12-2017

Evaluation of Opportunities and Challenges of Using INRIX Data for Real-Time Performance Monitoring and Historical Trend Assessment

Anuj Sharma

Vesal Ahsani

Sandeep Rawat

Evaluation of Opportunities and Challenges of Using INRIX Data for Real-Time Performance Monitoring and Historical Trend Assessment

Final Report
December 2017

NEBRASKA
Good Life. Great Journey.
DEPARTMENT OF TRANSPORTATION

Disclaimer

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the Nebraska Department of Transportation in the interest of information exchange. The contents do not necessarily reflect the official views of the Nebraska Department of Transportation. This report does not constitute a standard, specification, or regulation. The U.S. Government assumes no liability for the contents or use thereof.

About CTRE

This work was performed by the Center for Transportation Research and Education (CTRE) at Iowa State University. CTRE's mission is to develop and implement innovative methods, materials, and technologies for improving transportation efficiency, safety, and reliability while improving the learning environment of students, faculty, and staff in transportation-related fields.

Non-Discrimination Statement

Iowa State University does not discriminate on the basis of race, color, age, religion, national origin, pregnancy, sexual orientation, gender identity, genetic information, sex, marital status, disability, or status as a U.S. veteran. Inquiries regarding non-discrimination policies may be directed to Office of Equal Opportunity, Title IX/ADA Coordinator and Affirmative Action Officer, 3350 Beardshear Hall, Ames, Iowa 50011, 515-294-7612, eooffice@iastate.edu.

Technical Report Documentation Page

1. Report No. SPR-P1(14) M007	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Evaluation of Opportunities and Challenges of Using INRIX data for Real-Time Performance Monitoring and Historical Trend Assessment		5. Report Date December 2017
		6. Performing Organization Code
7. Author(s) Anuj Sharma, Vesal Ahsani, and Sandeep Rawat		8. Performing Organization Report No. SPR-P1(14) M007
9. Performing Organization Name and Address **Center for Transportation Research and Education** **Iowa State University** **2711 S. Loop Drive, Suite 4700** **Ames, IA 50010-8664**		10. Work Unit No. (TRAIS)
		11. Contract or Grant No.
12. Sponsoring Agency Name and Address Nebraska Department of Transportation 1500 Hwy. 2 Lincoln, NE 68502		13. Type of Report and Period Covered Final Report June 2016 – December 2017
		14. Sponsoring Agency Code
15. Supplementary Notes		

16. Abstract

In recent years there has been a growing desire for the use of probe vehicle technology for congestion detection and general infrastructure performance assessment. Unlike costly traditional data collection by loop detectors, wide-area detection using probe-sourced traffic data is significantly different in terms of measurement technique, pricing, coverage, etc. This affects how the new technology is applied and used to solve current traffic problems such as traffic incident management and roadway performance assessment. This report summarizes the experiences and lessons learned while using probe data for traffic operations and safety management in the state of Nebraska and makes recommendations for opportunities to maximize the use of probe data in light of its limitations. A detailed analysis of performance monitoring and historical trend analysis, including identification of the top 10 congested segments, congestion per mile across metro areas, congested hour(s) during summer and winter months, and yearly travel time reliability, for Interstate 80 segments in Nebraska were performed. Two main conclusions can be drawn from this study. First, there is almost always a speed bias between data streaming from probes and traditional infrastructure-mounted sensors. It is important to understand the factors that influence these biases and how to cope with them. Second, lack of confidence score 30 (real-time) probe data is a critical issue that should be considered precisely for incident detection, roadway performance assessment, travel time estimation, and other traffic analyses. Ultimately, the authors present several recommendations that will help transportation agencies gain the best value from their probe data.

17. Key Words Probe Data, Sensor Data, Freeway Performance, Reliability		18. Distribution Statement	
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 112	22. Price

Evaluation of Opportunities and Challenges of Using INRIX Data for Real-Time Performance Monitoring and Historical Trend Assessment

Final Report

Anuj Sharma, PhD
Research Scientist and Associate Professor
Center for Transportation Research and Education
Iowa State University

Vesal Ahsani, PhD
Graduate Research Assistant
Center for Transportation Research and Education
Iowa State University

Sandeep Rawat, PhD
Visiting Faculty
Civil, Construction, and Environmental Engineering
Iowa State University

A Report on Research Sponsored by

Nebraska Department of Transportation

December 2017

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AADT	Annual average daily traffic
AASHTO	American Society of State Highway And Transportation Officials
ATR	Automatic traffic recorder
AVI	Automatic vehicle identification
BTI	Buffer time index
CDF	Cumulative distribution function
CSI	Commuter stress index
DOT	Department of Transportation
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
GPS	Global positioning system
HPMS	Highway performance monitoring system
ILD	Inductive loop detector
LOS	Level of service
MAP-21	Moving Ahead for Progress in the 21st Century Act
NDOT	Nebraska Department of Transportation
NPMRDS	National Performance Management Research Dataset
PTI	Planning time index
PVR	Per-vehicle record
RCI	Roadway Congestion Index
RITIS	Regional Integrated Transportation Information System
TMC	Traffic message channel
TTI	Travel time index
TTPM	Travel time per mile
VMT	Vehicle miles traveled
VPP	Vehicle Probe Project
WSDOT	Washington State Department of Transportation

Executive Summary

Presently, there is an expanding interest among transportation agencies and state Departments of Transportation to consider augmenting traffic data collection with probe-based services, such as INRIX. The objective is to decrease the cost of deploying and maintaining sensors and increase the coverage under constrained budgets. This report documents a study evaluating the opportunities and challenges of using INRIX data in Nebraska. The objective of this study was twofold: (1) evaluate the reliability and accuracy of probe-data streams against fixed, infrastructure-mounted sensor data and (2) report the real-time performance monitoring and historical trend assessments.

This study demonstrates a systematic way to compare the reliability and accuracy of probe-data streams for monitoring traffic conditions and supporting operations decisions. Out of 65 automatic traffic recorders (ATRs) in Nebraska, 16 locations were identified based on various criteria. For each of the selected ATRs there were corresponding traffic message channels (TMCs), which are maintained by INRIX to collect the traffic details on major freeways and urban areas. Various traffic performance measures were used to help understand the traffic conditions across different road segments or different time periods and to identify bottlenecks in Nebraska. The data visualization program can also be used with a real-time data feed to monitor and analyze current traffic conditions.

The reliability and accuracy of the INRIX data were evaluated by comparing the data to PVR (per-vehicle record) sensor data. The factors that were taken into consideration for examining the performance of the INRIX data are as follows: (1) percentage availability of INRIX; (2) speed bias between INRIX segments and PVR sensors; (3) incident detection, which provides the number of congestions, and detection latency; and (4) performance measures, such as congested hour(s), buffer time index, and reliability curves. By comparing sensor traffic speed data with segments, it was observed that INRIX is consistent for almost all minutes of a day on interstates. Moreover, it was shown in this study that INRIX is more reliable during the day than at night, especially during peak hours. Regarding incident detection, INRIX is more reliable in detecting recurring congestion as compared to incident related congestion. The congestion duration error varies with the congestion type.

INRIX speed bias affected the process of congestion detection as well as calculation of congested hour duration. For instance, speed bias affects the magnitude of INRIX speed reported at segments with lower speed limits such that a 60-mph speed limit segment might shows speeds around 45 mph (the congestion threshold) or even less during non-congested times, whereas benchmarked sensor data reports speeds around 60 mph. Also, speed bias affects performance measures, such as congested hour, buffer time, and reliability curves, which are evaluated thoroughly in chapter 4. Accordingly, it is important to understand the factors that influence these biases and how to correct for them. Another critical issue that is discussed in this report is the quality of probe data, which depends heavily on the number of probes on the road network. Shortage of INRIX real-time data (confidence score 30), especially during off-peak hours or on arterials, influences the accuracy of the results. Substituting with historical data was not accurate and therefore not advised. In areas with limited probe penetration, transportation agencies can augment probe data with infrastructure-mounted sensors.

A comprehensive analysis of performance monitoring and historical trend analysis using different measures for Interstate 80 (I-80) segments in Nebraska was also performed. The top 10 congested segments on I-80 were identified and a detailed analysis of when congestion had occurred by month, day of week and time of day from 2013 through 2016 was performed. A

congestion-per-mile calculation was used to determine metro area congestion per mile, which supports contrasting performance given the varying amounts of segments and roadway lengths that exist. These values were calculated for each month for all metro areas across Nebraska to compare any trends in congestion. A yearly comparison is also provided for years 2013 through 2016. The number of hours of congestion was used to display the severity of congestion by segment along I-80. Each segment was color coded based on the number of hours of congestion by summer and winter months. Once identified, these locations can also be analyzed by year, month, week, day, or time of day. Finally, the severity of congestion was evaluated by observing the percentage of time speeds were within a 10-mph bin from 0 to 75+ mph.

1. Introduction

1.1 Background

For comprehensive performance assessments of freeways, highways, and arterials, state DOTs and many of transportation agencies conventionally rely on infrastructure-mounted sensors, but the cost of installing and retaining these sensors is high. Most of these infrastructure-mounted sensors are deployed on major freeways and in critical urban areas, and this leads to less coverage on highways and arterials. Also, in terms of geographical scalability, they need to be deployed in large numbers to be able to control the traffic situation in a given area. Considering all the limitations of fixed local sensors, it is essential to devise new data-streaming sources to augment the sensors.

The emergence of probe vehicle technology, which has grown over the past few years, has caused a remarkable change in traffic data collection, processing, analyses, and utilization. Being able to access a huge volume of historical and real-time traffic data without any of the cost of installation, configuration, and maintenance of infrastructure-mounted sensors interests many agencies that want to utilize a single, uniform data source for monitoring traffic conditions across most routes in the U.S. Traffic information is collected from millions of cell phones, vans, trucks, connected cars, commercial fleets, delivery vehicles and taxis, and other global position system (GPS)-enabled vehicles. Presently, several probe-data vendors, such as INRIX, HERE, TomTom, NAVTEQ, TrafficCast, etc., provide broad and high quality real-time and historical traffic data around the world.

INRIX provides speed, travel time, incidents, and quality data updates along each mile-long travel segment at a frequency of once every minute. The resulting stream for traffic message channels (TMCs) comprises approximately 9–10 GB/month, or more than 100 GB/year, and for XD segments is approximately 45 GB/month, or more than 545 GB/year for the entire Nebraska roadway system. With the addition of new higher spatial coverage and resolution, the size of input streams is expected to increase [1].

1.2 Vehicle Probe Data from INRIX

In this study, we utilized the historical and real-time traffic data collected through the INRIX TMC monitoring platform. Real-time traffic data, including speeds and travel times, as well as location information, were provided by INRIX, which is currently regarded as the largest crowd-sourced traffic dataset. With the help of today's technologies, including connected vehicles and smartphones, INRIX leverages the vast amount of historical and real-time data that can be analyzed and investigated to improve transportation networks' performance. INRIX's historical traffic flow data is a spatial and temporal database of average speeds for major roadways and arterials across all 50 states. These speeds are determined by algorithms that evaluate multiple years' worth of data collected using INRIX's patented Smart Dust Network system, which reports speed values on roads across the country. The speed data are then processed across several different temporal resolutions and reported on a customer-configurable basis for each temporal resolution.

1.2.1 INRIX Data Sources

INRIX derives historical flow data using the following:

- Traffic sensors – Sensors put in place by local DOTs or private sector companies, from which traffic speed is either reported or can be inferred. The sensors utilize one of several types of technology:
  - Induction loop sensors imbedded in the roadway,
  - Radar sensors, and/or
  - Toll tag readers along stretches of roadway
- Probe vehicles – The INRIX network includes hundreds of thousands of probe vehicles—trucks, taxis, buses, and passenger cars with onboard GPS devices and transmitting capability—to relay speed and location back to a main location. INRIX has agreements with several fleets to obtain the speed and location data anonymously.
- INRIX Smart Dust Network – This network works by combining real-time GPS probe data from more than 650,000 commercial vehicles across the U.S. that travel on a specific segment of road during a particular time window, physical sensor information, and other real-time traffic flow information with hundreds of market-specific criteria that affect traffic—such as construction and road closures, real-time incidents, sporting and entertainment events, weather forecasts, and school schedules. This component gathers all input points, weights them appropriately based on input quality and latency, and calculates the speed occurring on that road segment to a measured degree of accuracy.

1.2.2 INRIX Data Format

All the INRIX historical traffic flow data for the state of Nebraska is delivered in CSV (comma separated value) format. Data provided by INRIX [2] contains the following information (refer to Figure 1.1):

- TMC ID – the basic spatial unit used by INRIX to report the traffic flow data; INRIX uses a 9-digit TMC ID to define a unique segment.
- Time segment – a 19-digit time format used by INRIX to define the year:month:day: hours:minutes:seconds (e.g., 2014-09-30 23:59:33 for September 30, 2014 at the 23rd hour, 59th minute, and 33rd second) for each TMC.
- Speed – representing the average speed for a given TMC code, calculated from live data from the most current time slice.
- Referenced speed - an uncongested “free-flow” speed determined for each TMC segment using the INRIX traffic archive.
- Average speed – the historical average mean speed for the reporting segment for that time of day and day of the week in miles per hour.
- Travel time – reported by INRIX based on an aggregation of data provided by GPS probes.
- Confidence – an attribute reported by INRIX having three levels: 10, 20, and 30. A

```
118+04749,2016-09-01 00:00:22,69.0,66.0,67.0,0.03,30.0,96.0
118-08667,2016-09-01 00:00:22,57.0,57.0,57.0,8.58,20.0,0.0
118N08667,2016-09-01 00:00:22,12.0,12.0,20.0,0.03,20.0,0.0
118+13461,2016-09-01 00:00:22,64.0,64.0,62.0,4.85,20.0,0.0
118-11314,2016-09-01 00:00:22,61.0,61.0,62.0,1.8,20.0,0.0
118-08816,2016-09-01 00:00:22,60.0,60.0,60.0,14.45,20.0,0.0
118-08813,2016-09-01 00:00:22,59.0,59.0,60.0,2.51,20.0,0.0
118P10037,2016-09-01 00:00:22,59.0,59.0,58.0,0.01,20.0,0.0
118+07616,2016-09-01 00:00:22,64.0,64.0,61.0,5.62,20.0,0.0
118-11309,2016-09-01 00:00:22,60.0,60.0,60.0,4.93,20.0,0.0
118+08795,2016-09-01 00:00:22,64.0,64.0,64.0,29.0,20.0,0.0
118P11076,2016-09-01 00:00:22,62.0,62.0,60.0,0.09,20.0,0.0
118-07590,2016-09-01 00:00:22,34.0,34.0,40.0,3.37,20.0,0.0
118+10577,2016-09-01 00:00:22,37.0,60.0,61.0,17.98,30.0,0.0
```

Figure 1.1 An instant of Nebraska INRIX data confidence of 30 indicates that enough base data were available to estimate traffic conditions in real time, rather than using either historical speed based on time of day and day of week (indicated by confidence of 20) or free-flow speed for the road segment (indicated by a confidence of 10).

- C_value – the confidence value (range 0–100), designed to help agencies determine whether the INRIX value meets their criteria for real-time data.

1.3 Performance Measures

Transportation system reliability is defined in various ways, such as travel time reliability, connectivity reliability, and capacity reliability. The focus of this study was on travel time reliability, which is one of the key performance measures used by a majority of transportation agencies and state DOTs. Section 2.3 contains a summary of previous studies that were conducted on different kinds of probes and sensors as well as the accuracy and reliability of probe-sourced data using several measures such as congestion level percentage, travel time index, planning time index, buffer time index (BTI), user delay cost, average travel time, volume, space mean speed, density, average speed bias, absolute average speed error, absolute average travel time error, travel time bias, lane-miles congested, vehicle miles traveled, congested hour, latency, etc. Additionally, in section 4.2.4 congested hour, buffer time, and reliability curves are presented as three main measures for evaluating the performance of INRIX versus sensors data.

1.4 Conclusion

This report is organized as follows. A literature review summarizing previous related studies is provided in Chapter 2. Chapter 3 presents the how different criteria were used to select the 16 sites out of 65 ATRs in Nebraska. In Chapter 4 the experiments and results are explained in detail, the evaluation of reliability and accuracy of real-time INRIX data using different performance measures for selected ATRs is discussed, and insight is given about the observed results. In addition, the chapter includes a detailed analysis of some of the performance measures, such as congested hour, buffer time, and reliability curves, and a discussion about INRIX drawbacks such as speed bias and device penetration. Next, in Chapter 5, performance monitoring and historical trend analysis using the top 10 most congested roadways are discussed, and the number of hours of congestion in different metros, speed performance, and travel time reliability are identified for I-80 from 2013 through 2016. The report concludes with the findings of this study and a discussion of future recommendations in Chapter 6.

2. Literature Review

2.1 Introduction

This chapter provides a review of previous studies conducted on probe data, sensor technologies, and all performance measures using probe-sourced data.

2.2 Review of Existing Opportunities for and Challenges of Using INRIX Data

As demand for comprehensive traffic monitoring grows from both travelers and transportation agencies, a new technology that would reduce both installation and maintenance costs is needed for collecting accurate and real-time traffic details. Probe-based methods of measuring travel time and speed data can easily scale across large networks without the need for deploying any additional infrastructure [3].

The objective of this study was to evaluate the reliability and accuracy of probe data streams against fixed, infrastructure-mounted sensor data. This report, based on a critical evaluation of the INRIX stream, will highlight key considerations for incorporating probe data into traffic operations, planning, and management activities. The accuracy of the data stream was evaluated under different factors such as: INRIX coverage on freeways and non-freeways and during peak and non-peak hours; speed bias between INRIX TMC segments and PVR (per-vehicle record) infrastructure sensors; incident management; and performance measures such as congested hour, BTI, and reliability curves.

Although many studies comparing the accuracy and reliability of probe-sourced data against local sensor data such as radar sensor data, loop detector data, etc., have been conducted [4], [5], [6], [7], [8], [9], [10], Kim and Coifman [7] showed that INRIX speeds tend to lag behind loop detector measurements by almost 6 min. Although INRIX reports two measures of confidence, these confidence measures do not appear to reflect the latency or the occurrence of repeated INRIX reported speeds. Kim and Coifman used two months of concurrent data against the concurrent loop detector data to evaluate INRIX performance on 14 mi of I-71, including both recurrent and non-recurrent events. To calculate the amount of latency, they used a correlation coefficient with several months of continuous data from concurrent detectors while shifting the time-series loop detector with 10 sec steps [7].

The Federal Highway Administration (FHWA) conducted a survey to gather information on: (1) products and services offered by private sector data providers and (2) public sector agency uses of the private sector data products and services. It found that agencies are using a range of data sources including GPS data from fleet vehicles, commercial devices, cell phone applications, fixed sensors installed and maintained by other agencies, fixed sensors installed and maintained by data providers, and cell phone locations. Most providers did not disclose specific quality evaluation results or quality assurance algorithms. INRIX explicitly stated its capability of meeting an availability level of more than 99.9% and an accuracy of greater than 95% [8].

Nanthawichit et al. [9] proposed a method for treating probe vehicle data together with fixed detector data to estimate the traffic state variables of traffic volume, space mean speed, and density. The method uses a macroscopic model along with the Kalman filtering technique and was verified with several sets of hypothetical traffic data. They suggested the possibility of using estimated/predicted states to estimate/predict travel time. Coifman [5] has investigated various means of measuring link travel times on freeways. He used basic traffic flow theory to estimate link travel time using point detector data without requiring any new hardware. Sadrsadat and Young [10] worked on the Vehicle Probe Project (VPP) to determine the probability of real-time data as a function of hourly volume. They compared the VPP data against travel time collected using Bluetooth™ traffic monitoring equipment. The VPP provides an indication of real-time data by a confidence score attribute equal to 30, which is provided by INRIX. Their study confirmed the availability of real-time data with increasing traffic volume as measured by the percentage of 30 confidence scores. Feng et al. [4] investigated the analytical relationships between travel time prediction–estimation accuracy and sensor spacing, by means of two basic travel time prediction–estimation algorithms, and they also probed vehicle penetration rate. Their findings provide support for detector placement and probe vehicle deployment, especially along a freeway corridor with existing detectors. Online estimation and prediction of travel time using induction loop detectors were evaluated against observed travel time. Lindveld et al. [6] found reasonably accurate (10 to 15% root mean square error proportions) across different sites for uncongested to lightly congested traffic conditions. They used various travel time estimators, but only speed-based travel time estimators could be tested under congested conditions.

The Florida Department of Transportation (FDOT) used several metrics, such as absolute average speed error, average speed bias, absolute average travel time error, and travel time bias, to determine the accuracy of the vendors' (NAVTEQ, TrafficCast, and INRIX) system data. Overall, the data looked consistent with the ground truth and the license plate reader data, and no significant differences in data accuracy among the three vendors were observed [11]. Adu-Gyamfi et al. [12] explored the reliability of probe data for congestion detection and overall performance assessment using an adaptive, data-driven, multiscale data decomposition algorithm called the Empirical Mode Decomposition. The cost of deploying large-scale control strategies for traffic networks has increased the need for more reliable real-time traffic condition prediction. Liu et al. [13] discussed two approaches: dynamic mode decomposition and spatiotemporal pattern networks. Their results show that data-driven approaches have effectively detected changes in traffic system dynamics during different times of the day.

The FDOT's [14] technical memorandum summarizes the various data available for analyzing bottlenecks and congestion on Florida's Strategic Intermodal System. This technical memorandum also makes recommendations concerning the applicability of using existing FDOT data versus the vehicle probe data from INRIX. Rick and Ryan [15] discussed how INRIX launched the world's first crowd-sourced traffic network with sensors in fleet vehicles and mentioned how the INRIX XD™ gives greater traffic detail on any map and a traffic platform for planning, analysis, and operation of road networks. Matsumoto et al. [16], using probe data for CO2 emission reduction, defined three services (traffic flow analysis, improvement of the signal control performance, and priority control of bypass) that enhance traffic flow control. They confirmed detection of a bottleneck without depending on deployment rate of the in-vehicle unit by using probe data statistically in traffic flow analysis.

Different techniques (data assimilation, Newtonian relaxation) to incorporate probe data into macroscopic traffic flow models have been used to solve the optimization problem in urban areas, and they have confirmed the possibility of decreasing probe data for congested traffic with negligible degradation on the quality of traffic status estimation [17]. To reduce CO_2 emissions using intelligent traffic control requires many detectors and high installation costs. Nagashima et al. [18] used probe data collected by vehicles through GPS or other devices and a signal control system that calculates consecutive spatial traffic information (spatial data) such as queue length. They showed that it is possible to reduce the number of detectors [18]. Haghani et al. [19]

described a new validation scheme for comparing travel time data from two independent data sources with an emphasis on arterial applications. In addition, a context-dependent-based travel time fusion framework was developed to integrate data from INRIX and BT datasets to improve data quality. To minimize the impact of random errors that can occur with INRIX data, two new techniques, confidence value and smoothing, have been developed by a coalition of the University of Maryland and INRIX.. When used together, these techniques reduce both the frequency and severity of the sudden changes that have been observed [20]. Kobayashi et al. [21] suggested using probe data to collect spatial traffic information toward CO_2 emission reduction and verified the possibility of detecting bottleneck intersections based on traffic flow analysis utilizing infrared beacon probe data collected from the real field.

2.3 Review of Sensor Technologies

To evaluate the reliability and accuracy of a probe data stream against fixed infrastructure-mounted sensor data, it is important to understand the process for both data collection and data processing. The collection of real-time quality data depends on the reliability and accuracy of the sensor technology used. In this section, we focus on the characteristics of different types of sensors used for traffic operations. We differentiate between point-based sensors, which collect the traffic information at a single point on the roadway, and section type sensors, which provide the traffic characteristics over a section of roadway. The strengths and limitations of different sensor technologies are compared, and they can be divided into three categories: roadway based, probe based, and driver based, as shown in Figure 2.1.

Roadway-based sensors can be considered a part of the roadway infrastructure system. This technology generally involves the use of inductive loop detectors (ILDs) and loop emulators. Underwood [22] considered three types of detection means: magnetic sensing (i.e., ILDs and magnetic sensors), range sensing (i.e., microwave, infrared, ultrasonic, and acoustic sensors), and image sensing (i.e., video image processors). Roadway-based sensors are installed at the side of the road or below the road surface. They scan traffic and provide traffic information extracted from passing vehicles.

Probe-based sensors are carried by vehicles to collect traffic details. They generally come in automatic vehicle identification (AVI) systems, used for vehicle positioning and navigation. Compared to roadway-based sensors, probe-based sensors can probe traffic flow variation over space. Traffic flow information is collected only from a portion of vehicles traveling on roads due to the limitation of the current market penetration rate.

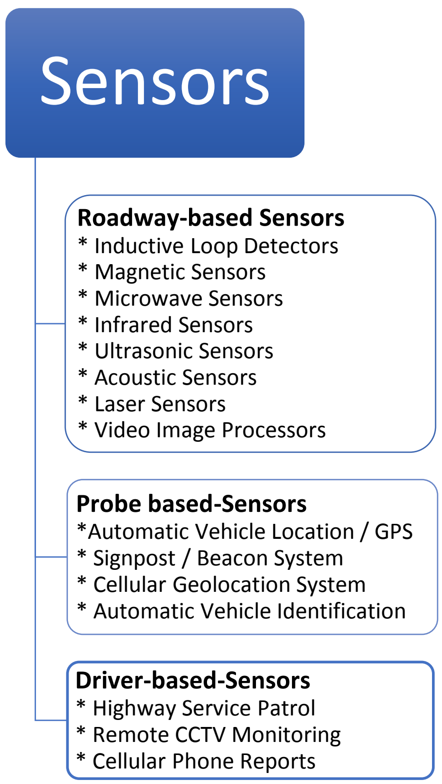


Figure 2.1 Types of sensors

Unlike the other two types of sensors, driver-based sensors provide manual incident-detection reports from drivers and/or service patrol crews, including wireless phone reports (to 911), freeway service patrol units, in-vehicle personal communication systems, and emergency centers. The term sensor used here refers to a device that includes software to detect vehicles and converts real-time data into data that a computer can understand. The software can be installed within the sensor device, in a roadside cabinet, or at the traffic management center. This software includes the processing algorithms, which provide other traffic information such as vehicle speed, travel time, etc. [23].

Roadway-based sensors refer to the use of ILDs and loop emulators. ILDs comprise a large-scale application for traffic surveillance and monitoring, and they help in traffic management and incident detection systems. As loops are limited to one or two short sections, they cannot represent comprehensive roadway situations. Traditionally, they measure spot time-average traffic parameters, such as speed, volume, occupancy, and vehicle classification, so it is difficult to collect the traffic details from urban arterial roads, where spatial variation of traffic flow is complex. Recent developments, such as vehicle identification techniques based on pairs of ILDs [24], [25], [26], video image processors [27], [28], and laser sensors [29], have provided promising results for traffic incident detection. Traffic surveillance and monitoring applications regularly use ILD sensors. Presently, most incident detection algorithms use traffic data derived from ILDs. ILDs are made up of insulated wire bent into a square or rectangular shape, and they are connected to a power source on both sides of the wire. When a vehicle passes over the loop, the oscillation frequency increases and causes the electronic unit to send a pulse to the controller, which registers its presence in its detection zone. With new developments, ILDs can be used to classify vehicles [23] and can also be tuned for different locations and environments, as the sensitivity of an ILD is adjustable. At times, readjustments are needed, as an ILD can go out of tune over time. All the collected traffic details can be used to calculate volume and occupancy. However, ILDs fail to detect long vehicles, as tractor-trailer units are too far above the loop, resulting in detection gaps. Also, when installed in poor pavement or in extreme weather conditions, ILDs are only poorly reliable. Moreover, most cities with mature systems report that 25 to 30% of their sensors are not working properly at any given time [22], and the installation and maintenance of ILDs require lane closures, causing traffic disturbances. Finally, ILDs are less effective for incident detection in low volume conditions.

Magnetic sensors work on the principle that the presence of a vehicle distorts the magnetic field within the earth. Although different in appearance and specific technology, they all operate on principle similar to ILDs. They are often installed in place of loops on bridge decks and in heavily reinforced pavement, where steel adversely affects loop performance [23]. Both types of sensors have their respective applications and tend to complement one another. There are two different types of magnetic sensors used for traffic flow management: active devices (two-axis fluxgate magnetometers), excited by an electrical current in windings around a magnetic core material, and passive devices, which sense perturbations in the earth's magnetic flux produced when a moving vehicle passes over the detection zone. The self-powered vehicle detector, a type of magnetometer developed with FHWA support, is connected to a remotely located controller via a radio link. It has installation and maintenance problems similar to ILDs, as traffic needs to be disrupted to remove and re-insert the sensor. Although they are similar in price, magnetic detectors are easier to install and maintain than are ILDs, and compared to ILDs, magnetic detectors can sustain more stress. However, one of the biggest disadvantages of magnetic detectors is that they cannot measure lane occupancy; although, lane occupancy can be measured using magnetic detectors, they may interfere with each other if two sensors are placed too close together [30].

In terms of working waveforms, microwave sensors can be divided into two types: constant-frequency waveforms and frequency-modulated waveforms. Continuous microwave detectors work under the same principle as Doppler to compute vehicle speed from constant-frequency waveform microwave radar that transmits electromagnetic energy at a constant frequency. This type of microwave sensor is not suitable for incident detection, as vehicle presence cannot be measured with this waveform. Pulse microwave detectors can count vehicles, record speeds, and detect vehicle presence [31]. Microwave sensors provide a cost-effective substitute for ILDs for detecting vehicle presence and for collecting other traffic details. Comparatively, microwave sensors are smaller, lighter in weight, and easier to install than are ILDs and magnetic sensors. They can be mounted overhead or in a side-looking configuration and can detect multi-lane traffic and cover a longer range. Because of their small size, low cost, and low power consumption, they are suitable for traffic surveillance at intersections and on highways. However, newly installed microwave sensors may interfere with other similar microwave-based devices in the vicinity.

Infrared sensors can work in active or passive modes. Active infrared sensors measure a vehicle's presence, speed, volume, occupancy, and classification, but they are vulnerable to weather conditions such as fog, clouds, shadows, mist, rain, and snow. When using these sensors in the active mode, a detection zone is "illuminated" with infrared energy transmitted from laser diodes operating in the near infrared spectrum, then a portion of transmitted energy is reflected to the sensor by vehicles travelling through the detection zone, and finally the reflected energy is converted into electrical signals that are analyzed in real time. Active sensors are not widely used in traffic surveillance, as they are more expensive than passive ones. Passive infrared sensors do not transmit their own energy but, instead, use an energy-sensitive element. They measure the same traffic parameters that active detectors do except for speed; because the extended nature of a vehicle distorts the infrared signature, passive infrared sensors have difficulty measuring the speed. Another type of passive infrared sensor, known as the multi-zone passive infrared sensor, can measure the speed and length of a vehicle. Like with active infrared sensors, the performance of this type of sensor may be adversely affected by fog, snow, and precipitation, which scatter energy and change light [32].

Ultrasonic sensors transmit pressure waves of sound energy at frequencies between 25 and 50 KHz [23],[30] and can be divided into two types: pulse-waveform ultrasonic sensors and constant-frequency ultrasonic sensors. Here, only the pulse waveform sensor is discussed, as most of the time it works with pulse waveforms. Pulse waveforms ultrasonic sensors can measure speed, occupancy, presence, queue length, and the distance to the road surface and the vehicle surface. Ultrasonic sensors are small and can be used as portable units, so they tend to be reliable and durable. However, bad weather can adversely affect their operational performance. If installed above the roadway, vehicle classification can be achieved for most vehicle types. Ultrasonic sensors work using the same technique is used by pulse microwave sensors, converting the received signal into electrical energy.

Acoustic sensors are configured as a two-dimensional dipole array of microphones that are sensitive to acoustic (audio sound) energy. They work in a passive mode: the time delay between the arrival of sound (at the upper and lower microphones) changes with time as the vehicle emits a sound. As soon as vehicle passes through or leaves the detection zone, it is detected by the signal-processing algorithm. The best results are achieved when the data are filtered to a bandwidth of 50–2000 Hz, and the preferred mounting is at a 10 to 30 degree angle from vertical. Acoustic sensors measure vehicle presence, speed, volume, occupancy, and they can count vehicles, but their performance is affected by low temperature, snow, and dense fog [31]. Another type of acoustic sensor can monitor up to 7 lanes of traffic using a fully populated microphone array, adaptive spatial processing, and mounting heights ranging from 20 and 40 feet.

Laser sensors operate in active mode and are used for traffic surveillance. They offer high-speed measurement accuracy and collect all vehicle characteristics such as vehicle presence, classification, speed, volume, and occupancy [29]. Moreover, they can uniquely identify vehicles by measuring the travel times between two locations. Generally, they can be mounted on highways, and each unit can provide coverage for two adjacent lanes. They transmit the information between the sensor and the control and processing computer using a wireless modem.

Video image processors automatically analyze traffic data, which are collected from closed circuit television systems using machine vision techniques. These units consist of one of more video cameras, a microprocessor for digitizing and processing the video imagery, and software for interpreting the image. They use an image-processing algorithm to calculate traffic flow information. These systems fall into three classes: tripline, closed-loop tracking, and data-association tracking. With tripline, the user can define the limited number of detection zones. With closed-loop tracking, vehicle detection is allowed along larger roadway sections, which provides additional traffic flow information such as lane-to-lane vehicle movements. Tracking a specific vehicle or group of vehicles as it passes through the field of view of the camera is possible using data-association tracking systems [27].

Probe-based sensors, also referred to as vehicle-mounted sensors, have the capability of transmitting real-time individual probe data. The sensors measure the point data, point-to-point data, and/or section data and then send these measurements to the traffic management center or traffic operations center. The sensors move within the traffic stream and report an individual vehicle’s movement parameters, i.e., position and velocity with a time tag, with a pre-selected frequency or as they pass reader locations. Compared to roadway-based sensors, they can sense the spatial variation of traffic flow over a wide area. If there are more probe vehicles equipped with sensors in a traffic network, traffic stream conditions can be determined temporally and spatially at the finest level and the collected information can better reflect actual traffic conditions. With the latest probe-based sensor technologies, including automatic vehicle location/global positioning systems, AVI, Signpost/beacon systems, and cellular locating systems, these sensors are highly recommended for incident detection.

Automatic vehicle location systems help to determine the position/location of a vehicle (typically using long-range communications) at a particular time. They use GPS, a satellite-based radio positioning, and a time transfer system. With a horizontal positioning accuracy of 5 meters 95% of time, they enhance the reliability of real-time traffic information collection. As a GPS signal is transmitted via high-frequency microwave, it cannot handle obstructions. Therefore, these systems may suffer from signal blockage in tunnels or under bridges. With the latest developments, other positioning techniques, such as dead reckoning, have been incorporated within or combined with receivers to improve reliability.

Signposts/beacons can be mounted at the sides of roadway or on existing cellular base stations. These can be infrared, microwave, or radio frequency devices, and they can transmit and receive the data from vehicles equipped with transceivers. Signposts/beacons can be either self-positioning, by which a tag in the vehicle picks up a signal from the beacon, or remote positioning, by which the beacon senses a tag on the vehicle. The devices consist of antennas, transmitter electronics, and receiver electronics. With applications for traffic surveillance and parking management, radio frequency beacon systems are becoming more popular. Petty et al. [33] explored an incident detection algorithm using probe vehicles equipped with radio transponders and discussed the feasibility, infrastructure requirements, and performance of radio frequency beacon systems.

Intelligent transportation system applications of cellular geolocation technology are currently being studied by many researchers. The main aim of this technology is to provide innovative services related to different modes of transport and to make the use of transport networks safer, more coordinated, and smarter. To determine locations, pattern recognitions using radio frequency signals are transmitted from a cellular phone. After identifying a signature based on the radio frequency pattern, the signature is then compared with a database of previously identified radio frequency signatures and their corresponding geographic locations. Finally, by matching the signature patterns, the caller's location is identified. The data stored in the cellular location system include: the mobile identification number of each call, the longitude/ latitude of the call location, instantaneous speed, the current compass heading of the call's mobile device, and a time stamp. This sensor technology used for traffic surveillance has several advantages, as it uses existing infrastructure and requires no alteration to the base station or subscriber handset, therefore significantly reducing the cost of establishing service.

Automatic vehicle identification systems have two main components: an in-vehicle unit (transponder/reader) and a wireless communications link. These systems help to identify vehicles at specific location at a specific time. Most AVI systems transmit information through microwave, infrared, or radio frequency. Under good conditions, the reported accuracy of an AVI system is usually in the 99.5% to 99.9% range. However, accuracy may be reduced by adverse weather conditions and interference from other radiation sources. AVI technology is applied principally for electronic toll collection, electronic congestion pricing, and fleet control.

Presently, most incident detection algorithms use traffic data derived from loop detectors. When a vehicle passes over the loop, the oscillation frequency increases, which causes the electronic unit to send a pulse to the controller and register its presence in its detection zone. With new developments, loop detectors can be used to classify vehicles. In this study, PVR sensors were considered the benchmark for evaluating the reliability of INRIX data. Hence, it was necessary to evaluate the performance of PVR sensors with another reliable source of data. Therefore, we utilized trailers to collect a few samples of Wavetronix sensor data to check the performance of PVR-reported data. Wavetronix sensors use radar technologies to collect traffic operations data. Each sensor unit consists of a Doppler radar, a wireless modem, a solar panel, and onboard processors for real-time processing of traffic information such as speed, volume, occupancy, etc.

2.4 Review of Performance Measures Used for INRIX Data

Numerous studies, using various methods, have been conducted on the evaluation of probe vehicle technology performance. An overview of reviewed freeway and non-freeway system performance measures is provided in Table 2.2.

