Big data driven assessment of probe-sourced data

by

Vesal Ahsani

A dissertation submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Civil Engineering (Intelligent Infrastructure Engineering)

Program of Study Committee:
Anuj Sharma, Major Professor
Christopher Day
Chinmay Hegde
Soumik Sarkar
Simon Laflamme

The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this dissertation. The Graduate College will ensure this dissertation is globally accessible and will not permit alterations after a degree is conferred.

Iowa State University

Ames, Iowa

2019

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

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 dissertation documents a study evaluating the opportunities and challenges of using INRIX data in Midwest. The objective of this study is threefold: (1) quantitative analysis of probe data characteristics: coverage, speed bias, and congestion detection precision (2) improving probe based congestion performance metrics accuracy by using change point detection, and (3) assessing the impact of game day schedule and opponents on travel patterns and route choice.

The first study utilizes real-time and historical traffic data which are collected through two different data sources; INRIX and Wavetronix. The INRIX probe data stream is compared to a benchmarked Wavetronix sensor data source in order to explain some of the challenges and opportunities associated with using wide area probe data. In the following, INRIX performance is thoroughly evaluated in three major criteria: coverage and penetration, speed bias, congestion detection precision.

The second study focuses on the number of congested events and congested hour as two important performance measures. To improve the accuracy and reliability of performance measures, this study addresses a big issue in calculating performance measures by comparing Wavetronix against INRIX. We examine the very traditional and common method of congestion detection and congested hour calculation which utilized a fixed-threshold and we show how unreliable and erroneous that method can be. After that, a novel traffic congestion identification

method is proposed in this paper and in the following the number of congested events and congested hour are computed as two performance measures.

After evaluating the accuracy and reliability of INRIX probe data in chapter 2 and 3, the purpose of the last study in chapter 4 is to assess the impacts of game day on travel pattern and route choice behaviors using INRIX, the accurate and reliable data source. It is shown that the impacts vary depending on the schedule and also the opponents. Also, novel methods are proposed for hotspot detection and prediction.

Overall, this dissertation evaluates probe-sourced streaming data from INRIX, to study its characteristics as a data source, challenges and opportunities associated with using wide area probe data, and finally make use of INRIX as a reliable data source for travel behavior analysis.

CHAPTER 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.

The objective of this study is 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 is 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 Wavetronix infrastructure sensors; incident management; and performance measures such as congested hour and the number of congested events.

Several studies have been conducted to compare the accuracy and reliability of probe sourced data against local sensor data such as radar sensor data, loop detector data, etc. (Adu-Gyamfi, Sharma, Knickerbocker, Hawkins, & Jackson, 2017; Coifman, 2002; FDOT, 2012; Feng, Bigazzi, Kothuri, & Bertini, 2010; Haghani, Hamedi, & Sadabadi, 2009; S. Kim & Coifman, 2014; Lindveld, Thijs, Bovy, & der Zijpp, 2000). Many of them evaluated performance of probe data by travel time reliability measures, such as 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, congestion hour, etc. (Aliari & Haghani, 2012; Araghi, Hammershøj Olesen, Krishnan, Tørholm Christensen, & Lahrmann, 2015; Pranamesh Chakraborty et al., 2018; Cookson & Pishue, 2016; C. Day et al., 2015; FHWA, 2017; Gong & Fan, 2017; Higatani et al., 2009; Hu et al., 2015; Tim Lomax, Schrank, Turner, & Margiotta, 2003; Miwa, Ishiguro, Yamamoto, & Morikawa, 2015; MoDOT, 2017; Pu, 2012; Rakha, El-Shawarby, & Arafeh, 2010; Remias et al., 2013; Sanaullah, Quddus, & Enoch, 2016; Schrank., Eisele., Lomax., & Bak., 2015; Schrank, Eisele, & Lomax, 2012; Sekuła, Marković, Laan, & Sadabadi, 2017; Sharifi et al., 2017; Turner, 2013; Uno, Kurauchi, Tamura, & Iida, 2009; Venkatanarayana, 2017; WSDOT, 2013, 2014; Zheng, Li, van Zuylen, Liu, & Yang, 2018).

1.2 Research Objectives

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. This research contains three studies and will answer the following research questions.

1.2.1 Research motivation 1: Evaluate the accuracy and reliability of probe-sourced data in terms of coverage, speed bias, and congestion detection precision

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-based traffic data is significantly different in terms of the nature of data collection, measurement technique, coverage, pricing, etc. Although many researches have studied probe-based data, there remains critical questions such as data coverage and penetration over time, or the influential factors in the accuracy of probe data. The first paper studies probe-sourced data from INRIX, to profoundly explore some of these questions. First, to explore coverage and penetration, INRIX real-time data is illustrated temporally over the entire state of Iowa, demonstrating the growth in real-time data over a four-year timespan. Furthermore, the availability of INRIX real-time and historical data based on type of road and time of day, are explored. Second, a comparison is made with Wavetronix smart sensors, commonly used sensors in traffic management, to explore INRIX's speed data quality. A statistical analysis on the behavior of INRIX speed bias, identifies some of the influential factors in defining the magnitude of speed bias. Finally, the accuracy and reliability of INRIX for congestion detection purposes is investigated based on the road segment characteristics and the congestion type. Overall, this work sheds light onto some of the less explored aspects of INRIX probe-based data to help traffic managers and decision makers in better understanding this source of data and any resultant analyses.

1.2.2 Research motivation 2: Improving probe based congestion performance metrics accuracy by using change point detection

Probe based speed data provide great value to agencies especially in areas which are not feasibly covered by traffic sensors. However, as with sensors, probe data are not without nuance and issues like latency prevent alignment between calculated metrics by data source. Both agencies and the public are sensitive to reported performance and have little appreciation for sudden shifts in magnitude just because a new data source is available. This paper examines the sources of error when using a fixed speed threshold to calculate two common performance metrics (the number of congested events and congested hours) using probe versus sensor data. The analysis shows that both latency, and use of a fixed speed threshold methodology, contribute to divergent performance values when using probe (INRIX) versus sensor (Wavetronix) data.

To address these differences, the analysis established sensor data as a base and used a change point detection methodology to calculate performance values from probe data. The change point detection algorithm was shown to improve the identification of both congested events as well as calculating congested hours versus using a fixed threshold methodology. The evaluation was expanded from a limited number of sensor-segment pairs on one specific route to five different routes with 64 sensor-segment pairs across the state of Iowa using data from the year 2017.

Change point detection appears to address errors observed when calculating traffic performance measures on probe data versus using a fixed speed congestion threshold. Agencies should consider this method prior to calculating and reporting performance metrics to the public.

1.2.3 Research motivation 3: Assessing the impact of game day schedule and opponents on travel patterns and route choice using big data analytics

In recent years, transportation system has become a critical infrastructure for the movement of people and goods. However, major events such as unexpected congestion and planned special events decrease its reliability. Sporting events concentrate people at a specific venue on game days. This study deals with issues of road traffic management during major sports events using widely available INRIX data. This research is intended to compare travel patterns and behaviors on game days against normal days. A comprehensive analysis is conducted on all Nebraska Cornhuskers football games and their impact on traffic congestion on 5 major routes in Nebraska over 5 years. In the next, hotspots, the abnormally high-risk regions in a spatiotemporal space that contains traffic congestion almost on all game days, are identified. For hotspot detection, we utilize an algorithm, called Multi-EigenSpot that is able to handle multiple hotspots by iteratively removing previously detected hotspots and re-running the algorithm until no more hotspots are found. With this method, we are able to detect traffic hotspot clusters on 5 chosen routes in Nebraska. After detecting hotspots, it is crucial to identify what factors affect the size of hotspots and other possible parameters. Start time of the game and opponents are two important factors affecting number of people coming to Lincoln, Nebraska on the game days. At the end, dynamic Bayesian network (DBN) approach is proposed to forecast the traffic congestion (hotspots) on game days. This approach is designed to provide real-time predictions even in case of incomplete data.

1.3 Dissertation Organization

This dissertation is organized in a manuscript-based format, consisting of 3 papers that address the research motivations and achieve the research objective accordingly. In chapter 2, INRIX performance is thoroughly evaluated in three major criteria: coverage and penetration, speed bias, and congestion detection precision. This chapter addresses research motivation 1. Chapter 3 evaluates the reliability of probe-sourced data (INRIX) using two performance measures; congested hour and the number of congested events. The study also introduces change point detection algorithm as a new robust method for detecting recurring and non-recurring traffic congestion and reductions in speed. This chapter addresses research motivation 2. The purpose of chapter 4 is to find out the impacts of game day on travel pattern and route choice behaviors using INRIX as a reliable data source. Also, two novel methods are proposed for congestion hotspot detection and prediction. This chapter addresses research motivation 3. Chapter 5 concludes the dissertation with research findings, limitations and future works.

CHAPTER 2. QUANTITATIVE ANALYSIS OF PROBE DATA CHARACTERISTICS: COVERAGE, SPEED BIAS, AND CONGESTION DETECTION PRECISION

Modified from a paper published in the *Journal of Intelligent Transportation Systems*

Vesal Ahsani, Mostafa Amin-Naseri, Skylar Knickerbocker, and Anuj Sharma

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-based traffic data is significantly different in terms of the nature of data collection, measurement technique, coverage, pricing, etc. Although many researches have studied probe-based data, there remains critical questions such as data coverage and penetration over time, or the influential factors in the accuracy of probe data. This research studied probe-sourced data from INRIX, to profoundly explore some of these questions. First, to explore coverage and penetration, INRIX real-time data was illustrated temporally over the entire state of Iowa, demonstrating the growth in real-time data over a four-year timespan. Furthermore, the availability of INRIX real-time and historical data based on type of road and time of day, were explored. Second, a comparison was made with Wavetronix smart sensors, commonly used sensors in traffic management, to explore INRIX's speed data quality. A statistical analysis on the behavior of INRIX speed bias, identified some of the influential factors in defining the magnitude of speed bias. Finally, the accuracy and reliability of INRIX for congestion detection purposes was investigated based on the road segment characteristics and the congestion type. Overall, this work sheds light onto some of the

less explored aspects of INRIX probe-based data to help traffic managers and decision makers in better understanding this source of data and any resultant analyses.

Keywords – probe data, sensor data, coverage, speed bias analysis, congestion detection.

Introduction

Many transportation agencies and state Departments of Transportation (DOT) utilize fixed, infrastructure – mounted sensors for collecting relatively accurate and real-time traffic information such as lane by lane traffic speed, volume, occupancy, etc. Compared to alternatives provided by most non-traditional data streaming sources, the cost of deploying and maintaining these sensors could be high. Another limitation of sensors is their geographical scalability; they need to be installed in a large number to determine the traffic situation in an area (S. Young, 2007). Accordingly, most Traffic Management Centres (TMC) install them on major freeways and critical urbanized areas rather than throughout the highways and arterials. The lack of sufficient coverage on highways and arterials spurs the interest to augment infrastructure mounted sensors with new data streaming sources.

With the rapid rise of telecommunication and wireless technologies over the past few years, traffic data collection, processing, analyses and utilization have changed significantly. Wide area probe technology is an example which collects traffic information from millions of mobile devices, connected cars, trucks, delivery vans, and other GPS-enabled fleet vehicles. Probe-based methods of measuring travel time and speed data can easily scale across large networks without the need for deploying any additional infrastructure (S. Young, 2007). This makes several agencies to use a single, uniform source of data as a cost-effective way for monitoring traffic across most roadways in a State (FHWA, 2013). Some of the third-party probe data providers are INRIX, HERE, TomTom, etc.

Several studies have been conducted to compare the accuracy and reliability of probe sourced data against local sensor data such as radar sensor data, loop detector data, etc. (Adu-Gyamfi et al., 2017; Coifman, 2002; FDOT, 2012; Feng et al., 2010; Haghani et al., 2009; S. Kim & Coifman, 2014; Lindveld et al., 2000). Many of them evaluated performance of probe data by travel time reliability measures, such as 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, congestion hour, etc. (Aliari & Haghani, 2012; Araghi et al., 2015; Pranamesh Chakraborty et al., 2018; Cookson & Pishue, 2016; C. Day et al., 2015; FHWA, 2017; Gong & Fan, 2017; Higatani et al., 2009; Hu et al., 2015; Tim Lomax et al., 2003; Miwa et al., 2015; MoDOT, 2017; Pu, 2012; Rakha et al., 2010; Remias et al., 2013; Sanaullah et al., 2016; Schrank. et al., 2015; Schrank et al., 2012; Sekuła et al., 2017; Sharifi et al., 2017; Turner, 2013; Uno et al., 2009; Venkatanarayana, 2017; WSDOT, 2013, 2014; Zheng et al., 2018). An overview of these studies and the performance measures used to evaluate travel time reliability of probe-source data is provided in Table 1.

Table 2.1 Overview of the studies and the performance measures used to evaluate travel time reliability of probe-source data

Study	Source of Probe Data Used	Performance Measures
(Pu, 2012)	not mentioned	95^{th} percentile travel time, standard deviation, coefficient of variation,, skew statistic buffer index, buffer index (w.r.t. median), planning time index, frequency of congestion, failure rate, failure rate, travel time index

Table 2.1. (Continued)

(Tim Lomax et al., 2003)	not mentioned	Travel time window, percent variation, variability index, displaying variation, buffer time, buffer time index, planning time index, travel rate envelope, on-time arrival, misery index
(Turner, 2013)	INRIX	Annual hours of delay per mile, hours of target delay per mile, Travel Time Index, Planning Time Index, top N congested segments
(Uno et al., 2009)	not mentioned	Average travel time, covariance of travel time, level of service (LOS)
(Rakha et al., 2010)	not mentioned	Travel time coefficient of variation
(C. Day et al., 2015; Remias et al., 2013)	INRIX	Congestion hours, distance-weighted congestion hours, congestion index, speed profile, speed deficit, travel time deficit, congestion cost, top N bottlenecks
(MoDOT, 2017)	not mentioned	Average travel time per 10 miles, additional travel time needed for on-time arrival (80% of time), annual congestion costs
(FHWA, 2017)	NPMRDS	Congested hours, planning time index, travel time index
(Schrank. et al., 2015; Schrank et al., 2012)	INRIX	Travel speed, travel delay, annual person delay, annual delay per auto commuter, total peak period travel time, travel time index, planning time index, number of rush hours, percent of daily and peak travel in congested conditions, percent of congested travel
(WSDOT, 2013, 2014)	not mentioned	Lane-miles congested, total and cost of delay, travel time index
(Sharma, Ahsani, & Rawat, 2017)	INRIX	Congestion detection latency, count of congestion, congestion durations, buffer time index, reliability curve
(Hu et al., 2015)	INRIX	Delay saving, buffer index, 95th percentile travel time

Table 2.1. (Continued)

(Cookson & Pishue, 2016)	INRIX	Travel time index, wasted time in congestion
(Aliari & Haghani, 2012)	INRIX	Travel time, average speed
(Gong & Fan, 2017)	INRIX	Travel time reliability, planning time index, frequency of congestion
(Sekuła et al., 2017)	INRIX	Hourly traffic volume
(Venkatanarayana, 2017)	INRIX, NPMRDS	Traffic delay, planning time index, travel time index, AASHTO reliability indexes (RI80, for all days and weekdays), congested hours, and congested miles

In addition to studies on INRIX travel time reliability, more recent studies have been conducted using INRIX data to evaluate other aspects of INRIX data. For instance, Eshragh and colleagues estimate the accuracy of probe speed data on arterial corridors using roadway geometric attributes (Eshragh, Young, Sharifi, Hamedi, & Sadabadi, 2017). It was also shown that INRIX and benchmarked results were most similar in external-external trips (Hard et al., 2017). Also, Lu and Dong compared INRIX with radar sensor data for travel time estimation and showed its reliability (C. Lu & Dong, 2018). Moreover, models were developed for detecting abnormal traffic patterns and traffic speed prediction using INRIX and Wavetronix data sets, and obtained satisfactory results (Barajas, Wang, Kaiser, & Zhu, 2017). Day and colleagues made use of INRIX XD and connected vehicle data to optimize traffic signal offsets (C. M. Day et al., 2017). Additionally, (Elhenawy, Chen, & Rakha, 2014) examined the quality of INRIX data and showed its good quality for travel time prediction.

Overall, the recent studies have reaffirmed the validity and value of INRIX data while pointing out improvement in its quality over years. The quality improvement is shown in Figure 2 of the paper. The figure shows a significant increase in the real-time data availability.

Moreover, based on the report performed by the University of Maryland and published by INRIX, INRIX was never penalized for data quality during the life of vehicle probe project (VPP). This report mentioned 57% and 46% improvement of INRIX speed error results in heavy and moderate congestion from 2008-09 to 2012-13 respectively. Moreover, 87% overall improvement was observed in INRIX speed bias results from 2008 to 2013 (INRIX, 2015).

Inversely, very few research has been conducted on probe data coverage, probe data penetration over time, speed bias and congestion detection performance with respect to segment's characteristics. This is while probe data, unlike sensor data, comes from an ever changing source, thus making it critical to study the patterns and trends in coverage and penetration. To the best of our knowledge, no other research has been looked into the coverage of probe-sourced data temporally over a 4-year timespan.

In terms of INRIX speed quality, several works have estimated the speed bias to be 6 mph on freeways relative to ground truth (Lattimer & Glotzbach, 2012) and more generally, the overall average speed errors were estimated to be within 10 mph throughout various levels of congestion (K. Kim, Motiani, Spasovic, Dimitrijevic, & Chien, 2014). Adu-Gyamfi, (2017) also noted that high speeds (>60 mph) generally have less error, whereas low speeds (<60 mph) show higher speed error. Table 2 below includes positive and negative results these mentioned papers have been concluded. Despite the invaluable information that these works provide, yet a quantitative analysis that studies the significant factors influencing speed bias is not in place. Similarly, a quantitative study on the factors (e.g., segment length or congestion type) that influence the congestion detection quality using probe-based data, have not been performed. This work studied INRIX data to learn more about this source of data from these less considered perspectives.

Table 2.2 Summary of the findings on INRIX speed bias analysis

Study	Source of Probe Data Used	Performance Measures	Pros	Cons
(FDOT, 2012)	NAVTEQ, TrafficCast, INRIX	Absolute average speed error, average speed bias, absolute average travel time error, travel time bias	1. All probe data sources are generally consistent with the ground truth data. 2. INRIX data in some cases appeared to be more accurate compared to other probe datasets.	1. TMC segments in urban areas with traffic signals experienced a larger variability in the results.
(Haghani et al., 2009)	INRIX	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.
(Lattimer & Glotzbach, 2012)	INRIX, NAVTEQ, TrafficCast	Travel time, Speed bias	----	1. INRIX speed has a 6 mph bias relative to ground truth on an uncongested freeway.

Table 2.2. (Continued)

(K. Kim et al., 2014)	INRIX, NAVTEQ, TrafficCast	Travel speed, Speed error	----	1. Overall average speed errors tend to be within 10 mph throughout various levels of congestion. 2. Data providers missed a major incident lasting more than 4 hours.
(Adu-Gyamfi et al., 2017)	INRIX	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.

Data

The different sources of data utilized in this work, are explained in this section.

Probe-sourced data

With the help of today's technologies including connected vehicles and smartphones, INRIX leverages the great amount of historical and real-time data which can be analyzed and investigated to improve transportation networks performance. This study utilized the historical and real-time traffic data collected through the INRIX TMC monitoring platform. For each of the TMC segments, the speed, as well as the corresponding date and time of traverse were provided for every 1 minute.

Infrastructure mounted sensors

The benchmark dataset used in this paper was obtained from Wavetronix sensors which utilizes radar technologies for data collection. Although we acknowledge that sensors might have some inherent errors, yet Wavetronix Smart Sensors have been commonly utilized as ground truth for comparison purposes (P Chakraborty, Adu-Gyamfi, Poddar, & Ahsani, 2018; X. Lu et al., 2014; Poddar, Ozcan, Chakraborty, & Ahsani, 2018; Sharifi, Elham & Hamedi, Masoud & Haghani, Ali & Sadrsadat, 2011). Each Wavetronix sensor unit is built up of a Doppler radar, a wireless modem, solar panel and on-board processors for real-time processing of traffic data such as speed, volume, etc. High-resolution (20 second) traffic speed data were provided by Wavetronix sensors.

Roadway Asset Management System (RAMS)

Information on the roadway geometry and characteristics can play an important role in studying performance of transportation networks. Iowa DOT's Roadway Asset Management System (RAMS) provides an inventory of roadway geometry and characteristics for the entire state. Information included in the database include the number of lanes, speed limit, AADT and surface type, as well as other information that may be useful when building a model. The RAMS database uses the DOT's linear referencing system which can be used when requesting information for a specific location. The coordinates for each TMC event were passed through the linear referencing systems REST services to provide the corresponding route and mileage values. The route and mileage could again be used with the REST services to retrieve the roadway geometry and characteristics. This system allows for the system to be deployed in real-time in the future to quickly obtain the roadway characteristics. The data requested for the model using this service are: 1) AADT, 2) Federal functional class, 3) Median type and width, 4) Number of lanes, 5) Right and left shoulders type and width, 6) Speed Limit, 7) Surface type and width, and 8) Terrain.

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 data 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 Wavetronix requires proper infrastructure and computational power to handle masses of data. A high performing cluster was used for data processing. Hadoop Distributed File System (HDFS) ("Apache Hadoop," 2017) was used for storage of the data and map-reduce was used for processing. Pig Latin ("Apache Pig," 2017) was used as the language to implement map-reduce algorithms.

Evaluation Procedure

Incorporating a probe data stream into traffic operations, planning, and management activities requires several key evaluations in the reliability and accuracy of the probe-sourced data. For this purpose, this study utilized real-time and historical traffic data which were collected through two different data sources; INRIX and Wavetronix. The INRIX probe data stream is compared to a benchmarked Wavetronix sensor data source in order to explain some of the challenges and opportunities associated with using wide area probe data. In the following, INRIX performance will be thoroughly evaluated in three major criteria:

1. Coverage and penetration
2. Speed bias
3. Congestion detection

Table 2.3 Summary of the INRIX Evaluation Procedure Steps

Step	Name	Research motivation	Data	
			Time	Location
1	Coverage	Temporal distribution of INRIX real-time data (score 30)	Whole 4 years of 2013,…, 2016	Entire state of Iowa
		Availability of INRIX real-time and historical data (scores 10,20,30) • Road type • Time of day	April 2016 to April 2017	Entire state of Iowa
2	Speed bias	Characteristics of INRIX speed bias • Speed value • Time of day • truck-AADT • Number of lanes • Type of TMC Segment • Segment length	April 2016 to April 2017	Des Moines Area (Iowa)
3	Congestion detection	Characteristics of congestion detection by INRIX • Type of congestion • Type of TMC segment • Segment length	April 2016 to April 2017	Des Moines Area (Iowa)

1. Coverage

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 addition to real-time data, INRIX provides historical data whenever real-time data are not available. The higher the device penetration (i.e., more probes), the better the data are. INRIX reports two measures of confidence, score and value. Based on Interface Guide for Public Sector Applications from INRIX, for each speed measurement, INRIX reports a measure of confidence, reported as one of three possible values (IowaDOT, 2017):

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).

Additionally, INRIX reports a second measure of confidence, which it is called the confidence value. Based on INRIX Interface Guide, the confidence value is based on a comparison against historical trends. It should be taken into consideration that the confidence value only applies when the confidence score is 30.

In Figure 1, the 2016 yearly coverage of INRIX real-time data (score 30) for interstate and non-interstate roadways in the state of Iowa is shown by a range of colors. Red represents minimum possible availability of real-time data on roads through green representing the maximum. However, the coverage and quality of probe-based data, due to its nature (being provided by probes), is not guaranteed to stay constant over time. Thus, it is critical to monitor the trends in coverage accuracy over time, a point which has been less considered in the literature.

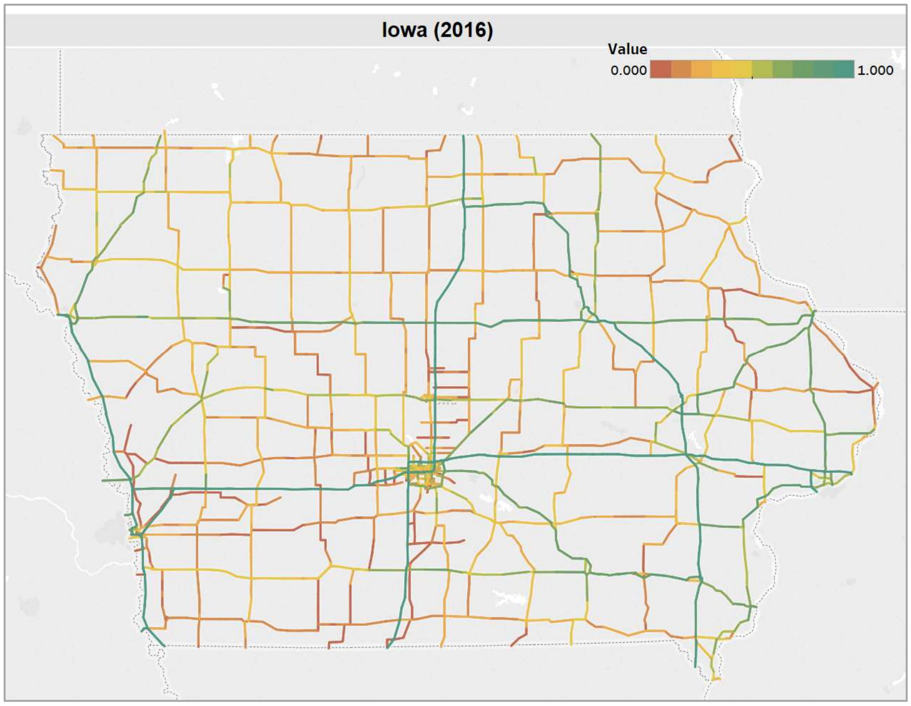


Figure 2.1 Geographical INRIX real-time data availability for the state of Iowa in year 2016.

Figures 2 (a) and (b) depict the empirical cumulative distribution function (CDF) of real-time INRIX data availability for years 2013-2016 on interstates and non-interstates respectively. The INRIX data are reported every minute for each TMC segment. It is visually apparent that the percentage of real-time INRIX data availability on both interstates and non-interstates for year 2016 is higher than the prior three years. For instance, red arrow in Figure 2 (a) indicates for the 60^{th} percentile of road segments on the interstates, the availability of real-time INRIX data was increased from nearly 70% for years of 2013-2015 to almost 90% for year 2016. Moreover, the number of roads that had no coverage in 2013 to 2015 had decreased in 2016, as the number of probes increased. INRIX has not shared the reason for this significant increase in the availability of real-time data but our hypothesis is that additional sources of data were procured which increased the penetration in Iowa. Therefore, the further analyses was conducted on 2016 data to capture the most recent characteristics of INRIX data.

