59.1	85.7	50.7
Florida	59	11,777	1,495	12.7	199.6	25.3
Idaho	0	2,993	-	-	-	-
Michigan	89	9,044	1,254	13.9	101.6	14.1
Minnesota	21	5,203	916	17.6	247.8	43.6
New Jersey	20	5,679	2,000	35.2	284.0	100.0
New York	176	12,638	-	-	71.8	-
Ohio	100	12,070	1,300	10.8	120.7	13.0
Oregon	45	3,389	730	21.5	75.3	16.2
Pennsylvania	34	11,524	1,867	16.2	338.9	54.9
Virginia	554	7,441	5,800	77.9	13.4	10.5
Washington	61	7,211	4,040	56.0	118.2	66.2

1) FHWA, Office of Highway Policy Information, Functional System Labe-Length 2017 (https://www.fhwa.dot.gov/policyinformation/statistics/2016/hm60.cfm)
2) Coverage miles were obtained from the survey.

3.4 Sensors for Volume Data Collection and the Level of Satisfaction

The survey also asked the level of satisfaction for each sensor type in collecting volume data. As shown in Figure 3.4, inductive loop detectors (ILD) and weigh-in-motion sensors (WIM) were rated best among all with the highest satisfaction rate (> 4.5 out of 5) in measuring traffic volume. Microwave radar, active/passive infrared and video image processing (VIP) sensors were also highly rated (around 4 out of 5). In Michigan similarly to other states, inductive loop detectors and weigh-in-motion sensors were very highly rated and followed by magnetic sensors, microwave radar and VIP sensors. The level of satisfaction for each sensor was depicted in Figure 3.3. However, it should be noted that the comparison was sorely based on the survey respondents' rating without any technical performance evaluation.

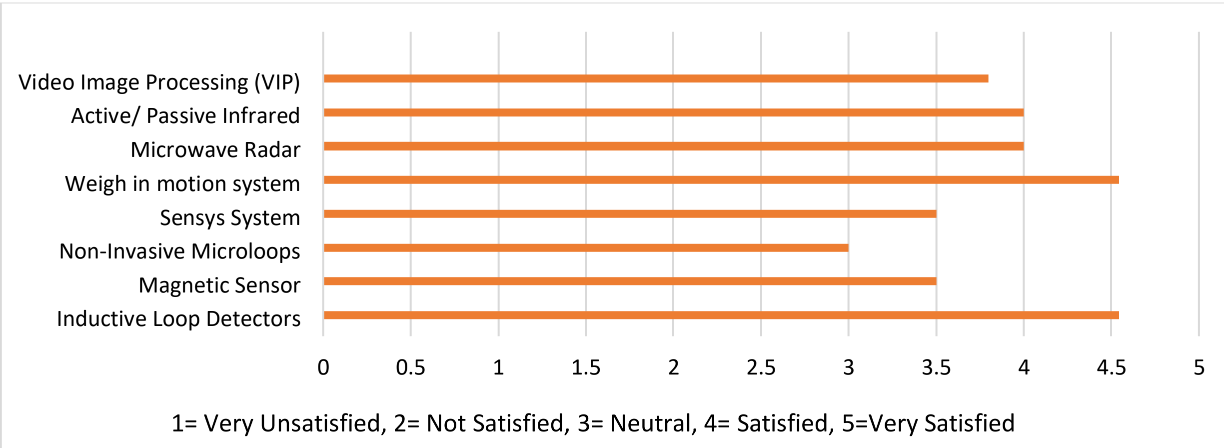


Figure 3.3 Sensors for volume data collection and the level of satisfaction

3.5 Sensors for Vehicle Classification and the Level of Satisfaction

In the survey, most states stated that they used loops and piezoelectric sensors for vehicle class data as a part of their traffic monitoring program. As shown in Figure 3.4, Bl, Kristler, and WIM sensors were also frequently used by many states for vehicle classification. The overall satisfaction rate for loop/piezo sensors was 4.3 out of 5, which is the highest among all.

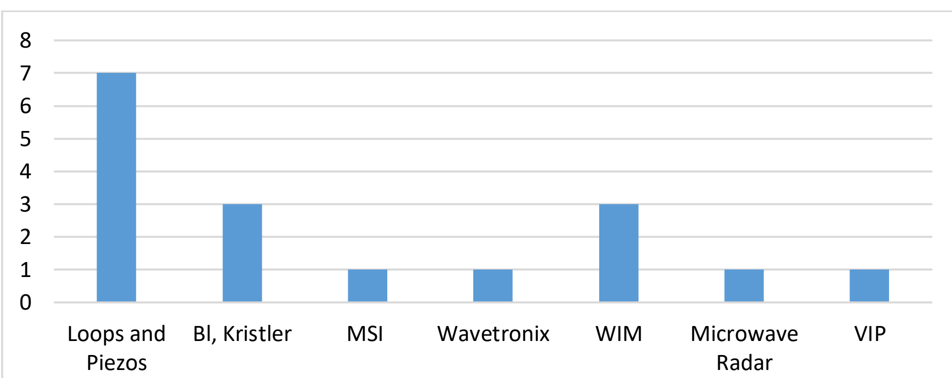


Figure 3.4 Sensors for vehicle classification and the level of satisfaction

3.6 Combining CCS Monitoring Program with Other Data Sources

As shown in Figure 3.5, about 90 percent of states surveyed stated that they used weigh-in-motion (WIM) sensor stations in addition to CCS for their statewide traffic-monitoring programs. More than 50 percent of states also stated that they used data from local Metropolitan Planning Organizations (MPO), cities and townships in addition to state-owned data for traffic monitoring purposes. ITS sensors and portable traffic recorder (PTR) stations were also used for traffic data. In Michigan, WIM sensors have also been used to collect data for traffic monitoring purposes in addition to CCS.

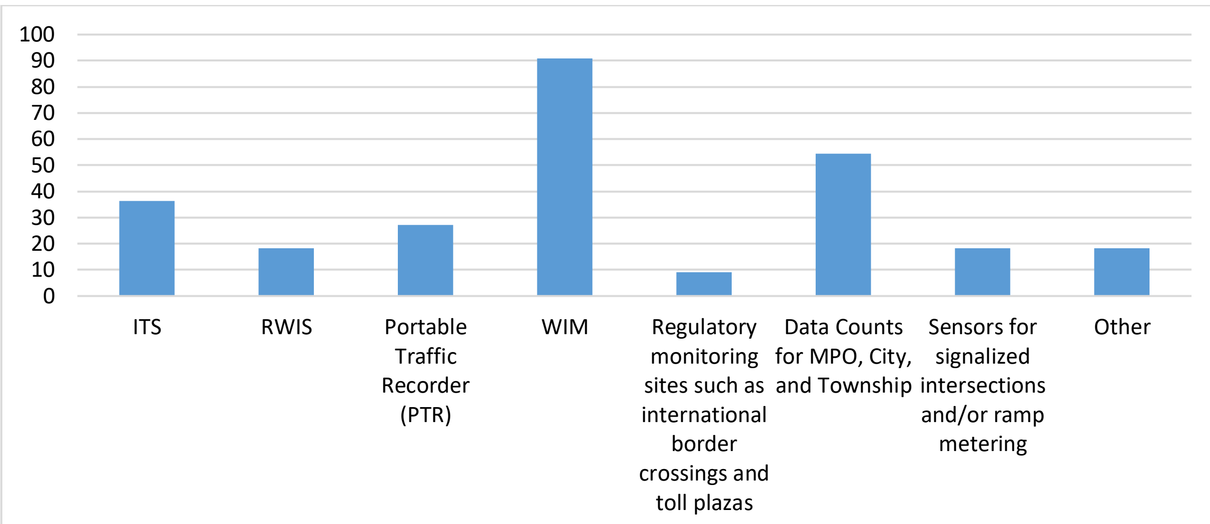


Figure 3.5 Traffic data from other sources

In another question, the survey asked their experiences in reviewing the quality and use of other sources of data within their monitoring program. For example, New Jersey indicated that they are going to build a new software that will analyze their PVR format data obtained from their other sources. Washington collects data from tube counts or short counts in-house and validates the tube sites on a daily basis for performance and data quality. For Oregon State, most local jurisdiction data is received without enough metadata to adequately review its quality; therefore, they used those data as is. In Pennsylvania, they usually completed annual inspections to check all equipment used in the monitoring program. In Virginia, data from ITS sources are collected with frequently missing intervals, and therefore they use the same quality checks for ITS sites as used for their CCS sites. In Michigan, bridge data is provided in daily totals and classified by totals rather than FHWA binned intervals, which limits the ability to do quality checks.

3.7 Traffic Data Management and Sharing System

In the survey, all states stated that they used on-line systems to share their traffic data with others. Many of them maintained an online traffic management system. For example, the MS2 web-based system has been used in Ohio, and other geoportal websites in Minnesota, Washington and California. In addition, most states stated that they used electronic files via email to communicate and share their database. Other systems for data sharing were hard copies, xml data feed, direct web connection, DVDs, mobile applications, etc.

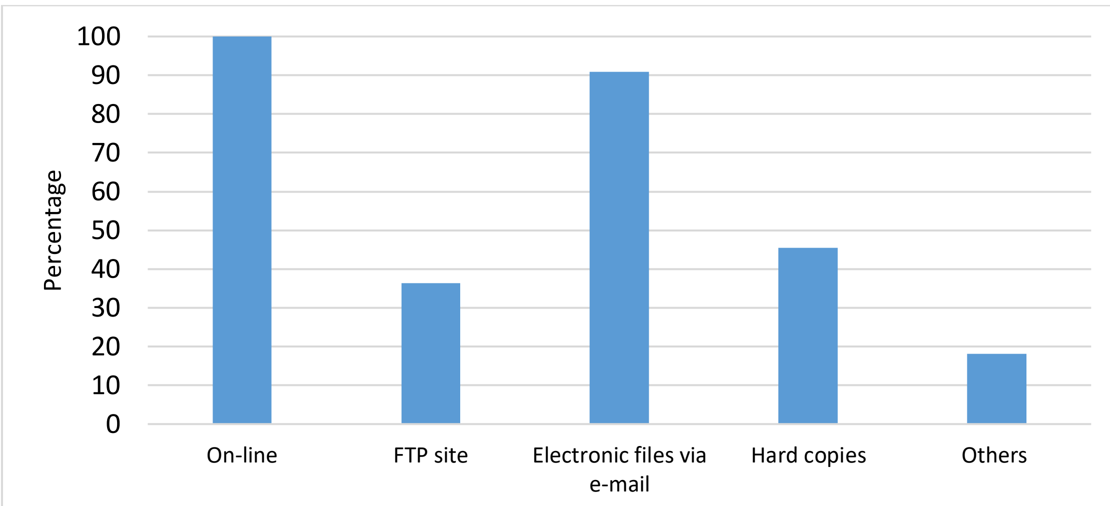


Figure 3.6 Traffic data sharing systems for different states

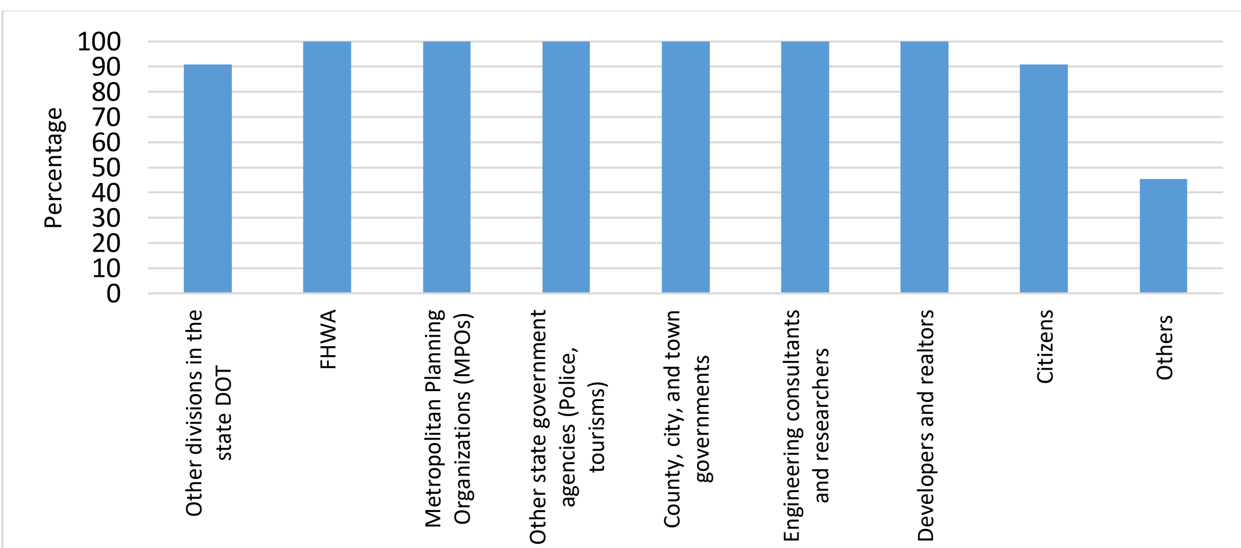


Figure 3.7 Traffic data users

In sharing data, almost all states stated that they shared their data sets with FHWA, MPOs, other state government agencies, county and city governments, researchers and consultants. Other data users were developers, realtors, and citizens. Like most other states, Michigan have used an online system, FTP sites, electronic files, and hard copies for sharing the data with FHWA, other divisions in the state DOT, MPOs, police offices, city and county goverments, researchers and citizens.

3.8 Traffic Data Management Plan and Improvement in Strategic Assessment for Sensor Locations

About 77 percent of the surveyed states shared their plans for improving their traffic management system. For example, ODOT is in the process of installing numerous non-intrusive sensors to collect vehicle volume, speed, and length data. Other states are continuously looking for ways to improve data quality (QA/QC) through improved equipment, materials, and installation techniques as well as through improvements in their dataset. Pennsylvania is currently in the process of adding new classification (CAVC) and weight (WIM) sites, along with converting pre-existing volume sites. Washington is currently upgrading an old, cumbersome database for storing, processing, and releasing traffic data with new equipment for data collection in the field.

From the survey responses, about 67 percent of states maintained their schedule to perform strategic assessments for sensor locations as part of the monitoring program. For example, New York State has currently three maintenance contractors who repair sites as needed. Ohio usually performs strategic assessments for sensor locations on an annual basis. Some states do not follow the regular assessment, while they periodically visit their sites as needed. For example, Washington State did not maintain any real set schedule, but they occasionally look at their count stations to check the best possible location for collecting traffic data. Currently, Michigan does not maintain a schedule to perform strategic assessments for sensor locations.

3.9 Reassessment of the Number of Sensors with Evaluating Missing Data

The survey revealed that most of the surveyed states have reassessed and expanded their current CCS program based on traffic volumes and other program needs upon funding availability. New York expanded their CCS stations from 110 to 176 in 2001 in order to maintain their huge volume on different roadways. In Oregon, they added several interstate sites in 2008 and currently engaged in analyzing their data to determine whether they need any more stations for factoring and ramp balancing. Following the TMG requirement, they installed an ATR on every 5 interchanges. In Minnesota, they expanded their system in 2009 on the county and local roads due to the concerning issues from the locals about collecting data of truck volumes and weight. In Michigan, the program was expanded for business needs, with new construction and to serve research purposes.

Missing data and/or data during traffic incidents were considered and evaluated in different ways by state DOT, and several stated missing data were deleted from their database. For example, Minnesota took average values of the data from the same day of the week during that month or looked at the same week from previous years to evaluate their missing data. In Virginia, days with missing data were assigned a quality level of 2 or 3 (for traffic incidents), which is not used for AADT calculations. California usually projects growth factors from AASHTO to evaluate and recover the missing data. In Oregon, default values or estimates are used in lieu of missing data. For Washington State, if one hour of the day is lost, that hour is estimated; moreover, if more than one hour in a day (or more than 2 days in week or 4 months in year) is missing, data is lost. For the case in Florida, incidents are flagged as "atypical" or "bad" in the TTMS data. Michigan does not use surrogate data; rather they keep notes the incident's time and date in their database.

3.10 Lessons Learned from the Survey

From the survey, several lessons were learned. While most state DOTs were trying to improve their CCS programs, they faced similar difficulties and had similar concerns. The common issues were how to maintain high quality data and treat missing data. Many state DOTs have tried to incorporate other sources of data into their traffic monitoring program to improve the data quality. Inductive loop detectors and WIMs were the most common sensors for the CCS program while microwave and inductive loop detectors were commonly used for the ITS system. Data from WIM, ITS sensors and local agencies were typically incorporated into the CCS program. Many states were using cloud-based data management systems for a better QA/QC process. Expansion of CCS stations was usually implemented on a need basis.

Chapter 4 Data Collection

4.1 Introduction

In this study, data was collected from CCS, ITS-MVDS, and WIM stations. A total of 126 CCS stations were geographically distributed throughout the state of Michigan. CCS data was collected for the past 5 years from 2012 to 2016. A total of 614 ITS-MVDS stations were located throughout the state, grouped by SEMTOC, WMTOC, and STOC regions. ITS-MVDS data was collected for 2015 and 2016. 2016 data was added due to missing months in the 2015 data. The WIM data was collected for the 2015 period from a total of 54 sites. All of the available data were processed and stored in a GIS-based format as an integrated multisource-traffic database.

4.2 Data Processing and Availability Computation

CCS data was received as a processed hourly data for volume, speed, and vehicle classification for the entire year. On the other hand, the ITS data was received in raw format, and the data format varied by TOCs. For example, the data from SEMTOC and STOC regions was collected in intervals of 30 seconds and 5 minutes, respectively, while data received from WMTOC were collected in hourly basis. Therefore, all data were aggregated to hourly intervals for consistency. Figure 4.1 shows the flowchart for processing and aggregating data into hourly intervals. At first, the text files were parsed by using python scripts and data were read from the file using a CSV reader. The keys were defined in the script's dictionary by using device ID, year of data, month of data, days of data, and hours of data. After that, traffic volume and vehicle class data were aggregated in an hourly interval and sorted in an hour, day, month, and year format. For vehicle speed, the hourly data was divided into 16 bins after aggregating and processing raw data from 30 seconds or 5 minutes into an hourly format.

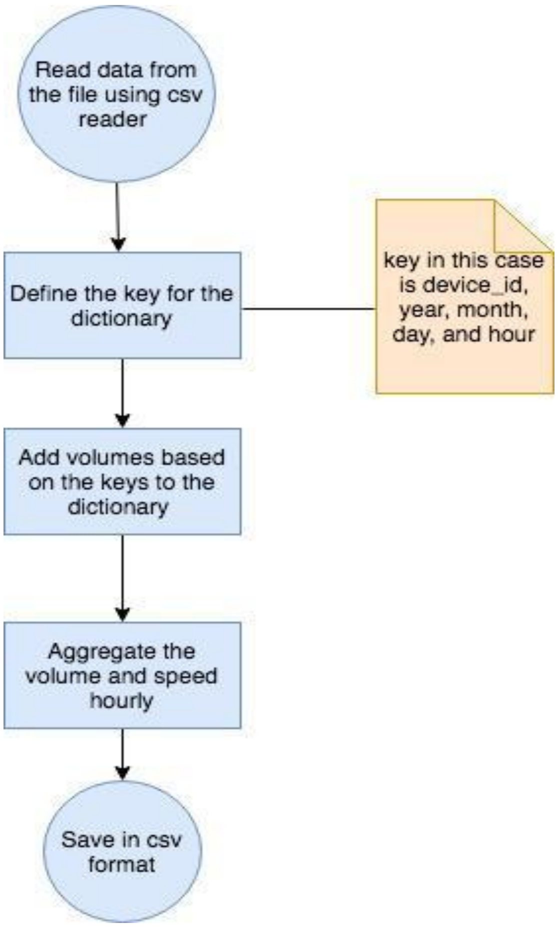


Figure 4.1 Flowchart for data processing

4.3 CCS Data Availability

The data availability was calculated by considering the yearly available hours over the total possible hours in a year, as shown in Equation 4.1.

$$\text{Data Availability} = \frac{\text{Available Hours per year}}{\text{Total Hours } (24\ \text{hr} * 365\ \text{days}) \text{per year}} * 100 \quad (4.1)$$

4.3.1 Comparison of CCS Data Availability by Year

Almost all CCS sensors (121 or more out of 126) provided data during the analysis period (2012 – 2016). As shown in Table 4.1, 87.6 percent of those sensors provided more than 90 percent of data during the five-year period, while only 3.2 percent of CCS sensors provided less than 50 percent of data. In 2016, 96.7 percent of CCS supplied more than 90 percent of data. In general, CCS sensors were very relable in supplying volume data.

Table 4.1 Comparison of CCS Data Availability by Device

% of Available Data	2012		2013		2014		2015		2016		Total	
	# of Devices	Percent	# of Devices	Percent	# of Devices	Percent	# of Devices	Percent	# of Devices	Percent	# of Devices	Percent
>90	100	82.6%	103	85.1%	108	87.8%	108	85.7%	118	96.7%	537	87.6%
80-90	11	9.1%	12	9.9%	8	6.5%	9	7.1%	3	2.4%	43	7%
70-80	2	1.6%	1	0.8%	2	1.6%	3	2.3%	0	0.0%	8	1.3%
60-70	2	1.6%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	2	0.3%
50-60	0	0.0%	1	0.8%	2	1.6%	0	0.0%	0	0.0%	3	0.4%
< 50	6	4.9%	4	3.3%	3	2.4%	6	4.7%	1	0.8%	20	3.2%
Total	121	100%	121	100%	123	100%	126	100%	122	100%	613	100%

Figure 4.2 shows data availability by month. More than 90 percent of CCS data was available for most months of the years except a couple of months in 2012. The analysis shows that the CCS sensors were reliable in proving volume data in each month.

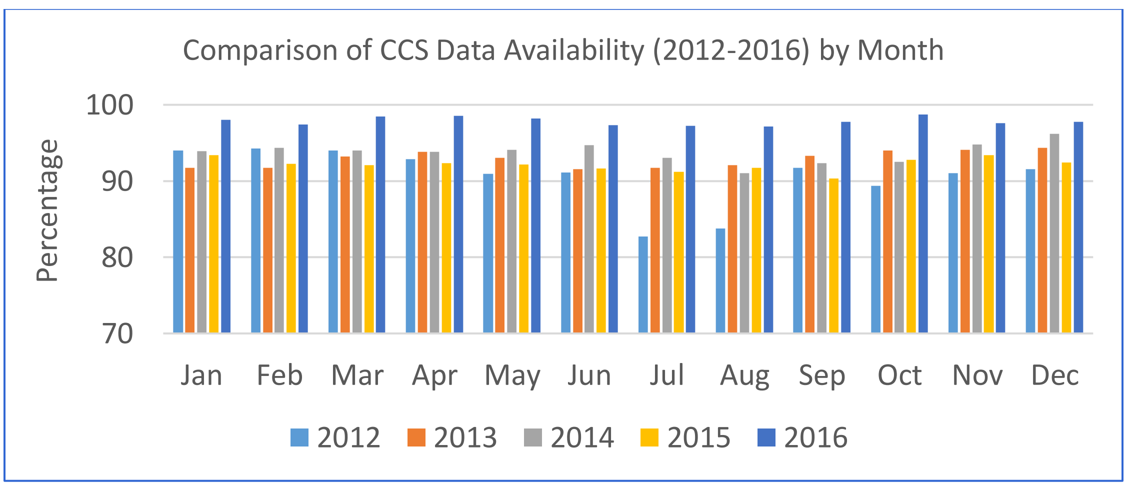


Figure 4.2 Comparison of CCS data availability by month

4.3.2 Computation and Comparison of Different Factors

The CCS volume data was used to compute the time varying factors for the analysis time period from 2012 to 2016. In this study, the time-varying patterns, such as monthly factors (MF), weekly factors (WF), monthly weekday factors (MWF) and hourly factors (HF), were carefully calculated and studied to analyze the trend of data variations during the analysis periods. The formulas for calculating the time varying patterns are shown in equations 4.2 to 4.5. These factors are used for examining the appropriate number of CCS stations in Chapter 6.

- $MF = \frac{Annual\ Average\ Daily\ Traffic\ (AADT)}{\text{Monthly Average Daily Traffic (MADT)}}$ ....(4.2)
- $WF = \frac{Annual\ Average\ Daily\ Traffic\ (AADT)}{\text{Weekly (the day of week)Average Daily Traffic (WADT)}}$..............................(4.3)
- $MWF = \frac{\text{Monthly Average Daily Traffic (MADT)}}{\text{Weekday Average Daily Traffic (WKADT)}}$..(4.4)
- $HF = \frac{Average\ of\ ith\ Hour\ Traffic\ (AHT)}{\text{Average of total Daily (24 hrs)Traffic (ATHT)}}$ … … … … … … … … … … ….(4.5)

During the analysis period, the trend of MF was similar except 2015. As shown in Figure 4.3, some of the months showed lower MF for the 2015 period. Moreover, this inconsistent trend for 2015 appeared in other patterns such as MWF and HF. However, WF showed a similar trend for all years.

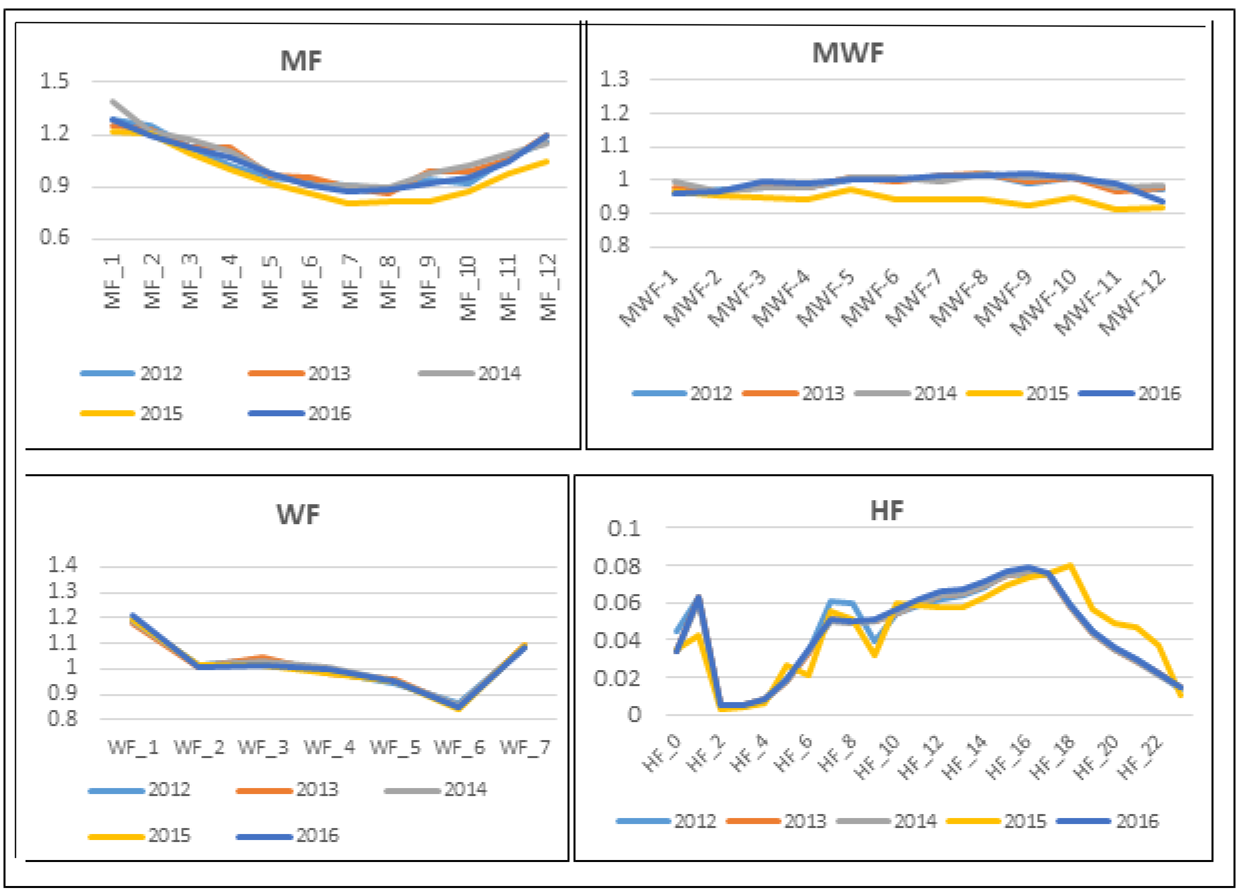


Figure 4.3 Yearly trend for CCS data based on MF, MWF, WF and HF

4.4 ITS Data Availability

In the analysis of ITS data availability, ITS sensor data were aggregated into hourly rates and the same method used in CCS availability was applied. First, the ITS sensor data available from devices in SEMTOC, WMTOC and STOC regions were processed for the 2015 and 2016 periods. Then, the data availability of individual ITS sensors was analyzed and compared by month and by TOC. The time frame of the study was during a transition to all ITS-MVDS reporting to the central ATMS software. Therefore, the puller software upgrades limited communications to field devices and the overall data availability was lower during the analysis period.