Table 2.1 Overview of literature review on performance measures

Source of Probe Data Used	Reference	Performance Measures	Comments: Positive	Comments: Negative
(not mentioned)	Chumchoke, N. et al. [9]	Traffic volume, space mean speed, density	1. Proposed method can treat both conventional fixed-detector data and probe-vehicle data in a unified manner, regardless of the observation conditions. 2. Estimation method that uses both fixed-detector and probe data provides the smallest errors. 3. Errors from both travel-time estimation and prediction are small, having a MARE below 0.04.	1. Findings were validated only for a single freeway section. 2. This study assumed that the probe data could be obtained perfectly and the effect of the biased data due to individual willingness of probe drivers was neglected.
(NAVTEQ, TrafficCast, and INRIX)	Technical Memorandum. (FDOT) [11]	Absolute average speed error, average speed bias, absolute average travel time error, travel time bias	1. NAVTEQ, TrafficCast, and INRIX are all generally consistent with the ground truth data. 2. INRIX data on Route 1 appeared to have a slight advantage in accuracy compared to other probe datasets.	1. TMC segments in urban areas with traffic signals experienced a larger variability in the results.
(not mentioned)	Pu, W. (2011). [35]	95^{th} percentile travel time, standard deviation, coefficient of variation, percent variation, skew statistic buffer index (w.r.t. average), buffer index (w.r.t. median), PTI, frequency of congestion, failure rate (w.r.t. average), failure rate (w.r.t. median), travel time index	1. The coefficient of variation is a good proxy for a number of reliability measures, including planning time index, median-based buffer index, and skew statistic. 2. Defining the buffer index and failure rate on the basis of the median, rather than the average, is recommended to avoid underestimating unreliability, especially for heavily right-skewed travel time distributions. 3. The mathematical relationship between the reliability measures revealed in the studycould easily be used to predict one measure on the basis of another, or estimate their relative magnitudes.	1. Standard deviation, is not recommended as a proxy because its magnitude relative to other measures is not stable. 2. Travel time reliability generally deteriorates as traffic congestion increases. 3. A notable limitation of this study was posed by the assumption of lognormal distributed travel times. In the real world, travel time distribution can have non-lognormal distributions, for example, bimodal, Weibull.
(not mentioned)	Lomax, T. et al. (2003) [36]	Travel time window, percent variation, variability index, displaying variation, buffer time, BTI, PTI, travel rate envelope, on-time arrival, misery index	Travel time reliability was described as a measure of the amount of congestion transportation system users experience at a given time.	
(INRIX)	(MnDOT Report) (Turner and Qu, 2013) [37]	Annual hours of delay per mile, hours of target delay per mile, TTI, PTI, top N congested segments	1. INRIX is immediately available at relatively low cost for the entire arterial street network. 2. Mobility performance measures for arterials should be travel speed-based measures that compare peak traffic speeds to speeds during light traffic, recognizing that the light traffic speed is not a target value but simply a reference point for performance	-----

Source of Probe Data Used / Reference	Performance Measures	Comments: Positive	Comments: Negative
		measures. Thus, INRIX is a reliable data source in this case. 3. PTI is the recommended reliability measure.	
(INRIX) *2012 Indiana Mobility Report* (Remias et al., 2013) and 2013-2014 *Indiana Mobility Report* (Day et al., 2014) [38]	Congestion hours, distance-weighted congestion hours, congestion index, speed profile, speed deficit, travel time deficit, congestion cost, top N bottlenecks	Focused mainly on freeway measures. Congestion hours were reported as total hours across all segments when average 15-minute speed fell below 45 mph (threshold).	
(INRIX) *2013 Maryland State Highway Mobility Report* (Mahapatra et al., 2013) [39]	Number of intersections and mile of roadway (direction-wise) for LOS categories (D or better, E, F), list of intersections and road segments at LOS E and F, top N bottlenecks for freeways	Focused mainly on freeway measures and also on an arterial route. It provided several pieces of information, such as speed limit, number of signals, number of lanes in each direction, average daily traffic, percentage of trucks, corridor length, etc. for each corridor and used INRIX data for bottlenecks and freeway measures.	
(not mentioned) MoDOT Tracker (MoDOT, 2013) [40]	Average travel time per 10 miles, additional travel time needed for on-time arrival (80% of time), annual congestion costs	Used RITIS and travel time data using wireless technology. Covered two metro areas and used mobility map, which showed high, medium and low levels in different colors.	
(INRIX, HERE, TomTom, and NPMRDS) RITIS VPP Suite (UMD CATT Lab, n.d.) [41]	TTI, BI, and PTI, user delays, user delay costs, bottlenecks	It hosted HERE, INRIX, TomTom and NPMRDS data and used INRIX historical average speed to calculate buffer index.	
(NPMRDS) (UCR) (FHWA, 2015b) [42]	Congested hours, PTI, TTI	Focused completely on freeways using HPMS volume data and 15-minute aggregated NPMRDS data by day of week and month.	
(INRIX) (UMR) (Schrank et al., 2012) (*Urban Mobility Scorecard* in 2015) [43], [44]	Travel speed, travel delay, annual person delay, annual delay per auto commuter, total peak period travel time, TTI, PTI, CSI, RCI, number of rush hours, percent of daily and peak travel in congested	1. Improvements in the INRIX traffic speed data. 2. Given availability and high quality of INRIX, they could track congestion problems for the midday, overnight and weekend time periods.	-----

Source of Probe Data Used / Reference	Performance Measures	Comments: Positive	Comments: Negative
	conditions, percent of congested travel		
(not mentioned) WSDOT *Gray Notebook* (WSDOT, 2014) and *Corridor Capacity Summary* (WSDOT, 2013) [45], [46]	Lane-miles congested, total and cost of delay, TTI	Defined congestion as speeds below 70% of the posted speed limit. Calculated delays on the basis of maximum throughput speeds (85% of posted speed limit). TTI was calculated using reference speed rather than free flow speed. It identified daily congested segments on individual corridors with segment length and hours. Several more measures like congested miles, etc. were calculated. Reports used loop detectors, automated license plate readers, Bluetooth, Wavetronix, vehicle detection, and private sector data.	
(INRIX) VDOT Pilot Study: *2010* [47]	Delay per vehicle, total delay, TTI, Buffer index, PTI, on-time arrival, congested travel, misery index	Used INRIX and focused on freeways and arterials. Percentage of on-time arrival calculated as proportion of days when peak period travel time was less than 1.1 times mean peak period travel time. It also defined Congested Travel as the product of corridor length and volume of peak period. Percentage of congested travel and misery index were also calculated.	
(not mentioned) FDOT *Performance Report* (FDOT, 2013b) [48]	Highway travel time reliability, vehicle hours of delay, percent of miles severely congested, VMT. Mobility performance measures grouped into quantity, quality, accessibility, and utilization.	Highway travel time reliability defined as percentage of travel greater than 45 mph on freeways. Percentage of miles severely congested was defined as percentage of roadway miles operating at LOS F during peak hours.	
(INRIX) *INRIX Traffic Scorecard* (INRIX, 2015) [49]	INRIX TTI, wasted time in congestion	Used INRIX speed data. It defined INRIX TTI as percentage increase in average travel time of a commute above free flow conditions. Used average delay of typical commute trip, length of typical commute trip, and number of trips a commuter takes monthly or annually to calculate wasted time in congestion.	
(TomTom) *TomTom Traffic Index* (TomTom, 2016) [50]	Congestion level percentage	Used TomTom speed data to calculate the extra travel time a driver experiences compared to an uncongested situation.	
(INRIX) Kim, S., Coifman, B. (2014) [7]	Latency, occurrence of repeated INRIX reported speed	1. Similar patterns of congestion, queue growth, and so forth between INRIX and ground-truth data.	1. INRIX speeds tend to lag the loop detector measurements by almost 6 min. 2. Most of the time, INRIX reported speed is identical to the previous sample and repeating for average 3 to 5 minutes. 3. INRIX confidence measures do not appear to reflect the latency or the occurrence of repeated INRIX reported speeds.
(INRIX)	Travel time, average speed	1. Paired-t method can be effectively applied for verification of probe data.	1. Paired-t method has a binary outcome which says probe data for

Source of Probe Data Used / Reference	Performance Measures	Comments	
		Positive	Negative
Aliari, Y., Haghani, A. (2012) [51]			specified speed bin is good or not. No additional info is provided. 2. Since the method uses average errors over all time, high variance outliers can invalidate the whole segment.
(INRIX, TomTom, Google, etc.) Belzowski, B., Ekstrom, A., (2013) [52]	Traffic jams, traffic jams on (surface streets, highways)	1. All probe sources reported traffic jams on highways significantly better than streets. 2. The longer the jam, the better chance probe can accurately report.	1. They experienced some type of operational failure or disruption during their study.
(INRIX) Haghani, A. et al. (2009) [53]	Speed error, speed error bias	1. Speed data provided by INRIX is generally of good quality.	1. Segments with length less than one mile are in-accurate. 2. Different confidence scores 30, 20, and 10 are not significant indicator of INRIX data quality. 3. For speeds below 45 mph, INRIX overestimates the speeds and for speeds over 60 mph, it underestimates the actual speed.
(INRIX, NAVTEQ, and TrafficCast) Lattimer and Glotzbach (2012) [54]	Travel time, Speed bias	-----	1. INRIX speed has a 6 mph bias relative to ground truth on an uncongested freeway.
(INRIX, NAVTEQ, and TrafficCast) Kim et al. (2014) [55]	Travel speed, Speed error	-----	1. Overall average speed errors to be within 10 mph throughout various levels of congestion. 2. Data providers missed a major incident lasting more than 4 hours. 3. INRIX reported speeds 30 mph higher than ground truth data while INRIX classified those speeds with "high confidence" during this major incident.
(INRIX) Adu Gyamfi Y. et al. (2017) [56]	Speed bias, latency, similarity index	1. Probe data is reliable for monitoring the performance of transportation infrastructure over time. 2. Latency on freeways is less than non-freeways.	1. Various levels of amplitude bias between INRIX and benchmarked data.
(INRIX) Gong, Linfeng, and Wei Fan (2017) [57]	Travel time reliability, PTI, FOC	1. Both FOC and PTI are capable to identify and rank recurrent freeway bottlenecks.	1. Using either FOC or PTI alone may not be possible to identify the intensity of bottlenecks' traffic congestion.
(INRIX) P Sekuła et al. [58]	Hourly traffic volume	1. Probe data is promising for estimating hourly traffic volume using machine learning models.	-----

PTI, Planning time index; BTI, Buffer time index; TTI, Travel time index; LOS, Level of service; MAP-21, Moving Ahead for Progress in the 21st Century Act; RITIS, Regional Integrated Transportation Information System; VPP, Vehicle Probe Project; BI, Buffer index; NPMRDS, National Performance Management Research Dataset; HPMS, Highway Performance Monitoring System; CSI, Commuter stress index; RCI, Roadway Congestion Index; WSDOT, Washington State DOT; VMT, vehicle miles traveled.

Transportation system reliability has been defined in various ways: first, as travel time reliability, which is the probability that trips can be successfully accomplished within a specified timeframe; second, as connectivity reliability, which focuses on trips carried out successfully based on the remaining connectivity between an origin–destination pair; and third, as capacity reliability, which refers to trips that can be completed at a certain level of link capacity [34]. The focus of this study was on travel time reliability, which is one of the key performance measures used by the majority of transportation agencies and state DOTs. More formally, FHWA defines travel time reliability as "the consistency or dependability in travel times, as measured from day-to-day and/or across different times of the day" [59]. Lomax et al. [36] describes travel time reliability as a measure of the amount of congestion users of the transportation system experience at a given time. The 1998 California Transportation Plan explains "reliability" as the inconsistency between the projected travel time, which is based on the scheduled or average travel time, and the real travel time due to the effects of nonrecurring congestion [60].

Travel time reliability in the transportation engineering field is measured in several ways: the 90th or 95th percentile of travel time, the standard deviation, the coefficient of variation, the percentage of variation, the buffer index, the planning time index, the travel time index, etc. FDOT used some metrics, such as absolute average speed error, average speed bias, absolute average travel time error, and travel time bias, to evaluate the accuracy of probe stream data of different vendors (INRIX, TrafficCast, etc.). Altogether, different vendors' data looked consistent with the ground truth and the license plate reader datasets, and there was no considerable difference between them in terms of data accuracy [11].

In a recent study conducted by Venkatanarayana [61], hours of congestion for a segment was considered the total number of hours when the average speed of the segment drops below a predetermined threshold. FHWA conducted a report to calculate congestion and reliability metrics with the National Performance Management Research Data Set. It defined hours of congestion as the amount of time when freeways operate at less than 90% of free-flow freeway speeds [62]. Another measure is the buffer index, which is defined as the extra time a traveler should take into account to arrive on time. Lomax et al. [36] calculated buffer time using the difference between the 95th percentile of travel time and the average travel time for a trip as a measure of the extra time a traveler would need to arrive on time. Similar to Pu [35], this study introduces a modified buffer time index (BTI) that incorporates the median, rather than average, travel time as a new travel time reliability measure. Pu [35] recommended using the median rather than the average travel time for calculating the buffer index, as this avoids trivializing the reliability in travel time, especially for heavily right-skewed travel time distributions.

2.5 Conclusion

This chapter comprised a summary of previous studies that were conducted on various kinds of probes and sensors as well as the accuracy and reliability of probe-sourced data using several measures such as congestion level percentage, travel time index, planning time index, BTI, user delay cost, average travel time, volume, space mean speed, density, average speed bias, absolute average speed error, absolute average travel time error, travel time bias, lane-miles congested, vehicle miles traveled, number of congested hours, latency, etc. In the next chapter, data collection for this study and how some specific locations were selected will be explained in detail.

3. Data Collection

3.1 Introduction

In today's complex global economy, transportation connections enable a business to locate in any region offering the best possible combination of labor, land, tax, and cost—while competing worldwide. All the state DOTs are relying on fixed-mounted sensors to collect traffic information such as travel time, traffic speed, volume, etc. This traffic information can be used by Nebraska Department of Transportation (NDOT) councils to identify which routes are used most and to decide whether to improve that road or provide an alternative if there is an excessive amount of traffic.

Presently, NDOT is maintaining 65 ATRs in different locations. However, the cost of deploying and maintaining these sensors is very high compared to alternatives provided by non-traditional data streaming sources. Probe-data collection is a set of relatively low-cost methods for obtaining travel time and speed data for vehicles traveling on freeways and other transportation routes. NDOT has already procured probe data streams through a third-party vendor, INRIX, to augment traffic data collection and assess the performance of its operations. INRIX is maintaining 4125 traffic management centers to collect the traffic information for major freeways and urban areas.

3.2 Selection of Sites

To evaluate the reliability and accuracy of probe data streams, it is important to identify the location of the ATRs. The research team and the technical advisory committee for the project decided to select 16 specific locations based on the following five criteria:

- Nearest TMC from the ATR mid-point,
- 2014 continuous traffic count data and traffic characteristics from Nebraska Streets and Highways (April 2015) and Automatic Traffic Recorder Data (June 2016),
- Winter segments (given by NDOT),
- Level of confidence available in particular areas, and
- Anomalies found from cumulative distribution function (CDF) distributions.

To improve decision making, we also considered the percentage of heavy truck usage and the interquartile range for each TMC.

The dashboard view of all the ATR locations in Nebraska, along with their reliability curves, nearby TMCs, average annual daily traffic, confidence levels, and minimum distance from ATR mid-point, is shown in Figure 3.1. The 16 sites selected are shown in Figure 3.2.

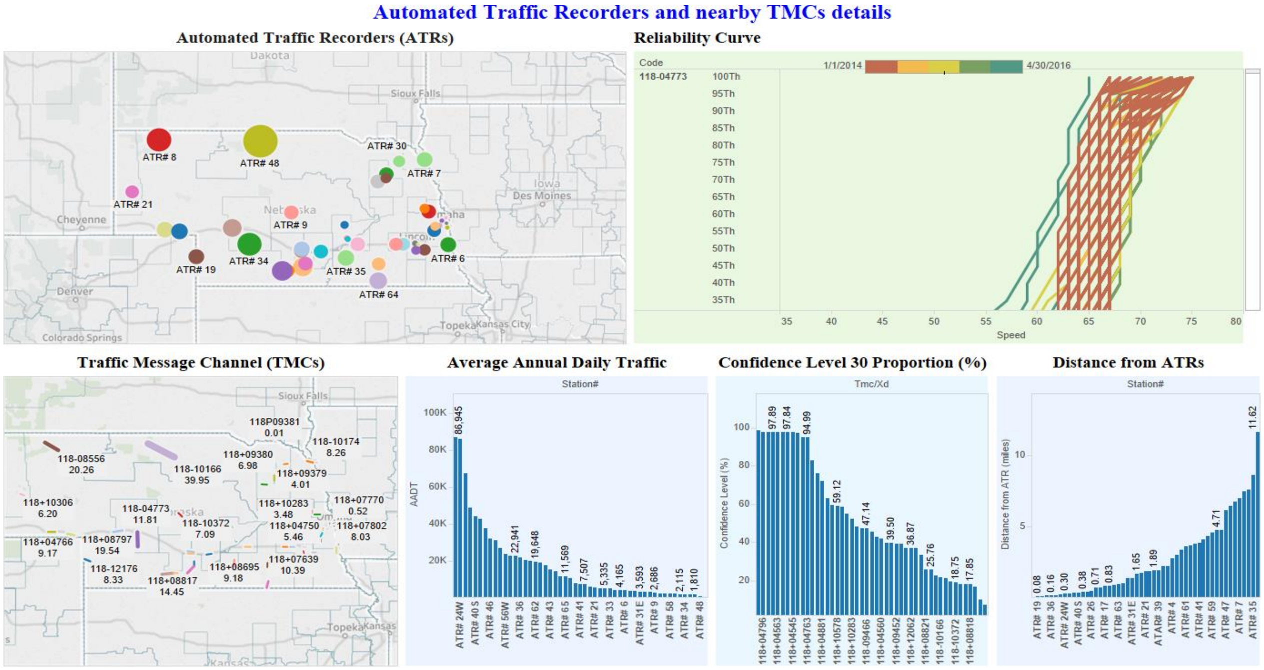


Figure 3.1 Dashboard view of 16 selected locations

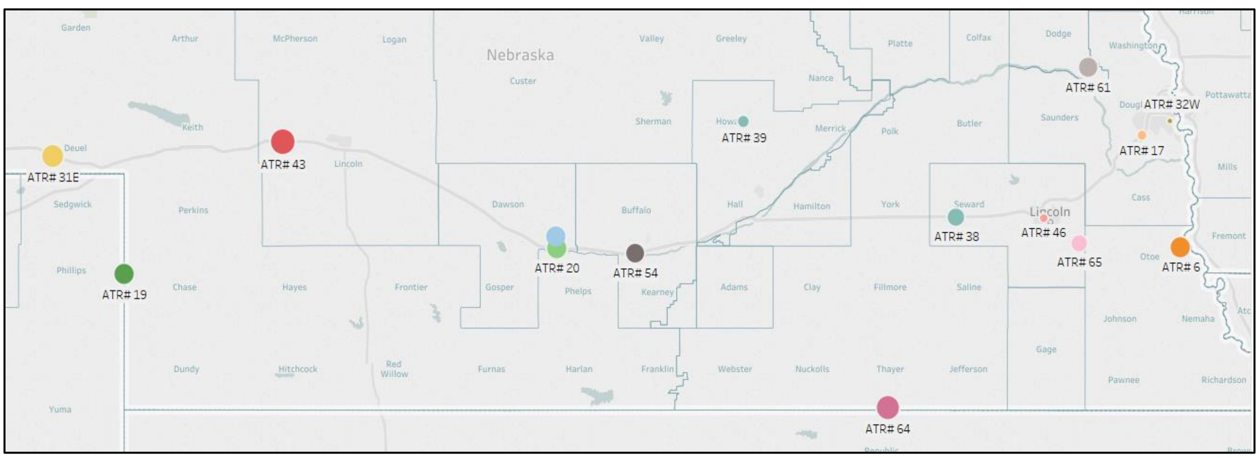


Figure 3.2 Location of 16 selected sites

Raw data files received from the INRIX server were parsed using Hadoop technology and then visualized with tools like Tableau and R programming to aid in choosing the final 16 sites for evaluating the reliability and accuracy of probe data streams against fixed, infrastructure-mounted sensor data. The 16 sites with above criteria selected for this study are shown in Table 3.1.

Table 3.1 Selected sites with different criteria

No.	TMC	Dir	County	Road	% of Confi-dence	AADT	IQR	Heavy Truck	Nearest TMC/XD	Remarks
1	118-12176	EB	Chase	US-6	7.10	570	3	188	118+12177 3096189 3096305	Nearest mid-point ATR#19
2	118-04527	WB	Douglas	I-680	67.08	16094	4	1600	118+04528 48151029 5111124	Nearest mid-point ATR#32
3	118-04559	SB	Lancaster	I-180	40.88	32399	7	837	118+04560 5115670 5115743	Nearest mid-point ATR#46
4	118-04752	WB	Sarpy	I-80	97.76	67773	2	10,075	118+04545 5118286 5118291	AADT ATR#17
5	118+04785	EB	Dawson	I-80	97.9	17917	3	7701	118-04784 5106319 5106309	AADT ATR#20
6	118+04552	EB	Douglas	I-80	98.62	173168	4	----	5111192	ATR#24 E
7	118+04805	EB	Seward	I-80	97.89	27086	3	7918	118-04804 5118482 5118490	Winter segments; near ATR #38
8	118-04787	WB	Buffalo	I-80	97.97	20673	3	----	118+04788 5105936 5105935	Winter segments; near ATR #54
9	118-04765	WB	Deuel	I-80	95.11	7297	2	4426	118+04766 3136954 3136959	High confidence; near ATR #31
10	118-04773	WB	Lincoln	I-80	97.87	15667	2	7195	118+04774 5116674 5116683	High confidence; near ATR #43
11	118-07638	SB	Thayer	US-81	66.68	3812	4	1270	118+07639 5059806 5059878	Middle confidence; near ATR #64
12	118-09466	EB	Dodge	US-30	47.14	5335	3	661	118+07729 5110005 5110018	Low confidence; near ATR #61
13	118-09439	EB	Dawson	US-30	10.08	2646	4	191	118+09438 5109780 5109790	Anomaly variance high; near ATR #2

14	118+07802	NB	Otoe	US-75	39.22	4122	3	630	118-11849 5107356 5107390	Anomaly variance high; near ATR #6
15	118+08702	NB	Howard	US-281	19.85	5434	3	528	118-08701 5114752 5114762	Anomaly variance middle; near ATR #39
16	118-11097	EB	Otoe	NE-2	82.67	11569	0	2872	118+11098 5116156 5116160	Anomaly variance middle; near ATR #65 (suggested by NDOT)

TMC: Traffic message channel; Dir: Direction; AADT: annual average daily traffic; IQR: Interquartile range.

3.3 Checking Performance of PVR against Wavetronix

To consider PVR data as benchmarked, it was necessary to evaluate the performance of PVR sensors using another reliable source of data. Therefore, to check the performance of PVR reported data we utilized trailers (as shown in Figure 3.3) to collect a few samples of Wavetronix sensor data. Wavetronix sensors use radar technology to collect traffic operations data. Each sensor unit consists of a Doppler radar unit, a wireless modem, a solar panel, and onboard processors for real-time processing of traffic information such as speed, volume, occupancy, etc. The date, time, and total number of minutes the data were collected by trailers for each location are shown in Table 3.2. Two locations, 17 and 24 Eastbound, were excluded from further analysis.

Figure 3.3 Wavetronix sensor during data collection

To evaluate the reliability of PVR data, the data were compared with data collected by the trailers (Wavetronix data). As shown in Figure 3.4, we used CDF to illustrate the difference in speed between PVR and Wave-tronix sensors. CDF is the probability that a variable takes a value less than or equal to x. In Figure 3.4, the horizontal axis represents the allowable domain for the given probability function (speed). Because the vertical axis reflects probability, it must fall between 0 and 1. In all images, the probability increases from 0 to 1 from left to right on the horizontal axis. The speeds shown on horizontal axis range from

Table 3.2 Wavetronix data collected with trailer

Sensor	Time	Number of minutes
2	11/22/2016 2:01:17 pm – 11/22/2016 4:03:43 pm	122
6	11/21/2016 4:16:23 pm – 11/21/2016 6:18:39 pm	122
17	11/22/2016 2:10:03 pm – 11/22/2016 4:19:59 pm	130
19	11/21/2016 2:45:37 pm – 11/21/2016 4:45:40 pm	120
20	11/22/2016 5:08:49 pm – 11/22/2016 7:11:35 pm	123
24E	11/21/2016 8:45:49 pm – 11/21/2016 10:47:42 pm	122
31E	11/21/2016 9:55:00 am – 11/21/2016 9:57:06 am 11/21/2016 10:02:24 am – 11/21/2016 10:08:40 am 11/21/2016 10:35:43 am – 11/21/2016 12:50:31 pm	33
32	11/23/2016 11:51:55 am – 11/23/2016 2:24:03 pm	153
38	11/20/2016 7:52:35 pm – 11/20/2016 9:53:29 pm	121
39	11/23/2016 11:20:12 am – 11/23/2016 1:23:11 pm	122
43	11/22/2016 9:29:05 am – 11/22/2016 11:47:28 am	138
46	11/21/2016 9:12:50 am – 11/21/2016 11:16:36 am	124
54	11/22/2016 8:29:29 pm – 11/22/2016 8:46:10 pm 11/22/2016 10:41:57 pm – 11/22/2016 10:59:44 pm 11/22/2016 11:01:16 pm – 11/22/2016 11:59:49 pm 11/23/2016 12:00:03 am – 11/23/2016 1:05:01 am	158
61	11/22/2016 5:59:28 pm – 11/22/2016 8:07:52 pm	128
64	11/20/2016 3:00:20 pm – 11/20/2016 5:02:20 pm 11/20/2016 6:52:01 pm – 11/20/2016 7:55:15 pm	185
65	11/21/2016 12:46:35 pm – 11/21/2016 2:55:42 pm	129

Note: Sensors appearing in red were excluded from further analysis.

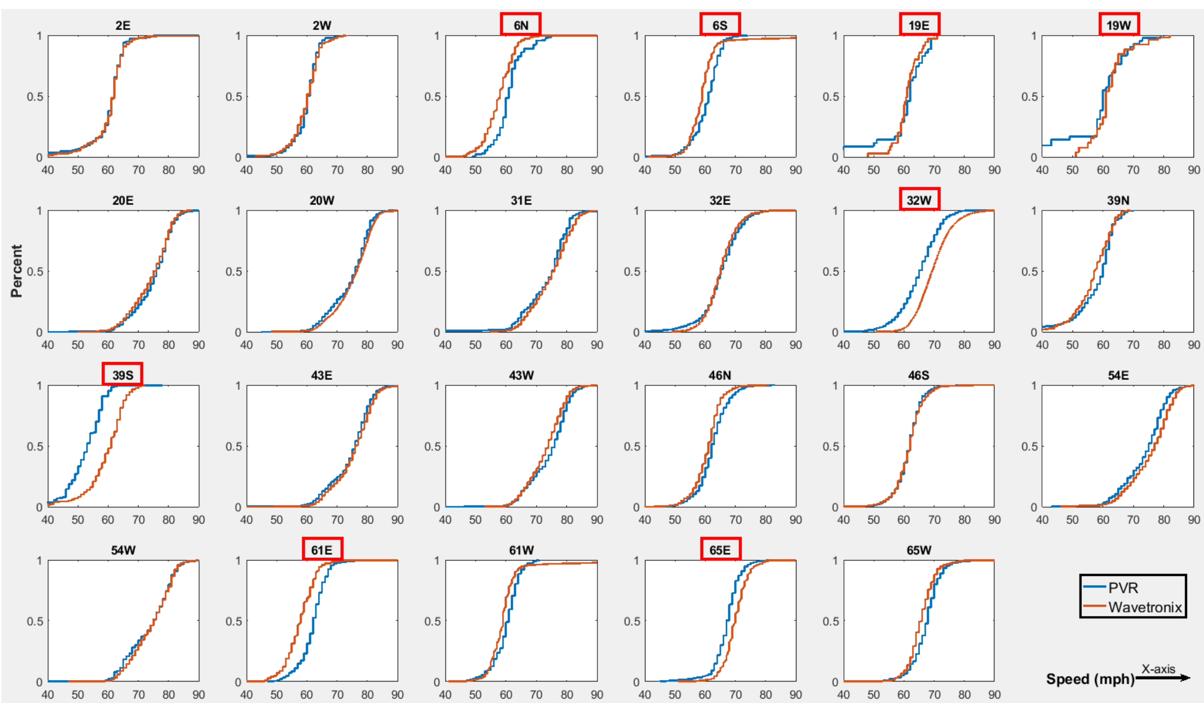


Figure 3.4 Cumulative distribution function of speed for PVR and Wavetronix datasets

40 to 90 mph. We expected that the two CDF lines for the PVR and Wavetronix sensors for each location would nearly overlap each other. However, it is obvious from Figure 3.4 that different traffic speed performance was detected by the two sensors at locations 6N, 6S, 19E, 19W, 32W, 39S, 61E, and 65E. Thus, these locations were excluded from further analysis. The location of the selected ATRs are shown in Figure 3.5 as red asterisks; excluded ATRs are shown as blue triangles.

Figure 3.5 Location of ATRs (red asterisk: selected location), (blue triangle: excluded locations)

3.4 Conclusion

In summary, this chapter provides a brief description of how the 16 sites, out of the 65 ATRs in Nebraska, were selected based on different criteria. For each selected ATR, there are corresponding TMCs, which are maintained by INRIX to collect traffic details on major freeways and urbanized areas. To make better informed decisions, we also considered the number of heavy trucks and the interquartile range for each TMC. Also, we examined the reliability of the PVR data by comparing those data with Wavetronix sensor traffic information collected by roadside trailers. In the next chapter, the reliability and accuracy of real-time INRIX data using different performance measures for selected ATRs is discussed.

4. Evaluation of Reliability and Accuracy of Real-Time INRIX Data

4.1 Introduction

For this study, real-time and historical traffic data, which were collected through two different methods—probe-sourced streamed data and fixed, infrastructure-mounted sensors—were utilized. The probe data stream used in the current study was obtained from INRIX, which aggregates traffic-related information from millions of GPS-enabled vehicles, mobile devices, road sensors, and other sources. The data collected were processed in real time, creating traffic speed information for major freeways, highways, and arterials in the state of Nebraska. The INRIX probe data stream was compared to a benchmarked sensor data source to explain some of the challenges and opportunities associated with using wide-area probe data. The benchmarked dataset used in this work was obtained from PVR sensors, which provided traffic data for each vehicle passing the sensor.

In the remainder of this chapter, INRIX performance will be thoroughly evaluated by various factors including coverage, speed bias, latency, count, congested hour, rank order for congested hour, BTI, rank order for BTI, and reliability curves. The performance measures that will be addressed in this chapter 4 are summarized in Table 4.1.

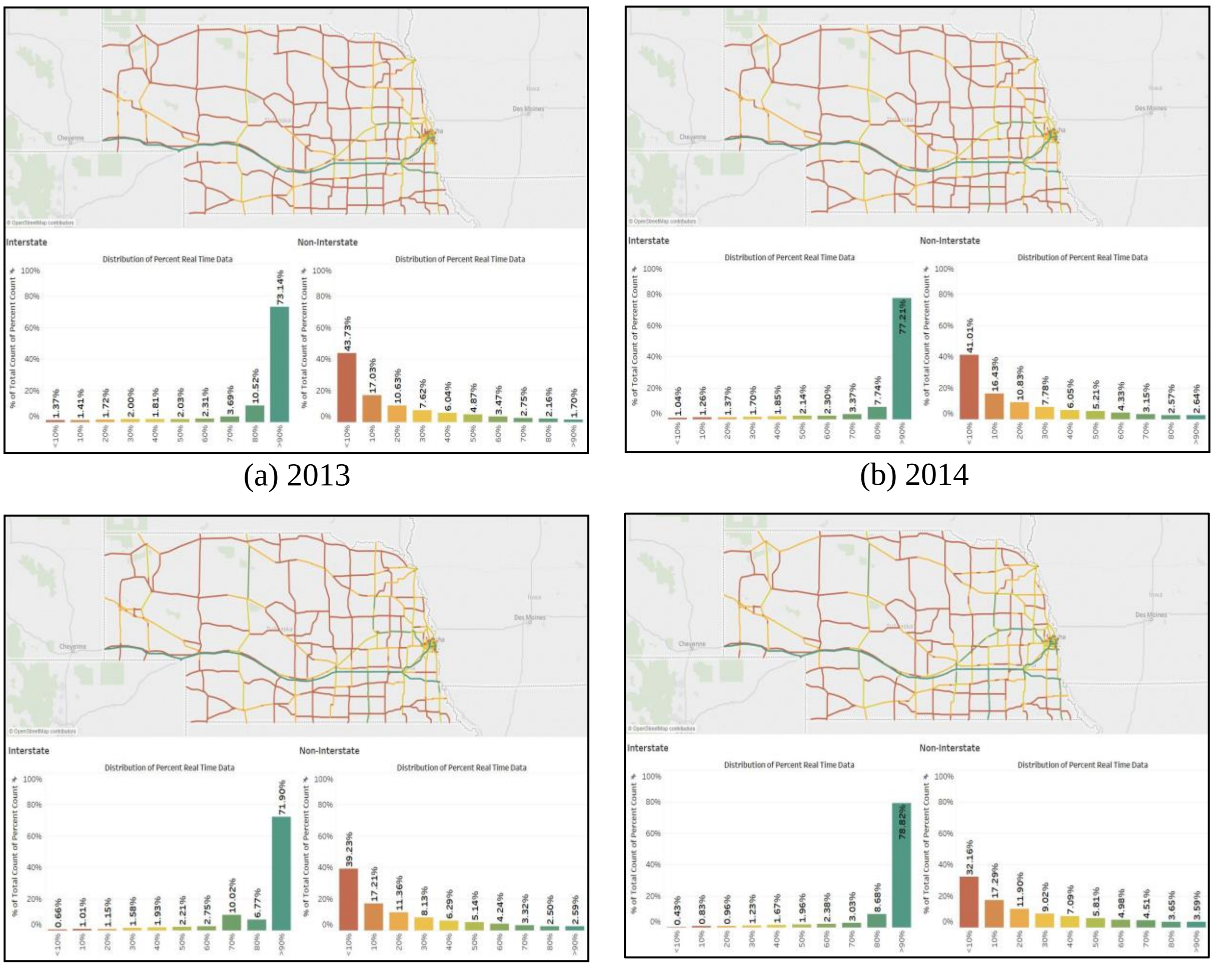
Table 4.2 Overview of performance measures

Performance Measures	Comments
Percentage availability of INRIX	Total percentage of time level 30 data is available for given TMC segment
Speed bias	Difference been speeds reported by INRIX as compared to the Wavetronix speed
Congestion detection latency	A measure of delay between two time series datasets, which is used to measure the difference of start times of a congestion detected by INRIX compared to PVR.
Congestion counts	Number of congestions detected by both INRIX segments and PVR sensors with latencies lower than 20 minutes.
Congested hour	In this study, two scenarios were considered for comparing number of hours of congestion between the INRIX and PVR datasets: • Scenario 1: total number of hours during which speed of each segment was less than 45 mph. • Scenario 2: duration of congestions that were detected by both INRIX segments and PVR sensors with detection latency lower than 20 minutes. The two scenarios were compared for two time periods: single day and three weeks.
Buffer time index	Calculated by subtracting the 85th percentile of TTPM (travel time per mile) from the median of TTPM and then dividing that result by the median TTPM; calculated for 1- and 3-week periods.
Reliability curves	The inverse of speed multiplied by 60 was considered TTPM in minutes.

4.2 Evaluating INRIX using PVR

4.2.1 Percentage Availability of INRIX

The most critical consideration in evaluating probe data is the geographic coverage provided by the vendor. The quality of probe data is heavily dependent on the number of probes on the road network. The more probes on the network, the better the coverage. In Figure 4.1, the yearly coverage for interstate and non-interstate roadways in the state of Nebraska is shown from 2013 through 2016. In 2013 there was 73.14% availability of real-time data from interstate roadways as compared to 43.73% from non-interstate roadways (Figure 4.1a). In 2014, there was an increase in availability of real-time data from interstate roadways with 77.21% and a decrease from non-interstate roadways with 41.01% (Figure 4.1b). The lowest availability of real-time data from interstate roadways during the time period studied (2013–2016) was in 2015 with 71.90% (Figure 4.1c), and the highest was in 2016 with 78.82% (Figure 4.1d). There were a number of roads that had no coverage; however, this may improve with time as the number of probes increases. In regions with limited probe data, vendors derive real-time data from historical traffic data trends. Agencies may rely on this dataset; however, the accuracy should be evaluated. However, in these areas, the agency could augment probe data with infrastructure-mounted sensors.



(a) 2013 (b) 2014

(c) 2015 (d) 2016

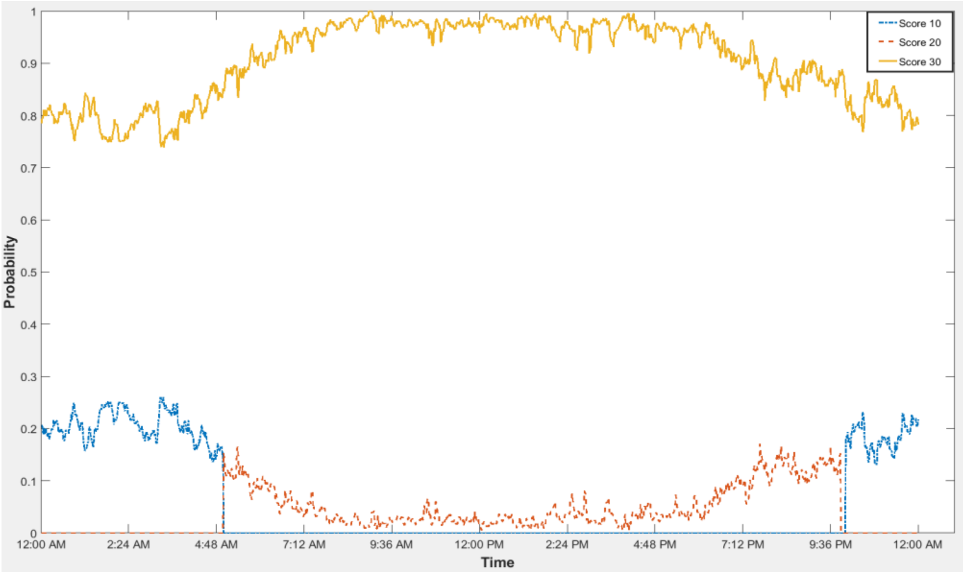
Figure 4.1 Percentage coverage of INRIX in the state of Nebraska

In addition to real-time data, INRIX provides historical data whenever real-time data are not available. The higher the device penetration (i.e., more cell phone probes), the better the data are. For each speed measurement, INRIX reports a measure of confidence, reported as one of three possible values:

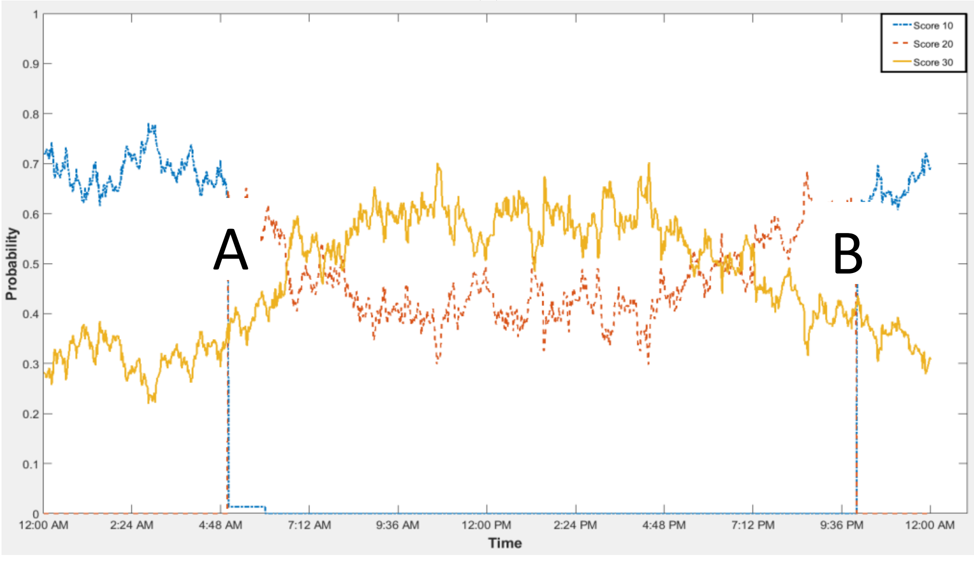
- Score 30: speed estimate for that segment based completely on real-time data (the highest confidence score),

- Score 20: speed estimate based on real-time data across multiple segments and /or based on a combination of expected and real-time data. and
- Score 10: speed estimate based primarily on historic data (the lowest confidence score).