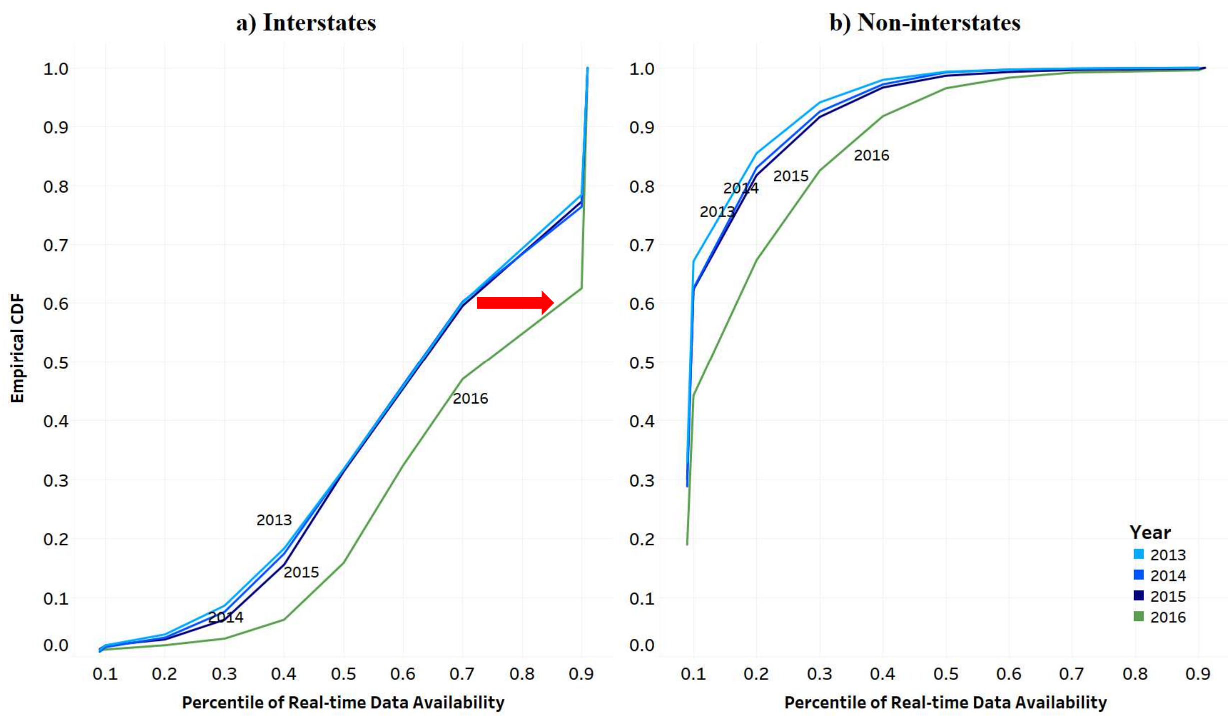
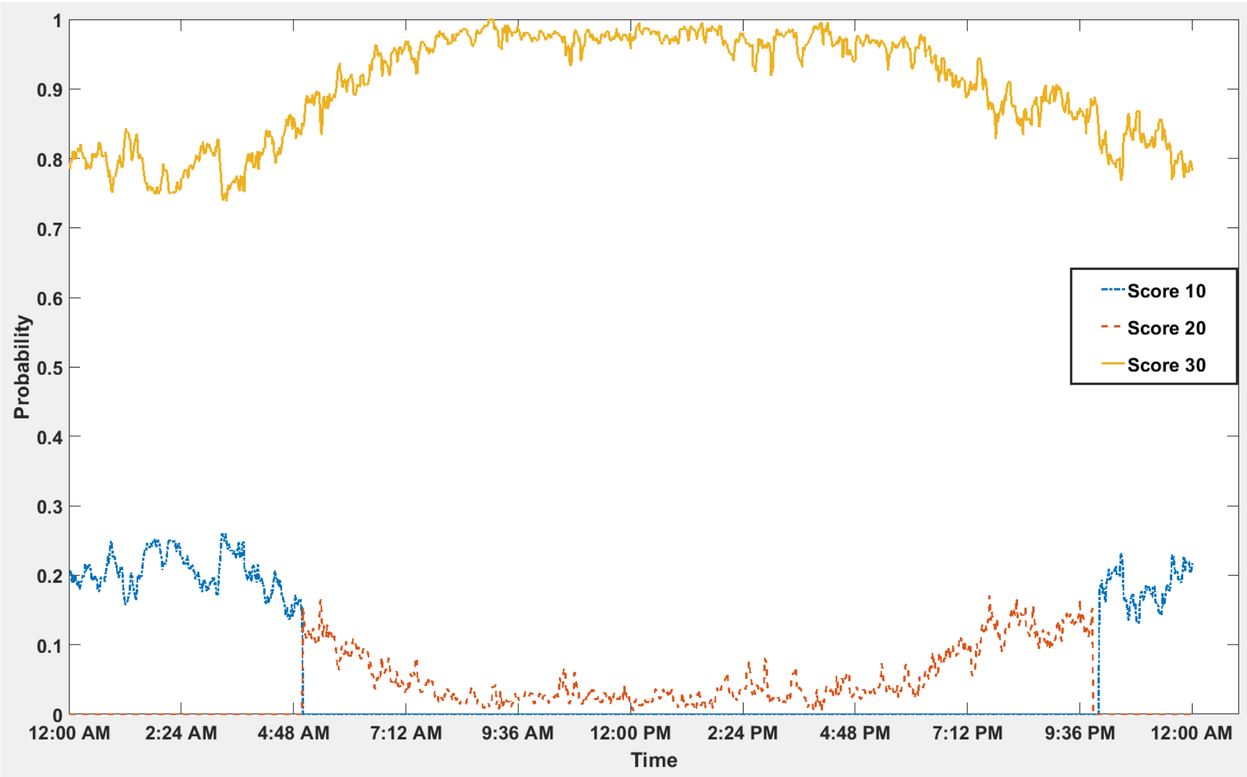


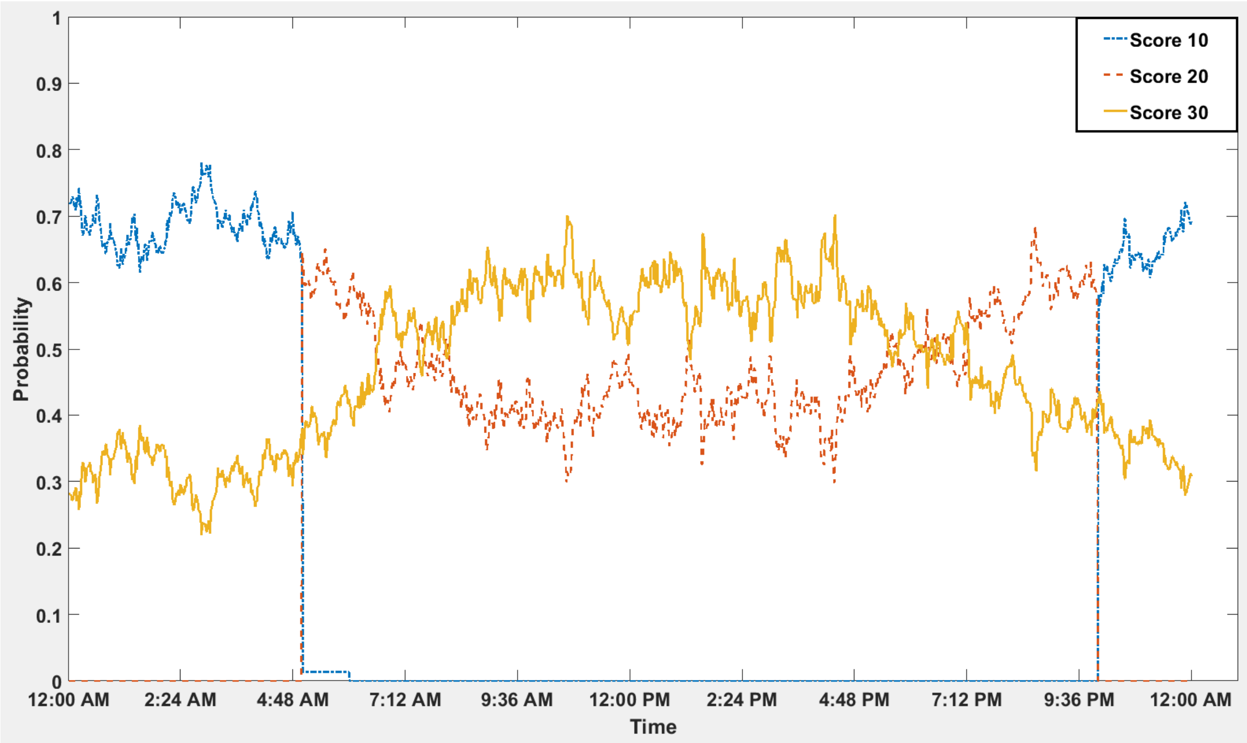
Figure 2.2 Temporal empirical CDF of INRIX real-time (score 30) data on **(a)** Interstates and **(b)** Non-interstates in the entire state of Iowa over 4 years of 2013-2016.

The daily availability of INRIX traffic data is shown in Figures 3 (a) and (b), 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. In Figure 3, the INRIX time interval is considered again as 1-min for the analysis. The horizontal axis shows 1440 minutes of a day. The vertical axis is the probability of having confidence score 10, 20, or 30 of INRIX data in each minute of a day with three colors of blue, red, and yellow respectively. The probability of having each of the scores in each minute of a day is computed by considering that specific minute for all days in one year, examine how many score 10, 20, and 30 were observed in that specific minute over the span of a year. In the analysis, each specific minute of a day is considered with all corresponding confidence scores (which can only be one of the values 10, 20, or 30), and calculate number of times score 10, 20, and 30 were seen in that specific minute of day over 365 days in a year. In other words, the summation of probabilities of scores 10, 20, and 30 in each minute always equals to 1. One point which should be noted here is that this figure does not show that it is probable to have multiple confidence scores for each minute. According to our analysis on INRIX data in the year 2016, for example in Figure 3 (a) at the time 4:48 am, it is 84% probable to have confidence score 30, 0% probable to have score 20, and 16% probable to have score 10. As expected, INRIX was able to provide real-time speed data (score 30) most of the day on the interstates (Figure 3 (a)), whereas on non-interstates, real-time data were provided mostly from around 6 am to 6 pm (Figure 3 (b)). 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 the night.

For the further analysis, we focus on performance on Interstates as the quality of data for Iowa Interstates was significantly superior to rest of the network. For this purpose, a specific location including a total of 163 TMC segments and Wavetronix sensors for approximately 164 miles of Iowa primary network along I-35, I-80 and I-235 near Des Moines area is selected, as shown in Figure 4. The criterion for selecting a sensor–segment pair was based on two main association rules. First, the Wavetronix sensor should be located in its corresponding INRIX segment, and, second, the bearing of the road on which the sensor and segment are located should be the same. There are several locations in Iowa which one TMC segment corresponds to multiple sensors.



a) Interstates



b) Non-interstates

Figure 2.3 Daily score-wise availability of INRIX traffic speed data on **(a)** Interstates and **(b)** Non-Interstates for whole year of 2016. Yellow, red, and blue lines represent scores 30, 20, and 10 data respectively.

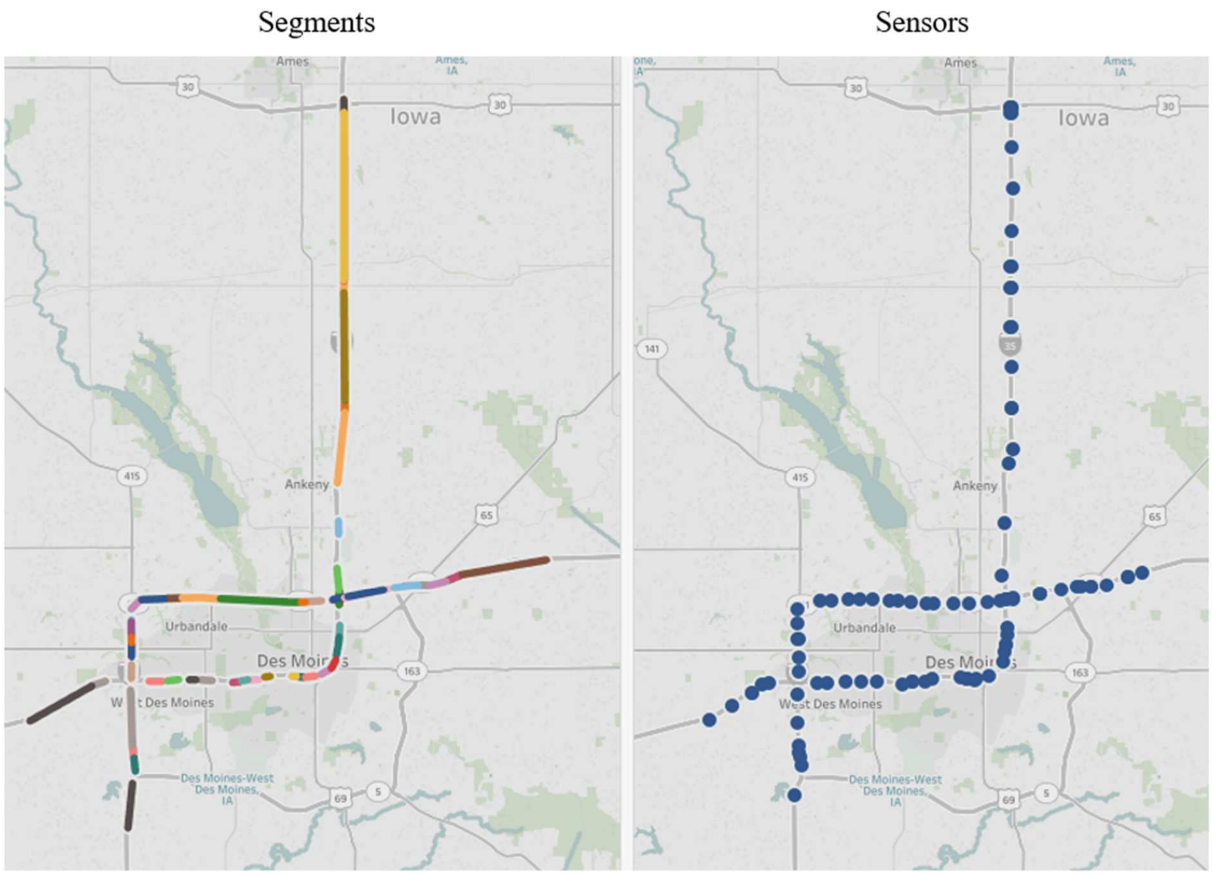


Figure 2.4 Location of segments and sensors used.

2. Speed bias

Speed bias is defined as the difference of speed between the two traffic speed data providers. There is almost always a speed bias between data streaming from probes and traditional infrastructure-mounted sensors. Although part of this difference is inevitable due to the differences in the two data collection methods, yet a model that provides insight about the underlying factors that influence speed bias, would further the community's understanding of this probe-sourced data. Different factors, such as INRIX speed value, time of the day, the number of probes on road, road segment type, number of lanes, etc., can be influential in the magnitude of probe data speed bias. A statistical model was used to investigate the role of these factors.

In this study, speed bias was calculated by subtracting INRIX speed from Wavetronix speed (Equation 1).

$$Speed\ bias = Wavetronix\ speed - INRIX\ speed \tag{1}$$

Probe technology calculates speed as the average speed of vehicles over a length of road which is called space mean speed (SMS). Time mean speed (TMS) which is arithmetic mean of vehicles' speed passing a point is the calculated speed for Wavetronix sensors. There is always a difference between SMS and TMS due to measurement technique. The relationship between TMS and SMS is shown in Equation 2 below (Knoop, Hoogendoorn, & Van Zuylen, 2009):

$$v_t = \frac{{\sigma_M}^2}{v_s} + v_s \tag{2}$$

Where

v_s = SMS,

v_t = TMS, and

σ_M = Variance of SMS

Ideally, TMS to SMS conversions (or vice versa) should be performed before the two data sets are compared. However, in this paper speed data obtained from Wavetronix and INRIX were already aggregated. For that reason, the speed variance (σ_M) could not be calculated within the 20-seconds and 1-minute period. However, a previous study showed that the most probable range of error introduced by the measurement technique is between 0 and 2 mph (Adu-Gyamfi et al., 2017).

To further explore the characteristics of speed bias in INRIX data, a statistical analysis was performed to quantitatively explore the significant contributors to INRIX speed bias.

First, INRIX speed values were explored by dividing observations into 5 groups (0-25, 25-45, 45-55, 55-65, and greater than 65 mph) and the box plot of speed bias for each group is depicted in Figure 5 (a). The notable observation in this figure is that as INRIX speed value increases, two attributes decrease: 1) the interquartile range (variation), and 2) median of speed bias. Smaller interquartile ranges with higher INRIX speeds, indicated there is less variation in speed bias when INRIX speed is greater than 45 mph.

To determine the effect of INRIX speed in the speed bias level, a one way analysis of variance (ANOVA) was performed on five predefined groups of INRIX speed. Based on the ANOVA, the differences of the mean INRIX speed bias among all groups of INRIX speed were statistically significant $\mathrm{F}(4{,}1948120) = 12323, p < .0001$. Tukey's post-hoc test showed that all five groups had statistically significant differences in the mean speed bias. Figure 5 (b) shows the location of all segment-sensor pairs and their corresponding speed biases for each speed group. Range of speed bias is from -20 (green color) to +20 (red color). Yellow and orange colors represent low magnitude of speed bias. It reaffirms the fact that speed bias decreases for most of the sensor-segment pairs as INRIX speed values increase. It should be noted that negative speed bias means that INRIX speed value is more than Wavetronix sensor speed value.

In terms of INRIX speed quality, Haghani et al., (2009) mentioned that INRIX overestimates speeds below 45 mph and for speeds over 60 mph, it underestimates the actual speed. Our observation in Figure 5 does not comply with their finding. Among the 163 segments and sensors which were used in this paper, although there were cases where the general understanding of speed underestimation and overestimation were observed, in many cases it was contradicted (i.e., INRIX overestimated for speeds greater than 60 mph and underestimated for less than 45 mph. Moreover, in cases the INRIX speed was almost equal to the actual speed).

The authors are further investigating the contributing factors, such as segment location, segment length, time of day, etc., to this inconsistent behavior. Furthermore, it should be noted that as mentioned in the literature, the quality of INRIX data has been improved over time which could be a contributor to this different observation. However, this topic is beyond the scope of this article and will be presented in separate forthcoming work.

As observed in Figure 5, five ranges of speed were chosen. According to Highway Capacity Manual version 6 (Transportation Research Board, 2016), 45 mph is considered as the breakdown speed. However, to delve deeper into the characteristics of lower speeds and their variations, the DOT has conventionally studied speeds less and greater than 25 mph to calculate congested hour. Thus, to align with these efforts and make the findings comparable, we determined the bins as presented.

Based on the exploratory analysis, the magnitude and variation of speed bias for INRIX speeds below 45 mph was found to be greater than others. This is while speed bias for INRIX speeds greater than 45 mph, had less variation within an acceptable range (mostly less than 3 mph). Therefore, a statistical model was run on 6331 observations to further dissect the influential factors in speed bias, within less than 45 mph INRIX speed. A linear regression model was performed to ascertain the effects of speed value, time of day, truck-AADT, number of lanes, type of TMC segment, and segment length on the magnitude of INRIX speed bias. The model was statistically significant $\mathrm{F}(28{,}6331) = 95.34, p < .0001$ and explained 39.35% (Adjusted R2) of the variability in speed bias. Of the twenty predictor variables, the statistically significant ones were noted with details in the Table 4.

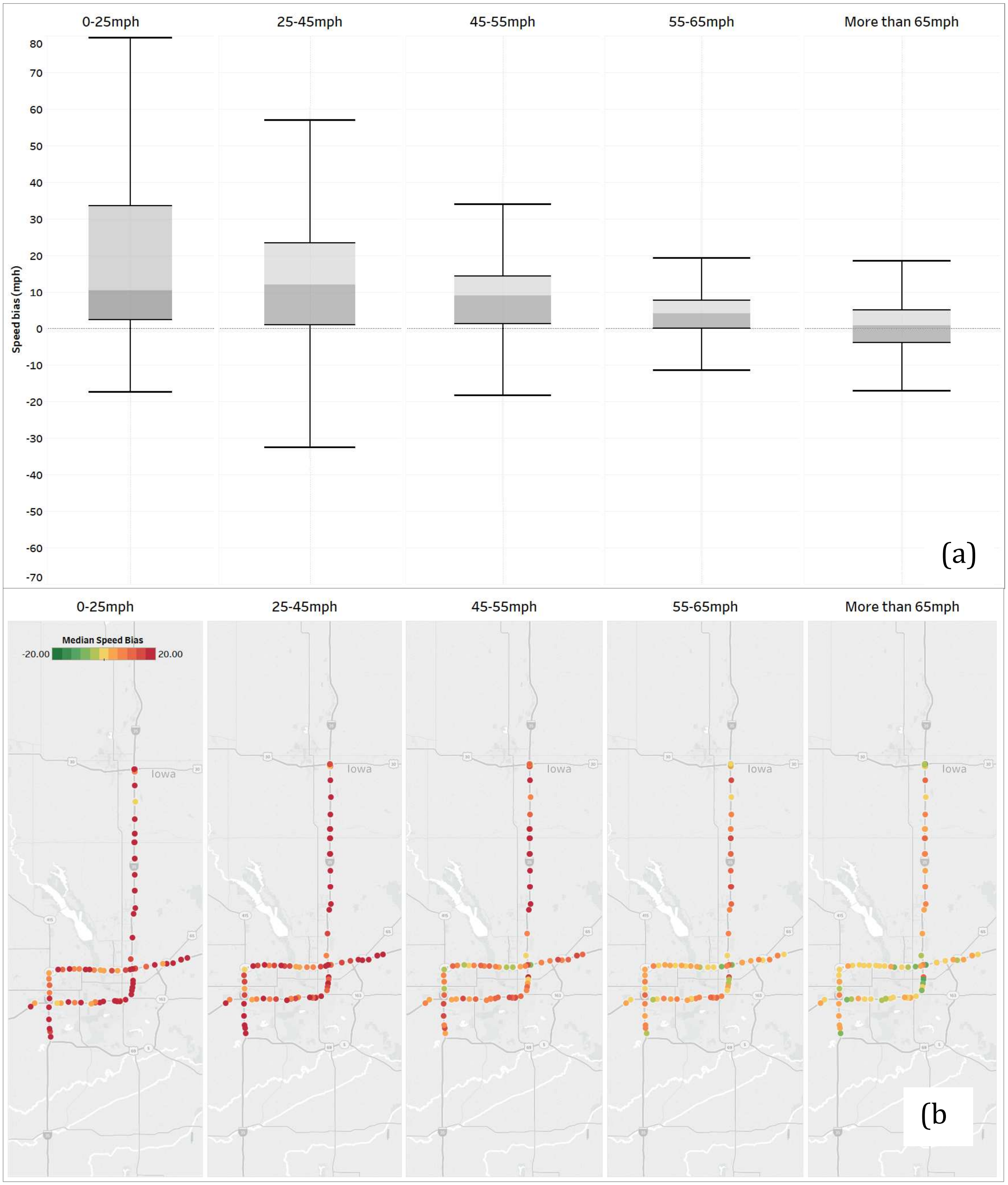


Figure 2.5 (a) Boxplots of speed bias for 5 different ranges of INRIX speed. **(b)** Location of all segment-sensor pairs and their corresponding speed biases for each group. Range of speed bias is from -20 (green color) to +20 (red color). Yellow and orange colors represent low magnitude of speed bias. It illustrates the fact that speed bias decreases for most of sensor-segment pairs by increase of INRIX speed. It should be noted that negative speed bias means that INRIX speed value is more than Wavetronix sensor speed value.

Table 2.4 Significant influencers in INRIX speed bias

$F(28{,}6331) = 95.34, p < .0001$, Adjusted $R^2 =$ 39.35%, sample size= 6360				
Variable		**Estimate**	**P-Value**	**Interpretation**
Speed value		-0.337	<.001***	(INRIX speed =< 45 mph) As INRIX speed increases, speed bias decreases (Figure 5 (a)).
Time of the day	06:00-09:00 (morning peak hour)	-16.31	<.001***	In morning and afternoon peak hours speed bias decreases significantly compared to off-peak hours (09:00-16:00).
	09:00-16:00	-8.47	0.005***	
	16:00-19:00 (afternoon peak hour)	-14.28	<.001***	
Truck-AADT		0.002	<.001***	Increased number of trucks yields a decrease in speed bias.
Segment length (mile)		0.393	<.001***	Longer segments have higher speed bias.
Number of lanes		-1.119	<.001***	Higher number of lanes yields lower speed bias.
Type of segment		1.240	<.001***	Internal TMC segments have higher speed bias.

The model indicated an inverse relationship between INRIX speed and speed bias (Less speed bias in higher speeds), confirming the observation in Figure 5 (a). Moreover, certain timespans of the day, had a significant impact on determining the speed bias. In general, day hours (6 a.m. -7 p.m.) have lower mean speed biases than the rest of the night. More specifically, during morning and afternoon peak traffic hours, speed bias is less than off-peak hours.

To examine the impact of traffic volume on speed bias, AADT was considered. Since INRIX mostly provides traffic data via trucks in the state of Iowa, between AADT and truck-

AADT, the truck-AADT was observed to have contributed more significantly to the model. Road segments with higher truck-AADT, have less speed bias. This implies, higher device penetration (number of probes) leads to more accurate traffic information (speed) from INRIX. This observation about the impact of volume on INRIX speed bias, reinforces our interpretation of the less speed bias in the crowded hours of the day. Moreover, the above model shows that road segments with higher number of lanes, lead to more capacity (volume) on the road, which again leads to lower of speed bias.

On the other hand, the model indicated that longer segments have higher speed bias. As mentioned before, INRIX calculates speed by averaging it over the length (space mean speed). As the length of the segment increases, the difference of space mean speed (INRIX speed) and time mean speed (sensor speed) increases.

Finally, considering the two types of TMC segments (internal and external), there was a significant impact in speed bias. The implication is that internal segments have higher speed bias than the external ones. The reason is completely explained in the next section.

3. Congestion Detection

Improving traffic safety and operations have long been areas of motivation among researchers and traffic 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. According to the United States Department of Transportation, traffic incidents are the main cause for more than half of traffic congestions that occur along US highways (Peniati, 2004). Generally, there are two types of congestion, recurring and nonrecurring. Recurring congestion is regarded as the congestion caused by the routine traffic in a normal environment which is somehow expected, whereas nonrecurring congestion is unexpected and is most likely caused by an incident. Nonrecurring congestion may emerge as a result of a variety of factors like lane blocking crashes or disabled vehicles, work zone lane closures, adverse weather conditions, etc. 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. This section of the paper evaluated the influence of type of congestion (recurring vs. non-recurring), type of TMC segment, and segment length on the performance of probe-sourced data in detecting congestion. For this purpose, Wavetronix sensors are considered as the benchmark.

Modified Congestion Detection Algorithm

After data pre-processing, an adaptive incident detection algorithm adopted by (Pranamesh Chakraborty, Hess, Sharma, & Knickerbocker, 2017) was modified to detect and classify congestion onset throughout the network for the study period. The algorithm calculates median and inter-quartile range for each time of day (15 min period) and day of week from two month history. A dynamic threshold value is set for each 15 min period for each weekday at median speed minus twice the inter-quartile range. Recurring congestion incidents were identified when speed dropped below 45 mph but it remained above the threshold calculated for that location. Most of the recurring congestions were also verified by CCTV cameras. Nonrecurring congestions were identified based on three criteria: (a) speed data of INRIX segment or the mean of 1-minute aggregated speed data of Wavetronix sensor for that location must drop below 45 mph, (b) it also drops below dynamic threshold calculated based on 2 months of historical data for that specific location for a significant period of time (15 minutes and more), and (c) a matching incident must be reported by Iowa Advanced Traffic Management System (ATMS). The Iowa ATMS records all incidents, hazards, and congestion detected by various sensors and cameras or the reports by the highway helpers or police. The incidents in this dataset are validated by the ATMS operators, thus serve as a reference for evaluating other sources of data. However, not all incidents, particularly congestion, are recorded in this dataset. The detection algorithm for recurring and non-recurring congestion is illustrated in Figure 6.

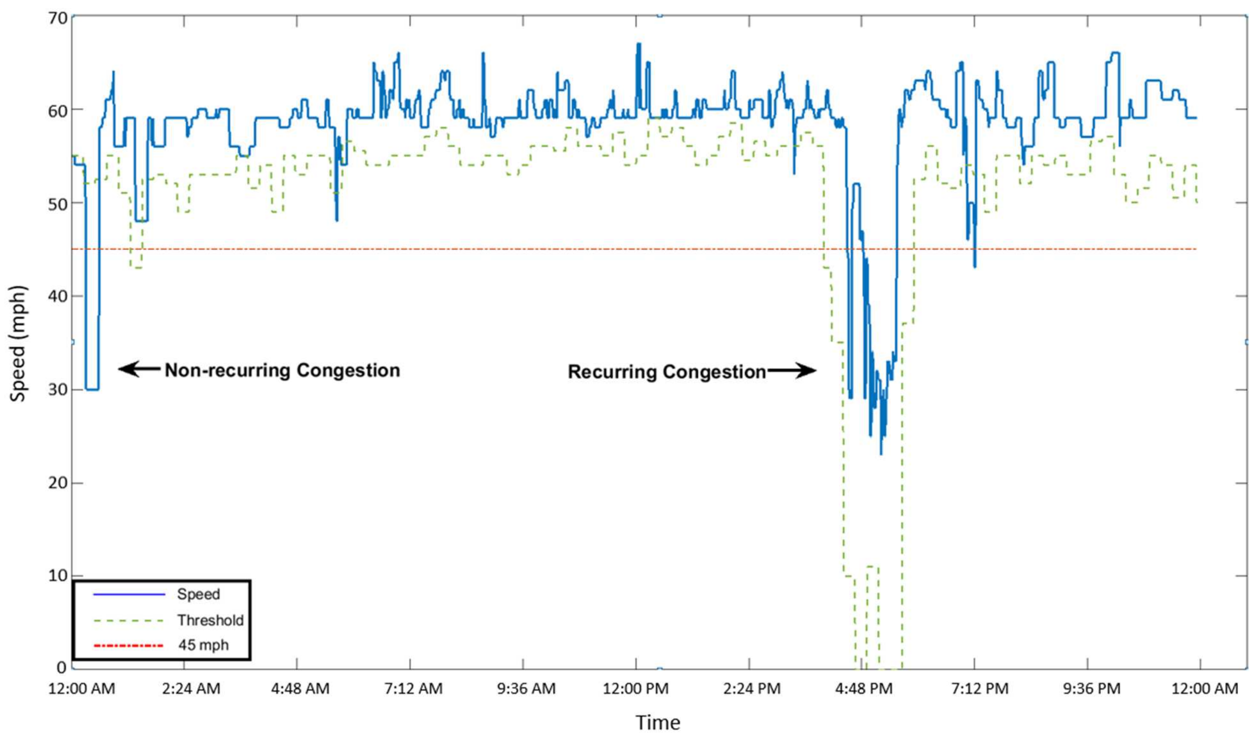


Figure 2.6 Visualization of the recurring and non-recurring congestion detection process with the modified dynamic threshold algorithm.

When studying the congestion detection performance and exploring recorded INRIX speeds, it was observed that some segments have low speeds virtually all of the times. The congestion events detected on these segments, however, were mainly false alarms. This negatively impacted the congestion detection performance. Moreover, in the regression speed bias model, TMC segment type turned out to have a significant impact on the value of speed bias. Thus, the characteristics of road segments (e.g., segment type, segment length, etc.) were thoroughly investigated to further understand their potential impact on congestion detection applications.

Segment Length

For different purposes, length of the road segments for which probe-sourced data are available vary significantly. INRIX uses either TMC segments or XD segments as their basis for defining road sections on which to report traffic data. XD segments with 1.5 miles as a maximum length are more constant than TMC segments which can vary remarkably to even more than 15 miles in the state of Iowa. There are two types of TMC codes in INRIX; internal and external. Traffic data, such as speed and travel time, are provided for both internal and external TMC codes. An external INRIX TMC code is the road segment between interchanges, typically from the last merge ramp of the upstream interchange to the first exit ramp of the downstream interchange, while an internal TMC code presents the road segment within an interchange, typically from the first exit ramp to the last entrance ramp (S. E. Young, Juster, & Kaushik, 2015). Hence, external TMC segments tend to be longer than internal TMC segments, which are usually less than 0.4 miles. Figure 7 (a) shows samples of external and internal INRIX TMC segments in this study. Figure 7 (b) provides one day's speed heat map for I-35, I-80 and I-235 near Des-Moines area in November 2016 as an example. Time of day is shown on the vertical axis and several sample TMC segments on the horizontal axis. Each cell represents the reported INRIX speed for that specific time and segment of the road. The cells are color coded based on the recorded speed values. Distinct recurring congestion events are observed during the morning and evening peak hours. There are few vertical light blue lines around segments 10 to 15, which represent speeds less than 45 mph for all minutes of the day. Those lines correspond to internal TMC segments.

