University Transportation Research Center - Region 2

Final Report

Data Driven Performance Measures for Effective Management of Complex Transportation Networks

Performing Organization: Rutgers University

February, 2014

Sponsor:
University Transportation Research Center - Region 2

University Transportation Research Center - Region 2

The Region 2 University Transportation Research Center (UTRC) is one of ten original University Transportation Centers established in 1987 by the U.S. Congress. These Centers were established with the recognition that transportation plays a key role in the nation's economy and the quality of life of its citizens. University faculty members provide a critical link in resolving our national and regional transportation problems while training the professionals who address our transportation systems and their customers on a daily basis.

The UTRC was established in order to support research, education and the transfer of technology in the field of transportation. The theme of the Center is "Planning and Managing Regional Transportation Systems in a Changing World." Presently, under the direction of Dr. Camille Kamga, the UTRC represents USDOT Region II, including New York, New Jersey, Puerto Rico and the U.S. Virgin Islands. Functioning as a consortium of twelve major Universities throughout the region, UTRC is located at the CUNY Institute for Transportation Systems at The City College of New York, the lead institution of the consortium. The Center, through its consortium, an Agency-Industry Council and its Director and Staff, supports research, education, and technology transfer under its theme. UTRC's three main goals are:

Research

The research program objectives are (1) to develop a theme based transportation research program that is responsive to the needs of regional transportation organizations and stakeholders, and (2) to conduct that program in cooperation with the partners. The program includes both studies that are identified with research partners of projects targeted to the theme, and targeted, short-term projects. The program develops competitive proposals, which are evaluated to insure the mostresponsive UTRC team conducts the work. The research program is responsive to the UTRC theme: "Planning and Managing Regional Transportation Systems in a Changing World." The complex transportation system of transit and infrastructure, and the rapidly changing environment impacts the nation's largest city and metropolitan area. The New York/New Jersey Metropolitan has over 19 million people, 600,000 businesses and 9 million workers. The Region's intermodal and multimodal systems must serve all customers and stakeholders within the region and globally.Under the current grant, the new research projects and the ongoing research projects concentrate the program efforts on the categories of Transportation Systems Performance and Information Infrastructure to provide needed services to the New Jersey Department of Transportation, New York City Department of Transportation, New York Metropolitan Transportation Council , New York State Department of Transportation, and the New York State Energy and Research Development Authorityand others, all while enhancing the center's theme.

Education and Workforce Development

The modern professional must combine the technical skills of engineering and planning with knowledge of economics, environmental science, management, finance, and law as well as negotiation skills, psychology and sociology. And, she/he must be computer literate, wired to the web, and knowledgeable about advances in information technology. UTRC's education and training efforts provide a multidisciplinary program of course work and experiential learning to train students and provide advanced training or retraining of practitioners to plan and manage regional transportation systems. UTRC must meet the need to educate the undergraduate and graduate student with a foundation of transportation fundamentals that allows for solving complex problems in a world much more dynamic than even a decade ago. Simultaneously, the demand for continuing education is growing – either because of professional license requirements or because the workplace demands it – and provides the opportunity to combine State of Practice education with tailored ways of delivering content.

Technology Transfer

UTRC's Technology Transfer Program goes beyond what might be considered "traditional" technology transfer activities. Its main objectives are (1) to increase the awareness and level of information concerning transportation issues facing Region 2; (2) to improve the knowledge base and approach to problem solving of the region's transportation workforce, from those operating the systems to those at the most senior level of managing the system; and by doing so, to improve the overall professional capability of the transportation workforce; (3) to stimulate discussion and debate concerning the integration of new technologies into our culture, our work and our transportation systems; (4) to provide the more traditional but extremely important job of disseminating research and project reports, studies, analysis and use of tools to the education, research and practicing community both nationally and internationally; and (5) to provide unbiased information and testimony to decision-makers concerning regional transportation issues consistent with the UTRC theme.

UTRC-RF Project No: 49111-25-23

Project Date: February 2014

Project Title: Data Driven Performance Measures for Effective Management of Complex Transportation Networks

Project's Website:
http://www.utrc2.org/research/projects/data-driven-performance-measures

Principal Investigator(s):
Dr. Kaan Ozbay
Professor , Department of Civil and Urban Engineering
NYU-Poly and Center for Urban Science and Progress (CUSP)
Email: ko772@poly.edu

Dr. Hani Nassif
Rutgers University
Email: nassif@rci.rutgers.edu

Co-Author(s)
Hong Yang, Sami Demiroluk, Ender Morgul, Bekir Bartinering

Performing Organization: Rutgers University

Sponsor:
University Transportation Research Center - Region 2, A Regional University Transportation Center sponsored by the U.S. Department of Transportation's Research and Innovative Technology Administration

To request a hard copy of our final reports, please send us an email at utrc@utrc2.org

Mailing Address:
University Transportation Reserch Center
The City College of New York
Marshak Hall, Suite 910
160 Convent Avenue
New York, NY 10031
Tel: 212-650-8051, Fax: 212-650-8374
Web: www.utrc2.org

Board of Directors

The UTRC Board of Directors consists of one or two members from each Consortium school (each school receives two votes regardless of the number of representatives on the board). The Center Director is an ex-officio member of the Board and The Center management team serves as staff to the Board.

City University of New York
Dr. Hongmian Gong - Geography
Dr. Neville A. Parker - Civil Engineering

Clarkson University
Dr. Kerop D. Janoyan - Civil Engineering

Columbia University
Dr. Raimondo Betti - Civil Engineering
Dr. Elliott Sclar - Urban and Regional Planning

Cornell University
Dr. Huaizhu (Oliver) Gao - Civil Engineering
Dr. Mark A. Turnquist - Civil Engineering

Hofstra University
Dr. Jean-Paul Rodrigue - Global Studies and Geography

Manhattan College
Dr. Anirban De - Civil & Environmental Engineering
Dominic Esposito - Research Administration

New Jersey Institute of Technology
Dr. Steven Chien - Civil Engineering
Dr. Joyoung Lee - Civil & Environmental Engineering

New York Institute of Technology
Dr. Nada Marie Anid - Engineering & Computing Sciences
Dr. Marta Panero - Engineering & Computing Sciences

New York University
Dr. Mitchell L. Moss - Urban Policy and Planning
Dr. Rae Zimmerman - Planning and Public Administration

Polytechnic Institute of NYU
Dr. John C. Falcocchio - Civil Engineering
Dr. Kaan Ozbay - Civil Engineering

Rensselaer Polytechnic Institute
Dr. José Holguín-Veras - Civil Engineering
Dr. William "Al" Wallace - Systems Engineering

Rochester Institute of Technology
Dr. J. Scott Hawker - Software Engineering
Dr. James Winebrake -Science, Technology, & Society/Public Policy

Rowan University
Dr. Yusuf Mehta - Civil Engineering
Dr. Beena Sukumaran - Civil Engineering

Rutgers University
Dr. Robert Noland - Planning and Public Policy

State University of New York
Michael M. Fancher - Nanoscience
Dr. Catherine T. Lawson - City & Regional Planning
Dr. Adel W. Sadek - Transportation Systems Engineering
Dr. Shmuel Yahalom - Economics

Stevens Institute of Technology
Dr. Sophia Hassiotis - Civil Engineering
Dr. Thomas H. Wakeman III - Civil Engineering

Syracuse University
Dr. Riyad S. Aboutaha - Civil Engineering
Dr. O. Sam Salem - Construction Engineering and Management

The College of New Jersey
Dr. Thomas M. Brennan Jr. - Civil Engineering

University of Puerto Rico - Mayagüez
Dr. Ismael Pagán-Trinidad - Civil Engineering
Dr. Didier M. Valdés-Díaz - Civil Engineering

UTRC Consortium Universities

The following universities/colleges are members of the UTRC consortium.