4.4.1 ITS Data Received by TOC

Even though there were 614 ITS sensors in Michigan, not all devices provided data. Many sensors were not able to supply data due to various reasons including the transition to the central ATMS software, highway construction, system maintenance, etc. ITS data received were from totals of 436 devices in 2015 and 547 devices in 2016, which is 75.8 percent and 89.0 percent of the total devices, respectively. As shown in Table 4.2, more ITS sensors provided data in 2016 except WMTOC. In 2016, more than 90 percent ITS sensors in SEMTOC and STOC provided data.

Table 4.2 Total ITS Data Received by TOC

		SEMTOC	WMTOC	STOC	Total
2015	Devices	286	128	161	575
	Received	225	110	101	436
	%	78.7%	85.9%	62.7%	75.8%
2016	Devices	302	128	184	614
	Received	275	101	171	547
	%	90.05%	78.9%	92.9%	89.0%

4.4.2 Comparison of ITS Data Availability by Year and TOC

As discussed in 4.4.1, 74.5 percent and 89 percent of ITS sensors provided data in 2015 and 2016, respectively. Even though those sensors provided data during the year, portion of data were missing for various reasons as discussed in the previous section. In this section, individual ITS data were further analyzed to investigate how many hours of data were available in the year. The data availability was computed same as the way for CCS data availability (Equation 4.1) among all devices that provided data during the period.

As depicted in Figure 4.4, the data availability varied by month and by area. In general, sensors in SEMTOC provided a higher percentage of data than those in WMTOC and STOC. However, the data from SEMTOC was completely missing for three months in 2015. On average, about 75 percent of data were available from WMTOC sensors in 2015, but the data availability significantly dropped in 2016, especially in March and June. The data availability in STOC was very low (about 20 - 30 percent) in 2015, but it increased to a 50 percent level in 2016.

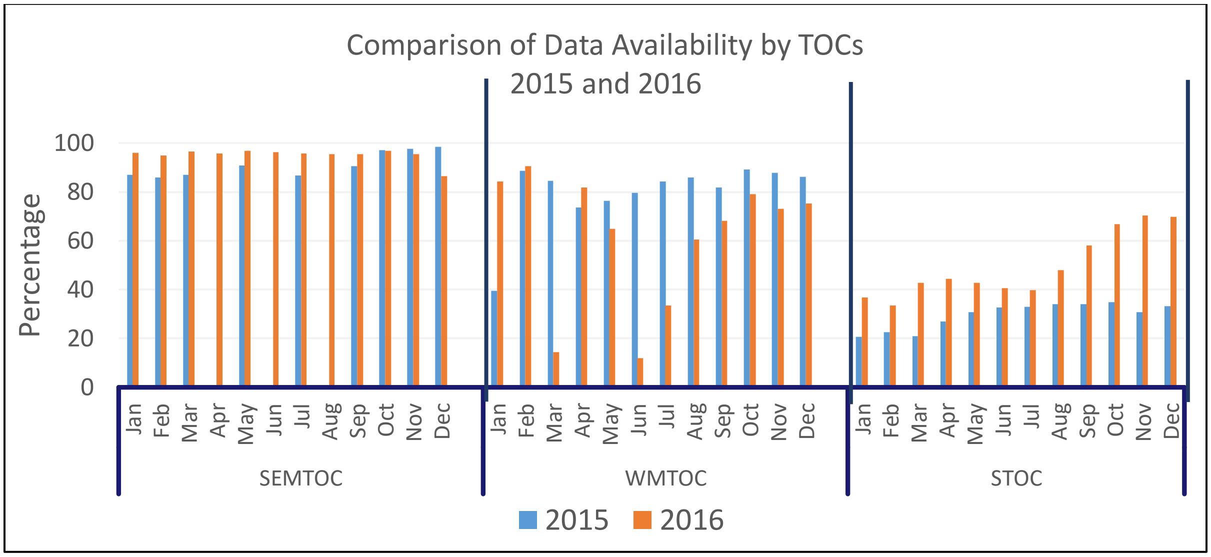


Figure 4.4 Comparison of ITS data availability by month

Table 4.3 Comparison of ITS Data Availability by Device

Percent of available data	SEMTOC (# of Devices)		WMTOC (# of Devices)		STOC (# of Devices)		Overall (# of Devices and %)			
	2015	2016	2015	2016	2015	2016	2015		2016	
>90	164	220	41	0	0	12	205	47.1%	232	42.4%
80-90	23	30	22	0	0	30	45	10.3%	60	10.9%
70-80	7	10	8	32	0	14	15	3.4%	56	10.2%
60-70	19	6	11	20	0	14	30	6.8%	40	7.3%
50-60	3	7	7	24	0	3	10	2.4%	34	6.2%
< 50	9	2	21	25	101	98	131	30%	125	22.8%
Total	225	275	110	101	101	171	436	100%	547	100%

The ITS data availability was further analyzed at an individual level. The number of individual sensors was tabulated by the data availability in Table 4.3. In SEMTOC, 73 percent of sensors in 2015 and 80 percent of sensors in 2016 were able to collect more than 90 percent of data. Only 5.3 percent of the devices collected less than 50 percent of data. On the other hand, more than 90 percent of data was collected only by 38 percent of the available WMTOC sensors in 2015. In STOC, more than 50 percent of sensors collected less than 50 percent of data in 2016. Overall, around 45 percent of ITS sensors collected more than 90 percent of data.

4.5 Summary of Findings

In this study, CCS data availability was examined for a total of 126 CCS stations. CCS sensors were very reliable and robust in supplying traffic volume data. In terms of time varying patterns, the trend was similar for almost all years except 2015. Unlike CCS sensor data, ITS sensors supplying data ranged between 62 percent and 93 percent. Data availability of those ITS sensors varied by month and by area, perhaps because of various reasons, such as the transition to new systems, highway constructions, system maintenance, etc. During past five years, less than 50 percent of ITS sensors were able to provide more than 90 percent of data in a year. This indicates that ITS sensors may need better maintenance in general.

Chapter 5 ITS Data Evaluation

5.1 Introduction

In this chapter, data from ITS MVDS sensors are evaluated and compared to nearby CCS sensors. Volume, speed, and vehicle classification data are considered and evaluated in this chapter to examine if ITS data are usable in the CCS program. ITS sensor data are evaluated and compared with CCS sensors for the years of 2015 and 2016. Data from CCS sensors were regarded as the ground truth data in this comparison. It should be noted that the time frame of the study was during a transition to all ITS-MVDS reporting to the central ATMS software. Therefore, the puller software upgrades limited communications to field devices and the overall data quality tends to lower during the analysis period.

5.2 Volume Data Evaluation

The consecutive hourly volume data for a whole year (January 1st to December 31th) was considered and evaluated for each comparable ITS sensor. The comparable ITS sensors were selected by spatial analysis through GIS mapping. The location of nearby CCS sites, route types, curvatures, ramps and access points, lane numbers, and directions were incorporated with the spatial analysis. ITS volume data was then compared with comparable CCS sensors and the accuracy was examined.

5.2.1 Approach for Volume Data Evaluation

Hourly volume data from an ITS sensor was matched with that from the comparable CCS sensor. ITS sensor data was compared with CCS data and examined by the model equation and the r-square value. Data accuracy was examined by following measures:

- Pearson's correlation
- Deviation from the 45 degree slope line
- Mean Average Percentage Error (MAPE).

The volume data from CCS sensors were considered as the ground truth for checking the accuracy of ITS sensors. Pearson's correlation was obtained through the correlation matrix between ITS and CCS volume data. A linear trend line of the relation between ITS and CCS data was observed and evaluated by the deviation from the 45-degree slope. The MAPE was considered as a key measure of volume accuracy. The Traffic Monitoring Guide (TMG) and other related resources typically regard a 10 percent error or less as acceptable accuracy.

5.2.2 Comparable ITS Sites for Volume Comparison

A total of 31 and 37 directional ITS sites were selected for the volume data evaluation for the years of 2015 and 2016, respectively. The ITS sites adjacent to CCS sensors were selected through a location analysis. Most of the comparable ITS sites identified were located in the SEMTOC region. The least number of comparable ITS sites was identified in the WMTOC region. While Table 5.1 summarizes the list of ITS sites for comparison, a detailed list of comparable ITS and CCS sensors for each TOC region is available in Appendix 5.1 - 5.3.

Table 5.1 List of ITS Sites to Compare

	2015			2016		
	Comparable ITS sites	Total ITS Sites	Percentage	Comparable ITS sites	Total ITS Sites	Percentage
SEMTOC	16	286	5.5%	22	302	7.2%
STOC	10	161	6.2%	10	184	5.4%
WMTOC	5	128	3.9%	5	128	3.9%
Total	31	575	5.3%	37	614	6.1%

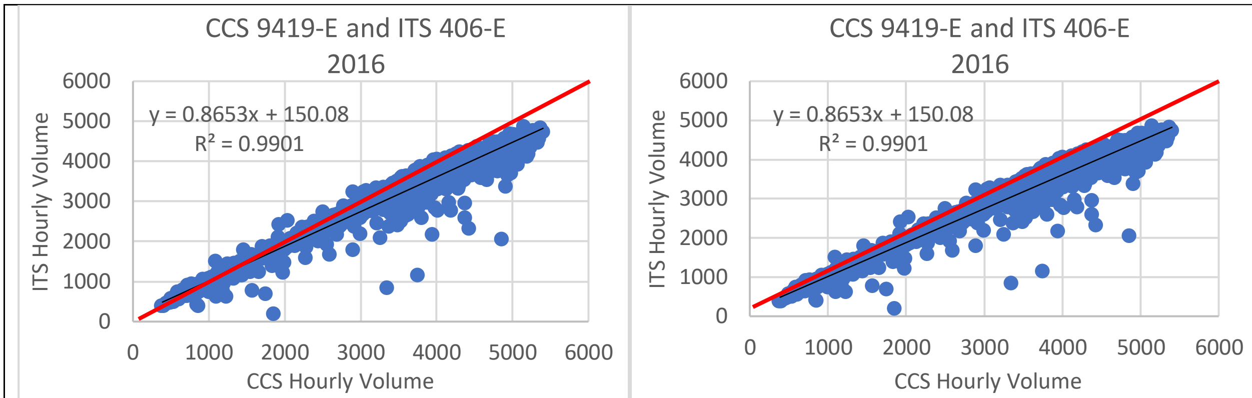
5.2.3 ITS Volume Data Evaluation

Each ITS volume data was compared with the data from an adjacent CCS sensor. The evaluation was performed through data availability, Pearson’s correlation, deviation from the 45-degree slope, and MAPE. An example of data evaluation result is shown in Table 5.2, and the detailed evaluation results are available in Appendix 3.

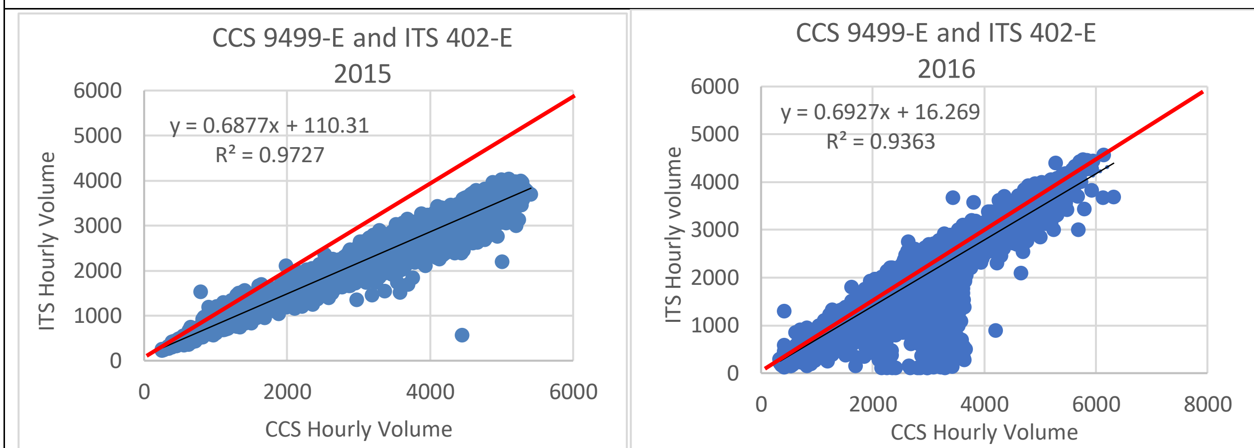
ITS sensor data in the SEMTOC region showed high data availability (98 percent in 2016; 77 percent in 2015). However, those in the STOC and WMTOC regions showed low availability. Another measure, Pearson’s correlation, explains how well both ITS and CCS data are correlated. The 45-degree slope line directly evaluates data accuracy. As shown in Figure 5.1, the higher data availability is, the more accurate the data is.

Table 5.2 Example Format of ITS Volume Data Evaluation

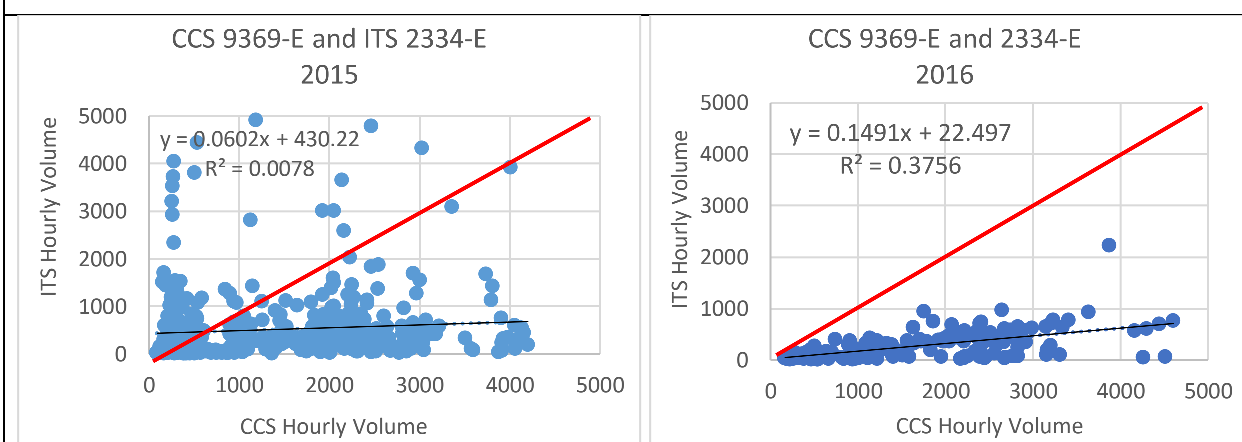
CCS ID	ITS ID	Direction	ITS Data Availability (%)		Data Accuracy					
					Pearson's Correlation		Slope for dataset		MAPE	
			2015	2016	2015	2016	2015	2016	2015	2016
9419	406	E	76	99	0.99	0.99	0.90	0.90	4.60	7.40
9419	407	W	76	99	0.99	0.99	0.96	0.95	2.33	3.10
9499	402	E	75.5	99	0.98	0.96	0.68	0.69	26.10	29.60
9499	403	W	76	99	0.98	0.97	0.90	0.90	7.90	10.01
9839	354	E	69.3	99	0.97	0.97	0.79	0.7	25.4	24.9
9839	355	W	70	99	0.96	0.96	0.99	1.1	21.1	14.5
9969	418	E	75.5	99	0.99	0.99	0.9	0.9	6.3	6.2
9969	419	W	76	99	0.99	0.99	0.96	0.95	2.72	3.3



a) Data Availability 99%



b) Data Availability 76%



c) Data Availability 2-3%

Figure 5.1 Example of volume data comparison

5.2.4 Accuracy of ITS Sensors for Volume Data

The accuracy of ITS sensor data was examined by MAPE. As shown in Table 5.3, around 30 percent of ITS sensors yielded an error of 10 percent or less while the other 30 percent yielded an error of 20 percent or more. More detailed and accurate results are available in Appendix 3. It should be noted that the transition to new system during the analysis period may have resulted in lower data quality lower than usual.

Table 5.3 Accuracy Checking of Comparable ITS Sites (2015 and 2016)

MAPE	SEMTOC				STOC				WMTOC				Total			
	2015		2016		2015		2016		2015		2016		2015		2016	
	No	%	No	%	No	%	No	%	No	%	No	%	No	%	No	%
Less than 10%	11	69	11	50	0	0	1	10	0	0	0	0	11	35	12	32
11% - 20%	1	6	5	23	0	0	6	60	1	20	1	20	2	6	12	32
More than 20%	4	25	6	27	10	100	3	30	4	80	4	80	18	58	13	35
Total	16	100	22	100	10	100	10	100	5	100	5	100	31	100	37	100

5.3 Speed and Vehicle Class Data Evaluation

The comparable ITS sites were selected based on the availability of speed and vehicle class data from adjacent CCS sites. In this study, speed data from ITS sensors were converted into a frequency table and vehicle classification data from CCS data were aggregated into 4 groups based on vehicle length.

5.3.1 Approach of Speed and Vehicle Class Evaluation

Speed data from ITS sensors were evaluated through speed distribution and accuracy checking with MAPE and Chi-square statistics. On the other side, ITS vehicle class data was evaluated through a proportional comparison with CCS classes.

Approach of Speed Data Evaluation:

In this study, 16 different speed bins (FHWA, 2016) were considered, ranging from an initial bin of 0 - 20.9 mph (bin 1) to the last bin of 91 mph or above (bin 16). First, the frequency of ITS speed data was reorganized to match with the same format of CCS data. Accuracy of speed data from ITS sensors was examined through a Chi-square goodness of fit test. The mean and standard deviation of the speed distribution data were calculated using equation 5.2 and 5.3.

$$\text{Average speed } (\bar{x}) = \frac{\sum n_i s_i}{N} \quad (5.2)$$

$$\text{Std. of Speed} = \sqrt{\frac{\sum n_i s_i^2 - N\overline{x^2}}{N-1}} \quad (5.3)$$

Approach of Vehicle Class Data Evaluation:

ITS sensors classify vehicles into four classes by vehicle length: small (SM), medium (MD), large (LG), and extra-large (EL). In order to compare data, 13 vehicle classes of CCS data were aggregated into 4 classes based on vehicle length and axle size (Jessberger, 2012). The vehicle classes are shown in Table 5.4, where SM refers to small size vehicles (typically 0 - 18 ft), MD refers to medium size vehicles (18-35 ft), LG refers to large size vehicle (truck) with single units (35-70 ft), and EL refers to extra large size vehicles (truck) with multiple units (typically more than 70 ft). The detail of original 13 classes are explained at Table A-11 in appendix.

Table 5.4 Vehicle Classes and Description

New Class	Description of FHWA Combined Classes
SM	Small size vehicle (class 1 and class 2)
MD	Medium size vehicle (class 3 and 4)
LG	Large size vehicle with single units (class 5-10)
EL	Extra Large size vehicle with multiple units (class 11,12, and 13)

5.3.2 Comparable ITS Sites for Speed and Vehicle Class Comparison

A set of ITS sites comparable for speed evaluation was selected. 10 and 13 directional ITS sites were selected from 2015 and 2016, respectively. Due to unavailability of vehicle class data in SEMTOC, there was a limitation in selecting sites. Only 7 directional ITS sites (2 in 2015 and 5 in 2016) in STOC and WMTOC were included in the vehicle class evaluation.

Table 5.5 List of Sites for Speed and Vehicle Class Comparison

	2015			2016		
	Comparable sites	Total ITS Sites	Percentage	Comparable sites	Total ITS Sites	Percentage
SEMTOC	8	286	2.8%	8	302	2.6%
STOC	0	161	0%	3	184	1.63%
WMTOC	2	128	1.6%	2	128	1.6%
Total	10	575	1.8%	13	614	2.1%

5.3.3 Speed Data Evaluation

The average speed from ITS sensors was deviated by 2-5 mph, compared to the average of CCS speed data. An example of speed data distribution is shown in Table 5.6. The detailed speed evaluation result is available in Appendix 3. The speed distributions between two datasets are compared in Figure 5.1

Table 5.6 ITS Speed Data Evaluation

Speed Distribution							
ID	**Direction**	**Average Speed (mph)**	**Std. of Speed**	**85th Percentile of Speed**	**Bin with Highest Frequency**	**ITS Data Availability**	**Deviation from 85th percentile speed**
CCS-8209	E	72.4	11.4	78.3	Bin 13(76-80.9)	99	2.1
ITS-136	E	67.2	12.9	76.2	Bin12(71-75.9)		
CCS-8209	W	72.7	10.2	78.1	Bin13(76-80.9)	99	-1.9
ITS-137	W	74.5	8.57	80	Bin13(76-80.9)		
CCS-8409	E	69.9	14.2	77.1	Bin12(71-75.9)	98	3.6
ITS-172	E	68.3	10.1	73.5	Bin12(71-75.9)		
CCS-8409	W	67.7	19.1	77.5	Bin12(71-75.9)	98	-3.5
ITS-172	W	75.2	8.78	81	Bin12(71-75.9)		
CCS-8839	E	78.4	8.9	77.5	Bin13(76-80.9)	98	4.1
ITS-306	E	71.1	5.8	73.4	Bin12(71-75.9)		

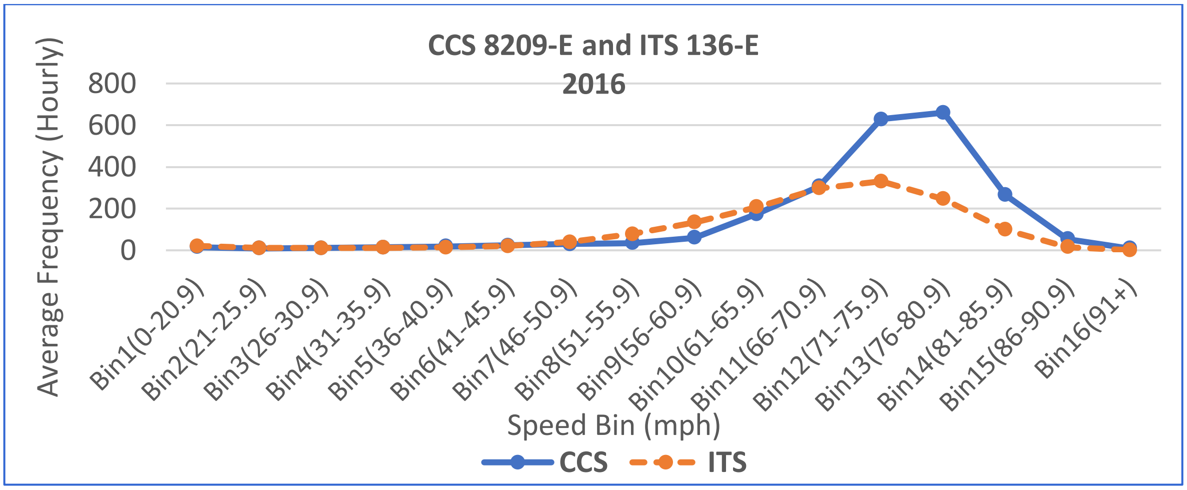


Figure 5.2 Example of speed data distribution

Table 5.7 Chi-square Test Value for the ITS Speed Distribution

SEMTOC				
ID	**p value**	**test-statistic**	**Decision**	
CCS-8209 ITS-136	0.006	31.7	Sig	H_0 Reject
CCS-8209 ITS-137	0.972	6.3	Not Sig.	H_0 Accept
CCS-8409 ITS-172	0.051	23.5	Not Sig.	H_0 Accept
CCS-8409 ITS-172	0.055	22.4	Not Sig.	H_0 Accept
CCS-8839 ITS-306	0.004	33	Sig	H_0 Reject
CCS-8839 ITS-307	0.052	24.8	Not Sig.	H_0 Accept
CCS-9699 ITS-182	0	80	Sig	H_0 Reject
CCS-9699 ITS-183	0.599	13	Not Sig.	H_0 Accept
WMTOC				
CCS-9759 ITS-303	0.001	37.6	Sig	H_0 Reject
CCS-9759 ITS-303	0	85	Sig	H_0 Reject
STOC				
CCS-6349 ITS-3634	0.058	21.5	Not Sig.	H_0 Accept
CCS-2199 ITS-3740	0.966	6.6	Not Sig.	H_0 Accept
CCS-4049 ITS-3642	0	129.5	Sig	H_0 Reject

The deviation of the 85th percentile speed value was very low between most of the comparable ITS sites and CCS sites, and this was true for both the 2015 and 2016 periods. Therefore, the comparable ITS and CCS speed data looked very similar to each other, and these ITS sites could be recommended for speed data collection.

The overall accuracy of ITS speed data was examined by the chi-square goodness of fit test. Table 5.7 shows the result of the p value and test statistics as an example. The hypothesis examines if two speed distributions from ITS data and CCS data are the same. The results show that speed distributions were found to be same for 53 percent of sites (7 out of 13 total sites) in 2016, and 60 percent (6 out of 10 total sites) in 2015 (see Appendix 3). Therefore, it could be concluded that ITS speed data were acceptably accurate.

5.3.4 Vehicle Class Data Evaluation

ITS vehicle class data were compared with those from CCS. Out of five sites, two sites were from WMTOC, and three sites were from STOC. Table 5.8 and 5.9 compare the composition of vehicle classes from ITS data and CCS data. Although the overall distribution does not match well due to differences in vehicle classification, ITS sensors successfully classified vehicle classes by length.

Table 5.8 Comparative Percentage of ITS Vehicle Classes for WMTOC

WMTOC Vehicle Class Comparison									
2015					2016				
ID	Direction	Class	CCS (percent)	ITS (Percent)	ID	Direction	Class	CCS (percent)	ITS (Percent)
CCS-9759 & ITS-303	E	1	62.2%	63.8%	CCS-9759 & ITS-303	E	1	72.8%	58.8%
		2	29.3%	20.0%			2	19.5%	23.2%
		3	7.9%	8.9%			3	7.3%	11.4%
		4	0.5%	7.2%			4	0.4%	6.5%
		Total	100.0%	100.0%			Total	100.0%	100.0%
CCS-9759 & ITS-303	W	1	66.3%	55.5%	CCS-9759 & ITS-303	W	1	76.9%	59.1%
		2	25.1%	34.6%			2	14.1%	27.0%
		3	8.0%	4.9%			3	8.5%	6.9%
		4	0.6%	4.9%			4	0.5%	7.0%
		Total	100.0%	100.0%			Total	100.0%	100.0%

Table 5.9 Comparative Percentage of ITS Vehicle Classes for STOC

STOC Vehicle Class Comparison-2016				
ID	Direction	Class	CCS (percent)	ITS (Percent)
CCS-6349 & ITS-3634	N	1	85.5%	70.4%
		2	9.2%	0.0%
		3	5.1%	29.6%
		4	0.2%	0.0%
		Total	100.0%	100.0%
CCS-2199 & ITS-3740	E	1	64.8%	42.0%
		2	26.4%	58.0%
		3	7.9%	0.0%
		4	1.0%	0.0%
		Total	100.0%	100.0%
CCS-4049 & ITS-3642	S	1	65.1%	78.6%
		2	27.9%	0.0%
		3	6.2%	21.4%
		4	0.8%	0.0%
		Total	100.0%	100.0%

5.4 ITS Data Quality by Locations

A total of 82 directional ITS sites were selected to evaluate the ITS data quality at curve areas. Most ITS sites located at curve areas were found in the SEMTOC and STOC regions. This section investigates if ITS data at curve areas are worse than the data in other areas.

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Table 5.10 List of ITS Sites at Curve Areas

	2015			2016		
	ITS Sites	Total ITS Sites	%	ITS Sites	Total ITS Sites	%
SEMTOC	18	286	6.2%	17	302	5.6%
STOC	18	161	11.2%	13	184	7.1%
WMTOC	9	128	7.1%	7	128	5.4%
Total	45	575	7.8%	37	614	5.9%

As shown in Figure 5.3 and 5.4, there was no evidence that the ITS data at curve areas were worse than those at other areas. In fact, the data at curve in SEMTOC showed better than overall quality.