The daily availability of INRIX traffic data is shown in Figure 4.2, reflecting how traffic speed data from interstates and non-interstates are spread over a span of a full day based on confidence scores 10, 20, and 30. As expected, INRIX was able to provide real-time speed data (score 30) most of the day on interstates, whereas on non-interstates, real-time data were provided mostly from around 6 am to 6 pm. For instance, at point A on Figure 4.2b, the blue and red lines (scores 10 and 20, respectively) descend drastically while the yellow line (score 30 = real-time) rises significantly. On the other hand, from midnight to 6 am (before point A) and around 6 pm to midnight (after point B), when there was less device penetration, historical data were used to predict speed and was reported with a confidence score value of 10. Thus, INRIX provides a higher percentage of real-time data on interstates compared to non-interstates and the data are more reliable during the day than at night.



(a)



(b)

Figure 4.2 Daily availability of traffic speed data for selected INRIX segments of (a) interstates and (b) non-interstates in the state of Nebraska

4.2.2 Speed Bias

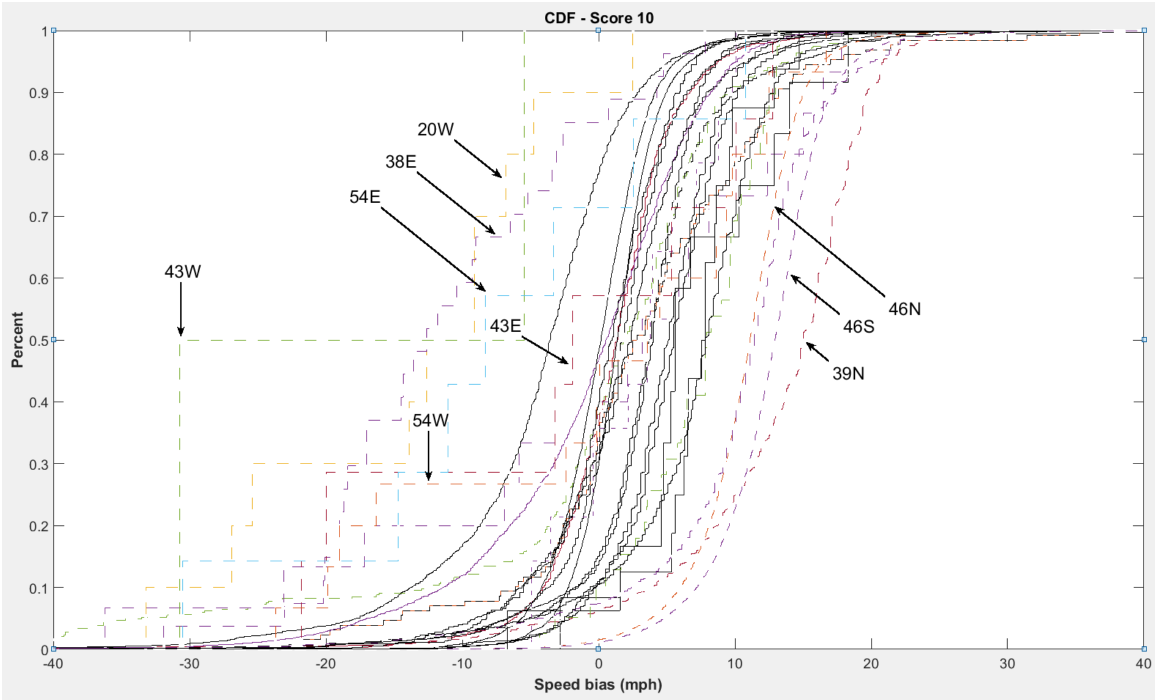
Speed bias is defined as the difference of speed between two traffic speed data providers. There is almost always a speed bias between data streaming from probes and traditional infrastructure-mounted sensors. Different factors, such as the measurement technique, the number of probes on road, roadway type (interstates or non–interstates), geographical location, etc., influence the magnitude of probe data speed bias. To use these data accurately, it is critical to understand the factors that influence and handle these biases. In this study, speed bias was calculated by subtracting INRIX speed from PVR speed (Equation 1).

$$Speed\ bias = PVR\ speed - INRIX\ speed \qquad (1)$$

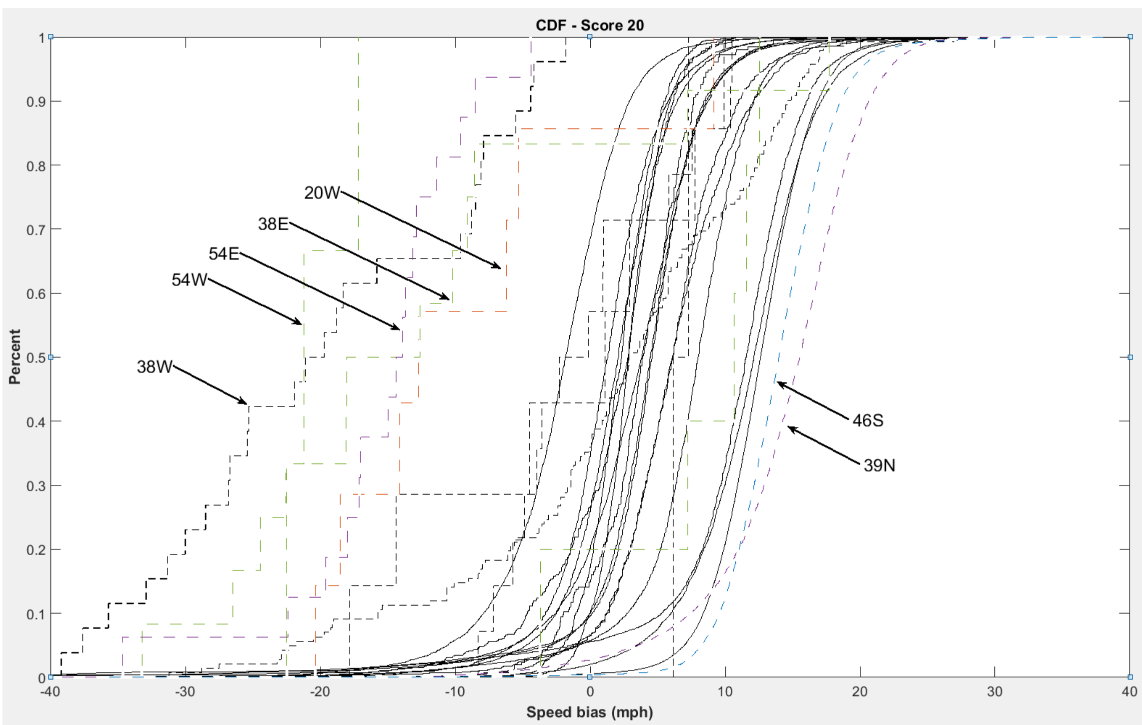
Speed bias was evaluated based on three different categories: (1) confidence scores, (2) locations, and (3) congestion vs. non-congestion times.

First, we examined how different speed biases are calculated using different scores. Probe technology calculates speed as the average speed of vehicles over a segment of a road, which is called space mean speed (SMS). Time mean speed (TMS), which is an arithmetic mean of vehicles' speed passing a point, is the calculated speed for benchmarked local sensor dataset. There is always a difference between space mean speed and time mean speed due to the measurement technique used. CDF can be used to illustrate the different speed biases for all sensors with respect to different scores (10, 20, and 30). As explained previously, CDF is the probability that a variable takes a value less than or equal to x. The horizontal axis represents the allowable domain for the given probability function. Because the vertical axis reflects probability, it must fall between 0 and 1; it increases from 0 to 1 from left to right on the horizontal axis.

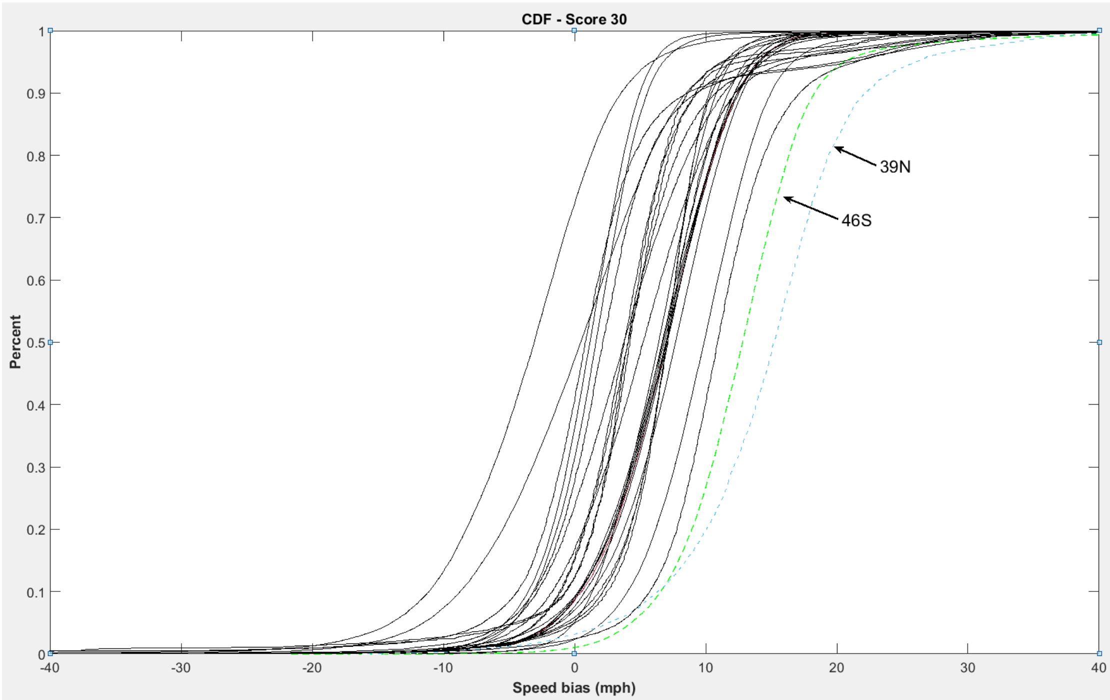
The CDF of speed bias between INRIX and PVR datasets for all selected location based on confidence scores 10, 20, and 30 is shown in Figure 4.3a–c. In Figures 4.3a and b, some CDF lines (43W, 20W, 38E, 54E, 43E, etc.) are not in the shape of a curve due to the lack of sufficient confidence score 10 or 20 data. High speed bias is shown in Figure 4.3a, for lines 46N, 46S, 39N, and for lines 46N and 39S of both Figures 4.3b and c. No trends in the speed biases of various locations are shown in Figures 4.3a and b; however, in Figure 4.3c, speed biases at all locations are shown in a nearly homogeneous cluster. Dashed lines at the very left and right of Figures 4.3a, b, and c depict the abnormal magnitude of speed bias. Accordingly, INRIX data with confidence scores 10 and 20, which represent historical data, should be excluded for speed bias analysis. Speed biases for all locations on aggregate by different confidence scores (10, 20, and 30) are shown in Figure 4.3d.



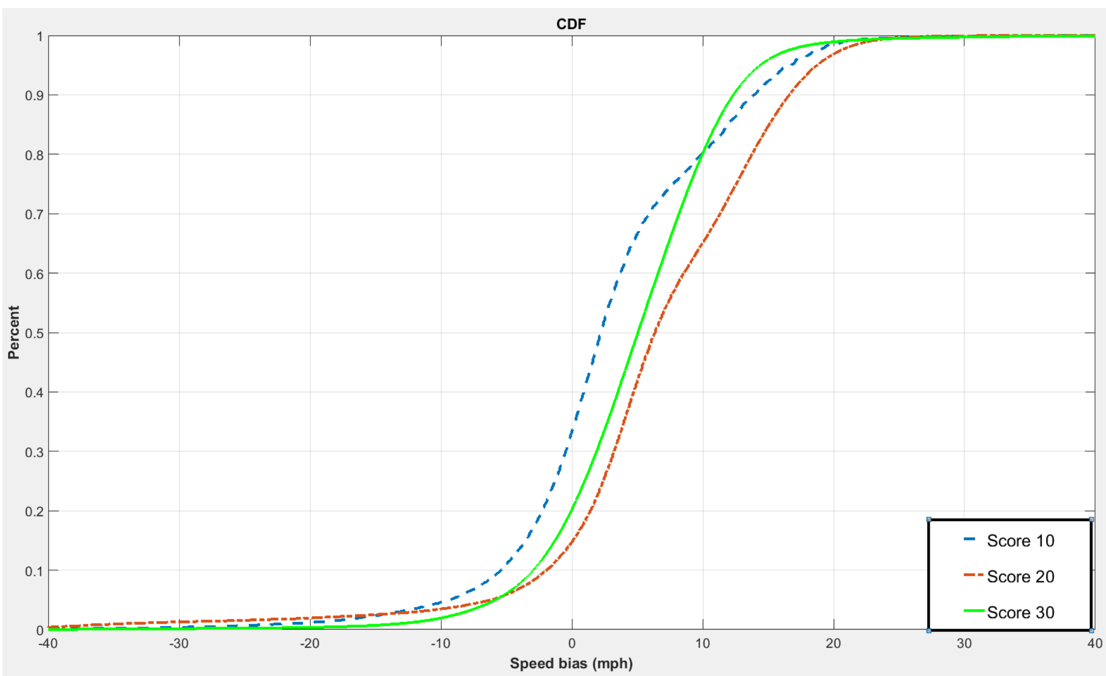
(a) CDF of speed bias for confidence score 10



(b) CDF of speed bias for confidence score 20



(c) CDF of speed bias for confidence score 30



(d) CDF of speed bias of all locations for confidence scores 10, 20, and 30

Figure 4.3 Segment–sensor pairwise cumulative distribution function of speed bias for: (a) confidence score 10, (b) confidence score 20, and (c) confidence score 30. (d) Score-wise cumulative distribution function of speed bias for all segment–sensor pairs.

After evaluating speed bias for the different confidence scores of 10, 20, and 30, we compared real-time speed biases of all locations separately. An example of errors associated with traffic speed reported using only real-time data for some sites is illustrated in Figure 4.4. In this case, because the magnitude of speed bias matters over all minutes of the day, error was defined as the absolute value of speed bias between PVR and INRIX data. The red dashed line in each image of Figure 4.4 shows the median error for each ATR site. At the right side of daily error plot for each site, CDF of the error is also plotted with a horizontal axis between 0 and 20. Due to a lack of sufficient real-time data from midnight to almost 6 am (point A in Figure 4.4), speed bias was higher compared to other times of a day. Plots for all other locations can be found in Appendix B (Figure B.1).

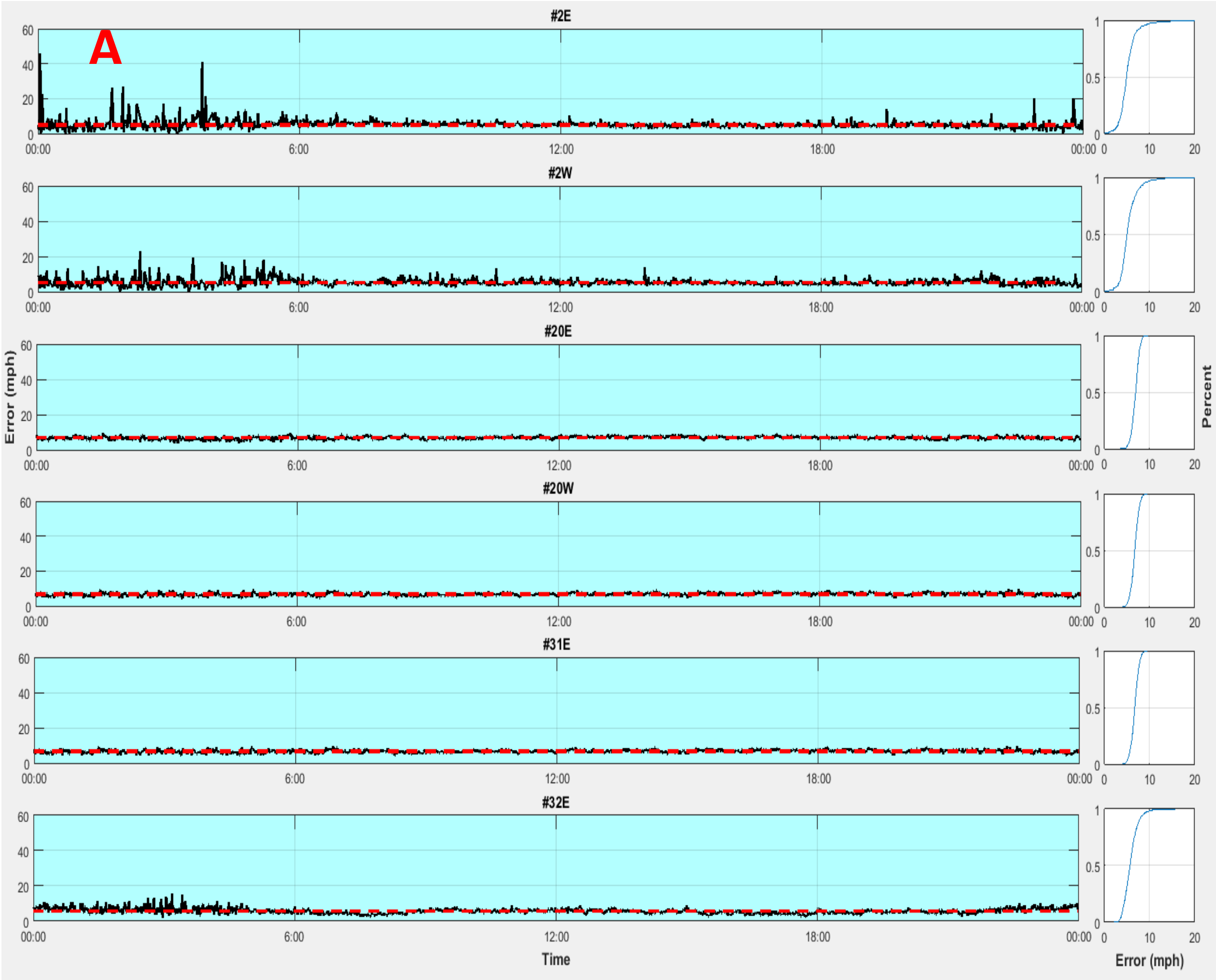


Figure 4.4 Errors associated with traffic speed reported using only real-time data for some sites

The median speed bias for each ATR with respect to each direction is shown in Table 4.2. ATR 39 Northbound, with a speed bias of 14.32 mph, accounts for the highest speed bias among all sites. The average speed bias of all other locations was 6.06 mph.

Table 4.2 Median error for each site

ATR	Median speed bias (mph)
2E	4.88
2W	5.00
20E	6.91
20W	6.71
31E	6.63
31W	5.25
32E	5.64
38E	7.55
38W	6.96
39N	14.32
40N	2.86
40S	2.67
43E	6.95
43W	6.81
46N	6.94
46S	5.95
54E	6.82
54W	7.53
56E	5.78
56W	6.33
61W	8.01
64N	5.54
64S	4.98
65W	6.67

Finally, we examined how speed bias varies during periods of congestion and no congestion. Generally, speed bias changes in different conditions, such as day vs. night, scores 10 vs. 20 vs. 30, freeway vs. non-freeway, congestion vs. no congestion, etc. A box plot of speed bias for each location during times of congestion and no congestion is shown in Figure 4.5. A box plot is a standard way of depicting the distribution of data based on five values: minimum, first quartile, median, third quartile, and maximum. In Figure 4.5, the central rectangle for each plot spans the first quartile to the third quartile (the interquartile range). The line inside the rectangle between the light- and dark-shaded areas represent the median, and the lines above and below the box represent the minimum and maximum values. The interquartile range, a measure of statistical dispersion, is equal to the difference between the 75th and 25th percentiles, or between the third and first quartiles. In Figure 4.5, there are two plots for each congested location, one showing the speed bias for non-congested periods (left) and the other showing the speed bias for congested periods (right). Based on the interquartile range of all boxes shown in Figure 4.5, on can observe that INRIX performance is constant and reliable both during periods of free flowing speed (non-congested periods) and congested periods; however, we could not determine any stable pattern for speed bias of congested versus non-congested periods. For instance, for sites 2W, 32E, and 38E, the speed biases for congested and non-congested periods were negative and close to zero, whereas they were positive for the 40N, 46S, and 61W sites. On the other hand, for 39N, 43E, 46N, 54W sites, the speed biases were positive during non-congested periods and negative during congested periods. According to available data, no patterns were found for speed bias between non-congested vs. congested periods; however, we concluded that INRIX performs reliably during both congested and non-congested periods.

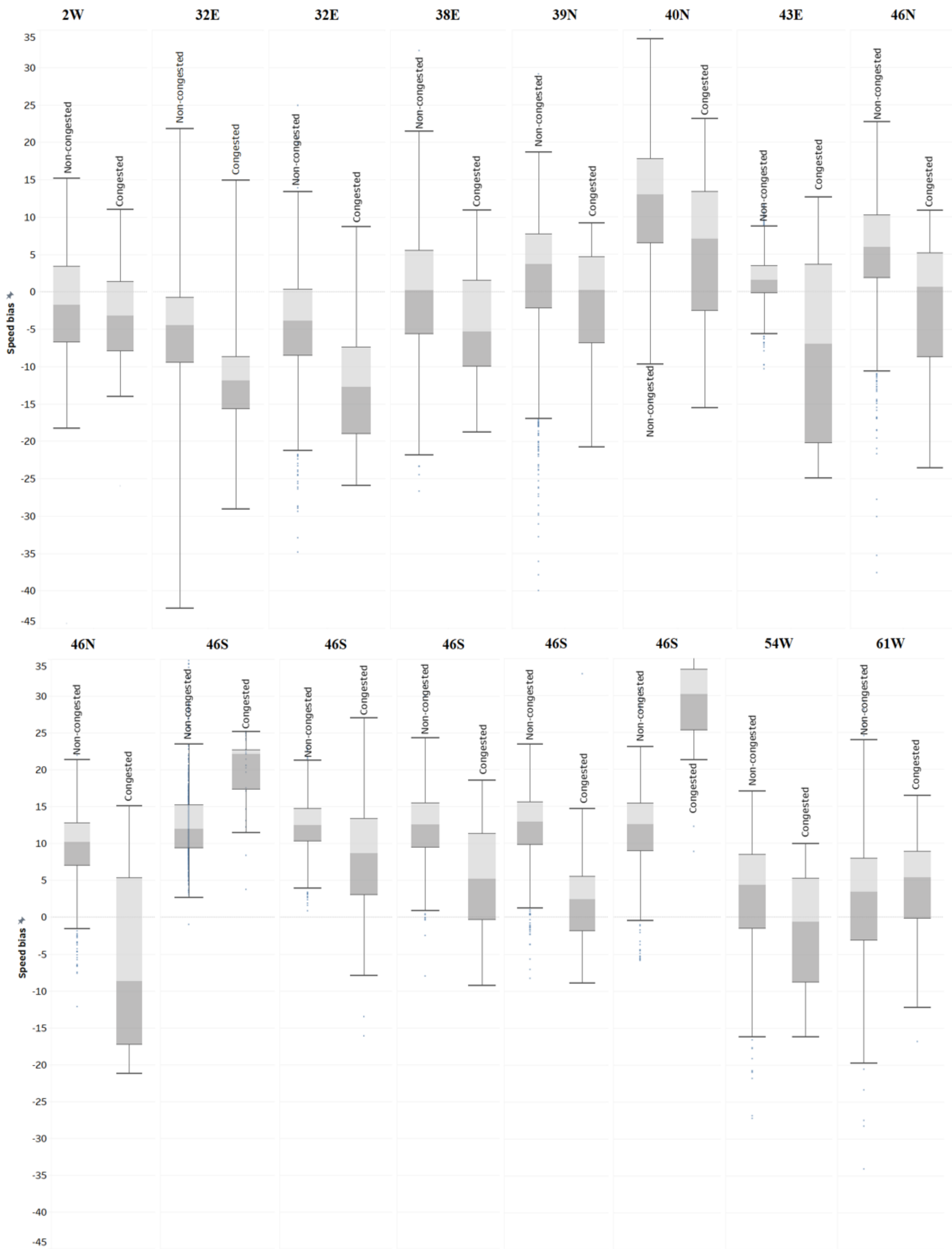


Figure 4.5 Speed bias during (left) non-congested and (right) congested periods

4.2.3 Incident Detection

Improving traffic safety and operations have long been areas of motivation among researchers and engineers. Traffic incidents, particularly traffic crashes, are of great interest due to the huge delay and costs that traffic injuries and fatalities impose on society. Traffic delays can be attributed to nonrecurring incidents including but not limited to traffic crashes, construction events, and adverse weather conditions. These incidents may also have other consequences, such as secondary crashes and delays in emergency medical services, which can cause further complications and impose additional costs. Consequently, monitoring the transportation network and being able to detect and report anomalies in real time are of great importance in the realm of traffic management.

4.2.3.1 Data Stream and Pre-Processing

Most of the time in real-world scenarios, raw traffic data are incomplete, highly susceptible to noise, and inconsistent for many reasons, such as sensor failures, measurement technique errors, huge size, etc. Data pre-processing can be used to try to detect and correct corrupt and erroneous traffic data. However, the storage and analysis of massive amounts of INRIX and PVR data are impossible using traditional methods, as they require the processing of more than 500 GB of data, which would be prohibitively time intensive on a traditional machine. For this study, a high performing cluster was used for data processing. The Hadoop Distributed File System [63] was used for storage of the data, and map-reduce was used for processing. Pig Latin [64] was used as the language to implement map-reduce algorithms.

4.2.3.2 Congestion Detection Algorithm

After data processing, a congestion detection algorithm was implemented to detect and classify the onset of congestion throughout the network for the study period. Congestions were identified as when the speed data of the INRIX segment or the mean of the 1-minute aggregated speed data of the PVR sensor for that location indicated that the speed dropped below 45 mph. According to the *Highway Capacity Manual* (version 6) [65], LOS (level of service) on basic freeway segments is defined by density. Although speed, as it relates to service quality, is a major concern of drivers, describing LOS on the basis of speed is difficult, as it remains constant up to high flow rates [i.e., 1,000 to 1,800 pc/h/ln for basic freeway segments (depending on the free flow speed)]. There are six levels of service defined for basic freeway segments (levels A–F). The minimum speed of around 50 mph for LOS E is almost constant for different free flowing speeds (from 75 to 55 mi/h). With an approximately 5 mph average speed bias, 45 mph is considered the threshold for traffic congestion.

How the algorithm recognizes congestions is illustrated in Figure 4.6. The blue line represents the original traffic speed, and red line represents the fixed threshold of 45 mph. The congestion start time is when the speed drops below 45 mph, and the congestion end time is when the speed rises above 45 mph.

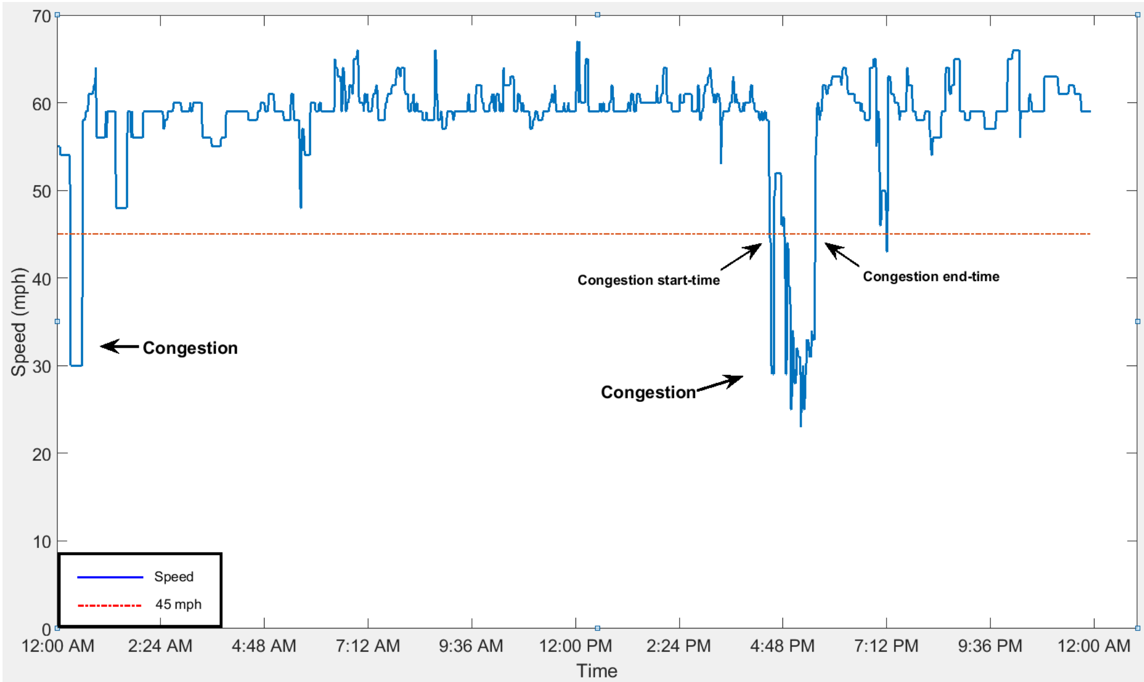
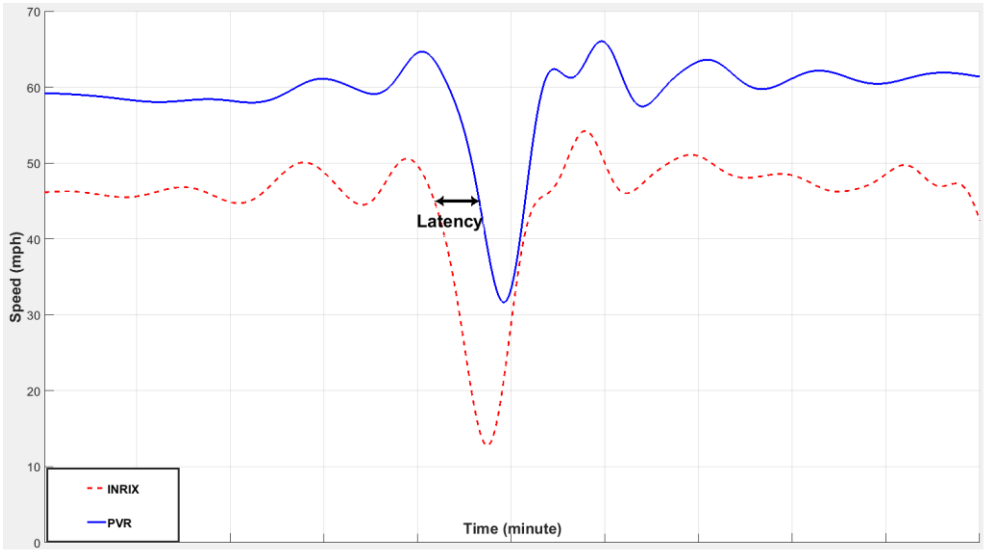


Figure 4.6 Example of congestion detection

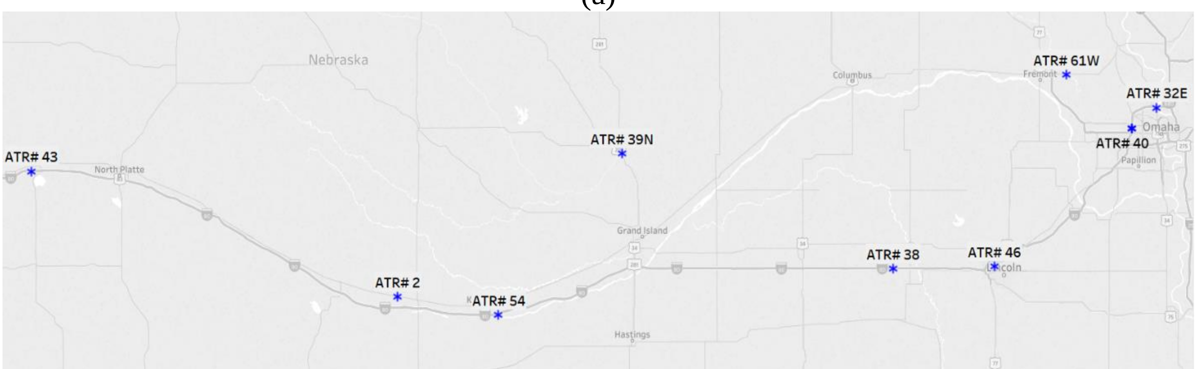
4.2.3.3 Latency and Count

Latency is a parameter that represents the measurement of the time delay between two time-series datasets. In this study, latency was used to measure the difference between congestion start times detected by INRIX vs. PVR (Figure 4.7a). It is crucial to verify latencies within probe data streams for timely detection of events on roads. Based on work by Adu Gyamfi et al. [12], the average ranges of latencies associated with probe vs. sensor data are between 3 and 12 minutes on freeways and between 7 and 20 minutes on non-freeways. In this study, we considered only congestions that were detected by both INRIX segments and PVR sensors with latencies lower than 20 minutes. The location of all sites experiencing congestion with latencies lower than 20 minutes is shown in Figure 4.7b.

Additionally, the number of congestions that occurred at each site and the average latency between INRIX and PVR associated with each site are shown in Figure 4.8. There were many instances when congestions with higher latencies were detected by both INRIX TMC segments and PVR sensors; however, it should be noted that we considered only congestions that were detected by INRIX TMC segments and PVR sensors with latency below 20 minutes. The average latency for all congestions detected by both the INRIX and PVR datasets was 4.97 minutes. As shown in Figure 4.8, the average latencies for a few ATRs (39N, 43E, and 46S) were negative, which means that the INRIX segments detected congestion earlier than PVR sensors did.



(a)



(b)

Figure 4.7 (a) Latency and (b) location of congestion at ATRs

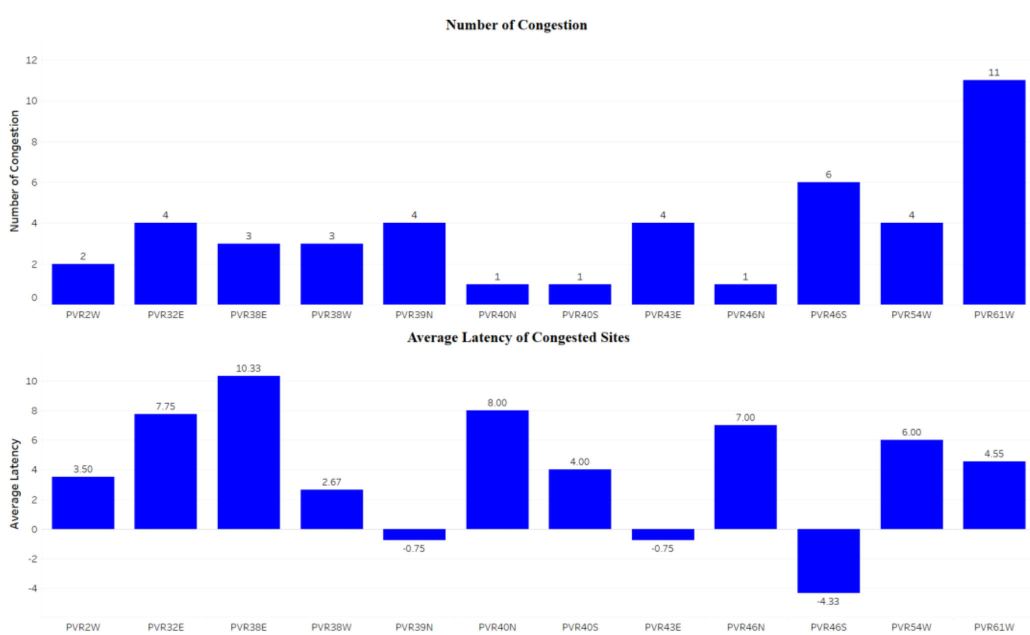


Figure 4.8 Number of congestions and average latency for each site

The number of congestions detected by either INRIX or PVR or by both during a 3-week fixed period of time for all sites is shown in Table 4.3. TP (true positive) indicates the rate of events that were detected by both INRIX and PV, FN (false negative) represents the rate of events detected by PVR but not by INRIX, and finally, FP (false positive) represents the rate of events detected by INRIX but not by PVR. The values in the last column show the precision of congestion detection by INRIX, calculated using Equation 2.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Table 4.3 Reliability of INRIX in detecting congestion events

Location	INRIX	PVR	Both	TP	FN	FP	Precision
2W	7	12	2	0.167	0.417	0.417	0.286
32E	6	21	4	0.190	0.714	0.095	0.667
38E	7	14	3	0.214	0.5	0.286	0.429
38W	6	22	3	0.136	0.727	0.136	0.5
39N	5	31	4	0.129	0.839	0.032	0.8
40N	1	1	1	1	0	0	1
40S	4	7	1	0.143	0.429	0.429	0.25
43E	4	8	3	0.375	0.5	0.125	0.75
46N	8	10	1	0.1	0.2	0.7	0.125
46S	7	10	3	0.3	0.3	0.4	0.429
54W	4	10	4	0.4	0.6	0	1
61W	13	36	10	0.278	0.639	0.083	0.769

It was difficult to derive any robust congestion detection results by comparing INRIX and PVR datasets using only 3 weeks of data and 16 different ATRs. For future studies, we strongly recommend using data from a longer period (1 year) and a larger number of sites. Using a congestion detection algorithm, 44 congestions were detected by both the INRIX and PVR datasets for all selected ATRs on all days. The timestamps for worst congestions for each congested site and the two worst congestions among all other sites are shown in Table 4.4.