City University of New York (CUNY)
Clarkson University (Clarkson)
Columbia University (Columbia)
Cornell University (Cornell)
Hofstra University (Hofstra)
Manhattan College
New Jersey Institute of Technology (NJIT)
New York Institute of Technology (NYIT)
New York University (NYU)
Polytechnic Institute of NYU (Poly)
Rensselaer Polytechnic Institute (RPI)
Rochester Institute of Technology (RIT)
Rowan University (Rowan)
Rutgers University (Rutgers)*
State University of New York (SUNY)
Stevens Institute of Technology (Stevens)
Syracuse University (SU)
The College of New Jersey (TCNJ)
University of Puerto Rico - Mayagüez (UPRM)

** Member under SAFETEA-LU Legislation*

UTRC Key Staff

Dr. Camille Kamga: *Director, UTRC*
Assistant Professor of Civil Engineering, CCNY

Dr. Robert E. Paaswell: *Director Emeritus of UTRC and Distin*guished Professor of Civil Engineering, The City College of New York

Herbert Levinson: *UTRC Icon Mentor, Transportation Consultant and Professor Emeritus of Transportation*

Dr. Ellen Thorson: *Senior Research Fellow, University Transportation Research Center*

Penny Eickemeyer: *Associate Director for Research, UTRC*

Dr. Alison Conway: *Associate Director for New Initiatives and Assistant Professor of Civil Engineering*

Nadia Aslam: *Assistant Director for Technology Transfer*

Dr. Anil Yazici: *Post-doc/ Senior Researcher*

Nathalie Martinez: *Research Associate/Budget Analyst*

TECHNICAL REPORT STANDARD TITLE PAGE

1. Report No.	2.Government Accession No.	3. Recipient's Catalog No.

4. Title and Subtitle	
Data Driven Performance Measures for Effective Management of Complex Transportation Networks	5. Report Date 2/1/2014
	6. Performing Organization Code
7. Author(s) Kaan Ozbay, Hong Yang, Sami Demiroluk, Ender Morgul, Bekir Bartin	8. Performing Organization Report No.
9. Performing Organization Name and Address Rutgers Intelligent Transportation Systems Laboratory (RITS) / Rutgers Infrastructure Monitoring and Evaluation (RIME) Group CoRE Building 7th Floor, Busch Campus Rutgers, The State University of New Jersey 96 Frelinghuysen Road, Piscataway, NJ 08854	10. Work Unit No. 11. Contract or Grant No. RF 49111-25-23
12. Sponsoring Agency Name and Address University Transportation Research Center, Region 2 The City College of New York, Marshak 910 137th Street and Convent Avenue. New York, NY 10031	13. Type of Report and Period Covered Final Report (January 1 2012 – July 31 2013) 14. Sponsoring Agency Code

15. Supplementary Notes

16. Abstract

This research aims to explore performance measures quantified based on different transportation data sources. It examined the major performance measures that can help describe both traffic operations and safety conditions. The available data sources that can be used to derive the performance measures were investigated. Particularly, performance measures related to travel time reliability, incident duration, and secondary crashes have been emphasized. Data-driven methodologies for performance quantification have been proposed for each category. Specifically, improved travel time estimation approaches based on probe vehicle data have been developed for traffic delays and travel time reliability analysis. Second, structure learning algorithms based on Bayesian Networks approach were proposed to mine incident records and predict incident durations that can be used for traffic incident management. Finally, both infrastructure sensor and virtual-sensor-based approaches have been developed to explore traffic sensor data as well as on-line traffic information for identifying secondary crashes. The results shown through the use of actual case studies illustrated that how key performance measures can be used to assess the performance of their systems. This research suggests that by mining existing traffic data sources, more performance measures can be more efficiently and accurately quantified without major expenditures in the deployment of new data collection technologies.

17. Key Words	18. Distribution Statement
Performance measures, traffic data, sensor data, travel time reliability, incidents, secondary crashes	

19. Security Classif (of this report)	20. Security Classif. (of this page)	21. No of Pages	22. Price
Unclassified	Unclassified		

Form DOT F 1700.7 (8-69)

Disclaimer

Table of Contents

1. INTRODUCTION 5
   1.1. Research Problem and Motivation 5
   1.2. Objectives and Goals 6
2. LITERATURE REVIEW 8
3. DATA SOURCES AND DATA ASSEMBLY 12
   3.1. Traffic Volume Counts 12
   3.2. Probe Vehicle Data 13
   3.3. Statewide Crash Records 14
   3.4. Weigh-In-Motion (WIM) Data 15
   3.5. Infrastructure-based Sensor Data 16
   3.6. On-Line Open Source Data 17
4. DATA DRIVEN PERFORMANCE MEASURES 18
   4.1. Traffic Congestion and Reliability Measures 19
      4.1.1. Travel Time Reliability 19
      4.1.2. Travel Delay 21
   4.2. Traffic Safety Performance Measures 21
   4.3. Incident Management Performance Measures 22
      4.3.1. Incident Duration 22
      4.3.2. Secondary Crashes 22
5. PROPOSED METHODOLOGIES FOR THE QUANTIFICATION OF SELECTED PERFORMANCE MEASURES 24
   5.1. Travel Time Estimation 24
      5.1.1. Problem Statement 24
      5.1.2. Travel Time Estimation Methodology 25

5.1.3. Probe Vehicle Based Travel Time Algorithm 28

5.1.4. Case Studies 31

5.1.5. Travel Time Comparisons... 34

5.1.6. Summary 35

5.2. Assessing Travel Time Reliability 36

5.3. Incident Duration Estimation 38

5.3.1. Problem Definition.. 38

5.3.2. Modeling Background 41

5.3.3. Case Study 44

5.3.4. Summary 54

5.4. Identification of Secondary Crashes 55

5.4.1. Secondary Crash Definition.. 56

5.4.2. Impact Range of Primary Incidents 57

5.4.3. Identifying Secondary Crashes 60

5.4.4. Case Study 63

5.4.5. Summary 69

5.5. On-Line Scalable Analysis of Performance Measures.. 70

5.5.1. Travel Time Reliability Application Example.. 71

5.5.2. On-Line Scalable Identification of Secondary Crashes 72

6. CONCLUSION and SUMMARY 76

7. REFERENCES 78

List of Tables

Table 3.1 Example of traffic volume counts collected at different sites (source: NJDOT).......... 12

Table 3.2 Description of sample probe vehicle data.. 13

Table 4.1 Travel time on selected routes during peak hours 19

Table 5.1 Pseudo code for filtering and aggregating travel time measurements obtained probe vehicles 30

Table 5.2 Comparison of travel time estimations based on different time intervals 34

Table 5.3 Annual reliability measures for transportation performance evaluation 36

Table 5.4 Description of the model variables... 46

Table 5.5 Summary statistics of the incident duration data.. 46

Table 5.6 BIC scores and accuracies of prediction models 51

Table 5.7 Performance of the model for 2011 data with adaptive learning................................. 55

List of Figures

Figure 3.1 Example of linking different crash information (source: NJDOT) 14

Figure 3.2 Weekday average information on vehicle classification at a WIM site in NJ [13] 15

Figure 3.3 RTMS on NJ Turnpike and Garden State Parkway (source: NJTA).......................... 16

Figure 3.4 Obtaining real-time speed data by deploying virtual sensors on maps [20]................. 18

Figure 5.1 Schematic of travel time analysis between two toll plazas 25

Figure 5.2 Estimate target link travel time between i and j based on other adjacent OD pairs.... 27

Figure 5.3 Analyzed links in selected section between Interchange 9 and Interchange 5............ 31