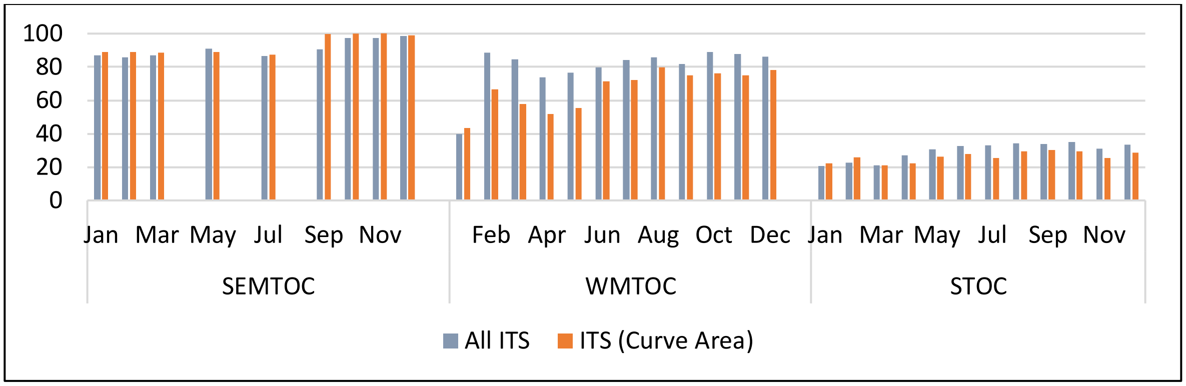


Figure 5.3 Comparisons for ITS data quality for curve areas in 2015

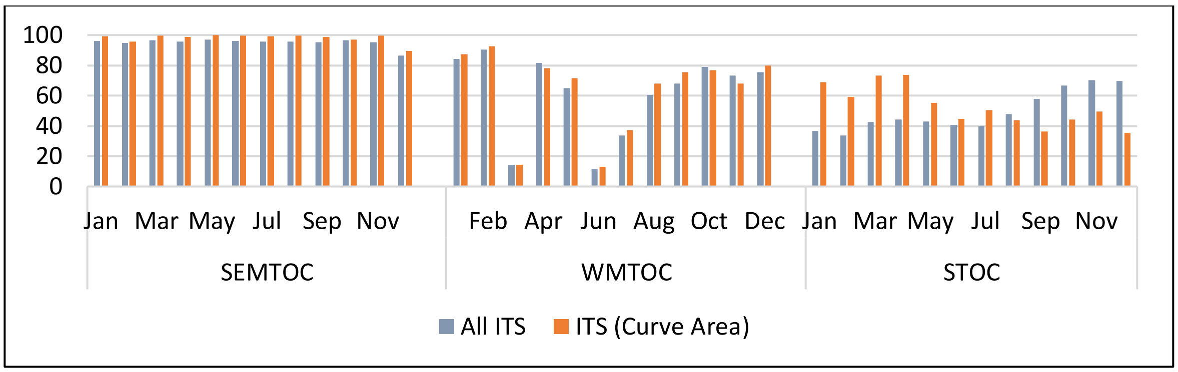


Figure 5.4 Comparisons for ITS data quality for curve areas in 2016

5.5 Conclusion and Summary Findings

In this chapter, data were collected from CCS, ITS, and WIM sensors and incorporated into a multi-source GIS database. CCS data were collected for the past five years (2012-2016). ITS sensor data were collected for 2015 and 2016. The data availability of ITS sensor data was around 80 percent, 50 percent, and 30 percent for SEMTOC, WMTOC, and STOC, respectively. ITS sensor data were evaluated and compared with data from adjacent CCS to examine if ITS sensors produced good quality data enough to be usable in the traffic monitoring program. In volume data comparison, approximately 35 percent of the total comparison sites showed high quality with less than 10 percent error. In speed data evaluation, more than 50 percent of the ITS sites yielded similar speed distribution with the nearby CCS sites. In vehicle classification, ITS sensors successfully classified vehicle classes by length although their accuracy may need further improvement. In conclusion, ITS sensors were capable of providing data with a quality high enough to support the traffic monitoring program when they are well calibrated and maintained.

Chapter 6 Evaluation of CCS Sites

6.1 Introduction

In this chapter, existing CCS sites are evaluated by two approaches: redundancy analysis and sufficiency analysis. The redundancy analysis is to identify sensor locations that do not benefit the traffic-monitoring program. Those sensors that are closely placed and produce similar data are regarded as redundant sensors. The traffic-monitoring program will be more cost-effective when these sensors are removed. The sufficiency analysis is to examine if the number of sensors in the program is statistically sufficient to meet the requirement of TMG. The analyses are conducted with the traffic data collected during 2012 to 2016.

6.2 Redundancy Analysis

The redundancy analysis was performed against 122 CCS sites where 2016 data were available out of all 126 sites distributed throughout the Michigan area.

6.2.1 Methodology and Analysis

The redundancy analysis considers two basic elements: correlation of data with other sensors and proximity with other sensors. Those sites highly correlated and closely placed were regarded as redundant sites. In this redundancy analysis, a correlation-coefficient matrix among 122 CCS sites was developed based on monthly factors (MF) and weekly factors (WF) of individual sites. Hourly factors (HF) and monthly weekday factors (MWF) were not considered in this analysis.

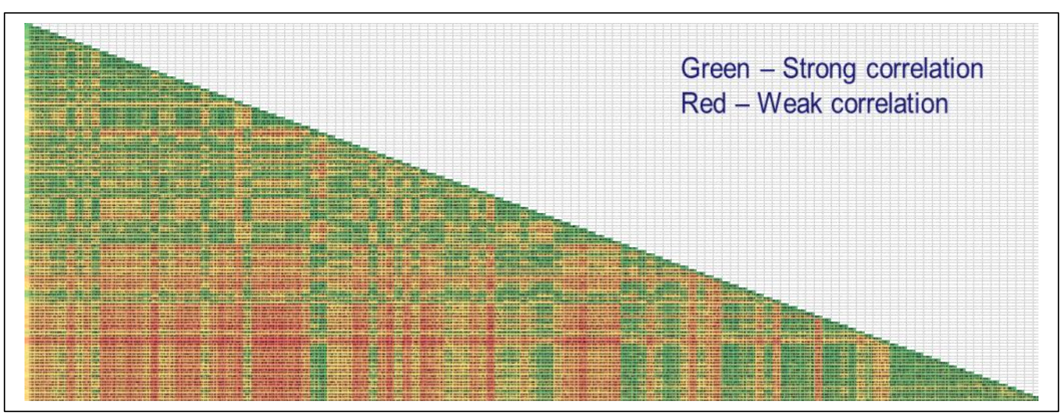


Figure 6.1 Example of the matrix formation for correlation-coefficient analysis

Figure 6.1 depicts the result of the correlation analysis. In the figure, those with green colors represent a strong correlation while those with red colors represent a weak correlation. A pair with a correlation value of 0.85 or above was regarded as strongly correlated.

The proximity analysis was performed by developing a distance matrix among the CCS sites. The distances between individual CCS sites were computed by employing the GIS network analyst tool. Figure 6.2 shows an example of the distance matrix between CCS sites. Since the distances between CCS sites vary by their location type (urban vs. rural), 8 miles and 6 miles were considered for proximity analysis between the CCS pairs.

Station	2229	3029	3039	3069	3079	3089	3109	3129	3149	3249	32
2229	0	294.6183	245.1014	226.5347	236.6863	294.0335	318.2771	258.5144	293.9978	311.3579	324.04
3029	294.6183	0	86.70742	70.39387	67.2206	19.41	57.31532	67.61543	19.3744	16.73961	68.881
3039	245.1014	86.70742	0	60.34308	58.87335	86.12259	78.98724	19.09199	86.08699	103.447	84.646
3069	226.5347	70.39387	60.34308	0	15.66251	69.80904	91.74239	41.39278	69.77344	87.13348	97.512
3079	236.6863	67.2206	58.87335	15.66251	0	66.63577	90.13097	39.78136	66.60017	83.96021	95.901
3089	294.0335	19.41	86.12259	69.80904	66.63577	0	38.67219	67.0306	0.731272	21.71609	50.238
3109	318.2771	57.31532	78.98724	91.74239	90.13097	38.67219	0	59.89525	37.94092	59.62141	15.94
3129	258.5144	67.61543	19.09199	41.39278	39.78136	67.0306	59.89525	0	66.995	84.35505	65.554
3149	293.9978	19.3744	86.08699	69.77344	66.60017	0.731272	37.94092	66.995	0	21.68048	49.507
3249	311.3579	16.73961	103.447	87.13348	83.96021	21.71609	59.62141	84.35505	21.68048	0	71.187
3269	324.0474	68.88154	84.64605	97.51265	95.90123	50.23842	15.9492	65.55406	49.50714	71.18763	
3300	278.4235	47.68531	39.02212	51.88872	50.2773	47.10048	41.80567	19.93013	47.06487	64.42492	47.464
4029	300.3223	168.0029	185.7489	142.5381	126.8756	167.4181	205.3234	166.6569	167.3825	173.7739	216.88

Figure 6.2 Example of distance matrix among CCS

6.2.2 Redundant CCS Sites

In order to select potentially redundant CCS sites, following two criteria were applied to the results of the correlation and proximity analyses.

- Correlation coefficient is higher than 0.85.
- Distance between sensors is less than 8 miles.

As a result, a total of 8 CCS pairs were identified as potentially redundant. Figure 6.3 shows those locations, and Table 6.4 shows characteristics of those pairs. As described in Table 6.1, potentially redundant CCS pairs were examined whether they were in the different clusters (different roadway types) or special sensors (e.g. WIM sensor or vehicle classifier). After excluding those in different clusters or special sensors, four pairs were identified as potentially removable. Among those four, two on interstate freeways were highly possible to remove while the other two on urban arterials were possible but not recommended to remove due to an insufficient number of CCS sites on urban arterials. Out of those four pairs of CCS sites, two highly removable sites are depicted Figure 6.4.

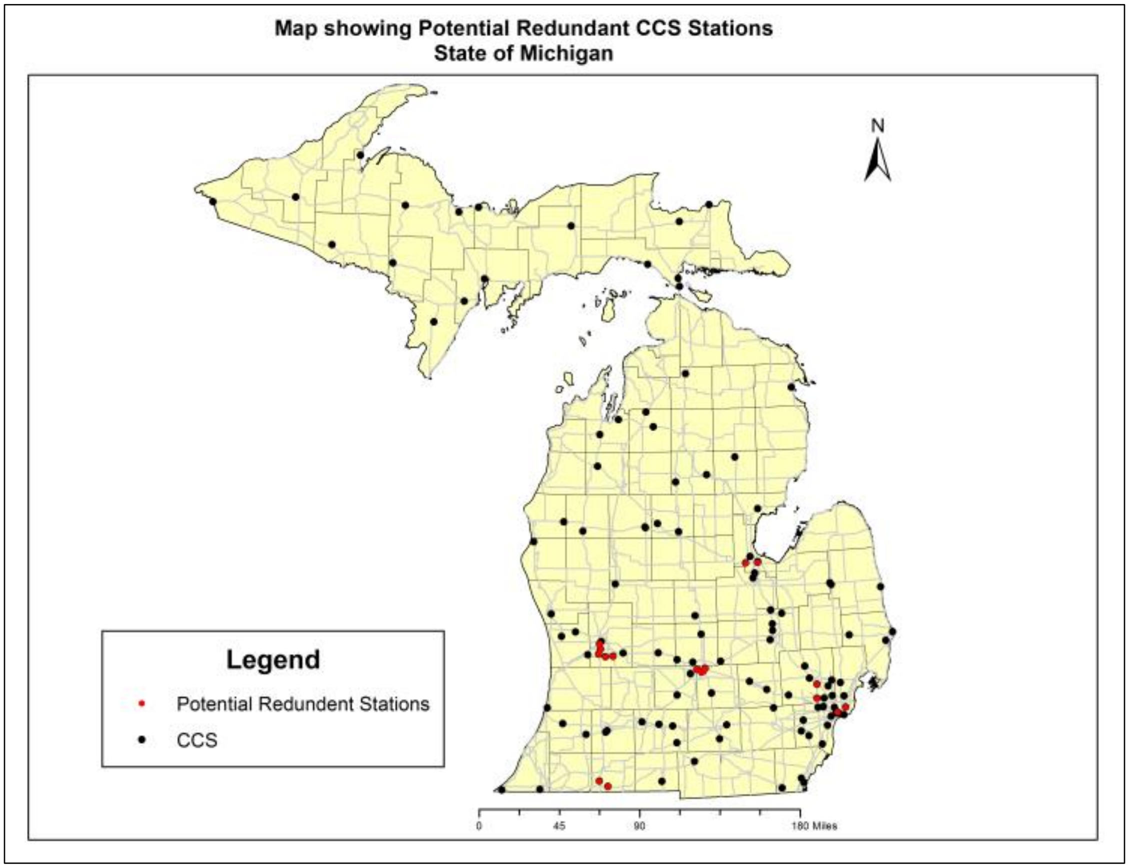


Figure 6.3 Potentially redundant CCS stations for Michigan

Table 6.1 Potentially Redundant CCS Pairs

Pair of CCS Stations	Correlation coefficient of Pairs	Distance between pairs (mile)	Route Type & Other Characteristics	Same Cluster	Removable
9419-9969	0.87	5	Both in Urban Interstate	Yes	**Highly Possible**
6479-9669	0.85	7	Rural Arterial-Rural Collector	No	No
7119-7329	0.98	6	Both in Rural Arterial **(Including WIM)**	Yes	No
8459-8470	0.96	8	Both in Urban Arterial	Yes	Possible
9020-9040	0.96	3	Both in Urban Arterial	Yes	Possible
9029-9040	0.92	4	Urban Arterial-Urban Interstate	No	No
9029-9049	0.9	2	Both in Urban Interstate	Yes	**Highly Possible**
9040-9049	0.88	5	Urban Arterial-Urban Freeway	No	No

Figure 6.4 Highly possible redundant locations

6.3 Sufficiency Analysis

The sufficiency analysis was to determine the number of sensors needed in each category to meet the requirement of FHWA's TMG. In this study, the appropriate number of CCS sites was evaluated based on three different classification types, such as the classifications by geographical region, highway functional type, MDOT's locational type. The appropriate number of CCS sites was calculated for 5 years from 2012 to 2016.

6.3.1 Methodology

The number of CCS sites required fluctuated by the variation of data in each category. The higher the variation of data (monthly factors, weekly factors, monthly weekday factors, and hourly factors) in the same category is, the more sites are required. The number of sites needed also varied by the desired level of precision.

This study determines the number of sites required in each category by the following equation:

$$n = \left(CV \frac{t_{1-\frac{\alpha}{2}, n-1}}{E} \right)^2 \quad \text{.......} \quad (6.1)$$

where n is the number of samples needed; CV is the coefficient of variation associated with the CCS data; $t_{1-\frac{\alpha}{2},n-1}$ is the t-score associated with the desired confidence level $1-\alpha$, $n-1$ degrees of freedom; E is the tolerance (in percentage) of the estimated traffic data.

FHWA's TMG recommends a 10 percent tolerance with a 95 percent level of confidence in determining the appropriate number of CCS sites.

6.3.2 Classification of CCS Sites by Geographical Region and Highway Type

Before analyzing the number of sites needed, CCS sites were classified into groups based on their locations (the geographical region) and functional classification (the highway type). As shown in Table 6.2, the whole Michigan area was divided into four geographical regions (Superior, North, West and East). The geographical regions were based on MDOT's seven regions while Grand and Southwest regions were combined into the West region and Bay, Metro, and University regions were grouped as the East region. Furthermore, highways were classified into four types (urban freeway, rural freeway, urban arterial, and rural arterial) based their functional characteristics. Based on these classifications, CCS sites were grouped into individual categories. Table 6.2 shows the number of CCS sites in each category. There were 16, 10, 30, and 66 CCS sites in Superior, North, West, and East regions, respectively. When classifying CCS sites by highway types, 42, 22, 15, and 43 CCS sites were on urban freeways, rural freeways, urban arterials, and rural arterials, respectively.

Table 6.2 CCS Sites by Geographical and Functional Types

	Superior	North	West	East	Total
Urban Freeway	1	-	8	33	42
Rural Freeway	2	2	9	9	22
Urban Arterial	2	1	4	8	15
Rural Arterial	11	7	9	16	43
Total	16	10	30	66	122

6.3.3 Number of CCS Sites Needed by Geographical Region

Table 6.3 and 6.4 summarize the required number of CCS sites based on the data types (monthly factors, weekly factors, monthly weekday factors, and hourly factors) by region and by highway type during the past five years (2012 – 2016). The tables also provide the mean and the standard deviation by the data type as well as the required number of CCS sites by different levels of confidence (85th, 90th and 95th percentile) in each region.

While the current number of CCS sites in the West or East region was sufficient for all data types, those in the Superior region do not meet the requirement for HF, and those in the North region do not meet the requirements for MF, WF, and HF. That is, more CCS sites were needed in the North region and the Superior region. Even if the ITS sensors in these regions were added into CCS, the numbers did not meet the requirements for HF.

Table 6.3 CCS Sites Needed by Geographical Region

Geographical Clusters	Cluster-1 (Superior)				Cluster-2 (North)				Cluster-3 (West)				Cluster-4 (East)			
	MF	WF	MWF	HF	MF	WF	MWF	HF	MF	WF	MWF	HF	MF	WF	MWF	HF
2012	9	4	1	39	7	20	4	33	9	19	3	25	24	11	3	20
2013	9	4	1	38	6	21	4	34	12	21	3	30	21	10	3	21
2014	6	2	1	33	8	20	4	32	21	20	4	21	36	10	3	20
2015	10	1	1	59	12	15	3	31	8	21	3	20	15	13	14	47
2016	11	4	2	43	8	20	5	29	8	20	3	29	12	10	3	19
Average	9	3	1.2	42.4	8.2	19.2	4	31.8	11.6	20.2	3.2	25	21.6	10.8	5.2	25.4
Standard Deviation	1.8	1.4	0.5	9.9	2.2	2.3	0.7	1.9	5.5	0.8	0.5	4.5	9.3	1.3	4.9	12
# of required CCS (85th Percentile)	10	4	1	49	10	21	5	33	15	21	3	29	29	12	7	32
# of required CCS (90th Percentile)	11	4	2	53	10	21	5	34	17	21	4	30	31	12	10	37
# of required CCS (95th Percentile)	11	4	2	56	11	21	5	34	19	21	4	30	34	13	12	42
# of Current CCS	16				10				30				66			
# of Current ITS	30				15				157				377			

Table 6.4 CCS Sites Needed by Highway Type

Functional clusters	Cluster-1 (Urban Freeway)				Cluster-2 (Rural Freeway)				Cluster-3 (Urban Arterial)				Cluster-4 (Rural Arterial)			
Year	MF	WF	MWF	HF	MF	WF	MWF	HF	MF	WF	MWF	HF	MF	WF	MWF	HF
2012	21	5	1	9	18	7	2	28	35	10	1	24	8	11	2	36
2013	19	4	1	9	7	8	2	28	37	11	1	25	12	12	3	40
2014	40	4	1	8	30	7	2	29	34	10	1	24	6	11	3	29
2015	13	5	11	26	5	6	1	21	15	12	35	25	9	13	7	67
2016	18	4	1	8	5	6	2	20	4	17	1	21	21	12	3	42
Average	22.2	4.4	3	12	13	6.8	1.8	25.2	25	12	7.8	23.8	11.2	11.8	3.6	42.8
Standard Deviation	10.4	0.5	4.5	7.8	10.9	0.8	0.4	4.3	14.7	2.9	15.2	1.6	5.9	0.8	1.9	14.4
# of required CCS (85th Percentile)	28	5	5	16	23	8	2	29	36	14	15	25	16	13	5	52
# of required CCS (90th Percentile)	32	5	7	19	25	8	2	29	36	15	21	25	17	13	5	57
# of required CCS (95th Percentile)	36	5	9	23	28	8	2	29	37	16	28	25	19	13	6	62
# of Current CCS	42				22				15				43			
# of Current ITS	501				21				28				31			

6.3.4 Number of CCS Sites Needed by Highway Type

The same calculation was conducted by the highway types. As shown in Table 6.4, the number of CCS sites on urban freeways (cluster-1) met the requirement for all data types. However, more CCS sites were needed on rural freeways (cluster-2) to meet the requirements of MF and HF, on urban arterials (cluster-3) for all data types, and on rural arterials (cluster-4) for HF. The requirements could be fulfilled by adding ITS sensors into CCS.

6.3.5 Number of CCS Sites Needed by MDOT Clusters

MDOT classified CCS sites into six categories by their locational characteristics: urban (cluster 1), urban rural (cluster 2), rural (cluster 3), rural north (cluster 4), recreational (cluster 5), and recreational corridor (cluster 6), taking the recreational areas and corridors into consideration. Figure 6.5 depicts CCS sites by cluster with different colors on highway routes.

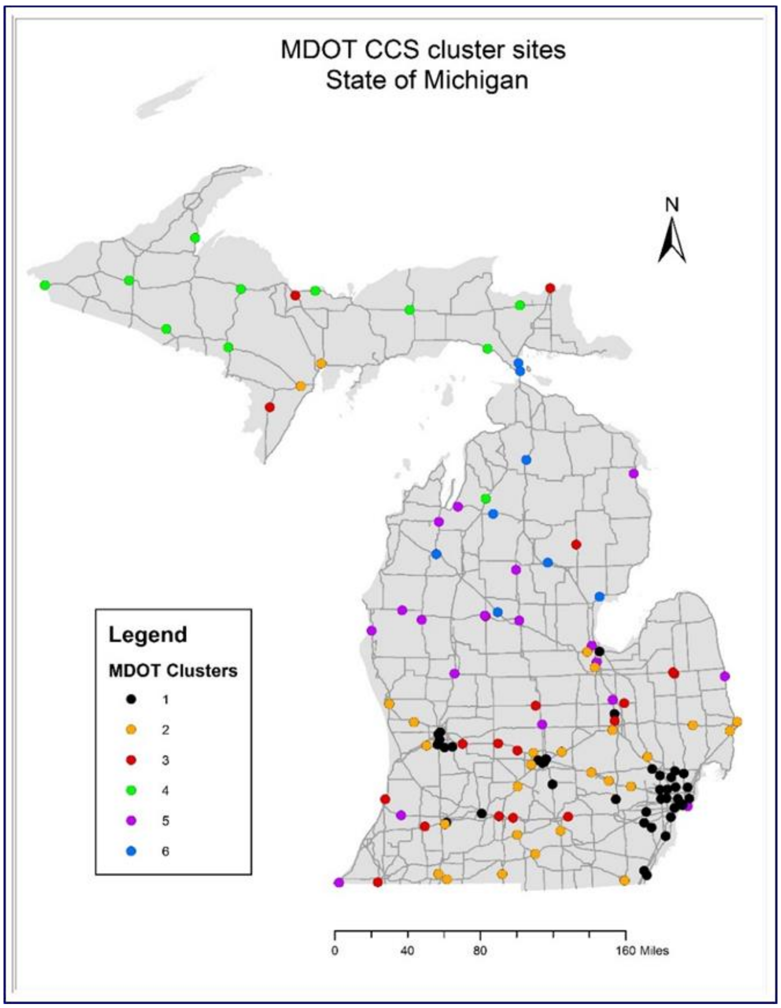


Figure 6.5 Locations of CCS by MDOT cluster

The number of CCS sites required by data type in each cluster is shown in Table 6.5. According to the calculation, no additional CCS sites were needed for cluster-1 (Urban) and cluster-3 (Rural) for all data types. However, the analysis shows that four additional sites were needed for Cluster-2 (Urban Rural) to meet the requirement of HF.

Table 6.5 CCS Sites Needed by MDOT Clusters

MDOT Clusters	Cluster-1 (Urban)				Cluster-2 (Urban Rural)				Cluster-3 (Rural)				Cluster-4 (Rural North)				Cluster-5 (Recreational)				Cluster-6 (Recreational Corridor)			
Year	MF	WF	MWF	HF	MF	WF	MWF	HF	MF	WF	MWF	HF	MF	WF	MWF	HF	HF	WF	MWF	HF	MF	WF	MWF	HF
2012	35	5	1	16	11	5	1	12	3	4	2	14	12	5	1	50	3	11	2	19	3	4	3	13
2013	21	5	1	15	26	4	1	14	5	4	2	15	12	7	3	59	3	13	2	20	3	4	2	13
2014	38	6	1	15	23	4	1	11	2	2	1	10	9	3	3	44	2	12	2	15	5	4	2	14
2015	14	6	4	40	14	5	2	35	3	3	1	17	15	6	3	59	11	11	7	23	5	3	3	19
2016	14	8	1	14	15	5	1	12	4	4	2	12	14	8	4	63	3	10	2	19	2	3	4	12
Average	24	6	3	20	17	4	1	16	3	3	1	13	12	5	2	55	5	11	3	19	3	3	2	14
Standard Deviation	24.4	6	1.6	20	17.8	4.6	1.2	16.8	3.4	3.4	1.6	13.6	12.4	5.8	2.8	55	4.4	11.4	3	19.2	3.6	3.6	2.8	14.2
# of required CCS (85th Percentile)	11.5	1.2	1.3	11.2	6.4	0.5	0.4	10.2	1.1	0.9	0.5	2.7	2.3	1.9	1.1	7.8	3.7	1.1	2.2	2.9	1.3	0.5	0.8	2.8
# of required CCS (90th Percentile)	37	7	3	30	25	5	2	27	5	4	2	16	15	8	4	61	8	13	5	22	5	4	4	17
# of required CCS (95th Percentile)	37	8	3	35	25	5	2	31	5	4	2	17	15	8	4	62	9	13	6	22	5	4	4	18
# of Current CCS	41				27				19				11				18				8			
# of Current ITS	424				88				21				23				8				15			

For cluster-4 (Rural North), the number of CCS sites was sufficient for all data types except MF and HF. The required number of CCS sites for HF was exceptionally high. It is because the hourly factors tend to highly fluctuate when traffic volume is very low. For both cluster-5 (Recreational) and cluster-6 (Recreational Corridor), additional CCS sites were required for HF but not for other factors. The result indicates that the requirements could be fulfilled when existing ITS sensors were added into the CCS program except for cluster 4 (Rural North).

6.4 Summary of Findings

In this chapter, CCS sites were evaluated by employing the redundancy analysis and the sufficiency analysis. Correlation and proximity analyses were performed to identify redundant CCS sites. Through the redundancy analysis, four CCS sites were identified as possibly redundant and potentially removable. Among those four, two on interstate freeways were highly possible to remove while the other two on urban arterials were possible but not recommended to remove due to a lack of CCS sites on urban arterials. However, these two CCS sites on urban arterials could be kept for potential relocation sites when they fail.

The number of CCS sites needed was evaluated by quantifying the numbers by data type and different classifications. The analysis results showed that more CCS sites were needed in the North region as well as on rural freeways and urban arterials. More specifically, the Rural-North (cluster 4 in MDOT's classification) needed at least four more CCS sites to meet the requirement for MF. When applying the requirement for hourly factors, four more sites were needed for cluster 3 and 5, and ten more sites for cluster 6.

Chapter 7 Combining ITS Sensors into the Traffic Monitoring Program

7.1 Introduction

The objective of this chapter is to identify the ITS sensors that are usable for the traffic monitoring program. As discussed in the previous chapter, MDOT's traffic monitoring program needs more sensors to meet the FHWA's TMG requirements. The gap could be fulfilled by using existing ITS sensors. Even though there are still data quality concerns in using these sensors in the traffic monitoring program, the ITS sensors could be a good source of traffic volume data when they are well calibrated and maintained as discussed in Chapter 5.

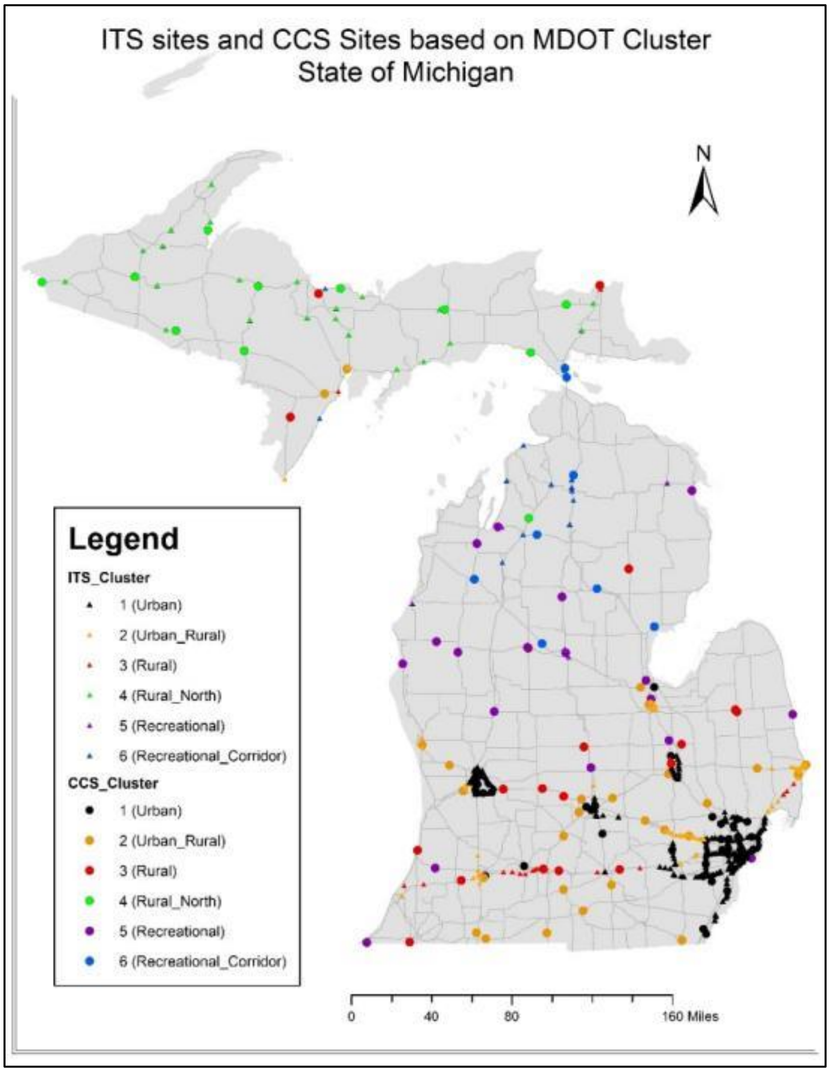


Figure 7.1 ITS sensor and CCS sites by the MDOT cluster

In this research, both CCS sites and ITS sites were analyzed in order to identify CCS sites that could be replaced with existing ITS sensors and ITS sensors that could be added into MDOT's traffic monitoring program. Those replaceable CCS sites and addable ITS sensors were analyzed by the MDOT's cluster. Figure 7.1 shows all ITS sensors and CCS sites analyzed by the MDOT's cluster.