Basically, internal TMC segments, due to their locations, commonly show low speeds throughout the day. In these segments cars are either accelerating to enter or decelerating to exit the freeways, thus the reported speed is mostly below 45 mph. This explains the reason why speed bias on internal segments is usually higher than external ones as shown in Table 4.

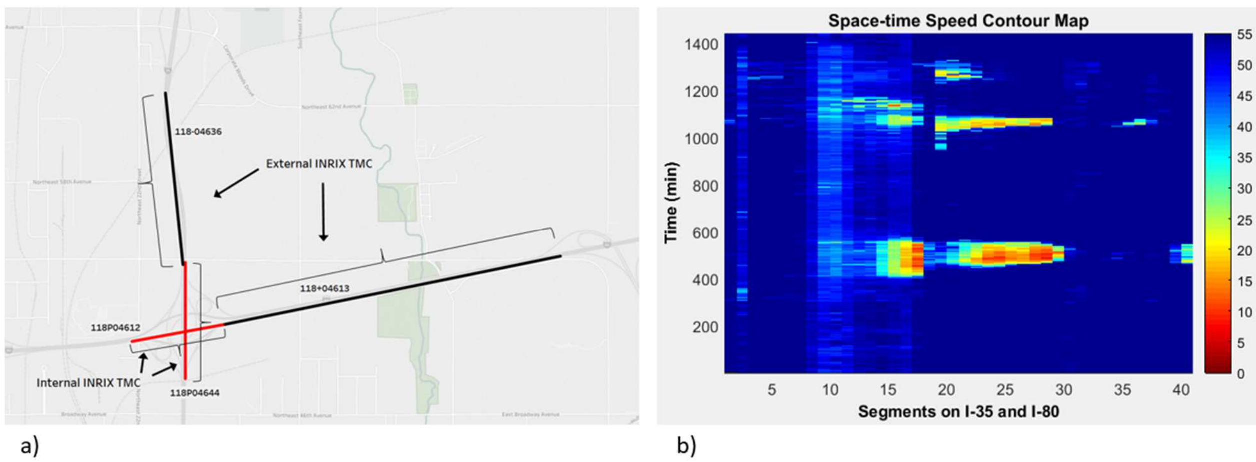


Figure 2.7 a) INRIX TMC code segmentation, b) Space-time speed contour map.

Moreover, segment type affects precision of the congestion detection algorithm. Thus, two scenarios were considered for further analysis; I) using all TMC segments in the study area, and II) removing internal TMC segments and segments with less than 0.4-mile length, to compare the congestion detection performance.

Table 5 shows the reliability of INRIX in detecting congestion events for the two predefined scenarios. True positive (TP) represents a similar event which is detected by both Wavetronix sensor and INRIX segment; false negative (FN) means an event detected in sensor data sets cannot be found in probe data set; and false positive (FP) denotes an event which is detected in probe data set and cannot be found in sensor data set. Finally, the values in the last column show the precision of congestion detection by INRIX, calculated using Equation 3.

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

The results are summarized in Table 5. As observed, by removing internal TMC codes and segments with length less than 0.4 miles and their corresponding sensors (scenario II), FP which shows false alarms associated with INRIX data were significantly decreased for both non-recurring and recurring congestion events. Simultaneously, the overall precision of the congestion detection algorithm was improved by excluding these segments. Thus, for congestion detection applications using TMC segments, it is recommended to exclude internal and less than 0.4 mile segments. Finally, it is evident from numbers that precision of congestion detection by probe-source streaming data (INRIX) is higher for recurring rather than non-recurring.

Table 2.5 Reliability of probe data in detecting congestion events.

Congestion Type	Test	Congestion Detection (%)		Precision (%)	
	Scenario	I	II	I	II
Non-recurring	TP	35.0	32.0	51.2	61.3
	FN	17.0	16.0		
	FP	33.3	20.2		
Recurring	TP	63.0	62.0	81.6	85.3
	FN	5.0	5.0		
	FP	14.2	10.7		

Conclusion and Recommendation

This research evaluated probe-sourced streaming data from INRIX, to study its characteristics as a data source for the ATMS. For this purpose, Wavetronix, a commonly used infrastructure sensor data source, was selected as benchmarked. Accuracy and reliability of INRIX was evaluated by 3 different measures; coverage, speed bias, and congestion detection.

In terms of coverage, INRIX covered almost all road networks in Iowa, however, it mostly provides real-time data on the interstates. It was also shown that INRIX virtually always provides real-time data throughout the day on the interstates. However, it is more reliable from 6 am to 6 pm on non-interstates. Moreover, the real-time availability of INRIX speed was compared for four consecutive years (2013-2016) and the results indicated a significant improvement in 2016.

INRIX speed bias analysis, found meaningful interpretations of influential factors in INRIX speed bias. These findings further our understanding of this probe-sourced data. In particular, INRIX speed value, time of day, truck-AADT, number of lanes, type of TMC segment, and segment length had significant effects on the magnitude of speed bias. It should be mentioned that use of XD data and higher market penetration rates can potentially reduce the bias.

For the congestion detection analysis, three factors of type of congestion, type of TMC segment, and segment length were thoroughly examined. It was concluded that probe segments with less than 0.4 miles length were observed to have the highest false calls with regards to congestion. The majority of such segments are located on interchanges where speeds are typically lower. Also, it is determined that precision of INRIX in detecting recurring congestion is more than non-recurring one.

Finally, a major limitation of the analysis carried out in this study was using sensor data as the benchmarked dataset. We acknowledge that sensor data would have its inherent errors and thus not really the ground truth. Yet, there is an inevitable error within the benchmarked sensor data that was unavoidable. However, we believe that this error does not meaningfully impact our findings.

The following recommendations are offered by the authors for transportation agencies and state DOTs considering the augmentation of traditional traffic data with probe-based services for wider coverage under restricted budgets:

- In terms of geographic coverage, INRIX was found reliable for throughout the day on the interstates. Moreover, this study showed that INRIX is more reliable during the day than at night, especially during peak hours. INRIX also has shown improvement in real-time data coverage over the years.
- Travel time estimation and incident detection applications should be completely based 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.
- The length of segments for which probe data are available varies greatly, from 0.2 miles to more than 15 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 (less than 0.4 miles) are recommended to be excluded.
- 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.

In the next chapter, we evaluate the reliability of probe-sourced data (INRIX) using two performance measures; congested hour and the number of congested events. The study also introduces change point detection algorithm as a new robust method for detecting recurring and non-recurring traffic congestion and reductions in speed.

References

Adu-Gyamfi, Y. O., Sharma, A., Knickerbocker, S., Hawkins, N., & Jackson, M. (2017). Framework for Evaluating the Reliability of Wide-Area Probe Data. *Transportation Research Record: Journal of the Transportation Research Board*, (2643), 93–104. https://doi.org/10.3141/2643-11

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*, *2308*, 167–172. https://doi.org/10.3141/2308-18

Apache Hadoop. (2017). Retrieved November 28, 2017, from http://hadoop.apache.org/

Apache Pig. (2017). Retrieved November 28, 2017, from https://pig.apache.org/

Araghi, B. N., Hammershøj Olesen, J., Krishnan, R., Tørholm Christensen, L., & Lahrmann, H. (2015). Reliability of Bluetooth Technology for Travel Time Estimation. *Journal of Intelligent Transportation Systems*, *19*(3), 240–255. https://doi.org/10.1080/15472450.2013.856727

Barajas, V. L., Wang, Z., Kaiser, M., & Zhu, Z. (2017). Improving Estimates of Real-Time Traffic Speeds During Weather Events for Winter Maintenance Performance Measurement. Retrieved from https://trid.trb.org/view/1465615

Chakraborty, P., Adu-Gyamfi, Y. O., Poddar, S., Ahsani, V., Sharma, A., & Sarkar, S. (2018). Traffic Congestion Detection from Camera Images using Deep Convolution Neural Networks. *Transportation Research Record: Journal of the Transportation Research Board*, 036119811877763. https://doi.org/10.1177/0361198118777631

Chakraborty, P., Hess, J. R., Sharma, A., & Knickerbocker, S. (2017). Outlier Mining Based Traffic Incident Detection Using Big Data Analytics. Retrieved from https://trid.trb.org/view.aspx?id=1439336

Coifman, B. (2002). Estimating travel times and vehicle trajectories on freeways using dual loop detectors. *Transportation Research Part A: Policy and Practice*, *36*(4), 351–364.

https://doi.org/10.1016/S0965-8564(01)00007-6

Cookson, G., & Pishue, B. (2016). INRIX Global Traffic Scorecard. *Inrix Global Traffic Scorecard*, (February), 44. Retrieved from https://media.bizj.us/view/img/10360454/inrix2016trafficscorecarden.pdf

Day, C. M., Li, H., Richardson, L. M., Howard, J., Platte, T., Sturdevant, J. R., & Bullock, D. M. (2017). Detector-Free Optimization of Traffic Signal Offsets with Connected Vehicle Data. *Transportation Research Record: Journal of the Transportation Research Board*, *2620*, 54–68. https://doi.org/10.3141/2620-06

Day, C., Remias, S., Li, H., Mekker, M., Mcnamara, M., Cox, E., … Wasson, J. (2015). *2013-2014 Indiana Mobility Report*. Retrieved from https://docs.lib.purdue.edu/cgi/viewcontent.cgi?article=1006&context=imr

Elhenawy, M., Chen, H., & Rakha, H. A. (2014). Dynamic travel time prediction using data clustering and genetic programming. *Transportation Research Part C: Emerging Technologies*, *42*, 82–98. https://doi.org/10.1016/J.TRC.2014.02.016

Eshragh, S., Young, S. E., Sharifi, E., Hamedi, M., & Sadabadi, K. F. (2017). Indirect Validation of Probe Speed Data on Arterial Corridors. *Transportation Research Record: Journal of the Transportation Research Board*, *2643*, 105–111. https://doi.org/10.3141/2643-12

FDOT. (2012). *Probe Data Analysis Evaluation of NAVTEQ, TrafficCast, and INRIX ® Travel Time System Data in the Tallahassee Region Evaluation of NAVTEQ, TrafficCast, and INRIX ® Travel Time System Data*. Retrieved from http://www.fdot.gov/traffic/ITS/Projects_Deploy/2012-03-26_Probe_Data_Analysis_v2-0.pdf

Feng, W., Bigazzi, A., Kothuri, S., & Bertini, R. (2010). Freeway sensor spacing and probe vehicle penetration: Impacts on travel time prediction and estimation accuracy. *Transportation Research Record: Journal of the Transportation Research Board*, (2178), 67–78. https://doi.org/10.3141/2178-08

FHWA. (2013). *Work Zone Performance Measurement Using Probe Data*. Retrieved from https://ops.fhwa.dot.gov/wz/resources/publications/fhwahop13043/fhwahop13043.pdf

FHWA. (2017). *2016 Urban Congestion Trends*. Retrieved from https://ops.fhwa.dot.gov/publications/fhwahop17010/fhwahop17010.pdf

Gong, L., & Fan, W. (2017). Applying Travel-Time Reliability Measures in Identifying and Ranking Recurrent Freeway Bottlenecks at the Network Level. https://doi.org/10.1061/JTEPBS.0000072

Haghani, A., Hamedi, M., & Sadabadi, K. F. (2009). *I-95 Corridor Coalition Vehicle Probe Project: Validation of INRIX Data July-September 2008*. Retrieved from http://www.i95coalition.org/wp-content/uploads/2015/02/I-95-CC-Final-Report-Jan-28-2009.pdf

Hard, E. N., Chigoy, B. T., Songchitruksa, P., Farnsworth, S. P., Borchardt, D. W., & Green, L. L. (2017). Comparison of Cell, GPS, and Bluetooth Derived External O-D Data – Results from the 2014 Tyler, Texas Study. *Transportation Research Record: Journal of the Transportation Research Board*. Retrieved from https://trid.trb.org/view/1439253

Higatani, A., Kitazawa, T., Tanabe, J., Suga, Y., Sekhar, R., & Asakura, Y. (2009). Empirical Analysis of Travel Time Reliability Measures in Hanshin Expressway Network. *Journal of Intelligent Transportation Systems*, *13*(1), 28–38. https://doi.org/10.1080/15472450802644454

Hu, J., Ph, D., Fontaine, M. D., Ph, D., Park, B. B., Ph, D., … Ph, D. (2015). Field Evaluations of an Adaptive Traffic Signal — Using Private-Sector Probe Data. *Journal of Transportation Engineering*, *142*(1), 1–9. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000806.

INRIX. (2015). *INRIX | I-95 Corridor Coalition: Vehicle Probe Project Data Validation Summary*. Retrieved from http://inrix.com/wp-content/uploads/2016/11/INRIX-I-95-VPP-Data-Summary-Validation-1.pdf

IowaDOT. (2017). *Advanced Traveler Management System/Advanced Traveler Information System Combination*. Retrieved from https://iowadot.gov/purchasing/20227pro.pdf

Kim, K., Motiani, D., Spasovic, L. N., Dimitrijevic, B., & Chien, S. (2014). Assessment of Speed Information Based on Probe Vehicle Data: A Case Study in New Jersey. *Transportation Research Board, 93rd Annual Meeting*, *9*(January). Retrieved from http://trid.trb.org/view/2014/C/1289396%5Cnhttp://assets.conferencespot.org/fileserver/file/166151/filename/14-4464.pdf

Kim, S., & Coifman, B. (2014). Comparing INRIX speed data against concurrent loop detector stations over several months. *Transportation Research Part C: Emerging Technologies*, *49*, 59–72. https://doi.org/10.1016/j.trc.2014.10.002

Knoop, V., Hoogendoorn, S. P., & Van Zuylen, H. (2009). Empirical differences between time mean speed and space mean speed. In *Traffic and Granular Flow 2007* (pp. 351–356). https://doi.org/10.1007/978-3-540-77074-9-36

Lattimer, C., & Glotzbach, G. (2012). EVALUATION OF THIRD-PARTY TRAVEL TIME DATA IN TALLAHASSEE, FL. Retrieved from https://itswc.confex.com/itswc/AM2012/webprogram/Paper10870.html

Lindveld, C. D. R., Thijs, R., Bovy, P. H. L., & der Zijpp, N. J. (2000). Evaluation of online travel time estimators and predictors. *Transportation Research Record*, *1719*, 45–53.

Lomax, T., Schrank, D., Turner, S., & Margiotta, R. (2003). SELECTING TRAVEL RELIABILITY MEASURES. Retrieved from https://static.tti.tamu.edu/tti.tamu.edu/documents/TTI-2003-3.pdfMcleod, D. S., Morgan, G., & Mcleod, M. (2012). Florida's Mobility Performance Measures and Experience. *Transportation Research Board, 91st Annual Meeting*.

Lu, C., & Dong, J. (2018). Estimating freeway travel time and its reliability using radar sensor data. *Transportmetrica B: Transport Dynamics*, *6*(2), 97–114. https://doi.org/10.1080/21680566.2017.1325785

Lu, X., Lee, J., Chen, D., Bared, J., Dailey, D., & Shladover, S. E. (2014). Freeway Micro-simulation Calibration : Case Study Using Aimsun and VISSIM with Detailed Field Data. *Transportation Research Board 93rd Annual Meeting. January 12-16, Washington, D.C.*, 1–17.

Miwa, T., Ishiguro, Y., Yamamoto, T., & Morikawa, T. (2015). Allocation Planning for Probe Taxi Devices Aimed at Minimizing Losses to Travel Time Information Users. *Journal of Intelligent Transportation Systems*, *19*(4), 399–410. https://doi.org/10.1080/15472450.2014.995760

MoDOT. (2017). *Tracker: Measures of Departmental Performance*. Retrieved from http://www.modot.org/about/documents/Tracker_July17/July2017FinalTracker.pdf

Peniati, J. (2004). Operational Solutions to Traffic Congestion.

Poddar, S., Ozcan, K., Chakraborty, P., & Ahsani, V. (2018). Comparison of Machine Learning Algorithms to Determine Traffic Congestion from Camera Images. Retrieved from https://trid.trb.org/view/1496348

Pu, W. (2012). Analytic Relationships Between Travel Time Reliability Measures. *Transportation Research Record: Journal of the Transportation Research Board*, *2254*(1), 122–130. https://doi.org/10.3141/2254-13

Rakha, H., El-Shawarby, I., & Arafeh, M. (2010). Trip travel-time reliability: Issues and proposed solutions. *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*, *14*(4), 232–250. https://doi.org/10.1080/15472450.2010.517477

Remias, S., Brennan, T., Day, C., Summers, H., Cox, E., Horton, D., & Bullock, D. (2013). *2012 Indiana Mobility Report*. Retrieved from https://docs.lib.purdue.edu/cgi/viewcontent.cgi?article=1004&context=imr

Sanaullah, I., Quddus, M., & Enoch, M. (2016). Developing travel time estimation methods using sparse GPS data. *Journal of Intelligent Transportation Systems*, *20*(6), 532–544. https://doi.org/10.1080/15472450.2016.1154764

Schrank., D., Eisele., B., Lomax., T., & Bak., J. (2015). *2015 Urban Mobility Scorecard*. *Texas A&M Transportation Institue* (Vol. 39). https://doi.org/DTRT06-G-0044

Schrank, D., Eisele, B., & Lomax, T. (2012). *TTI's 2012 urban mobility report*. *Texas A&M Transportation Institute*. Retrieved from http://d2dtl5nnlpfr0r.cloudfront.net/tti.tamu.edu/documents/mobility-report-2012.pdf

Sekuła, P., Marković, N., Laan, Z. Vander, & Sadabadi, K. F. (2017). Estimating Historical Hourly Traffic Volumes via Machine Learning and Vehicle Probe Data: A Maryland Case Study. Retrieved from http://arxiv.org/abs/1711.00721

Sharifi, Elham & Hamedi, Masoud & Haghani, Ali & Sadrsadat, H. (2011). Analysis of Vehicle Detection Rate for Bluetooth Traffic Sensors: A Case Study in Maryland and Delaware.

Sharifi, E., Young, S. E., Eshragh, S., Hamedi, M., Juster, R. M., & Kaushik, K. (2017). Outsourced probe data effectiveness on signalized arterials. *Journal of Intelligent Transportation Systems*, *21*(6), 478–491. https://doi.org/10.1080/15472450.2017.1359093

Sharma, A., Ahsani, V., & Rawat, S. (2017). *Evaluation of Opportunities and Challenges of Using INRIX Data for Real-Time Performance Monitoring and Historical Trend Assessment*. Reports and White Papers. 24. Retrieved from https://lib.dr.iastate.edu/ccee_reports/24/

Subrat Mahapatra, Matthew Wolniak, E. B., & Sadabadi, K. F. (2015). *2015 Maryland State Highway Mobility Report*.

Transportation Research Board. (2016). *Highway Capacity Manual, Sixth Edition: A Guide for Multimodal Mobility Analysis*. Transportation Research Board. Retrieved from http://app.knovel.com/hotlink/toc/id:kpHCMAGMM2/highway-capacity-manual/highway-capacity-manual

Turner, S. (2013). Developing Twin Cities Arterial Mobility Performance Measures Using GPS Speed Data. Retrieved from https://www.lrrb.org/pdf/201314.pdf

Uno, N., Kurauchi, F., Tamura, H., & Iida, Y. (2009). Using Bus Probe Data for Analysis of Travel Time Variability. *Journal of Intelligent Transportation Systems*, *13*(1), 2–15. https://doi.org/Pii 908329318\rDoi 10.1080/15472450802644439

Venkatanarayana, R. (2017). *Considerations for Calculating Arterial System Performance Measures In Virginia*. Retrieved from http://www.virginiadot.org/vtrc/main/online_reports/pdf/17-r2.pdf

Vesal Ahsani, Mostafa Amin-Naseri, Skylar Knickerbocker & Anuj Sharma (2019) Quantitative analysis of probe data characteristics: Coverage, speed bias and congestion detection precision, Journal of Intelligent Transportation Systems, 23:2, 103-119, DOI: 10.1080/15472450.2018.1502667

WSDOT. (2013). *The 2013 Corridor Capacity Summary*. Retrieved from http://wsdot.wa.gov/publications/fulltext/graynotebook/CCS13.pdf

WSDOT. (2014). *Gray Notebook 52 - For the Quarter Ending December 31, 2013*. Retrieved from http://wsdot.wa.gov/publications/fulltext/graynotebook/Dec13.pdf

Young, S. (2007). Real-Time Traffic Operations Data Using Vehicle Probe Technology. *2007 Mid-Continent Transportation Research Symposium*. Retrieved from http://www.ctre.iastate.edu/pubs/midcon2007/YoungVehicleProbe.pdf

Young, S. E., Juster, R. M., & Kaushik, K. (2015). *Traffic Message Channel Codes: Impact and Use within the I-95 Corridor Coalition's Vehicle Probe Project*. Retrieved from http://i95coalition.org/wp-content/uploads/2015/02/TMC_White_Paper-Final.pdf?x70560

Zheng, F., Li, J., van Zuylen, H., Liu, X., & Yang, H. (2018). Urban travel time reliability at different traffic conditions. *Journal of Intelligent Transportation Systems*, *22*(2), 106–120. https://doi.org/10.1080/15472450.2017.1412829

CHAPTER 3. IMPROVING PROBE BASED CONGESTION PERFORMANCE METRICS ACCURACY BY USING CHANGE POINT DETECTION

Modified from a paper which is under review by the *Journal of Intelligent Transportation Systems*

Vesal Ahsani, Anuj Sharma, Chinmay Hegde, Skylar Knickerbocker, and Neal Hawkins

Abstract

Probe based speed data provide great value to agencies especially in areas which are not feasibly covered by traffic sensors. However, as with sensors, probe data are not without nuance and issues like latency prevent alignment between calculated metrics by data source. Both agencies and the public are sensitive to reported performance and have little appreciation for sudden shifts in magnitude just because a new data source is available. This paper examines the sources of error when using a fixed speed threshold to calculate two common performance metrics (the number of congested events and congested hours) using probe versus sensor data. The analysis shows that both latency, and use of a fixed speed threshold methodology, contribute to divergent performance values when using probe (INRIX) versus sensor (Wavetronix) data.

To address these differences, the analysis established sensor data as a base and used a change point detection methodology to calculate performance values from probe data. The change point detection algorithm was shown to improve the identification of both congested events as well as calculating congested hours versus using a fixed threshold methodology. The evaluation was expanded from a limited number of sensor-segment pairs on one specific route to five different routes with 64 sensor-segment pairs across the state of Iowa using data from the year 2017.

Change point detection appears to address errors observed when calculating traffic performance measures on probe data versus using a fixed speed congestion threshold. Agencies should consider this method prior to calculating and reporting performance metrics to the public.

Keywords – probe data, sensor data, congestion detection, number of congested events, congested hour, fixed speed threshold, change point detection.

Introduction

Monitoring the performance of the transportation system is fundamental to any transportation operations and planning strategy. Traditionally, monitoring performance of transportation systems was based on average travel time. However, it should be noted that travel time is not adequately capable to represent the quality and level of service that daily commuters experience and it may also inaccurately estimate the actual level of congestion by not accounting for unexpected congestion.

Traffic congestion directly translates into transportation costs and plays a key role in assessing the transportation system performance and impacting planning decisions. When a road reaches its capacity, every extra vehicles creates overload which in turn delays other vehicles. Increased travel time, accidents, unpredictability of arrival times, increased fuel consumption and increased pollution emissions, are some of the impacts of congestion. Generally, two types of congestion are defined: recurring and non-recurring. Recurring congestion is occurred by usual traffic in a normal environment and is repetitive in nature and observed during peak periods, whereas non-recurring one is unexpected and is often occurred by weather, work zones, and incidents.

Map-21, the Moving Ahead for Progress in the 21st Century Act (P.L. 112-141), asks state departments of transportation (DOTs) and agencies to monitor and report mobility performance measures. There are several performance measures which require traffic count information that is limited by point sensors such as volume, capacity, delay, etc. However, the recent availability of wide spread data through vehicle probes has agencies leaning towards probe based performance measures. The US federal government in 2013 developed National Performance Management Research Data Set (NPMRDS) which was a nation-wide dataset of average travel times and was fully available for States and Metropolitan Planning Organizations (MPOs) to utilize for their transportation activities. NPMRDS is a vehicle probe-sourced travel time dataset having data records collected from various sources. The database contains billions of records that fully cover the whole National Highway System (NHS) which includes all US interstates and highways. The hope is that all project decisions might be improved through use of probe-based data as opposed to only relying on infrastructure mounted sensors.

The Regional Integrated Transportation Information System (RITIS), provides use of NPMRDS data including travel time per mile (reliability), delay, duration of congestion, number of congested events, congested hour, congested mile, congestion intensity, speed drop, etc. So further reliance on this emerging source of data requires assurance that the data represent what is actually being experienced on the roadway. The goal of this paper is to compare the precision of performance measure methodologies between probe and sensor based sources.

The number of congested events is a performance measure which explains how reliable probe-sourced data is in detecting congestion (recurring and non-recurring). This performance measure actually is the number of congested events reflected within the probe data. On the other hand, the congested hours of a segment reflect the summation of hours vehicle speeds are below a defined speed threshold. A state-wide analysis reveals both the location and magnitude of congestion with the information aggregated by year, month, day of week (DOW), and time of day (TOD). Congested hour calculations require comparing each minute of measured speed data, for all state-wide segments, to the congestion threshold. If the probe source speed data are both "real time", as opposed to historical, and below the fixed congestion threshold, that 1 minute of time is considered as "congested". Summation of these congested minutes (reported in units of hours) is defined as the total number of congested hours.

A literature review shows that congested hour and number of congested events are two essential performance metrics which allow transportation planners and policy makers to more effectively allocate resources to address and improve network performance (National Academies of Sciences, Engineering, 2008). Regarding costs of congestion, some organizations and agencies only consider costs of recurring congestion, while others include non-recurring costs in addition to recurring.

Recurring congestion is very common in U.S. with travellers expecting and planning for some delay, particularly during peak hours. Many commuters modify their schedules or assign additional time to allow for these typical traffic delays. In contrast, non-recurring, unexpected delays, can have severe impacts on motorist's safety and mobility. Motorists want to be confident that a trip that takes 30 minutes today will also take 30 minutes tomorrow and so travel time reliability calculates the extent of this unexpected delay. Reliability is formally defined as the consistency or dependability in travel times, as measured from day to day or across different time periods of the day.

Delay is also important to many users of transportation systems, from passenger vehicle and truck drivers, transit riders, freight shippers, pedestrians, etc. Reliability is valuable for personal and business travellers as it allows them to use their time better. Additinally, it is a priceless service that can be afforded on privately-financed or privately-operated routes. That's why transportation planners should consider delay, congested hour, number of congested events, and travel time reliability as essential performance measures since they are so vital for transportation system users.

Transportation agencies and regional planning organizations increasingly utilize travel time performance as reliability and variability measure (Nam, Park, & Khamkongkhun, 2005). In 2003, Bell and Lida defined travel time reliability as the probability of on-time arrival (Bell & Iida, 2003). In addition, Lomax et al. in the same year introduced travel time reliability as a variability of travel time that commuters experience and as a consistency of a specific mode during a certain period of time (T Lomax, Schrank, Turner, & Margiotta, 2003). Additionally, Lomax recommended a focus on duration, extent, and intensity of a congestion and reliability measures in addition to travel time alone in order to assess transportation system performance. Adapting different methods to measure traffic congestion intensity helps to rank and prioritize congested segments, and in providing a more comprehensive spatial and temporal understanding of congestion duration, extent and severity.

In this study, we attempt to evaluate the reliability of probe-sourced data (INRIX) using two performance measures; congested hour and the number of congested events. The study will introduce a new robust method for detecting recurring and non-recurring traffic congestion and reductions in speed. Finally, two other important performance measures, delay and travel time reliability, will be discussed as a preface to a follow-up study.

Wide area probe data

State Departments of Transportation (DOT) and many transportation agencies use infrastructure sensors to collect comparatively accurate real-time traffic-related information such as occupancy, traffic speed for each lane, and vehicle class. The cost to deploy and maintain these infrastructure based sensors can be high. The other major limitation for fixed sensors is their geographical scalability; many units must be installed on the roadsides to adequately determine and measure the traffic situation in any particular area (Young, 2008). Access to power and communications leans towards major freeways, interstates and critical urban areas rather than an even distribution a state. Lack of sufficient coverage on highways and arterials generate the desire for DOTs to consider augmenting existing traffic data collection with probe-based services for wider coverage under limited budgets.

Advancements in telecommunication and wireless technologies have facilitated new ways to collect traffic data on, process the information, and analyse the data. Probe-based technologies can be used to collect traffic-related information from millions of mobile devices, GPS-enabled vehicles and other sources. Probe-based methods of measuring travel time and speed data can easily be scaled across large networks without need for deploying additional infrastructure (Young, 2007). This can allow state agencies to cost-effectively use a single uniform source of data for monitoring traffic across most roadways (FHWA, 2013). INRIX, HERE, and TomTom are some of the established third-party providers of such probes.