Figure 5.4 Travel time estimation under normal conditions... 32

Figure 5.5 Travel time estimation under incident conditions 33

Figure 5.6 Comparisons between travel times based on RTMS and probe vehicles (7A to 8) 35

Figure 5.7 Variations of travel time reliability measures by month 38

Figure 5.8 Use of BNs for real-time incident duration prediction... 40

Figure 5.9 Example BN 41

Figure 5.10 BN structures from (a) Naïve Bayes, (b) TAN and (c) K2 50

Figure 5.11 Adaptive learning mechanism in the BN model.. 53

Figure 5.12 Percent increase in prediction accuracy of the model with adaptive learning with monthly and quarterly 2011 data 55

Figure 5.13 Defining secondary crashes under some typical conditions [52] 57
Figure 5.14 Speed contour plots: (a) without incident, (b) with incident..................................... 58
Figure 5.15 Converting SCP into a binary speed contour plot 60
Figure 5.16 Binary speed contour plot with multiple crashes 61
Figure 5.17 Estimate lines between a prior crash and a possible secondary crash....................... 61
Figure 5.18 Visual depiction of the proposed algorithm that determines the relationship between two crashes.. 63
Figure 5.19 Schematic of the studied freeway section. 64
Figure 5.20 Identified secondary crashes using different methods.. 68
Figure 5.21 Virtual sensor speed versus infrastructure-based sensor output. 70
Figure 5.22 Buffer index analysis using virtual sensor data. 72
Figure 5.23 Framework of using virtual sensor data for identifying secondary crash. 73
Figure 5.24 Example of potential primary-secondary crashes shown on 511NJ map. 74
Figure 5.25 A crash with significant impact (10-mile maximum queue; queue presented 3+ hours). 74

1. INTRODUCTION

1.1. Research Problem and Motivation

In the past transportation data was collected through the limited deployment of infrastructure-based sensors and manual spot counts and surveys. These "planning oriented data collection" approaches continued to be used extensively for decision making in transportation projects. However, with the advent of Intelligent Transportation Systems, an increasing amount of on-line operational transportation data for every component of a transportation system continue to become readily available. A wide variety of new technologies—from probe-based data captured by freely roaming cars and buses to electronic payment systems that can nearly capture every detail of a car, bus or train commuter's trip—provide us new opportunities for improved monitoring and management of our complex transportation systems. Thanks in large part to on-line data being collected on a nearly 24/7 basis, researchers and transportation managers alike are now able to quantify a number of realistic "**performance measures**" that allow transportation agencies to make timely and proactive decisions. Here are four of the major categories of performance measures identified by recent research:

1. Preservation of assets mainly dealing with infrastructure conditions
2. Mobility and accessibility
3. Operations and maintenance
4. Safety

Previously, performance measurements have been utilized to develop long-term plans. Likewise, on-line transportation data have historically been used for short-run operational decisions regarding the operation of traffic adaptive signal systems or the real-time management of traffic incidents. **In this project we propose the integration of these new on-line operational data with performance measurements not only to make long-term strategic planning decisions but also for the execution of relatively short-term tactical decisions.**

Among the myriad of new on-line transportation data sources, traffic flow and safety data are the two most significant categories that can be used to assess *system performance* and make better tactical decisions on a day-to-day basis. For example, if there are data about day-to-day traffic conditions and accidents while a major construction project is active on a given section of a network, *tactical performance measures* of the number of accidents around the work zone, the time it takes to clear them, and travel times can be used to re-adjust the work zone configuration and the incident response operations to minimize *delays* and improve *reliability*. This is a **real tactical approach** to assess the behavior of the transportation system through the use of short-term performance measures and on-line data. Likewise, mid-term and long-term decisions can be made using a similar approach, integrating particular performance measures with newly available extensive on-line data.

1.2. Objectives and Goals

Our primary objective is to present and evaluate *network-wide performance measures* that can be quantified with "on-line data" from some of the general transportation system performance categories listed above. Although on-line data use for the quantification of individual performance measures such as "link travel times", "queue lengths", and "incident clearance times" is an important goal, it is not sufficient when a full evaluation of a system's performance is needed. We are proposing the development of a new methodology that will both integrate these performance measurements and offer an improved understanding of the interactions among them. The body of data that this methodology will produce can then be coupled with estimated planning data from demand forecasting models such as NJTPA's NJRTM-E and NYMTC's NYBPM to better predict transportation system's long-term behavior.

As with the development of any new methodology, unexpected problems can arise, and there might be some difficulty in acquiring, processing and utilizing the data generated by a wide variety of sources, particularly when the data will be used to produce performance measures for various transportation management systems and planning objectives. At the outset, then, we have identified the most pressing research task as thus: to define the most important *performance measures that can be quantified using this real-world on-line data*.

The key challenge behind our proposed approach is the effective use of "*real-world on-line data to quantify selected performance measures*". The data sources that the research team have considered are:

1. Traditional infrastructure based detector data such as loop detectors, remote traffic microwave sensors (RTMS), traffic cameras.

2. Emerging probe-vehicle data obtained from a variety of sources such as, INRIX[1], TomTom[2], TRANSCOM[3], EZ-Pass, and Bluetooth readers.
3. Incident management and other operational and planning data available from sources such as NJ safety patrol database, New York's IIMS, NJDOT's on-line accident database, etc.
4. Road inventories containing information about link characteristics, traffic signals, etc.

The overall objective, as stated above, can be achieved by effectively executing the following goals:

Goal 1: Identify the short, mid and long-term **performance measures** that are the most important to all the stakeholders in our region.

Goal 2: Identify and acquire all the **on-line operational data sources** that can be used to quantify selected performance measures.

Goal 3: With the close cooperation of the stakeholders, design a comprehensive yet practical software development life cycle process to capture the data, process the data, and then estimate selected performance measures.

Goal 4: Demonstrate the use of the developed performance-based **off-line** and **on-line** data source through real-world case studies.

[1] www.inrix.com/
[2] www.tomtom.com/
[3] http://www.xcm.org/

2. LITERATURE REVIEW

NCHRP Synthesis 238 [1] explains the state practices for the development of performance measures, which themselves were influenced by trends defined in ISTEA (Intermodal Surface Transportation Efficiency Act of 1991). These trends can be identified as "*strategic decision support, the need for better accountability, the need to be competitive, and being more customer-oriented*". The study focuses on an agency's multimodal transportation functions and explains data, methods and measures that can be used for multimodal functions based on the findings of DOT surveys. It is stated that although many well-known performance measures are in place for road maintenance and traffic safety, new performance measures are constantly being developed. The new developments tend to utilize performance measures for strategic plans as they relate to policy goals and objectives.

NCHRP Report 446 [2] serves as a guidebook for performance-based transportation planning. This study emphasizes the use of performance measurement and monitoring in multimodal transportation planning. In the study, the reasoning for performance-based planning and the criteria for performance measure selection are discussed. The applications are provided in the form of case studies. A comprehensive library of performance measures is provided, culled from the literature, case studies and field visits to agencies. Based on the different goals and objectives of transportation operations agencies, the measures are categorized into different groups, including accessibility, mobility, economic development, quality of life, environmental and resource conservation, safety, operational efficiency, and system condition and performance. [2, 3]

NCHRP Synthesis 326 [4] examines the experiences of state transportation departments with strategic management, and synthesizes current approaches for linking strategic planning with other key decision-making processes. The survey results show that many DOTs used performance measures to monitor the implementation of strategic initiatives and track the success in achieving strategic goals and objectives. Although it is a challenge to define meaningful, reliable, accessible, and cost-effective performance measures in some areas, it was found that DOTs tend to focus more on real outcome measures than they used to. They began to establish numerical targets for their strategic goals and objectives.