Based on proximity and roadway type, CCS sites that could be replaced with ITS sensors were identified. When determining the ITS sensors into MDOT's traffic monitoring program, the following factors were considered (MetroCount, 2002; FDOT, 2007):

- Consider high volume highways.
- Consider adequate geographical coverage.
- Place them away from intersections/ramps.
- Avoid sharp curves.
- Avoid acceleration/deceleration areas.
- Avoid high pedestrian traffic areas.

7.2 Proposed Traffic Monitoring Program

7.2.1 CCS Sites Replaceable with ITS Sensors

Through careful investigation of CCS sites and ITS sensor sites, we identified a total of 12 CCS sites replaceable with ITS sensors. Out of 12 sites, 11 of them were those in cluster-1 (Urban), and one of them was that in cluster-2 (Urban Rural). Geographical locations of those CCS stations replaceable with ITS sensors were shown in Figure 7.2. WIM, vehicle classifiers or other special purpose sites were avoided when selecting replaceable CCS sites.

Table 7.1 shows a list of CCS sites and corresponding ITS sensors along with the percentage of ITS sensors' data availability. Note that most ITS sensors in the list hold good data availability, but a routine calibration and maintenance effort is needed to maintain better data quality and availability.

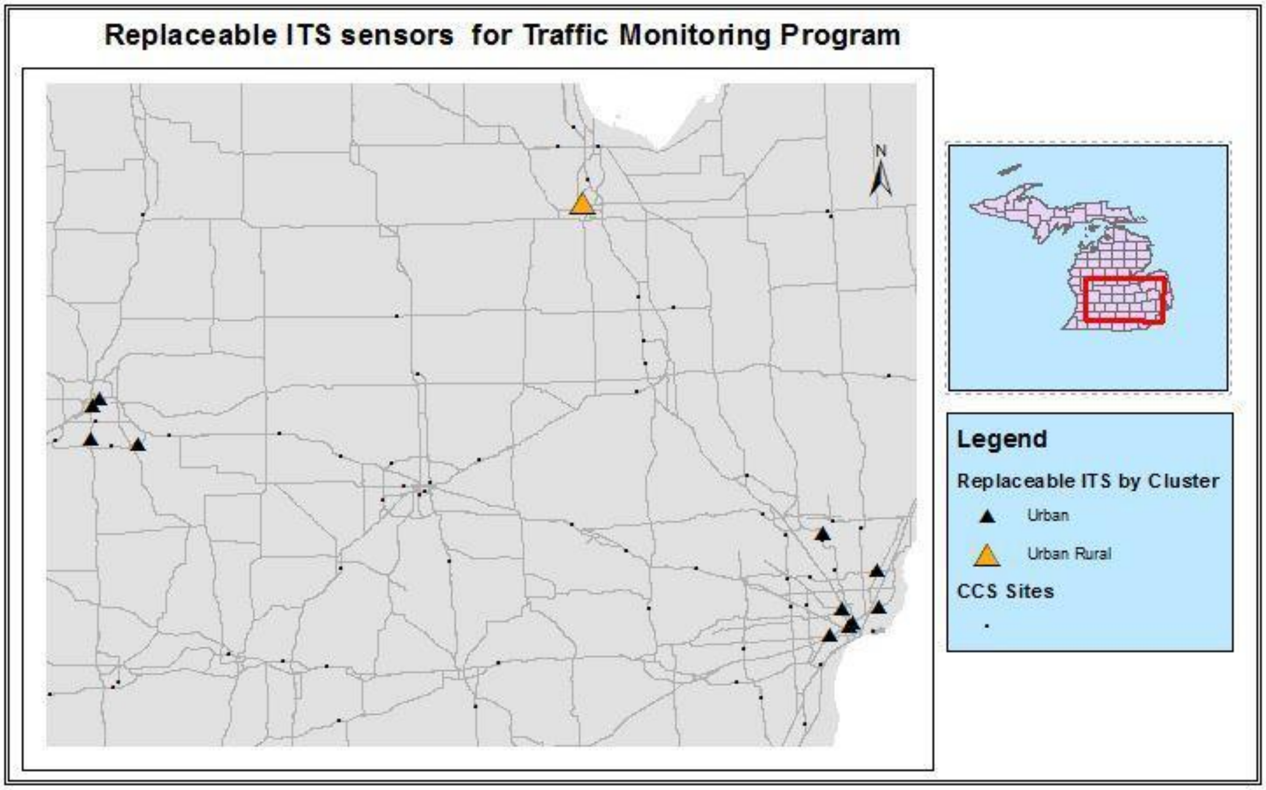


Figure 7.2 Location of replaceable ITS sites by MDOT clusters

Table 7.1 Replaceable Sensor Sites

Replaceable Sensors	Device ID	Data Availability	Total
Cluster-1	CCS-9839 and ITS-354&355	99%	11
	CCS-9969 and ITS-418&419	99%	
	CCS-9419 and ITS-406&407	99%	
	CCS-9499 and ITS-402&403	99%	
	CCS-9489 and ITS-11&12	99%	
	CCS-9979 and ITS-160&161	98%	
	CCS-9999 and ITS-184&185	99%	
	CCS-9729 and ITS-118	50%	
	CCS-9739 and ITS-305	25%	
	CCS-5069 and ITS-240	25%	
	CCS-9769 and ITS-213	91%	
Cluster-2	CCS-9229 and ITS-2412	37%	1

7.2.2 Addable ITS Sensor Sites

In order to meet the requirement of FHWA's TMG, ITS sensors were reviewed for possible addition into MDOT's traffic monitoring program. In order to enhance the quality of the traffic monitoring program by utilizing existing ITS sensors, a total of 37 ITS sensors were recommended for addition into the program. Figure 7.3 depicts all addable ITS sensor sites by cluster along with existing CCS sites. Table 7.2 presents all addable ITS sensors and their data availability in each cluster.

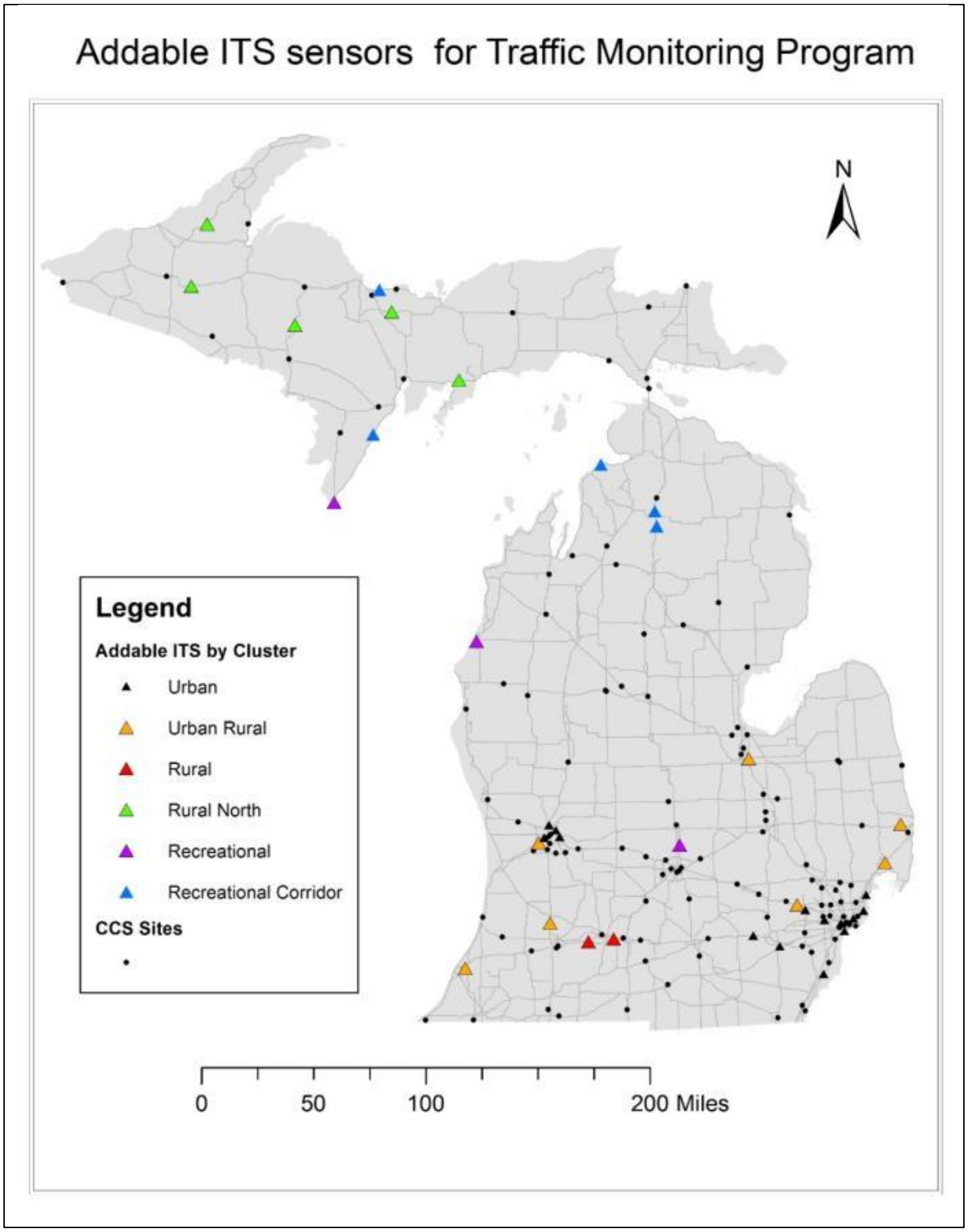


Figure 7.3 Location of addable ITS sites by MDOT clusters

Table 7.2 Addable ITS Sensor Sites

Cluster-1		Cluster-2		Cluster-3		Cluster-4		Cluster-5		Cluster-6	
ID	Data Av.	ID	Data Av.	ID	Data Av.	ID	Data Av.	ID	Data Av.	ID	Data Av.
141	99%	116	85%	3491	42%	3535	2%	3052	38%	3636	38%
413	90%	3136	18%	3497	43%	3743	17%	3741	15%	3637	38%
424	97%	2412	37%			3749	15%	3168	45%	3638	39%
104	99%	110	99%			3750	15%			3053	37%
35	99%	3058	11%			3737	16%			3739	17%
47	99%	3505	39%							3545	42%
53	93%	140	36%								
36	99%										
3151	37%										
3156	24%										
104	57%										
153	53%										
151	48%										
232	68%										
14		7		2		5		3		6	

As shown in Table 7.2, out of 37 ITS sensors addable to MDOT's traffic monitoring program, a total of 14 ITS sensors were in cluster 1. Moreover, 7, 2, 5, 3, and 6 ITS sensors were in each cluster 2, 3, 4, 5 and 6, respectively. Among 14 ITS sensors in cluster-1, 10 ITS sensors were in the Southeast Michigan area, and 4 sensors were in the Grand Rapids area. Unlike other clusters, the total number of sensors in cluster-1 exceeded the number of CCS required and met the requirement at a tolerance limit of 8 percent instead of 10 percent.

7.2.3 Traffic Sensors in the Proposed Traffic Monitoring Program

Combining all existing CCS and ITS sensor sites, the study proposes to have a total of 159 sensors in MDOT's traffic monitoring program (TMP) as summarized in Table 7.3. Out of 124 existing CCS sites as of 2017, it is proposed to keep 110 CCS sites by removing 2 CCS sites and replacing 12 sites with ITS sensors. Meantime, it is also proposed to add 37 ITS sensors into MDOT's TMP. Eventually, MDOT's TMP will combine existing 110 CCS sites and 49 ITS sensors.

The number of sensor sites in TMP will sufficiently meet the requirements of MF for all clusters and HF for cluster 1, 2 and 3. The number does not meet the guideline of HF for clusters 4, 5 and 6 mainly because of low traffic volume and high variations in these clusters. For that reason, FHWA's TMG does not mandate to meet the HF guideline.

Table 7.3 Summary of Sensors in the Proposed Traffic Monitoring Program

	Cluster-1	Cluster-2	Cluster-3	Cluster-4	Cluster-5	Cluster-6	Total
Number of existing CCS sites	41	27	19	11	18	8	124
Number of CCS sites required by MF	37	25	5	15	9	5	96
Number of CCS sites required by HF	35	31	17	62	22	18	185
Number of removable CCS sites	2	0	0	0	0	0	2
Number of CCS sites replaceable with ITS	11	1	0	0	0	0	12
Number of ITS sites addable to TMP	14	7	2	5	3	6	37
Total number of sites in proposed TMP	53	34	21	16	21	14	159
Number of CCS sites	28	26	19	11	18	8	110
Number of ITS sites	25	8	2	5	3	6	49

7.3 Cost Analysis in the Proposed Traffic Monitoring Program

7.3.1 CCS Costs

Table 7.4 summarizes the construction costs and the operation & maintenance (O&M) costs for a CCS system on a 4-lane divided highway. Four types of costs were included in the construction costs: 1) cabinet installation cost, 2) class sensor installation cost, 3) speed sensor installation cost, and 4) system connection cost. The costs included required vehicle, supplies, and manpower. Multiple bores were added for the required number of lanes, and it was assumed that one iSinc and Phoenix installation was enough for multiple lanes. Overall, the CCS construction costs were estimated as $73,462 per device.

In estimating operation and maintenance (O&M) costs, two types of costs were included: 1) sensor replacement and calibration costs and 2) annual average mowing cost. Vehicle supplies, utilities, manpower, and sensor replacement costs were included in sensor replacement and calibration costs. In addition, annual mowing cost includes mowing equipment and manpower. Accordingly, the total O&M cost for a CCS device was estimated as $6,122 per year.

Table 7.4 Summary of CCS Construction and Maintenance Costs

CCS Construction Costs		
Cost Types	Cost-breakdown	Total Cost/device
1. Cabinet Installation		$6,056
2. 4 lane Class (with 1 iSinc and 2 bores)	4 class @$5,342 each + 1 iSinc @$12,000 each+2 bores @$2613 each	$38,594
3. 4 lane speed (with 1 Phoenix and 2 bores)	4 speed @ $5,037 each+ 1 Phoenix @$1800 each+2 bores @$2613 each	$27,174
4. System Connection		$1,638
Total construction cost per device		**$73,462**
CCS Operation &Maintenance Costs		
Cost Types	Cost-breakdown	Total Cost/device
1. Sensor Replacement and Calibration	Vehicle supplies + Manpower + 4 sensor replacement@$5,342 each	$5,342
2. Average Mowing Cost		$780
Total O&M cost per device per year		**$6,122**

7.3.2 ITS-MVDS Costs

ITS-MVDS cost data was obtained from a previous MDOT research reports, "Costs and Benefits of MDOT ITS Deployments," conducted by the research team. The average construction cost include: 1) design contract cost, 2) construction contract cost, and 3) system manager contract cost. As shown in Table 7.5, the average construction cost for an MVDS sensor was estimated as $45,845 per device from the average cost of those sensors in the STOC region. ITS-MVDS O&M costs were subdivided into maintenance contract, Transportation Operations Center (TOC) contract, utility costs and MDOT staff costs. An annual maintenance cost per ITS-MVDS was estimated as $1,908.

Table 7.5 Summary of ITS-MVDS Construction and Maintenance Costs

ITS-MVDS Construction Costs		
Cost Types	Break-down for Cost Items	Total Cost/device
Average construction cost per device	Design Contract Cost, Construction Contract Cost, and System Manager Contract Cost	$45,845
ITS-MVDS Operation &Maintenance Costs		
Cost Types	Break-down for Cost Items	Total Cost/device
Average O&M cost per device per year	Maintenance Contract Cost, TOC Operation Cost, Utility Cost (Power and Communication), and Manpower cost	$1,908

7.3.3 Estimation of Cost Savings

Based on costs of CCS and ITS sensors, this study estimated the cost saving when using existing ITS sensors in the traffic monitoring program. In this cost analysis, an equivalent annual cost was calculated in order to reflect the future opportunity costs by applying an annual discount rate. The equivalent annual cost is calculated as follows:

$$EAC = \frac{\sum_{t=0}^{20} \frac{FV}{(1+i)^t}}{20} \quad \text{.....} \quad (7.1)$$

where:

EAC= Equivalent annual cost

FV_t = Future value in year t

i = Discount rate

t = Year (base year t = 0 and the terminal year t = 20)

The analysis period extended to 20 years from the base year of 2016, and the discount rate of 2.5 percent was applied (Executive Office of the President, Office of Management and Budget, OMB, 2016). The lifespan of sensors was assumed 20 years for CCS sites and 10 years for ITS sensors., respectively. In calculating the equivalent annual costs, ITS sensors were assumed to be replaced every 10 years with an initial replacement in five years from the base year. Table 7.6 summarizes equivalent annual costs for both CCS and ITS MVDS.

Table 7.6 Summary of Equivalent Annual Costs

	Annual Costs		Equivalent Annual Costs for 20 Years		
	Construction	O & M	Construction	O & M	Total
CCS (A)	$73,462	$6,122	$3,673.1	$4,771.8	$8,444.9
ITS MVDS (B)	$45,853	$1,908	$2,821.8	$1,487.2	$4,309.0
A – B	$27,609	$4,214	$851.3	$3,284.6	$4,136.0

The proposed MDOT's TMP (Table 7.3) includes: 1) removing 2 CCS stations; 2) replacing 12 CCS sites with ITS sensors; and 3) adding 37 ITS sensors. The annual equivalent cost savings from these changes can be estimated:

- Annual cost saving from removing 2 CCS sites = \$4,771.8 x 2 = <u>\$9,544</u>
- Annual cost saving from replacing 12 CCS sites with ITS = \$3,285 x 12 = <u>\$39,416</u>
- Annual cost saving from adding 37 ITS sensors instead of CCS = \$4,136 x 37 = <u>\$153,031</u>

In summary, the proposed TMP saves \$48,959 annually by removing 2 CCS sites and replacing 12 sites with ITS sensors. When including the savings from using 37 ITS sensors instead of adding new CCS sites, the total annual saving is estimated to be \$201,990 annually for next 20 years. Note that this analysis does not account the possible additional costs for better maintenance of existing ITS MVDS.

Chapter 8 Data Maintenance and Implementation Plan

8.1 Data Quality and Management Plan

8.1.1 Sensor Calibration and Maintenance

As discussed in Chapter 5, ITS MVDS sensors are able to provide data with a good quality when they are well maintained and calibrated. Compared to the conventional inductive loop detectors, they are easy to maintain without interruption of traffic. Although current MVDS maintenance practices may be sufficient for current ITS practices, the ITS MVDS sensors to be used in the CCS program will need better calibration and maintenance. In order to continue to obtain good quality, ITS MVDS sensors need following routine maintenance and management.

1) Checking setup position: MVDS sensors use microwave wave radar technology. The sensors are supposed to face perpendicular to the direction of traffic, and it is desirable to avoid locations with reflecting objects like guidelines that may cause disturbance to the sensor system.
2) On-site calibration: ITS MVDS sensors are easy to calibrate on site. The system allows visualization of individual vehicle shapes passing the highway segment. The on-site calibration ensures good quality of data.
3) Data communication: Data loss may occur due to communication problems. Highway construction and other highway activities may interrupt data communication. Routine checkups on the communication systems will minimize the data loss.
4) Data management: Currently, ITS sensor data are managed by individual Traffic Operation Centers (TOC). A statewide data management system is necessary to store and manage the data in a consistent manner. Inconsistency in data format often causes difficulties in centralizing the management system.

The research team proposes to conduct routine on-site calibration and maintenance at least twice a year (spring and fall) for those ITS sensors to be used in the traffic monitoring program. While the spring maintenance entails an on-site system calibration checking if they sense vehicles properly, the fall maintenance includes the on-site system calibration as well as data comparison with 24-hour volume data and one-hour samples of speed data manually collected.

8.1.2 Data Management

MDOT is in the process of migrating the data management system to the MS2. It is expected to provide powerful data management capacity. Even though the traffic monitoring program and the ITS sensor data are currently separately managed, it will be desirable to combine both datasets in one management system.

8.1.3 Sensor Testbed

Traffic sensing technology is evolving every year. MDOT can improve the traffic monitoring capacity by adopting new sensing technologies. However, it takes time to examine interoperability and effectiveness of new sensing technologies. In order to enhance the testing capacity, it is recommended that MDOT routinely test new sensor systems in a sensor testbed that is capable of examining new devices and sensors together with existing sensing systems. The sensor testbed should be equipped with not only sensors but also a communication and data processing system.

8.2 Data Imputation

Due to communication failure, or other reasons, the system fails to collect data during a certain period. Missing data imputation has been a common problem that data managers often face. In this study, a novel deep-stacked unidirectional deep Neural Network (DNN) approach is proposed to impute the missing data from CCS and ITS sensors.

8.2.1 Data Imputation Approach

This study used two deep learning techniques, LSTM (Long Short Term Memory) and DNN. LSTM was considered due to its usefulness in dealing with time series dataset. DNN is a sequential model with only feed forward layers. The main difference of these two techniques is the loop for each neuron in LSTM where DNN does not have such a loop.

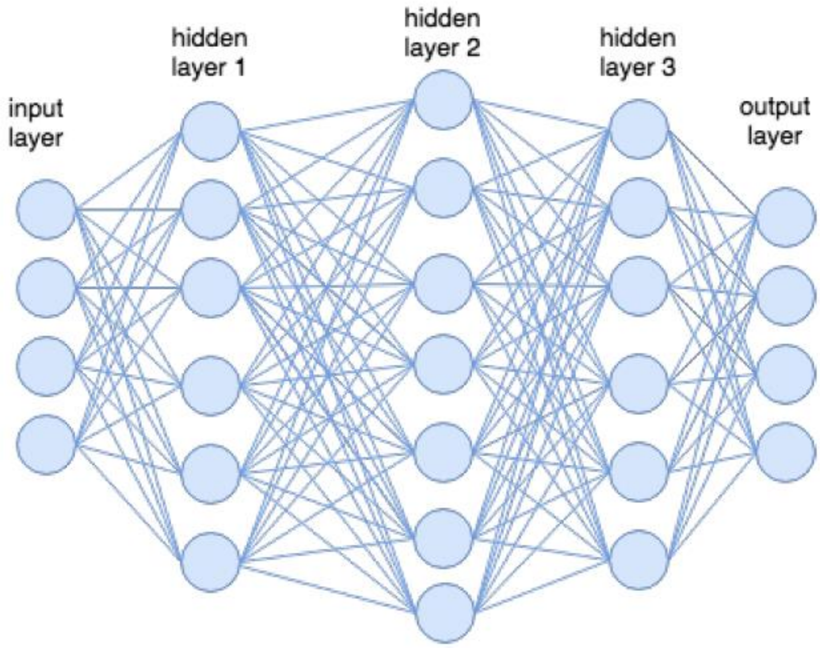


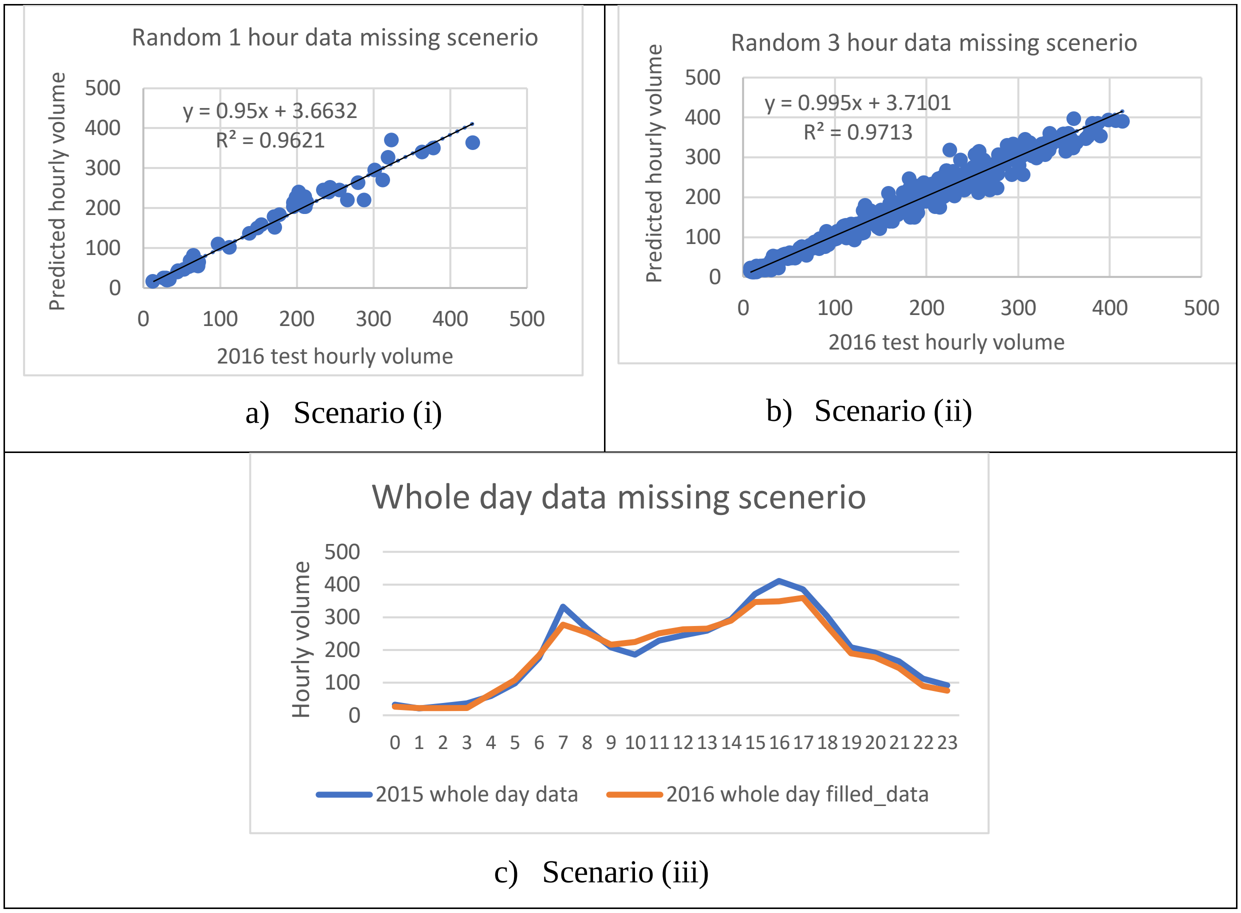
Figure 8.1 Structure of a deep learning neural network

8.2.2 Performance of the Proposed Data Imputation

The proposed methods were tested for CCS and ITS sensors. Two sensor data (CCS ID-8169 and ITS ID-8409) were used for testing in three different scenarios: 1) 1-hour data missing, 2) 3-hour data missing, and 3) one-day data missing.

The input data in this study included the week of year (WOY), the day of week (DOW), hourly volume, and past immediate two-hour volume (T-2) for 2016. For CCS data imputation, data from the past six-years, from 2010 to 2015, were considered as a set of training data. However, only 2015 data was considered as training data for the ITS case due to the unavailability of the dataset.

The results for CCS data were depicted in Figure 8.2. The proposed model successfully estimated the missing data: the mean absolute percentage errors (MAPE) for scenario 1, 2 and 3 were 10.8 percent, 11.39 percent and 12.69 percent, respectively.



a) Scenario (i)

b) Scenario (ii)

c) Scenario (iii)

Figure 8.2 Data imputation results

The model was also applied to the missing data imputation for ITS data as shown in Figure 8.3. The last two months (November and December) of data from 2016 was considered as missed data to evaluate the Tuesday missing data. MAPE of 11.46 was obtained for the whole day missing data.