Table 4.4 Worst congestions

ATR	Worst Congestions
2W	02/24/2017 08:38 am, 02/24/2017 09:25 am
32E	10/31/2016 12:28 pm, 11/01/2016 09:27 am
38E	02/24/2017 05:02 am, 2/24/2017 10:58 am
38W	02/23/2017 08:45 pm, 2/24/2017 09:05 am
39N	02/23/2017 05:01 pm, 2/24/2017 10:29 am
40N	03/28/2017 05:13 pm
40S	04/19/2017 07:47 am
43E	02/24/2017 02:13 am, 02/24/2017 04:29 am
46N	04/19/2017 05:24 pm
46S	10/28/2016 07:49 am, 11/29/2016 07:42 am
54W	02/24/2017 02:16 am, 02/24/2017 01:55 am
61W	02/24/2017 05:39 pm, 02/24/2017 12:30 pm
Two worst congestions among all ATRS	ATR 46s: 02/23/2017 08:13 pm ATR 32e: 11/01/2016 09:27 am

4.2.4 Performance Measures

4.2.4.1 Congested Hour

Traffic congestion is widely known as a transport cost. It plays a key role in transport system performance evaluation and affects transport planning decisions. When a road system reaches its capacity, each additional vehicle makes it more overloaded and imposes more delay on other vehicles. Some impacts of congestion include increased travel time, accidents, unreliability of arrival times, increased fuel consumption and pollution emissions, adverse health effects, etc. Generally, there are two types of congestion: recurring and nonrecurring. Recurring congestion is considered congestion caused by routine traffic in a normal environment and is somewhat expected, whereas nonrecurring congestion is unexpected and most likely caused by an incident. Nonrecurring congestion may occur as a result of a variety of factors such as lane-blocking crashes or disabled vehicles, work-zone lane closures, adverse weather conditions, etc. When computing congestion costs, some organizations consider only recurring costs, whereas others include both recurring and non-recurring costs. In this study, we attempted to evaluate the reliability of INRIX using a cost–benefit analysis. We also discuss the limitations of INRIX with regard to the detection of recurring and non-recurring traffic congestions. Congested hour is one of the measures that indicate how reliable INRIX can be when evaluating the cost of congestion.

In this study, if the speed of a road segment fell below 45 mph for a period of time, the segment was defined as being congested for that period. After considering all congestions detected by INRIX and sensor datasets in a similar study conducted for state of Iowa, we determined 6 minutes as the threshold for the minimum duration when determining the period of traffic congestion (Figure 4.9). The distribution of congested traffic periods from two datasets (sensor and INRIX) over the span of a year in the state of Iowa is shown in Figure 4.9 (the horizontal axis in the original image extended to more than 400 minutes, but here the image was zoomed in to from 1 to 100 minutes for clearer visualization). Looking at the distribution of the two datasets, especially from the sensor data, it is clear that congestion periods of less than 6 minutes are very different from others in terms of trend.

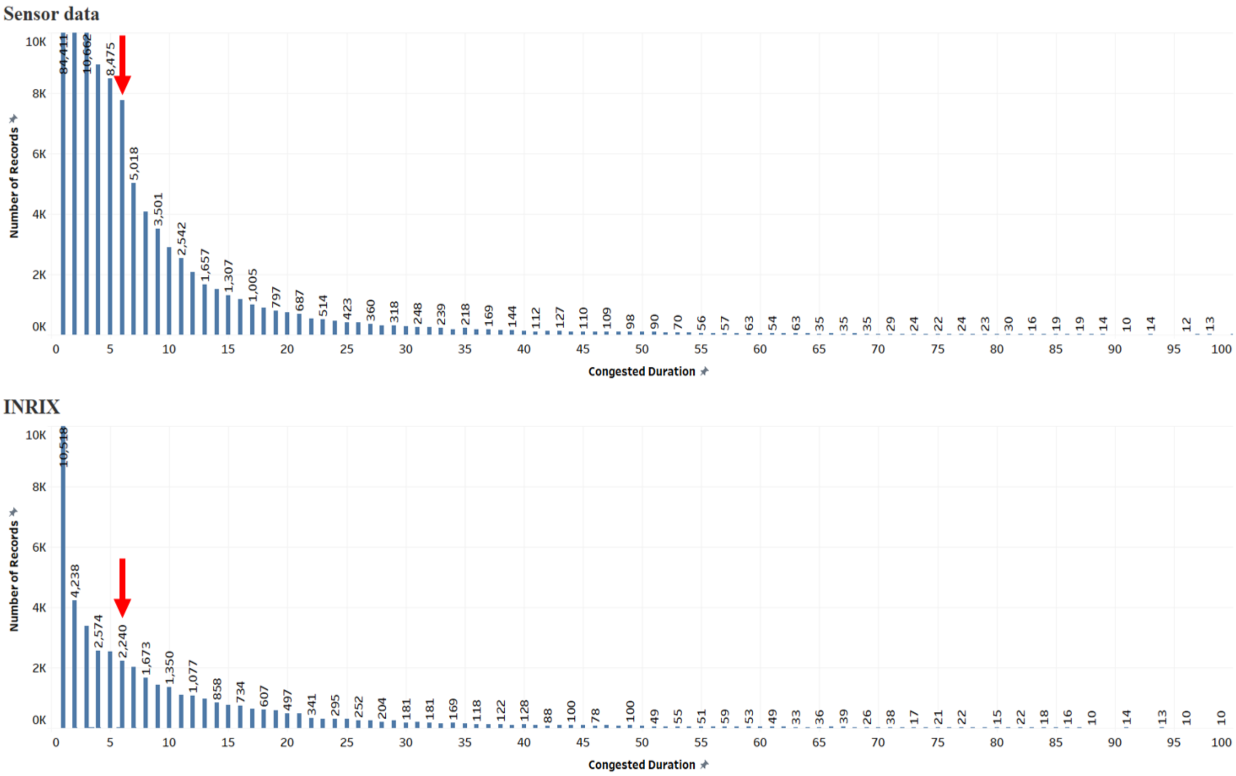


Figure 4.9 Distribution of congestion periods (in minutes) for sensor and INRIX data in the state of Iowa for 2016 (the red arrows indicate 6 minutes as the minimum acceptable threshold for a period of congestion)

In this study, we considered two scenarios for comparing INRIX and PVR datasets in terms of congested hour. For the first scenario, we considered the congestion period as the total number of hours for which the speed of each segment was less than 45 mph for a minimum 6 continuous minutes, which is a very common scenario. For the second scenario, we considered the congestion period as the total duration of congestions detected by both INRIX segments and PVR sensors with detection latency lower than 20 minutes.

The above-described scenarios were compared for two time periods: (1) a single day and (2) 3 weeks. Because the total number of days of data varied for different ATRs, a 3-week period was considered the fixed maximum period of time for all ATRs in our analysis. However, this period of time did not occur in the same month for the different ATRs; for instance, for location 46 southbound, the 3 weeks were in April 2017, and for location 46 northbound the 3 weeks were in November 2016. Scatter plots for congested hour determined by the INRIX and PVR single-day and 3-week datasets for the two predefined scenarios are shown in Figure 4.10. Congested hour were aggregated for the respective time periods (single day and 3 weeks). In the scatter plots, the vertical and horizontal axes of the plots represent the congested hour determined by INRIX and PVR data, respectively. Each point on the plot represents the total duration of congestion of a segment–sensor pair (in hours) over the period of time that was plotted. For instance, the scatter plot in Figure 4.10c for scenario 1 illustrates all days with congestion for all ATRs over 3 weeks. Additionally, a regression line is plotted for each scatter plot using its equation and R^2 values.

Single day

a) Scenario 1 **b) Scenario 2**

3 weeks

c) Scenario 1 **d) Scenario 2**

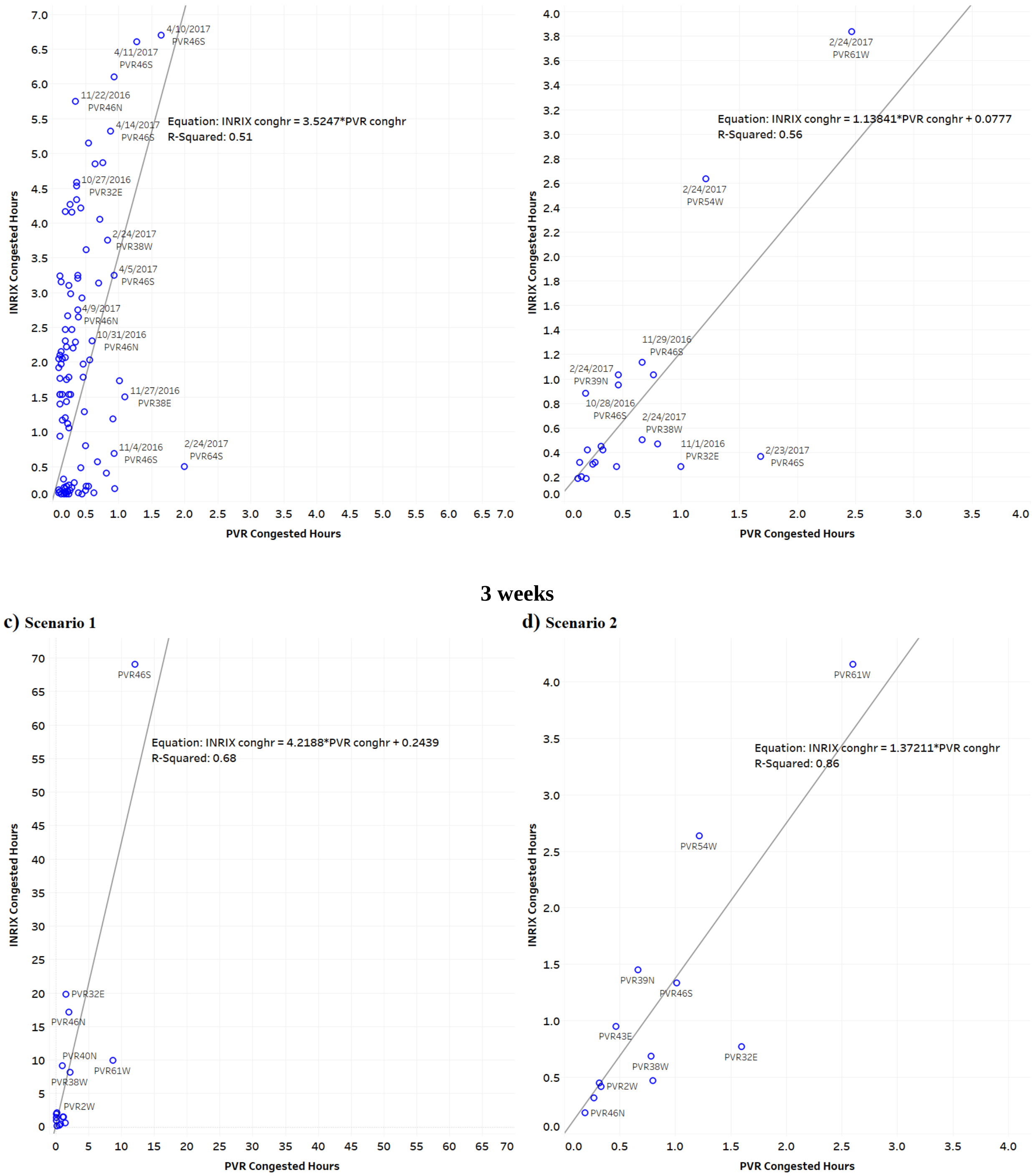
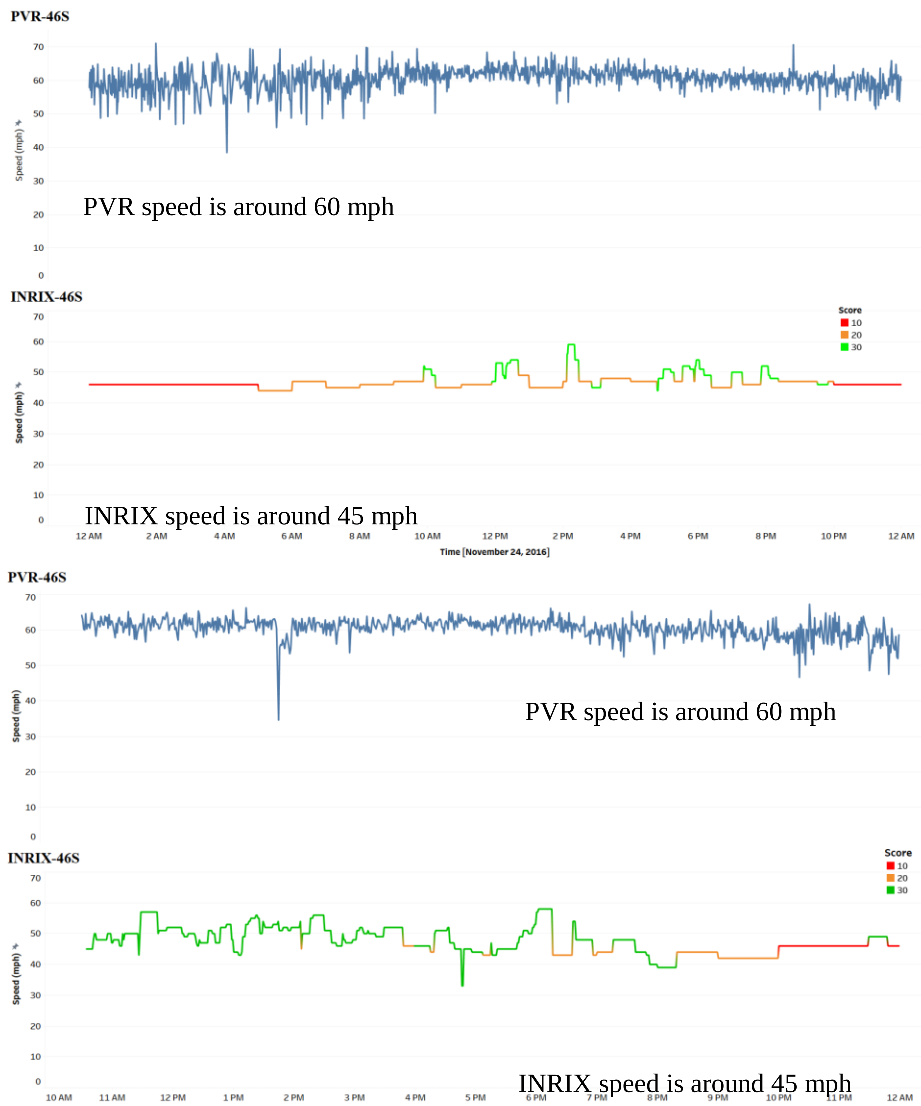
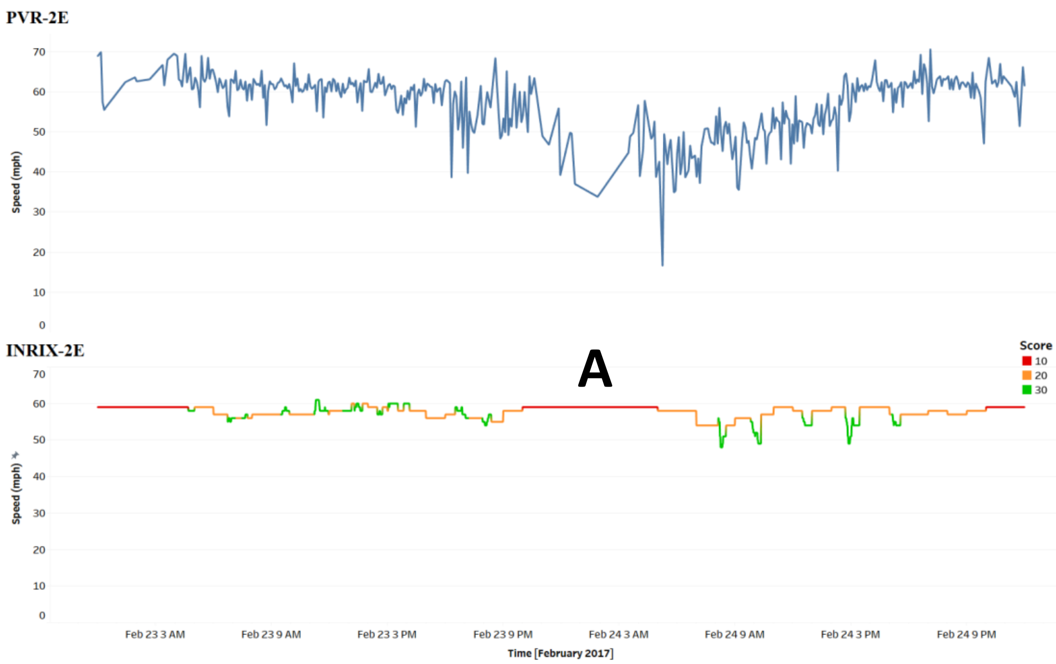


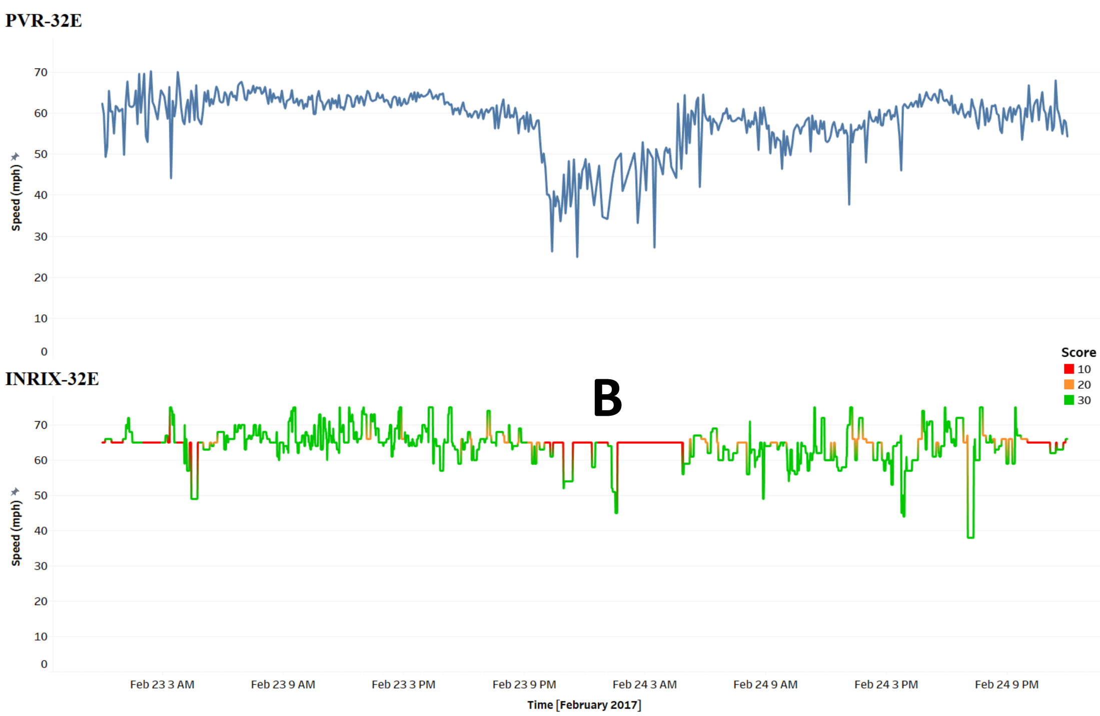
Figure 4.10 (a, b) Single-day and (c, d) 3-week periods of congested traffic duration (in hours) for scenarios 1 and 2. All congestions reflect traffic speed of less than 45 mph, and all congestions were detected by both the INRIX and PVR datasets

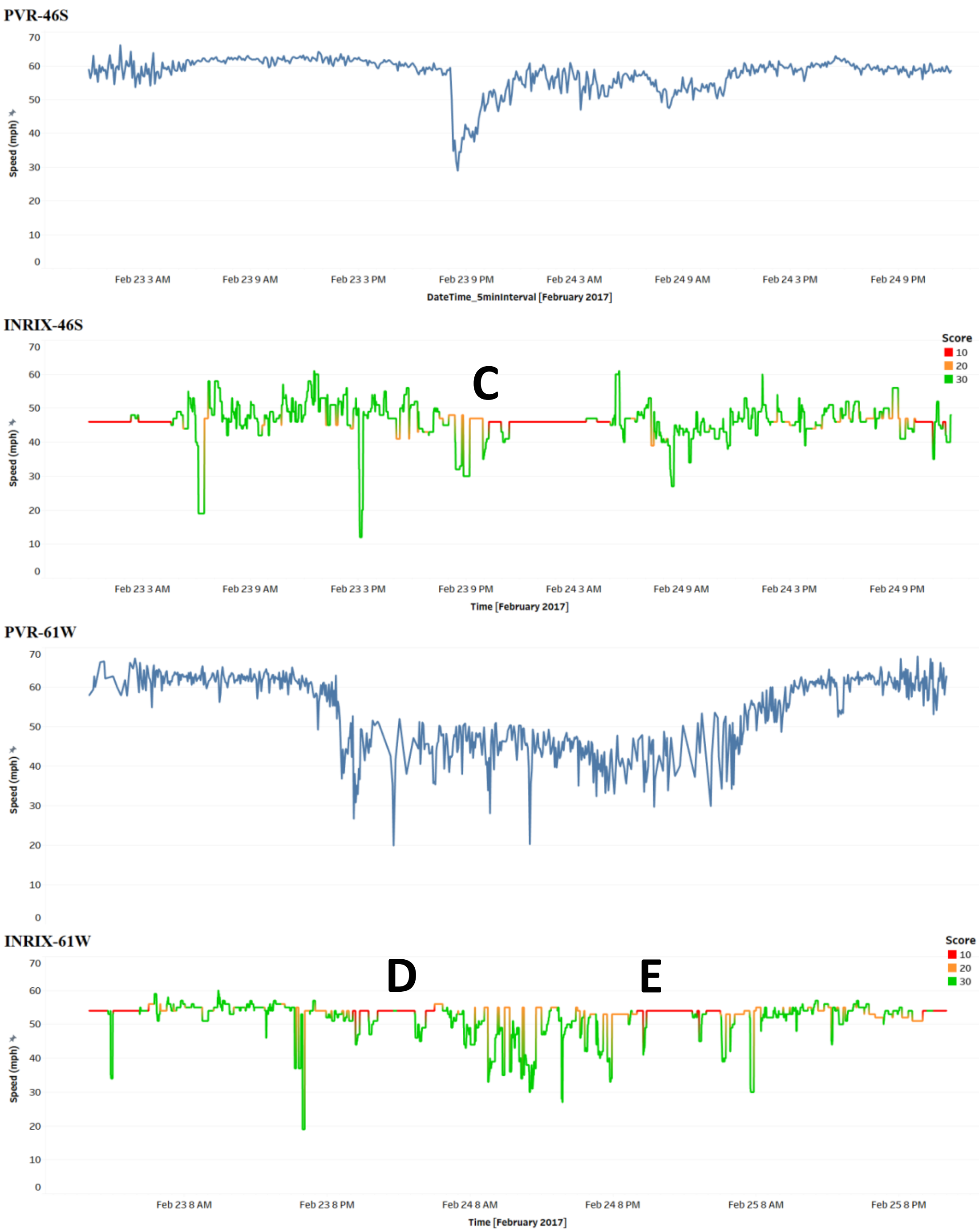
Because for some ATRs INRIX reported traffic speed as being close to 45 mph or even slower for most of the time, the duration of congestion from the INRIX database compared to the PVR database was observed as tending to be longer, as shown in Figure 4.10a and c. The lack of sufficient confidence score 30 (real-time) data negatively influenced this situation. Two examples of when INRIX detected speed at mostly around 45 mph for location 46S are shown in Figure 4.11a. In both INRIX-46S time series shown, the speed was almost always around 45 mph, even though no congestion occurred on that day. Moreover, the four samples shown in Figure 4.11b indicate a lack of real-time data, especially during periods of congestion. Points A, B, C, D, and E in Figure 4.11b depict the change in confidence scores from real time (score 30) to historical (scores 20 or 10) data during periods of congestion. These critical issues with INRIX data, especially during periods of congestion, persuaded us to make use of scenario 2 for further analyses. Using scenario 2, for which we considered all congestions detected by both INRIX and PVR with detection latency lower than 20 minutes, we obtained reliable results for comparing the two datasets.



a) INRIX reported speed is around 45 mph for most of the day


PVR-2E
Speed (mph)
70
60
50
40
30
20
10
0
INRIX-2E
A
Score
10
20
30
Feb 23 3 AM
Feb 23 9 AM
Feb 23 3 PM
Feb 23 9 PM
Feb 24 3 AM
Feb 24 9 AM
Feb 24 3 PM
Feb 24 9 PM
Time [February 2017]


PVR-32E
Speed (mph)
70
60
50
40
30
20
10
0
INRIX-32E
B
Score
10
20
30
Feb 23 3 AM
Feb 23 9 AM
Feb 23 3 PM
Feb 23 9 PM
Feb 24 3 AM
Feb 24 9 AM
Feb 24 3 PM
Feb 24 9 PM
Time [February 2017]



b) Insufficient INRIX confidence score 30 data during congestion

Figure 4.11 Speed time series of PVR and INRIX data showing (a) INRIX speed being reported as around 45 mph and (b) lack of real-time (score 30) data during congestion

The congestion duration rank order from the PVR and INRIX data for selected ATRs, after evaluating INRIX performance for calculating congestion duration, is shown in Figure 4.12. As shown in the figure, 8 out of 12 sensors and their corresponding segments had nearly the same rank in terms of congestion duration. The INRIX performance for congestion duration was mostly reliable; however, it would be better to have been able evaluate its performance on more segments with a higher number of congestions over a longer period of time.

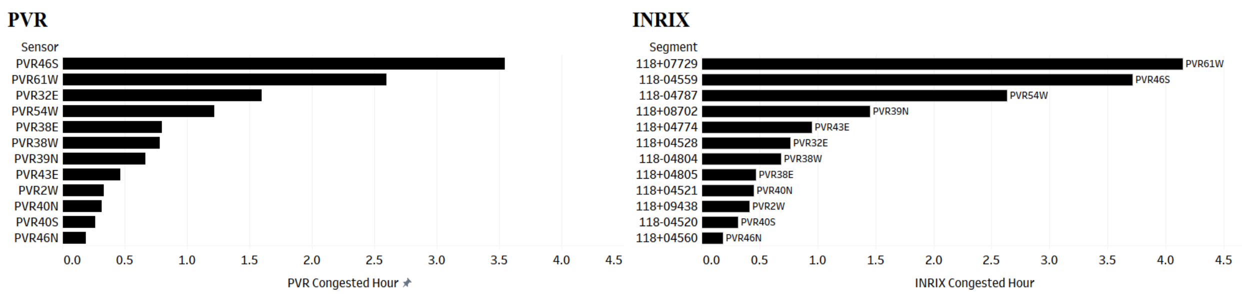


Figure 4.12 Rank order of segments and sensors based on congestion duration

4.2.4.2 Buffer-Time Index (BTI)

In this study, BTI was calculated by subtracting the 85th percentile of TTPM (travel time per mile) from the median TTPM and then dividing that result by the median TTPM (see Equation 3). BTI represents the percentage of extra travel time that almost all travelers would need to add to their trips to reach their destination on time in a given time-of-day and/or day-of-week period. For example, a buffer index of 60% at 7 am on a freeway where the travel time is 10 min when there is no congestion, would indicate that travelers should allow for 16 min at 7 am to make sure that they arrive on time.

$$\text{BTI}\ (\%) = \frac{\text{85th percentile ttpm} - \text{median ttpm}}{\text{median ttpm}} \tag{3}$$

A comparison of the INRIX data stream versus the PVR sensor datasets based on weekly and three-weekly BTIs is shown in Figure 4.13. A BTI was calculated for each time period (weekly and three-weekly). Additionally, a regression line is plotted for each scatter plot using its equation and R^2 values.

As observed in Figure 4.13, the BTI for the PVR data was almost always more than that for the INRIX database. The main reason for this is low variation of the INRIX data. Because in Nebraska INRIX provides traffic data mostly via trucks traveling on the roads, it is hard to find considerable variability in the magnitude of the speed. On the other hand, local infrastructure sensors record traffic information from every vehicle on road, which leads to higher variability, or in other words, a wider range of speed. The speed profiles from raw, smoothed PVR sensor, and INRIX segment data corresponding to ATR 65 Westbound for a 1-week period of time are shown in Figure 4.14. It can be observed that level of variation for the INRIX data is less than the raw and even the de-noised sensor data. Considering variability as noise is one critical misunderstanding by many researchers. As can be seen in Figure 4.14, the time series of raw and de-noised PVR-65W data shows a wide range of speed compared to its corresponding INRIX-65W segment.

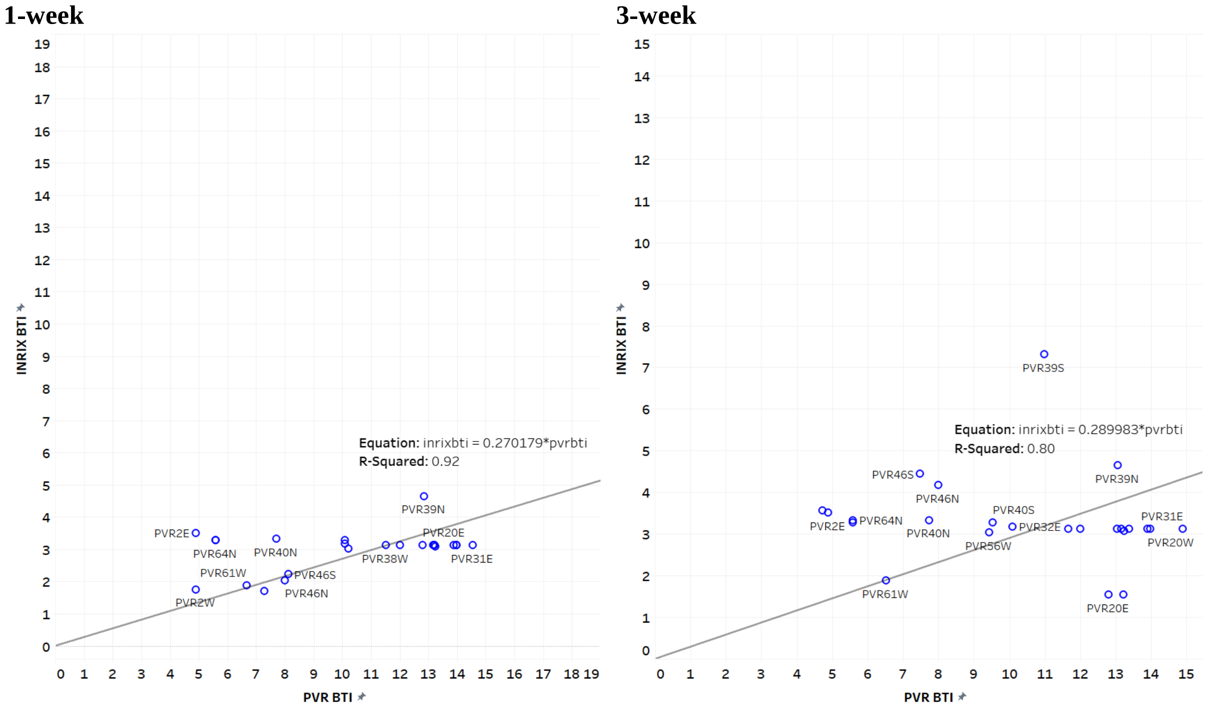


Figure 4.13 1-week and 3-weekly BTIs for probe and sensor datasets

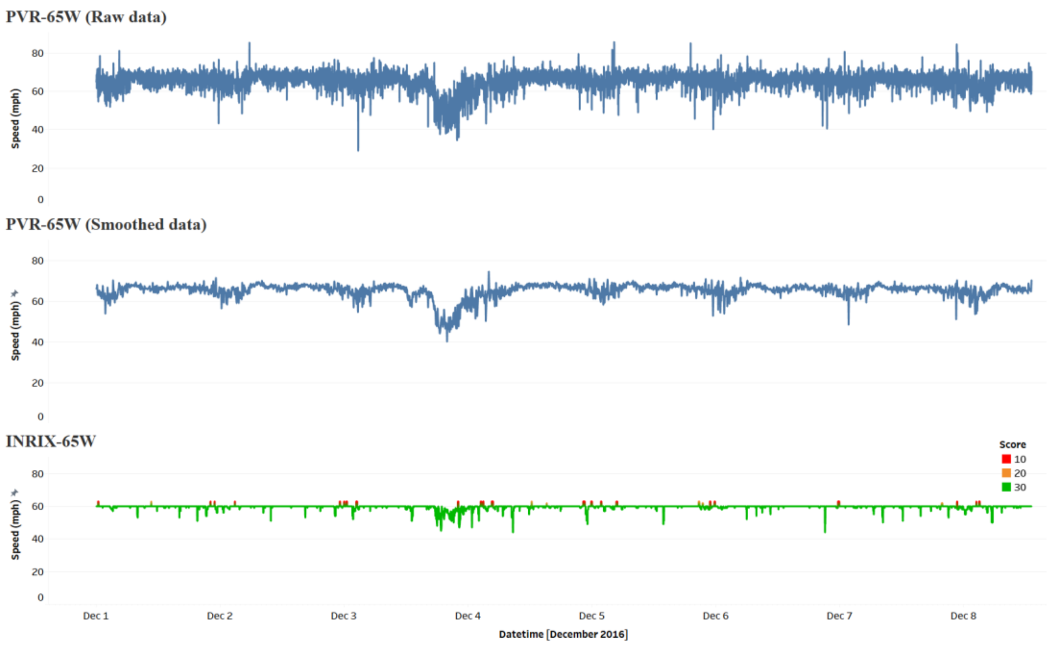
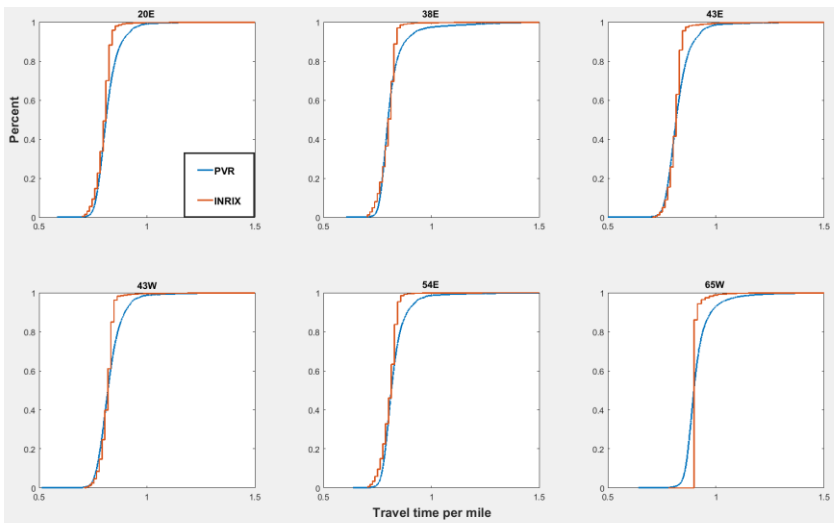
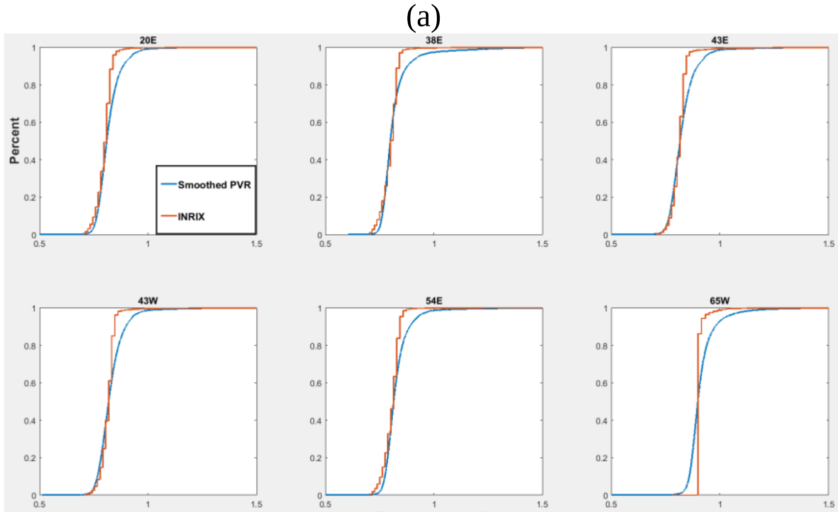


Figure 4.14 Sample time series showing difference of variability between probe and benchmarked data

Considering the definition of BTI, a wider range of travel time would lead to a higher BTI. In this study, TTPM was calculated using the inverse of speed multiplied by 60. Thus, a wider range of speeds would result in a higher BTI. It is important to note that noise does not affect the BTI significantly; however, this depends on the magnitude of noise reduction in the smoothing process. CDF of TTPM for some sample ATRs is shown in Figure 4.15. The bias shown between the PVR and INRIX CDF lines was corrected by shifting back the INRIX 50th percentile point to overlap on to the PVR 50th percentile point. By looking at the 85th percentile of TTPM on both CDF lines, it is clear that the magnitude of the 85th percentile of TTPM for PVR (blue line) was always higher than that for INRIX (red line), which led to a greater BTI. The comparison between INRIX and PVR raw data is shown in Figure 4.15a, whereas the comparison between the INRIX with the de-noised PVR datasets is shown in Figure 4.15b. Comparing the plots in Figure 4.15a with those in Figure 4.15b, it is clear that noise reduction did not drastically affect buffer time. Thus, we concluded that INRIX is not reliable for calculating BTI.