Similarly, NCHRP Report 551 [5] explores the best set of performance measures for good asset management. Additionally, some procedures are developed in the study to assist transportation agencies in the selection of performance measures. With these procedures, agencies can select performance measures for their specific needs and set measure targets. [5] In order to understand the current performance measures most commonly in use, as well as proposed ones and how they are applied in different agencies, 15 transportation agencies are interviewed in the report. The key benefits in using performance measures for decision making was summarized.

The American Association of State Highway and Transportation Officials (AASHTO) [6] explores comparative performance measurements among state DOTs. The study summarizes the basic elements for developing a comparative framework. Based upon a peer group study of multiple states, two-tracked performance measures, on-time performance, and on-budget performance were found to have great variation among states. This variation might explain why certain agencies remain skeptical about benchmarking while other agencies have expressed an interest to try it.

Baird and Stammer Jr. [7] state there is a need for the implementation of organizational and program performance measures at DOTs. The authors believe that DOTs need to consider two other disciplines (business management and public administration) while implementing performance measures. The study reviewed the current practice and analyzed the different views of these disciplines. The performance measurement issues considered in the study included motivations for performance-based planning, stakeholder perspectives, dimensions for performance measurement, comparisons as a way of measurement, and guidelines for performance measurement. The performance measurement systems in 10 DOTs are investigated from the view points of three different disciplines and five issues of performance measurement.

Vandervalk-Ostrander [8] considers the performance measures from the perspective of small communities. The study identifies operations performance measures and its elements such as data collection and analysis, performance reporting, and decision-support. It also discusses the state-of-practice in small communities and recommends the implementation of certain performance measure programs.

MacDonald et al. [9] presents certain international findings on the performance measures for transportation planning and decision making. The countries scanned for performance measures include Australia, Canada, Japan, and New Zealand. It is found that these countries "use performance measures for setting priorities and making investment and management decisions to a greater extent than is typical in the United States". Especially notable in the discussion is the approaches on road safety and their success in reducing fatalities. More specifically, agencies in these countries utilized performance measures to demonstrate greater accountability and visibility to the public as well as key decision-makers.

Poister [10] reviews the current practice of performance measures and offers a way to use them efficiently. The study emphasizes the use of performance measures by DOTs and explains "what is measured, how performance is measured, how performance data are reported, and how performance measures are used". The study suggests that only a few agencies currently use sophisticated systems for performance measurement, and that because of this limited use the practice of utilizing performance measures is still in its infancy, with much room for growth. The challenges and recent trends in this area of study are also outlined.

Haas et al. [11] presents a comprehensive approach for developing performance measures. This approach considers the basic issues in performance-based modeling such as "a balance in use and reporting, efficiency and effectiveness, a tie to transportation values, objectivity in the measurements used and the stakeholders involved". Based on the current Canadian and international examples, the study proposes a basic framework for performance-based modeling, which consists of two levels: (1) General macro-level overview and (2) Detailed level. The latter examines quality of service, institutional productivity, and effectiveness. The study includes performance measure examples from OECD, Australia and the United States. The study concludes that there should be a link between performance measures, objectives, and targets or acceptable level of performance.

Moore et al. [12] indicates that MPOs are very different from each other and generally do not have the power to raise revenue or allocate funds. In spite of having a transportation plan at the local level to direct funds, they often do not have the resources to identify and implement performance measures in their transportation plans. The study provides a review of the current performance measures practice and guidance to MPOs and other transportation agencies for integrating performance measures into their transportation plans. The study argued that the federally mandated one-size-fits-all performance measurement approach is unsuitable, particularly for smaller transportation agencies with limited funds and personnel. However, the smaller MPOs can still employ performance measures in their planning process using historical and trend data in their area.

This review of the literature indicates that many transportation agencies have committed to using performance measures, but the degrees to which performance measures are developed may differ widely. Different goals and objectives at various levels require transportation agencies to use different measurable performance indicators. Although the review revealed occasional instances of inspired performance measure implementations, overall there were a limited number of studies specifically focused on exploring different performance measures based on existing data sources.

3. DATA SOURCES AND DATA ASSEMBLY

The development of performance measures relies on the availability of related data. This chapter summarizes data sources commonly made available by agencies like State DOTs.

3.1. Traffic Volume Counts

The Federal Highway Administration (FHWA) requires traffic monitoring system (TMS) to be used for collecting traffic volume counts at many roadways. Currently, there are 3,000 such traffic detection stations in place on public roads throughout NJ. [13] Some sites provide continuous traffic counts while others may only measure traffic counts for particular instances, such as an estimate of the annual average daily traffic (AADT). Table 3.1 shows an example of traffic volume counts maintained by the NJDOT. Important information such as location, facility name, count time period, traffic counts and station types are usually provided. Some agencies like NJDOT and NYSDOT have also developed interactive map programs to display published traffic data graphically. [13, 14] Data for individual traffic stations, the type of data availability, and count sites can be queried from these programs. Estimates of AADT are usually included for roadway segments that contain a traffic station. Depending on the detection capability of the traffic station, additional short-term data may be also available. These data can be easily integrated into other compatible programs.

Table 3.1 Example of traffic volume counts collected at different sites (source: NJDOT[4])

SI_STATION_NUM	SI_MP	SI_STREET_NAME	SI_LAT	SI_LON	CYEAR	INSTALL_DATE	REM_DATE	AADT	AADT_N_E	AADT_S_W	DIR	STATION_TYPE
4-4-206	18.68	US 202	40.55072079	-74.730965	1/1/2011	8/22/2011	8/24/2011	37883	18826	19057	North/South	Volume 48hrs
4-4-206	18.68	US 202	40.55072079	-74.730965	1/1/2008	7/7/2008	7/11/2008	34038	16461	17577	North/South	Volume 48hrs
4-4-207	24.78	US 202	40.57916183	-74.62464901	1/1/2010	10/6/2010	10/8/2010	86403	44403	42000	North/South	Volume 48hrs
4-4-207	24.78	US 202	40.57916183	-74.62464901	1/1/2007	7/17/2007	7/20/2007	81475	38313	43162	North/South	Volume 48hrs
4-4-208	25.36	US 202	40.5871027	-74.62249067	1/1/2011	4/26/2011	4/29/2011	71824	37811	34013	North/South	Volume 48hrs
4-4-208	25.36	US 202	40.5871027	-74.62249067	1/1/2008	9/29/2008	10/1/2008	71000	37556	33444	North/South	Volume 48hrs
4-4-210	40.88	US 1&9	40.62511819	-74.24455608	1/1/2011	7/25/2011	7/27/2011	58915	30454	28461	North/South	Volume 48hrs
4-4-210	40.88	US 1&9	40.62511819	-74.24455608	1/1/2008	7/21/2008	7/24/2008	58342	29403	28939	North/South	Volume 48hrs
4-4-211	68.6	US 206	40.53969962	-74.61401962	1/1/2006	5/8/2006	5/11/2006	32883	17338	15545	North/South	Classification 48hrs
4-4-211	68.6	US 206	40.53969962	-74.61401962	1/1/2009	4/28/2009	5/1/2009	30990	16236	14754	North/South	Classification 48hrs
4-4-212	35.3	US 22	40.57951716	-74.59692818	1/1/2009	7/27/2009	7/29/2009	89580	46528	43052	East/West	Volume 48hrs
4-4-212	35.3	US 22	40.57951716	-74.59692818	1/1/2006	10/30/2006	11/3/2006	96597	50362	46235	East/West	Volume 48hrs
4-4-213	19.51	US 202	40.5558201	-74.71666708	1/1/2010	6/29/2010	7/1/2010	39323	19627	19696	North/South	Volume 48hrs
4-4-213	19.51	US 202	40.5558201	-74.71666708	1/1/2007	7/16/2007	7/20/2007	39760	19676	20084	North/South	Volume 48hrs
4-4-215	31.26	US 22	40.59488923	-74.66845294	1/1/2011	9/21/2011	9/23/2011	34162	18702	15460	East/West	Volume 48hrs
4-4-215	31.26	US 22	40.59488923	-74.66845294	1/1/2008	9/8/2008	9/10/2008	36694	19354	17340	East/West	Volume 48hrs
4-4-301	40.17	NJ 18	40.48002263	-74.41105816	1/1/2011	4/19/2011	4/21/2011	101562	53557	48005	North/South	Volume 48hrs
4-4-301	40.17	NJ 18	40.48002263	-74.41105816	1/1/2008	10/13/2008	11/16/2008	91978	45796	46182	North/South	Volume 48hrs
4-4-302	41	NJ 18	40.4857278	-74.4260889	1/1/2008	11/18/2008	11/20/2008	62694	29147	33547	North/South	Volume 48hrs
4-4-303	43.3	NJ 18	40.4993944	-74.4409417	1/1/2009	8/4/2009	8/7/2009	35712	17895	17817	North/South	Volume 48hrs
4-4-303	43.3	NJ 18	40.4993944	-74.4409417	1/1/2006	11/14/2006	11/17/2006	52811	28748	24063	North/South	Volume 48hrs
4-4-304	16.9	NJ 33	40.26756028	-74.47411469	1/1/2010	6/1/2010	6/4/2010	27201	13896	13305	East/West	Volume 48hrs
4-4-304	16.9	NJ 33	40.26756028	-74.47411469	1/1/2007	4/23/2007	4/26/2007	27860	13483	14377	East/West	Volume 48hrs
4-4-305	48.48	NJ 35	40.46671503	-74.280438	1/1/2011	5/3/2011	5/5/2011	26161	11056	15105	North/South	Volume 48hrs
4-4-305	48.48	NJ 35	40.46671503	-74.280438	1/1/2008	8/4/2008	8/6/2008	30473	14645	15828	North/South	Volume 48hrs