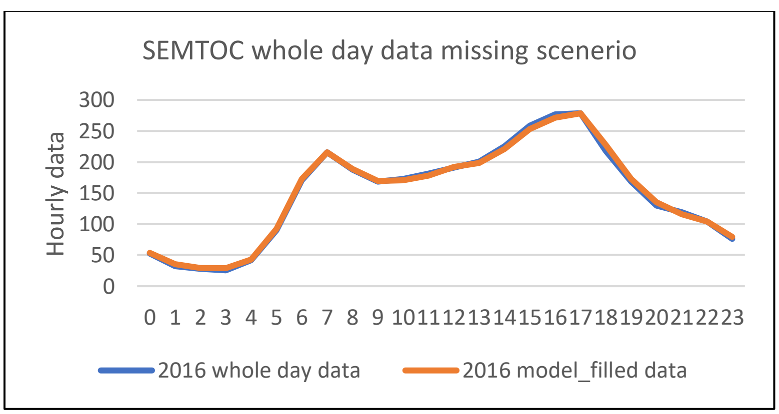


Figure 8.3 Output for SEMTOC data filling

8.2.3 Findings and Suggestion

It was found that the deep learning model for data imputation was a powerful tool in imputing missing data as demonstrated in two examples. The proposed model could be directly used in the data management system by using historic data. A good feature of the approach is that it can be improved when more data are available. Applications of deep learning are expected to enhance the traffic monitoring program by allowing better treatment of missing data. It is suggested to implement this imputation method after further investigating its applicability and effectiveness in the traffic monitoring program.

8.3 Suggested Implementation Plan

In order implement the research outcome, the research team presents five implementation items by their characteristics in terms of urgency and timeline.

8.3.1 Removal of CCS Sites from MDOT's TMP

According to our analysis, two CCS sites (ID 9029 or 9049; ID 9419 or 9969) were redundant and removable. From removing these two CCS sites, the cost saving is expected to be $9,544 annually for next 20 years. This removal can be implemented immediately.

8.3.2 Replacing 12 CCS sites with ITS Sensors

We have identified a total of 12 CCS sites replaceable with existing ITS sensors. The replacement can be implemented in two years after completing the QA/QC of ITS sensors. Replacing those 12 CCS sites is expected to save $39,416 annually for 20 years. However, not all ITS sensors provide data with a good quality as of 2016 as summarized in Table 8.1. Therefore, it is suggested that those 12 ITS sensors be recalibrated and evaluated for the replacement. The calibration process includes on-site calibration, data comparison, and decision making as follows:

1) Conduct on-site calibration of 12 replaceable ITS MVDS.
2) Collect data for a month.
3) Check data communication.
4) Compare ITS data with adjacent CCS data.
5) Develop a performance report (data availability and data quality).
6) Decide to adopt each ITS sensor to TMP.

Table 8.1 List of CCS Sites Replaceable with ITS Sensors and ITS Data Quality

Device ID	ITS Data Availability	R-square Value	MAPE (%)
CCS-9839 and ITS-354&355	99%	0.89	11.0%
CCS-9969 and ITS-418&419	99%	0.96	4.8%
CCS-9419 and ITS-406&407	99%	0.90	5.3%
CCS-9499 and ITS-402&403	99%	0.93	15.0%
CCS-9489 and ITS-11&12	99%	0.92	12.8%
CCS-9979 and ITS-160&161	98%	0.93	8.3%
CCS-9999 and ITS-184&185	99%	0.95	8.4%
CCS-9729 and ITS-118	50%	0.89	13.6%
CCS-9739 and ITS-305	25%	0.72	15.0%
CCS-5069 and ITS-240	25%	0.78	11.1%
CCS-9769 and ITS-213	91%	0.85	12.8%
CCS-9229 and ITS-2412	37%	0.97	7.6%

Table 8.2 ITS Sensor Sites to be Added into TMP

Cluster-1		Cluster-2		Cluster-3		Cluster-4		Cluster-5		Cluster-6	
ID	Data Avail.	ID	Data Avail.	ID	Data Avail.	ID	Data Avail.	ID	Data Avail.	ID	Data Avail.
141	99%	116	85%	3491	42%	3535	2%	3052	38%	3636	38%
413	90%	3136	18%	3497	43%	3743	17%	3741	15%	3637	38%
424	97%	2412	37%			3749	15%	3168	45%	3638	39%
104	99%	110	99%			3750	15%			3053	37%
35	99%	3058	11%			3737	16%			3739	17%
47	99%	3505	39%							3545	42%
53	93%	140	36%								
36	99%										
3151	37%										
3156	24%										
104	57%										
153	53%										
151	48%										
232	68%										
14		7		2		5		3		6	

8.3.3 Adding ITS Sensors into TMP

We have identified a total of 37 ITS sensors that may benefit the MDOT's TMP. Thanks to the ease of ITS sensor calibration and maintenance, the equivalent annual cost for ITS sensors is more economic than CCS. As presented before, when adding ITS sensors instead of CCS sensors, the annual cost saving is expected to be $153,031 annually for 20 years. To add these ITS sensors into TMO, the same calibration process as described in section 8.3.2 is also required. Table 8.2 presents ITS sensor sites to be added into TMP.

8.3.4 Utilizing a Comprehensive Sensor Testbed

As described in section 8.1.3, the sensor testbed can help MDOT in improving the traffic monitoring capacity by allowing new sensing technologies to be easily tested. The sensor testbed is capable of examining new devices and sensors together with existing sensing systems. As MDOT uses many traffic sensors for TMP as well as ITS, continuous investigation of new sensor systems benefits MDOT in managing these programs in a cost-effective manner.

8.3.5 Incorporation of Data Imputation Method

As presented in section 8.2, the artificial intelligence (AI) approach in imputing missing data was promising. In order to implement the proposed approach, a further research is needed. The proposed research includes data analysis, development of imputation method, model validation, and system integration. Success of the incorporation is expected to allow imputing of missing data while enhancing data analytics and the prediction capacity with existing data.

Chapter 9 Conclusion and Recommendation

Traffic count stations play an important role for measuring the traffic characteristics along the roadways and overall transportation systems. Accurate and reliable traffic data are essential for transportation research and management as well as for traffic monitoring, planning, and design. Among the traffic count stations, continuous count stations (CCS) collect vehicle volume throughout 24 hours a day, seven days a week, and 356 days a year. The data obtained from CCS stations are usually used to develop hour of day (HOD), day of week (DOW), and month of year (MOY) factors to predict ADT for short counts. This study focused on evaluating Michigan's current traffic monitoring program including the site placement appropriateness, redundant count locations, incorporating ITS and other system sites with on-site maintenance and a calibration implementation plan.

A web-based online survey was conducted for 11 neighboring states to understand current CCS programs, other monitoring sources (ITS and WIM), state-of-the-practices in managing the traffic monitoring program. The survey showed that inductive loop, WIM, and microwave detectors were the most common sensors for CCS and ITS. Most states typically incorporate WIM, ITS and data from local agencies into CCS programs in a way. Many states were using cloud-based data management systems for better QA/QC process as well as for traffic incidents and missing data treatment.

This research used data collected from CCS, ITS, and WIM sensors, and incorporated into a multi-source GIS database. Data used include CCS data for the past five years ranging from 2012-2016 and ITS sensor data for 2015 and 2016. The data availability of ITS sensor data was around 80 percent, 50 percent, and 30 percent for SEMTOC, WMTOC, and STOC, respectively. It should be noted that the transition to central ATIM software also affected the overall quality of data during the period. ITS data were evaluated and compared with data from adjacent CCS to examine if ITS sites are usable in the traffic monitoring program. In volume data comparison, approximately 35 percent of the total comparable sites showed high quality with less than 10% error. In speed data evaluation, more than 50 percent of comparable ITS sites yielded similar speed distribution with nearby CCS sites. In vehicle classification, ITS sensors successfully classified vehicle classes by length although their accuracy in classifying vehicles was not great.

In this study, CCS sites were evaluated by employing the redundancy analysis and the sufficiency analysis. Correlation and proximity analyses were performed to identify redundant CCS sites. Through the redundant analysis, four CCS sites were identified as possibly redundant and potentially removable. Among those four, two on instate freeways are highly possible to remove while the other two on urban arterials are possible but not recommended to remove due to insufficient number of CCS sites on urban arterials. These two CCS on urban arterials could be kept for potential relocation sites. The number of CCS sites needed was evaluated by quantifying the numbers by data type and different classifications. The analysis results showed that more CCS sites were needed in the North region, on rural freeways, and on urban arterials. More specifically, the Rural-North (cluster 4 in MDOT's classification) needed at least four more CCS sites to meet the requirement for MF. When applying the requirement for hourly factors, four more sites were needed for cluster 3 and 5, and ten more sites for cluster 6.

This research analyzed both CCS sites and ITS sites to identify replaceable CCS sites and usable ITS sensor sites. Through careful investigation of CCS sites and ITS sensor sites, this study found that a total of 12 CCS sites were replaceable with ITS sensors. In order to enhance the quality of the traffic monitoring program by utilizing existing ITS sensors, a total of 37 ITS sensors were recommended to add into the program. In sum, this research proposes removing 2 redundant CCS sites, replacing 12 CCS sites with ITS sensors, and adding 37 ITS sensors. The cost analysis reveals that the proposed TMP saves $48,959 annually by removing 2 CCS sites and replacing 12 sites with ITS sensors. When including the saving from using 37 ITS sensors instead of adding new CCS sites, the total saving is estimated to be $201,990 annually for next 20 years.

This research recommended five implementable items: 1) removing 2 CCS sites, 2) replacing 12 CCS sites with existing ITS sensors, 3) adding 37 ITS sensors into MDOT TMP, 4) utilizing a comprehensive sensor testbed, and 5) incorporating a deep learning-based data imputation method. In order to ensure data quality, the research also provided an ITS sensor calibration and maintenance plan along with a case example of a data imputation method using a deep learning approach.

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Appendix 1: Survey Questionnaire

Background Information

1. Which state do you work for?

2. What types of sensors do you use for your Continuous Counting Stations (CCS), Intelligent Transportation Systems (ITS) and other monitoring purposes? (Please check all applicable.)

	CCS	ITS	Others
Inductive Loop Detectors	❑	❑	❑
Magnetic Sensor	❑	❑	❑
Non-Invasive Microloops	❑	❑	❑
Sensys System	❑	❑	❑
Weigh in motion system	❑	❑	❑
Microwave Radar	❑	❑	❑
Active/ Passive Infrared	❑	❑	❑

3. How many staff members are involved in performing CCS data quality?

4. How many miles of highway does your DOT manage and how many Continuous Count Stations (CCS) does your DOT use for the highways by type?

	Total Coverage (mile)	Number of CCS
Interstate	❑	❑
Highway	❑	❑
Local road	❑	❑

5. How would you rate sensor data quality for obtaining volume data by type of sensor that you have in your CCS system?

	Very satisfied	satisfied	neutral	Not satisfied	Very dissatisfied
Inductive Loop Detectors	❑	❑	❑	❑	❑
Magnetic Sensor	❑	❑	❑	❑	❑
Non-Invasive Microloops	❑	❑	❑	❑	❑
Sensys System	❑	❑	❑	❑	❑
Weigh in motion system	❑	❑	❑	❑	❑
Microwave Radar	❑	❑	❑	❑	❑
Active/ Passive Infrared	❑	❑	❑	❑	❑

6. What sensor(s) do you use for obtaining vehicle class data?

7. How would you rate data quality of the sensor (in question 6) for obtaining vehicle class data?

Very satisfied	satisfied	neutral	Not satisfied	Very dissatisfied
❑	❑	❑	❑	❑

8. Are you collecting vehicle class data with ITS or other systems?
   a. No
   b. Yes (Please identify the system and the number of vehicle classes)
9. Are you combining other sources of information in your CCS monitoring program? Please select all applicable.
   a. None
   b. Intelligent Transportation Systems (ITS)
   c. Road Weather Information System (RWIS)
   d. Portable Traffic Recorder (PTR)
   e. Weigh-in-motion (WIM) sensors
   f. Regulatory monitoring sites such as international border crossings and toll plazas
   g. Data Counts for MPO, City, and Township
   h. Sensors for signalized intersections and/or ramp metering
   i. Other
10. Do you use other sources in the developing adjustment factors?
    a. No
    b. Yes (Please identify those)
11. If you use other sources, are they meeting Traffic Monitoring Guide (FHWA, 2013) standards?
    a. No
    b. Yes
12. Would you please share your experience for reviewing the quality and use of other sources within your monitoring program?

13. Are you collecting vehicle class and speed as part of those other sources in addition to CCS monitoring program?
    a. No
    b. Yes (Please describe about the other sources.)
14. Do you have on-line traffic data management system incorporated with CCS and other sources?
    a. No
    b. Yes (Would you tell us more details or the web link if accessible by others?)

15. How do you share your traffic data? (Check all applicable.)

a. On-line
b. FTP site
c. Electronic files via e-mail
d. Hard copies
e. Others (Please Specify):

16. Who are the data users? (Check all applicable.)

a. Other divisions in the state DOT
b. FHWA
c. Metropolitan Planning Organizations (MPOs)
d. Other state government agencies (Police, tourisms)
e. County, city, and town governments
f. Engineering consultants and researchers
g. Developers and realtors
h. Citizens
i. Others (Please Specify.)

17. Do you have any plan to improve your traffic monitoring program for CCS?

a. No
b. Yes (Please describe those plans.)

18. Do you have a schedule to perform strategic assessments of your sensor locations (as part of your monitoring program)?

a. No
b. Yes (Please add more details about the schedule.)

19. When do you usually expand or change the number of sensors for the network/systems of CCS, and how do you re-assess them?

20. How do you treat missing data or traffic incidents?

21. Please provide your contact information if you are willing to be contacted regarding your comments:

Name

Affiliation

Phone

Email Address

22. Other comments: (Future plans and anticipated the difficulties in using other sources for the CCS program.)

Appendix 2: Data Format and Dictionary

<u>Data Format:</u>

Hourly data format is considered for all of the types of counts (CCS, ITS, WIM) for this research.

<u>Continuous count station data format:</u>

Volume Dataset Format

Station Number	Direction	Travel Lane	Year	Month	Day	Hour	Total Volume	Day of Week

Speed Dataset Format

County	Station	Direction	Year	Month	Day	Hour	Total	Day of	Bin 1	Bin 2	Bin 3	Bin 4	Bin 5	Bin 6	Bin 7	Bin 8	Bin 9	Bin 10	Bin 11	Bin 12	Bin 13	Bin 14	Bin 15	Bin 16

Vehicle Class data Format

County	Station Number	Direction	Year	Month	Day	Hour	Total Volume	Day of Week	SM	MD	LG	Extra LG

<u>ITS Data Format:</u>

Device ID/ Station Number	Lane ID	Lane ID Description	Year	Month	Day	Hour	Total Volume	Avg. Higher Speed	SM vehicle	MD vehicle	LG vehicle	Extra LG vehicle

<u>WIM data format:</u>

(file.WIM data format):

State	County	Station Number/ID	Direction	Lane	Year	Month	Day	Hour	Total Volume	Avg. Speed	Std. Dev of Speed	Speed Bin 1	Speed Bin 2	Speed Bin 3	Speed Bin 4	Speed Bin 5	Speed Bin 6	Speed Bin 7	Speed Bin 8	Speed Bin 9	Speed Bin 10	Speed Bin 11	Speed Bin 12	Speed Bin 13	Speed Bin 14	Speed Bin 15	Speed Bin 16	SM Vehicle	MD Vehicle	LG Vehicle	Extra LG Vehicle

(file.CLA data format):

State	County	Station Number	Direction	Lane	Year	Month	Day	Hour	Total Volume	SM vehicle	MD vehicle	LG vehicle	Extra LG vehicle

Data Dictionary:

Direction of Travel for CCS and WIM:

Code	Direction
1	North
2	Northeast
3	East
4	Southeast
5	South
6	Southwest
7	West
8	Northwest
9	North-South or Northeast-Southwest combined (volume stations only)
0	East-West or Southeast-Northwest combined (volume stations only)

Lane of Travel:

Code	Lane
0	Data with lanes combined
1	Outside (rightmost) lane
2-9	Other lanes

Day of Week:

01	Sunday
02	Monday
03	Tuesday
04	Wednesday
05	Thursday
06	Friday
07	Saturday

Month of Year:

01	January
02	February
03	March

04	April
05	May
06	June
07	July
08	August
09	September
10	October
11	November
12	December

Hour Code:

Hour Code	Description
0	After 00:00 to 01:00
1	After 00:00 to 01:00
2	After 01:00 to 02:00
3	After 02:00 to 03:00
4	After 03:00 to 04:00
5	After 04:00 to 05:00
6	After 05:00 to 06:00
7	After 07:00 to 08:00
8	After 08:00 to 9:00
9	After 9:00 to 10:00
10	After 10:00 to 11:00
11	After 11:00 to 12:00
12	After 12:00 to 13:00
13	After 13:00 to 14:00
14	After 14:00 to 15:00
15	After 15:00 to 16:00
16	After 16:00 to 17:00
17	After 17:00 to 18:00

18	After 18:00 to 19:00
19	After 19:00 to 20:00
20	After 20:00 to 21:00
21	After 21:00 to 22:00
22	After 22:00 to 23:00
23	After 23:00 to 24:00

Speed Bin:

Bin	Speed limit (mph)
Bin 1	0-20.9
Bin 2	21-25.9
Bin 3	26-30.09
Bin 4	31-35.9
Bin 5	36-40.9
Bin 6	41-45.9
Bin 7	16-50.9
Bin 8	51-55.9
Bin 9	56-60.9
Bin 10	61-65.9
Bin 11	66-70.9
Bin 12	71-75.9
Bin 13	76-80.9
Bin 14	81-85.9
Bin 15	86-90.9
Bin 16	91+

Appendix 3: ITS Data Evaluation

Table A-1 Volume Comparison of SEMTOC sensors with corresponding CCS sensors

Semtoc Region-24 ITS comparison					
Route	**Type**	**Lane (Per Direction)**	**CCS**	**ITS**	**ITS**
I-96	Urban Interstate	3	8209	136-E	137-W
M-59	Urban Other Freeways	3	8409	172-E	173-W
I-696	Urban Interstate	4	9839	354-E	355-W
I-94	Urban Interstate	3	9969	418-E	419-W
			9419	406-E	407-W
			9499	402-E	403-W
			9489	11-E	12-W
			8839	306-E	307-W
I-75	Urban Interstate	3	9699	182-N	183-S
			9979	160-N	161-S
M-39	Urban Other Freeways	3	9809	337-N	338-S
M-8	Urban Other Freeway	5	9999	184-E	185-W

Table A-2 Volume Comparison of STOC sensors with corresponding CCS sensors

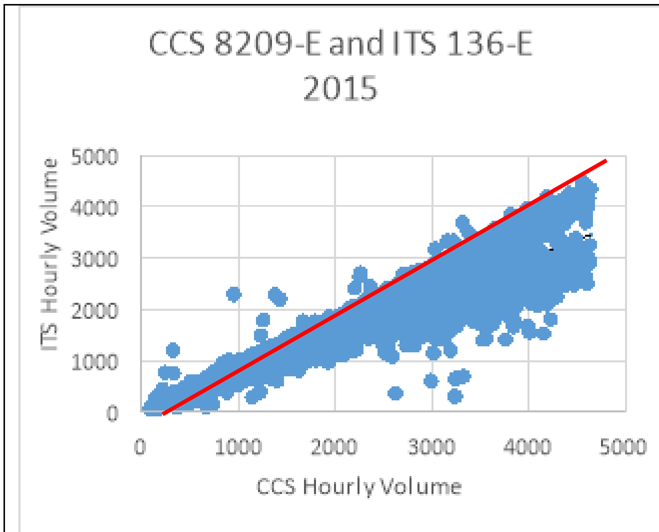
Route	**Type**	**Lane (Per Direction)**	**CCS**	**ITS**	**ITS**	**WIM**
I-675	Urban Interstate	2	9229	2412-N		
I-69	Rural Interstate	2	6369	3136-E	3135-W	6396
I96	Urban Interstate	2	9729		3480-W	
		3	8219	2129-E	2134-W	8219
		3	9369	2334-E	2335-W	9369
		2	7159		2339-W	7159
I-496	Urban Interstate	2	9029		3173-W	

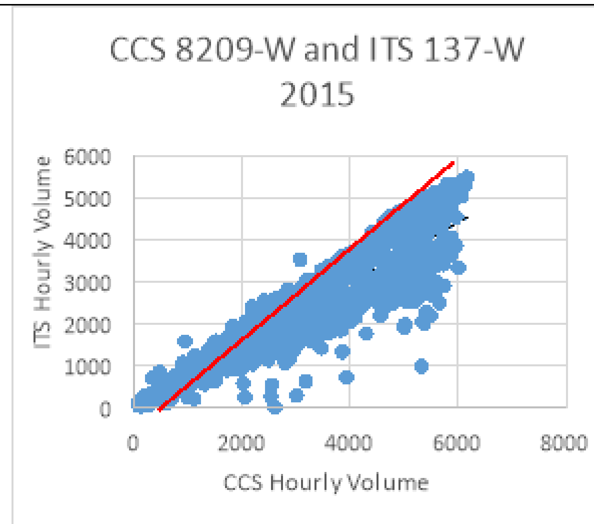
Table A-3 Volume Comparison of WMTOC sensors with corresponding CCS sensors

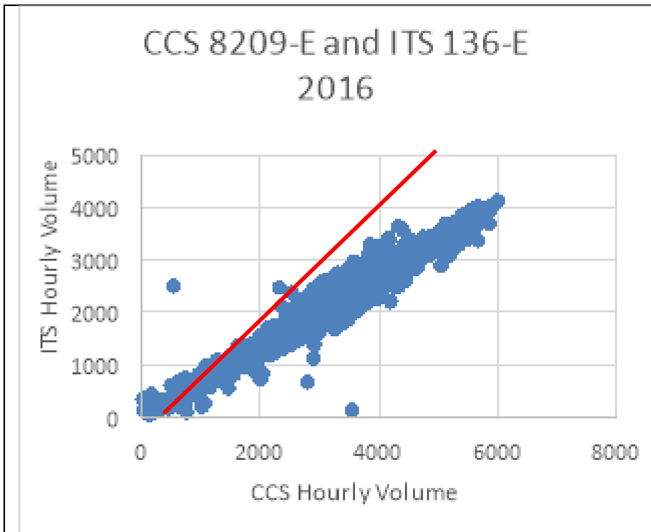
Route	Type	Lane (Per Direction)	CCS	ITS	ITS	WIM
M-6	Urban Other Freeway	2	9739	305-E	305-W	
M-6	Urban Other Freeway	2	9759	303-E	303-W	9759
US-131	Urban Other Freeway	4	5069	240-N	240-S	5069
		3	9769	213-N		
I-196	Urban Interstate	4	9729	118-E	118-W	

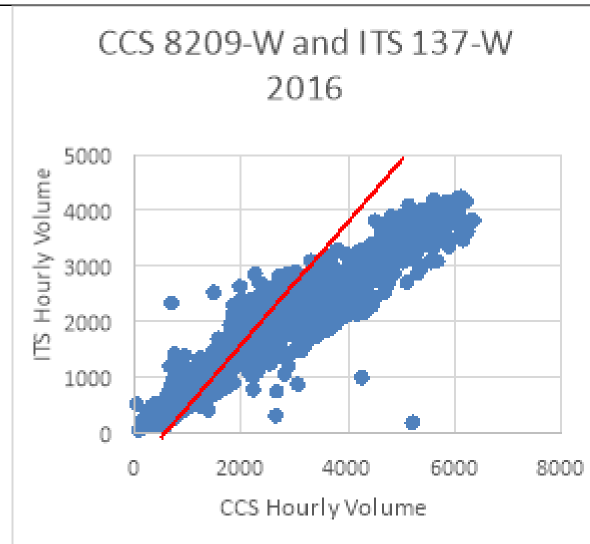
Table A-4 Volume Data evaluation with corresponding CCS sensor