Various studies have been carried out to compare the reliability and accuracy of probe data with sensor data from radar sensors, loop detectors, etc. (Adu-Gyamfi, Sharma, Knickerbocker, Hawkins, & Jackson, 2017; Coifman, 2002; FDOT, 2012; Feng, Bigazzi, Kothuri, & Bertini, 2010; Haghani, Hamedi, & Sadabadi, 2009; Kim & Coifman, 2014; Lindveld, Thijs, Bovy, & der Zijpp, 2000). Many of these studies evaluated probe performance using travel-time reliability measures such as the 90th or 95th percentile of travel time, standard deviation, percentage of variation, buffer-time index (BTI), planning-time index (PTI), travel-time index (TTI), frequency of congestion, failure rate (with respect to average), on-time arrival, misery index, congestion detection latency, count of congestion, congestion duration, reliability curve, hourly traffic volume, congested hours, etc. (Aliari & Haghani, 2012; Araghi, Hammershøj Olesen, Krishnan, Tørholm Christensen, & Lahrmann, 2015; Belzowski, Bruce M., Ekstrom, 2014; Cookson & Pishue, 2016; Day et al., 2015; FHWA, 2017; Gong & Fan, 2017; Tim Lomax, Schrank, Turner, & Margiotta, 2003; Mcleod, Morgan, & Mcleod, 2012; MoDOT, 2017; Peniati, 2004; Pu, 2012; Remias et al., 2013; Schrank., Eisele., Lomax., & Bak., 2015; Schrank, Eisele, & Lomax, 2012; Sekuła, Marković, Laan, & Sadabadi, 2017; Subrat Mahapatra, Matthew Wolniak & Sadabadi, 2015; Turner, 2013; Venkatanarayana, 2017; WSDOT, 2013, 2014; Zheng, Li, van Zuylen, Liu, & Yang, 2018).

Fixed threshold

A Traffic congestion has become one of the most expensive problems in the world, especially in large cities and metropolitan areas. Effectively addressing congestion requires the ability to use real-time traffic data towards improved timely decision making. Traffic flow parameter based detection methods have been widely accepted since they can be implemented automatically and are not affected by weather conditions. Many congestion detection methods based on traffic flow parameters have been studied. Dudek, Messer and Nuckles developed the California method in 1974, which has been widely accepted and applied in traffic congestion and incident detection. The California algorithm is mostly used as a basis of comparison between congestion and incident detection methods (Dudek, Messer, Record, & 1974, n.d.). McMaster's incident detection method was developed by Persaud in 1990. Many other methods were also developed in the following years and all are convenient to be used in practice. The difficult task is to define the threshold values of these methods which are often subjective according to experience (Persaud, Hall, Record, & 1990, n.d.).

When these same subjective threshold values are used in performance measures, such as the number of congested events and congested hours, this can lead to erroneous decisions. The number of congested events is a performance measure which explains how reliable probe data are in detecting congestion (recurring and non-recurring) compared to a benchmark dataset (sensors). Average number of hours when the vehicle speeds are less than 90 percent of free-flow speed (FFS) is considered as congested hour. For instance, when the FFS is 60 mph, congested hour is computed as the average number of hours when vehicle speeds are less than 54 mph. This performance measure is typically computed only for weekdays from 6 am to 10 pm.

Calculating delays from travel time or speed data requires threshold speeds (also referred as the reference speed). The literature includes several methods mostly focused on freeways for determining threshold speeds. Remias, et al., (2013) measured freeway congestion at 45 mph. Eisele, et al., (2014) recommended 85th percentile of speed during off-peak hours for estimating FFS. The Texas A&M Transportation Institute, in its 2013 freeway performance measurement report for VDOT (unpublished data) defined FFS as the INRIX reference speed. The Missouri Department of Transportation (MoDOT) Tracker (MoDOT, 2013) indicated that conformance with the posted speed limit (PSL) is the desired outcome for travel conditions. Short, et al., (2009) utilized 55 mph as the free flow speed to measure freight congestion and consequent bottlenecks. Gordon Proctor & Associates, et al., (2011) measured freight congestion at 50 mph. The AASHTO SCOPM report (AASHTO, 2012) described several methods for determining thresholds; a speed of 35 mph was used in California to identify serious congestion problems, while rural areas might use either speed limits or free flow speeds. Factors, such as corridor characteristics, local conditions, population growth, rural and urban differentiation, etc., were also listed to utilize in setting location-wise specific threshold speeds. Accordingly, it is common to use a threshold for calculating delay, however it will be shown further in this paper that this traditional fixed-threshold does not work for wide area probe data properly.

Data

The sources of data utilized in this work are explained in this section.

Probe-sourced Data

With the help of today's technologies, e.g., connected vehicles and smartphones, probe data can leverage both historic and real-time data to report on transportation network operations. This study used both historical and real-time traffic data collected through the INRIX TMC monitoring platform. For each of TMC segment, speed, average length of segments, and corresponding date and time of traverse, are provided each minute.

Infrastructure-mounted sensors

The benchmark data utilized in this study were provided by Wavetronix sensors which uses radar technologies for collecting traffic-related data. Although admittedly sensors might have some inherent errors, Wavetronix Smart Sensors have been commonly used for comparison purposes in various studies (P Chakraborty, Adu-Gyamfi, Poddar, & Ahsani, 2018; X. Lu et al., 2014; Poddar, Ozcan, Chakraborty, & Ahsani, 2018; Sharifi, Elham & Hamedi, Masoud & Haghani, Ali & Sadrsadat, 2011). Each Wavetronix sensor unit consists of a side-fire radar and hard wired power for real-time processing of traffic data such as speed, volume, etc. Wavetronix sensors provide high resolution traffic data every 20 seconds.

In this paper, speed is the only traffic parameter which is utilized from Wavetronix sensors and INRIX segments. Table 1 below indicates the statistics of the probe and sensor data that were utilized in this paper. Also, Figure 1 below shows speed distribution for INRIX and Wavetronix over 5 routes across Iowa in 2017.

Table 3.1 Descriptive statistics of probe and sensor data used in this study

Parameters	Min	Max	Mean	Standard deviation
INRIX speed	2 mph	92.6 mph	61.3 mph	5.8 mph
INRIX speed < 45 mph	2 mph	44.9 mph	30.7 mph	9.1 mph
INRIX segment length (mile)	0.1 mile	4.3 mile	1.6 mile	0.8 mile
Wavetronix speed	1 mph	98.2 mph	65.8 mph	9.2 mph
Wavetronix speed < 45 mph	1 mph	44.9 mph	25.1 mph	11.1 mph

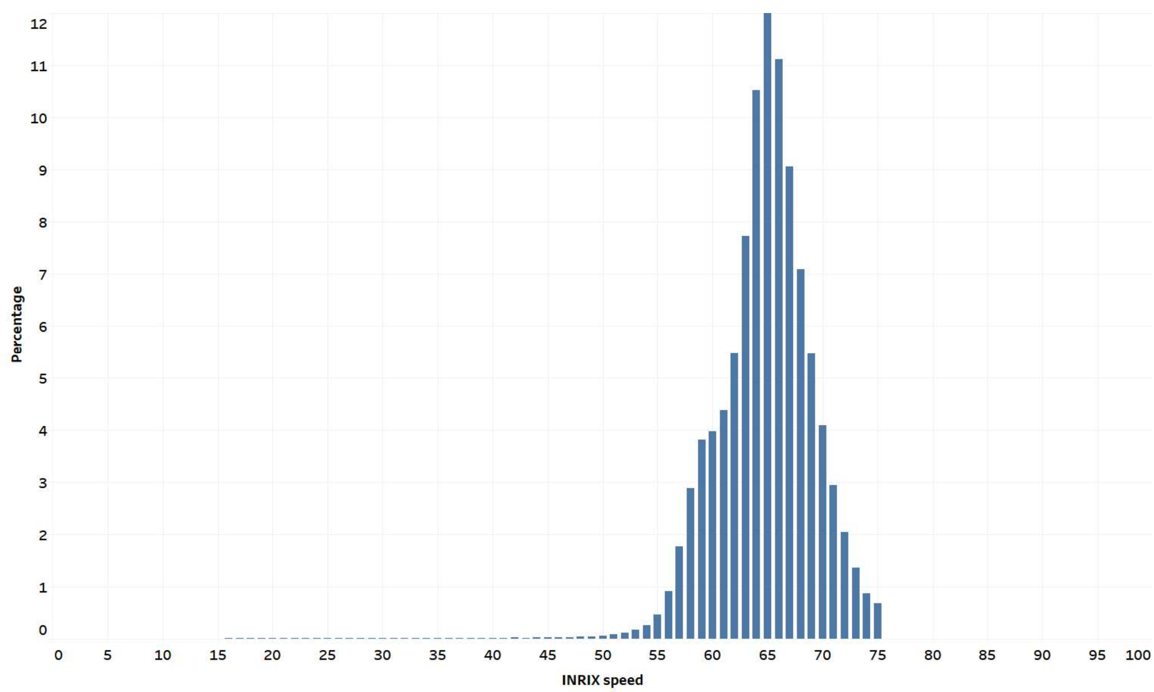


Figure 3.1 Distribution of speed for INRIX and Wavetronix over 5 routes across Iowa in 2017.

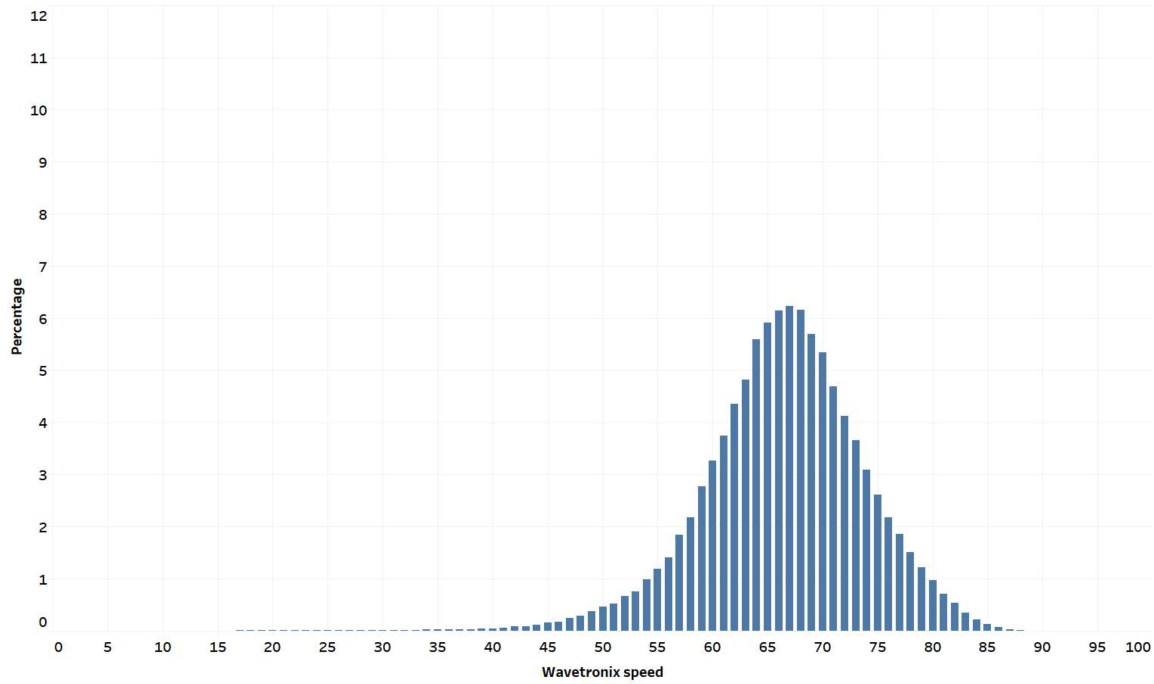


Figure 3.1. (Continued)

Data Stream and Pre-processing

In real-world scenarios, since most raw datasets are incomplete, highly susceptible to noise, and inconsistent due to sensor failures, measurement technique errors, or data volume, data pre-processing plays a key role in detecting and correcting corrupt and erroneous traffic-related data. Since storing and analyzing huge amounts of INRIX and Wavetronix data needs proper infrastructure and computational power to manage the large volume of data, a high-performance computing cluster should be utilized for data processing. A Hadoop Distributed File System (HDFS) ("Apache Hadoop," 2018) was utilized for data storage and map-reducing was utilized for processing.

Analysis

In the following section, a very traditional and common method of congestion detection is examined which utilizes a fixed-threshold speed and demonstrates how unreliable and erroneous the process can be. After that, an improved traffic congestion identification method is proposed and the number of congested events and congested hours are computed as performance measures.

In the preliminary stage, an analysis of a specific number of sensor-segment pairs in the state of Iowa was conducted and the results compared for different scenarios. For this purpose, ten sensor-segment pairs were chosen in the Des Moines metropolitan area. Performance measures were calculated for the entire year of 2016. The data were limited to the period of 5 am to 10 pm because the reliability of the Wavetronix sensors (benchmark data) is lower during the low volume late night hours. Also, the minimum duration for congestion was set to be greater than or equal to 15 minutes. Table 2 shows the reliability of probe data in detecting congested events. The fixed threshold congestion detection method which utilized in this study is thoroughly explained in our previous paper (Ahsani, Amin-Naseri, Knickerbocker, & Sharma, 2018). To have a brief explanation, the threshold speed in traditional congestion detection method is computed by subtracting twice the interquantile range from median speed for each 15 minute period for each weekday from eight week history. All the speeds below this threshold and 45 mph are considered as non-recurring congestion while speeds above this threshold but below 45 mph are considered as recurring congestion.

The first performance measure computed for this analysis is the number of congested events, as shown in Table 2. True positive (TP) represents a similar congested event which is detected by both Wavetronix sensor and INRIX segment; false negative (FN) means a congested event was detected by Wavetronix but not INRIX; false positive (FP) denotes a congested event was detected by INRIX but not Wavetronix; and true negative (TN) represents a congested event which is detected by neither Wavetronix nor INRIX. It should be noted that there is no value for

TN in the table below since we do not know the true number of congested events (not detected by either) which is why Wavetronix sensors are considered the benchmark for this analysis.

Table 2 shows that the number of congested events detected by both datasets were 343. There were 202 events not detected by INRIX or 37% of events missed. FP are the other way around an additional false alerts that an operator would spend time on that did not actually occur. R and NR represents recurring and non-recurring congestion respectively.

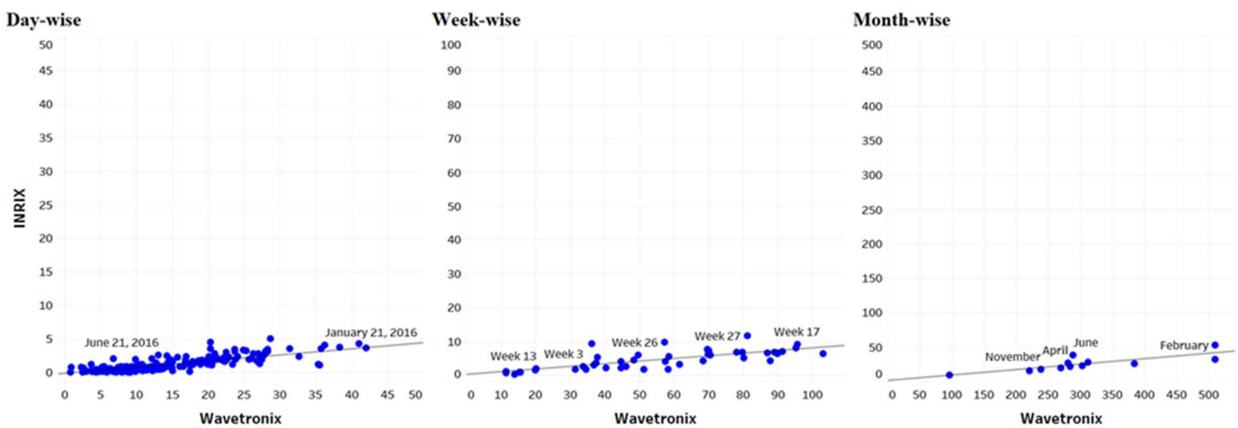
Table 3.2 Reliability of probe data in detecting congestion events using fixed threshold method

<table>
<tr><th colspan="2" rowspan="2"></th><th colspan="4">INRIX</th></tr>
<tr><th colspan="2">Detect congestion</th><th colspan="2">No congestion detected</th></tr>
<tr><td rowspan="6">WAVETRONIX</td><td rowspan="3">Detect congestion</td><td colspan="2">True Positive: 343</td><td colspan="2">False Negative: 202</td></tr>
<tr><td>Recurring</td><td>Non-Recurring</td><td>Recurring</td><td>Non-Recurring</td></tr>
<tr><td>304</td><td>39</td><td>190</td><td>12</td></tr>
<tr><td rowspan="3">No congestion detected</td><td colspan="2">False Positive: 81</td><td colspan="2">True Negative: --</td></tr>
<tr><td>Recurring</td><td>Non-Recurring</td><td>Recurring</td><td>Non-Recurring</td></tr>
<tr><td>70</td><td>11</td><td></td><td></td></tr>
</table>

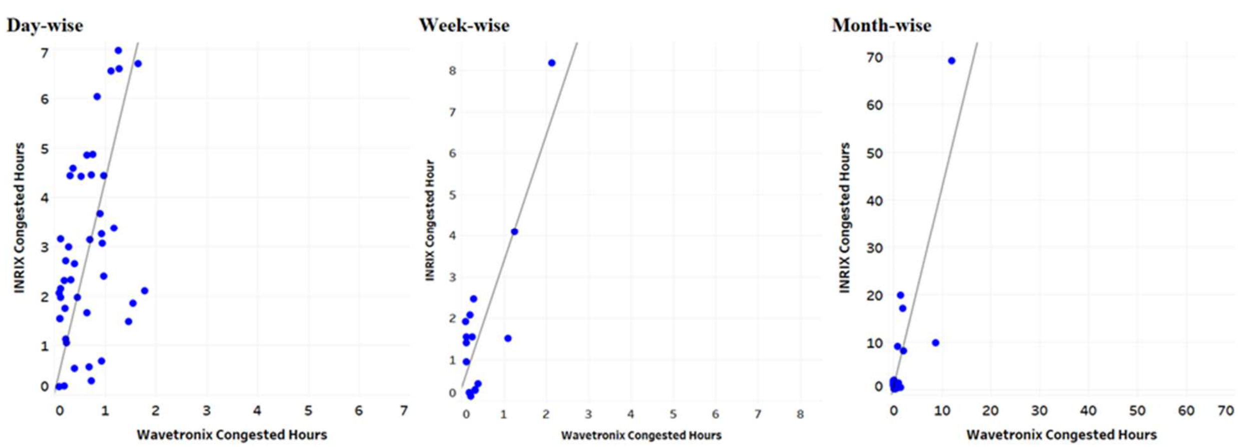
Table 2 shows a large discrepancy in the number of congested events detected by both the Wavetronix and INRIX. The measures do not imply there is a problem in the structure of the congestion detection algorithm but instead represent errors in the congestion detection method.

Thus, it is imperative to come up with a solution to this issue which will be discussed further in this paper.

The second performance measure computed for this analysis is congested hours which is calculated by using a fixed threshold speed of 45 mph. Figure 1 compares congested hours for INRIX against Wavetronix sensors (benchmarked dataset) for two different routes in Iowa under three different scenarios; daily, weekly, and monthly. As displayed in the figure, no pattern can be recognized in the diagrams for either route 1 or route 2. In an ideal diagram, all points would be plotted close to a 45 degree line which is not the case and suggests a less than ideal agreement.



Route 1



Route 2

Figure 3.2 Day-wise, week-wise, and month-wise congested hours for INRIX vs Wavetronix computed using a fixed threshold method for Route 1 (upper) and Route 2 (lower) in Iowa.

Methodological Flaws

Figure 2 shows a sample daily speed profile at the same location for INRIX and Wavetronix data. Point A shows a drop in speed which is detected by both INRIX (blue) and Wavetronix (orange). The latency (delay) between INRIX and Wavetronix can also be seen at point A with the INRIX data detecting the slowdown after the Wavetronix. A major problem contributing to the discrepancy in the number of congested events is latency.

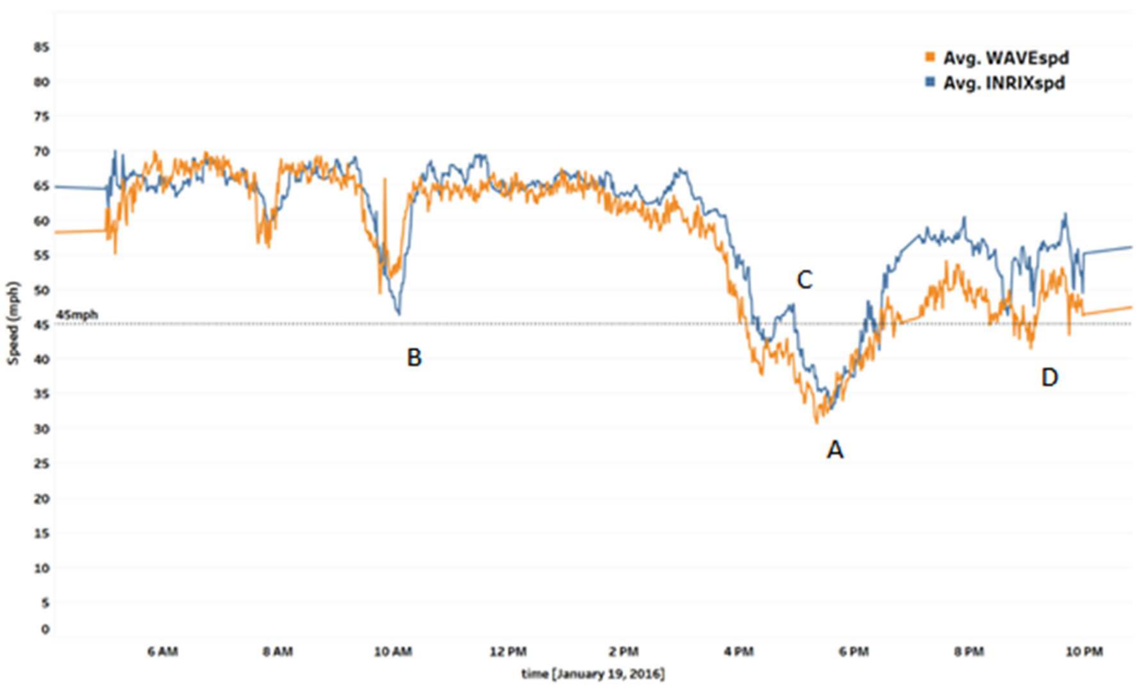


Figure 3.3 Speed time series of INRIX (blue) and Wavetronix (orange)

Point B shows a speed drop in both time series but they occurred above the 45 mph threshold line. In other words, both datasets detect a considerable speed drop but are not identified as "congested" since they are above the predefined threshold (45 mph). At point C, part of the INRIX time series goes above the 45 mph threshold line indicating it was uncongested for that period. Similarly, point D indicates a small drop (still greater than 15 minutes) labelled as congested for Wavetronix, but not for INRIX. These example contradictions compelled us to consider the detection algorithm and identify alternatives to using a fixed speed threshold for performance calculations.

According to the research conducted by Adu-Gyamfi et al., 2017, it is recommended to consider 12 minutes as the maximum allowable latency (delay) time between sensor and segment reported traffic speeds. In our analysis, we examined the distribution of both detection and recovery latencies. Figure 3 shows that expanding the maximum allowable latency to 16 minutes yields a much higher agreement between Wavetronix and INRIX datasets. Detection latency is defined by subtracting Wavetronix detection time from INRIX detection time. For instance, if a congestion is detected at 4:00 PM and 4:06 PM by Wavetronix and INRIX respectively, the detection latency would be +6 minutes implying 6 minutes of delay in congestion detection using INRIX. Same happens for recovery latency. It should be noted that negative latency means INRIX is detected or recovered a congestion earlier than Wavetronix which occurs very rare.

Based on the methodological concerns shown, it was concluded that an alternative method to capture big changes in speed profile (slope) should be considered and that this should be free of any fixed threshold. To capture the maximum number of speed drops, a change point detection algorithm was considered.

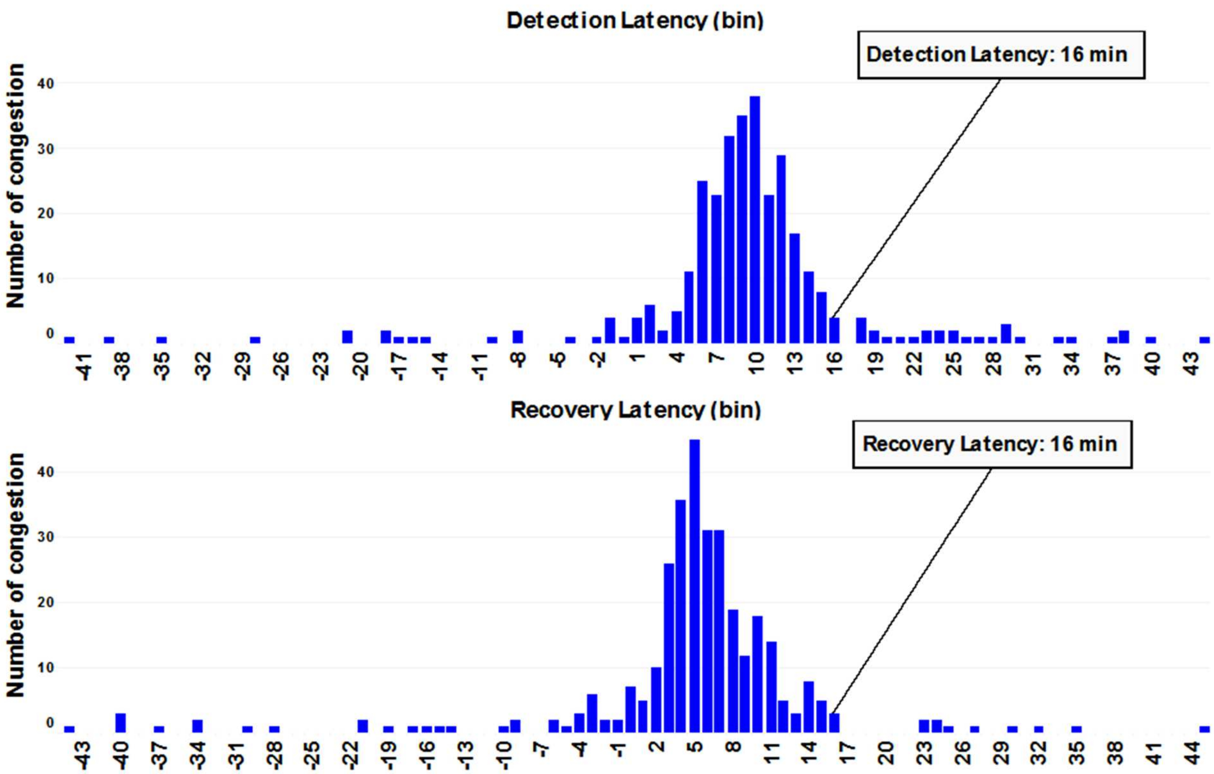


Figure 3.4 Distribution of a) detection latency and b) recovery latency

Methodology

Change point detection algorithm

Time series analysis is used widely in fields such as medicine, aerospace, finance, business, entertainment, and transportation. Time series data are sequences of temporal measurements that describe the behaviour of systems. These behaviours can vary over time due to external circumstances and/or internal systematic changes (Montanez, Amizadeh, AAAI, & 2015, n.d.). Change point detection (CPD) is a method of finding sudden changes in data when a property of the time series changes (Kawahara, …, & 2012, n.d.). Change point detection is similar in concept to segmentation, edge detection, event detection, and anomaly detection all of which are commonly used in industry. Change point detection is also used to model and predict events like medical condition, climate change, speech recognition, image analysis, and human activity and preferences. Generally, a change point detection algorithm has two parts which are the search method and cost function. The search method solves the change point detection problem with a known or unknown number of segments. The cost function measures the goodness-of-fit for the sub-signal to a specific model. In this analysis, a bottom-up segmentation method performed better than other search methods including dynamic programming, pruned exact linear time (PELT), binary segmentation, and window-based change point detection. For the cost function, a kernelized mean change outperformed other functions including least absolute deviation, least squared deviation, gaussian process change, linear model change, autoregressive model change, and Mahalanobis-type metric.

Bottom-up change point detection

A bottom-up change point detection is a sequential approach used to perform fast signal segmentation. It is a generous procedure contrary to binary segmentation. It starts with many change points and successively deletes the less significant ones. As the first step, the signal is divided in numerous segments along a regular grid. Then adjacent segments are successively merged according to their similarities. The benefits of a bottom-up segmentation includes low complexity (of the order of O(nlogn), where n is the number of samples), the ability to extend any single change point detection method to multiple change points, and finally the ability to perform in any number of regimes whether already known or not.

Kernelized mean change

In this method, we assumed a positive semi-definite kernel $k(\cdot,\cdot) : R^d \times R^d \mapsto R$ and its associated feature map $\Phi : R^d \mapsto H$ (where H is an appropriate Hilbert space), this cost function is able to detect changes in the mean of the embedded signal $\{\Phi(y_t)\}t$ (Arlot, Celisse, arXiv:1202.3878, & 2012, n.d.; Arthur Gretton, Karsten Borgwardt, Malte Rasch, n.d.). Formally, for a signal $\{y_t\}_t$ on an interval I,

$$c(y_I) \;=\; \sum_{t \in I} \;||\Phi(y_t) - \bar{\mu}||\,_H^2 \qquad (1)$$

where $\bar{\mu}$ is the empirical mean of the embedded segment $\{\Phi(y_t)\}_t \in I$. Also, kernel is the radial basis function (rbf):

$$k(x,y)=\exp(-\gamma||x-y||^2) \qquad (2)$$

where $||\cdot||$ is the Euclidean norm and $\gamma>0$ is the so-called bandwidth parameter. It is determined based on median heuristics. In other words, it is equal to the inverse of median of all pairwise distances.

Figure 3.5 Change point detection method with bottom-up segmentation as search method and kernelized mean change as cost function. Two speed drops are detected in red.

Based on this analysis, of the same number of segment-sensor pairs over the same period of time, Table 3 indicates significant improvements in calculating the number of congested events. Additionally, Figure 5 shows updated daily congested hour computations by the change point detection method. As can be seen, it has significantly improved and is very close to the ideal situation which is a 45 degree line.

Table 3.3 Reliability of probe data in detecting congestion events using change point detection method.