[4] http://www.state.nj.us/transportation/refdata/roadway/traffic.shtm

Traffic volume counts are the most common traffic data collected and archived by transportation agencies. They are the fundamental elements used to develop performance measures such as congestion indicators and crash rates.

3.2. Probe Vehicle Data

Direct measurement techniques such as those used in electronic toll collection systems can also provide useful probe vehicle data. After the implementation of the E-ZPass system along the east coast, vehicle-by-vehicle disaggregate data became available. Although these data were processed and archived, they were seldom made publicly available. At certain toll road plazas, however, only probe vehicle data will be available, such as traffic volume/composition at each time period. For distance-based toll roads, each toll plaza transaction is recorded in the system database with both entry and exit information (time, interchange, type of vehicle, etc.). This type of probe data is more useful as it not only provides traffic volume counts but also travel time related information. Although probe vehicle data are usually not available in real-time, examining archived travel time information is valuable when monitoring a facility’s operational efficiency.

Table 3.2 is an example of this kind of probe vehicle data that can be obtained from vehicles equipped with a toll tag and used to support the development of possible performance measures. The detailed description of the sample data sets and considered time periods are shown in Table 3.2.

Table 3.2 Description of sample probe vehicle data

Type	Data Description
Disaggregated data	Vehicle-by-vehicle entry/exit times and locations, and tolls paid for each vehicle equipped with electronic toll collection tags
Aggregated data	Hourly, daily, weekly traffic counts for each interchange entry and exit toll plaza

3.3. Statewide Crash Records

Statewide crash records are commonly maintained by DOTs and/or transportation agencies. The example crash data shown in Figure 3.1 were obtained from the crash database of the New Jersey Department of Transportation (NJDOT)[5]. Crash related attributes including roadway characteristics, environmental conditions, crash characteristics, driver information, vehicle information, and occupant information are collected for each crash in the database. The original data are kept in four separate tables, including accident table (crash summary), driver table (driver information), vehicle table (vehicle information), pedestrian table (pedestrian information), and occupant table (occupant information). In the crash table, each crash is described by one single data row regardless of the number of vehicles involved. The other three tables describe information about each individual (vehicle/person) in a row because multiple vehicles, drivers, and occupants may be involved in the same crash. A unique case number is shared among these tables to link together essential information about the crash, vehicles and victims in involved in the same crash. Figure 3.1 shows an example of linking different parts of crash information.

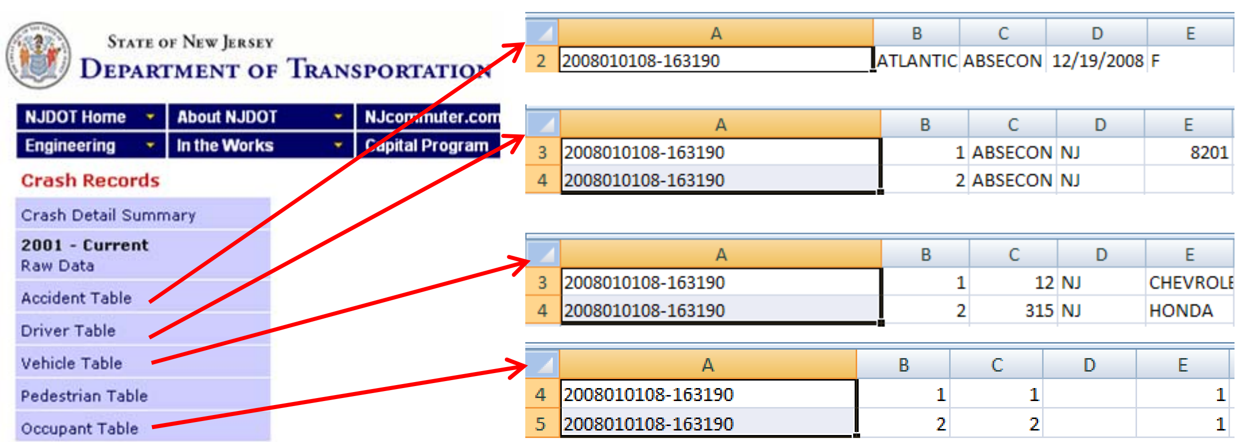


Figure 3.1 Example of linking different crash information (source: NJDOT)

The statewide crash data are very useful to develop safety performance measures such as crash rates, which can be used by the transportation system operators to evaluate safety issues, crash characteristics, and the effectiveness of countermeasures. Depending on the capability of the

5 http://www.state.nj.us/transportation/refdata/accident/

agencies, these crash data can be available for on-line and off-line applications. Depending on data aggregation levels, they can be examined at specific sites, corridors, or networks.

3.4. Weigh-In-Motion (WIM) Data

The weigh-in-motion (WIM) technology provides opportunities for collecting 24-hour truck load data at many key locations in an efficient and effective manner. Typical information collected at WIM stations includes time, axle load, axle spacing and number, and vehicle classification. In addition, speed information, lane of operation, and traffic volume may also be available, depending, of course, on the capability of the WIM stations. The records of the individual vehicles can be then aggregated by vehicle class, time period, direction, and lanes. Figure 3.2 shows an example of the aggregated weekday average information on vehicle classification at a WIM site in New Jersey.