A-3.1 ITS 136 and 137 with corresponding CCS for 2015 and 2016

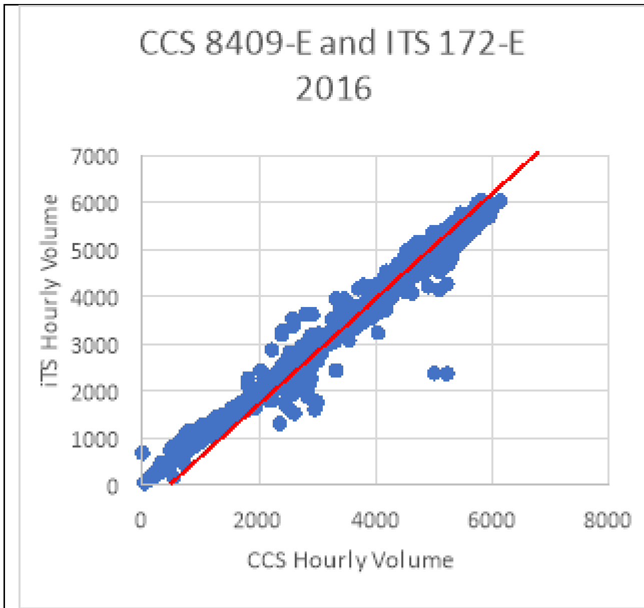


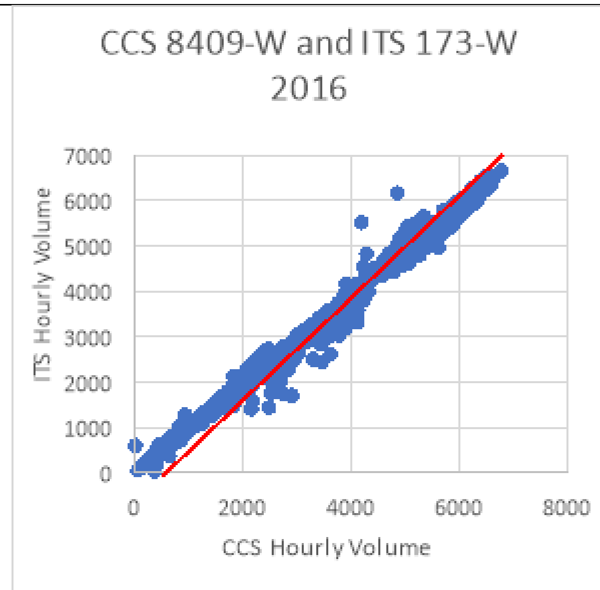


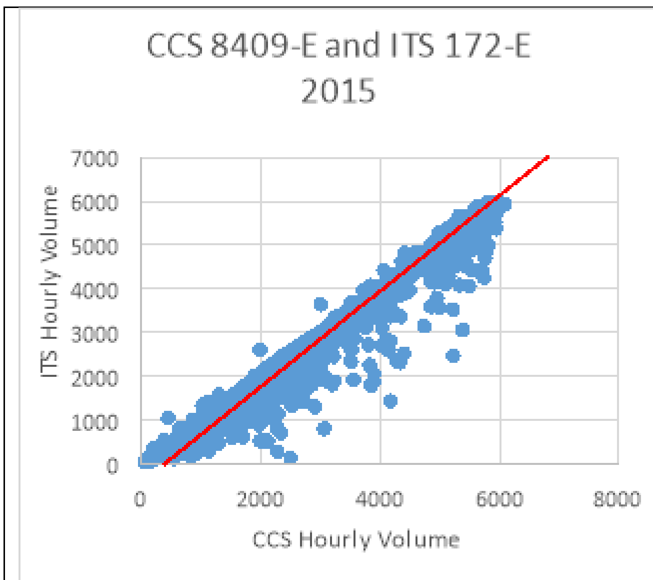


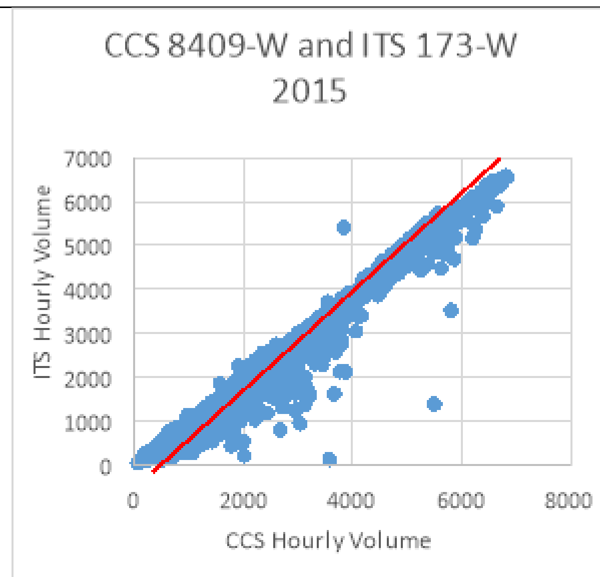


A-3.2 ITS 172 and 173 with corresponding CCS for 2015 and 2016

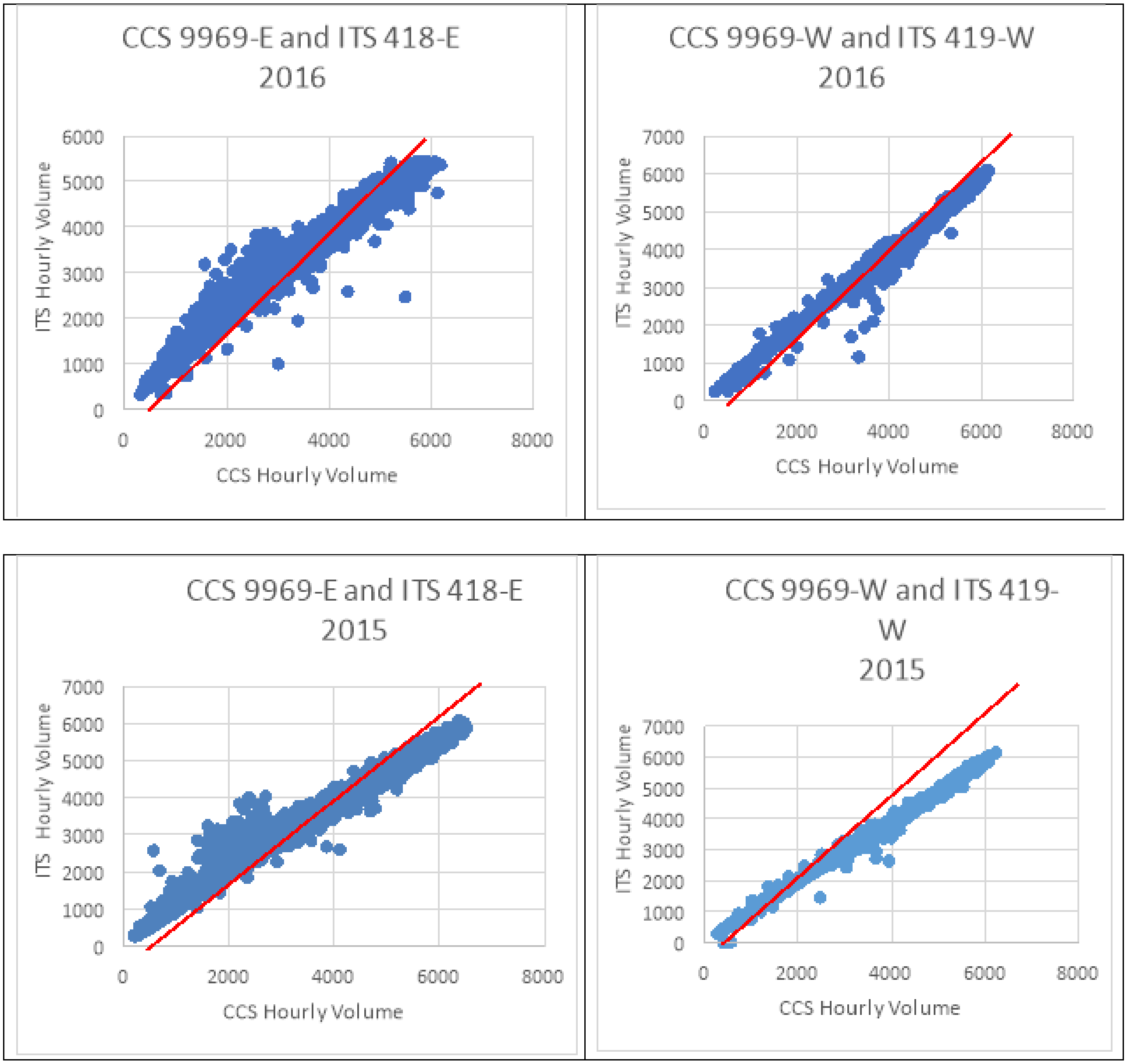




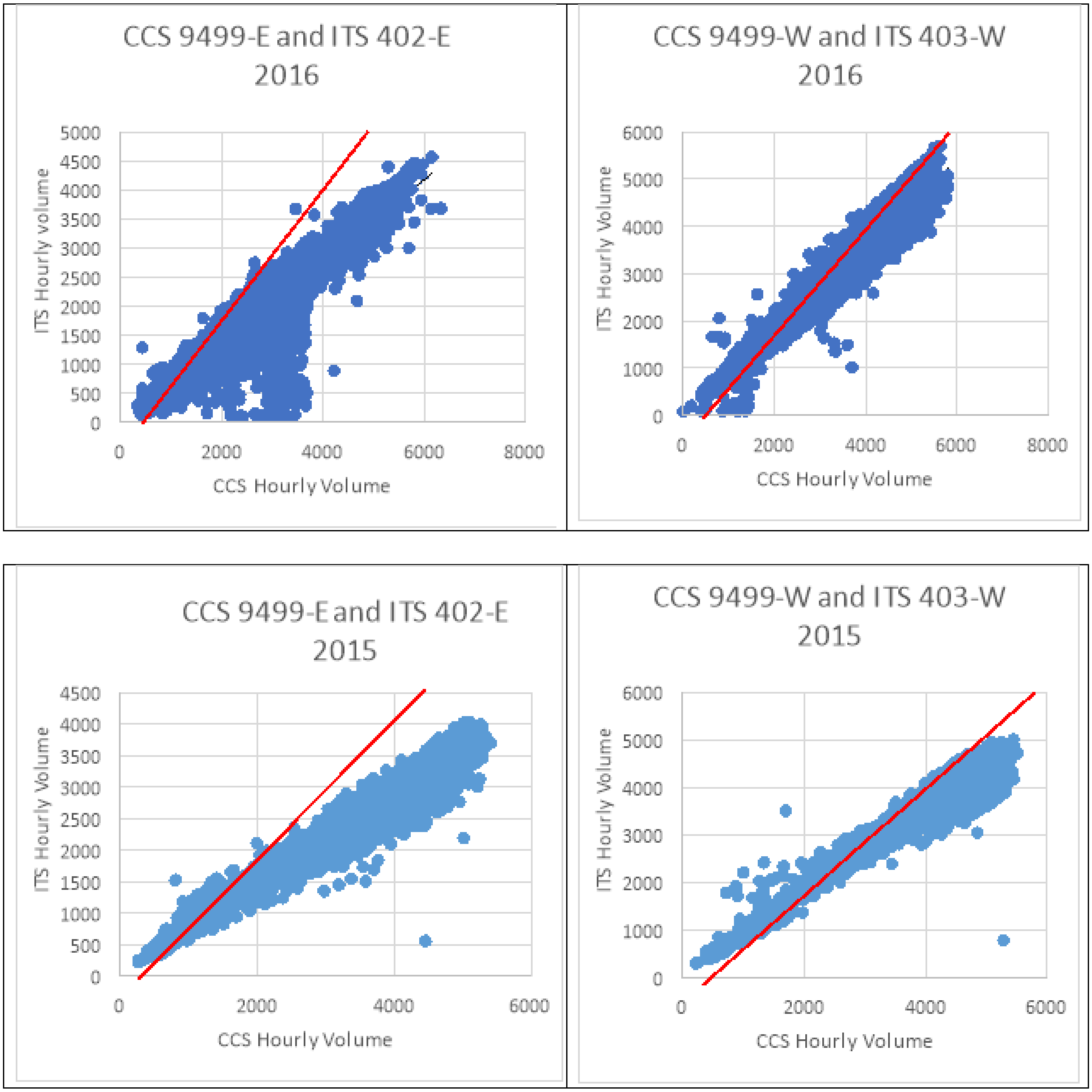




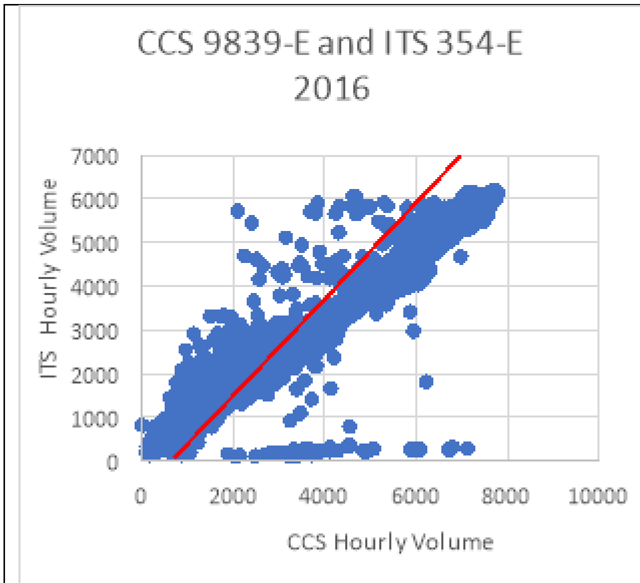
A-3.3 ITS 418 and 419 with corresponding CCS for 2015 and 2016

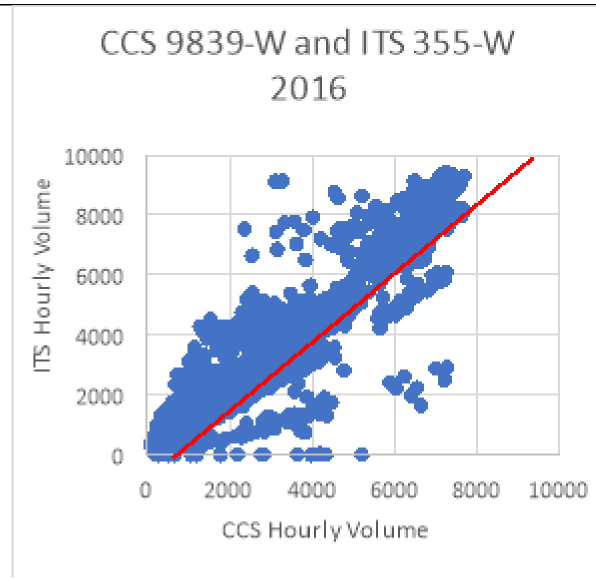


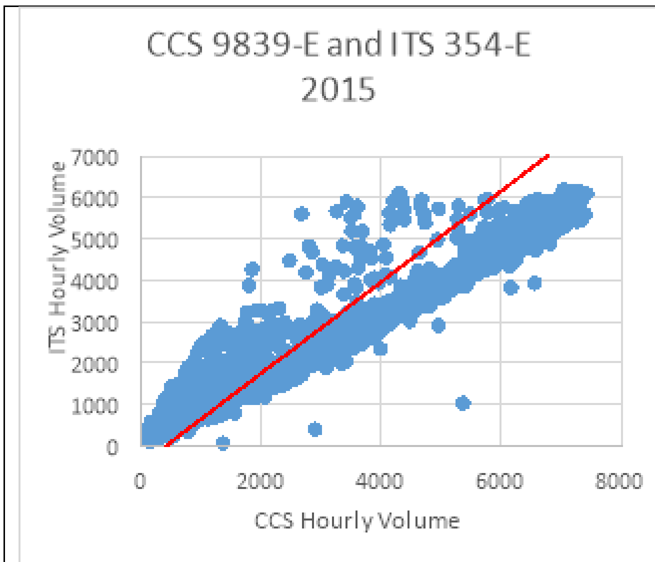
A-3.4 ITS 402 and 403 with corresponding CCS for 2015 and 2016