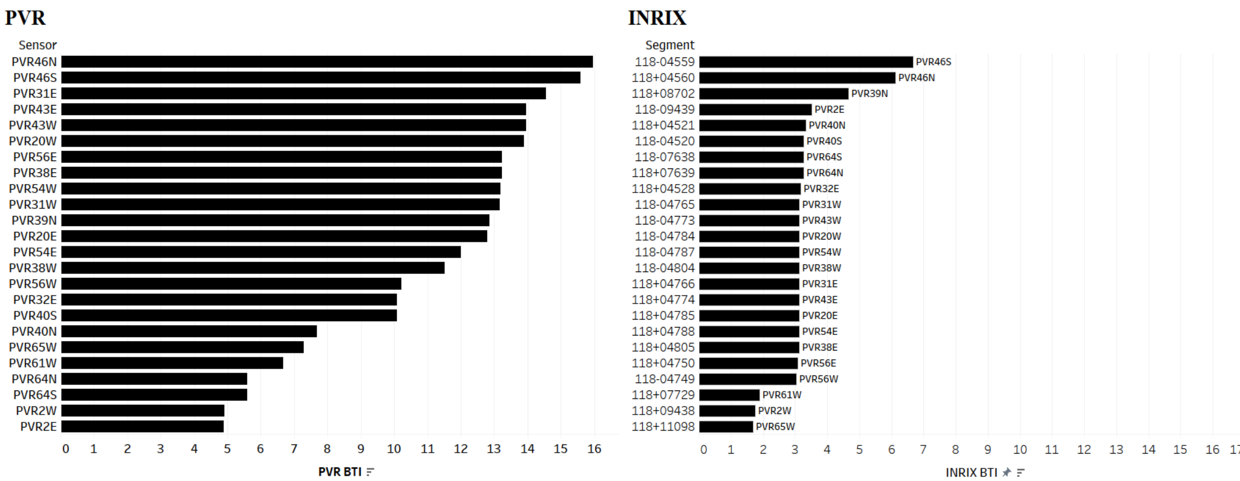
(a)



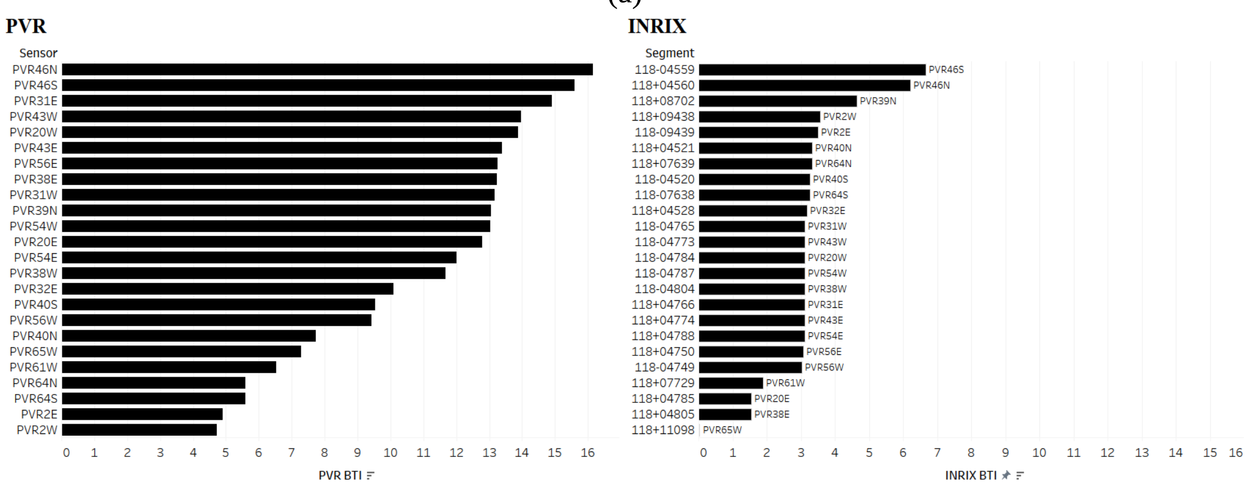
(b)

Figure 4.15 Cumulative distribution function of travel time showing difference of 85th percentile between probe and (a) raw sensor data and (b) smoothed sensor data

After observing the poor performance of INRIX in calculating BTI, we calculated the BTI rank order of INRIX and PVR data for 1-week and 3-week periods of time (Figures 4.16a and 4.16b, respectively). Only 3 out of 24 sensors and their corresponding segments had almost in the same rank in terms of BTI. Therefore, it can be concluded that, for this analysis, INRIX performance was not reliable for either BTI or BTI rank order. However, it should be noted that this analysis was conducted on a limited number of ATRs over a short period of time. We recommend that more sites and longer period of time be used for further analyses.



(a)



(b)

Figure 4.16 Rank order of segments and sensors based on BTI for (a) 1-week and (b) 3-week periods

4.2.4.3 Reliability Curves

As mentioned previously, TTPM was calculated as the inverse of speed multiplied by 60. A reliability curve is defined as the CDF of TTPM for each segment or sensor. The TTPM reliability curves for all ATRs for each direction are shown in Figure 4.17. As revealed in the graphs, there was almost always a visible shift between probe and sensor curves, known as travel time bias. Because TTPM was calculated using speed, speed bias was the reason for the small differences in reliability curves at all locations. Equations (4) to (8) show how we calculated the travel time bias for this study.

$$\text{Travel time bias (minutes)} = \text{Sensor TTPM} - \text{INRIX TTPM}, \tag{4}$$

where sensor TTPM and INRIX TTPM are explained in Equations (5) and (6) respectively.

$$\text{Sensor TTPM (minute)} = \frac{1}{\text{X}} * 60 \qquad \left(X = sensor's\ speed\ (mph)\right) \tag{5}$$

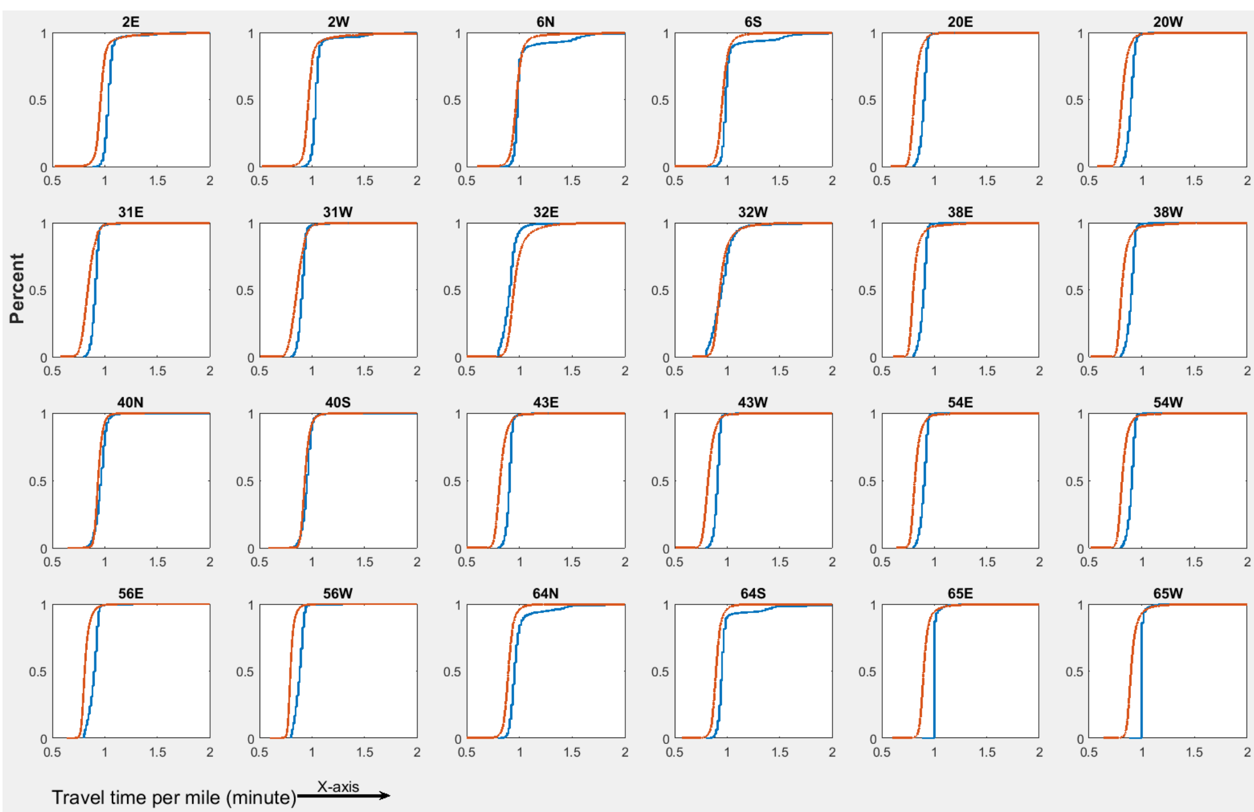
$$\text{INRIX TTPM (minute)} = \frac{1}{\text{X}-6} * 60 \tag{6}$$

After considering the average speed bias as 6 mph, travel time bias can be calculated as follows:

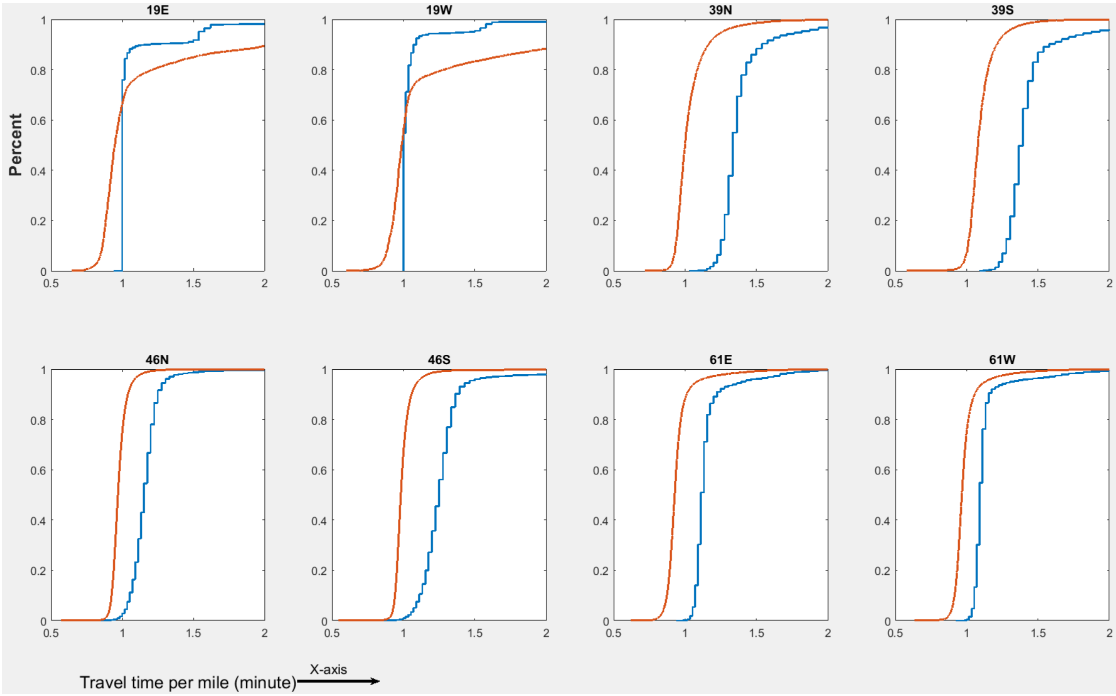
$$\text{Travel time bias (minute)} = \frac{1}{\text{X}} * 60 - \frac{1}{\text{X}-6} * 60 \tag{7}$$

$$\text{Travel time bias } = \frac{6}{\text{X}(\text{X}-6)} * 60 \tag{8}$$

Reliability curves for all locations shown in Figure 4.17b have huge differences in TTPM (travel time bias) compared to the normal locations shown in Figure 4.17a. With regard to travel time bias, it was concluded that INRIX performance is usually reliable and consistent.



(a)



(b)

Figure 4.17 Cumulative distribution function of travel time per mile for (a) normal sites and (b) outlier sites

4.3 Conclusion

To sum up, there are some critical points that state DOTs and transportation agencies should consider when using a probe data stream like INRIX. Some advantages and limitations of INRIX are as follows:

- In terms of geographic coverage, INRIX has been evaluated for interstates and non-interstates and has been shown to be reliable for almost all times of day on interstates.
- This study showed that INRIX is more reliable during the day than at night, especially during peak hours.
- Regarding incident detection, INRIX is reliable for detecting merely congestion, especially recurring congestion. When it detects congestion, it gets all the information related to the congestion, such as the duration of the congestion.
- There is almost always a time delay (latency) for INRIX congestion detection. Congestion detection latency was evaluated in this chapter for 16 specific locations over a short period of time. Other data streaming sources, such as sensors, are more preferred for incident detection application; however, they are very costly and not applicable for many places. Thus, for locations without other data sources, detecting congestion by INRIX, even with latency, is better than not detecting it at all.
- There will always be a bias between traffic speed data from probe sources and benchmarked sensors. Speed bias directly affects incident detection, travel time estimation, calculation of performance measures (such as congested hour, BTI, reliability curves, etc.) and other traffic-related measures. For instance, it could be observed from

Figure 4.11a that speed bias caused INRIX speeds to be shown as approximately 45 mph, which is usually considered the threshold for congestion. Accordingly, it is important to understand the factors that influence these biases and how to correct for them.
- Traffic incident management, roadway performance assessment, and travel time estimation applications should be developed based on real-time data. The lack of confidence score 30 data (real time), especially during congestion, leads to incorrect results. Substitutions with historical data are not accurate and therefore not advised. In areas with limited probe penetration, the agency could augment probe data with infrastructure-mounted sensors.

Finally, many different tests, analyses, and experiments have been left for future studies due to lack of sufficient data. The main point that should be taken into consideration is the length of time of data collection. Increasing collection time to a year or more would make possible the measurement of the performance of probe data versus local sensors over a longer period of time.

5. Performance Monitoring and Historical Trend Analysis

5.1 Introduction

In this chapter, performance monitoring and historical trend analysis of Interstate 80 (I-80) is discussed. First, the top 10 congested segments were identified through a detailed analysis of when congestion occurred by month, day of week, and time of day. Second, congestion per mile was calculated for monthly and yearly comparisons of metro areas across Nebraska to determine any trends in congestion. Third, congestion duration was used to show the severity of congestion by segment during summer vs. winter months. Finally, yearly travel time reliability was calculated to measure the level of confidence that the traveler would arrive within an acceptable travel time.

5.2 Top Congested Roadways on Interstate 80

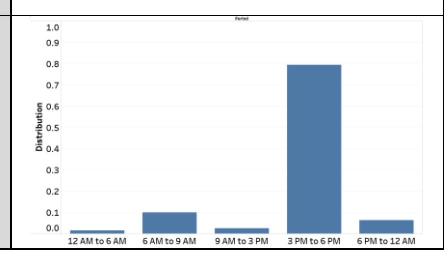
The top congested segments on I-80 in Nebraska are those that experience congestion throughout the year. The top 10 congested roadway lists were compiled by determining the segments with the most congestion and then identifying where the congestion began and ended. For our analysis, we included only segments with a length greater than 0.3 miles. A detailed analysis for each segment was conducted to determine when congestion occurred by month, day of week, and time of day. The top 10 list for each year was also compared to those of other years to determine trends in congestion along the segment. The top 10 most congested segments from 2013 through 2015 are shown in Appendix C.

5.2.1 Top 10 most congested segments in 2016

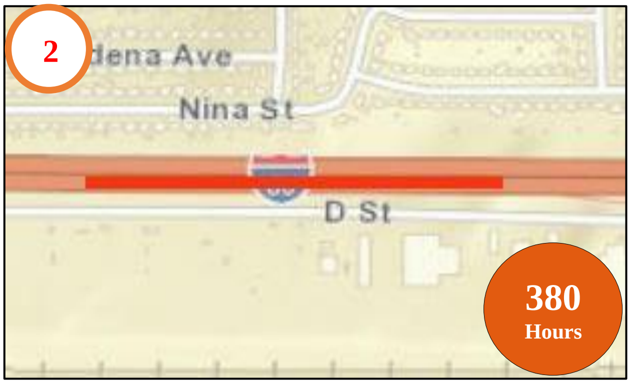
The top 10 most congested segments in Nebraska in 2016 are shown in Figure 5.1. Compared with 2013 and 2015, the top 10 most congested locations were generally much more congested in 2016, but less than in 2014. Most segments were consistent throughout year, except during February and March across weekdays and between 3 pm and 6 pm. The top segments were located in the Omaha and Lincoln areas. A summary of each of the top 10 locations is included below.

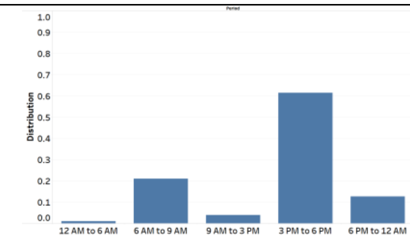
Figure 5.1 Top 10 congested segments on I-80 in Nebraska in 2016

I-80 Omaha WB | S 72ND ST **|** 0.39 miles

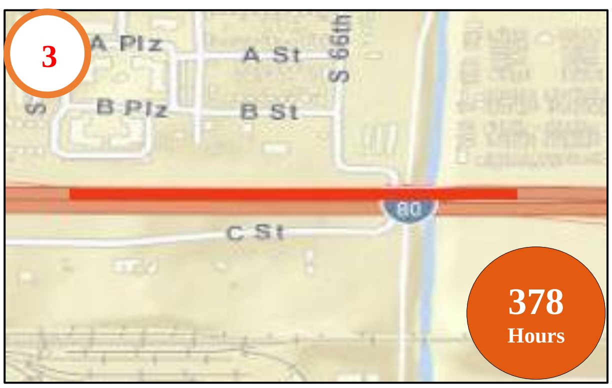
Annual number of hours of congestion	Second year at the top of the list; increased by 174 hours from 2015
Highest monthly and weekday total hours of congestion	Consistent by month and entire weekdays
Longest conges-tion duration by time of day	3 pm to 6 pm
Distribution of times of congestion times	

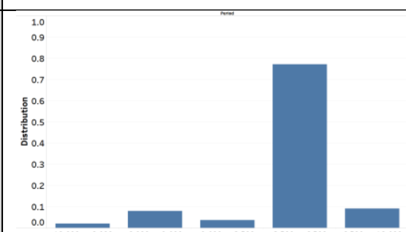
I-80 Omaha WB | S 72ND ST | 0.39 miles



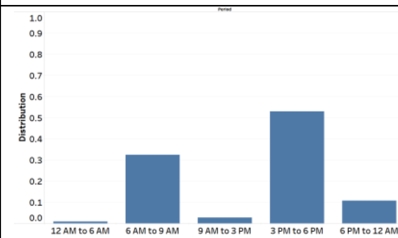
Annual number of hours of congestion	Increased from 98 hours in 2015
Highest monthly and weekday total hours of congestion	Throughout the year with a high in June at 60 hours, consistent across weekdays
Longest congestion duration by time of day	3 pm to 6 pm and 6 am to 9 am
Distribution of times of congestion	

I-80 Omaha WB | S 72ND ST | 0.39 miles

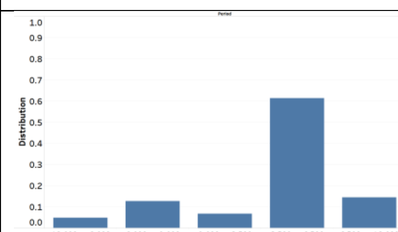


Annual number of hours of congestion	Increased from 138 hours in 2015
Highest monthly and weekday total hours of congestion	Throughout the year with a high in August at 45 hours, consistent across weekdays
Longest congestion duration by time of day	3 pm to 6 pm
Distribution of times of congestion	

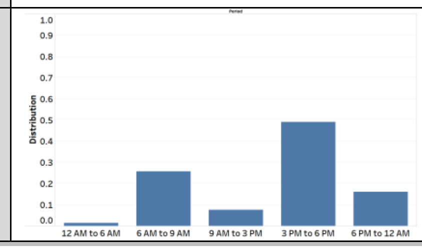
I-80 Omaha EB | S 84TH ST | 1.2 miles

Annual number of hours of congestion	Increased from 105 hours in 2015
Highest monthly and weekday total hours of congestion	Throughout the year with a high in June at 45 hours, consistent across weekdays
Longest congestion duration by time of day	3 pm to 6 pm and 6 am to 9 am
Distribution of times of congestion	

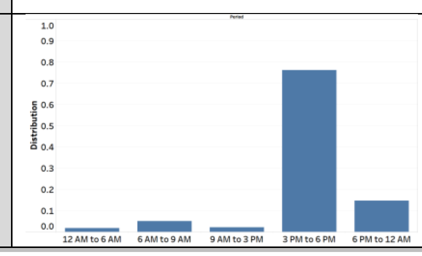
I-80 Omaha WB | S 84TH ST | 0.41 miles

Annual number of hours of congestion	172 hours
Highest monthly and weekday total hours of congestion	Throughout the year with a high in January at 30 hours, consistent across weekdays
Longest congestion duration by time of day	3 pm to 6 pm
Distribution of times of congestion	

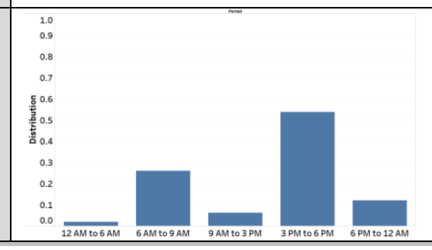
I-80 Omaha EB | S 60TH ST | 0.37 miles

Annual number of hours of congestion	Increased from 34 hours in 2015
Highest monthly and weekday total hours of congestion	High in January and June, consistent across weekdays
Longest congestion duration by time of day	3 pm to 6 pm and 6 am to 9 am
Distribution of times of congestion	

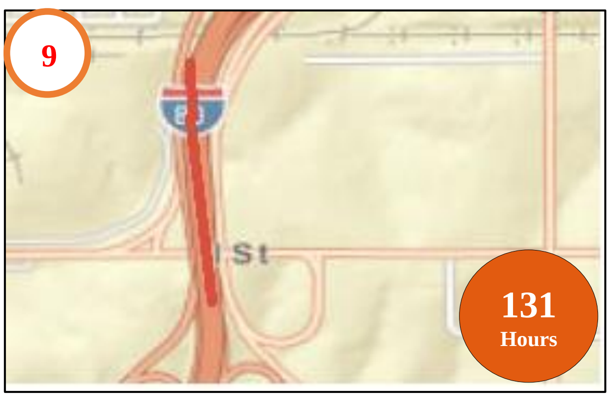
I-80 Omaha WB | S 126TH ST | 1.4 mile

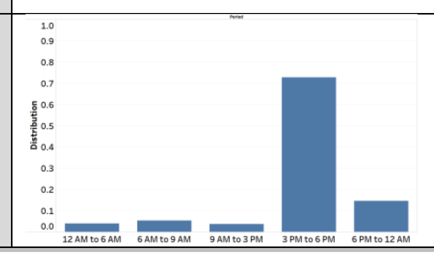
Annual number of hours of congestion	152 hours
Highest monthly and weekday total hours of congestion	Throughout the year, except in March, consistent across weekdays
Longest congestion duration by time of day	3 pm to 6 pm
Distribution of times of congestion times	

I-80 Omaha EB | I-680 | 1.25 miles

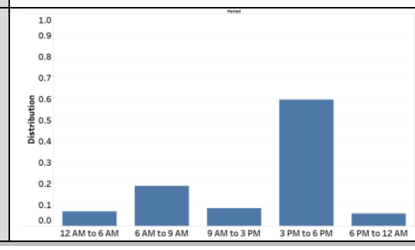
Annual number of hours of congestion	Increased from 32 hours in 2015
Highest monthly and weekday total hours of congestion	Throughout the year, except in March, consistent across weekdays
Longest congestion duration by time of day	3 pm to 6 pm and 6 am to 9 am
Distribution of times of congestion	

I-80 Omaha WB | L ST | 0.42 mile



Annual number of hours of congestion	131 hours
Highest monthly and weekday total hours of congestion	Throughout the year, except in March and April, consistent across weekdays
Longest congestion duration by time of day	3 pm to 6 pm
Distribution of times of congestion	

I-80 Omaha WB | I-480/US-75 | 1.27 miles

Annual number of hours of congestion	Slight decrease from last year
Highest monthly and weekday total hours of congestion	Throughout the year, except in March; consistent across weekdays
Longest conges-tion duration by time of day	3 pm to 6 pm
Distribution of times of congestion	

Many I-80 segments appeared on the top 10 list repeatedly over the years of the study. For example, a 1.45-mile-long segment at the interchange with L St. appeared on the list twice, ranking in the top position for 2013 and 2014. Similarly, a 2.5-mile-long segment near Exit 382 also appeared on the list for both 2013 and 2014. Seven segments appeared on the list for more than one year, but their rank order changed over the years. The segments of I-80 that appeared on the top 10 list more than once from 2013 through 2016 are listed in Table 5.1. The top 10 congested segments on I-80 from 2013 through 2016 are shown in Figure 5.2.

Table 5.1 Interstate 80 segments appearing on the top 10 list more than once from 2013 through 2016

No.	TMC segment	Year (Rank)	Intersection | Length of Segment
1	118+04546	2013 (1) 2014 (1)	L ST | 1.45
2	118N04552	2013 (2) 2014 (2) 2015 (7) 2016 (10)	I-480/US-75 | 1.27
3	118+04549	2013 (3) 2014 (4) 2015 (2) 2016 (2)	S 72ND ST | 0.33
4	118+04806	2013 (4) 2014 (3)	Exit 382 | 2.5
5	118-04549	2013 (5) 2014 (8) 2015 (3) 2016 (3)	S 72ND ST | 0.39
6	118-04550	2013 (6) 2014 (6) 2015 (1) 2016 (1)	S 60TH ST | 0.83
7	118+04548	2013 (7) 2014 (5) 2015 (4) 2016 (4)	S 84TH ST | 1.2
8	118+04550	2013 (8) 2014 (7) 2015 (9) 2016 (6)	S 60TH ST | 0.37
9	118P04547	2013 (10) 2014 (9) 2015 (10) 2016 (8)	I-680 | 1.25

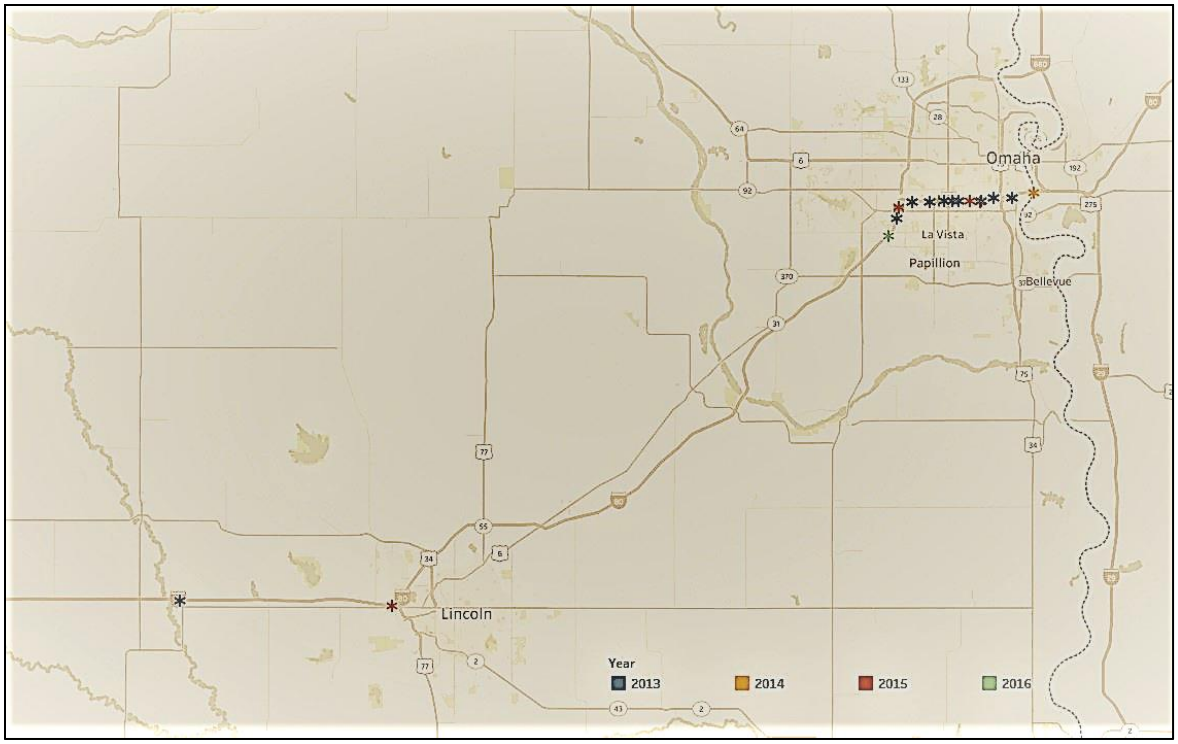


Figure 5.2 Top 10 congested segments on Interstate 80 from 2013 through 2016

5.3 Comparison of Metro Congestion Duration

Most of the congestion experienced in Nebraska is within urban areas, which have higher volumes of traffic. Given the varying numbers of segments and roadway lengths that were being considered, congestion per mile calculations for metro segments were used to contrast performance on different segments.

The metro area segments were defined based on the last interchange when entering and exiting the urban area. Three commuter corridors—Dodge Street Omaha (US-6), North Platte (US-83), and NE–IA Border (US-275) were also included in the analysis. The durations of congestion for each segment along the route were added to determine the total number of hours of congestion. By dividing this value by the total route length, the average congestion per mile was determined. These values were calculated for each month for all metro areas across Nebraska to compare any trends in congestion. A yearly comparison is also provided for the years 2013 through 2016. Comparisons of metro congestion duration from 2013 through 2015 are shown in Appendix C.

5.3.1 Metro Congestion per Mile in 2016

The average amount of congestion per mile in 2016 for metro areas across Nebraska is shown in Figure 5.3. The US 275 NE–IA border to Venice and US 6 Dodge Street Omaha segments were consistently among the most congested metro segments across the state.

An annual comparison of the number of hours of congestion by roadway and selected metro areas are shown in Figures 5.4 and 5.5, respectively. The US 275 near NE–IA border to

Venice segment exhibited a consistent increase in the amount of congestion per mile in 2015 and 2016. The congestion on the US 6 Dodge Street Omaha and I-129 in Sioux City segments significantly increased in 2014, 2015, and 2016. The I-180 in Lincoln segment exhibited a consistent amount of congestion per mile with slight increases in 2014, 2015, and 2016. Each of the remaining segments (I-80 Harrison St. to Omaha, US-83 North Platte, and I-690 Iowa border) exhibited consistent levels of congestion during the four reporting years.

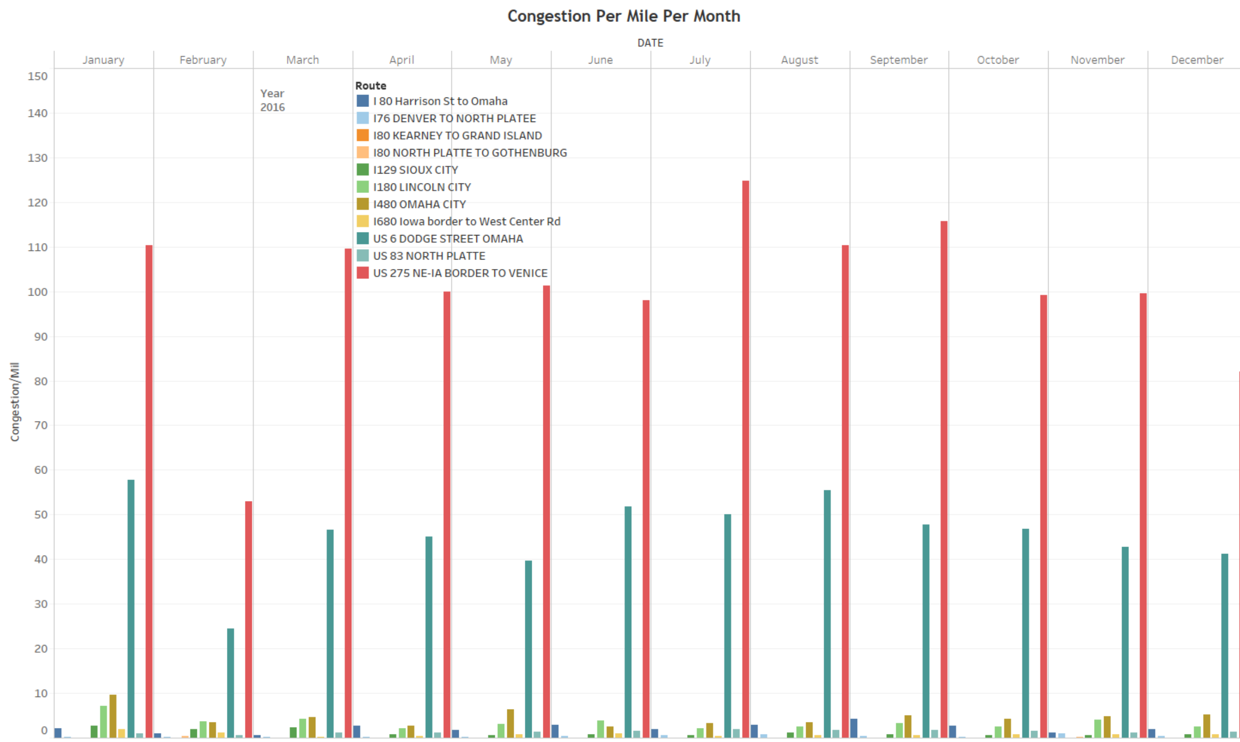


Figure 5.3 Congestion duration (hours) per mile metro area comparisons, 2016

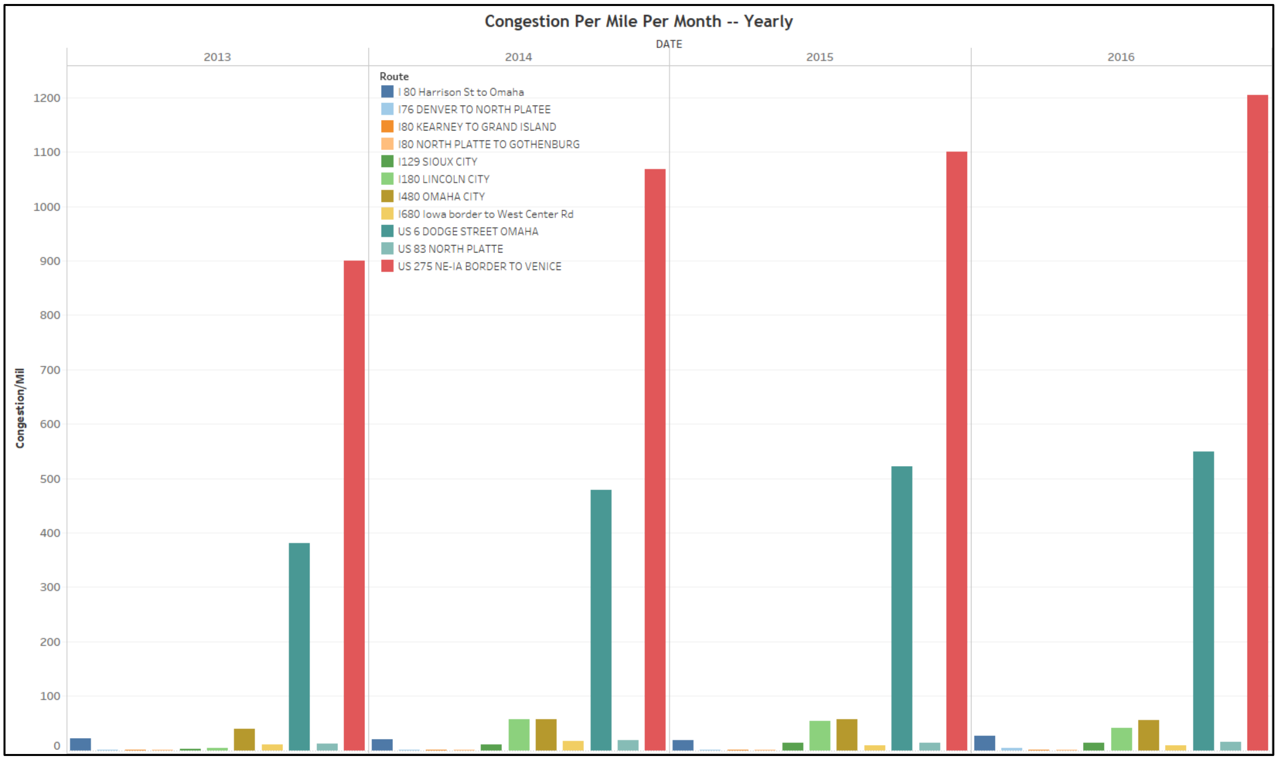


Figure 5.4 Congestion duration (hours) per mile metro area comparison by year

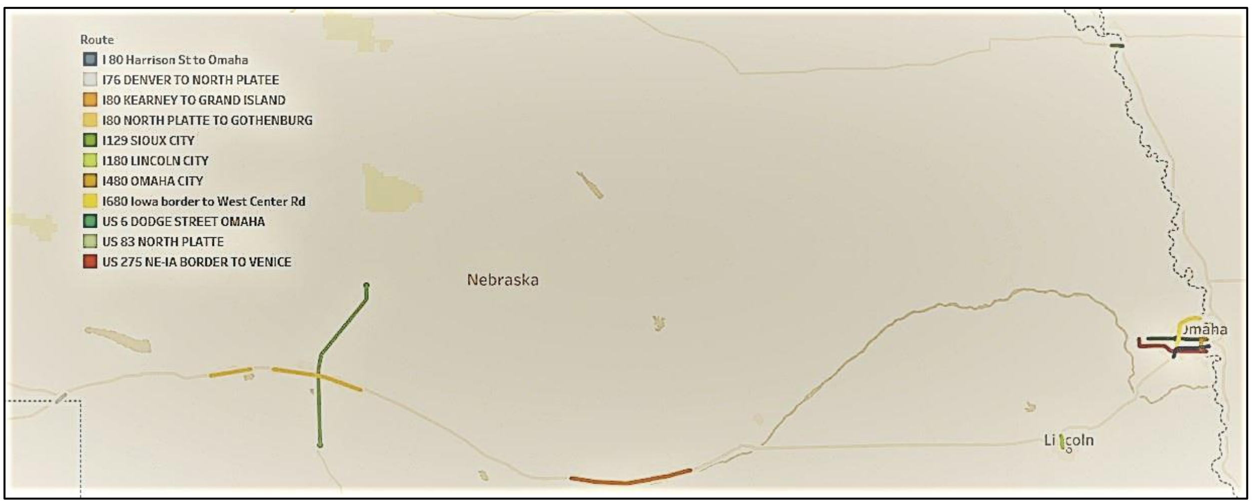


Figure 5.5 Selected metro routes with congestion

5.4 Congestion Duration on Interstate 80

In this section, we provide a detailed view of all segments along the I-80 corridor in Nebraska. Congestion duration (hours) were used to determine the severity of congestion by segment along I-80. This allowed for the locations with congestion, as well as the extent of where the congestion occurred, to be quickly identified. Once identified, the locations could also be analyzed by year, month, day, week, or time of day.

The congestion duration for the I-80 corridor from the Kimball to Omaha by direction of travel is shown in Figure 5.6. The right side of the chart represents the eastbound direction, and the left side represents the westbound direction, both sides directly across from each other representing the same location along I-80. The scale along each x-axis is the number of hours of congestion. Each segment is color coded based on the number of hours of congestion by summer (March, April, May, June, July, August, September, and October) and winter (November, December, January, and February) months.