LOCATION: US-1 MP 12.9, Plainsboro Twp., Middlesex(000001) ~ NB
F.C.=14

MONTH	DIR	Unclass 0	Motor-cycle 1	Auto 2	2-Axle 4-Tire 3	Bus 4	2-Axle 6-Tire 5	3-Axle 1-Unit 6	4-Axle 1-Unit 7	<=4-Axle 1-Trailer 8	5-Axle 1-Trailer 9	>=6-Axle 1-Trailer 10	<=6-Axle 2-Trailer 11	6-Axle 2-Trailer 12	>=7-Axle 2-Trailer 13	MONTHLY ADT NB	MONTHLY ADT COMBINE
JAN 2011	NB	54	-	23,008	4,028	14	486	117	22	77	650	5	1	-	-	28,462	28,462
FEB 2011	NB	72	-	23,714	5,571	17	625	124	16	86	658	6	3	-	-	30,892	30,892
MAR 2011	NB	100	2	24,280	6,023	16	668	174	19	96	715	5	5	-	1	32,104	32,104
APR 2011	NB	134	7	23,035	7,617	20	845	252	47	99	713	9	6	-	1	32,785	32,785
MAY 2011	NB	107	19	22,869	8,040	21	736	232	29	97	758	8	6	1	1	32,924	32,924
JUN 2011	NB	61	27	24,363	6,784	24	648	233	30	105	756	8	6	1	1	33,047	33,047
JUL 2011	NB	58	26	24,996	6,244	27	588	258	44	111	759	6	6	1	1	33,125	33,125
AUG 2011	NB	73	22	24,437	6,324	26	583	301	47	118	782	7	8	1	1	32,730	32,730
SEP 2011	NB	78	12	25,317	5,733	19	590	305	35	106	758	8	8	-	1	32,970	32,970
OCT 2011	NB	69	6	26,366	5,121	21	549	352	31	114	765	9	8	-	1	33,412	33,412
NOV 2011	NB	123	3	25,522	5,103	21	588	331	38	109	685	8	8	-	1	32,540	32,540
DEC 2011	NB	58	1	25,980	4,211	17	493	250	25	108	701	7	7	-	1	31,859	31,859
AVERAGE	NB	82	10	24,491	5,900	20	617	244	32	102	725	7	6	0	1	32,238	32,238
TOTAL		82	10	24,491	5,900	20	617	244	32	102	725	7	6	0	1	32,238	
%DAILY	NB	0.3%	0.0%	76.0%	18.3%	0.1%	1.9%	0.8%	0.1%	0.3%	2.2%	0.0%	0.0%	0.0%	0.0%	100.0%	
%TOTAL		0.3%	0.0%	76.0%	18.3%	0.1%	1.9%	0.8%	0.1%	0.3%	2.2%	0.0%	0.0%	0.0%	0.0%	100.0%	

Figure 3.2 Weekday average information on vehicle classification at a WIM site in NJ [13]

Timely WIM data is essential for pavement/bridge condition studies, highway monitoring and capacity studies, accident rate calculations, and the examination of truck activities. It can also be used for predicting future traffic loading. Important traffic characteristics such as future truck volume and axle weight frequency distributions can be derived from historical WIM observations.

3.5. Infrastructure-based Sensor Data

Various infrastructure-based sensors such as inductive-loop detectors and remote traffic microware sensors (RTMS) are frequently deployed to collect traffic counts, occupancy, speed, and vehicle type. Figure 3.3 shows an example of the various RTMS on the NJ Turnpike and the Garden State Parkway. Both short- and long-term measurements from these sensors are widely used to evaluate the performance of the facilities as well as the whole transportation system. For instance, the traffic counts from the sensors provide the basis for determining vehicle miles traveled (VMT) and AADT during long-term assessments. In addition, short-term counts, speed, and/or occupancy data can be used to investigate the short-term performance of the facilities under both normal and disrupted traffic conditions (e.g., construction and incidents).

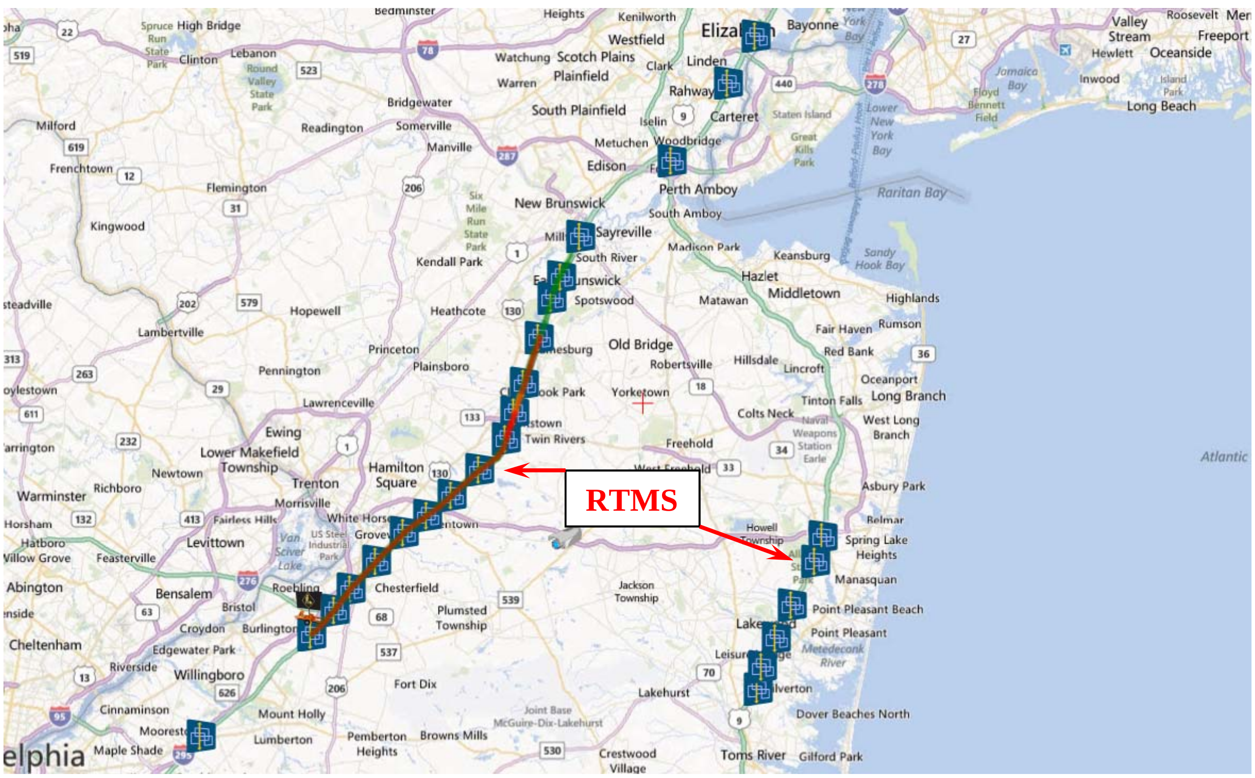


Figure 3.3 RTMS on NJ Turnpike and Garden State Parkway (source: NJTA[6])

The availability of the infrastructure-based sensors is limited due to the high cost associated with installation, maintenance, and so on. Generally, only a relatively small portion of the

[6] www.state.nj.us/turnpike/

transportation network is covered with these sensors. Thus, they can generally provide data for some but not all performance measures for a state highway system.

3.6. On-Line Open Source Data

A number of third-party map services such as Google Maps™, Bing Maps™ and MapQuest™ provide publicly available real-time traffic information. Travelers can now easily find out about prevailing traffic conditions and incidents that might disrupt their journeys. These data come from a variety of sources, including government agencies and private data providers. More recently, much of the traffic data used by these map service providers are sourced from thousands of commuters from their GPS feature enabled smartphones while traveling in their cars. For instance, Microsoft™ has indicated that their Bing Maps now uses traffic information offered by Nokia (HERE) Maps™ [15]. This allows Bing Maps to acquire traffic data from many locations around the world as Nokia has access to millions of devices powered by their Symbian platform. These data from such a large number of devices allows Bing Maps to expand its coverage to an even larger number of roadways. For example, traffic information in the United States already available on Bing Maps now includes local roadways. Similarly, Google Maps taps into GPS data received from Android handset users through traffic crowdsourcing [16]. Any user that has enabled "My Location" with Google Maps on their device contributes anonymous GPS data and help Google capture and display live traffic conditions.