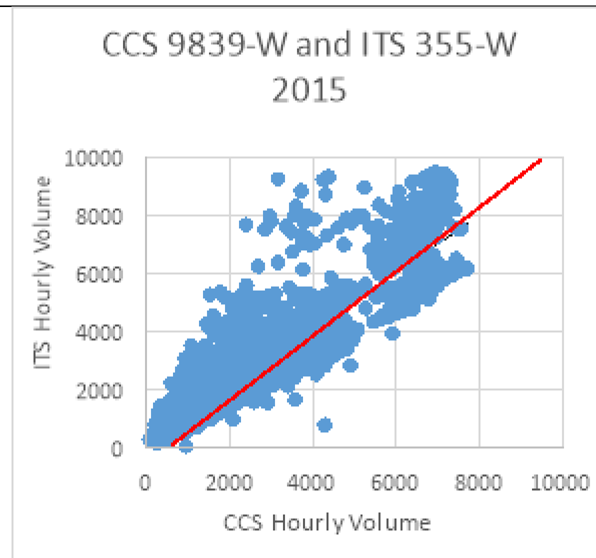


A-3.5 ITS 354 and 355 with corresponding CCS for 2015 and 2016

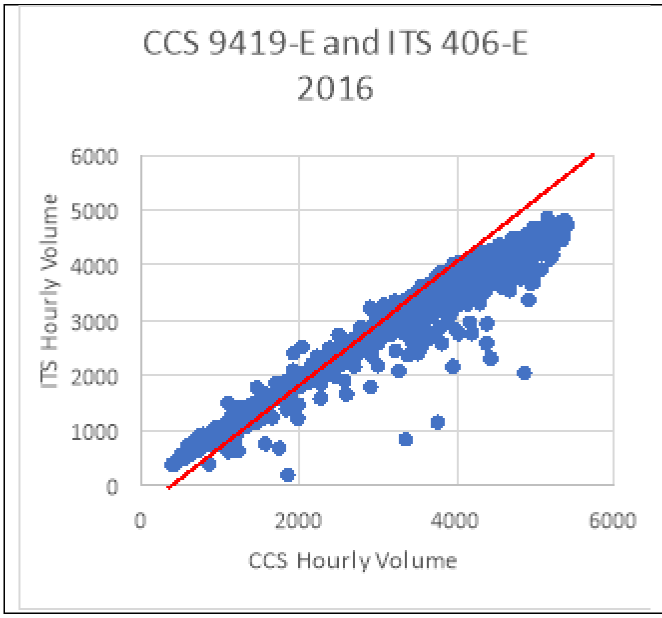


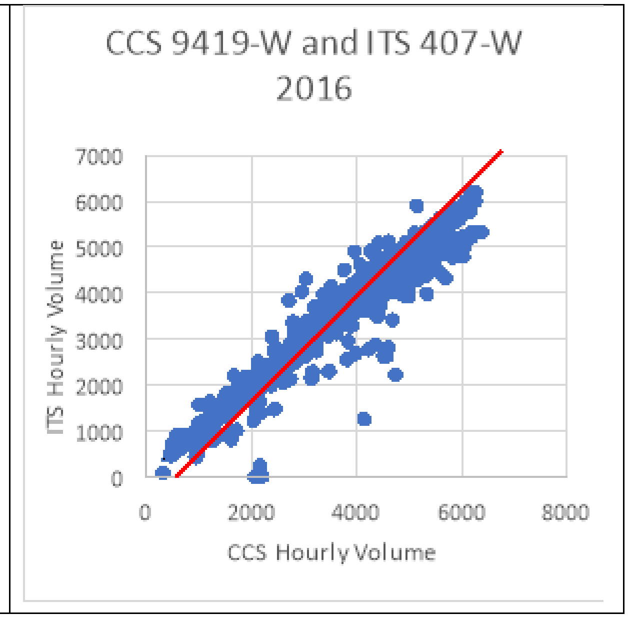


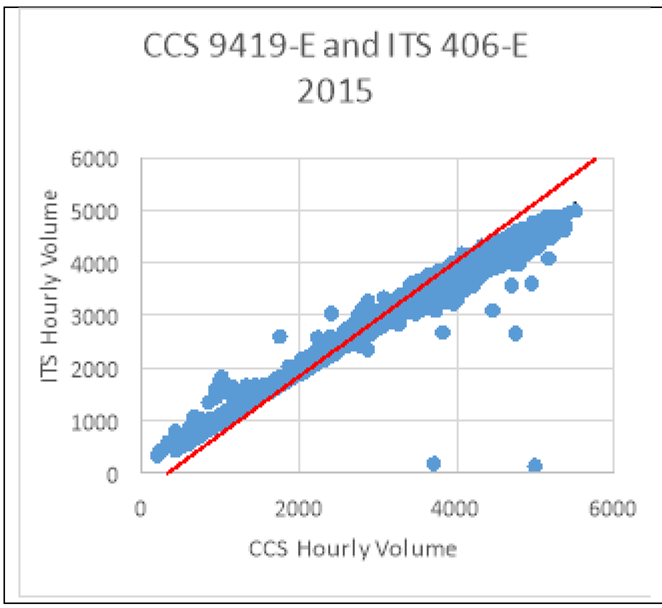


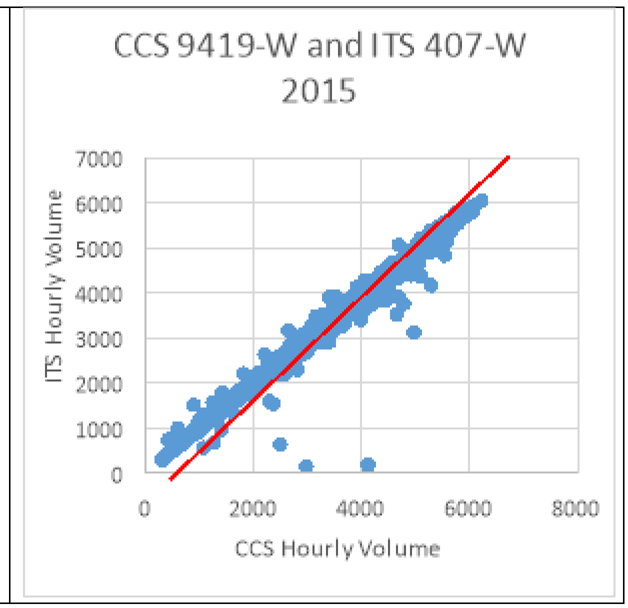


A-3.6 ITS 406 and 407 with corresponding CCS for 2015 and 2016

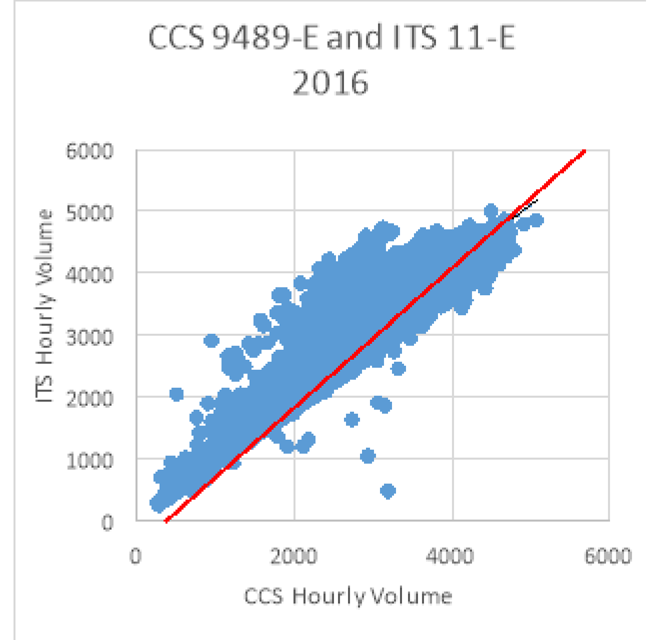


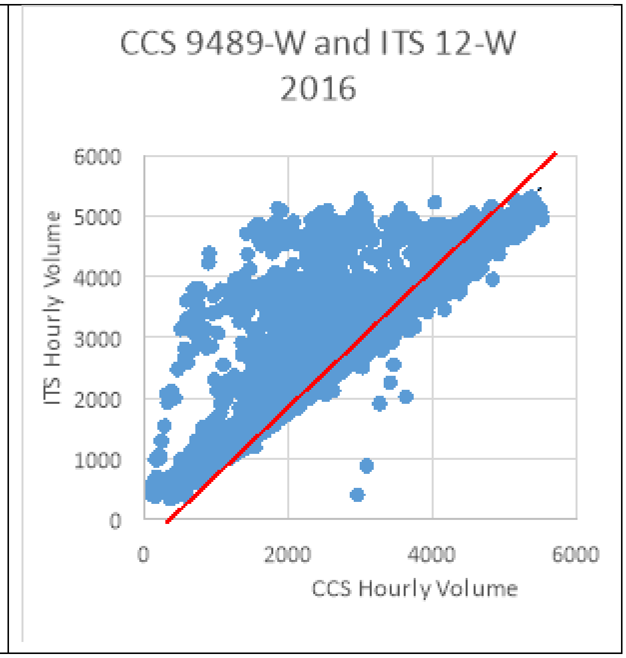


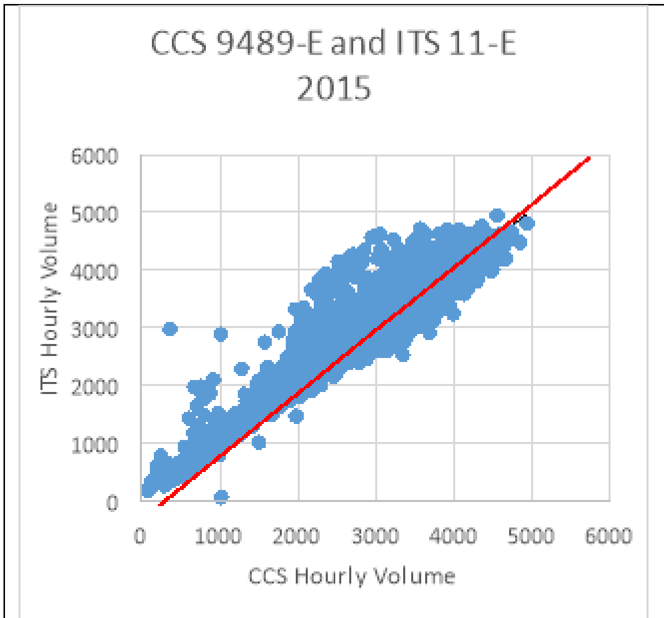


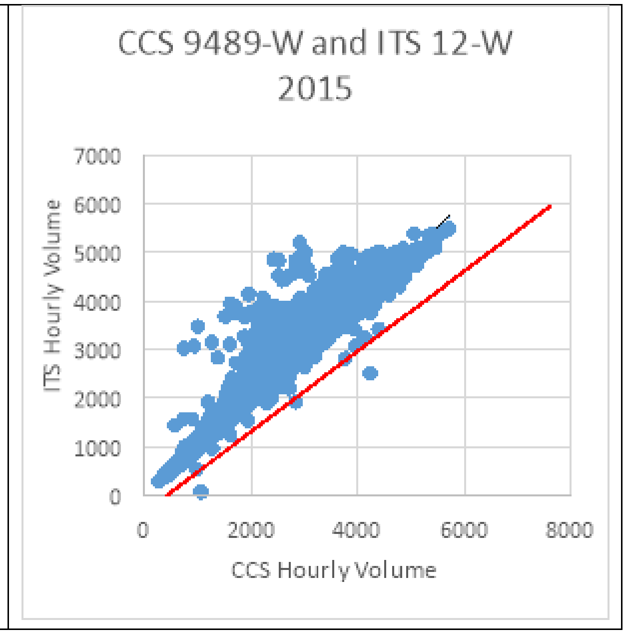


A-3.7 ITS 11 and 12 with corresponding CCS for 2015 and 2016

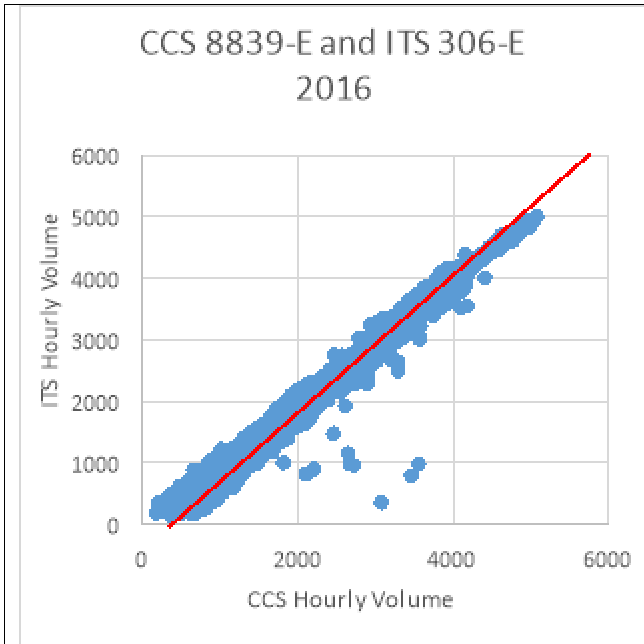


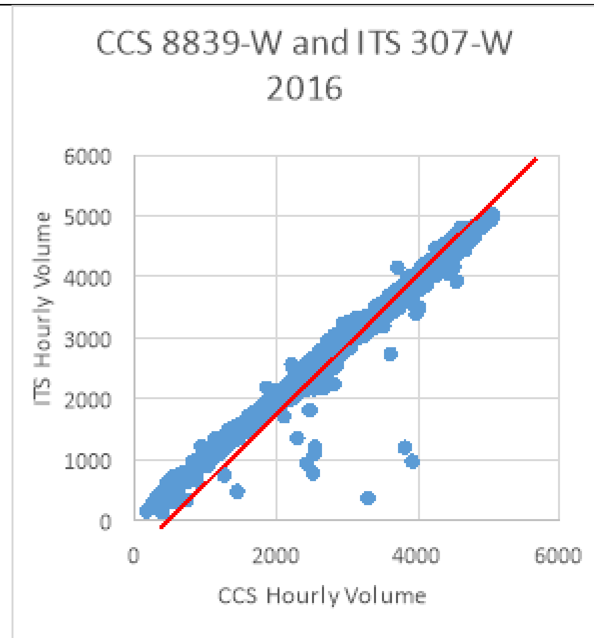


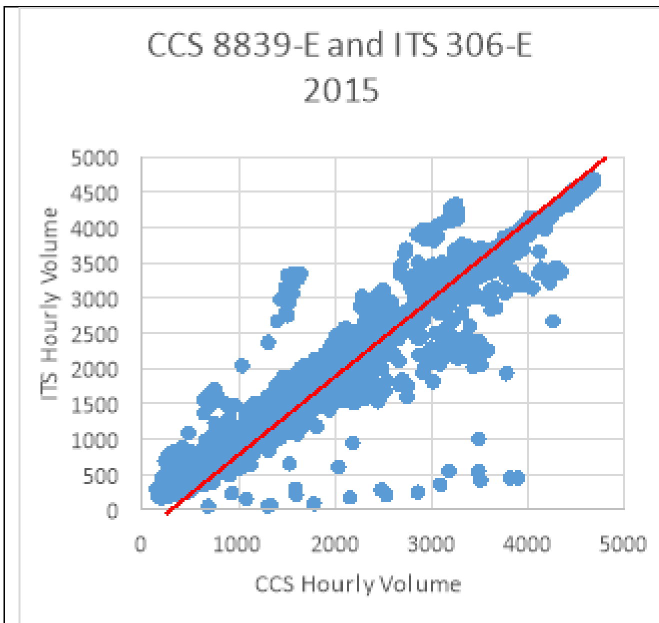


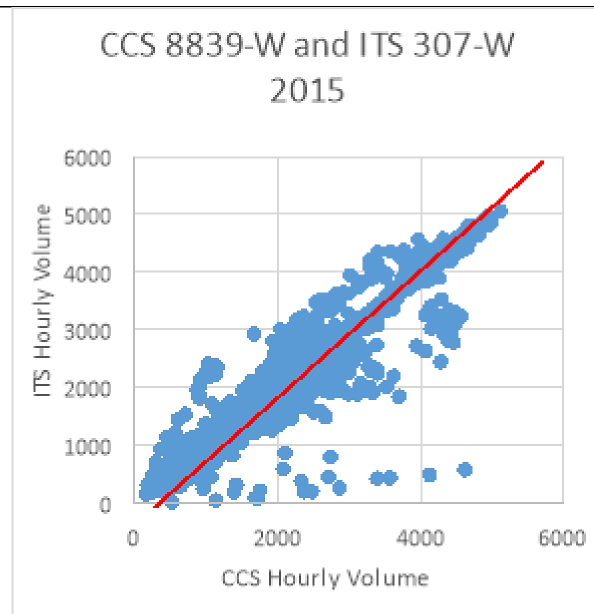


A-3.8 ITS 306 and 307 with corresponding CCS for 2015 and 2016

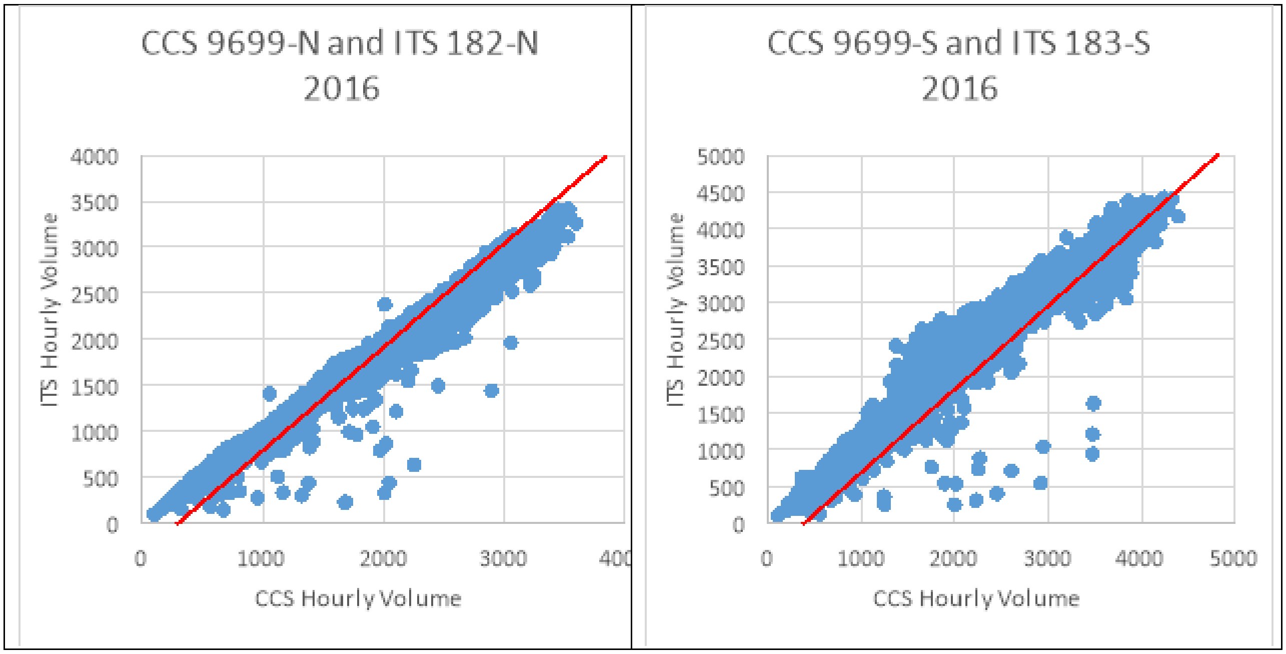




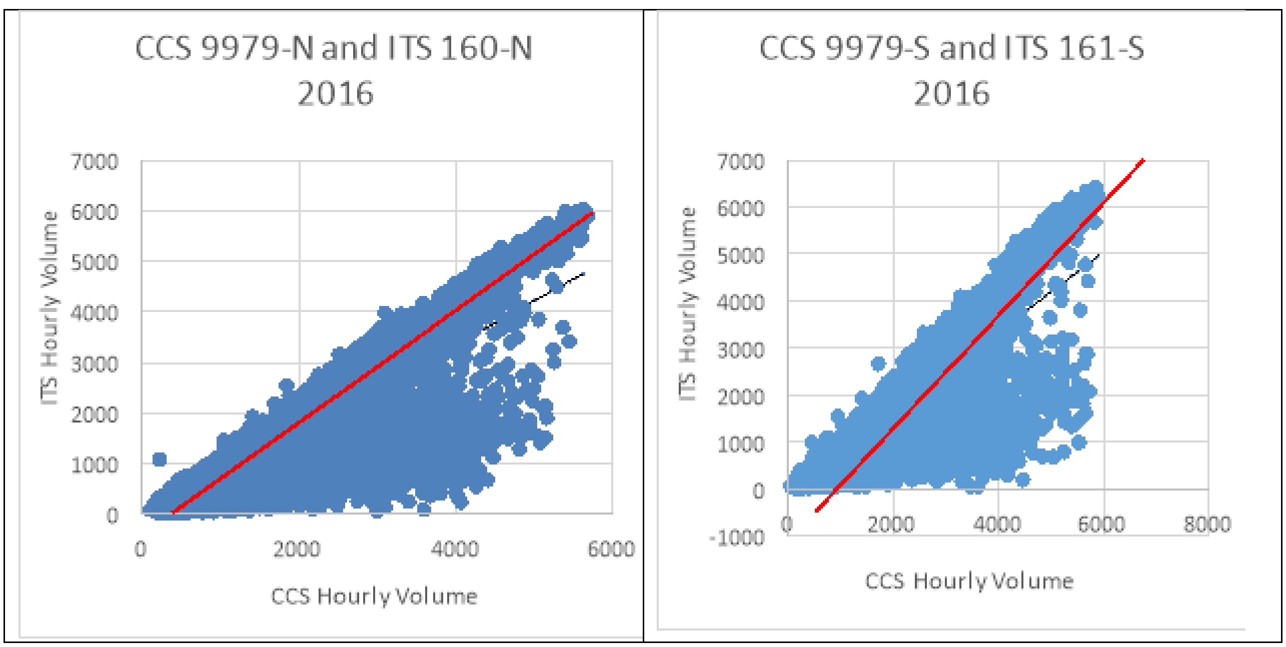




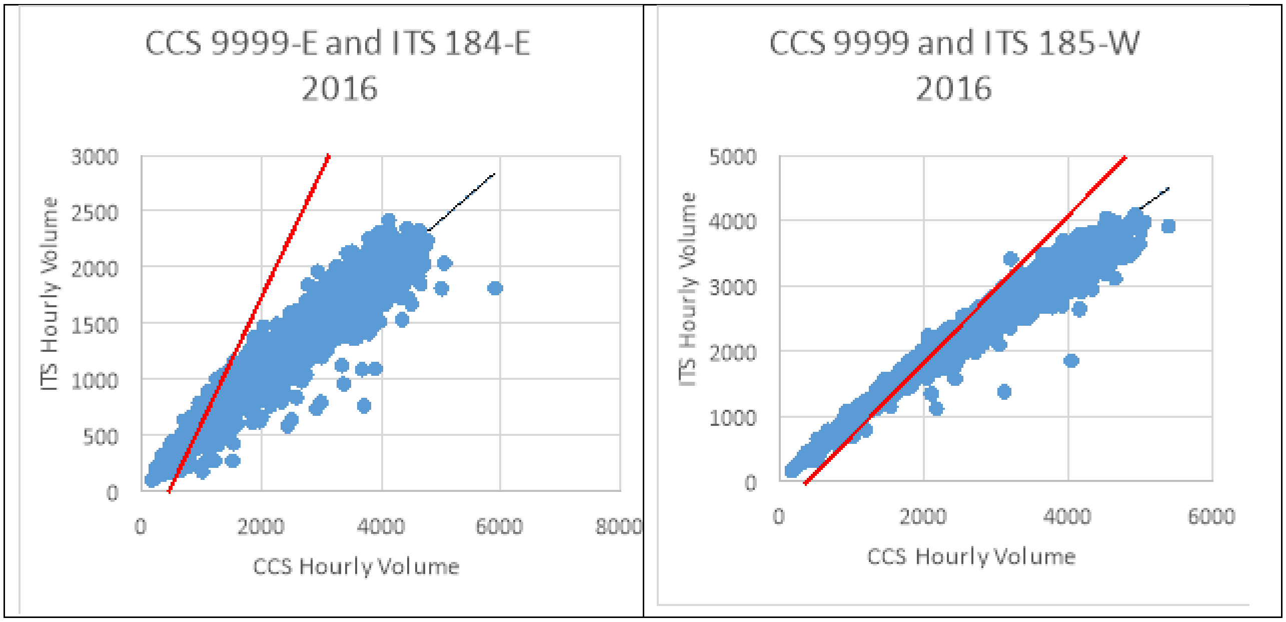
A-3.9 ITS 182 and 183 with corresponding CCS for 2016



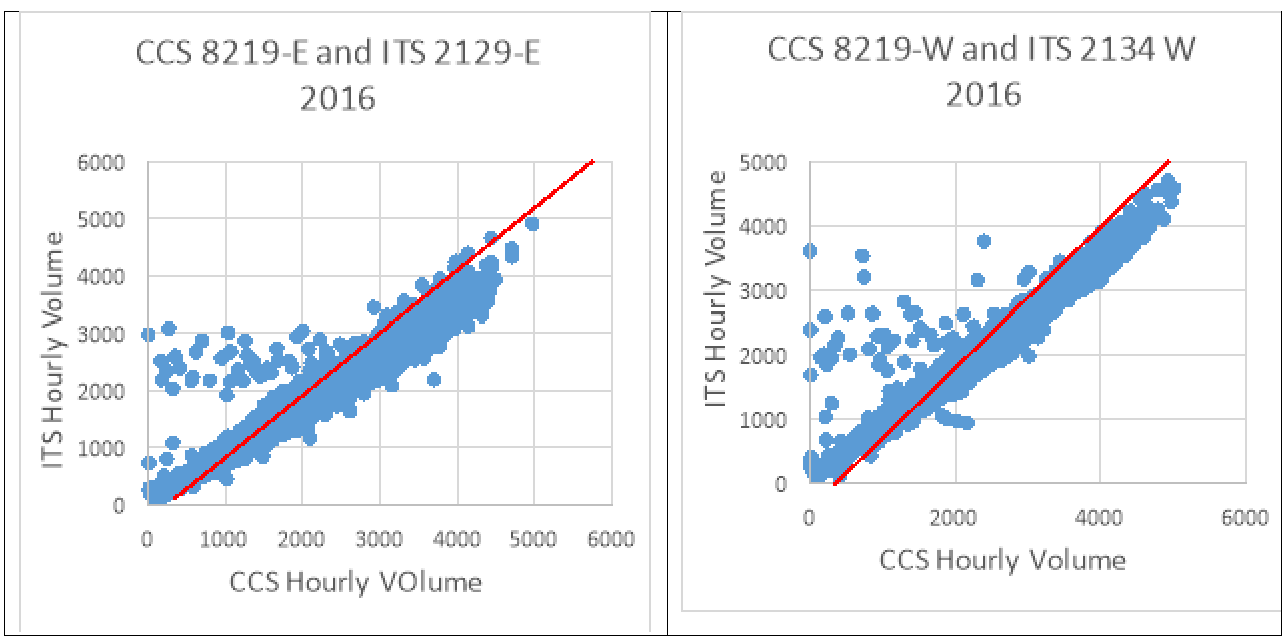
A-3.10 ITS 160 and 161 with corresponding CCS for 2016

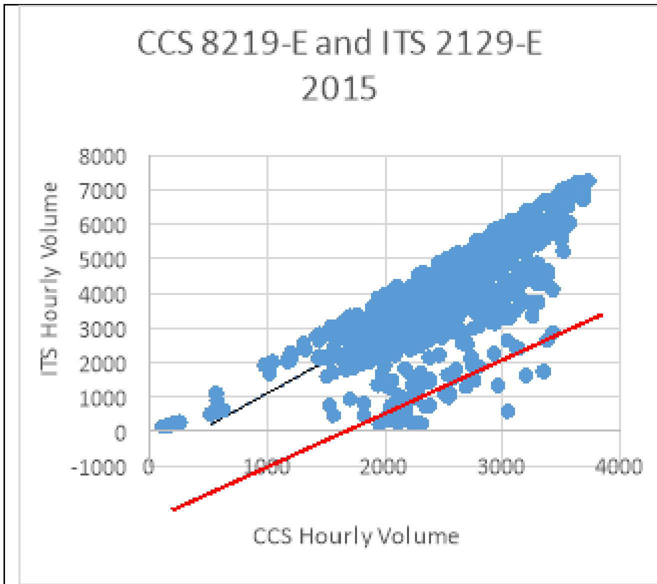


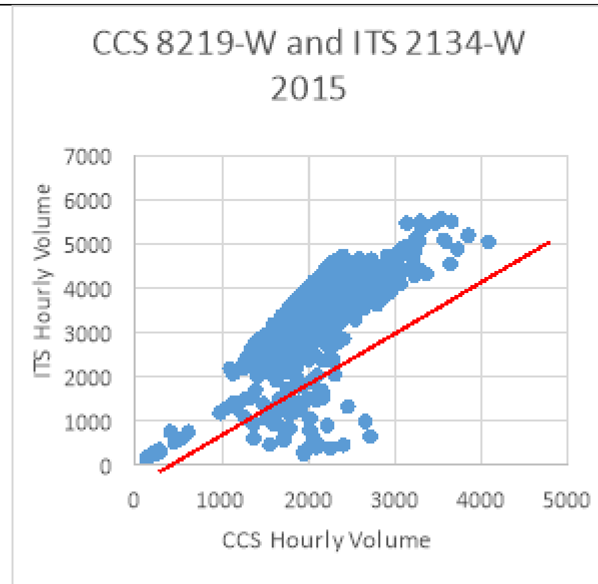
A-3.11 ITS 184 and 185 with corresponding CCS for 2016



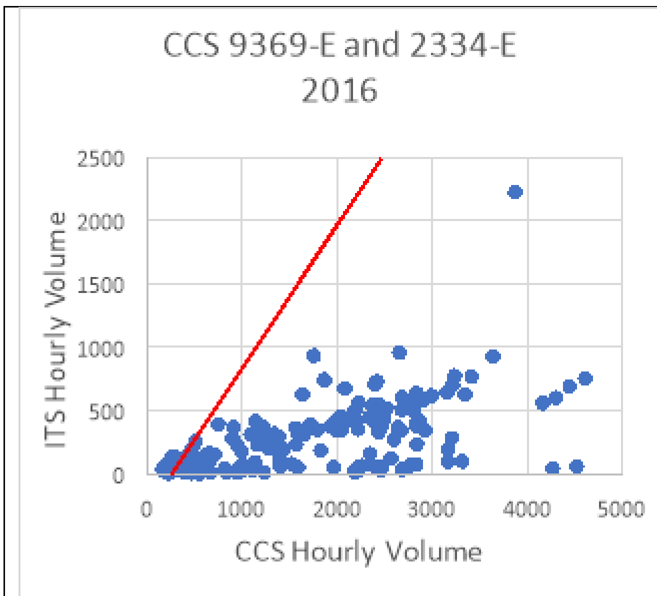
A-3.12 ITS 2129 and 2134 with corresponding CCS for 2015 and 2016

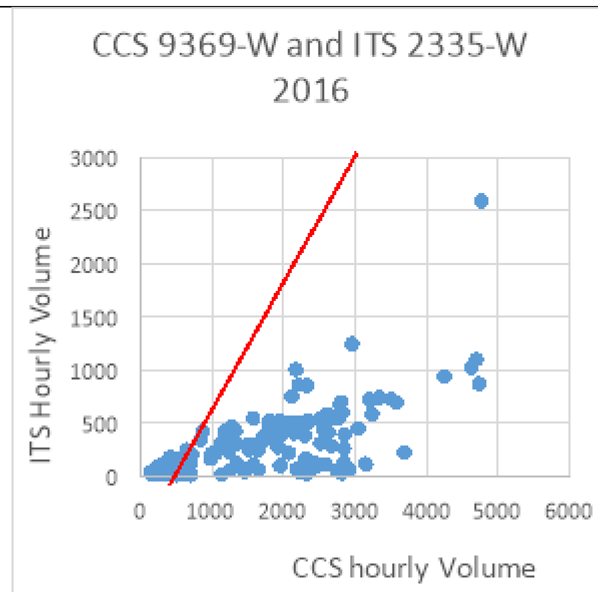


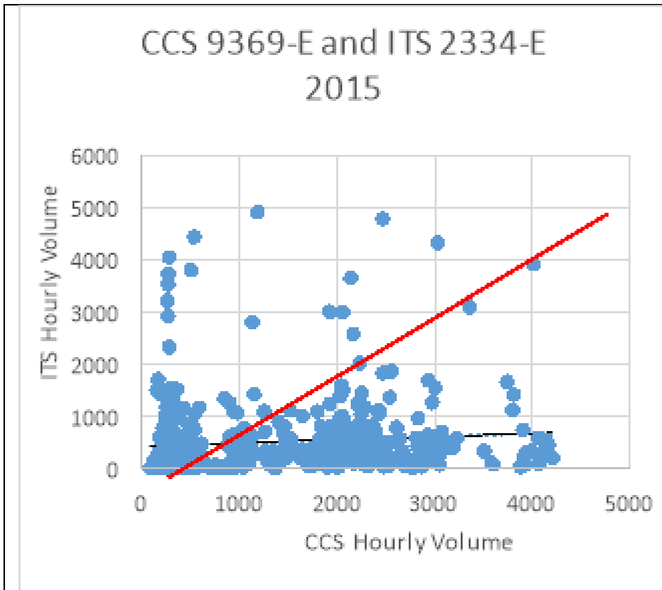


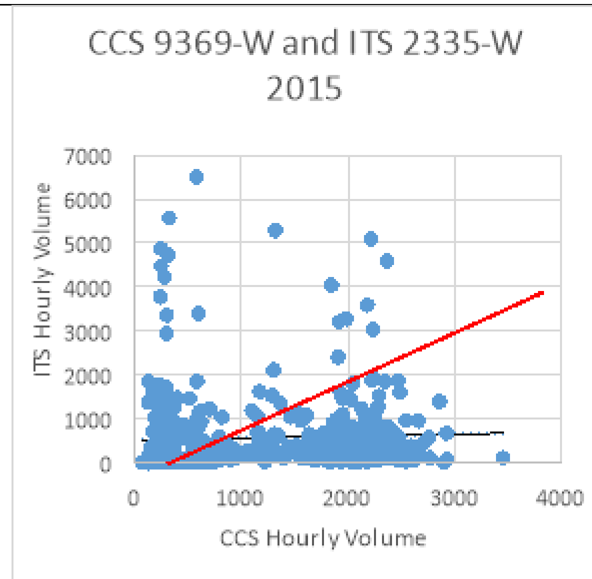


A-3.13 ITS 2334 and 2335 with corresponding CCS for 2015 and 2016

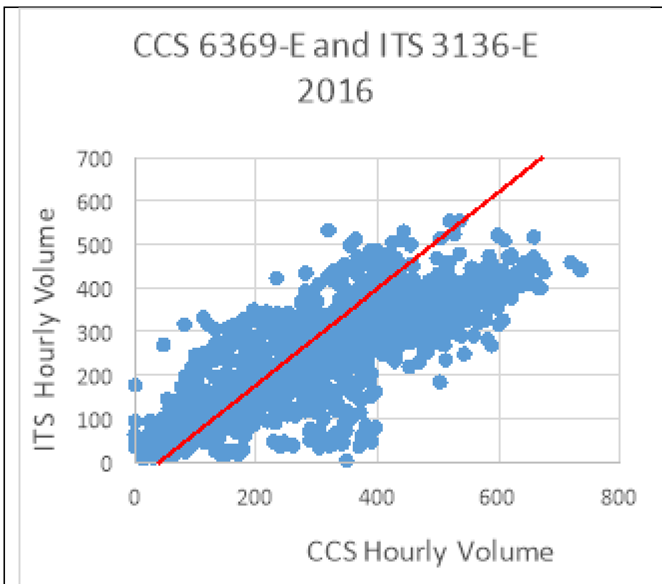


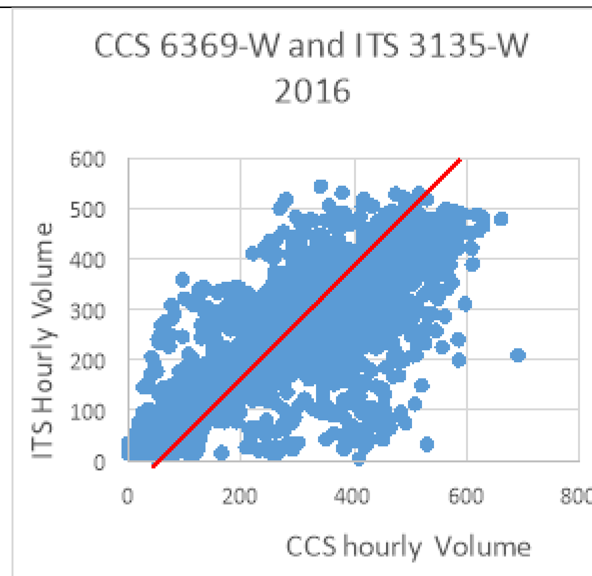


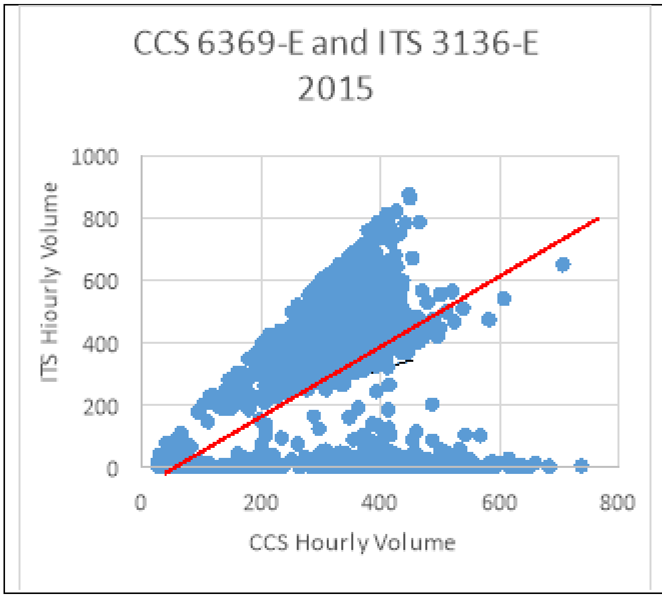


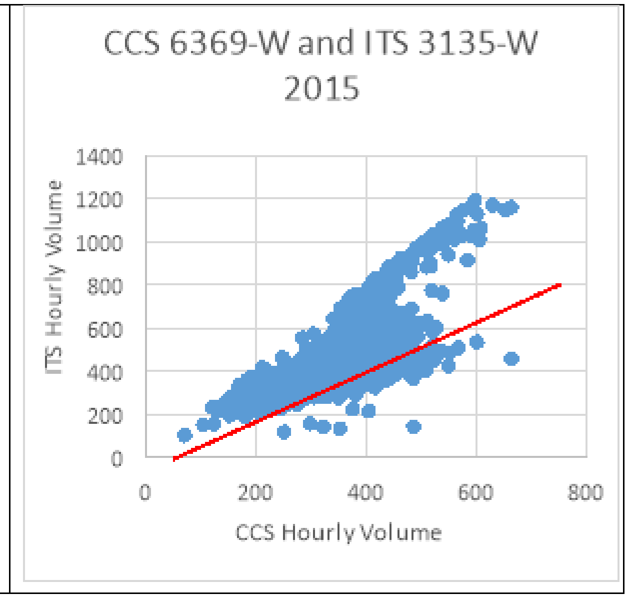


A-3.14 ITS 3136 and 3135 with corresponding CCS for 2015 and 2016

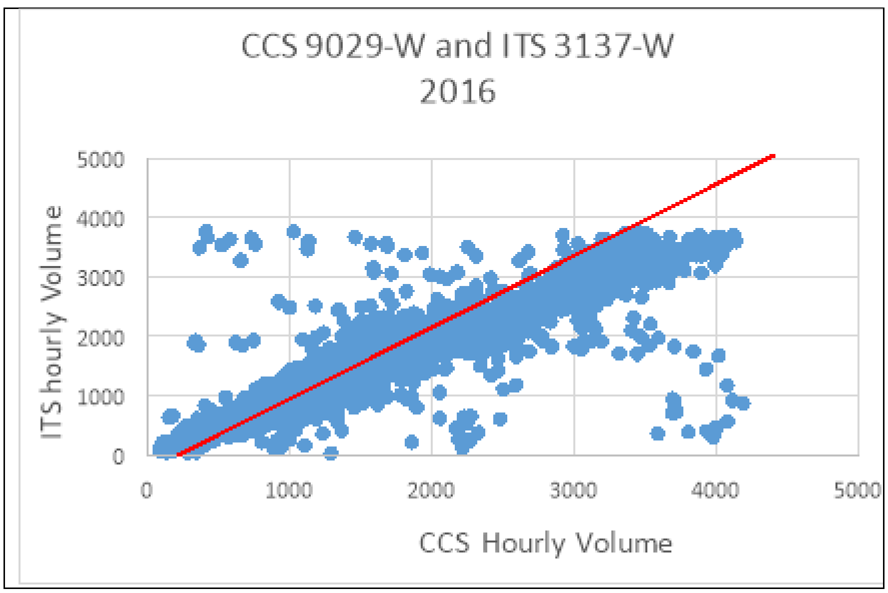




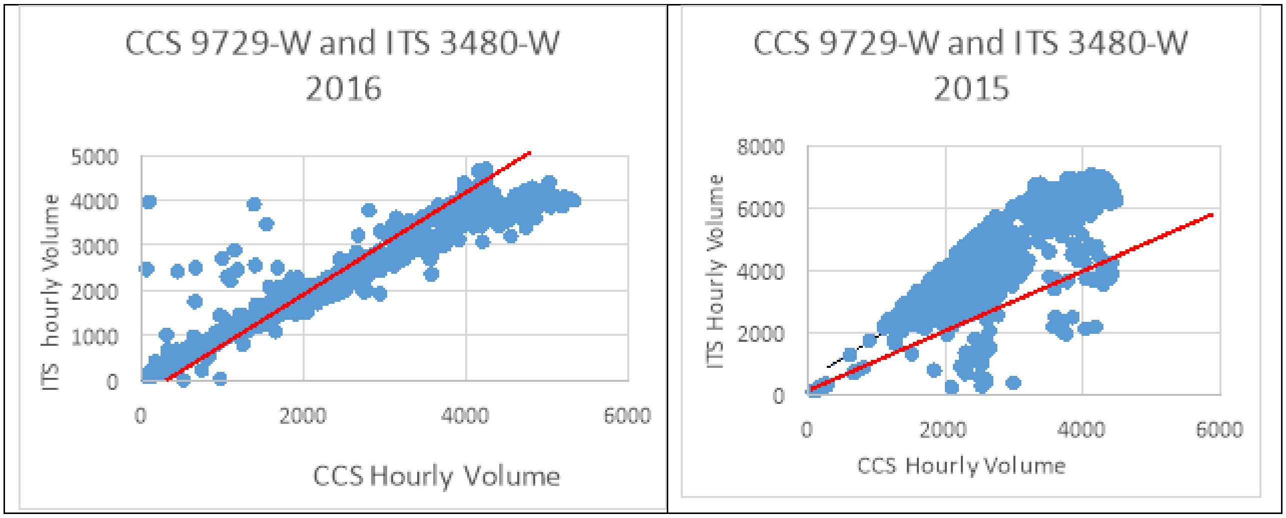




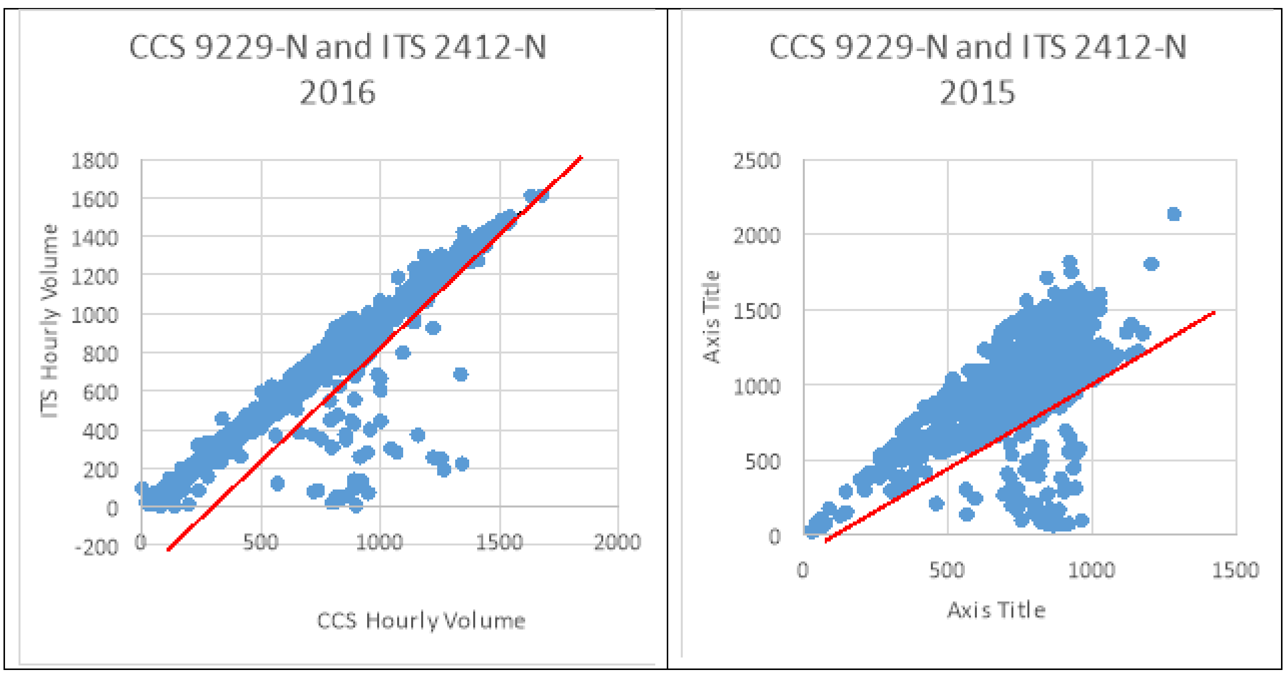
A-3.15 ITS 3137 with corresponding CCS for 2016