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="4">INRIX</td></tr>
<tr><td colspan="2">Detect congestion</td><td colspan="2">No congestion detected</td></tr>
<tr><td rowspan="6">WAVETRONIX</td><td rowspan="3">Detect congestion</td><td colspan="2">True Positive: 794</td><td colspan="2">False Negative: 19</td></tr>
<tr><td>Recurring</td><td>Non-Recurring</td><td>Recurring</td><td>Non-Recurring</td></tr>
<tr><td>732</td><td>62</td><td>17</td><td>2</td></tr>
<tr><td rowspan="3">No congestion detected</td><td colspan="2">False Positive: 16</td><td colspan="2">True Negative: --</td></tr>
<tr><td>Recurring</td><td>Non-Recurring</td><td>Recurring</td><td>Non-Recurring</td></tr>
<tr><td>15</td><td>1</td><td></td><td></td></tr>
</table>

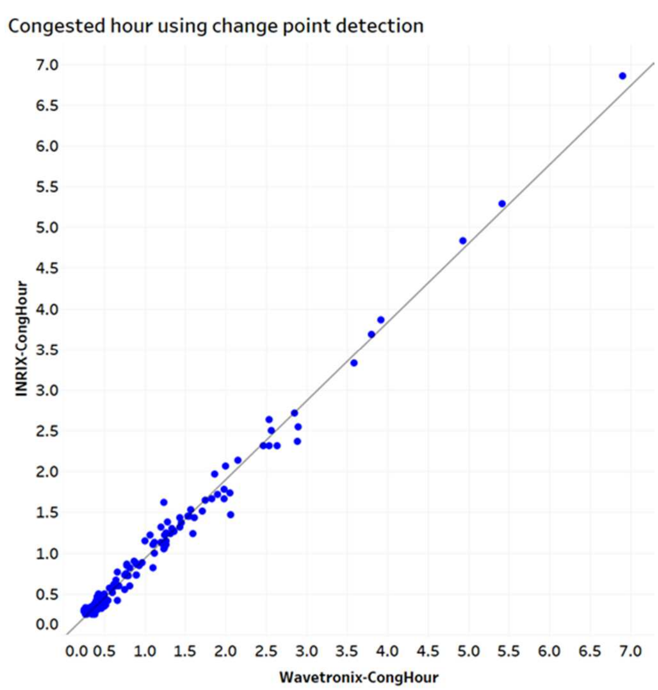


Figure 3.6 Congested hour of INRIX vs Wavetronix computed by change point detection method

The change point detection algorithm delivered a higher accuracy and significantly improved congestion detection compared to the traditional fixed threshold method. As it only applied to a limited number of sensor-segment pairs on one specific route, it was decided to develop and test this method on different routes with an increased number of locations. Therefore, five different routes with 64 sensor-segment pairs were chosen in the state of Iowa over the year 2017. Figure 6 shows the segments and sensors for all five routes across Iowa. Moreover, Table 4 shows the number of segment-sensor pairs in each considered route.

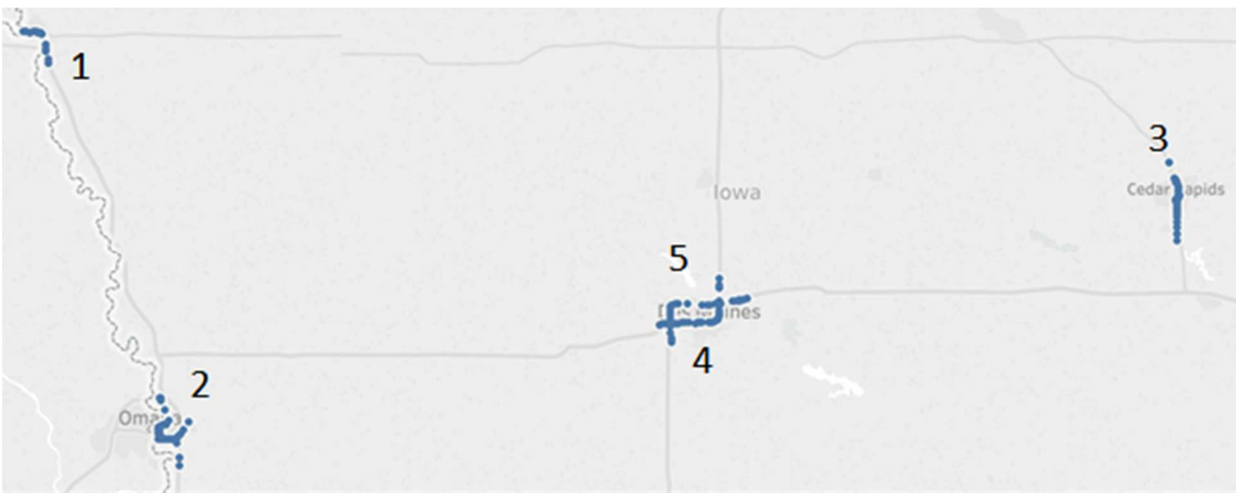


Figure 3.7 Location of sensors and segments on 5 different routes in Iowa

Table 3.4 Number of sensors and segments on 5 different routes in Iowa

Route	Corridor	Number of segment-sensor pairs
1	I-29	8
2	I-29/80	12
3	I-380	16
4	I-235	15
5	I-35/80	13

Table 5 demonstrates the high accuracy using the change point detection method in calculating the number of congested events and speed drops using probe-sourced and sensor-based datasets.

Table 3.5 Reliability of probe data in detecting congestion events for 5 major routes using change point detection method. R = Recurring congestion, NR = Non-recurring congestion

Route	True Positive (Total/R/NR)	False Negative (Total/R/NR)	False Positive (Total/R/NR)
I-29	274/226/48	3/1/2	5/3/2
I-29/80	151/114/37	4/1/3	2/2/0
I-380	96/30/66	0/0/0	1/1/0
I-235	782/559/223	5/3/2	13/11/2
I-35/80	515/395/120	3/1/2	18/7/11

Regarding congested hour as a second performance measure, Figure 7 below shows the significant improvement in calculation using the change point detection algorithm.

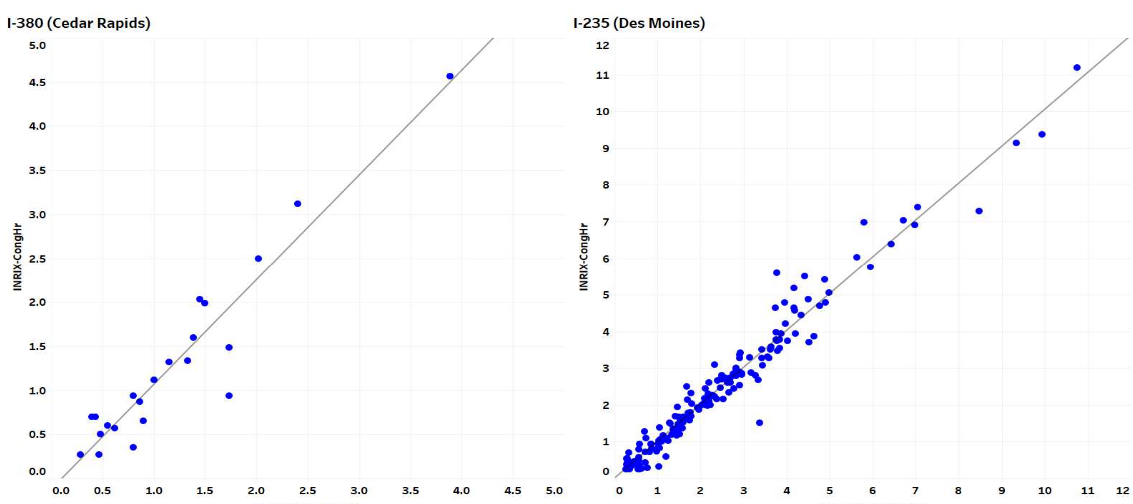


Figure 3.8 Congested hour of INRIX vs Wavetronix for 5 major routes computed by change point detection method

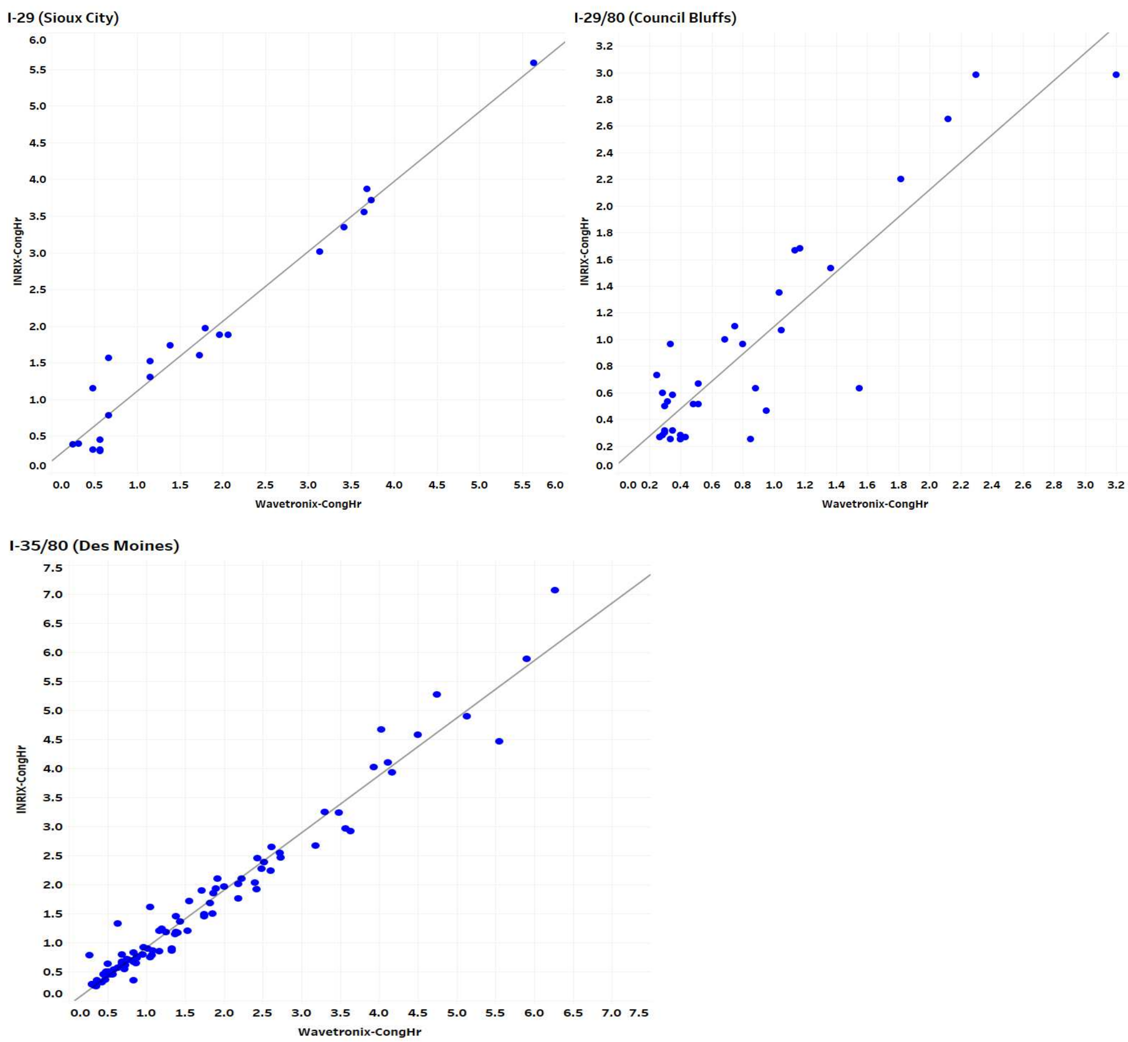


Figure 3.8. (Continued)

Conclusion and Recommendation

This research evaluated probe-sourced streaming data from INRIX, to study its characteristics as a data source for calculating traffic performance measures. For this purpose, Wavetronix, a commonly used infrastructure sensor data source, was selected as the benchmark. The agreement between data sources was evaluated by two different measures; number of congested events and congested hours.

For both performance measures, a traditional fixed-threshold congestion detection method was initially used. The lack of efficiency and high number of errors in congestion detection by probe data and the lack of overlaps between probe congested hour data and Wavetronix inspired the development of a robust solution for congestion detection. Consequently, a change point detection method was utilized and its robustness and accuracy was proven by applying the new method to five different routes in Iowa. Finally, a major limitation of this analysis is the use of sensor data as the benchmarked dataset. We acknowledge that sensor data have inherent errors and therefore are not fool proof, however, it is felt that this error is not significant enough to impact the findings.

The following recommendations are offered for transportation agencies who are augmenting traditional traffic data with probe-based services for wider coverage under restricted budgets:

- Probe based speed data provide great value to agencies especially in areas not covered by sensors. However, as with sensors, probe data are not without error. Therefore, it is critical that agencies understand these issues and continue to examine and consider alternative methods to remove error prior to calculating and reporting performance metrics to the public.
- Change point detection appears to address errors observed when calculating traffic performance measures using a fixed speed congestion threshold. Agencies should consider this method when using probe data to calculate performance measures.

Future Work

The great potential of probe data encourages deeper exploration into the characteristics of this data source, to build models that encourage traffic experts to trust probe-based reports without need for cross-checking or further validation.

The authors plan to compute other important performance measures including delay and travel time per mile (reliability) and check their efficiency and accuracy using proposed change point detection method against traditional method. Moreover, authors attempt to develop models for potential use in automatically correcting latency measurements from probe data.

Delay

Congested hours have the ability to identify locations with slow speeds but do not account for the volume of traffic exposed to congested conditions. For example, although speeds are less than 45 mph, a roadway with twice the volume has a much greater impact on mobility. A performance measure for delay, on the other hand, takes into account both traffic volume and the length of the segment to represent an overall impact on performance. Delay is computed for each segment by calculating the difference in the travel time observed and the free-flow travel time when the observed speed is lower than 45 mph (congestion threshold). This delay, in travel time, is then multiplied by the Annual Average Daily Traffic (AADT) for the segment along with the monthly, hourly and weekday factors to produce delay in units of vehicle hours. Finally, a factor for the appropriate roadway truck percentage is applied and multiplied by the cost of delay per hour of person travel ($17.67) and per hour of truck time ($94.04). Figure 9 shows daily delay for probes and sensors using a fixed threshold method.

The travel time delay is computed by finding out the difference in free flow travel time and the actual travel time observed. To account for the delay resulting from congestion only, delay is computed when observed real-time speed (confidence score = 30) is lower than the congestion speed threshold of 45 mph.

To get the free-flow travel time of each segment, the reference speed provided by INRIX is used. Similarly, free flow speed is calculated for Wavetronix in order to calculate free-flow travel time. Equation 1 shows the delay ($Delay_i^{h,d,m}$) in terms of hours for segment (i), hour (h) of the day (d) of month (m).

$$(Delay_i^{h,d,m}) = \frac{\sum_{\forall min}[\frac{Travel\ time_{i,min}^{h,d,m}}{60} - \frac{Length}{Ref\ speed}]}{60} \tag{3}$$

where

$Length$= length of the segment i in miles,

$Ref\ speed$ = reference speed in miles/hour and

$Travel\ time_{i,min}^{h,d,m}$ denotes the travel time in minutes.

Similar to congested hour calculations by fixed threshold, Figure 8 shows that daily delay does not follow any meaningful pattern for any of the five routes examined in Iowa. For each route, Wavetronix delay was always more than the INRIX delay. The possible reason for this difference is the speed difference between infrastructure mounted sensors and probe data. As it is proven in the previous research (Haghani, Hamedi, & Sadabadi, 2009), INRIX usually overestimate the speed when the real speed is less than 45 mph. It means that INRIX speed is almost always greater than Wavetronix (benchmark) speed for speeds less than 45 mph. This overestimation leads to lower travel time in the numerator of equation 3 which results in lower delay cost estimates for INRIX compared to Wavetronix. Further research is needed to examine this differences and come up reliability measures for such delay estimation prior to using it as project investment decision criteria.

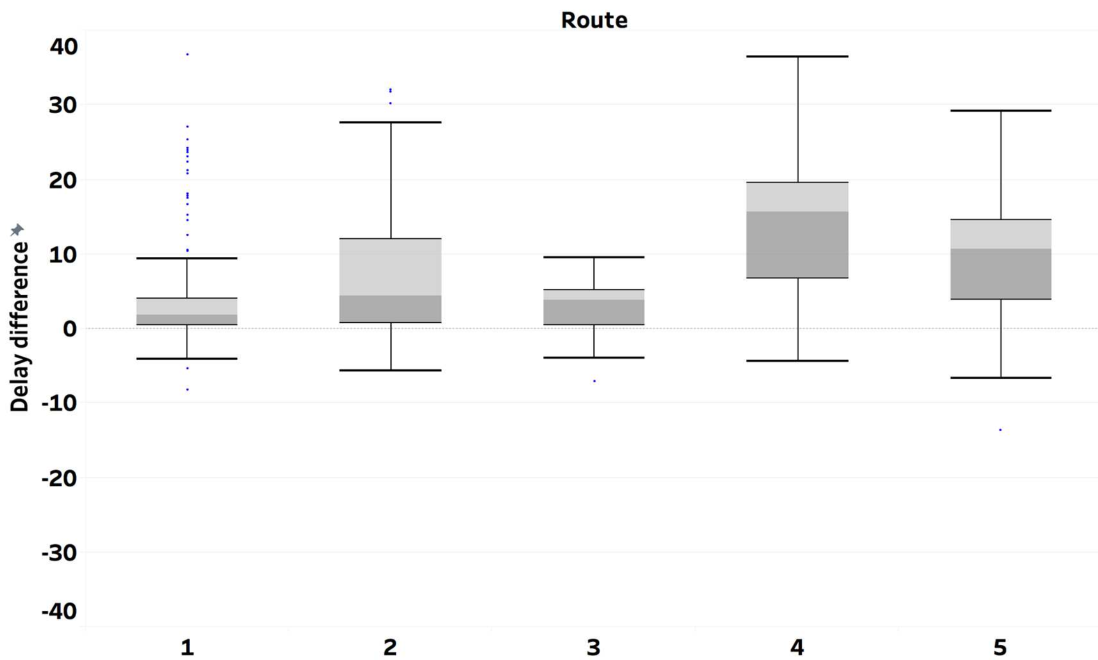


Figure 3.9 Daily delay of INRIX vs Wavetronix for 5 major routes computed by traditional fixed threshold.

Travel time per mile (reliability)

Inverse of speed multiplying by 60 is considered as travel time per mile in minutes. It is calculated as follows:

$$\text{ttpm} = 1/v_s * 60 \tag{4}$$

ttpm = travel time per mile (min)

v_s = speed (mph)

A reliability curve is defined as the CDF of travel time per mile for each segment or sensor. Figure 9 shows travel time per mile reliability curves for most segments and their corresponding sensors. In some subplots (for example, subplot 1), there is one segment reliability curve but two or more Wavetronix curves. The reason is that there are multiple sensors within that segment. Subplots annotated with stars account for the most deviated curves. Also, there is almost always a visible shift between segment and sensor CDFs which is called travel-time bias. This bias comes from the speed difference which was explained in the delay section. It was mentioned that INRIX overestimates speed while it is less than 45 mph. On the other hand, it usually underestimates speed while it is greater than 45 mph. Thus, there is always a bias between Wavetronix and INRIX speeds which leads to travel time bias. Accordingly, these are areas of focus for further analysis.

To sum up, delay and travel time per mile were calculated for INRIX segments and Wavetronix sensors. Based on the results, a speed bias was observed between the probe and sensor datasets. Since travel time is calculated based on speed, it always leads to similar bias in travel time calculations. Thus, there was a difference in delay calculation for probe data compared to point detector (sensor) data.

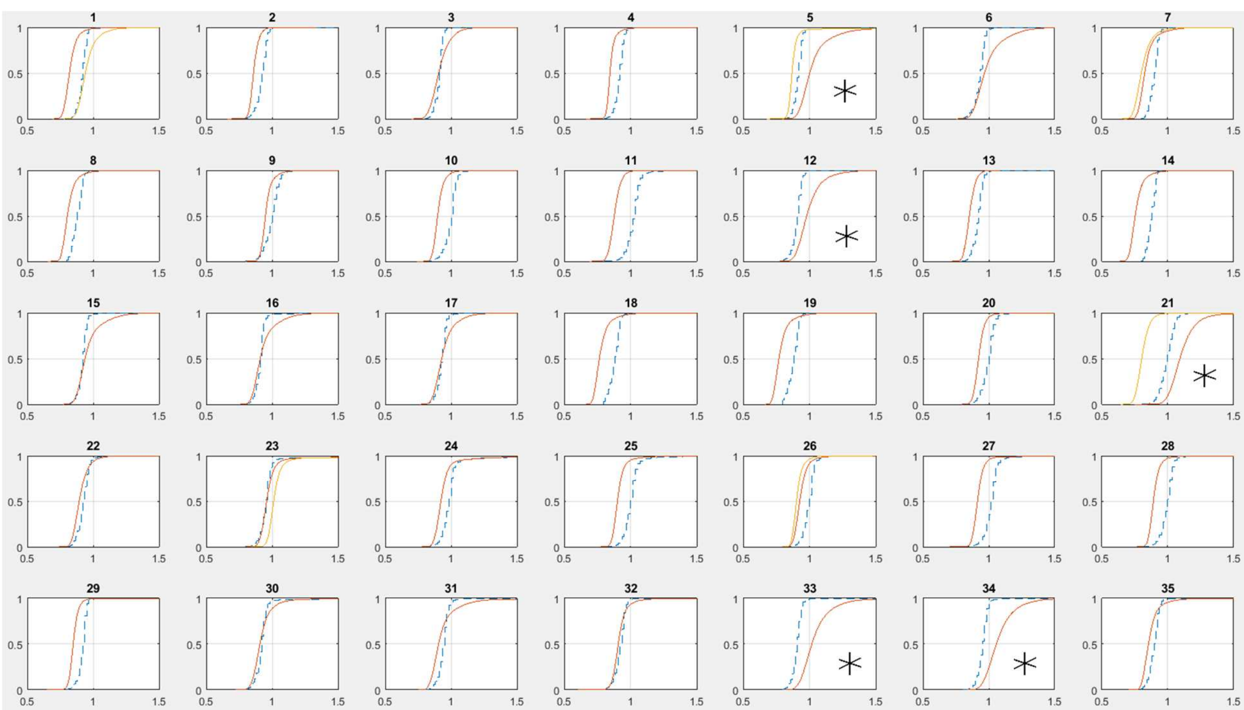


Figure 3.10 Travel time per mile reliability curves of all sensor-segment pairs for 5 routes

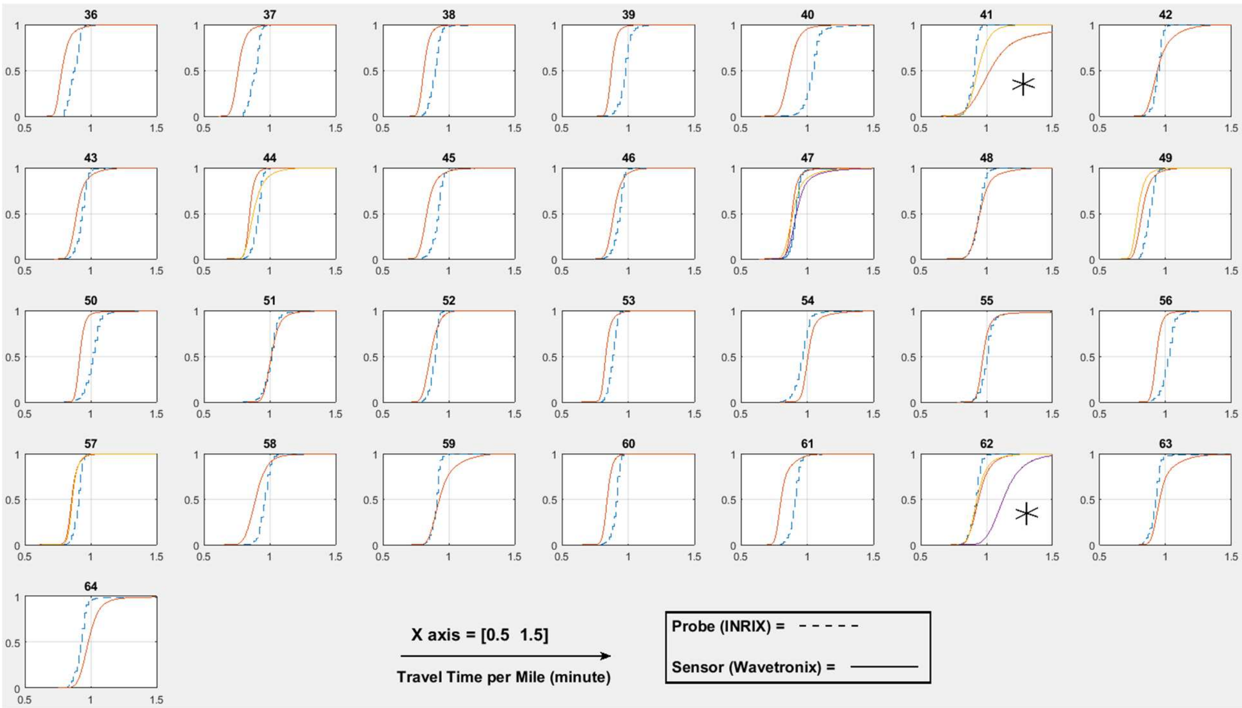


Figure 3.10. (Continued)

After evaluating the accuracy and reliability of INRIX probe data in two previous chapters (chapters 2 and 3), the purpose of the next chapter is to assess the impacts of game day on travel pattern and route choice behaviors using INRIX, the proven accurate and reliable data source. It is shown that the impacts vary depending on the schedule and also the opponents. Also, two novel methods, Multi-EigenSpot algorithm and dynamic Bayesian Networks) are proposed for hotspot detection and prediction.

References

Adu-Gyamfi, Y. O., Sharma, A., Knickerbocker, S., Hawkins, N., & Jackson, M. (2017). Framework for Evaluating the Reliability of Wide-Area Probe Data. *Transportation Research Record: Journal of the Transportation Research Board*, (2643), 93–104. https://doi.org/10.3141/2643-11

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*, *2308*, 167–172. https://doi.org/10.3141/2308-18

Araghi, B. N., Hammershøj Olesen, J., Krishnan, R., Tørholm Christensen, L., & Lahrmann, H. (2015). Reliability of Bluetooth Technology for Travel Time Estimation. *Journal of Intelligent Transportation Systems*, *19*(3), 240–255. https://doi.org/10.1080/15472450.2013.856727

Arlot, S., Celisse, A., arXiv:1202.3878, Z. H. preprint, & 2012, undefined. (n.d.). Kernel change- point detection. *Citeseer*. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.751.542&rep=rep1&type=pdf

Arthur Gretton, Karsten Borgwardt, Malte Rasch, et al. (n.d.). A kernel two-sample test. *Jmlr.Org*. Retrieved from http://www.jmlr.org/papers/v13/gretton12a.html

Bell, M. G. H., & Iida, Y. (2003). *The network reliability of transport : proceedings of the 1st International Symposium on Transportation Network Reliability (INSTR)*. Pergamon.

Belzowski, Bruce M., Ekstrom, A. (2014). Stuck in Traffic: Analyzing Real Time Traffic Capabilities of Personal Navigation Devices and Traffic Phone Applications. Retrieved from https://deepblue.lib.umich.edu/bitstream/handle/2027.42/102509/102984.pdf?sequence=1&isAllowed=y

Coifman, B. (2002). Estimating travel times and vehicle trajectories on freeways using dual loop detectors. *Transportation Research Part A: Policy and Practice*, *36*(4), 351–364. https://doi.org/10.1016/S0965-8564(01)00007-6

Cookson, G., & Pishue, B. (2016). INRIX Global Traffic Scorecard. *Inrix Global Traffic Scorecard*, (February), 44. Retrieved from https://media.bizj.us/view/img/10360454/inrix2016trafficscorecarden.pdf

Day, C., Remias, S., Li, H., Mekker, M., Mcnamara, M., Cox, E., … Wasson, J. (2015). *2013-2014 Indiana Mobility Report*. Retrieved from https://docs.lib.purdue.edu/cgi/viewcontent.cgi?article=1006&context=imr

Dudek, C., Messer, C., Record, N. N.-T. R., & 1974, undefined. (n.d.). Incident detection on urban freeways. *Safetylit.Org*. Retrieved from https://www.safetylit.org/citations/index.php?fuseaction=citations.viewdetails&citationIds[]=citjournalarticle_483374_38

FDOT. (2012). *Probe Data Analysis Evaluation of NAVTEQ, TrafficCast, and INRIX ® Travel Time System Data in the Tallahassee Region Evaluation of NAVTEQ, TrafficCast, and INRIX ® Travel Time System Data*. Retrieved from http://www.fdot.gov/traffic/ITS/Projects_Deploy/2012-03-26_Probe_Data_Analysis_v2-0.pdf

Feng, W., Bigazzi, A., Kothuri, S., & Bertini, R. (2010). Freeway sensor spacing and probe vehicle penetration: Impacts on travel time prediction and estimation accuracy. *Transportation Research Record: Journal of the Transportation Research Board*, (2178), 67–78. https://doi.org/10.3141/2178-08

FHWA. (2013). *Work Zone Performance Measurement Using Probe Data*. Retrieved from https://ops.fhwa.dot.gov/wz/resources/publications/fhwahop13043/fhwahop13043.pdf

FHWA. (2017). *2016 Urban Congestion Trends*. Retrieved from https://ops.fhwa.dot.gov/publications/fhwahop17010/fhwahop17010.pdf

Gong, L., & Fan, W. (2017). Applying Travel-Time Reliability Measures in Identifying and Ranking Recurrent Freeway Bottlenecks at the Network Level. https://doi.org/10.1061/JTEPBS.0000072

Haghani, A., Hamedi, M., & Sadabadi, K. F. (2009). *I-95 Corridor Coalition Vehicle Probe Project: Validation of INRIX Data July-September 2008*. Retrieved from http://www.i95coalition.org/wp-content/uploads/2015/02/I-95-CC-Final-Report-Jan-28-2009.pdf

Hu, J., Ph, D., Fontaine, M. D., Ph, D., Park, B. B., Ph, D., … Ph, D. (2015). Field Evaluations of an Adaptive Traffic Signal — Using Private-Sector Probe Data. *Journal of Transportation Engineering*, *142*(1), 1–9. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000806.