Most of these third-party map service providers provide the Application Programming Interface (API) for developers to (partially) access their live traffic information displayed on their maps. For instance, Bing Maps REST Services API offers a Representational State Transfer (REST) interface which allows users to create a route and geocode an address [17]. More importantly for our purposes here, the Bing Map traffic API provides access to real-time information such as incidents, congestion and construction sites. Similarly, Google Maps, MapQuest and many others provide APIs to access their traffic information [18, 19].

To be able to use on-line open data for performance measure analysis, we propose the creation of virtual sensors that can capture traffic data through a customized API. One implementation of this idea, depicted in Figure 3.4, could be a highway segment of AB featuring eight virtual sensors. These virtual sensors would, at their essence, be a number of user-defined pushpins with coordinate information. The distance between two of the virtual sensors can then be calculated by the virtual sensor coordinates. Depending on the needs of the user, a pair of adjacent virtual sensors can be placed to collect traffic information for a short link or a longer route, either a tenth, a half or a full mile in length. Similar to the regular query often performed on these maps, one could use the API's query function to easily obtain travel time information in Extensible Markup Language (XML) format between two adjacent sensors. The obtained travel time information would then be converted into a speed calculation based on the section length.

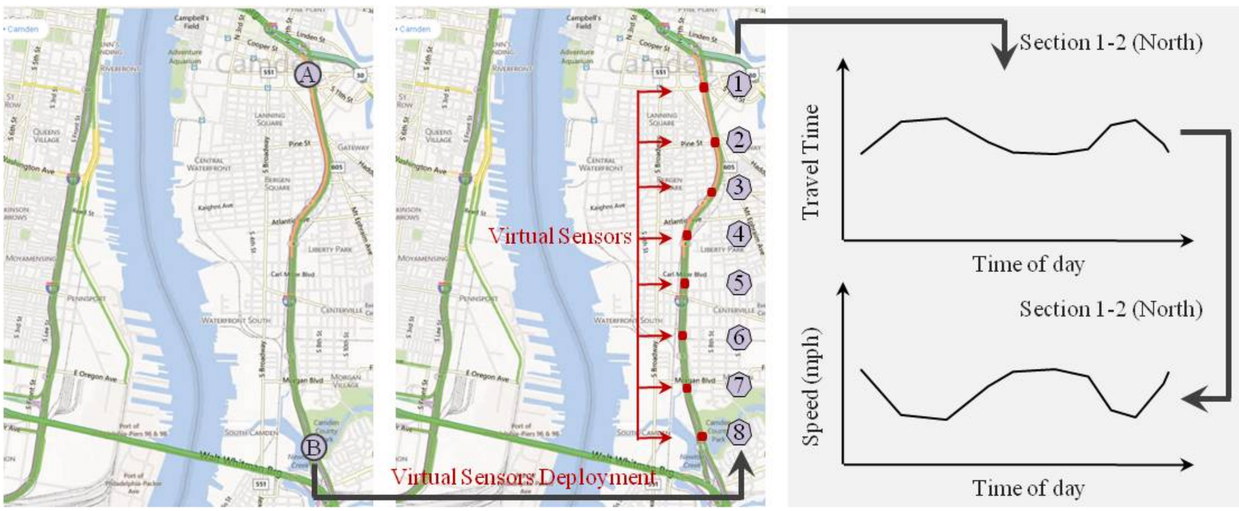


Figure 3.4 Obtaining real-time speed data by deploying virtual sensors on maps [20]

Rather than relying on limited infrastructure-based sensor data on a single road, users can also create a large number of virtual sensors to cover the entirety of the highway network. This approach, in turn, enables us to obtain more traffic data to support many applications [21], i.e., the identification of secondary crashes for networks without infrastructure-based sensors.

4. DATA DRIVEN PERFORMANCE MEASURES

Performance measures provide quantitative information to transportation agencies and key decision makers. The use of these measures can lead to a more comprehensive view of the overall health of our transportation systems. They are the fundamental decision support tools called upon when selecting and deploying appropriate countermeasures, either through investment and operational decisions, strategies, innovations, or partnerships. The development of performance measures should be an iterative process involving all related agencies associated with a transportation project or action. Although there are many useful performance measures, the final performance measures must be easily and accurately quantifiable using existing data or new data that only requires limited effort to collect. The next section summarizes the important performance measures that can be derived from the easily available and accessible data sources in NJ.

4.1. Traffic Congestion and Reliability Measures

4.1.1. Travel Time Reliability

Travel time represents the amount of time that has elapsed when a traveler moves between two locations in a transportation system. Many factors such as road network conditions, driver characteristics, travel modes, traffic regulations and management, weather patterns, and traffic incidents can affect the travel time of a single trip. For instance, as seen in Table 4.1, travel times can vary from month to month. In general, both travelers and facility operators are even more concerned with the variations of the travel times rather than the magnitude of the travel time for a given route/trip. Therefore, a measure known as ***travel time reliability*** is used to describe the variation of travel times along a given route.

Table 4.1 Travel time on selected routes during peak hours

Route	Month	Total Mileage	Average Travel Times (AM Peak)	Average Travel Times (PM Peak)	Travel Times at Speed Limit
I-33 WB	March	6.5 miles	8.8 minutes	9.5 minutes	8.0 minutes
I-33 WB	July	6.5 miles	15.4 minutes	14.6 minutes	8.0 minutes
I-33 WB	October	6.5 miles	12.6 minutes	13.5 minutes	8.0 minutes
I-9 SB	February	3.8 miles	6.0 minutes	5.8 minutes	4.5 minutes
I-9 SB	April	3.8 miles	7.8 minutes	6.0 minutes	4.5 minutes
I-9 SB	December	3.8 miles	7.9 minutes	7.6 minutes	4.5 minutes

Travel time reliability, then can be described as a measure of the amount of congestion travelers experienced at a given time. It is defined as the consistency or dependability in travel times, as measured from day-to-day and/or across different times within a day.[22] It is aimed to quantify the temporal variability of travel times on a road facility or network. A facility that offers a high level of service has a high level of travel time reliability, and vice versa. Reliability measure also reflects the extent of unexpected travel time delays due to external events. Travel time reliability is determined with travel time estimates derived from data sets such as continuous loop detector data and / or probe vehicle data. According to the FHWA [22], there are five standard measures of travel time reliability most frequently used:

- **90th or 95th percentile travel time (PTT) —** how much delay there will be on the busiest travel days for specific travel routes or trips. This measure is reported in minutes and seconds and can be easily understood by daily commuters that are familiar with their routes. [22]
- **Travel time index (TTI) —** used to measure the peak period travel time in excess of that experienced in free-flow conditions. [22] It is calculated as the ratio of the peak period travel time to free-flow travel time (FFTT) with the following equation.

$$Travel\ Time\ Index = \frac{peak\ period\ travel\ time}{free\ flow\ travel\ time} \tag{1}$$

- **Buffer index (BI) —** represents the extra time (or time cushion) that most travelers add to their average travel time when planning trips to ensure on-time arrival. It is calculated as the ratio of the difference between the 95th percentile travel time and mean travel time to the mean travel time (MTT). [22] For a specific route trip and time period, the buffer index is computed using the following equation.

$$Buffer\ Index(\%) = \frac{95^{th}\ percentile\ travel\ time - average\ travel\ time}{average\ travel\ time} \tag{2}$$