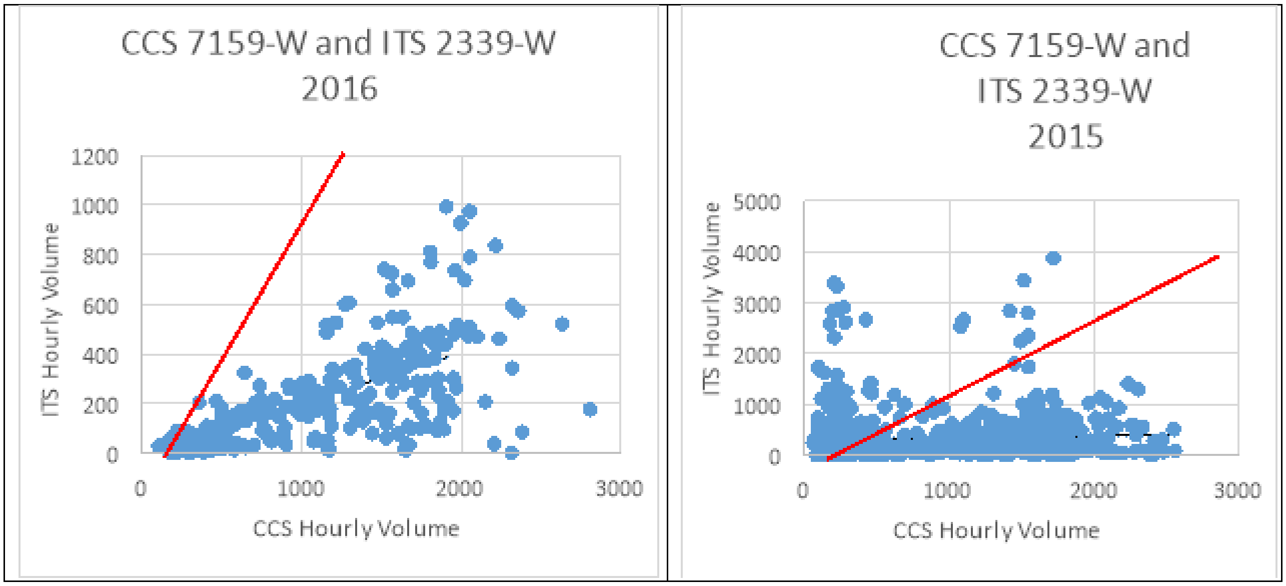
A-3.16 ITS 3480 with corresponding CCS for 2015 and 2016



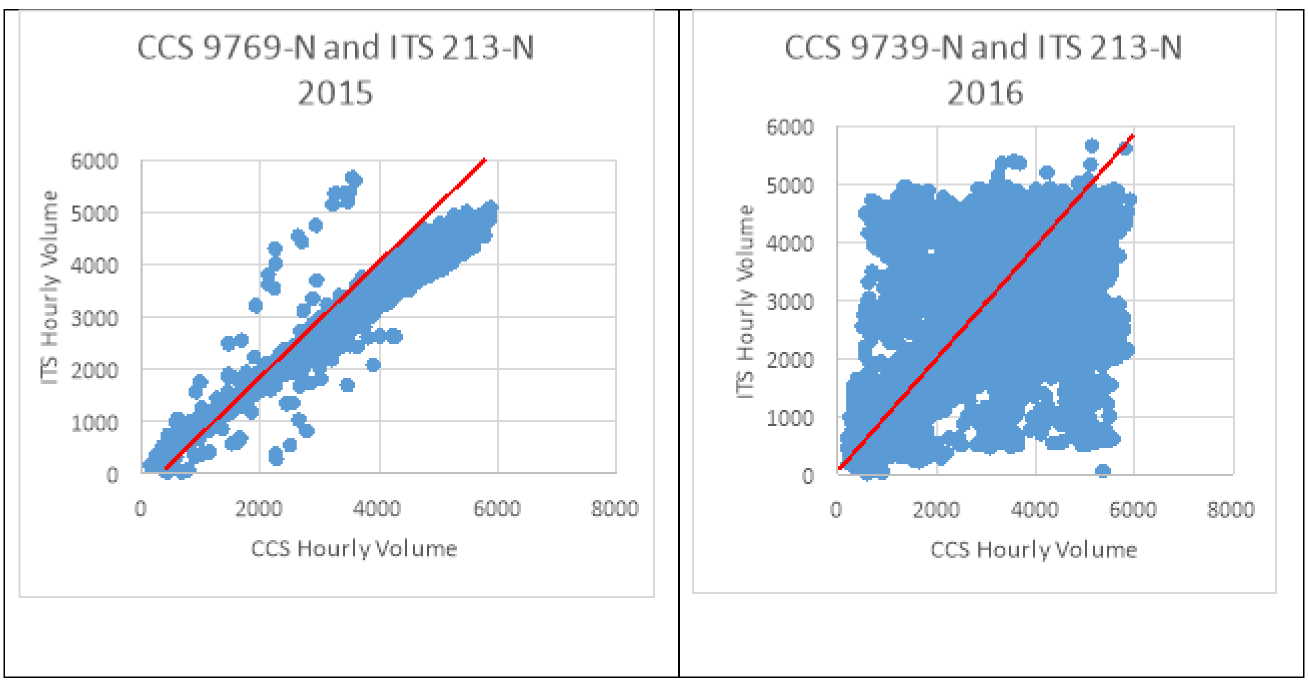
A-3.17 ITS 2412 with corresponding CCS for 2015 and 2016



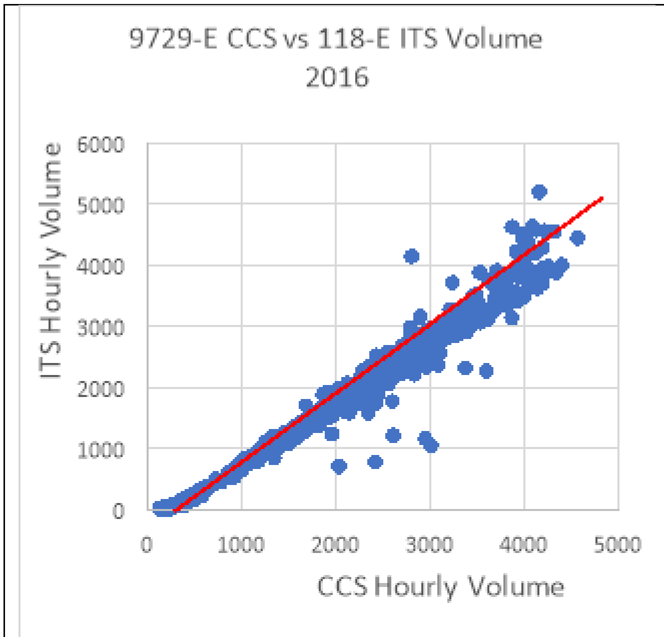
A-3.18 ITS 2339 with corresponding CCS for 2015 and 2016

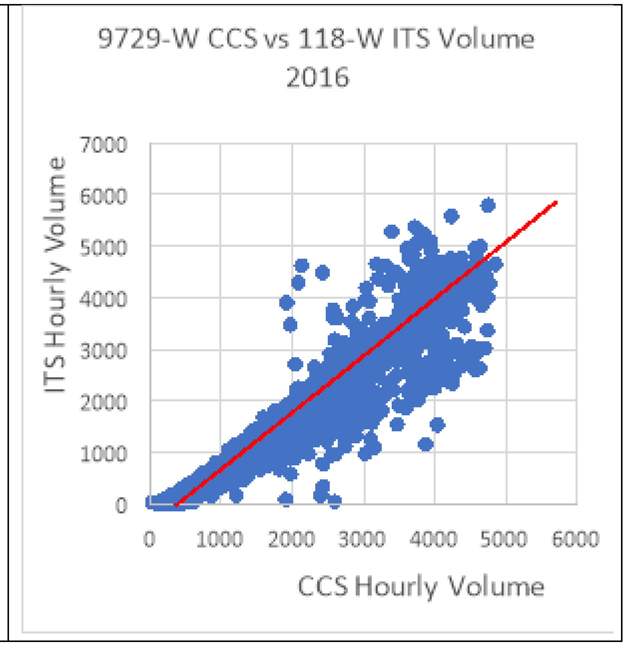


A-3.19 ITS 213 with corresponding CCS for 2015 and 2016

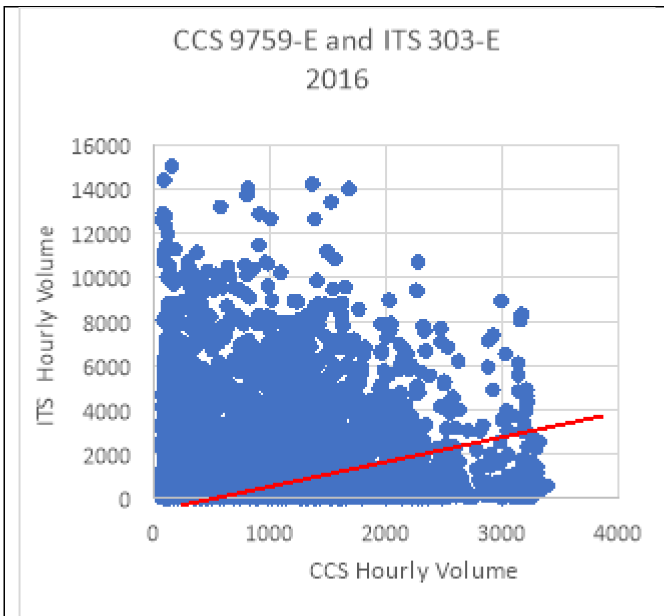


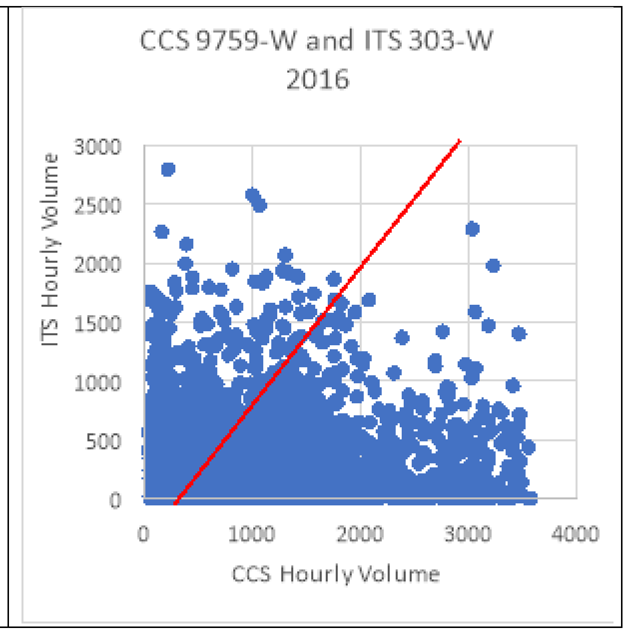
A-3.20 ITS 118 with corresponding CCS for 2016



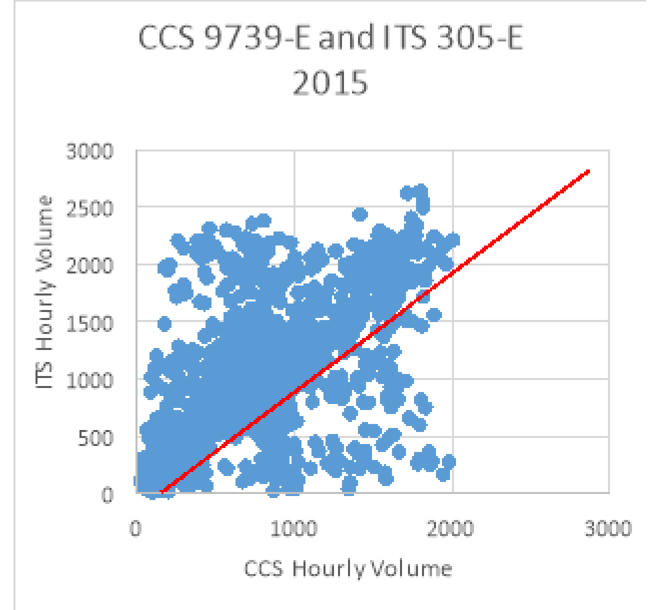


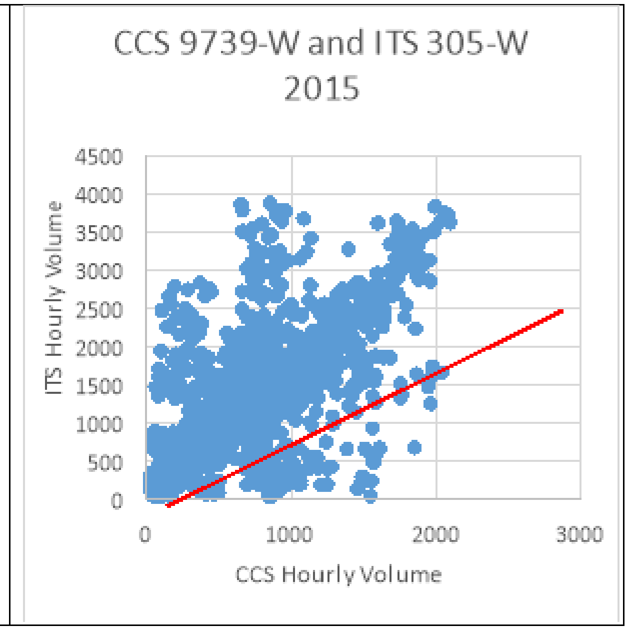
A-3.21 ITS 303 with corresponding CCS for 2016



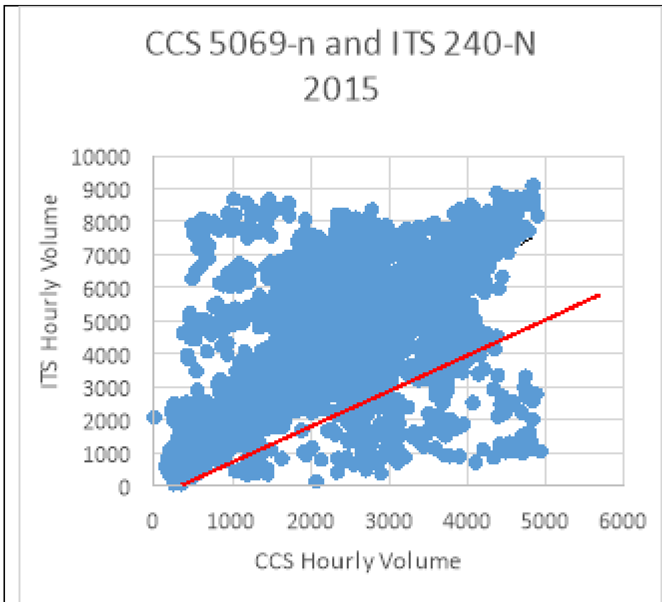


A-3.22 ITS 305 with corresponding CCS for 2015





A-3.23 ITS 303 with corresponding CCS for 2015



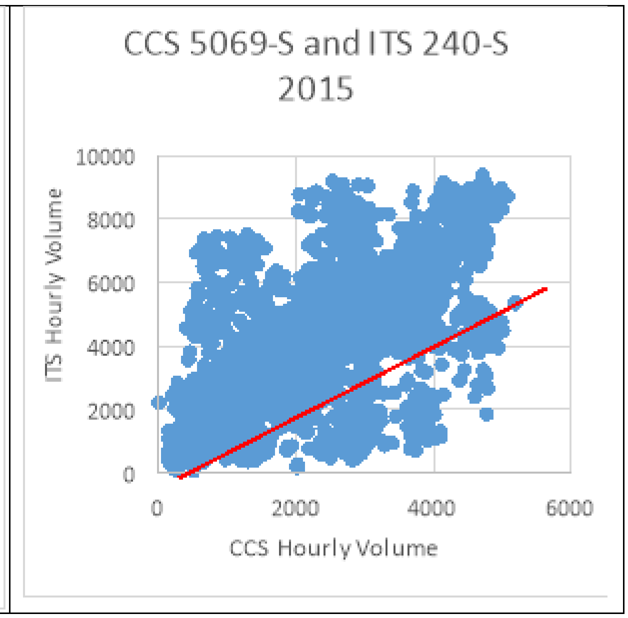


Table A-5 Summary of ITS SEMTOC Volume Comparison

Direction	CCS Id	ITS Id	Sample size/ITS Data availability (percent)		Pearson's Correlation		Data Accuracy (MAPE)		Deviation (percent) from 45 deg. Slope	
			2015	2016	2015	2016	2015	2016	2015	2016
E	8209	136	66	99	0.95	0.99	22.04	31.10	20.69	29.79
W	8209	137	66	99	0.94	0.98	22.74	27.00	22.38	25.11
E	8409	172	74	98	0.99	0.99	4.50	3.38	2.05	0.29
W	8409	173	74	98	0.99	0.99	4.90	3.80	3.80	0.35
E	9839	354	69.3	99	0.97	0.97	25.40	24.90	18.40	21.09
W	9839	355	70	99	0.96	0.96	21.10	14.50	1.10	7.29
E	9969	418	75.5	99	0.99	0.99	6.30	6.20	1.05	1.04
W	9969	419	76	99	0.99	0.99	2.72	3.30	0.42	0.68
E	9419	406	76	99	0.99	0.99	4.60	7.40	2.80	2.44
W	9419	407	76	99	0.99	0.99	2.33	3.10	0.03	0.80
E	9499	402	75.5	99	0.98	0.96	26.10	29.60	25.90	29.50
W	9499	403	76	99	0.98	0.97	7.90	10.30	6.90	8.68
E	9489	11	75.3	98	0.97	0.95	7.00	10.50	4.18	1.38
W	9489	12	75	98	0.97	0.9	5.70	15.00	2.06	1.50
E	8839	306	75.5	98.6	0.99	0.99	6.20	2.90	1.10	0.05
W	8839	307	75.4	98.6	0.99	0.99	5.47	1.90	0.62	0.06
N	9699	182		99		0.99		4.25		3.18
S	9699	183		99		0.97		10.80		6.48
N	9979	160		97		0.82		27.71		19.30
S	9979	161		97		0.81		28.01		19.30
N	9999	184		99		0.97		46.09		40.20
S	9999	185		99		0.98		8.40		7.66

Table A-6 Summary of ITS STOC Volume Comparison

STOC										
Direction	**CCS Id**	**ITS Id**	**Sample size/ITS Data availability (percent)**		**Pearson's Correlation**		**MAPE**		**Deviation from 45 degree slope (percent)**	
			2015	**2016**	**2015**	**2016**	**2015**	**2016**	**2015**	**2016**
E	8219.0	2129.0	38.8	66.0	0.70	0.98	56.6	16.3	53.5	13.6
W	8219.0	2134.0	39.0	66.0	0.78	0.98	59.4	14.7	55.4	11.8
E	9369.0	2334.0	5.7	2.0	0.09	0.61	106.5	82.2	90.5	82.6
W	9369.0	2335.0	5.7	3.0	0.08	0.20	127.5	84.8	93.2	80.5
E	6369.0	3136.0	40.8	36.0	0.33	0.98	61.8	19.4	19.2	19.0
W	6369.0	3135.0	40.0	36.0	0.68	0.97	30.5	17.3	27.7	15.5
W	9029.0	3137.0		34.0		0.97		15.8		9.8
W	9729.0	3480.0	34.1	19.0	0.79	0.97	59.2	13.6	56.0	6.7
N	**9229.0**	**2412.0**	37.5	**70.0**	0.73	**0.99**	36.0	**7.6**	31.1	**6.9**
W	7159.0	2339.0	4.9	5.0	0.04	0.70	108.0	80.0	90.5	80.2

Table A-7 Summary of ITS WMTOC Volume Comparison

WMTOC										
Direction	CCS Id	ITS Id	Sample size/ITS Data availability (percent)		Pearson's Correlation		MAPE		Deviation from the 45 degree slope (percent)	
			2015	2016	2015	2016	2015	2016	2015	2016
E	9759	303		65		-0.06		418.0		335.5
W	9759	303		65		-0.04		111.8		15.7
E	9729	118		50		0.98		19.51		8.85
W	9729	118		52		0.96		22.22		10.8
E	9739	305	25		0.74		77.2		66.49	
W	9739	305	25		0.75		130		123.29	
E	5069	240	25		0.76		112		107	
W	5069	240	25		0.78		109		104	
N	9769	213	92.1	91	0.99	0.73	12.78	38.8	12.13	0.57

Table A-8 Summary of usable ITS SEMTOC sensors

	2015				2016			
Criteria	Total Number of ITS	Percentage	ITS	CCS	Total number of ITS	Percentage	ITS	CCS
Error Less than10%	11	68.8%	172-E & 173-W	8409	11	50.0%	172-E & 173-W	8409
			418-E & 419-W	9969			418-E & 419-W	9969
			406-E & 407-W	9419			406-E & 407-W	9419
			403-W	9499			306-E & 307-W	8839
			11-E & 12-W	9489			182-N & 183-S	9699
			306-E & 307-W	8839			185-S	9999
Error (10-20%)	1	6.3%	355-W	9839	5	22.7%	11-E & 12-W	9489
			-	-			403-W	9499
			-	-			183-S	9699
			-	-			355-W	9839
Error (More than 20%)	4	25.0%	136-E & 137-W	8209	6	27.0%	160-N & 161-S	9979
			354-E	9839			136-E & 137-W	8209
			402-E	9499			402-E	9499
							1894-N	9999
Total	16	100.0%			22	100.0%		

Table A-8 Summary of usable ITS STOC sensors

	2015				2016			
Criteria	Total Number of ITS	Percentage	ITS	CCS	Total number of ITS	Percentage	ITS	CCS
Error (Less than 10%)	0	0%	-	-	1	10%	2412-N	9229
Error (10-20%)	0	0%	-	-	6	60%	2129-E & 2134-W	8219
			-	-			3136-E & 3135-W	6369
			-	-			3480-W	9729
			-	-			3137-W	9029
Error (More than 20%)	10	100%	2129-E & 2134-W	8219	3	30%	2334-E & 2335-W	9369
			2334-E & 2335-W	9369			2339-W	7159
			3136-E & 3135-W	6369			-	-
			3137-W	9029			-	-
			3480-W	9729			-	-
			2412-N	9229			-	-
			2339-W	7159			-	-
Total	10	100%			10	100%		

Table A-8 Summary of usable ITS WMTOC sensors

	2015				2016			
Criteria	Total Number of ITS	Percentage	ITS	CCS	Total number of ITS	Percentage	ITS	CCS
Error (Less than 10%)	0	0%	-	-	0	0%	-	-
Error (10-20%)	1	20%	213-N	9769	1	20%	118-E	9729
Error (More than 20%)	4	80%	240-E & 240-W	5069	4	80%	118-W	9729
			305-E & 305-W	9739			213-N	9769
			-	-			303-E & 303-W	9759
Total	5	100%			5	100%		

Table A-9 Summary of ITS speed distribution for SEMTOC, STOC, and WMTOC

SEMTOC							
Speed Distribution							
ID	Direction	Average Speed (mph)	Std. of Speed	85th Percentile of Speed	Bin with Highest Frequency	ITS Data Availability	Deviation of 85th percentile of speed
CCS-8209	E	72.4	11.4	78.3	Bin 13(76-80.9)	99	2.1
ITS-136	E	67.2	12.9	76.2	Bin12(71-75.9)		
CCS-8209	W	72.7	10.2	78.1	Bin13(76-80.9)	99	-1.9
ITS-137	W	74.5	8.57	80	Bin13(76-80.9)		
CCS-8409	E	69.9	14.2	77.1	Bin12(71-75.9)	98	3.6
ITS-172	E	68.3	10.1	73.5	Bin12(71-75.9)		
CCS-8409	W	67.7	19.1	77.5	Bin12(71-75.9)	98	-3.5
ITS-172	W	75.2	8.78	81	Bin12(71-75.9)		
CCS-8839	E	78.4	8.9	77.5	Bin13(76-80.9)	98	4.1
ITS-306	E	71.1	5.8	73.4	Bin12(71-75.9)		
CCS-8839	W	73.45	7.5	77.5	Bin12(71-75.9)	98	4.1
ITS-307	W	73.48	5.9	73.4	Bin12(71-75.9)		
CCS-9699	E	72.4	7.9	77.1	Bin13(76-80.9)	99	4
ITS-182	E	68.4	7.5	73.1	Bin12(71-75.9)		
CCS-9699	W	71.3	9.6	77.1	Bin12(71-75.9)	99	1.1
ITS-183	W	72.27	5.6	76	Bin12(71-75.9)		

WMTOC							
		Speed Distribution					
ID	Direction	Average Speed (mph)	Std. of Speed	85th Percentile of Speed	Bin with Highest Frequency	ITS Data Availability	Deviation of 85th percentile of speed
CCS-9759	E	73.69	8.4	77.8	Bin13(76-80.9)	65	0.7
ITS-303	E	70.1	19.6	77.1	Bin13(76-80.9)		
CCS-9759	W	68.7	16.1	77.5	Bin12(71-75.9)	66	-12.5
ITS-303	W	71.5	24.6	90	Bin13(76-80.9)		

STOC							
	Speed Distribution						
ID	Direction	Average Speed (mph)	Std. of Speed	85th Percentile of Speed	Bin with Highest Frequency	ITS Data Availability	Deviation of 85th percentile of speed
CCS-6349	N	73.9	6.8	77.9	Bin12(71-75.9)	36	4.7
ITS-3634	N	72.1	4.9	73.2	Bin12(71-75.9)		
CCS-2199	E	61.8	8.2	64	Bin10(61-65.9)	16	1.9
ITS-3740	E	61.7	5.2	62.1	Bin10(61-65.9)		
CCS-4049	S	73.3	6.6	76.2	Bin12(71-75.9)	36	4.1
ITS-3642	S	67.6	6.3	72.1	Bin10(61-65.9)		

Table A-10 Summary of Chi-square speed distribution for SEMTOC, STOC, and WMTOC for 2015

SEMTOC				
ID	**p value**	**test-statistic**	**Decision**	
CCS-8209 ITS-136	0.008	21.7	Sig	H_0 Reject
CCS-8209 ITS-137	1.972	10.3	Not Sig.	H_0 Accept
CCS-8409 ITS-172	0.085	19.5	Not Sig.	H_0 Accept
CCS-8409 ITS-172	0.065	19.4	Not Sig.	H_0 Accept
CCS-8839 ITS-306	0.001	43	Sig	H_0 Reject
CCS-8839 ITS-307	0.082	20.8	Not Sig.	H_0 Accept
CCS-9699 ITS-182	0	78	Sig	H_0 Reject
CCS-9699 ITS-183	0.699	13	Not Sig.	H_0 Accept
WMTOC				
CCS-9759 ITS-303	0.51	17.6	Not Sig	H_0 Accept
CCS-9759 ITS-303 ITS-3642	0	74	Sig	H_0 Reject

Table A-11 Summary of Combining 13 CCS classes to 4 classes for vehicle comparison purposes

(We have 13 classes in current dataset and converting 13 classes to 4 classes for comparison purposes as below, since the ITS dataset has 4 classes):

SM	Small size vehicle (class 1 and Class 2) Size: 0-18 feet
MD	Medium size vehicle (class 3 and 4) Size: 18-35 feet
LG	Large size vehicle (truck) with single units (Class 5-10) Size: 35-70 feet
Extra LG	Extra Large size vehicle (truck) with multiple units(class 11,12, and 13) Size: more than 70 feet

(Source: Jessberger, S. (2012). Axle and Length classification. FHWA Highway Community Exchange (CoP). Federal Highway Administration 2012 Highway Information Seminar Session 3B. **)**

Original 13 classes:

Class 1	Motorcycle
Class 2	Passenger car
Class 3	Light Duty (2-axle, four-tire) Pick-up Trucks
Class 4	Buses
Class 5	Two-Axle, Six-Tire, Single-Unit Trucks
Class 6	Three-Axle, Single-Unit Trucks
Class 7	Four-or-More Axle, Single-Unit Trucks
Class 8	Four-or-Less Axle, Single-Trailer Trucks
Class 9	Five-Axle, Single-Trailer Trucks
Class 10	Six-or-More Axle, Single-Trailer Trucks
Class 11	Five-or-Less Axle, Multi-Trailer Trucks
Class 12	Six-Axle, Multi-Trailer Trucks
Class 13	Seven-or-More Axle, Multi-Trailer Trucks