Kawahara, Y., … M. S.-A. and D. M. T. A., & 2012, undefined. (n.d.). Sequential change-point detection based on direct density-ratio estimation. *Wiley Online Library*. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1002/sam.10124

Kim, S., & Coifman, B. (2014). Comparing INRIX speed data against concurrent loop detector stations over several months. *Transportation Research Part C: Emerging Technologies*, *49*, 59–72. https://doi.org/10.1016/j.trc.2014.10.002

Lindveld, C. D. R., Thijs, R., Bovy, P. H. L., & der Zijpp, N. J. (2000). Evaluation of online travel time estimators and predictors. *Transportation Research Record*, *1719*, 45–53.

Lomax, T. J., Texas Transportation Institute., & National Research Council (U.S.). Transportation Research Board. (1997). *Quantifying congestion*. National Academy Press. Retrieved from https://books.google.co.uk/books?hl=en&lr=&id=q6NSRBQ3uGIC&oi=fnd&pg=PA12&dq=Lomax,+T.%3B+Turner,+S.%3B+Shunk,+G.+NCHRP,+R.+398:+Quantifying+Congestion%3B+Transportation+Research+Board:+Washington,+DC,+USA,+1997.&ots=NQiYk5spRv&sig=0FdQfJEDPXiAI-ijLJMbrFGpwFw#v=onepage&q&f=false

Lomax, T., Schrank, D., Turner, S., & Margiotta, R. (2003). Selecting travel reliability measures. texas transportation institute, cambridge systematics.

Lomax, T., Schrank, D., Turner, S., & Margiotta, R. (2003). SELECTING TRAVEL RELIABILITY MEASURES. Retrieved from https://static.tti.tamu.edu/tti.tamu.edu/documents/TTI-2003-3.pdfMcleod, D. S., Morgan, G., & Mcleod, M. (2012). Florida's Mobility Performance Measures and Experience. *Transportation Research Board, 91st Annual Meeting*.

Mcleod, D. S., Morgan, G., & Mcleod, M. (2012). Florida's Mobility Performance Measures and Experience. *Transportation Research Board, 91st Annual Meeting*.

MoDOT. (2017). *Tracker: Measures of Departmental Performance*. Retrieved from http://www.modot.org/about/documents/Tracker_July17/July2017FinalTracker.pdf

Montanez, G., Amizadeh, S., AAAI, N. L.-, & 2015, undefined. (n.d.). Inertial Hidden Markov Models: Modeling Change in Multivariate Time Series. *Aaai.Org*. Retrieved from http://www.aaai.org/ocs/index.php/AAAI/AAAI15/paper/viewFile/9475/9470

Nam, D., Park, D., & Khamkongkhun, A. (2005). Estimation of value of travel time reliability. *Journal of Advanced Transportation*, *39*(1), 39–61. https://doi.org/10.1002/atr.5670390105

Peniati, J. (2004). Operational Solutions to Traffic Congestion.

Persaud, B., Hall, F., Record, L. H.-T. R., & 1990, undefined. (n.d.). Congestion identification aspects of the McMaster incident detection algorithm. *Trid.Trb.Org*. Retrieved from https://trid.trb.org/view/352877

Pu, W. (2012). Analytic Relationships Between Travel Time Reliability Measures. *Transportation Research Record: Journal of the Transportation Research Board*, *2254*(1), 122–130. https://doi.org/10.3141/2254-13

Rakha, H., El-Shawarby, I., & Arafeh, M. (2010). Trip travel-time reliability: Issues and proposed solutions. *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*, *14*(4), 232–250. https://doi.org/10.1080/15472450.2010.517477

Remias, S., Brennan, T., Day, C., Summers, H., Cox, E., Horton, D., & Bullock, D. (2013). *2012 Indiana Mobility Report*. Retrieved from https://docs.lib.purdue.edu/cgi/viewcontent.cgi?article=1004&context=imr

Schrank., D., Eisele., B., Lomax., T., & Bak., J. (2015). *2015 Urban Mobility Scorecard*. *Texas A&M Transportation Institue* (Vol. 39). https://doi.org/DTRT06-G-0044

Schrank, D., Eisele, B., & Lomax, T. (2012). *TTI's 2012 urban mobility report*. *Texas A&M Transportation Institute*. Retrieved from http://d2dtl5nnlpfr0r.cloudfront.net/tti.tamu.edu/documents/mobility-report-2012.pdf

Sekuła, P., Marković, N., Laan, Z. Vander, & Sadabadi, K. F. (2017). Estimating Historical Hourly Traffic Volumes via Machine Learning and Vehicle Probe Data: A Maryland Case Study. Retrieved from http://arxiv.org/abs/1711.00721

Sharma, A., Ahsani, V., & Rawat, S. (2017). *Evaluation of Opportunities and Challenges of Using INRIX Data for Real-Time Performance Monitoring and Historical Trend Assessment*. Reports and White Papers. 24. Retrieved from https://lib.dr.iastate.edu/ccee_reports/24/

Subrat Mahapatra, Matthew Wolniak, E. B., & Sadabadi, K. F. (2015). *2015 Maryland State Highway Mobility Report*.

Sun, Z., Gu, W., Feng, J., International, X. Z.-P. of the, & 2011, undefined. (n.d.). Threshold Value Based Traffic Congestion Identification Method. *Researchgate.Net*. Retrieved from https://www.researchgate.net/profile/Zhanquan_Sun/publication/267244613_Threshold_Value_Based_Traffic_Congestion_Identification_Method/links/55aac7eb08aea9946724163f.pdf

Turner, S. (2013). Developing Twin Cities Arterial Mobility Performance Measures Using GPS

Speed Data. Retrieved from https://www.lrrb.org/pdf/201314.pdf

Uno, N., Kurauchi, F., Tamura, H., & Iida, Y. (2009). Using Bus Probe Data for Analysis of Travel Time Variability. *Journal of Intelligent Transportation Systems*, *13*(1), 2–15. https://doi.org/Pii 908329318\rDoi 10.1080/15472450802644439

Venkatanarayana, R. (2017). *Considerations for Calculating Arterial System Performance Measures In Virginia*. Retrieved from http://www.virginiadot.org/vtrc/main/online_reports/pdf/17-r2.pdf

Vesal Ahsani, Mostafa Amin-Naseri, Skylar Knickerbocker & Anuj Sharma (2019) Quantitative analysis of probe data characteristics: Coverage, speed bias and congestion detection precision, Journal of Intelligent Transportation Systems, 23:2, 103-119, DOI: 10.1080/15472450.2018.1502667

WSDOT. (2013). *The 2013 Corridor Capacity Summary*. Retrieved from http://wsdot.wa.gov/publications/fulltext/graynotebook/CCS13.pdf

WSDOT. (2014). *Gray Notebook 52 - For the Quarter Ending December 31, 2013*. Retrieved from http://wsdot.wa.gov/publications/fulltext/graynotebook/Dec13.pdf

Young, S. (2007). Real-Time Traffic Operations Data Using Vehicle Probe Technology. *2007 Mid-Continent Transportation Research Symposium*. Retrieved from http://www.ctre.iastate.edu/pubs/midcon2007/YoungVehicleProbe.pdf

Zheng, F., Li, J., van Zuylen, H., Liu, X., & Yang, H. (2018). Urban travel time reliability at different traffic conditions. *Journal of Intelligent Transportation Systems*, *22*(2), 106–120. https://doi.org/10.1080/15472450.2017.1412829

CHAPTER 4. ASSESSING THE IMPACT OF GAME DAY SCHEDULE AND OPPONENTS ON TRAVEL PATTERNS AND ROUTE CHOICE USING BIG DATA ANALYTICS

A paper to be submitted to the *Journal of Big Data Analytics in Transportation*

Vesal Ahsani, Anuj Sharma, Soumik Sarkar, and Chinmay Hegde

Abstract

In recent years transportation system has become a crucial infrastructure for transferring people and goods from point A to point B. However, its reliability can be decreased by major events such as unanticipated congestion or planned special events. Sporting events collect people to a specific venue on game days. This study attempts to deal with issues of road traffic management during major sporting events using widely available INRIX data. This research is intended to compare travel patterns and behaviors on game days against normal days. A comprehensive analysis is conducted on all Nebraska Cornhuskers football games and their impact on traffic congestion on 5 major routes in Nebraska over 5 years. In the next, we attempt to identify hotspots, the unusually high-risk zones in a spatiotemporal space containing traffic congestion almost on all game days. For hotspot detection, we utilize a method, called Multi-EigenSpot which is able to detect multiple hotspots in a spatiotemporal space. With this algorithm, we are able to detect traffic hotspot clusters on 5 chosen routes in Nebraska. After detecting hotspots, it is crucial to identify what factors affect the size of hotspots and other possible parameters. Start time of the game and opponents are two important factors affecting number of people coming to Lincoln, Nebraska on the game days. At the end, Dynamic

Bayesian Networks (DBN) approach is applied to forecast the start-time and location of hotspot clusters in 2018 with the WMAPE of 13.8%.

Introduction

Background

Monitoring the performance of the transportation system is a fundamental element of any transportation operation and planning strategy. Traditionally, the performance monitoring of the transport system was based on average travel times. Travel time, however, cannot adequately represent the quality of service that travelers experience every day and can also estimate the actual level of congestion incorrectly by not taking into account unexpected congestion.

Traffic congestion directly translates into transportation costs and plays a key role in assessing the transportation system performance and impacting planning decisions. When a road reaches its capacity, every extra vehicles creates overload which in turn delays other vehicles. Increased travel time, accidents, unpredictability of arrival times, increased fuel consumption and increased pollution emissions, are some of the impacts of congestion. Generally, two types of congestion are defined: recurring and non-recurring. Recurring congestion is occurred by usual traffic in a normal environment and is repetitive in nature and observed during peak periods, whereas non-recurring one is unexpected and is often occurred by weather, work zones, and incidents.

Recurring congestion is very common in U.S. with travellers expecting and planning for some delay, particularly during peak hours. Many commuters modify their schedules or assign additional time to allow for these typical traffic delays. In contrast, non-recurring, unexpected delays, can have severe impacts on motorist’s safety and mobility. Motorists want to be confident that a trip that takes 30 minutes today will also take 30 minutes tomorrow and so travel time reliability calculates the extent of this unexpected delay. Reliability is defined formally as consistency or dependability in travel times, as measured from day to day or over different times of the day.

Planned Special Events (PSE)

Irregular events with an anticipated large attendance (also known as Planned Special Events, or PSE), such as festivals, concerts, football games, etc., play a key role for delays in daily transportation. All various events have one common attribute which is imposing an abnormal stress to the network leading to safety issues and capacity reduction.

The presence of a professional sports team in a city can have a significant impact on the city's local economy. In previous research, the benefits of professional sport teams in the local economy were mainly assessed; without any focuses on the problems created by sports teams, and their games. The problems are divided to direct and indirect costs generated by teams. Direct costs include facility construction, salary for players, managers, and officials, and costs of public safety while all negative aspects of the games such as traffic, crowds, air and noise pollution, crime, etc. are counted as indirect costs. In this paper, the authors pragmatically analyze the relationship between attendance at NCAA Division I Football Bowl Subdivision (FBS) games and traffic congestion in the U.S. metropolitan areas, an indirect cost generated by the presence of a college football team.

The FBS is the NCAA Division I's most competitive subdivision, which consists of the National Collegiate Athletic Association (NCAA)'s largest and most competitive schools. There are 10 conferences and 130 schools in FBS, according to the 2017 college football season. College football is very popular in the United States, and top schools generate tens of millions of dollars in annual revenue. Top FBS teams attract hundred thousands of people to stadiums, and the largest American stadiums by capacity all host FBS teams. Football teams typically play at least six home games per season.

The Nebraska Cornhuskers Football team is home to the Memorial Stadium in Lincoln. It is commonly referred to on game days as Nebraska's "third - largest city." The stadium holds the NCAA record of successive sellouts for each game since 1962 - a series of more than 300 games. With an extended capacity of more than 85,000, game days typically affect Lincoln's and neighboring regions' travel patterns. Most of the existing research focuses on either financial costs or crime associated with sporting events while this study attempts to analyze the link between professional sporting events and traffic congestion, another overlooked cost of hosting sporting events.

Hotspot Detection

Hotspot detection is used in many disciplines, as in crime analysis, for analyzing where crimes occur with a certain frequency, in fire analysis for studying the phenomenon of forest fires, and in disease analysis for studying the localization and the focuses of diseases. A realistic scenario of the application of the hotspot detection is in traffic incident detection. Suppose that we have several detectors across a city recording speeds of vehicle passing the detectors. Considering speeds of vehicle on normal days over years as the baseline information and vehicles' speeds on game days throughout different years as the cases dataset. The goal is to detect those spatiotemporal regions that contain unexpected lower speeds which led to non-recurring congestion. Additionally, this study aims to identify what factors affect the size of hotspots, their location and other possible parameters.

This paper is organized accordingly. A literature review is provided that summarizes previous related studies. After that, the data used in this study are presented. It also contains all selected routes and some preliminary analysis. After that, a complete traffic hotspot analysis is conducted, novel hotspot detection method in proposed, and insight is given about the observed results. Finally, dynamic Bayesian networks approach is utilized to forecast traffic congestion and hotspots for 2018.

Literature Review

Traffic congestion is an important problem in many urban areas. Duranton and Turner note that in 2001, the average American households spend more than 2.5 hours a day on a passenger car. They also examine the effects of road construction and other factors on congestion. Rappaport expands the standard single-city model to include traffic and traffic congestion identification as an important factor in limiting local growth. Another research which recently conducted concludes that commuting to and from work are among urban house-hold's least enjoyable activities, It suggests that extra time in a car at the end of the day involves a lot of psychological costs and time.

Irregular events with an anticipated large attendance (also known as Planned Special Events, or PSE), such as festivals, concerts, football games, etc., play a key role for delays in daily transportation. All various events have one common attribute which is imposing an abnormal stress to the network leading to safety issues and capacity reduction. Major events can be recognized by their spatio-temporal size compared to recurring congestion. But they are hardly defined. What should be noted here is that when an event is considered to be major. Mueller proposed a methodology containing four parameters for the definition of major events; number of visitors, media coverage, costs and urban transformation. The Event Transport Manual (Handbuch Eventverkehr) similarly categorizes events according to a substantial list of factors, including, but not limited to, the number of expected visitors, relative size, open or closed access, location, weather, duration and financing. For example, the Rihanna's concert in South Africa in October 2013 forced people to drive more than five hours trying to reach the stadium. Similarly, Robbie Williams' concert in London in 2003 created a 10-mile tailback on the A1 highway towards the stadium. Traffic congestion which is created by special events has a quite typical behavior, having two subsequent waves of congestion. The first is made by people who go to the event, the second by people who leave the venue. It is interesting to know that the second one may be even bigger that the first wave. Very few research has been conducted to predict the congestion due to special events. At the same time, there is almost no way to predict this kind of non-recurring traffic ahead of time. In this paper, we examine the effects of one specific type of special events, football games, on traffic patterns and travel behaviors in city of Lincoln in the state of Nebraska.

Professional sporting events draw great numbers of fans to stadiums which usually are located in small areas in the core of large cities. Big parking lots and parking structures near to the stadiums and sport facilities show that most of the fans drive to game venues. Also, football games mostly take place on Fridays or Saturdays. Considering all these indicators, sporting events can have a significant impact on traffic congestion. Most of the fans travel between their home or place of work and the location where the game takes place in order to attend the game. Consequently, many facilities and amenities are provided spatially and temporally on game days. Humphreys and Zhou approved the statement that concentration of people near to the venue that game takes place has impacts on the local economy. They developed a model indicating increased fan activity in and around sporting events on game day. The model also showed the increase in the values of nearby properties and increased housing market activities near the sport facilities. They also asserted that employees of the recreation and entertaining industries in the cities hosting professional sports teams earn more compared to the cities without professional sport teams. These results supported the idea of increased economic activities in and near sports facilities.

The concentration of people around game venue on game day, along with increased nearby population, clearly leads to traffic congestion. The previous research on professional sports teams in North America asserts that stadiums and arenas attract fans and economic activities to game venues on game days. It mentions that the number of businesses and residents near sports facilities may be increased. All these factors are able to increase urban traffic significantly. However, it should be noticed that this increase can only be observed around the stadiums, arenas, and sport facilities, not all around a metropolitan area.

Generally, traffic congestion prediction in urban environments is an extremely complex task. In general, two types of congestion are defined: recurring and non-recurring. Recurring congestion is occurred by usual traffic in a normal environment and is repetitive in nature and observed during peak periods, whereas non-recurring one is unexpected and is often occurred by weather, work zones, and incidents. Simulations and theoretical modeling were utilized as early approaches for traffic forecasting. Having massive traffic datasets these days has brought out several different statistic and data driven approaches to the community. Linear regression, nonlinear time series, Kalman filters, support vector regression and various neural network models are numerous examples. The unpredictable effects of traffic congestion and their prediction have been extensively studied topics within the research community. However, to the best of our knowledge, there is only one work available focusing on the impacts of PSEs on traffic congestion. The authors report a general theory of the impact of PSE on a road network defined by an event classification defined by the Chinese government council. They also introduce management plans for different types of events, but there are no measurable solutions to predict traffic.

Over the years, many researchers attempted to utilize mathematical prediction methods in traffic prediction. In the field of traffic flow prediction research, traffic flow has always been regarded as a two - dimensional stochastic process (temporal and spatial). Parametric models try to find a mathematical model parameters that describe traffic flow as a time series process. In 1979, a first parameter approach was proposed to predict short - term freeway flow by an autoregressive integrated moving average (ARIMA) model. Many studies have shown ARIMA value, but these approaches suffer from a tendency to focus on average values of the time series, so that they are not able to predict extremism. In order to predict the flow of traffic to the study area, other parametric models such as the Kalman filtering model and local linear regression were also suggested.

Since 1990, researchers were inclined to make use of nonparametric models, instead of parametric models. In order to define the model structure and number of parameters, non - parametric models rely on training data. Non-parametric models would be more promising because of the non-linear nature of traffic flow. Many of the proposed methods only focus on the traffic flow temporally, as a time series process. This paper continues to investigate Bayesian Networks (BN) in the prediction of traffic flows with spatial and temporal information. Consequently, Dynamic Bayesian Networks (DBN) extend Bayesian networks to model systems evolving over time. In other words, a DBN is a BN which relates variables to each other over contiguous time stamps.

Data

In today's complex global economy, transportation communications provide businesses in every region that provides the best possible combination of work, land, taxes, and costs, while competing around the world. All government DOTs use fixed-mounted sensors to collect traffic information such as travel time, traffic speed, volume, etc. This traffic information can be provided by the Nebraska Road Administration Board (NDOR) to identify routes that are most used and determine whether to improve this road or if there is an excessive amount of traffic.

Probe data is a collection of relatively low - cost methods to obtain travel time and speed information for road and other vehicles. NDOR has already purchased probe data through a third-party INRIX vendor to collect traffic data and evaluate the performance of its operations. INRIX maintains 4,125 traffic management centers to collect traffic information for highways and urban areas. In this study, the data from INRIX available through the Nebraska DOT will be used to conduct analysis on game days and normal days over the past several years and thereby compare travel patterns and behaviors on game days against normal days.

Game days attract significant high volume of traffic and hence result in congestion and higher travel time to the road users. This project helps to gain insights on the impact of game day schedule and opponent on travel pattern and route choice. The insights gained from this study helps to implement active traffic assignment thereby reducing congestion. Table 1 below shows Nebraska Cornhuskers football schedule of all home games from 2013 to 2017.

Table 4.1 Nebraska Cornhuskers schedule and results from 2013 to 2017.

DATE	DAY	OPPONENT	LOCATION	RESULT	STATUS	TIME
GAME DAYS 2013						
8/2/2013	Fri	Fan Day	Memorial Stadium			
8/31/2013	Sat	Wyoming	Memorial Stadium	W, 37-34		7:00 PM
9/7/2013	Sat	Southern Miss	Memorial Stadium	W, 56-13		5:00 PM
9/14/2013	Sat	UCLA	Memorial Stadium	L, 41-21		11:00 AM
9/21/2013	Sat	South Dakota State	Memorial Stadium	W, 59-20		
10/5/2013	Sat	Illinois	Memorial Stadium	W, 39-19		11:00 AM
11/2/2013	Sat	Northwestern	Memorial Stadium	W, 27-24		
11/16/2013	Sat	Michigan State	Memorial Stadium	L, 41-28		
11/29/2013	Fri	Iowa	Memorial Stadium	L, 38-17		11:00 AM
GAME DAYS 2014						
8/30/2014	Sat	Florida Atlantic	Memorial Stadium	W, 55-7		2:30 PM
9/6/2014	Sat	McNeese State	Memorial Stadium	W, 31-24		11:00 AM
9/20/2014	Sat	Miami FL	Memorial Stadium	W, 41-31		7:00 PM
9/27/2014	Sat	Illinois	Memorial Stadium	W, 45-14	Homecoming	8:00 PM
10/25/2014	Sat	Rutgers	Memorial Stadium	W, 42-24		11:00 AM
11/1/2014	Sat	Purdue	Memorial Stadium	W, 35-14		2:30 PM
11/22/2014	Sat	Minnesota	Memorial Stadium	L, 28-24		11:00 AM

Table 4.1. (Continued)

GAME DAYS 2015						
4/11/2015	Sat	Red-White Spring Game	Memorial Stadium	Red 24, White 15		11:00 AM
8/5/2015	Wed	Nebraska Football Fan Day	Memorial Stadium		Presented by US Cellular	
9/5/2015	Sat	Brigham Young	Memorial Stadium	L, 33-28		2:30 PM
9/12/2015	Sat	South Alabama	Memorial Stadium	W, 48-9		7:00 PM
9/26/2015	Sat	Southern Miss	Memorial Stadium	W, 36-28	Homecoming	11:00 AM
10/10/2015	Sat	Wisconsin	Memorial Stadium	L, 23-21		2:30 PM
10/24/2015	Sat	Northwestern	Memorial Stadium	L, 30-28		11:00 AM
11/7/2015	Sat	Michigan State	Memorial Stadium	W, 39-38		6:00 PM
11/27/2015	Fri	Iowa	Memorial Stadium	L, 28-20		2:30 PM
GAME DAYS 2016						
8/3/2016	Wed	Fan Day	Memorial Stadium			
9/3/2016	Sat	Fresno State	Memorial Stadium	W, 43-10		7:00 PM
9/10/2016	Sat	Wyoming	Memorial Stadium	W, 52-17		11:00 AM
9/17/2016	Sat	Oregon	Memorial Stadium	W, 35-32		2:30 PM
10/1/2016	Sat	Illinois	Memorial Stadium	W, 31-16	Homecoming	2:30 PM
10/22/2016	Sat	Purdue	Memorial Stadium	W, 27-14		2:30 PM
11/12/2016	Sat	Minnesota	Memorial Stadium	W, 24-17		6:30 PM

Table 4.1. (Continued)

11/19/2016	**SAT**	**MARYLAND**	**MEMORIAL STADIUM**	**W, 28-7**		**11:00 AM**
GAME DAYS 2017						
4/15/2017	Sat	Spring Game	Memorial Stadium	Red 55, White 7		
9/2/2017	Sat	Arkansas State	Memorial Stadium	W, 43-36		7:00 PM
9/16/2017	Sat	Northern Illinois	Memorial Stadium	L, 21-17		11:00 AM
9/23/2017	Sat	Rutgers	Memorial Stadium	W, 27-17		2:30 PM
10/7/2017	Sat	Wisconsin	Memorial Stadium	L, 38-17		7:00 PM
10/14/2017	Sat	Ohio State	Memorial Stadium	L, 56-14		6:30 PM
11/4/2017	Sat	Northwestern	Memorial Stadium	L, 31-24		2:30 PM
11/24/2017	Fri	Iowa	Memorial Stadium	W, 56-14		3:00 PM

Methodology

Traffic Hotspot Analysis

Incident Detection

Researchers and engineers have long been motivated to improve traffic safety and operations. Traffic accidents, especially traffic accidents and special events traffic, are of great importance because of the delays and costs that cause casualties in the community. Traffic delays can be pointed out to unauthorized things, including but not limited to traffic accidents and adverse weather conditions. These incidents may also have other effects, such as secondary collapse and delays in emergency medical services, which may result in additional costs. As a result, in the area of traffic management, monitoring of the transport network and the ability to detect and report abnormalities in real time is very important.

Data stream and pre-processing

In real scenarios, incomplete raw traffic data are usually highly sensitive to noise and unstable for many reasons, such as sensor failure, measurement errors, large size, etc. Preprocessing data can be used to try to identify and correct corrupt traffic information. However, it is impossible to store and analyze large amounts of INRIX data using traditional methods because they require more than 500 GB of data processing, which in traditional devices takes a great deal of time. A high - performance cluster is used to process data for this study. Data was stored and processed using the Hadoop distribution file system. As a language, Latin pig was used to map and reduce algorithms.

Hotspot detection

Hotspot detection is utilized in many disciplines, such as crime analysis, for identifying where crimes occur with a certain frequency, in fire analysis for studying the phenomenon of forest fires, and in disease analysis for examining the localization and the focuses of diseases. Nowadays, there is great interest in spatiotemporal data analysis because of the availability of huge amount of data. Among different analysis tasks that can be performed on spatiotemporal data, hotspot analysis is found as an important tool in security informatics and bio-surveillance. For instance in crime hotspot application, an outcome such as specific Shopping Mall between hours 5 to 8 pm would be a spatiotemporal hotspot. Outcome like Shopping Mall or City Center would be strict spatial hotspots and 5 to 8 pm and 9 to 11 am are samples of temporal hotspots. Hotspot analysis goal consists of detecting spatiotemporal regions among data. As an example, in structural engineering, the vibration of structures can be assessed by the eigenvalue and eigenvectors. In face recognition, the images of the human face are approximated by the specific set of the largest eigenvectors. Moreover, in control engineering, the stability and response of the system are evaluated by the eigenvalues of the linear system.

A realistic scenario of the application of the hotspot detection is in traffic incident detection. Suppose that we have several detectors across a city recording speeds of vehicle passing the detectors. Considering speeds of vehicle on normal days over years as the baseline information and vehicles' speeds on game days throughout different years as the cases dataset. The objective is to detect spatiotemporal regions with unexpected lower speeds leading to non-recurring congestion. For instance, the output like segments S1, S2 and S3 during the years Y1, Y2, and Y3 might be considered a spatiotemporal hotspot. The detection of these hotspots enables officials to better understand their focus on key interventions and preventive measures.

Each cell in both matrices of baseline and case represents a count corresponding to a specific region and time. In particular, for traffic incident detection, each cell in the baseline matrix represents the speeds corresponding to a segment in a specific time period in normal days. Each cell in the case matrix also represents the value of the speed reported in a particular segment within a given time period, but on the day of the game. The purpose is to determine those subgroups of the spatiotemporal space whose reported cases are abnormal. We are interested in developing a method that has the following characteristics: 1) requires no input parameters; and 2) weighs all possible hotspots on the basis of a standard metric such as statistical significance (p - value). The alpha threshold is also easy to estimate (usually alpha=0.15).

EigenSpot, an Eigenspace-based algorithm, has recently been suggested to identify space-time clusters without any limitation in the distribution and quality of data or cluster form. However, the main limitation of this method is that it can only detect the focal point and can detect multiple clusters. In detecting traffic accidents when a cluster (incident) is detected, there is interest in recognizing whether there are additional clusters in high-risk areas in temporary space.

In this study, the Multi-EigenSpot algorithm uses the EigenSpot algorithm to identify multiple clusters in spatial temporal space. The proposed algorithm uses the spatiotemporal matrix as basic information for expected congestion cases. Using the expected case matrix as the basis information, we can replace the items with the expected cases in spatiotemporal space for the previously identified regions and re-run the algorithm to detect additional clusters, if any. Because our proposed algorithm is based on the EigenSpot method, the following section presents a brief review of the EigenSpot method.

EigenSpot algorithm

EigenSpot algorithm inputs are two spatiotemporal $m \times n$ matrices, C, game day's speeds and B, base information (typical day's speeds) where m denotes the number of sections and n represents the number of time points. Each cell in each matrix represents the speed reported by INRIX for a particular section and time. With respect to these matrices, the EigenSpot algorithm tries to detect a subgroup of regions in the spatiotemporal space in which the reported speed is unexpected due to basic information. Each matrix is decomposed using a one - rank SVD (singular decomposition of values) to obtain the main left and right single vectors. The elements of the principla left and right singular vectors are related to spatial dimensions and temporal dimensions, respectively. The next step includes the distances between the corresponding elements of pairwise vectors which were calculated. The subtract vector can be calculated as follows if (sb_1, sb_2, …, sb_n) represents the spatial singular vector for the normal day's matrix and (sc_1, sc_2, …, sc_n) for game day's (case) matrix:

$$ds = [ds_1 = sc_1 - sb_1 \; ds_2 = sc_2 - sb_2 \; . \; . \; . \; ds_n = sc_n - sb_n]$$

Similarly, for the temporal dimension, the subtract vector is given by:

$$dt = [dt_1 = tc_1 - tb_1 \; dt_2 = tc_2 - tb_2 \; . \; . \; . \; dt_m = tc_m - tb_m]$$

A z - score control diagram for vectors ds and dt should be applied with a significant level α to identify abnormal spatial and temporal components. Finally, the locations of hotspot regions in spatiotemporal space are approximated by the combination of spatial and temporal components that are out of control.