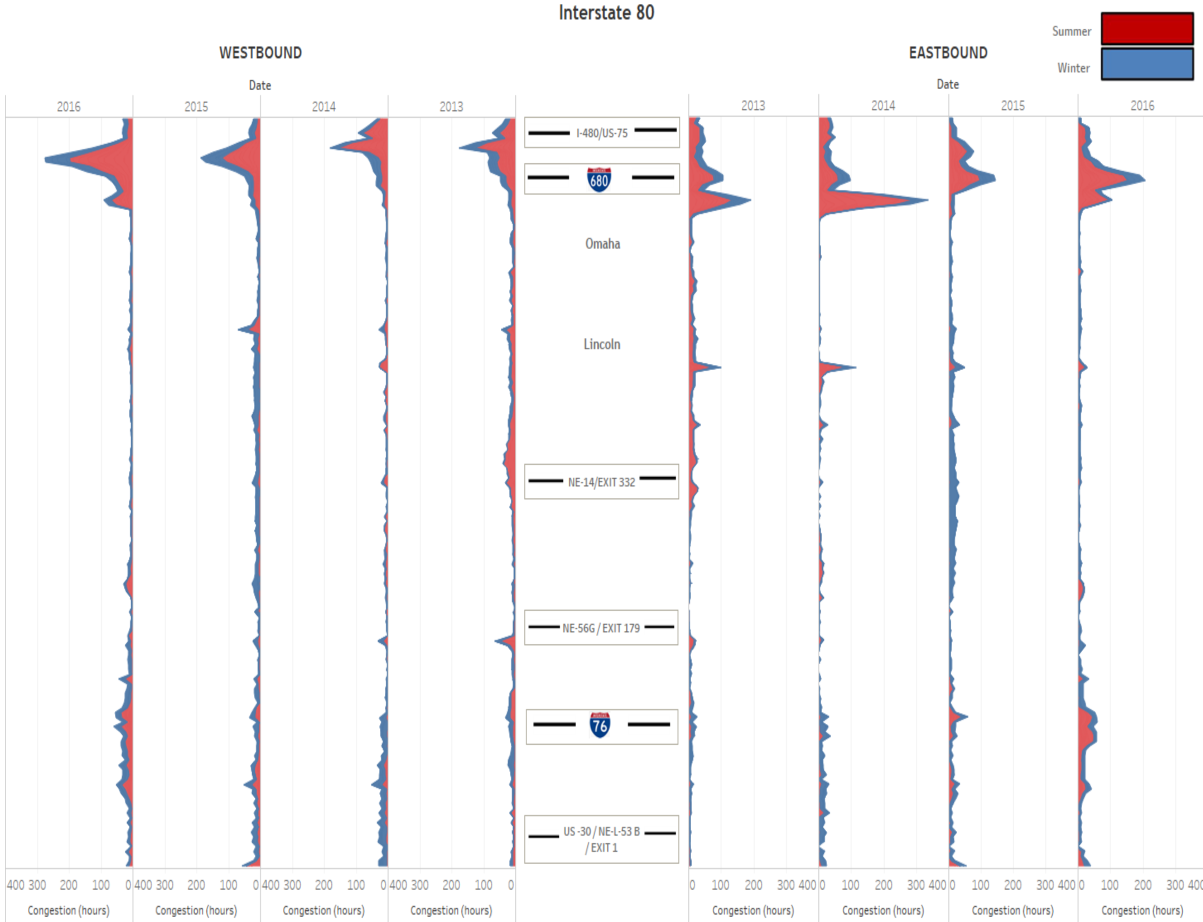


Figure 5.6 Congestion duration (hours) for westbound and eastbound Interstate 80 in 2013, 2014, 2015, and 2016

5.4.1 Eastbound

Congestion on I-80 eastbound was limited to the Omaha, Lincoln, and Julesburg areas:

• Near the L ST interchange through Omaha

Most congested year	2014 saw significant congestion.
Most congested month	Peaked in May but significant from April through November
Most congested day	All weekdays with peak on Thursday
Most congested time of day	6 am – 9 am

• Near I-80/EXIT 382 interchange through Lincoln

Most congested year	2014
Most congested month	May
Most congested day	All weekdays with peak on Wednesday
Most congested time of day	12 am – 6 am

• Near NE-25B/EXIT 107, I-76, US-138/EXIT 101 interchanges

Most congested year	2016
Most congested month	November
Most congested day	All weekdays with peak on Friday
Most congested time of day	12 am – 6 am

5.4.2 Westbound

Congestion on I-80 westbound was limited to the Omaha, Lincoln, and near I-76 interchanges.

• Near S 60TH ST interchange through Omaha

Most congested year	2016 saw significant congestion.
Most congested month	Peaked in August but significant from April through January
Most congested day	All weekdays with peak on Wednesday
Most congested time of day	3 pm – 6 pm

• Near US-6/EXIT 396 interchange through Lincoln

Most congested year	2015
Most congested month	February
Most congested day	All weekdays with peak on Sunday
Most congested time of day	12 am – 6 am

• Near NE-56G/EXIT 179 interchange through North Platte

Most congested year	2013
Most congested month	February and August
Most congested day	All weekdays with peak on Sunday
Most congested time of day	12 am – 6 am

5.5 Speed Performance for Interstate 80

One limitation with using congestion duration is the limited ability to evaluate additional speed thresholds lower than 45 mph without a web-based tool. One solution was to develop speed performance charts that allowed for the severity of the congestion to be evaluated by observing the percentage of time speeds were within 10-mph bins from 0 to 75+ mph.

Similar to congestion duration, each segment is evaluated based on the number of minutes speeds are within a speed bin, using real-time data from the probe data source. Each segment varied in the amount of data that was provided in real time. To account for this, the number of minutes in each speed bin was divided by the total number of minutes of real-time speed data for that segment. This allowed for the data to be plotted on a chart running from 0 to 100% to see what percentage of time speeds were within a defined range.

The speed performance along I-80 in the eastbound and westbound directions is shown in Figures 5.7 and 5.8, respectively. Similar to the graph of the number of hours of congestion, the I-80 corridor through Nebraska is represented along with a reference bar along the left showing the nearest state routes. Each column of the chart represents a separate month, which allows for comparisons to be made. Each speed bin is represented by a separate color with lowest speeds represented by red and higher speeds represented by dark green. The scale along the x-axis identifies what percentage of the real-time data is within the designated bin. Speed performance data for I-80 for 2013 through 2015 are shown in Appendix C.

As shown in Figures 5.7 and 5.8, the severity of congestion significantly increased near the Omaha and Lincoln areas in 2014, 2015, and 2016, as indicated by the larger percentage of slower speeds. No other significant changes in speed were identified along I-80.

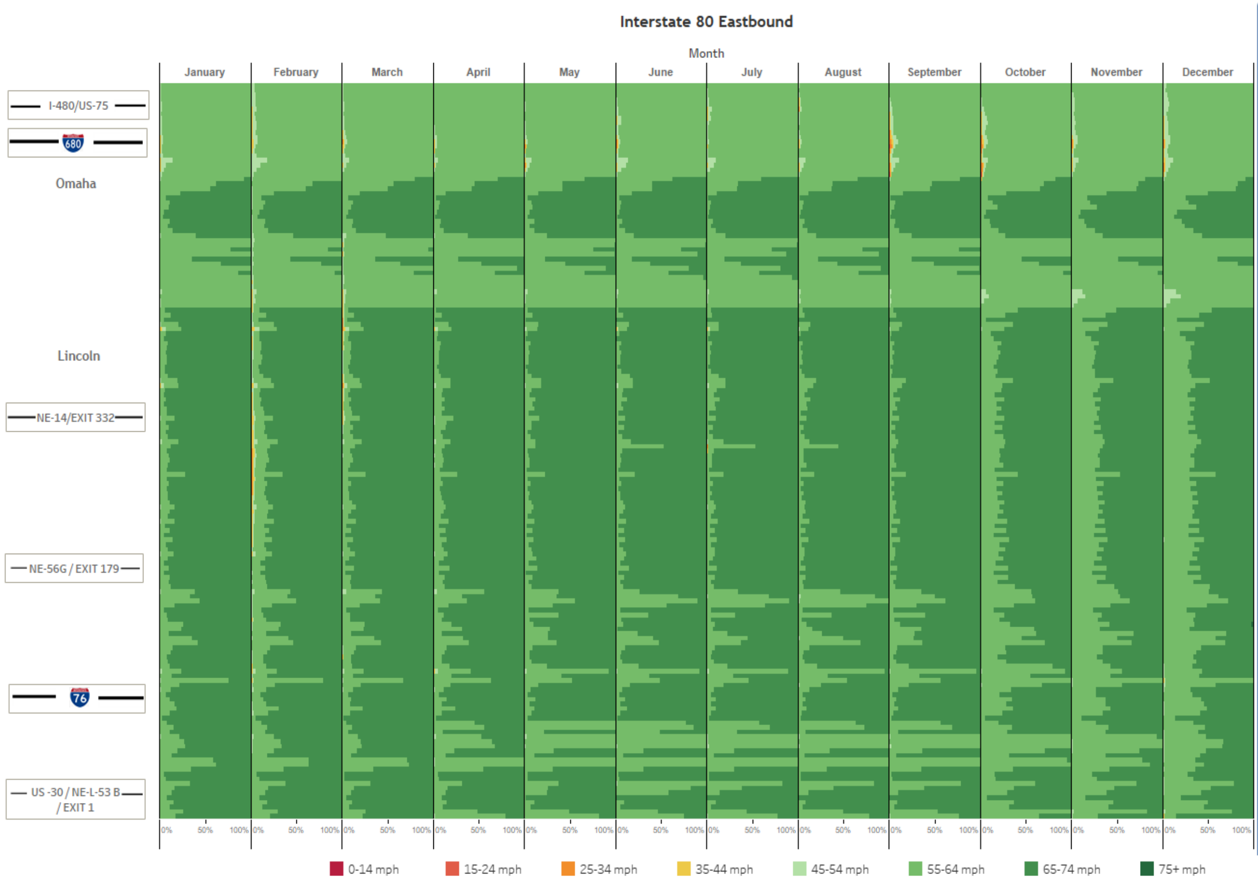


Figure 5.7 Interstate 80 EB speed percentage in 2016

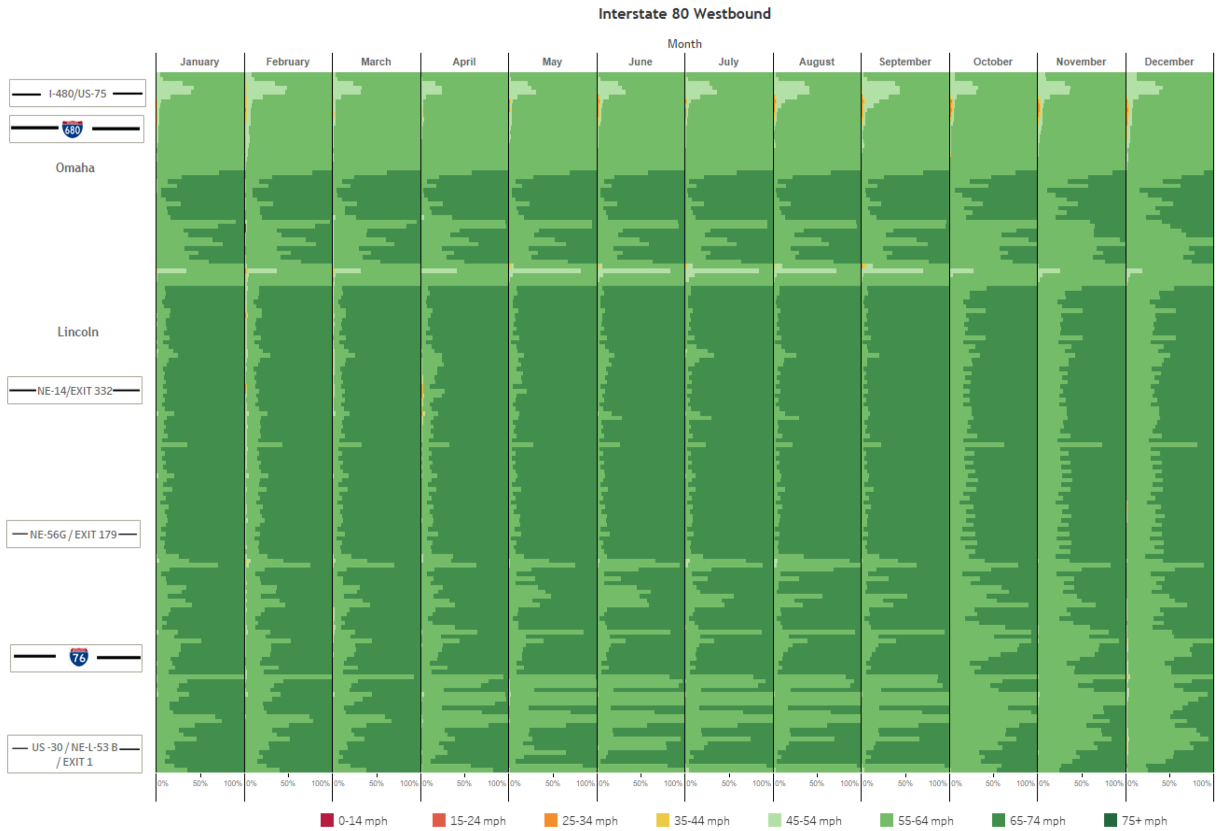


Figure 5.8 Interstate 80 WB speed percentage in 2016

5.6 Travel Time Reliability for Interstate 80

5.6.1 Yearly Travel Time Reliability

Drivers across Nebraska expect to have few delays and to be able drive a similar route with little or no change in their travel time. Travel time reliability is an important performance measure that is used to measure drivers' confidence that they will arrive within an acceptable travel time. In this report, the percentage increase in typical travel time was used to measure the increase in travel time that would be needed for 95% of trips to arrive on time. To compare this reliability between other routes with of different lengths, the increase for 95% confidence in travel time was divided by the average travel time to determine the percentage of additional travel time needed.

Interstate 80 was divided into eight routes: through Omaha, from Chalco to Waverly, through Lincoln, from Lincoln to York, from York to Kearney, from Kearney to North Platte, from North Platte to Chappel, and from Lodge Pole to the NE–WY border. The travel time represents the time it took to travel all the segments through each route. After the travel time through each route was calculated every minute using the probe-based speed data, the average and 95th percentile of travel times were calculated. The 95th percentile travel time was determined for the entire year for the morning and evening peak periods during weekdays. This allowed for the reliability of the travel time to be analyzed during the more heavily congested hours of day.

Both directions of travel for I-80 are displayed in the charts of Figure 5.9. The center banner identifies the route along the interstate where the reliability was measured. The different colored bars represent the different times of day during which the reliability was measured and a comparison for the years from 2013 through 2016. The percentage increases in typical travel times along I-80 are displayed. Both directions of the NE–WY border segment experienced an increase in typical travel time from 2013 through 2016. Percentage increase in travel time reliability was fairly low from York to North Platte and remained consistent during all time periods. The segment from Waverly to Lincoln experienced a significant increase in the typical travel time from 2013 through 2016.

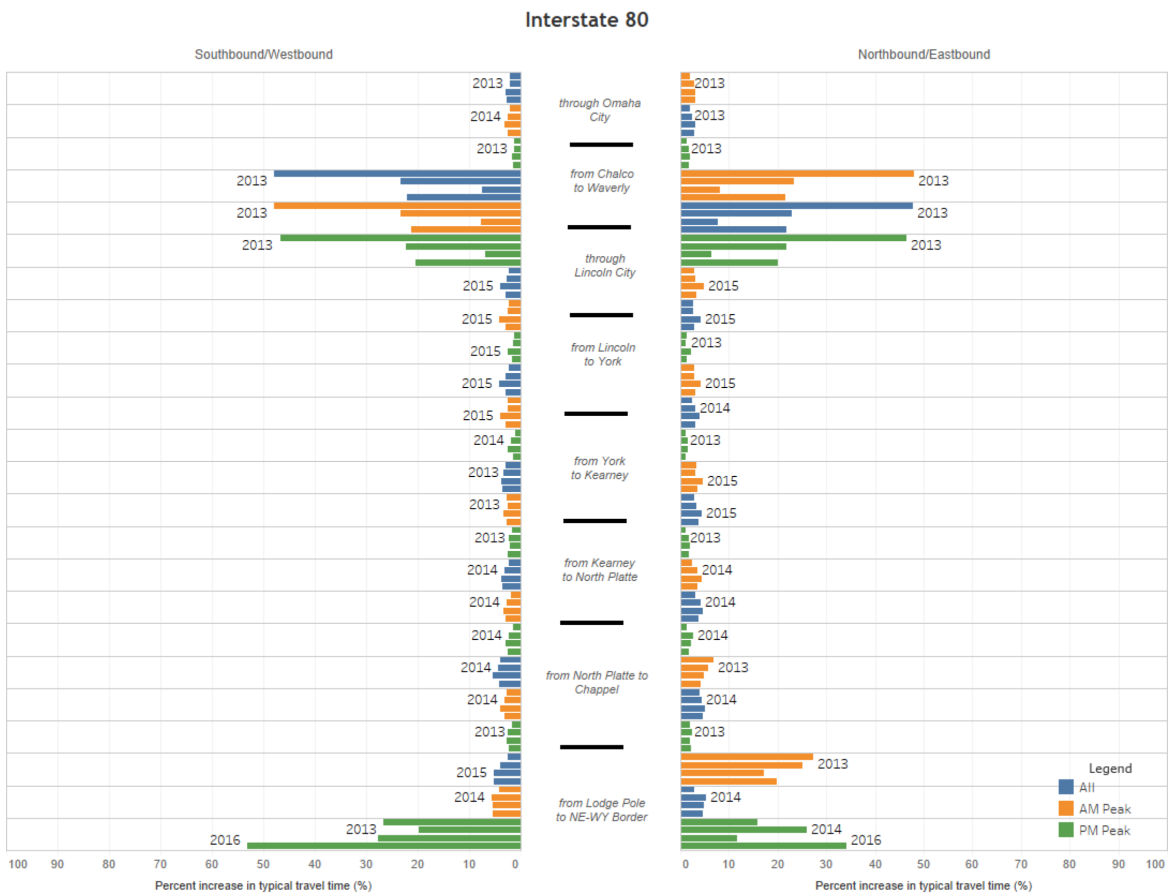


Figure 5.9 Percentage increase in typical travel time on Interstate 80

5.7 Conclusion

In this chapter, we reported how we explored performance monitoring and historical trend analysis from INRIX data using different measures for I-80 in Nebraska. First, we identified the top 10 congested roadways by determining which segments had the most congestion and then the beginning and end of where the congestion occurred; we also included a detailed analysis of when congestion occurred by month, day of week, and time of day. Next, we presented the congestion per mile calculations that were used to determine metro area congestion per mile, which supported comparing performance given the varying number and length of roadway segments that we investigated. These values were calculated for each month for all metro areas across Nebraska to compare congestion trends. A yearly comparison for years 2013 through 2016 was also provided. Third, we reported on how congestion duration was used to show the severity of congestion by segment along I-80. Each segment was color coded based on the number of hours of congestion by summer and winter months. Once identified, the locations can also be analyzed by year, month, week, day, or time of day. Next, we presented how the severity of congestion could be evaluated by observing the percentage of time speeds were within a 10-mph bin from 0 to 75+ mph. Finally, we described how we divided I-80 into eight sections to calculate the change in travel time reliability from 2013 to 2016.

6. Conclusions and Recommendations

6.2 Summary and Conclusions

Traffic monitoring using wide-area probe-sourced data is growing as a viable means of comprehensive traffic monitoring without a large investment in deploying physical assets in right-of-ways and its associated costs and maintenance burden. Real-time and archived probe data streams have many uses, provided the above-mentioned considerations have been addressed. Real-time probe data is useful for traffic operations and safety management activities such as travel time estimation and incident management.

For travel time estimation, real-time probe data streams can serve as a good data source for calculating and displaying travel times on message signs on major freeways and highways. However, it is important to know how some of the challenges, as discussed in Chapter 4, may affect this travel time estimation. It was very complicated and not very efficient using point-based detection models for incident management until the emergence of wide-area probe data streaming. Incident management activities, such as detecting the back of a queue, were previously nearly impossible. This problem has now been simplified through the use of probe data streams. Probe data are being used in Iowa and Indiana for a real-time application, which allows for the identification of locations experiencing queuing in an effort to eliminate back-of-queue crashes.

In this study, we focused on several specific locations in the state of Nebraska to evaluate the reliability of INRIX data by comparing that data with data from PVR sensors using selected performance measures. A summary of the study appears in Table 6.1.

Table 6.1 Summary of performance measures used in the study

Performance Measures	Comments
Congestion detection latency	This measure of delay between two time series datasets was used to measure the difference in detection of start times of a congestion period between INRIX and PVR sensors. The average latency calculated in this study was 4.97 minutes.
Count of congestions	Number of congestions that were detected by both INRIX segments and PVR sensors with latencies lower than 20 minutes. Using the congestion detection algorithm, 44 congestions were detected by both INRIX and PVR datasets for all selected ATRs for all days.
Congestion durations	Two scenarios for comparing INRIX and PVR datasets in terms of congested hour were considered: • Scenario 1: total number of hours for which the speed of each segment is less than 45 mph. • Scenario 2: congestion durations detected by both INRIX segments and PVR sensors with detection latency lower than 20 minutes. The two scenarios were compared for two time periods; 1 day and 3 weeks. Scenario 1 showed INRIX duration of congestion hour tended to be longer than for PVR because, for some ATRs, INRIX reported speed close to 45 mph or even less for most of the time. Also, lack of sufficient confidence score 30 (real-time) data negatively affected this situation. Using scenario 2, we obtained reliable results for comparing the two datasets.
Buffer time index	BTI was calculated by subtracting the 85th percentile of TTPM (travel time per mile) from the TTPM median and then dividing that result by the TTPM median. It was calculated for 1-week and 3-week periods. Due to low variation of INRIX data, BTI for PVR is almost always greater than that for INRIX. In summary, INRIX did not perform reliably for calculating the BTI.
Reliability curve	Calculated as the inverse of speed multiplied by 60, was considered as TTPM in minutes. Except for some locations, INRIX performance was acceptable in terms of reliability curves.

Archived probe data is useful for general transportation asset performance assessment and planning. Archived data can be used to build models to understand the performance of such assets, especially for low volume and low speed roadways where real-time operational activities cannot be performed due to high speed bias and latencies. A comprehensive analysis of performance monitoring and historical trend analysis using different measures for I-80 segments in Nebraska was also performed in this study. Almost all top 10 congested segments from 2013 through 2016 were located near Omaha and Lincoln on I-80.

Observations:

- In 2013, most segments exhibited slightly longer hours of congestion hours during September and October, across weekdays, and between 3 pm and 6 pm.
- In contrast to 2013, the top 10 most congested locations in 2014 were much more congested. Most segments exhibited consistent congestion throughout year, except from May through October, across weekdays and between 3 pm and 6 pm and between 6 am and 9 am.
- In contrast to 2013 and 2014, the top 10 most congested locations exhibited less congestion in 2015. Most segments saw slightly longer hours of congestion in November and December, across weekdays and between 3 pm and 6 pm.
- Finally, in contrast to 2013 and 2015, the top 10 most congested locations exhibited more congestion in 2016 but less than in 2014. Most segments exhibited consistent congestion throughout the year, except in February and March, across weekdays and between 3 pm and 6 pm.

The average amount of congestion per mile was calculated across metro areas in Nebraska from 2013 through 2016. Three commuter corridors—Dodge Street Omaha (US-6), North Platte (US-83), and NE–IA Border (US-275)—were also included in the analysis.

Observations:

- US 275 near the NE–IA border to Venice exhibited a consistent increase in congestion per mile in 2015 and 2016.
- The congestion on US 6 Dodge Street Omaha and I-129 in Sioux City significantly increased in 2014, 2015, and 2016.
- I-180 in Lincoln exhibited a consistent amount of congestion per mile with slight increases in 2014, 2015, and 2016.
- Each of the remaining routes (I-80 Harrison St. to Omaha, US-83 North Platte, and I-690 Iowa border) experienced consistent levels of congestion during the four reporting years.

The duration of congestion was calculated to show the severity of congestion by summer and winter months and by direction for all segments along the I-80 corridor in Nebraska from 2013 through 2016.

Observations:

- Congestion on I-80 eastbound was limited to the Omaha, Lincoln, and Julesburg areas. In 2014, significant congestion was exhibited near the L ST interchange through Omaha, peaking in May but significant from April through November, all weekdays with a peak on Thursday, and mostly between 6 am and 9 am. Also, in 2016 congestion was exhibited near the NE-25B/EXIT 107, I-76, and US-138/EXIT 101 interchanges, peaking in November, all weekdays with a peak on Friday, and mostly between 12 am and 6 am.

- Congestion on I-80 westbound was limited to areas in Omaha and Lincoln and near the I-76 interchange. In 2016 significant congestion was exhibited near the S 60TH ST interchange in Omaha, peaking in August but significant from April through January, all weekdays with a peak on Wednesdays, and mostly between 3 pm and 6 pm In 2015, there was significant congestion near the US-6/EXIT 396 interchange through Lincoln, peaking in February, all weekdays with peaks on Sunday, and mostly between 12 am and 6 am. In 2013, congestion was exhibited near the NE-56G/EXIT 179 interchange through North Platte, peaking in February and August, all weekdays with peaks on Sunday, and mostly between 12 am and 6 am.

The severity of congestion was evaluated by observing the percentage of time speeds were within 10-mph bins from 0 to 75+ mph in both the eastbound and westbound directions. In 2014, 2015, and 2016, the severity of congestion significantly increased near the Omaha and Lincoln areas, as shown by the larger percentage of slower speeds. No other significant changes in speed were identified along I-80.

The NE–WY border segment exhibited an increase in typical travel time from 2013 through 2016 in both directions. The travel time reliability was low from York to North Platte and remained consistent during all time periods. From Waverly to Lincoln a significant increase in typical travel time was evident from 2013 through 2016.

6.2 Recommendations

Ultimately, wide-area probe data offers a wide array of opportunities for the transportation industry. With connected vehicles and sophistication of personal and commercial technologies in the future, these innovative data streams, which can also provide user feedback, are going to continue to influence and support innovation within the transportation industry. We offer the following recommendations to agencies considering the use of a probe data streams to support traffic operations management and decision making:

- Most transportation agencies define road segments based on a linear referencing system. To easily associate probe data with other significant data sources, such as weather and crash data, agencies must conflate the probe data segmentation to the linear referencing system.
- The length of segments for which probe data are available varies greatly, from 0.5 miles to about 8 miles. Agencies must examine whether the space granularity of probe data is sufficient for the intended application. For incident detection applications, high space granularity may lead to false alarms. Segments with shorter lengths should be excluded. On the other hand, for work zone performance assessment, high space granularity is preferred for estimating measures such as queue lengths, total delays, etc.
- Agencies should arrange to work with probe data vendors toward identifying, communicating, and ultimately automatically detecting lane configuration changes to vendors.
- In terms of geographic coverage, INRIX has been evaluated for interstates and non-interstates, showing that INRIX is reliable for almost all minutes of a day on interstates.

Moreover, this study showed that INRIX is more reliable during the day than at night, especially during peak hours.

- Regarding incident detection, INRIX is reliable for merely detecting congestion, especially recurring congestion; when it detects congestion, it gets almost all the information related to the congestion.
- There will always be a bias between traffic speed data from probe sources and benchmarked sensors. Speed bias directly affects incident detection, travel time estimation, calculating performance measures (such as congested hour, BTI, etc.), and other traffic-related measures. It is important to understand the factors that influence these biases and how to correct for them.
- Travel time estimation and incident detection applications should be developed based completely on real-time data. Substitutions with historical data are not accurate and therefore not advised. In areas with limited probe penetration, an agency could augment probe data with infrastructure-mounted sensors.
- Agencies should note that there is almost always a time delay in probe-based streaming data. Compared to loop detectors and radar sensors, latency increases on low-volume roadways and especially when traffic is moving at lower speeds. Thus, for time-sensitive applications, it is important to know the possible range of expected latencies and plan appropriately; however, sensors are very costly and not applicable for many places. Thus, for locations without other data providers, detecting congestion with latency by INRIX is better than not detecting it at all.
- Internal TMC segments with lengths less than 0.5 miles should also be excluded from traffic performance evaluations.
- In this era of big data, all transportation agencies and state DOTs must be able to handle a huge volume of data. Apache Hadoop, Apache Pig, and Apache Spark [66] are high-level open-source "big data" technologies that allow for the analysis of "big" probe data streams.

Many different tests, analyses, and experiments have been left for the future due to lack of sufficient data. Because this study was focused mainly on freeways, future work should be focused on a deeper analysis of arterials and urban areas. This would be possible by deploying more infrastructure sensors on both freeways and arterials. Another main point that should be taken into consideration is the length of time that data is collected. In the best case scenario for this study, the longest time period available data for each sensor was almost a month. By increasing it to a year or more, it would be possible to measure the performance of probe data versus local sensors over a longer period of time.

References

1. INRIX: http://inrix.com/. Accessed September 27, 2017.
2. I-95 Vehicle Probe Project II Interface Guide, December 2014. http://i95coalition.org/wp-content/uploads/2015/02/I-95-VPP-II-INRIX-Inteface-Guide-v1-Dec-2014.pdf. Accessed August 25, 2016.
3. Young, S., “Real-Time Traffic Operations Data Using Vehicle Probe Technology”, Proceedings of the Mid-Continent Transportation Research Symposium, Ames, IOWA, 2007.
4. W. Feng A. Bigazzi S. Kothuri and R. Bertini “Freeway sensor spacing and probe vehicle penetration: Impacts on travel time prediction and estimation accuracy” Transportation Research Record: Journal of the Transportation Research Board no. 2178 pp. 67–78 2010.
5. Coifman, B. Estimating Travel Times and Vehicle Trajectories on Freeways Using Dual Loop Detectors. Transportation Research Part A, Vol. 36, No. 4, 2002, pp. 351–364.
6. Lindveld, C. D. R., R. Thijs, P. H. L. Bovy, and N. J. Van der Zijpp, “Evaluation of Online Travel Time Estimators and Predictors”. In Transportation Research Record: Journal of the Transportation Research Board, No. 1719, TRB, National Research Council, Washington, D.C., 2000, pp. 45–53.
7. Kim, S., Coifman, B., "Comparing INRIX speed data against concurrent loop detector stations over several months," Transportation Research-Part C, Vol. 49, 2014, pp 59–72.
8. Federal Highway Administration (FHWA), “Private Sector Data for Performance Management: Final Report”, http://ops.fhwa.dot.gov/publications/fhwahop11029/ch3.htm, Accessed September 27, 2017.
9. Chumchoke Nanthawichit,Takashi Nakatsuji and Hironori Suzuki, “Application of Probe Vehicle Data for Real-Time Traffic State Estimation and ShortTerm Travel Time Prediction on a Freeway”, Proceeding of 82nd TRB Meeting, Washington D.C., 2003.
10. Hadi Sadrsadat and Stanley Ernest Young, “Probability of Real-Time Data as a Function of Hourly Volume”, VPPI Technical Documents, ITSWC, 2011.
11. Technical Memorandum, “Evaluation of NAVTEQ, TrafficCast, and INRIX® Travel Time System Data in the Tallahassee Region”, Florida Department of Transportation Intelligent Transportation Systems Program, Version 2.0, March 27, 2012.
12. Y. Adu-Gyamfi A. Sharma S. Knickerbocker N. Hawkins and M. Jackson “Reliability of probe speed data for detecting congestion trends” in Intelligent Transportation Systems (ITSC) 2015 IEEE 18th International Conference on pp. 2243 – 2249 IEEE 2015.
13. Chao Liu, Bowen Huang, Mo Zhao, Soumik Sarkar, Umesh Vaidya, Anuj Sharma. “Data Driven Exploration of Traffic Network System Dynamics using High Resolution Probe Data”. The 55th IEEE Conference on Decision and Control, USA, December 12–14, 2016.
14. Florida Department of Transportation (FDOT), “SIS Bottleneck study TECHNICAL MEMORANDUM NO. 1 Data Review”, http://www.fdot.gov/planning/systems/programs/mspi/pdf/Tech%20Memo%201.pdf.
15. Rick Schuman, Ryan Glancy, “How Freight Probe Data is Revolutionizing the Industry”, Publication: Purdue Road School, http://docs.lib.purdue.edu/roadschool/2015/presentations/76/, March 2015.
16. Hiroshi Matsumoto, Masafumi Kobayashi and Kunihiro Kamata, "Traffic Flow Control Using Probe Vehicle Data", Proceeding of 17th ITS World Congress, Busan, 2010.

17. Kang-Ching Chu and Kazuhiro Saitou, "Optimization of probe vehicle deployment for traffic status estimation", Proceeding of IEEE International Conference on Automation Science and Engineering (CASE), 2013.
18. Nagashima, Y., O. Hattori, and M. Kobayashi, "Improvement of Traffic Signal Control Using Probe Data". SEI Technical Review, Vol. 78, April 2014, pp. 44–47.
19. Ali Haghani, Xuechi Zhang and Masoud Hamedi, "Validation and Augmentation of Inrix Arterial Travel Time Data Using Independent Sources", State Highway Administration, Maryland Department of Transportation, Feb 2015.
20. White Paper – "I-95 Corridor Coalition Vehicle Probe Project Confidence Value and Smoothing", April 2010.
21. M. Kobayashi, K.Suzuki, S. Nishimura, "Utilization of Probe Data for Traffic Flow Control", 18th WC on ITS, 2011.
22. Underwood, S.E., "A review and classification of sensors for intelligent vehicle-highway systems." IVHS Technical Report No. DTFH61-89-P-00827, Department of Electrical Engineering and Computer Science, University of Michigan, Ann Arbor, MI, August 1990.
23. Nelson, D., "ITS subsystems and technologies—managing traffic, vehicles and systems." Intelligent Transportation Primer, Chapter 14, Institute of Transportation Engineers.
24. Sun, C., Ritchie, S.G. and Tsai, K., "Algorithm development for derivation of section-related measures of traffic system performance using inductive loop detectors." Transportation Research Record, No. 1643, TRB, National Research Council, pp. 171–180, 1998.
25. Coifman, B., "Vehicle reidentification and travel time measurement in real-time on freeways using the existing loop detector infrastructure." Transportation Research Record, No. 1643, TRB, National Research Council, pp 181–191, 1998.
26. Coifman, B., "Estimating travel times and vehicle trajectories on freeways using dual loop detectors." Transportation Research Part B, 2000.
27. Washburn, S.S. and Nihan, N.L., "Estimating link travel time with the mobilizer video image tracking system." Journal of Transportation Engineering, Vol. 125, No. 1, ASCE, pp. 15–20, 1999.
28. Shuldiner, P.W. and Upchurch, J.E., "Automated travel time data for a regional traveller information system." Proceedings of the ITE 2001 Annual Meeting, Institute of Transportation Engineers, Chicago, IL, August 18–22, 2001.
29. Abramson, N.J. and Chenoweth, A., "Ray of light." Traffic Technology International: The 2000 International Review of Advanced Traffic Management, Section 7: Detection and Monitoring, UK & International Press, pp. 219–222, 2000.
30. Labell, L.N. and May, A.D., "Detectors for freeway surveillance and control: final report." Research Report No. UCB-ITS-RR-90-18, Institute of Transportation Studies, University of California, Berkeley, CA, August 1990.
31. Black, J. and Loukakos, D., "Traffic surveillance–other detectors." ITS Decision Database in PATH, October 2000.
32. Klein, L.A., "Sensor technologies and data requirement for ITS." Artech House, Norwood, MA, 2001.
33. Petty, K. F., Skabardonis, A. and Varaiya, P. P., "Incident detection with probe vehicles: performance, infrastructure requirements and feasibility." Transportation Systems 1997: A Proceedings Volume from the 8th IFAC/IFIP/IFORS Symposium, Chania, Greece, June 16–18, 1997, Vol. 1, pp. 125–130, 1997.

34. Bell, M.G.H & Iida, Y., “The Network Reliability of Transport: Proceedings of the 1st International Symposium on Transportation Network Reliability (INSTR)”. Oxford, Elsevier Science, 2003.
35. Pu, W., "Analytic Relationships Between Travel Time Reliability Measures." Transportation Research Record: Journal of the Transportation Research Board 2254(-1): 122–130, 2011.
36. Lomax, T., Schrank, D., Turner, S., Margiotta, R., “Selecting travel reliability measures”, Texas Transportation Institute, Cambridge Systematics Inc, 2003
37. Turner, S., and Qu, T., “Developing Twin Cities Arterial Mobility Performance Measures Using GPS Speed Data”, Minnesota Department of Transportation, St. Paul, 2013
38. Day, C., Remias, S., Li, H., Mekker, M., McNamara, M., Cox, E., Horton, D., and Bullock, D. 2013–2014 Indiana Mobility Report: Full Version. Purdue University, West Lafayette, IN, 2014. http://dx.doi.org/10.5703/1288284315508. Accessed September 27, 2017.
39. Mahapatra, S., Wolniak, M., Sadabadi, K.F., Beckett, E., and Jacobs, T. 2013 Maryland State Highway Mobility Report. Maryland State Highway Administration, Baltimore, 2013.
40. Missouri Department of Transportation. Tracker: Measures of Departmental Performance. Jefferson City, 2013.
41. University of Maryland Center for Advanced Transportation Technology Laboratory. The RITIS Vehicle Probe Project Suite. https://vpp.ritis.org/suite/faq/#/performance-measures. Accessed September 27, 2017.
42. Federal Highway Administration. The Urban Congestion Report (UCR): Documentation and Definitions. 2015b. http://www.ops.fhwa.dot.gov/perf_measurement/ucr/documentation.htm. Accessed September 27, 2017.
43. Schrank, D.L., Eisele, W.L., and Lomax, T. TTI’s 2012 Urban Mobility Report. Texas A&M Transportation Institute, College Station, 2012.
44. Schrank, D., Eisele, B., Lomax, T., and Bak, J. 2015 Urban Mobility Scorecard. 2015. https://mobility.tamu.edu/ums/report/. Accessed September 27, 2017.
45. Washington State Department of Transportation. Gray Notebook 52: For the Quarter Ending December 31, 2013. Olympia, 2014.
46. Washington State Department of Transportation. 2013 Corridor Capacity Summary. Olympia, 2013.
47. JMT Technology Group and Vanasse Hangen Brustlin, Inc. 2010 Traffic Performance Measures Development Using INRIX Travel Time Data. Virginia Department of Transportation, Richmond, 2012.
48. Florida Department of Transportation. FDOT Mobility Performance Measures Program, Consensus Items. Tallahassee, 2013b. http://www.fdot.gov/planning/statistics/mobilitymeasures/consensusitems.pdf. Accessed September 27, 2017.
49. INRIX. Methodology: INRIX Traffic Scorecard, 2015.
50. TomTom. Traffic Index Press Release. 2016. https://www.tomtom.com/en_gb/trafficindex/press. September 27, 2017.
51. Aliari, Y., Haghani, A. (2012). “Bluetooth Sensor Data and Ground Truth Testing of Reported Travel Times.” Transportation Research Record: Journal of the Transportation Research Board, Issue 2308, pp 167-172.
52. Belzowski, B., Ekstrom, A., (2013). “Stuck in Traffic: Analyzing Real Time Traffic Capabilities of Personal Navigation Devices and Traffic Phone Applications”, University of Michigan Transportation Research, Institute, UMTRI-2013-36, 38p.