Multi-EigenSpot algorithm

For the proposed algorithm, we consider the situation in which data on the speeds of vehicles on the day of the game and normal day are aggregated over a period of time for different sub - regions. In the proposed algorithm, the speed of the vehicle on the day of the game and the normal day shall be arranged in the form of identical matrices C and B, where m indicates the number of components in the spatial dimension (segments) and n the number of components in the spatial dimension (time points).

Given the spatiotemporal matrices, C, (game day's speeds) and, B, (normal day' speeds), two spatiotemporal matrices, E (expected speeds) and, R (relative risks) are calculated. If there is no cluster in the spatiotemporal space for the expected traffic congestion, we use the proposed formula, which assumes that the reported cases are distributed over the spatiotemporal space in proportion to the speed of the normal day. The risk measure, RR, is also calculated as the proportion of the C to the E. The Singular Value Decomposition (SVD) is applied on each matrix, C and E, and singular vectors are calculated on the left and right. The SVD of a spatiotemporal matrix, M, is the form M= UDV, where the columns of U are the single vectors corresponding to the spatial dimension, and the columns of V are the single vectors corresponding to the temporal dimension. D is a diagonal matrix with the matrix's Eigenvalue diagonal entries, M. If we assume that C and E are identical, their main left and right single vectors are also identical, i.e. the distance between the corresponding elements in the single vectors of the pair is zero. If there is a change in C, this change can be detected by the changes in the elements of the main single vector. In these cases, for the components corresponding to the affected areas in both spatial and temporal dimensions, some distances between the corresponding elements of the pair of individual vectors become abnormal.

This approach uses the z-control chart to monitor the distances between the individual vectors of the pair. The spatial components of a cluster and the pair right singular vectors to the temporal components are associated with an abnormal difference in the corresponding elements of the pair left single vectors. If the abnormal components are found in both spatial and temporal dimensions, the matrix C is upgraded by the corresponding expected cases to replace the elements (lower speeds of game days) corresponding to the out - of - control components of space and time. In order to further visualize these elements on the heat map, matrix R is also upgraded by replacing the elements corresponding to the out of control components with their average value. The matrices, C and R, are upgraded iteratively until no spatial or temporal component is found out of control. The resulting matrix R is then displayed on the heat map showing the various average relative risks of different colours. If there is no cluster of space-time, the resulting heat map will have all elements equal to 1 showing only a dark-blue colour. Apart from dark-blue, different colors on the heat map approximate different space-time clusters.

Three types of tools are required for Multi-EigenSpot algorithm: 1) SVD for the identification of the single vectors of the matrix, 2) a statistical process control tool to monitor the distances between the relevant elements of the single vectors and 3) a visualization tool (heat map) for the visualization of the detected clusters. The detailed step-by-step process and the deployment of these techniques in the algorithm are given below.

- Step-1: Calculate the space-time matrices of the expected speed of the vehicle and relative risks.

$$E_{ij} = \frac{C_{.j}}{B_{.j}} \times B_{ij}$$

$$E = \begin{bmatrix} E_{11} & \cdots & E_{1n} \\ \vdots & \ddots & \vdots \\ E_{m1} & \cdots & E_{mn} \end{bmatrix}$$

where

$C_{.j}$ is the j_{th} column-average of matrix C

$B_{.j}$ is the j_{th} column-average of matrix B

B_{ij} is the speed in the i_{th} sub-region over the j_{th} time-point.

$$R_{ij} = \frac{C_{ij}}{E_{ij}}$$

$$R = \begin{bmatrix} R_{11} & \cdots & R_{1n} \\ \vdots & \ddots & \vdots \\ R_{m1} & \cdots & R_{mn} \end{bmatrix}$$

Having matrix R, we will be able to visualize hotspot clusters on the heat map.

- Step-2: SVD of matrices, C and E.
- Step-3: Calculate the subtract vectors.
- Step-4: Identify abnormally higher distances in the corresponding elements of the pair singular vectors.
- Step-5: Upgrade matrices, C and R.
- Step-6: Find additional spatial and temporal abnormal components. Repeat steps (2 - 5) until each dimension has no abnormal component.
- Step-7: Visualize the resulting matrix R on the heat map showing different colors of the average RR - values.

After implementing the proposed method on all routes in our case study, 19 hotspots are identified. Figure 1 below is an example output of the proposed method. The colored regions on the heat map show multiple space - time hotspots corresponding to different average RR - values (less than 1). If there is no cluster, all heat map data values are equal to 1, showing only a dark - blue color.

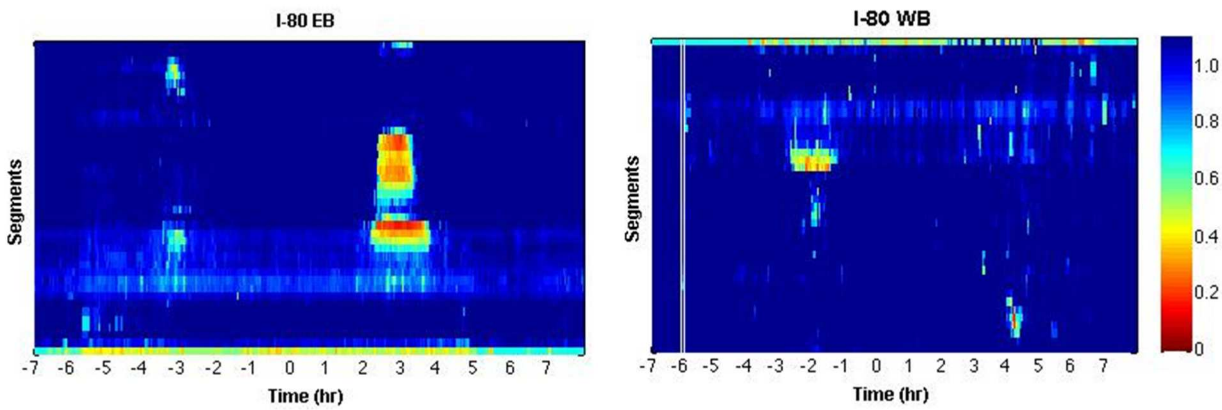


Figure 4.1 Sample result of the proposed algorithm. Heat map shows spatiotemporal matrix of I-80 route as an example.

After detecting hotspots, it is crucial to identify what factors affect the size of hotspots, their location and other possible parameters. Start time of the game and opponents are two important factors affecting number of people coming to Lincoln, Nebraska on the game days. Start time of the game can be divided into two parts; noon and evening. Noon contains games start at 11 am or 2:30 pm. Similarly, evening contains all games kick off at 6:30 or 7 pm. On the other hand, Cornhuskers opponent teams can significantly influence on the importance of the game. As an example, Cornhuskers toughest 2018 opponents are as follows: 1. Ohio State, 2. Wisconsin, 3. Northwestern, 4. Michigan State, 5. Iowa, etc.. Thus, it is important to assess the impacts of these two factors (start-time and opponent) on the hotspot size. Hotspot size can be defined as congestion length and congestion duration. In the following, impacts of start-time of the game and toughness of opponent on the hotspot size (congestion length and duration) are assessed.

Start-time of the game

Using the proposed method for hotspot detection, it is possible to find out the number of consecutive segments in each hotspot. Having segments length and the number of consecutive segments for each hotspot, it is possible to approximate the length of each congestion (hotspot).

Figure 2 below illustrates how the congestion length changes for noon and evening games with respect to the time congestion occurred, before start time of the game (negative values) or after that (positive values). Among 19 hotspots identified in the case study from the proposed hotspot detection algorithm, it is clearly observed that for most of the hotspots, congestion length when the start-time of the game is noon is higher than evening games, no matter congestion occurred before or after the start of the game.

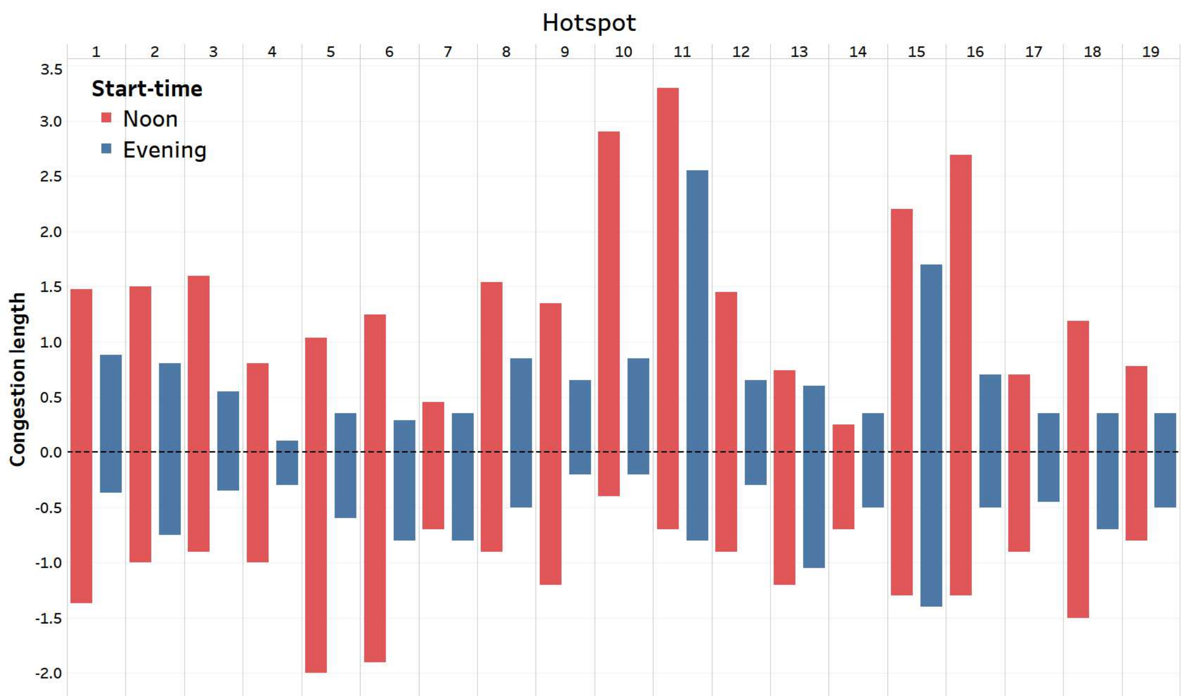


Figure 4.2 Start-time of the game impact on congestion (hotspot) length.

Multi-EigenSpot algorithm is capable to identify traffic duration of each hotspot cluster. As shown in Figure 1 as an example, time (congestion duration) and number of segments (congestion length) of traffic hotspot cluster are easily visible. Thus, we estimated congestion duration by the proposed method. Figure 3 below shows the average congestion duration of 19 hotspots during noon and evening football games with respect to the time congestion occurred, before start time of the game (negative values) or after that (positive values). As can be seen in the figure, all games kicked off in the evening are accounted for less average congestion duration than noon games, no matter congestion occurred before or after the start of the game.

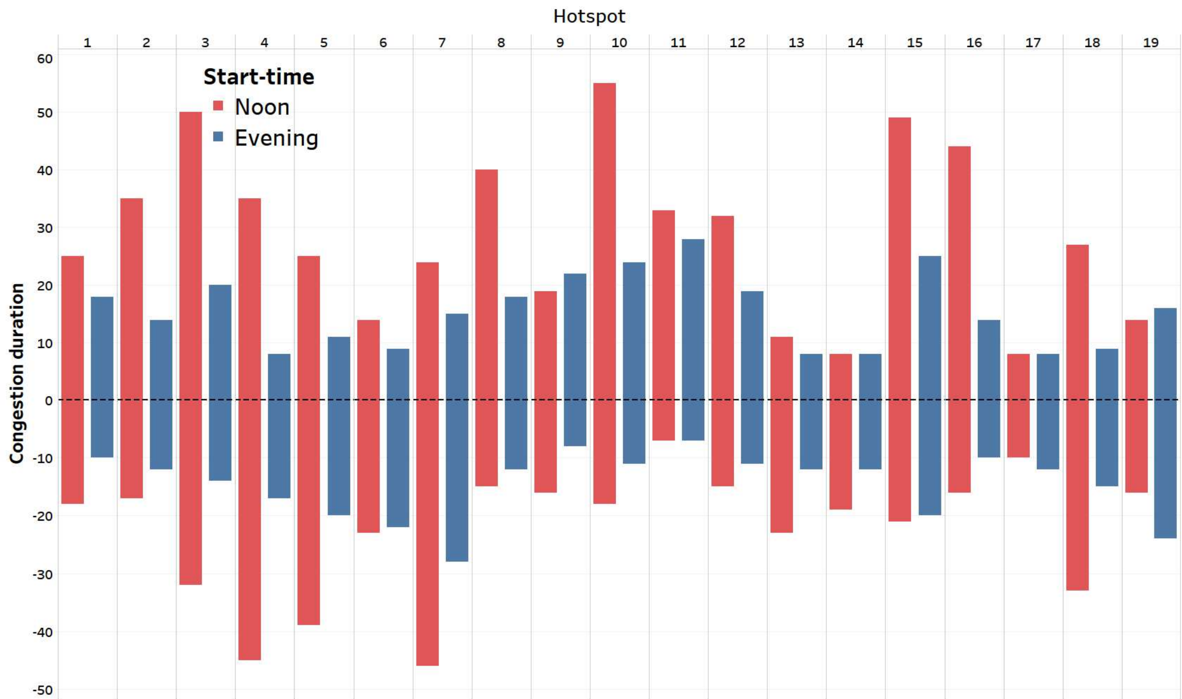


Figure 4.3 Start-time of the game impact on congestion (hotspot) duration.

Toughness of opponent

Nebraska Cornhuskers opponents play a significant role in the importance of the game. According to the last 5 years, Cornhuskers toughest opponents were: 1. Ohio State, 2. Wisconsin, 3. Northwestern, 4. Iowa, 5. Michigan State, 6. Purdue, etc.. It is important to evaluate the role of opponent on game days' traffic congestion.

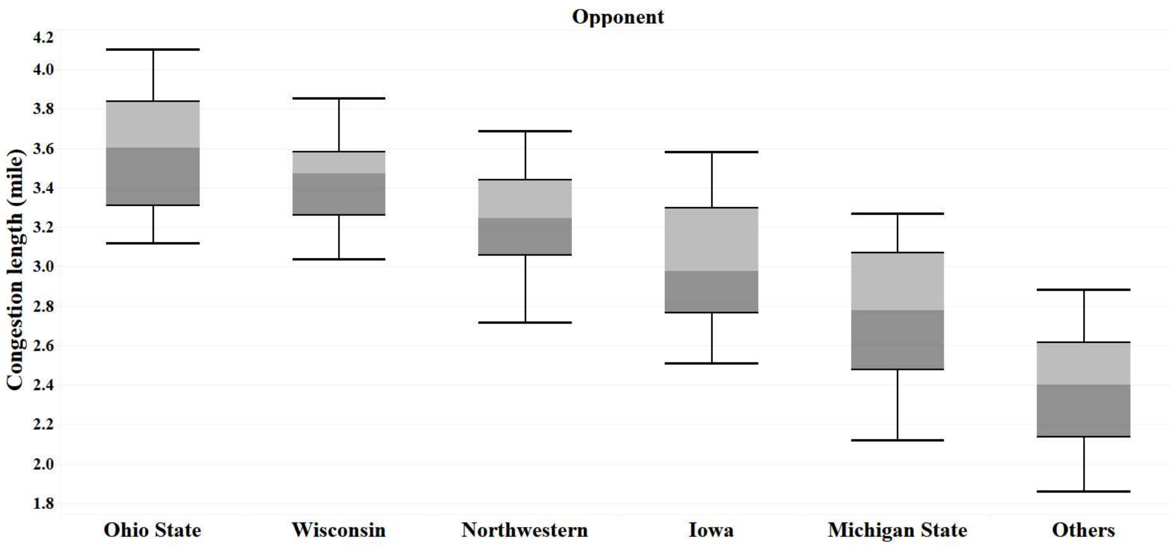


Figure 4.4 Impact of Cornhuskers opponents on the congestion length.

Using the proposed method for hotspot detection, we are also able to find out the duration of traffic hotspots. The goal of this section is to find out the impact of Cornhuskers opponents on the traffic congestion duration. For instance, is there a longer traffic duration in the Lincoln area when the game is between Cornhuskers and Ohio State compared to the game against Rutgers?

In the Figure 5 below, the horizontal axis shows top 5 opponents of Nebraska Cornhuskers during past 5 years. The other category is others which implies all other teams usually couldn't win Cornhuskers at all. As obviously can be seen in the boxplot, there is a decreasing trend from Ohio State (toughest opponent) to others (weaker teams) implying the fact that duration of traffic hotspots is influenced by the opponents.

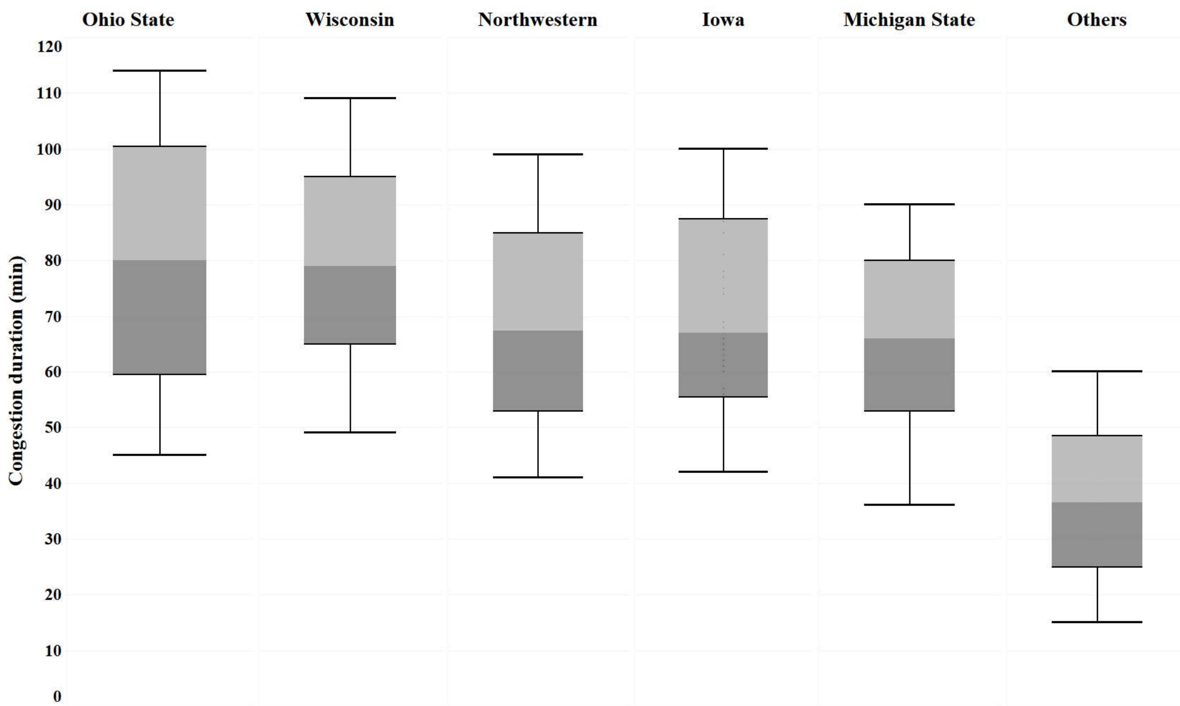


Figure 4.5 Impact of Cornhuskers opponents on the congestion duration.

Based on the exploratory analysis conducted above, the traffic hotspot size is influenced by start-time of the game and toughness of opponents. In the next step, this research aims to predict traffic congestion based on the available variables, and identify hotspot clusters for the year 2018 based on the predicted dataset. Given start-time of the game (Noon or Evening), toughness of opponents, specific congested segments for each route, it is possible to forecast speeds on game days of next year (2018) using Dynamic Bayesian Networks and identify hotspot clusters based on predicted dataset. Data of 2018 are utilized as validation set.

Dynamic Bayesian networks

Pearl (1988) introduced Bayesian networks as probabilistic graphic models that explain the dependence and independence of random variables on conditions. These dependencies are represented by a directed acyclic graph and measured by a joint probability distribution that breaks down into a product of local conditional distributions:

$$p(X1, \ldots, Xn) = \prod_{i=1}^{n} p(Xi|Pa(Xi))$$

Where *Pa(Xi)* is the set of parents of *Xi*. Bayesian networks' flexibility allows different sources of information to be combined. For example, you can use your own knowledge to set a part of the model and the other part can be learned automatically from data (Leray, 2006). Additionally, inference (the forecasting process) is possible to be made by the information propagation mechanism even in case of incomplete data. This feature is especially useful in real - time applications where it can be harmful to implement a further imputation process.

Dynamic Bayesian networks are extended to models evolving over time (Dean and Kanazawa, 1989). Each node $X_i^{(t)}$ represents the instantiation of the variable X_i at time slice *t*. The parents of $X_i^{(t)}$ can belong to *t*, *t-1*, …, *t-r*, where *r* is the order of the dynamic Bayesian network (Ghahramani, 1998).

Due to the limited number of available observations, 10-fold cross - validation is evaluated in the forecasting performance (Kohavi, 1995). This method involves dividing the dataset *X* randomly into 10 subsets $X_1, \ldots, X_{10}$ of (approximately) the same size. The model is trained on $X \backslash X_k$ and tested on X for each $K \in \{1, \ldots, 10\}$. The final performance is estimated by an average of 10 measurements of accuracy. The weighted average absolute percentage error (WMAPE) is adopted in this paper:

$$WMAPE(x, \hat{x}) = \frac{\sum_{t=1}^{N} \left| x^{(t)} - \hat{x}^{(t)} \right|}{\sum_{t=1}^{N} x^{(t)}}$$

Where $\hat{x}$ is the estimate of x and *N* Is the number of comments in the dataset. The WMAPE is easy to interpret, like the average absolute percentage error (MAPE). On the other hand, it favors models that predict high values effectively.

Learning with incomplete data

In this study with having several routes in Nebraska over 5 years, the missing data is too dispersed to delete list-wise. Sun et al. (2006) proposed to replace the parents of the dynamic Bayesian network with the variables whose values are missing. Unfortunately, this method is hardly applicable because it means that parents are complete, which in many situations does not necessarily apply.

The expectation - maximization (EM) algorithm, proposed by Dempster et al. (1977), is a method for iteratively estimating the maximum likelihood of parameters when missing (or hidden) values in the training dataset. This method carries out two steps at each iteration starting from an initial parameter estimation. It completes the data set of observed data and current estimates of the expectation (E) parameters. This completed dataset is used in the M step to update parameters by maximizing the probability of logging. As Dempster et al. (1977) shows, the log likelihood increases at each iteration until the maximum local convergence is achieved.

The next time slice forecasting process can be considered a problem of inference in the dynamic Bayesian network. In Murphy's thesis (2002) or in Koller and Friedman's recent book (2009), for dynamic Bayesian networks, a comprehensive review of inference methods can be found. The approximate inference methods normally take less time than the exact methods. They seem to be a better choice to ensure real - time forecasts given the complexity of our model. The bootstrap filter (Gordon et al., 1993), also known as the fittest survival (Kanazawa et al., 1995), is a stochastic simulation algorithm that can be inferred in real time. It generates weighted sample sequences by sampling unobserved values. These sequences are time collected - multiplied in proportion to their weight, which reflects their probability of time.

Experimental method

The data are collected during 41 game days and 41 normal days over 5 years from 2013 to 2017. As explained earlier, start time of the game and toughness of opponents are two significant factors affecting hotspot clusters detected by the Multi-EigenSpot algorithm. Start time of the game can be divided into two parts; noon and evening. Noon contains games start at 11 am or 2:30 pm. Similarly, evening contains all games kick off at 6:30 or 7 pm. On the other hand, Cornhuskers opponent teams can significantly influence on the importance of the game. As an example, Cornhuskers toughest 2018 opponents are as follows: 1. Ohio State, 2. Wisconsin, 3. Northwestern, 4. Iowa, 5. Michigan State, etc. For toughness variable, it is considered as two classes; tough opponents, and normal opponents. The prediction algorithm is applied on each route separately. To predict speed and thereby find hotspots which are the locations always experiencing congestion on game days, start time of the game and opponent's toughness are two discrete variables. In the model's structure, time windows of 15 minutes is considered. In other words, each frame of model contains 15 minutes of traffic speed as a vector.

In this study, the dynamic Bayesian networks approach performs well on each route. Corresponding WMAPE for each route is provided in the Table 2 below. Average WMAPE for all routes is **13.8 %**. The opponent toughness has not changed significantly with 5 classes rather than 2 classes. The accuracy of the model is well illustrated by Figure 6, which shows the actual and predicted values on I-80 as a sample. Heat maps of other routes are provided in Figure 1 in appendix. 2018 game days are utilized for the validation set. After forecasting speed by DBN, we utilize Multi-EigenSpot algorithm again to find the hotspot clusters, both for predicted scenario and actual scenario. As can be seen in the Figure below, the predicted and actual values are nearly same showing the high accuracy of the proposed prediction method.

Table 4.2 Average forecasting errors (WMAPE in %).

Route	WMAPE
I-80	12.2
NE-31	10.6
US-6	11.4
US-77	18.1
NE-2	16.5

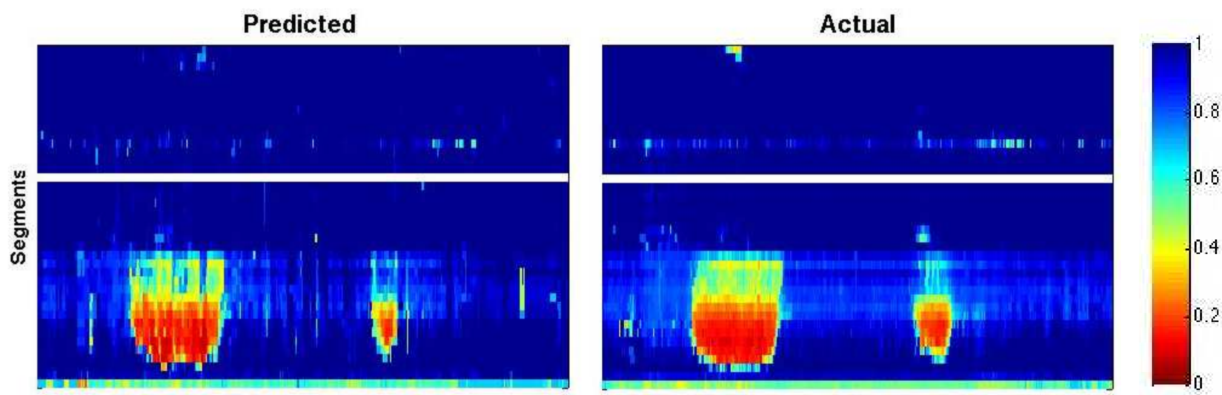


Figure 4.6 Predicted and actual hotspot clusters showing traffic congestion of game days on I-80 over the year 2018.

Conclusion

In recent years, traffic congestion has become a significant issue in urban areas. People in the United States travel extra billion hours and spent extra billion gallons of fuel due to traffic congestion every year. Thus, monitoring the performance of the transportation system play an important role in any transportation operation and planning strategy. Non-recurring congestion is called congestion caused by accidents, road work, special events or adverse weather. Non -

periodic events with a high attendance expected (such as planned special events or PSE), such as concerts, football games, etc., play an important role in delays in everyday transport.

The Nebraska Cornhuskers Football team's home is Memorial Stadium, Lincoln. It is commonly referred to on game days as Nebraska's "third largest city." With an extended capacity of more than 85,000, game days typically affect Lincoln's and neighboring regions ' travel patterns. This paper has evaluated the relationship between professional sports events and traffic congestion using INRIX data over past 5 years in Nebraska. This study demonstrates a systematic way to assess travel patterns and traffic hotspot clusters in football game days compared to normal days. 5 major routes in Nebraska are selected to conduct this study. Also, we used historical and real - time traffic data from the monitoring platform of INRIX TMC. Real - time traffic data, including speed and travel times, as well as location information, have been provided by INRIX, which is currently considered to be the largest traffic data set for crowds.

For detection hotspots, the Multi-EigenSpot algorithm which is the extension of EigenSpot algorithm was utilized. The spatiotemporal analysis of real world data on congestion cases has shown that the proposed method addresses the two main limitations of the existing EigenSpot algorithm (multiple cluster detection and visualization).

At the end, DBN approach to forecast the traffic congestion (hotspots) on game days is proposed. This approach is designed to provide predictions in real time even when incomplete data are present. In the presence of incomplete data, the structural EM algorithm is used both to reduce the structure dimension and to find the parameter's maximum probability estimates. The bootstrap filter is then used to predict. The experiment carried out on all game days and corresponding normal days from 2013 to 2017. The year 2018 is used for validation.

References

Amini S, … EP-DMP, 2016 undefined. Traffic management for major events. mediatum.ub.tum.de [Internet]. [cited 2018 Nov 7]; Available from: https://mediatum.ub.tum.de/doc/1324021/file.pdf#page=197

Barajas, V. L., Wang, Z., Kaiser, M., & Zhu, Z. (2017). Improving Estimates of Real-Time Traffic Speeds During Weather Events for Winter Maintenance Performance Measurement. Retrieved from https://trid.trb.org/view/1465615

Chase J, Geography MH-A, 1995 undefined. The spatial externality effects of football matches and rock concerts: The case of Portman Road Stadium, Ipswich, Suffolk. Elsevier [Internet]. [cited 2018 Nov 7]; Available from: https://www.sciencedirect.com/science/article/pii/014362289591060

Chrobok R, Kaumann O, … JW-EJ of, 2004 undefined. Different methods of traffic forecast based on real data. Elsevier [Internet]. [cited 2018 Nov 7]; Available from: https://www.sciencedirect.com/science/article/pii/S0377221703004788

Clark S. Traffic Prediction Using Multivariate Nonparametric Regression. J Transp Eng [Internet]. 2003 Mar [cited 2018 Nov 7];129(2):161–8. Available from: http://ascelibrary.org/doi/10.1061/%28ASCE%290733-947X%282003%29129%3A2%28161%29

Coates D, Management BH-PF and, 2003 undefined. Professional sports facilities, franchises and urban economic development. core.ac.uk [Internet]. [cited 2018 Nov 7]; Available from: https://core.ac.uk/download/pdf/7068694.pdf

Cookson, G., & Pishue, B. (2016). INRIX Global Traffic Scorecard. *Inrix Global Traffic Scorecard*, (February), 44. Retrieved from https://media.bizj.us/view/img/10360454/inrix2016trafficscorecarden.pdf

Dudek, C., Messer, C., Record, N. N.-T. R., & 1974, undefined. (n.d.). Incident detection on urban freeways. *Safetylit.Org*. Retrieved from https://www.safetylit.org/citations/index.php?fuseaction=citations.viewdetails&citationIds[]=citjournalarticle_483374_38

Duranton G, Turner MA. The Fundamental Law of Road Congestion: Evidence from US Cities. Am Econ Rev [Internet]. 2011 Oct [cited 2018 Nov 7];101(6):2616–52. Available from: http://pubs.aeaweb.org/doi/10.1257/aer.101.6.2616

Elhenawy, M., Chen, H., & Rakha, H. A. (2014). Dynamic travel time prediction using data clustering and genetic programming. *Transportation Research Part C: Emerging Technologies*, *42*, 82–98. https://doi.org/10.1016/J.TRC.2014.02.016

Feng, W., Bigazzi, A., Kothuri, S., & Bertini, R. (2010). Freeway sensor spacing and probe vehicle penetration: Impacts on travel time prediction and estimation accuracy. *Transportation Research Record: Journal of the Transportation Research Board*, (2178), 67–78. https://doi.org/10.3141/2178-08

FHWA. (2017). *2016 Urban Congestion Trends*. Retrieved from https://ops.fhwa.dot.gov/publications/fhwahop17010/fhwahop17010.pdf

Horvitz E, Apacible J, Sarin R, arXiv:1207.1352 LL preprint, 2012 undefined. Prediction, expectation, and surprise: Methods, designs, and study of a deployed traffic forecasting service. arxiv.org [Internet]. [cited 2018 Nov 7]; Available from: https://arxiv.org/abs/1207.1352

Huang H, Humphreys BR. NEW SPORTS FACILITIES AND RESIDENTIAL HOUSING MARKETS. J Reg Sci [Internet]. 2014 Sep [cited 2018 Nov 7];54(4):629–63. Available from: http://doi.wiley.com/10.1111/jors.12120

Humphreys B, Economics LZ-RS and U, 2015 undefined. Sports facilities, agglomeration, and public subsidies. Elsevier [Internet]. [cited 2018 Nov 7]; Available from: https://www.sciencedirect.com/science/article/pii/S0166046215000630

Ishak S, Al-Deek H. Performance Evaluation of Short-Term Time-Series Traffic Prediction Model. J Transp Eng [Internet]. 2002 Nov [cited 2018 Nov 7];128(6):490–8. Available from: http://ascelibrary.org/doi/10.1061/%28ASCE%290733-947X%282002%29128%3A6%28490%29

Kim, S., & Coifman, B. (2014). Comparing INRIX speed data against concurrent loop detector stations over several months. *Transportation Research Part C: Emerging Technologies*, *49*, 59–72. https://doi.org/10.1016/j.trc.2014.10.002

Kobayashi M, Suzuki K, Congress SN-18th IW, 2011 undefined. Utilization of probe data for traffic flow control. global-sei.com [Internet]. [cited 2018 Nov 7]; Available from: http://global-sei.com/its/common/pdf/2011_ITSWC_TS132-3167.pdf

Kulldorff M, Heffernan R, Hartman J, Assunção R, Mostashari F. A Space–Time Permutation Scan Statistic for Disease Outbreak Detection. Blower SM, editor. PLoS Med [Internet]. 2005 Feb 15 [cited 2018 Nov 7];2(3):e59. Available from: https://dx.plos.org/10.1371/journal.pmed.0020059

Kwoczek S, Martino S Di, DMS WN-, 2014 undefined. Predicting Traffic Congestion in Presence of Planned Special Events. pdfs.semanticscholar.org [Internet]. [cited 2018 Nov 7]; Available from: https://pdfs.semanticscholar.org/f234/f844608d5f0cfa0b70ae85bc875df08c98f8.pdf

Kwon J, Mauch M, Research PV-T, 2006 undefined. Components of congestion: Delay from incidents, special events, lane closures, weather, potential ramp metering gain, and excess demand. journals.sagepub.com [Internet]. [cited 2018 Nov 7]; Available from: http://journals.sagepub.com/doi/abs/10.1177/0361198106195900110

Leilei D, Zheng-liang S, … GJ-SS and, 2012 undefined. Study on traffic organization and management strategies for large special events. ieeexplore.ieee.org [Internet]. [cited 2018 Nov 7]; Available from: https://ieeexplore.ieee.org/abstract/document/6257222/

Mason C, Humphreys D, Geoforum SP-, 1983 undefined. The externality fields of football grounds: a case study of the Dell, Southampton. Elsevier [Internet]. [cited 2018 Nov 7]; Available from: https://www.sciencedirect.com/science/article/pii/0016718583900374

Mcleod, D. S., Morgan, G., & Mcleod, M. (2012). Florida's Mobility Performance Measures and Experience. *Transportation Research Board, 91st Annual Meeting*.

Miller M, computing CG-S international workshop on urban, 2012 undefined. Mining traffic incidents to forecast impact. dl.acm.org [Internet]. [cited 2018 Nov 7]; Available from: https://dl.acm.org/citation.cfm?id=2346502

Miwa, T., Ishiguro, Y., Yamamoto, T., & Morikawa, T. (2015). Allocation Planning for Probe Taxi Devices Aimed at Minimizing Losses to Travel Time Information Users. *Journal of Intelligent Transportation Systems*, *19*(4), 399–410. https://doi.org/10.1080/15472450.2014.995760

MoDOT. (2017). *Tracker: Measures of Departmental Performance*. Retrieved from http://www.modot.org/about/documents/Tracker_July17/July2017FinalTracker.pdf

Montanez, G., Amizadeh, S., AAAI, N. L.-, & 2015, undefined. (n.d.). Inertial Hidden Markov Models: Modeling Change in Multivariate Time Series. *Aaai.Org*. Retrieved from http://www.aaai.org/ocs/index.php/AAAI/AAAI15/paper/viewFile/9475/9470

Müller M. What makes an event a mega-event? Definitions and sizes. Leis Stud [Internet]. 2015 Nov 2 [cited 2018 Nov 7];34(6):627–42. Available from: http://www.tandfonline.com/doi/full/10.1080/02614367.2014.993333

National Academies of Sciences, Engineering, and M. (2008). *Cost-Effective Performance Measures for Travel Time Delay, Variation, and Reliability*. Washington, D.C.: National Academies Press. https://doi.org/10.17226/14167

Nam, D., Park, D., & Khamkongkhun, A. (2005). Estimation of value of travel time reliability. *Journal of Advanced Transportation*, *39*(1), 39–61. https://doi.org/10.1002/atr.5670390105

Nanthawichit C, … TN-… RJ of the, 2003 undefined. Application of probe-vehicle data for real-time traffic-state estimation and short-term travel-time prediction on a freeway. trrjournalonline.trb.org [Internet]. [cited 2018 Nov 7]; Available from: http://trrjournalonline.trb.org/doi/abs/10.3141/1855-06

Pan B, Demiryurek U, on CS-IC, 2012 undefined. Utilizing real-world transportation data for accurate traffic prediction. ieeexplore.ieee.org [Internet]. [cited 2018 Nov 7]; Available from: https://ieeexplore.ieee.org/abstract/document/6413867/

Pan B, Demiryurek U, … CS-DM (ICDM), 2013 undefined. Forecasting spatiotemporal impact of traffic incidents on road networks. ieeexplore.ieee.org [Internet]. [cited 2018 Nov 7]; Available from: https://ieeexplore.ieee.org/abstract/document/6729543/

Park D, Rilett L, Engineering GH-J of T, 1999 undefined. Spectral basis neural networks for real-time travel time forecasting. ascelibrary.org [Internet]. [cited 2018 Nov 7]; Available from: https://ascelibrary.org/doi/abs/10.1061/(ASCE)0733-947X(1999)125:6(515)

Persaud, B., Hall, F., Record, L. H.-T. R., & 1990, undefined. (n.d.). Congestion identification aspects of the McMaster incident detection algorithm. *Trid.Trb.Org*. Retrieved from https://trid.trb.org/view/352877

Pyun H, Hall J. Does the presence of professional football cause crime in a city? evidence from Pontiac. 2016;

Rappaport J. Productivity, congested commuting, and metro size. 2016 [cited 2018 Nov 7]; Available from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2727441

Sadrsadat H, CongressTransCoreITS SY-18th IW, 2011 undefined. Probability of Real-Time Data as a Function of Hourly Volume, Assessment of the I-95 Vehicle Probe Project Data. trid.trb.org [Internet]. [cited 2018 Nov 7]; Available from: https://trid.trb.org/view/1215736

Sharma, A., Ahsani, V., & Rawat, S. (2017). *Evaluation of Opportunities and Challenges of Using INRIX Data for Real-Time Performance Monitoring and Historical Trend Assessment*. Reports and White Papers. 24. Retrieved from https://lib.dr.iastate.edu/ccee_reports/24/

Tavassoli Hojati A, Ferreira L, Washington S, Charles P, Shobeirinejad A. Reprint of: Modelling the impact of traffic incidents on travel time reliability. Transp Res Part C Emerg Technol [Internet]. 2016 Sep 1 [cited 2018 Nov 7];70:86–97. Available from: https://www.sciencedirect.com/science/article/pii/S0968090X16300833

Vanajakshi L, Symposium LR-IV, 2004 undefined, 2004 undefined. A comparison of the performance of artificial neural networks and support vector machines for the prediction of traffic speed. ieeexplore.ieee.org [Internet]. [cited 2018 Nov 7]; Available from: https://ieeexplore.ieee.org/abstract/document/1336380/

Vesal Ahsani, Mostafa Amin-Naseri, Skylar Knickerbocker & Anuj Sharma (2019) Quantitative analysis of probe data characteristics: Coverage, speed bias and congestion detection precision, Journal of Intelligent Transportation Systems, 23:2, 103-119, DOI: 10.1080/15472450.2018.1502667

Wu C, Ho J, intelligent DL-I transactions on, 2004 undefined. Travel-time prediction with support vector regression. ieeexplore.ieee.org [Internet]. [cited 2018 Nov 7]; Available from: https://ieeexplore.ieee.org/abstract/document/1364002/

Young S. Real-Time Traffic Operations Data Using Vehicle Probe Technology [Internet]. 2007 Mid-Continent Transportation Research Symposium. 2007. p. 8p. Available from: http://www.ctre.iastate.edu/pubs/midcon2007/YoungVehicleProbe.pdf

CHAPTER 5. CONSOLIDATED CONCLUSIONS

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 dissertation documents a study evaluating the opportunities and challenges of using INRIX data in Midwest. The objective of this study is threefold: (1) quantitative analysis of probe data characteristics: coverage, speed bias, and congestion detection precision (2) improving probe based congestion performance metrics accuracy by using change point detection, and (3) assessing the impact of game day schedule and opponents on travel patterns and route choice.

The first study utilizes real-time and historical traffic data which are collected through two different data sources; INRIX and Wavetronix. The INRIX probe data stream is compared to a benchmarked Wavetronix sensor data source in order to explain some of the challenges and opportunities associated with using wide area probe data. In the following, INRIX performance is thoroughly evaluated in three major criteria: coverage and penetration, speed bias, congestion detection precision. In terms of coverage, INRIX covered almost all road networks in Iowa, however, it mostly provides real-time data on the interstates. INRIX speed bias analysis, found meaningful interpretations of influential factors in INRIX speed bias. These findings further our understanding of this probe-sourced data. In particular, INRIX speed value, time of day, truck-AADT, number of lanes, type of TMC segment, and segment length had significant effects on the magnitude of speed bias. For the congestion detection analysis, three factors of type of congestion, type of TMC segment, and segment length were thoroughly examined.

The second study focuses on congested hour and the number of congested events as two performance measures. To improve the accuracy and reliability of performance measures, this study addresses a big issue in calculating congested hour. For both performance measures, a traditional fixed-threshold congestion detection method was initially used. The lack of efficiency and high number of errors in congestion detection by probe data and the lack of overlaps between probe congested hour data and Wavetronix inspired the development of a robust solution for congestion detection. After that, a novel traffic congestion identification method is proposed in this paper and in the following, the number of congested events and congested hour are computed as the performance measures.

After evaluating the accuracy and reliability of INRIX probe data in chapter 2 and 3, the purpose of the last study in chapter 4 is to find out the impacts of game days on travel pattern and route choice behaviors. This paper has evaluated the relationship between professional sports events and traffic congestion using INRIX data over past 5 years in Nebraska. This study demonstrates a systematic way to assess travel patterns and traffic hotspot clusters on football game days compared to normal days. 5 major routes in Nebraska are selected to conduct this study. For detection hotspots, the Multi-EigenSpot algorithm which is the extension of EigenSpot algorithm was utilized. At the end, dynamic Bayesian network approach to forecast the traffic congestion (hotspots) on game days is proposed. It is shown that the impacts vary depending on the schedule and also the opponents.

Overall, this dissertation evaluates probe-sourced streaming data from INRIX, to study its characteristics as a data source, challenges and opportunities associated with using wide area probe data, and finally make use of INRIX as a reliable data source for travel behavior analysis.

REFERENCES

Adu-Gyamfi, Y. O., Sharma, A., Knickerbocker, S., Hawkins, N., & Jackson, M. (2017). Framework for Evaluating the Reliability of Wide-Area Probe Data. *Transportation Research Record: Journal of the Transportation Research Board*, (2643), 93–104. https://doi.org/10.3141/2643-11

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*, *2308*, 167–172. https://doi.org/10.3141/2308-18

Araghi, B. N., Hammershøj Olesen, J., Krishnan, R., Tørholm Christensen, L., & Lahrmann, H. (2015). Reliability of Bluetooth Technology for Travel Time Estimation. *Journal of Intelligent Transportation Systems*, *19*(3), 240–255. https://doi.org/10.1080/15472450.2013.856727

Bell, M. G. H., & Iida, Y. (2003). *The network reliability of transport : proceedings of the 1st International Symposium on Transportation Network Reliability (INSTR)*. Pergamon.

Belzowski, Bruce M., Ekstrom, A. (2014). Stuck in Traffic: Analyzing Real Time Traffic Capabilities of Personal Navigation Devices and Traffic Phone Applications. Retrieved from https://deepblue.lib.umich.edu/bitstream/handle/2027.42/102509/102984.pdf?sequence=1&isAllowed=y

Chakraborty, P., Adu-Gyamfi, Y. O., Poddar, S., Ahsani, V., Sharma, A., & Sarkar, S. (2018). Traffic Congestion Detection from Camera Images using Deep Convolution Neural Networks. *Transportation Research Record: Journal of the Transportation Research Board*, 036119811877763. https://doi.org/10.1177/0361198118777631

Coifman, B. (2002). Estimating travel times and vehicle trajectories on freeways using dual loop detectors. *Transportation Research Part A: Policy and Practice*, *36*(4), 351–364. https://doi.org/10.1016/S0965-8564(01)00007-6

Cookson, G., & Pishue, B. (2016). INRIX Global Traffic Scorecard. *Inrix Global Traffic Scorecard*, (February), 44. Retrieved from https://media.bizj.us/view/img/10360454/inrix2016trafficscorecarden.pdf

Day, C. M., Li, H., Richardson, L. M., Howard, J., Platte, T., Sturdevant, J. R., & Bullock, D. M. (2017). Detector-Free Optimization of Traffic Signal Offsets with Connected Vehicle Data. *Transportation Research Record: Journal of the Transportation Research Board*, *2620*, 54–68. https://doi.org/10.3141/2620-06

Elhenawy, M., Chen, H., & Rakha, H. A. (2014). Dynamic travel time prediction using data clustering and genetic programming. *Transportation Research Part C: Emerging Technologies*, *42*, 82–98. https://doi.org/10.1016/J.TRC.2014.02.016

Eshragh, S., Young, S. E., Sharifi, E., Hamedi, M., & Sadabadi, K. F. (2017). Indirect Validation of Probe Speed Data on Arterial Corridors. *Transportation Research Record: Journal of the Transportation Research Board*, *2643*, 105–111.

https://doi.org/10.3141/2643-12

FDOT. (2012). *Probe Data Analysis Evaluation of NAVTEQ, TrafficCast, and INRIX ® Travel Time System Data in the Tallahassee Region Evaluation of NAVTEQ, TrafficCast, and INRIX ® Travel Time System Data*. Retrieved from http://www.fdot.gov/traffic/ITS/Projects_Deploy/2012-03-26_Probe_Data_Analysis_v2-0.pdf

Feng, W., Bigazzi, A., Kothuri, S., & Bertini, R. (2010). Freeway sensor spacing and probe vehicle penetration: Impacts on travel time prediction and estimation accuracy. *Transportation Research Record: Journal of the Transportation Research Board*, (2178), 67–78. https://doi.org/10.3141/2178-08

FHWA. (2017). *2016 Urban Congestion Trends*. Retrieved from https://ops.fhwa.dot.gov/publications/fhwahop17010/fhwahop17010.pdf

Gong, L., & Fan, W. (2017). Applying Travel-Time Reliability Measures in Identifying and Ranking Recurrent Freeway Bottlenecks at the Network Level. https://doi.org/10.1061/JTEPBS.0000072

Haghani, A., Hamedi, M., & Sadabadi, K. F. (2009). *I-95 Corridor Coalition Vehicle Probe Project: Validation of INRIX Data July-September 2008*. Retrieved from http://www.i95coalition.org/wp-content/uploads/2015/02/I-95-CC-Final-Report-Jan-28-2009.pdf

INRIX. (2015). *INRIX | I-95 Corridor Coalition: Vehicle Probe Project Data Validation Summary*. Retrieved from http://inrix.com/wp-content/uploads/2016/11/INRIX-I-95-VPP-Data-Summary-Validation-1.pdf

IowaDOT. (2017). *Advanced Traveler Management System/Advanced Traveler Information System Combination*. Retrieved from https://iowadot.gov/purchasing/20227pro.pdf

Kim, S., & Coifman, B. (2014). Comparing INRIX speed data against concurrent loop detector stations over several months. *Transportation Research Part C: Emerging Technologies*, *49*, 59–72. https://doi.org/10.1016/j.trc.2014.10.002

Lattimer, C., & Glotzbach, G. (2012). EVALUATION OF THIRD-PARTY TRAVEL TIME DATA IN TALLAHASSEE, FL. Retrieved from https://itswc.confex.com/itswc/AM2012/webprogram/Paper10870.html

Lomax, T., Schrank, D., Turner, S., & Margiotta, R. (2003). SELECTING TRAVEL RELIABILITY MEASURES. Retrieved from https://static.tti.tamu.edu/tti.tamu.edu/documents/TTI-2003-3.pdfMcleod, D. S., Morgan, G., & Mcleod, M. (2012). Florida's Mobility Performance Measures and Experience. *Transportation Research Board, 91st Annual Meeting*.

Lu, C., & Dong, J. (2018). Estimating freeway travel time and its reliability using radar sensor data. *Transportmetrica B: Transport Dynamics*, *6*(2), 97–114. https://doi.org/10.1080/21680566.2017.1325785

MoDOT. (2017). *Tracker: Measures of Departmental Performance*. Retrieved from http://www.modot.org/about/documents/Tracker_July17/July2017FinalTracker.pdf

Persaud, B., Hall, F., Record, L. H.-T. R., & 1990, undefined. (n.d.). Congestion identification aspects of the McMaster incident detection algorithm. *Trid.Trb.Org*. Retrieved from https://trid.trb.org/view/352877

Pu, W. (2012). Analytic Relationships Between Travel Time Reliability Measures. *Transportation Research Record: Journal of the Transportation Research Board*, *2254*(1), 122–130. https://doi.org/10.3141/2254-13

Rakha, H., El-Shawarby, I., & Arafeh, M. (2010). Trip travel-time reliability: Issues and proposed solutions. *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*, *14*(4), 232–250. https://doi.org/10.1080/15472450.2010.517477

Remias, S., Brennan, T., Day, C., Summers, H., Cox, E., Horton, D., & Bullock, D. (2013). *2012 Indiana Mobility Report*. Retrieved from https://docs.lib.purdue.edu/cgi/viewcontent.cgi?article=1004&context=imr

Schrank., D., Eisele., B., Lomax., T., & Bak., J. (2015). *2015 Urban Mobility Scorecard*. *Texas A&M Transportation Institue* (Vol. 39). https://doi.org/DTRT06-G-0044

Schrank, D., Eisele, B., & Lomax, T. (2012). *TTI's 2012 urban mobility report*. *Texas A&M Transportation Institute*. Retrieved from http://d2dtl5nnlpfr0r.cloudfront.net/tti.tamu.edu/documents/mobility-report-2012.pdf

Sekuła, P., Marković, N., Laan, Z. Vander, & Sadabadi, K. F. (2017). Estimating Historical Hourly Traffic Volumes via Machine Learning and Vehicle Probe Data: A Maryland Case Study. Retrieved from http://arxiv.org/abs/1711.00721

Sharifi, Elham & Hamedi, Masoud & Haghani, Ali & Sadrsadat, H. (2011). Analysis of Vehicle Detection Rate for Bluetooth Traffic Sensors: A Case Study in Maryland and Delaware.

Sharma, A., Ahsani, V., & Rawat, S. (2017). *Evaluation of Opportunities and Challenges of Using INRIX Data for Real-Time Performance Monitoring and Historical Trend Assessment*. Reports and White Papers. 24. Retrieved from https://lib.dr.iastate.edu/ccee_reports/24/

Subrat Mahapatra, Matthew Wolniak, E. B., & Sadabadi, K. F. (2015). *2015 Maryland State Highway Mobility Report*.

Venkatanarayana, R. (2017). *Considerations for Calculating Arterial System Performance Measures In Virginia*. Retrieved from http://www.virginiadot.org/vtrc/main/online_reports/pdf/17-r2.pdf

Vesal Ahsani, Mostafa Amin-Naseri, Skylar Knickerbocker & Anuj Sharma (2019) Quantitative analysis of probe data characteristics: Coverage, speed bias and congestion detection precision, Journal of Intelligent Transportation Systems, 23:2, 103-119, DOI: 10.1080/15472450.2018.1502667

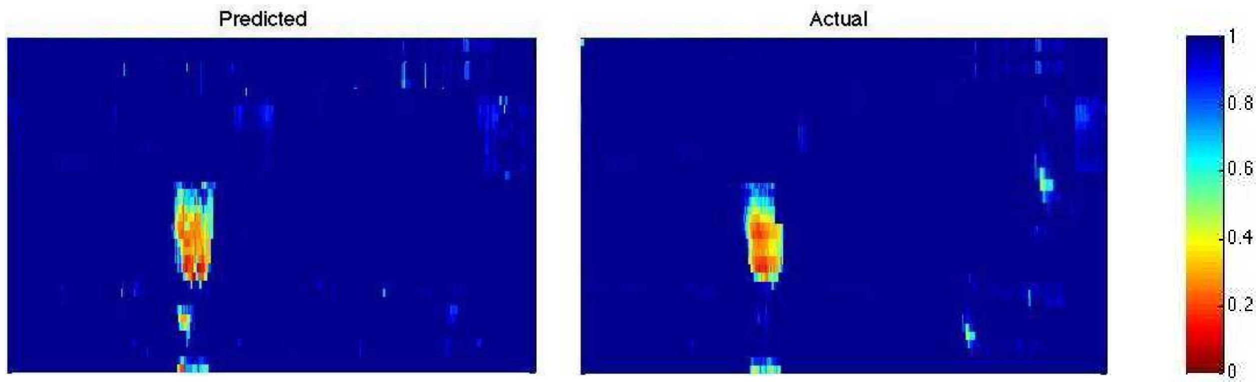
WSDOT. (2013). *The 2013 Corridor Capacity Summary*. Retrieved from http://wsdot.wa.gov/publications/fulltext/graynotebook/CCS13.pdf

WSDOT. (2014). *Gray Notebook 52 - For the Quarter Ending December 31, 2013*. Retrieved from http://wsdot.wa.gov/publications/fulltext/graynotebook/Dec13.pdf

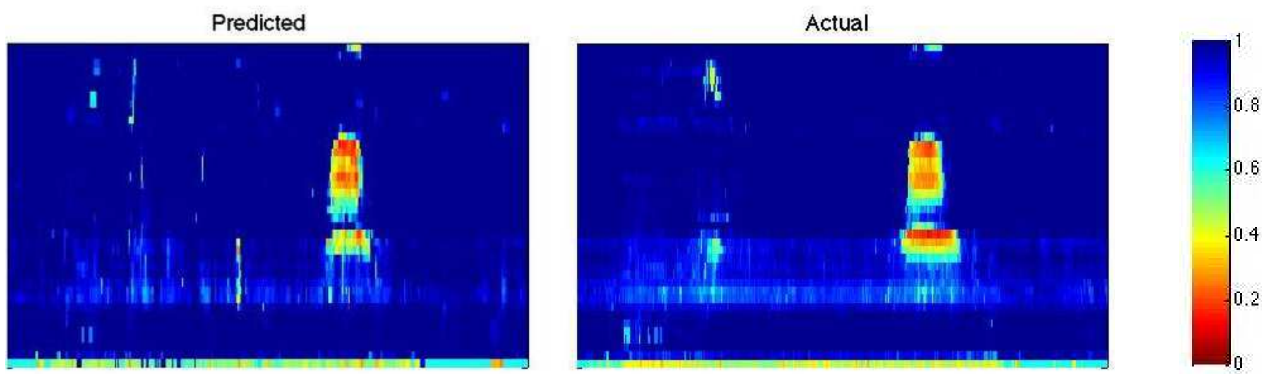
Young, S. (2007). Real-Time Traffic Operations Data Using Vehicle Probe Technology. *2007 Mid-Continent Transportation Research Symposium*. Retrieved from http://www.ctre.iastate.edu/pubs/midcon2007/YoungVehicleProbe.pdf

Zheng, F., Li, J., van Zuylen, H., Liu, X., & Yang, H. (2018). Urban travel time reliability at different traffic conditions. *Journal of Intelligent Transportation Systems*, *22*(2), 106–120. https://doi.org/10.1080/15472450.2017.1412829

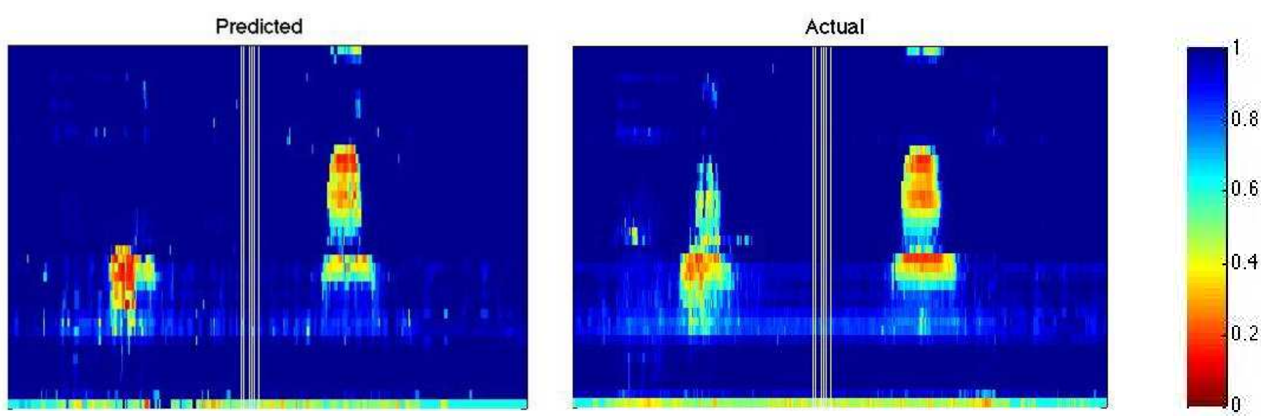
APPENDIX: PREDICTED HOTSPOT CLUSTERS USING DBN



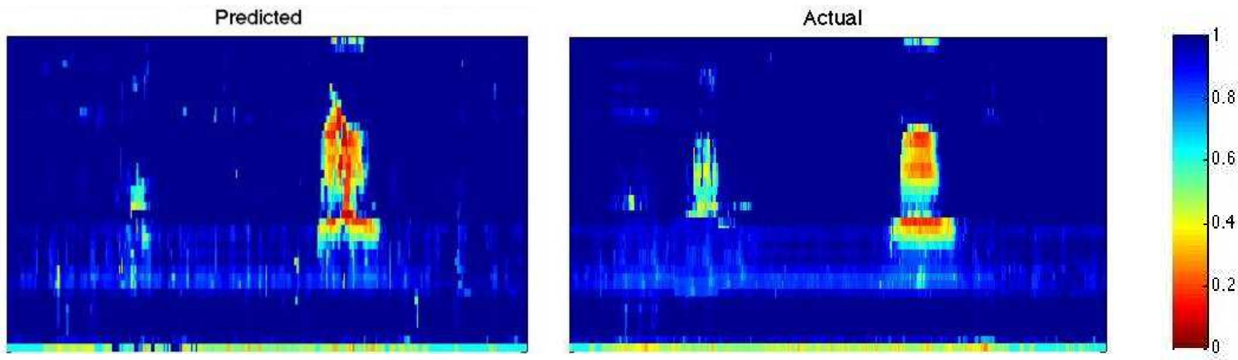
<u>NE-31</u>



<u>US-6</u>



<u>US-77</u>



NE-2

Figure 1 Predicted and actual hotspot clusters showing traffic congestion of game days on 4 routes of NE-31, US-6, US-77, and NE-2 over 2018.