53. Haghani, A., Hamedi, M., Sadabadi, K., (2009). “I-95 Corridor Coalition Vehicle Probe Project: Validation Of Inrix, Data July-September 2008”, Final Report, I-95 Corridor Coalition, 129p.
54. Lattimer, C., Glotzbach, G. (2012). “Evaluation of Third Party Travel Time Data.” Proc. of the ITS America 22nd, Annual Meeting & Exposition, ITS America, 8p.
55. Kim, K., Motiani, D., Spasovic, L., Dimitrijevic, B., Chien, S., (2014). “Assessment of Speed Information Based on, Probe Vehicle Data: A Case Study in New Jersey.” Proc. of the Transportation Research Board 93rd Annual Meeting, 19p.
56. Adu-Gyamfi, Yaw Okyere, et al. “Framework for Evaluating the Reliability of Wide-Area Probe Data.” Transportation Research Record: Journal of the Transportation Research Board 2643 (2017): 93-104.
57. Gong, Linfeng, and Wei Fan. “Applying Travel-Time Reliability Measures in Identifying and Ranking Recurrent Freeway Bottlenecks at the Network Level.” Journal of Transportation Engineering, Part A: Systems 143.8 (2017): 04017042.
58. P Sekuła, N Marković, ZV Laan, KF Sadabadi. “Estimating Historical Hourly Traffic Volumes via Machine Learning and Vehicle Probe Data: A Maryland Case Study.” arXiv preprint arXiv:1711.00721, 2017
59. Texas Transportation Institute and Cambridge Systems, Inc. Travel Time Reliability: Making It There on Time, All the time. FHWA Office of Operations, U.S. Department of Transportation. https://ops.fhwa.dot.gov/publications/tt_reliability/brochure/ttr_brochure.pdf. Accessed September 27, 2017.
60. Booz□Allen & Hamilton, Inc. "1998 California Transportation Plan: Transportation System Performance Measures: Final Report," Sacramento, CA: California Department of Transportation, Booz□Allen & Hamilton, Inc, 1998.
61. Ramkumar Venkatanarayana, “Considerations for Calculating Arterial System Performance Measures in Virginia”, Virginia Transportation Research Council, February 2017. http://www.virginiadot.org/vtrc/main/online_reports/pdf/17-r2.pdf. Accessed September 27, 2017.
62. Federal Highway Administration. The Urban Congestion Trends: Using Technology to Measure, Manage, and Improve Operations. 2016. https://ops.fhwa.dot.gov/publications/fhwahop17010/index.htm Accessed September 26, 2017.
63. Apache Hadoop. http://hadoop.apache.org/. Accessed September 27, 2017.
64. Apache Pig Latin. https://pig.apache.org/. Accessed September 27, 2017.
65. Transportation Research Board. (2016). Highway Capacity Manual - A Guide for Multimodal Mobility Analysis (6th Edition). Transportation Research Board. Online version available at: http://app.knovel.com/hotlink/toc/id:kpHCMAGMM2/highway-capacity-manual/highway-capacity-manual. Accessed September 27, 2017.
66. Spark, Lightning – fast cluster computing. http://spark.apache.org/. Accessed September 27, 2017.

Appendix A: Total PVR Data Available for All ATRs

The table below shows each ATR, its direction, and the total number of days in each month for which data were provided by NDOT. To evaluate the reliability of PVR data, a comparison was made with data collected by trailers (Wavetronix data). In chapter 3, cumulative distribution function (CDF) was used in Figure 3.3 to illustrate the differences in speeds detected between PVR and Wavetronix sensors. It was expected that the two CDF lines for PVR and Wavetronix sensor data for each location would nearly overlap each other. However, it is obvious from Figure 3.3 that sites 6N, 6S, 19E, 19W, 32W, 39S, 61E, and 65E showed different traffic speed performance. Thus, these locations were excluded from further analysis. The data from these ATRs are shown in red in the table.

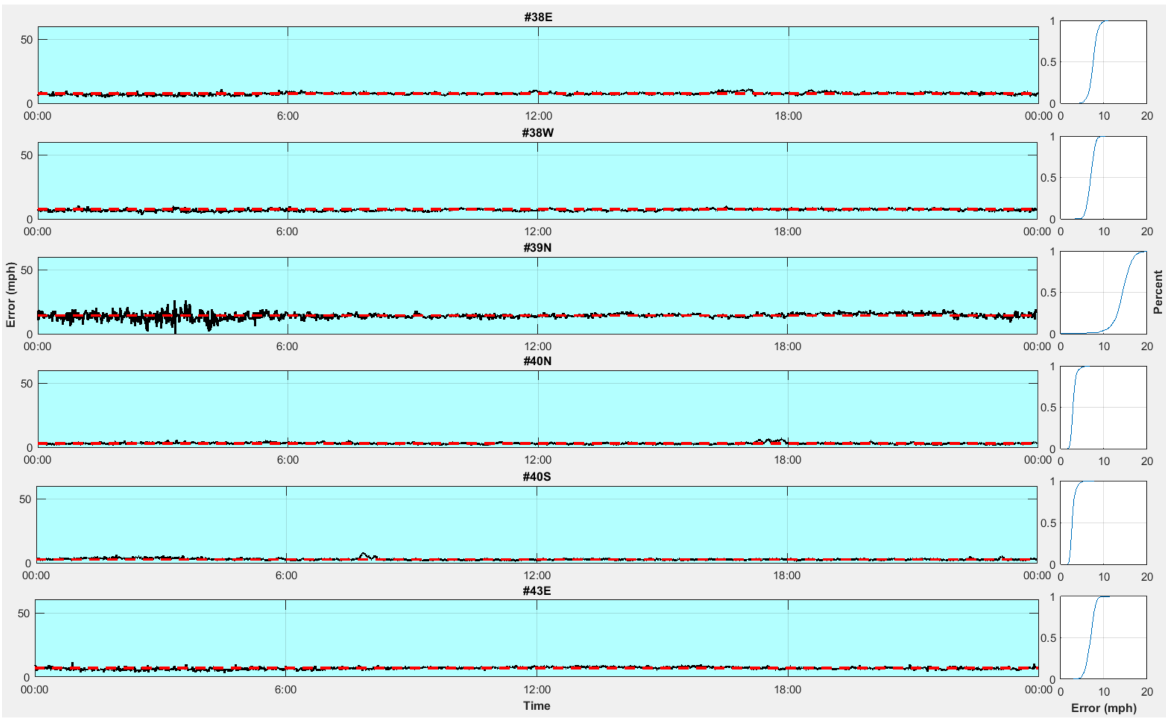
Table A.1 Total PVR data available for all ATRs

ATR	Dir	Number of Days						
		Oct	Nov	Dec	Feb	Mar	Apr	Total
2	E	7	14	2	6	-	-	29
2	W	7	14	2	6	-	-	29
6	N	-	24	2	-	-	-	26
6	S	-	24	2	-	-	-	26
19	E	7	14	2	6	-	-	29
19	W	7	14	2	6	-	-	29
20	E	7	14	2	6	-	-	29
20	W	7	14	2	6	-	-	29
31	E	7	14	2	6	-	-	29
31	W	6	14	2	6	-	-	28
32	E	7	14	2	6	-	-	29
32	W	7	14	2	6	-	-	29
38	E	7	14	2	6	-	-	29
38	W	7	14	2	6	-	-	29
39	N	7	14	2	6	--	-	29
39	S	7	14	2	6	-	-	29
40	N	-	-	-	-	9	21	30
40	S	-	-	-	-	9	21	30
43	E	7	14	2	6	-	-	29
43	W	7	14	2	6	-	-	29
46	N	7	14	2	6	9	21	59
46	S	7	14	2	6	9	21	59
54	E	7	14	2	6	-	-	29
54	W	7	14	2	6	-	-	29
56	E	-	-	-	-	8	21	29
56	W	-	-	-	-	8	21	29
61	E	-	24	2	6	-	-	32

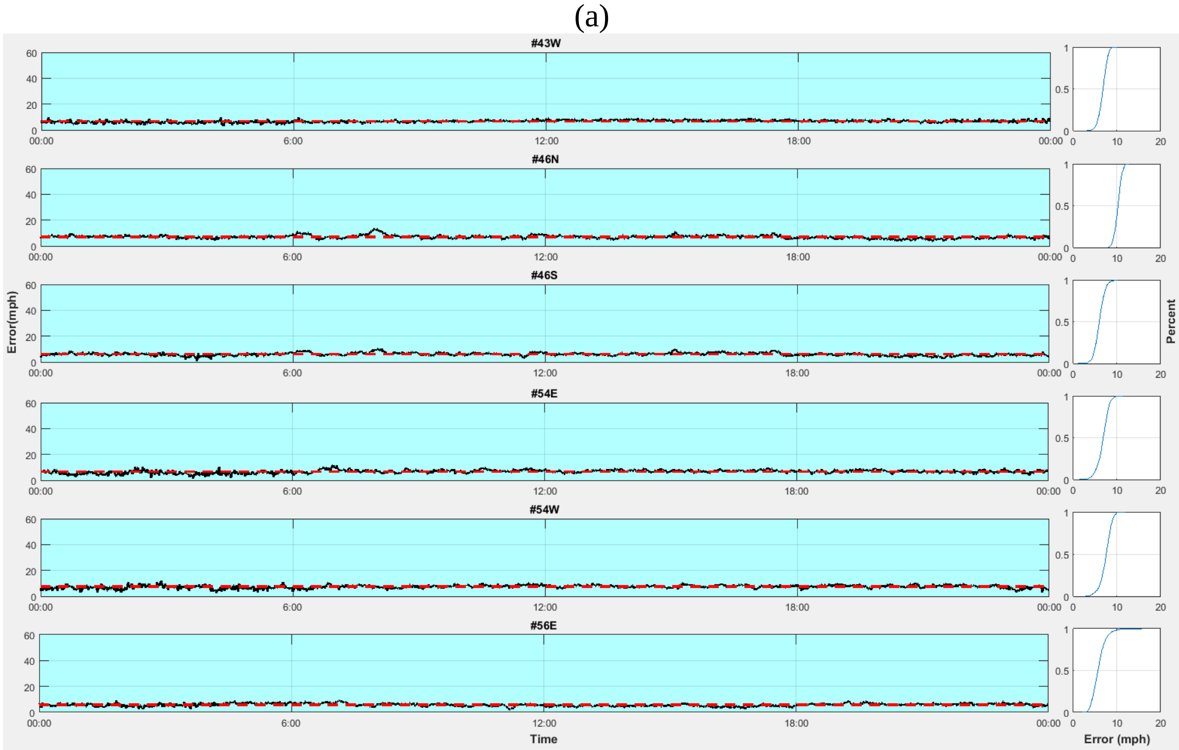
61	**W**	**-**	**24**	**2**	**6**	**-**	**-**	**32**
64	**N**	**7**	**14**	**2**	**6**	**-**	**-**	**29**
64	**S**	**7**	**14**	**2**	**6**	**-**	**-**	**29**
65	**E**	**5**	**14**	**8**	**6**	**-**	**-**	**33**
65	**W**	**5**	**14**	**8**	**6**	**-**	**-**	**33**

Appendix B. Errors Associated with Traffic Speed Reported Using Only Real-Time Data for Some Sites

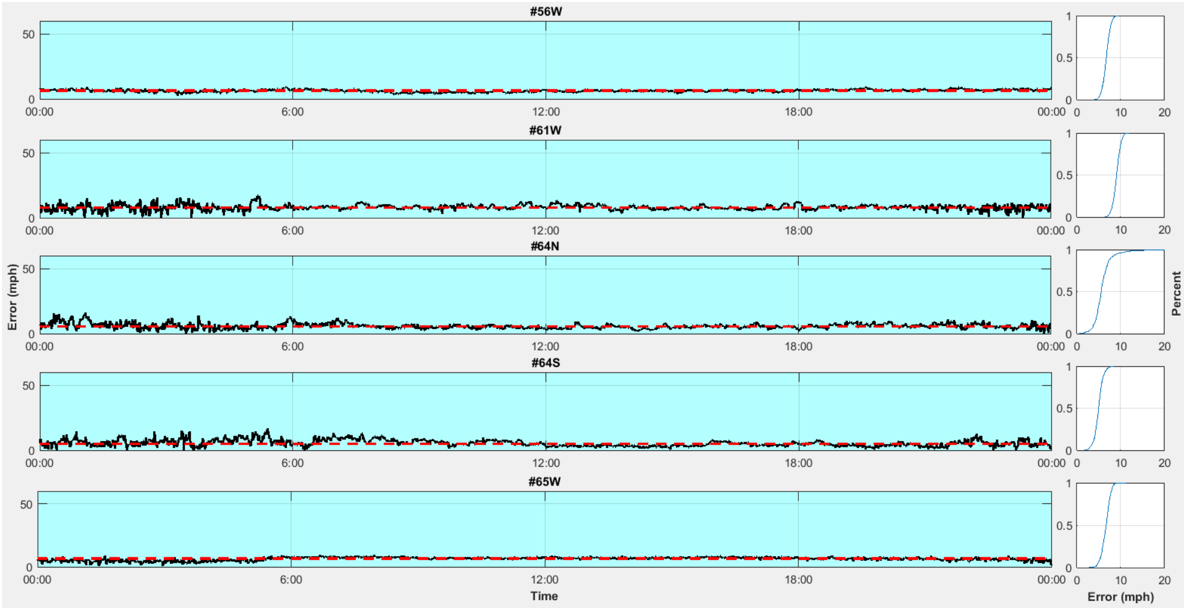
Figure B.1 is continuation of Figure 4.4, illustrating the errors associated with real-time traffic speed data for the sites that were not shown in Figure 4.4.



(a)



(b)



(c)

Figure B.1 Errors associated with traffic speed reported using only real-time data for some sites

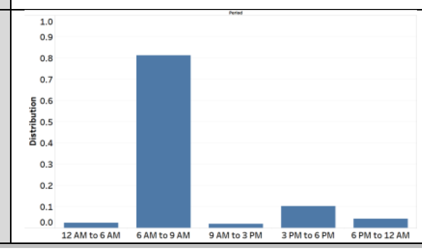
Appendix C. Top 10 Most Congested Segments. Metro Congestion per Mile, and Speed Performance for Interstate 80 in 2013, 2014, and 2015

Top 10 Most Congested Segments in 2013

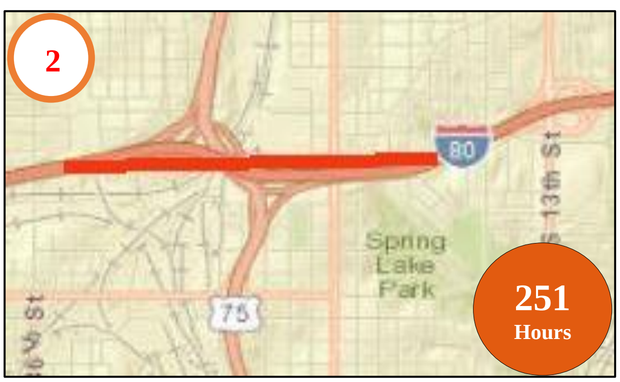
The top 10 most congested segments in 2013 are shown in Figure C.1. All of the segments were located in the Omaha and Lincoln areas. Nine of the ten locations were in Omaha; the other top congested segment was near Lincoln. Most segments exhibited slightly higher congested hours during September and October across weekdays and between 3 pm and 6 pm. A summary of each of the top ten locations are included below.

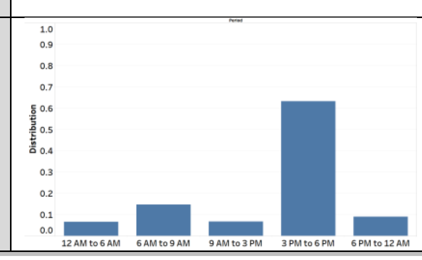
Figure C.1 Top 10 congested segments in 2013

I-80 Omaha EB | L ST | 1.45 miles

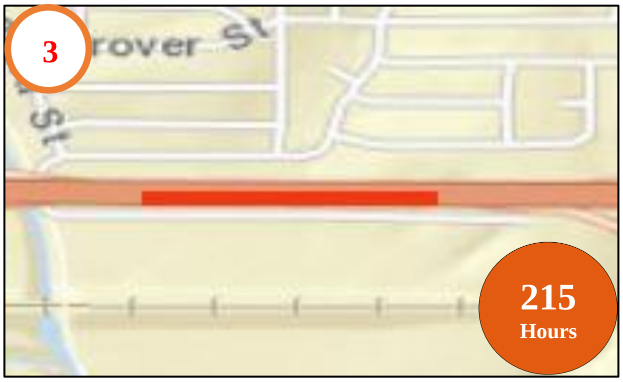
Annual number of hours of congestion	Around 319 hours
Highest monthly and weekday total hours of congestion	Throughout year with a high in October at 46 hours, consistent across weekdays
Longest congestion duration by time of day	6 am to 9 am
Distribution of times of congestion	

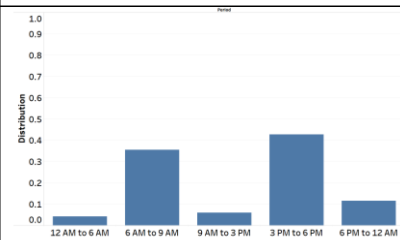
I-80 Omaha WB | I-480/US-75 | 1.27 miles



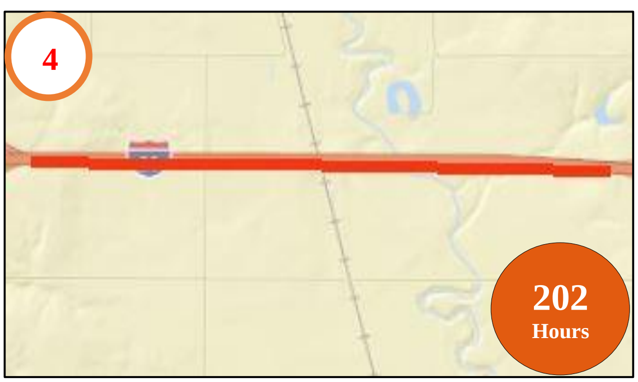
Annual number of hours of congestion	251 hours
Highest monthly and weekday total hours of congestion	Throughout year with a high in June at 29 hours, consistent across entire week, except Saturday
Longest congestion duration by time of day	3 pm to 6 pm
Distribution of times of congestion	

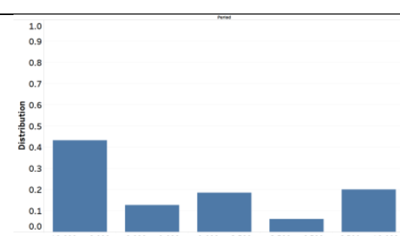
I-80 EB Omaha EB | S 72ND ST **|** 0.33 miles



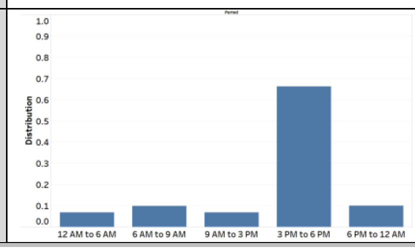
Annual number of hours of congestion	215 hours
Highest monthly and weekday total hours of congestion	Throughout year with a high in September at 43 hours, consistent across entire week, except Saturday
Longest congestion duration by time of day	Primarily between 6 am to 9 am, peak from 3 pm to 6 pm with 91 hours
Distribution of times of congestion	

I-80 Near Lincoln EB| Exit 382 **|** 2.5 miles

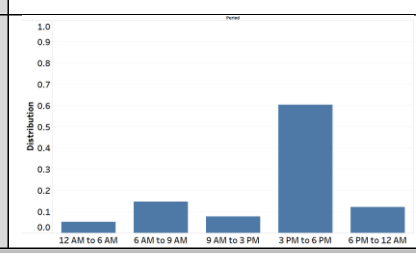


Annual number of hours of congestion	202 hours
Highest monthly and weekday total hours of congestion	January to July with a high in March at 45 hours, consistent across entire week
Longest congestion duration by time of day	12 am to 6 am
Distribution of times of congestion	

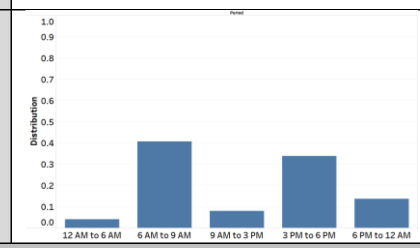
I-80 Omaha WB | S 72ND ST | 0.39 miles

Annual number of hours of congestion	167 hours
Highest monthly and weekday total hours of congestion	Throughout year with a high in February at 17 hours and Tuesday being the highest day
Longest conges-tion duration by time of day	3 pm to 6 pm
Distribution of times of congestion	

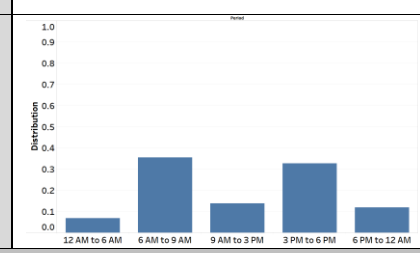
I-80 Omaha WB | S 60TH ST | 0.83 miles

Annual number of hours of congestion	159 hours
Highest monthly and weekday total hours of congestion	Throughout year with a high in June at 19 hours, consistent across entire week, except Saturday
Longest conges-tion duration by time of day	3 pm to 6 pm
Distribution of times of congestion	

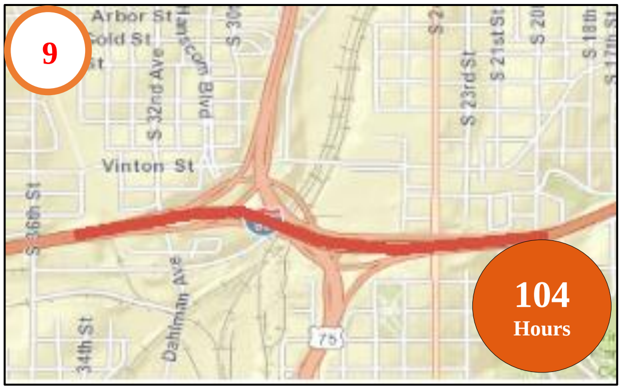
I-80 Omaha EB | S 84TH ST | 1.2 miles

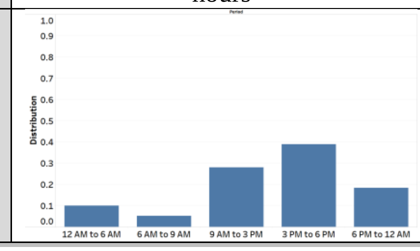
Annual number of hours of congestion	133 hours
Highest monthly and weekday total hours of congestion	Throughout year with a high in September at 28 hours, consistent across entire week, except Saturday
Longest conges-tion duration by time of day	Primarily between 3 pm to 6 pm, peak from 6 am to 9 am with 54 hours
Distribution of times of congestion	

I-80 Omaha EB | S 60TH ST | 0.37 miles

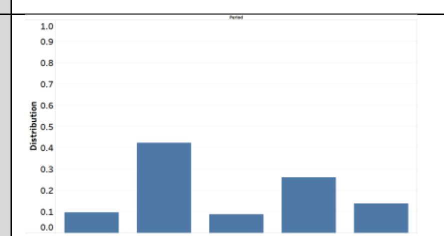
Annual number of hours of congestion	116 hours
Highest monthly and weekday total hours of congestion	Throughout year with a high in September at 24 hours, consistent across entire week, except Saturday
Longest conges-tion duration by time of day	Primarily between 3 pm to 6 pm, peak from 6 am to 9 am with 41 hours
Distribution of times of congestion	

I-80 Omaha EB | I-480/US-75 | 1.09 miles



Annual number of hours of congestion	104 hours
Highest monthly and weekday total hours of congestion	February to August with a high in August at 19 hours, consistent across entire week, except Tuesday
Longest conges-tion duration by time of day	Primarily between 9 am to 3 pm, peak from 3 pm to 6 pm with 40 hours
Distribution of times of congestion	

I-80 Omaha EB | I-680 | 1.25 miles

Annual number of hours of congestion	95 hours
Highest monthly and weekday total hours of congestion	Throughout the year with a high in September at 11 hours, consistent across entire week
Longest conges-tion duration by time of day	Primarily between 3 pm to 6 pm, peak from 6 am to 9 am with 40 hours
Distribution of times of congestion	

Top 10 Most Congested Segments in 2014

In contrast to 2013, the top 10 most congested locations were much higher in 2014. Nine of the ten locations were in Omaha, and the remaining segment was near Lincoln (see Figure C.2). Most segments exhibited consistent congestion throughout year, except for May through October across weekdays and between 3 pm and 6 pm and 6 am and 9 am. A summary of each of the top ten locations are included below.

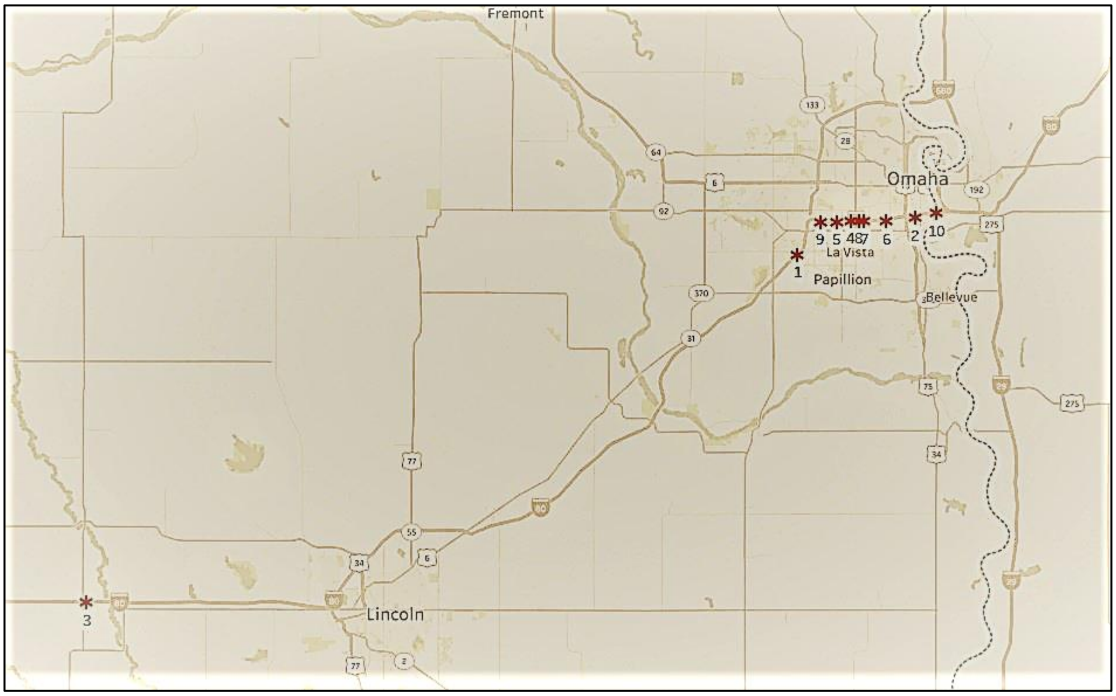
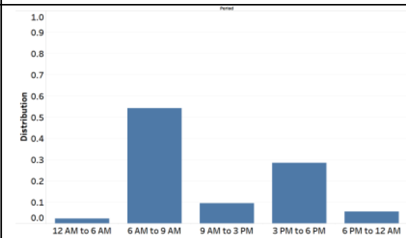
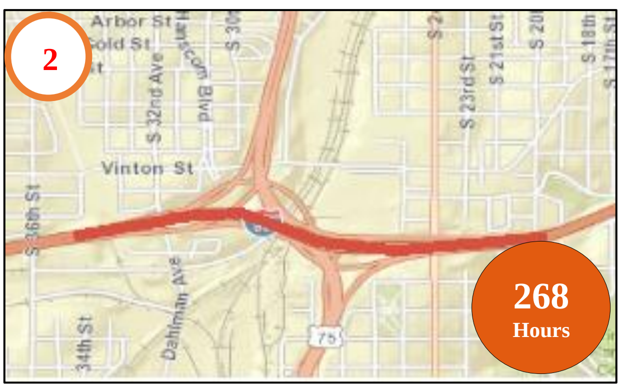


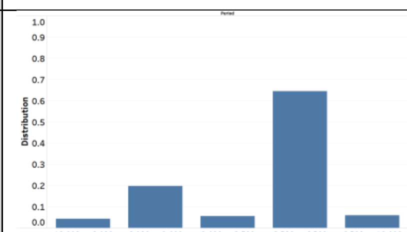
Figure C.2 Top 10 congested segments in 2014

I-80 Omaha EB | L ST | 1.45 miles

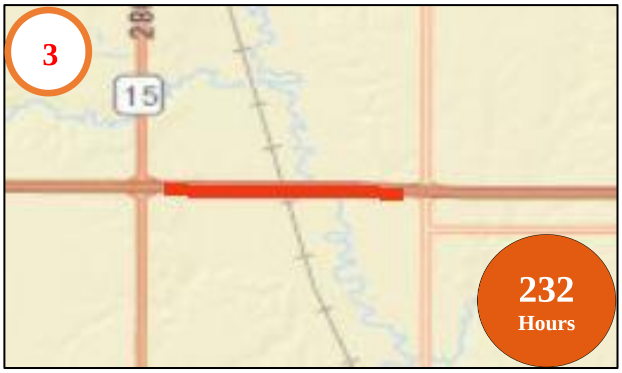
Annual number of hours of congestion	Second year at the top of the list increased from 248 hours in 2013
Highest monthly and weekday total hours of congestion	April to November with a high in May at 105 hours
Longest congestion duration by time of day	Primarily between 3 pm to 6 pm, peak from 6 am to 9 am with 307 hours
Distribution of times of congestion	

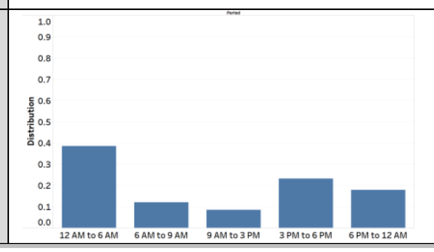
I-80 Omaha WB | I-480/US-75 | 1.27 miles



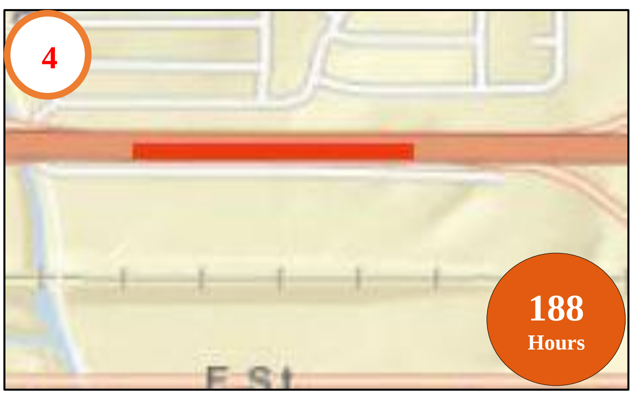
Annual number of hours of congestion	Increased from 17 hours in 2013
Highest monthly and weekday total hours of congestion	February to October with a high in July at 40 hours. Consistent across weekdays
Longest congestion duration by time of day	3 pm to 6 pm
Distribution of times of congestion	

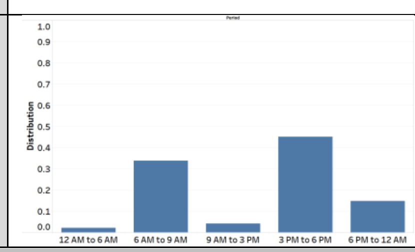
I-80 Near Lincoln EB| Exit 382 **|** 2.5 miles



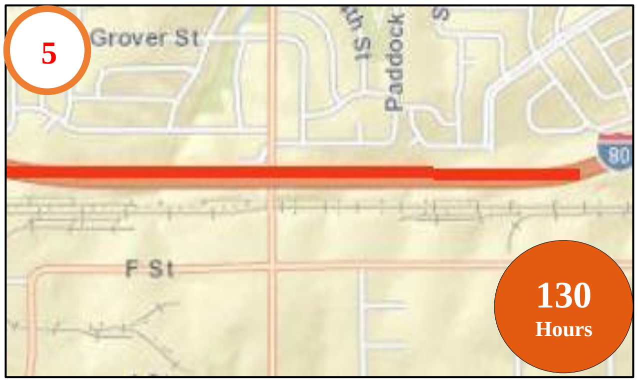
Annual number of hours of congestion	Increased from 30 hours in 2013
Highest monthly and weekday total hours of congestion	May to July with a high in September at 43 hours, consistent across entire week
Longest congestion duration by time of day	Primarily between 3 pm to 6 pm, peak from 12 am to 6 am with 89 hours
Distribution of times of congestion	

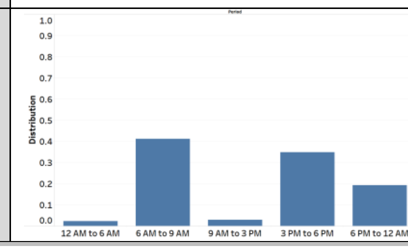
I-80 Omaha EB| S 72ND ST **|** 0.33 miles



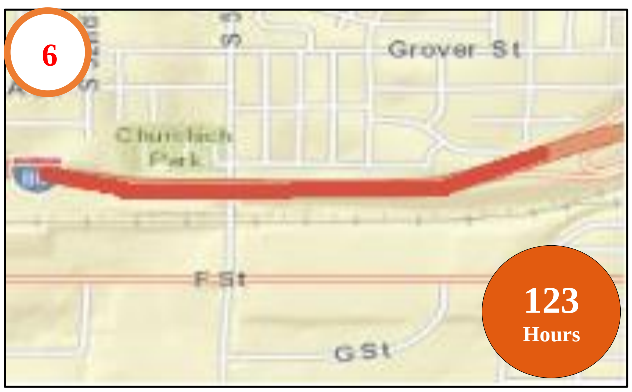
Annual number of hours of congestion	Decreased from 27 hours in 2013
Highest monthly and weekday total hours of congestion	Throughout the year with a high in February at 28 hours, primarily on Thursday
Longest congestion duration by time of day	3 pm to 6 pm and 6 am to 9 am
Distribution of times of congestion	

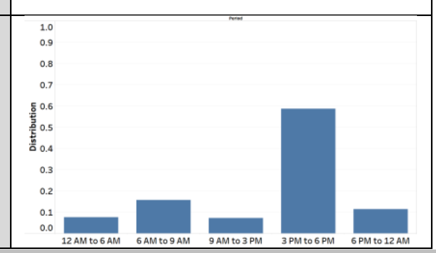
I-80 Omaha WB | S 84TH ST | 1.2 miles



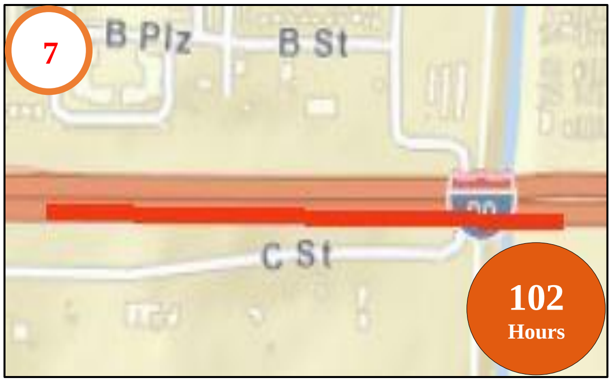
Annual number of hours of congestion	Slight decrease from last year
Highest monthly and weekday total hours of congestion	Consistent by month and entire week, except July and Sunday
Longest congestion duration by time of day	6 am to 9 am and 3 pm to 6 pm
Distribution of times of congestion	

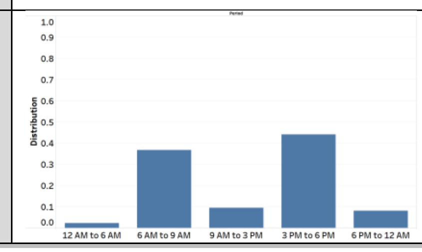
I-80 Omaha WB | S 60TH ST) | 0.83 miles



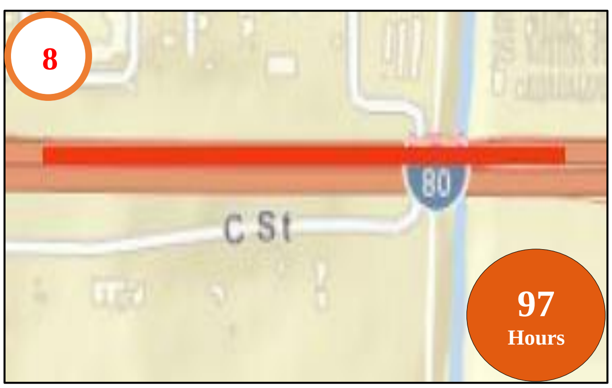
Annual number of hours of congestion	Decreased from 36 hours in year 2013
Highest monthly and weekday total hours of congestion	Consistent by month and entire week, except May and Saturday
Longest congestion duration by time of day	3 pm to 6 pm
Distribution of times of congestion	

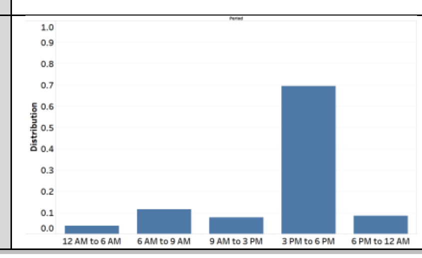
I-80 Omaha EB | S 60TH ST | 0.37 miles



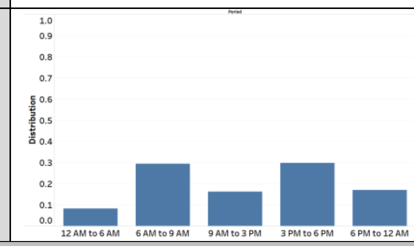
Annual number of hours of congestion	Decreased from 14 hours in year 2013
Highest monthly and weekday total hours of congestion	Throughout the year with a high in February at 18 hours, consistent across weekdays
Longest congestion duration by time of day	Primarily between 6 am to 9 am, peak from 3 pm to 6 pm with 45 hours
Distribution of times of congestion	

I-80 Omaha WB | S 72ND ST | 0.39 miles

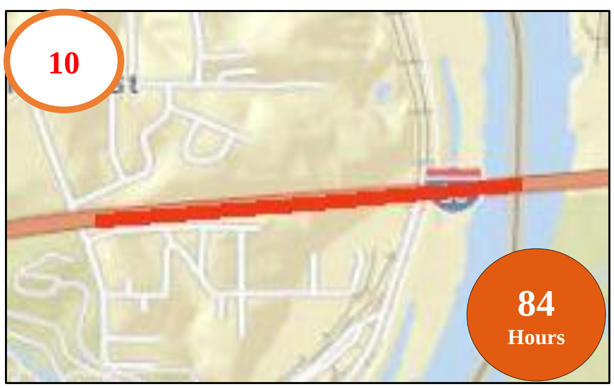


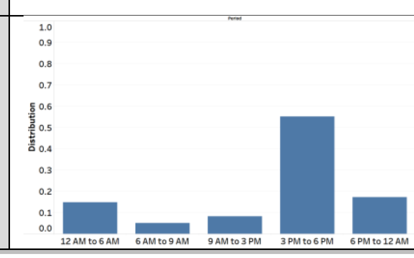
Annual number of hours of congestion	Decreased from 70 hours in year 2013
Highest monthly and weekday total hours of congestion	Throughout year with a high in February, consistent across weekdays
Longest congestion duration by time of day	3 pm to 6 pm
Distribution of times of congestion	

I-80 Omaha EB | I-680 | 1.25 miles

Annual number of hours of congestion	Slight decrease from last year
Highest monthly and weekday total hours of congestion	June and December with consistent across entire week, except Sunday
Longest congestion duration by time of day	3 pm to 6 pm and 6 am to 9 am
Distribution of times of congestion	

I-80 Omaha EB | NE -- IA STATE BORDER | 0.67 miles



Annual number of hours of congestion	84 hours
Highest monthly and weekday total hours of congestion	May to October with consistent across entire week, except Saturday
Longest congestion duration by time of day	3 pm to 6 pm
Distribution of times of congestion	

Top 10 Most Congested Segments in 2015

In contrast to 2013 and 2014, the top 10 most congested locations exhibited less congestion in 2015. Most segments had a slightly higher number of hours of congestions in November and December, across weekdays and from 3 pm to 6 pm. The top 10 segments were located in the Omaha and Lincoln areas (see Figure C.3). A summary of each of the top ten locations are included below.

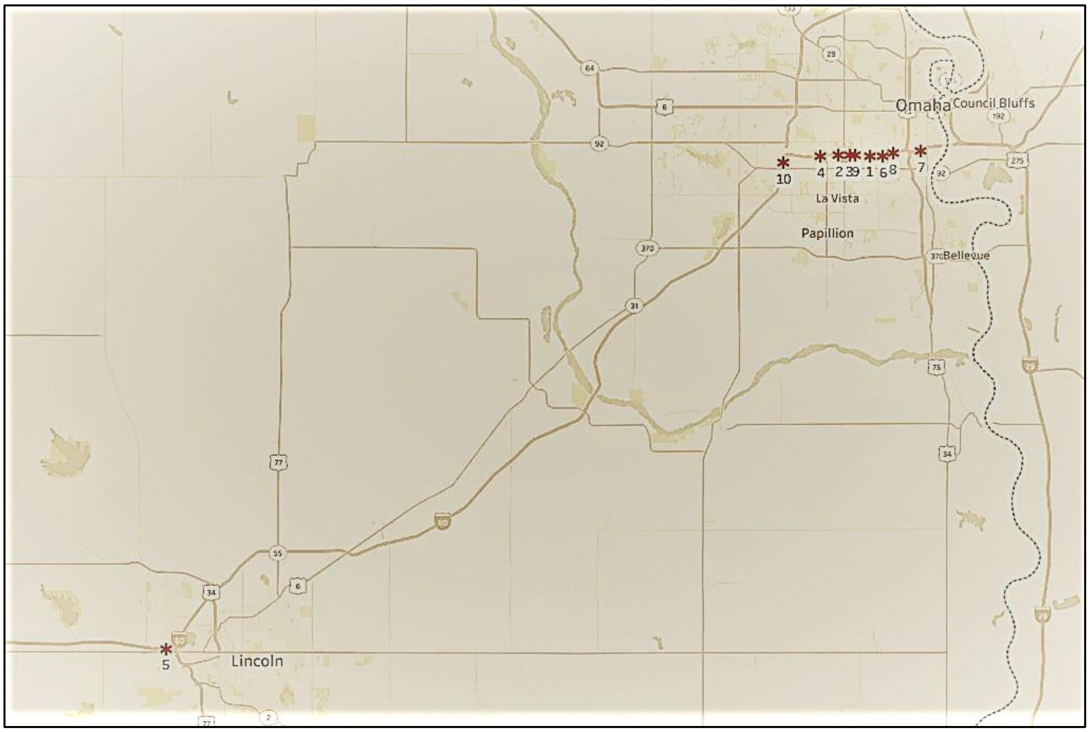
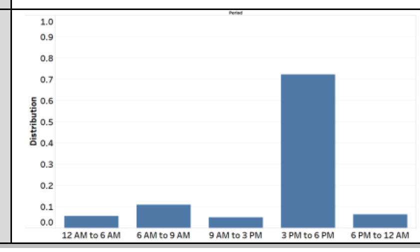
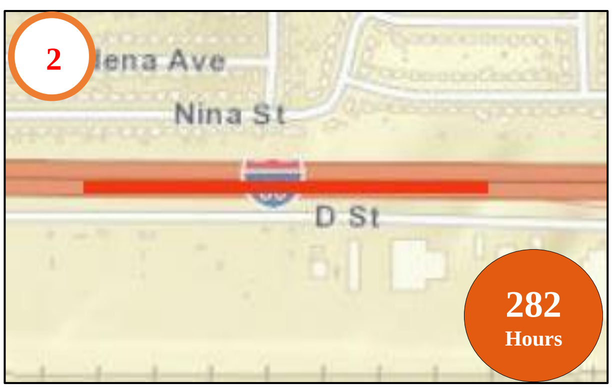


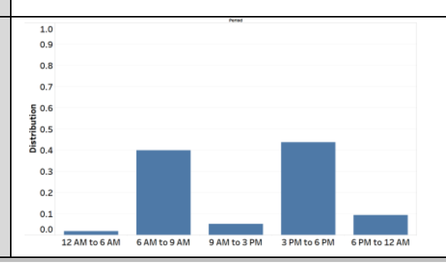
Figure C.3 Top 10 congested locations in 2015

I-80 Omaha WB | S 60TH ST | 0.83 miles

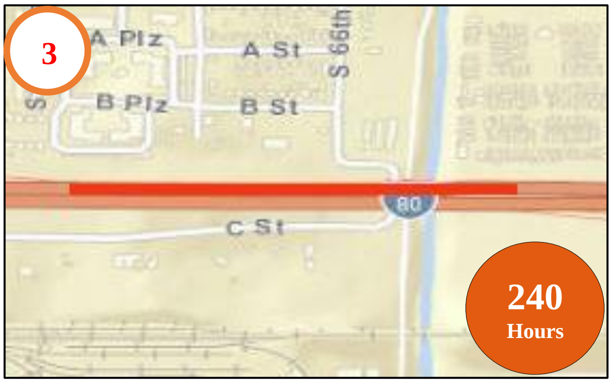
Annual number of hours of congestion	Increased progressively from 253 hours in 2014
Highest monthly and weekday total hours of congestion	Consistent by month and entire weekdays
Longest congestion duration by time of day	3 pm to 6 pm
Distribution of times of congestion	

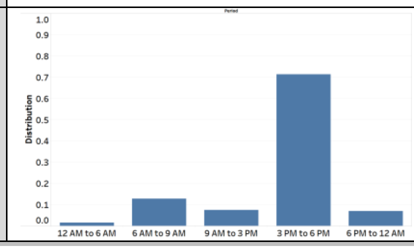
I-80 Omaha EB| S 72ND ST | 0.33 miles



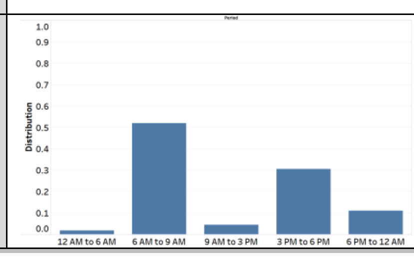
Annual number of hours of congestion	Increased progressively from 94 hours in 2014
Highest monthly and weekday total hours of congestion	Throughout the year with a high in December at 35 hours, primarily on Thursday
Longest congestion duration by time of day	Primarily between 6 am to 9 am, peak from 3 pm to 6 pm with 123 hours
Distribution of times of congestion	

I-80 Omaha WB | S 72ND ST | 0.39 miles

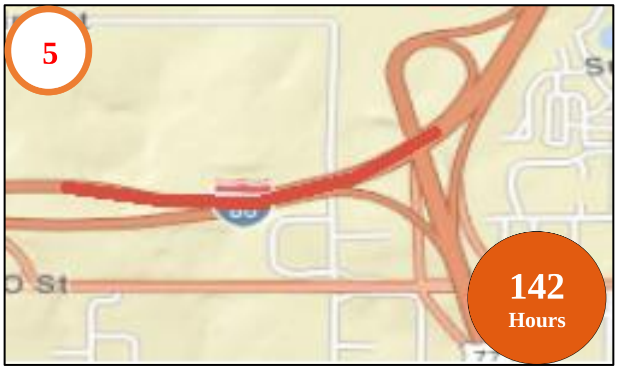


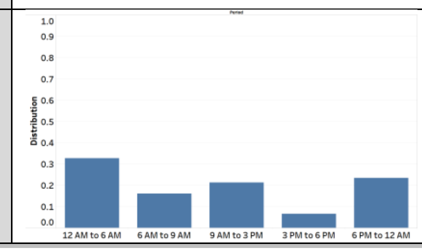
Annual number of hours of congestion	Increased progressively from 143 hours in 2014
Highest monthly and weekday total hours of congestion	Throughout year with a high in December, consistent across weekdays
Longest congestion duration by time of day	3 pm to 6 pm
Distribution of times of congestion	

I-80 Omaha WB | S 84TH ST | 1.2 miles

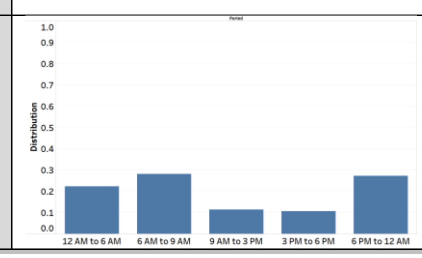
Annual number of hours of congestion	Increased progressively from 72 hours in 2014
Highest monthly and weekday total hours of congestion	Consistent by month and entire week, except August and weekends
Longest congestion duration by time of day	6 am to 9 am and 3 pm to 6 pm
Distribution of times of congestion	

I-80 Near Lincoln WB | US - 6/EXIT 396 | 0.59 miles

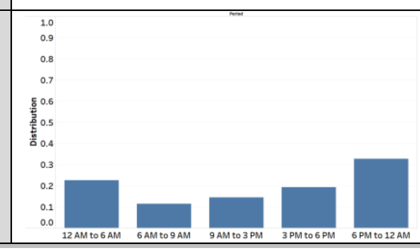


Annual number of hours of congestion	142 hours
Highest monthly and weekday total hours of congestion	High in February and consistent across entire week
Longest congestion duration by time of day	12 am to 6 am and 6 pm to 12 am
Distribution of times of congestion	

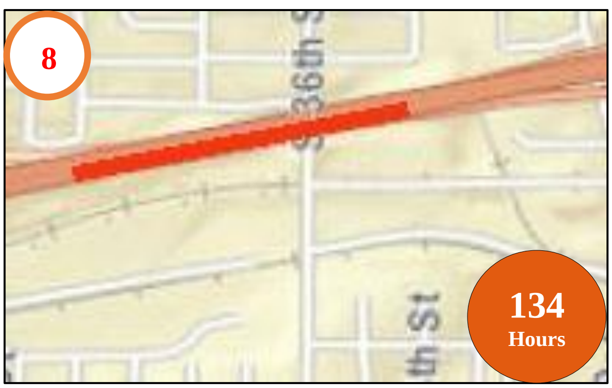
I-80 Omaha WB | S 42ND ST | 0.859 mile

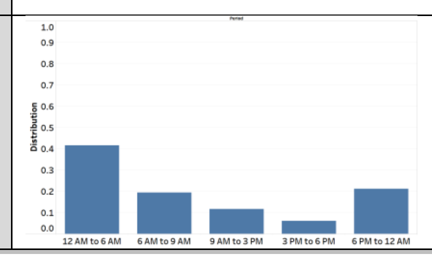
Annual number of hours of congestion	137 hours
Highest monthly and weekday total hours of congestion	Throughout year and across weekdays, except April
Longest congestion duration by time of day	6 am to 9 am and 6 pm to 12 am
Distribution of times of congestion	

I-80 Omaha WB | I-480/US-75 | 1.27 miles

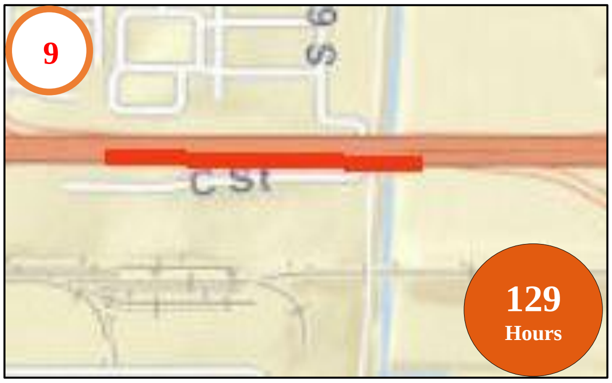
Annual number of hours of congestion	Decreased from 134 hours in 2014
Highest monthly and weekday total hours of congestion	February, August and September with consistent across entire week
Longest congestion duration by time of day	6 pm to 12 am and 12 am to 6 am
Distribution of times of congestion	

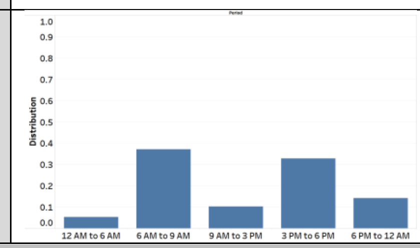
I-80 Omaha WB | I-480/US-75 | 0.39 mile



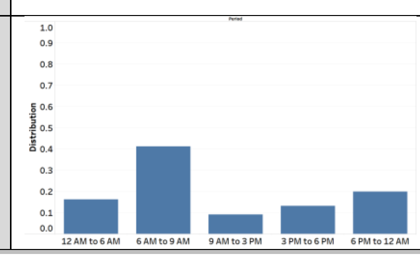
Annual number of hours of congestion	134 hours
Highest monthly and weekday total hours of congestion	June through February with a high in July at 28 hours, consistent across entire week
Longest congestion duration by time of day	12 am to 6 am
Distribution of times of congestion	

I-80 Omaha WB | S 60TH ST | 0.37 miles



Annual number of hours of congestion	Slight increase from past two years
Highest monthly and weekday total hours of congestion	September through June with a high in October at 20 hours, across weekdays
Longest congestion duration by time of day	6 am to 9 am and 3 pm to 6 pm
Distribution of times of congestion	

I-80 Omaha EB | I-680 | 1.25 miles

Annual number of hours of congestion	Slight increase from past two years
Highest monthly and weekday total hours of congestion	Throughout the year with a high in October at 23 hours, across entire week
Longest congestion duration by time of day	6 am to 9 am
Distribution of times of congestion	

Metro Congestion per Mile in 2013

The average amount of congestion per mile in 2013 for metro areas across Nebraska is shown in Figure C.4. US 275 NE–IA border to Venice and US 6 Dodge Street Omaha were consistently among the most congested metro routes across the state.

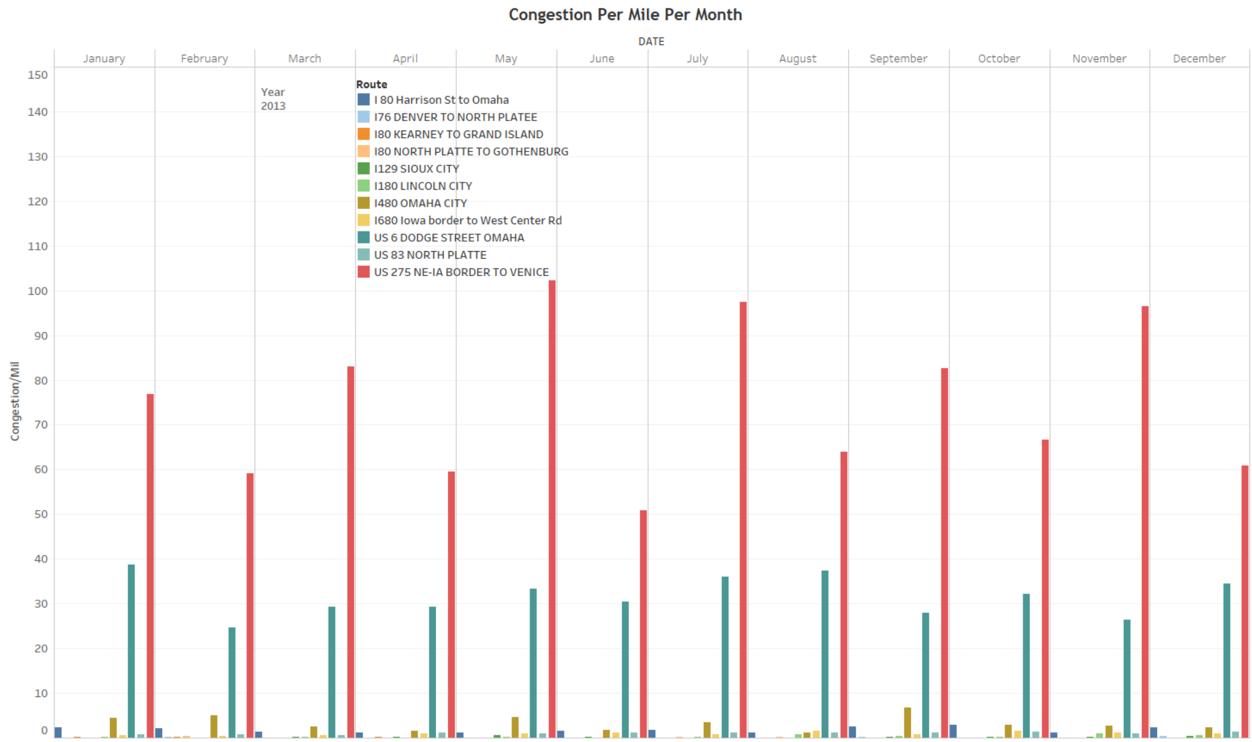


Figure C.4 Comparison of the number of hours of congestion per mile in metro areas, 2013

Metro Congestion per Mile in 2014

The average amount of congestion per mile in 2014 for metro areas across Nebraska is shown in Figure C.5. US 275 NE–IA border to Venice and US 6 Dodge Street Omaha were consistently among the most congested metro routes across the state. A noticeable increase in congestion is seen for I-180 near Lincoln during June, July, August, September, and October.

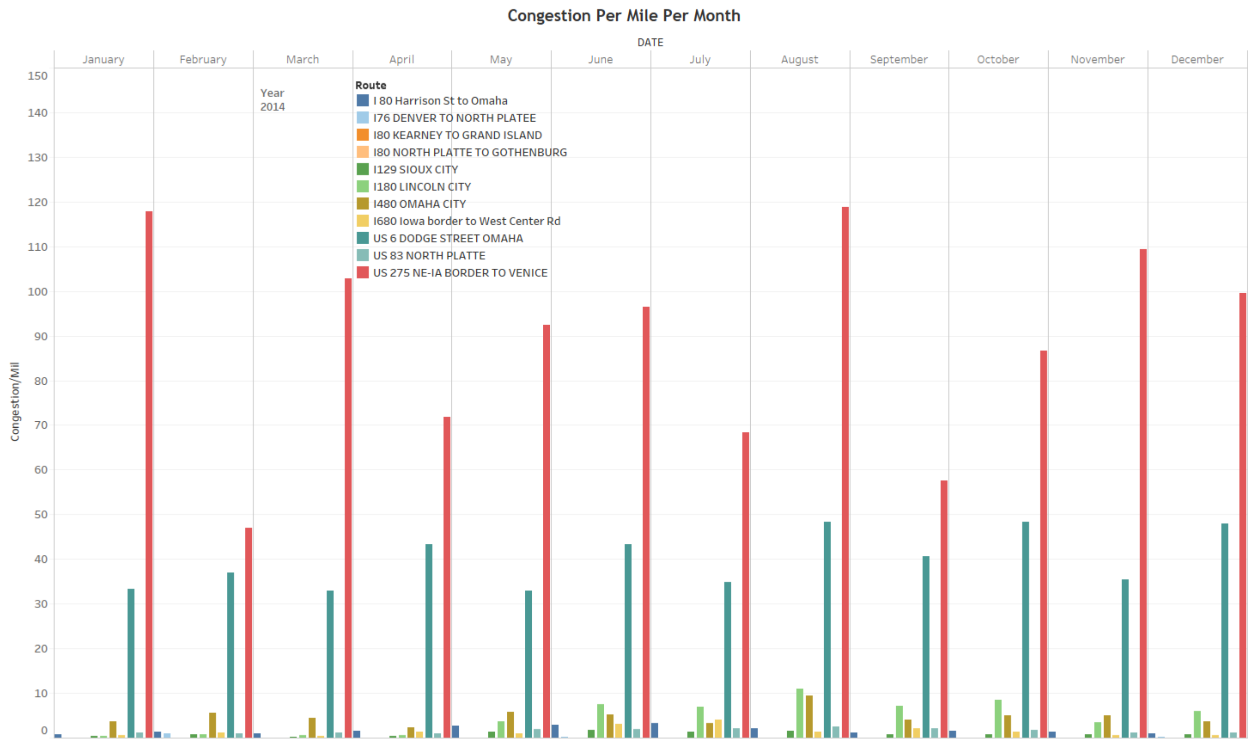


Figure C.5 Comparison of the number of hours of congestion per mile in metro areas, 2014

Metro Congestion per Mile in 2015

The average amount of congestion per mile in 2015 for metro areas across Nebraska is shown in Figure C.6. US 275 NE–IA border to Venice and US 6 Dodge Street Omaha were consistently among the most congested metro routes across the state.

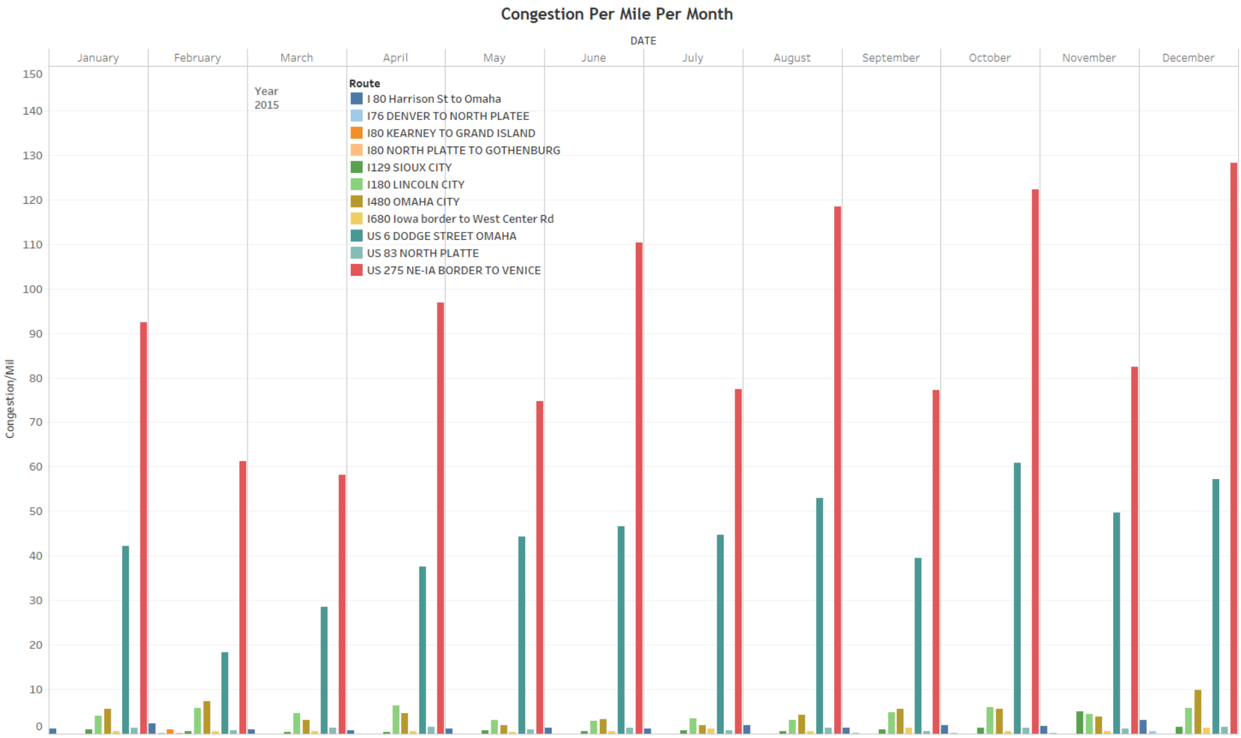


Figure C.6 Comparison of the number of hours of congestion per mile in metro areas, 2015

Speed Performance for Interstate 80

The speed performance along I-80 in the eastbound and westbound directions for 2013, 2014 and 2015 is shown in Figures C.7 through C.12.

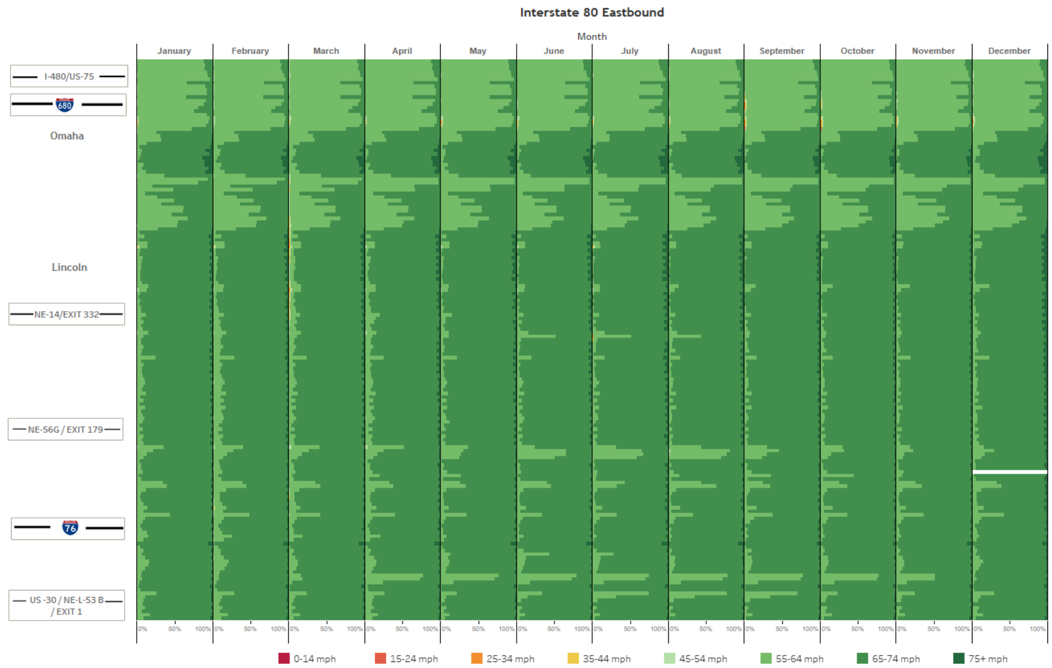


Figure C.7 Interstate 80 EB Speed Percentage in 2013

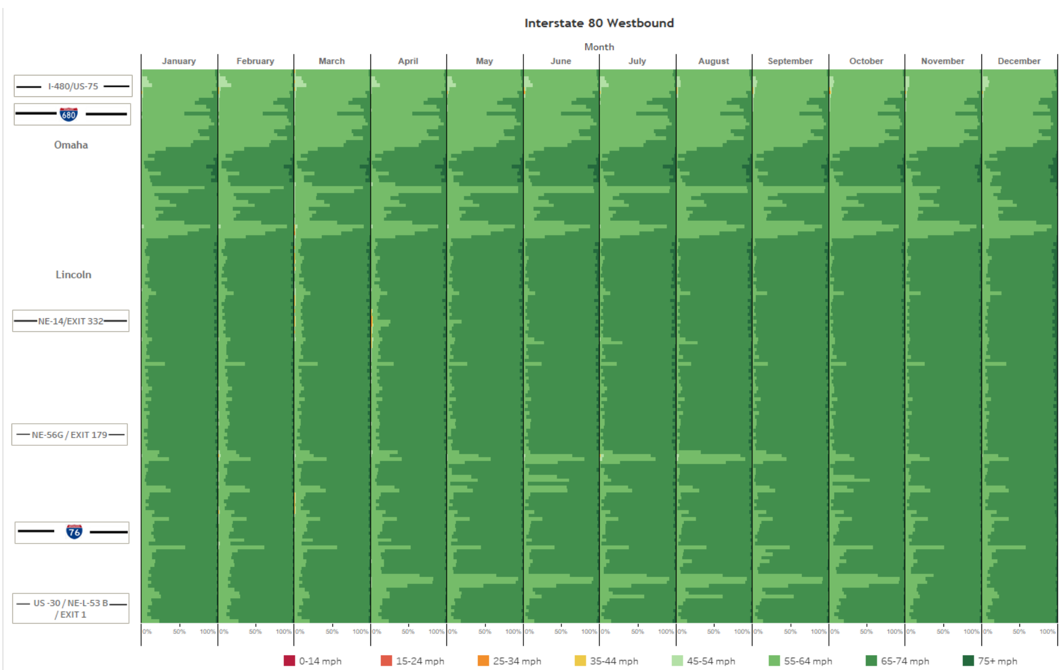


Figure C.8 Interstate 80 WB Speed Percentage in 2013

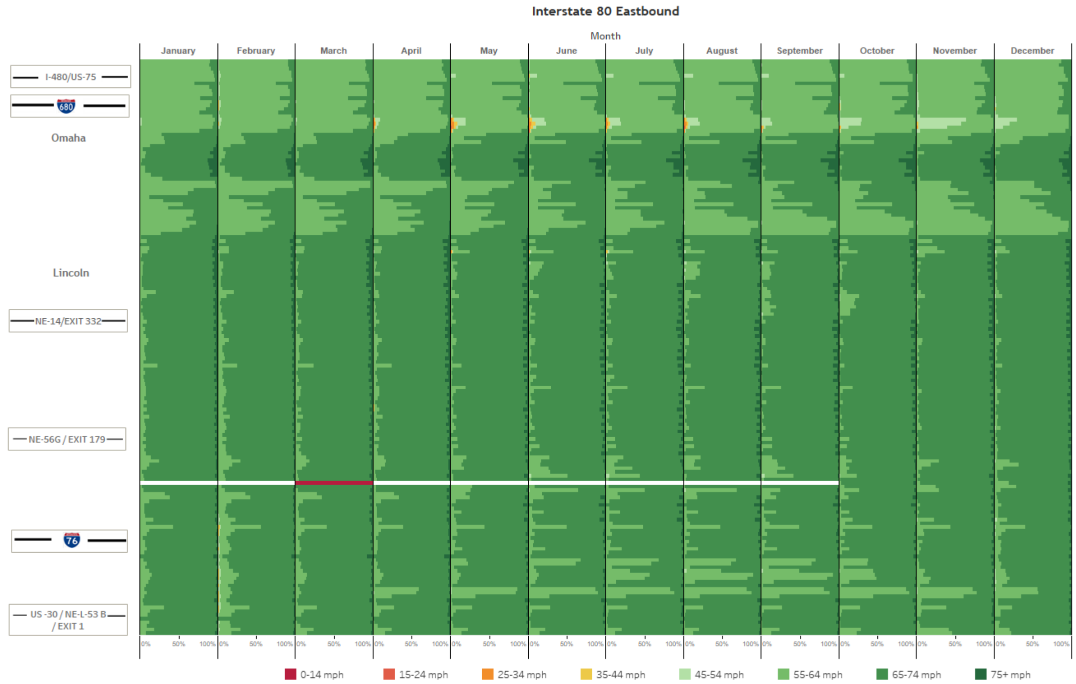


Figure C.9 Interstate 80 EB Speed Percentage in 2014

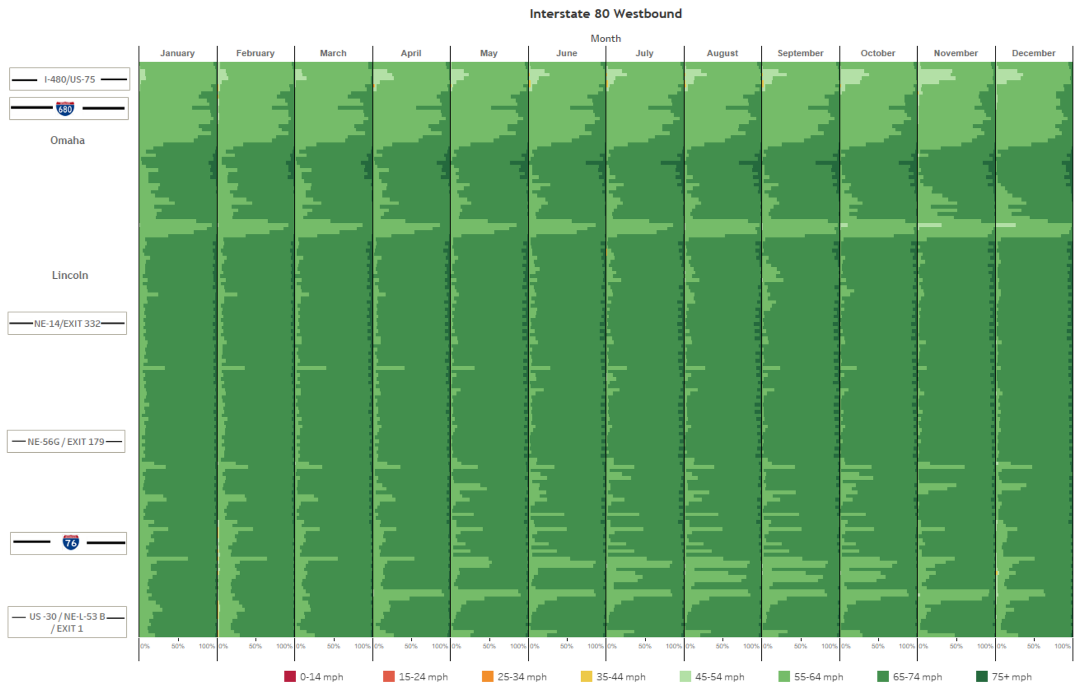


Figure C.10 Interstate 80 WB Speed Percentage in 2014

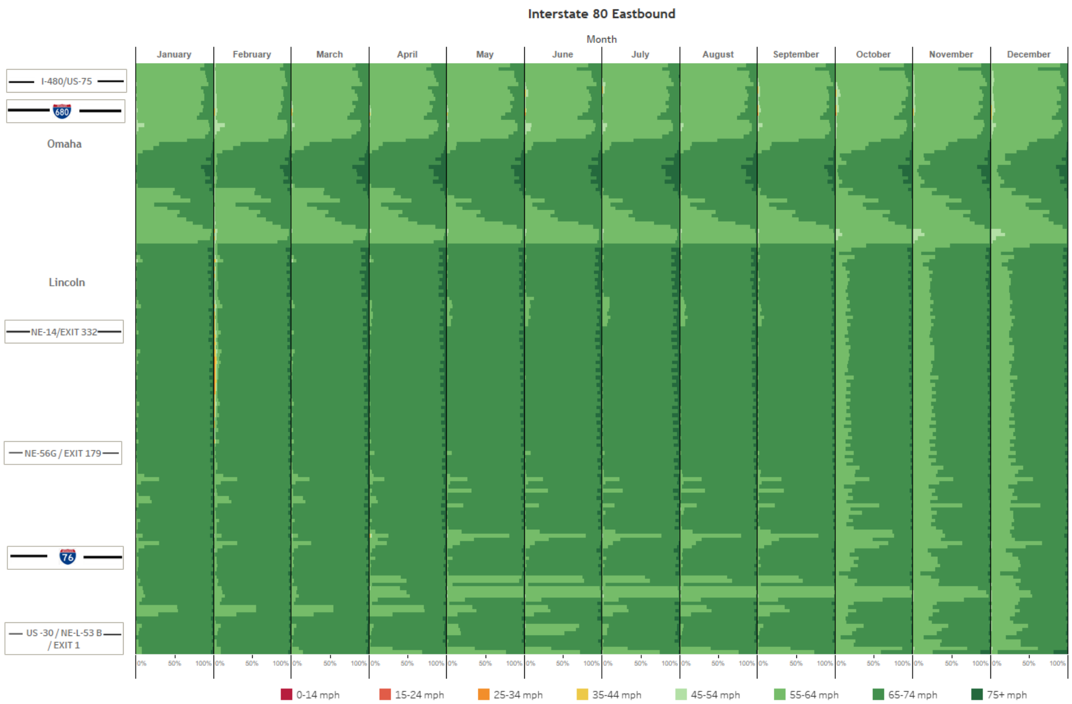


Figure C.11 Interstate 80 EB Speed Percentage in 2015

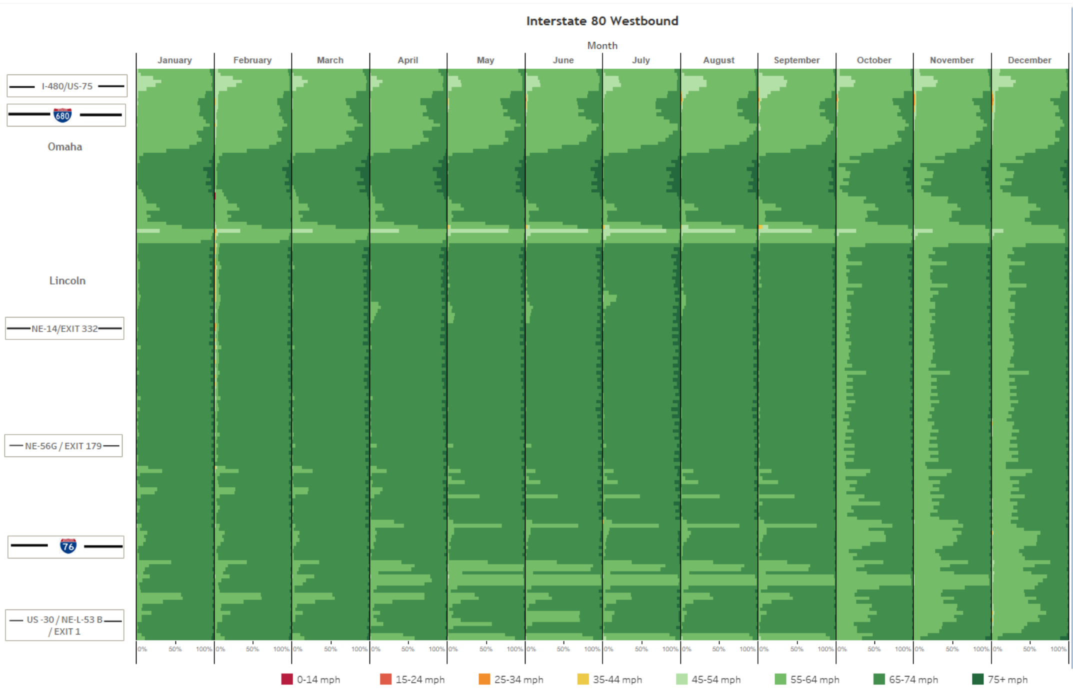


Figure C.12 Interstate 80 WB Speed Percentage in 2015