- **Planning time index(PTI) —** it means the total travel time needed to plan for an on-time arrival 95% of the time. [22] It is computed as the 95th percentile travel time divided by free-flow travel time. For a specific route trip and time period, the planning time index is computed using the following equation.

$$Planning\ Time\ Index = \frac{95^{th}\ percentile\ travel\ time}{free\ flow\ travel\ time} \tag{3}$$

- **Congestion frequency index (CFI) —** the percent of days or time during which the mean speed falls below a certain speed, or the travel time exceeds a certain threshold. [22] It can be easily calculated by counting the frequency that traffic conditions exceed a preset threshold; for instance, 1.5 times the free flow travel time:

$$Congestion\ Frequency(\%) = \frac{number\ of\ periods\ with\ travel\ time\ exceeds\ a\ threshold}{total\ number\ periods} \tag{4}$$

4.1.2. Travel Delay

Travel delay represents the additional travel time experienced by a traveler to complete his/her trip. It is calculated as the total travel time on a segment of highway minus the travel time for the vehicle under free-flow condition (see below for the equation).

$$Travel\ Delay\ (time) = actual\ travel\ time\ -\ free\ flow\ travel\ time \tag{5}$$

It is an important and frequently used indicator to examine the impact of different sources of congestion. A particular interest of many transportation agencies is to understand the travel delays due to traffic incidents, work zones, adverse weather, fluctuations in normal traffic, special events, traffic control and management, and the physical bottlenecks of roadways. Depending on various objectives, travel delays can be aggregated by different user groups such as trucks, passenger cars, and by time periods such as a weekday peak period, weekday off-peak period, and so on.

4.2. Traffic Safety Performance Measures

Traffic safety performance measures aim to monitor the evolution of traffic safety conditions in transportation systems. One measure that is often employed is the number of crashes on public roads. The characteristics of the traffic crashes such as their frequency, types, level of severity, and distribution are of great interest. Examining this information allows transportation agencies to screen and identify hot spots, and to evaluate and implement safety countermeasures. The major data source used to examine this safety performance is the statewide crash database.

Some other supplemental and emerging measures such as crashes per 100 million vehicle miles and crash costs can be also be derived with this data source, if used with other related information. Given that the data are accurate, these measures can be used for comparisons across time, facilities and locations etc.

4.3. Incident Management Performance Measures

4.3.1. Incident Duration

Incident duration is a measure used to depict how long it takes to clear non-recurring events that affect traffic. It represents the time elapsed between an incident being verified and logged and the time when responders have it cleared. Depending on the availability of event records, the incident duration can be reported for various time periods (daily, weekly, monthly, and annually). In addition, transportation agencies are interested in the relationship between incident durations and different factors, including but not limited to incident type, number of lanes blocked, incident occurrence time, number and types of vehicles involved, facility type, and weather conditions. Understanding these relationships can help transportation agencies compare and optimize their incident management programs so that the impact of future, similar incidents can be predicted and minimized by deploying faster clearance strategies.

4.3.2. Secondary Crashes

In spite of their notable impact on mobility, one of the most serious problems associated with traffic incidents is the risk of secondary crashes.[23] One notable study by Tedesco et al. [24] found that the crash risk can be six times higher in the presence of a prior crash. Similarly, Karlaftis et al. [25] estimated that each additional minute that a primary incident remains on the roadway increases the likelihood of a secondary crash by about three percent. Likewise, other studies have shown that more than ten percent of crashes were the direct result of previous incidents.[26-28] In the United States, secondary crashes alone were responsible for an estimated eighteen percent of all fatalities on freeways and twenty percent of all crashes annually.[29, 30] The occurrence of secondary crashes can further increase congestion and impede incident management operations. Therefore, it is crucial to examine secondary crashes, understand their characteristics, and provide necessary countermeasures.

While traffic incidents have been widely analyzed in the literature, limited research has been conducted to explore secondary crashes. This is largely due to the lack of detailed incident data and corresponding traffic data required to identify secondary crashes.[31] It is difficult to identify secondary crashes solely by using the crash databases provided by many transportation agencies. A common method adopted by earlier studies [28, 32, 33] is to simply mark the secondary crashes that occurred within a pre-defined impact range of the primary crash. However, the impact of a motor vehicle crash on traffic flow depends upon various factors such as crash characteristics, roadway conditions, traffic flow levels and weather conditions. Therefore, the validity of secondary crashes measured by this method is questionable.

Traffic sensors such as inductive loop and microwave radar detectors are now being extensively used to automate the collection of traffic data. Large sets of high-quality, high-time resolution traffic data are now becoming available for a growing number of roadways. A more robust method for identifying secondary crashes can thus be developed by integrating this kind of emerging rich traffic data sources with available crash databases.

Driven by this massive amount of newly available yet underutilized data, this study aims to develop an enhanced method for the measurement of secondary crashes that both utilizes archived traffic sensor data and existing crash records. The detailed algorithm is presented in the next chapter. The number of secondary crashes on roadways with instrumented sensors can be quantified as an important and novel performance measure for incident management.

5. PROPOSED METHODOLOGIES FOR THE QUANTIFICATION OF SELECTED PERFORMANCE MEASURES

In the rest of this report, three different but extremely important performance measures namely, travel time reliability, incident duration, number of secondary crashes will be further studied to illustrate the opportunities that exist to estimate this type of performance measures using various extensive and emerging data sources. Moreover, novel estimation methodologies for the estimation of each one of these performance measures will be described in detailed. Finally, real-world case studies will be used to illustrate the usefulness of these new data driven methodologies proposed to estimate selected performance measures.

5.1. Travel Time Estimation

As presented in the previous section, travel time is a fundamental element used to derive a number of performance measures. This section provides a basic understanding of the estimation of travel time using vehicles instrumented with toll tags as probes. It develops improved models to estimate experienced travel time for closed tolling networks. Finally, sensitivity analysis of the model with respect to its parameters is performed.

5.1.1. Problem Statement

Automatic vehicle identification (AVI) systems record the exact times at which vehicles enter and exit the network. The EZ-Pass electronic toll collection (ETC) systems on the New Jersey Turnpike, Pennsylvania Turnpike, and New York Thruway are examples of such AVI systems. These systems provide very rich traffic information including traffic volume, traffic composition, time stamps, and type of payment. One important yet understudied topic is how to better utilize the large amount of transaction data generated from the ETC systems in an effort to improve the estimation of travel time.

Since the ETC systems capture the enter and exit time stamps, the experienced travel time of a vehicle completing its trip between two toll plazas is directly accessible. However, there are several challenges associated with the use of the measured travel time as an estimation of the trip travel time. The most notable challenge is that the traffic demand between two toll plazas might be too low to develop a reliable estimation of the travel time. For example, the demand between two consecutive junctions can be extremely low, since travelers do not prefer using tolling roads for short-distance trips. Furthermore, an estimation of travel time for a section based on measurements from a single OD pair would be biased by the experience of those vehicles. Travel time estimation should incorporate other through traffic data as well. Therefore, the problem is how to efficiently utilize EZ-Pass data to accurately estimate link travel times.

5.1.2. *Travel Time Estimation Methodology*

The travel time between an entry toll plaza i and an exit toll plaza j for vehicles that enter the toll plaza i at k^{th} time interval, as shown in Figure 5.1, can be simply represented by the following equation:

$$t_{ijk} = t_{Oik} + \Delta t_{ijk} + t_{Djk} \tag{6}$$

where t_{ijk} is the travel time calculated based on the entry time and exit time; t_{Oik} is the entry travel time for vehicles to reach the merge area on mainline; t_{Djk} is the exit travel time for vehicles to leave the exit toll plaza; Δt_{ijk} represents the travel time for the section between the on-ramp merge area of the entry toll plaza i and the off-ramp diverge area of the exit toll plaza j .

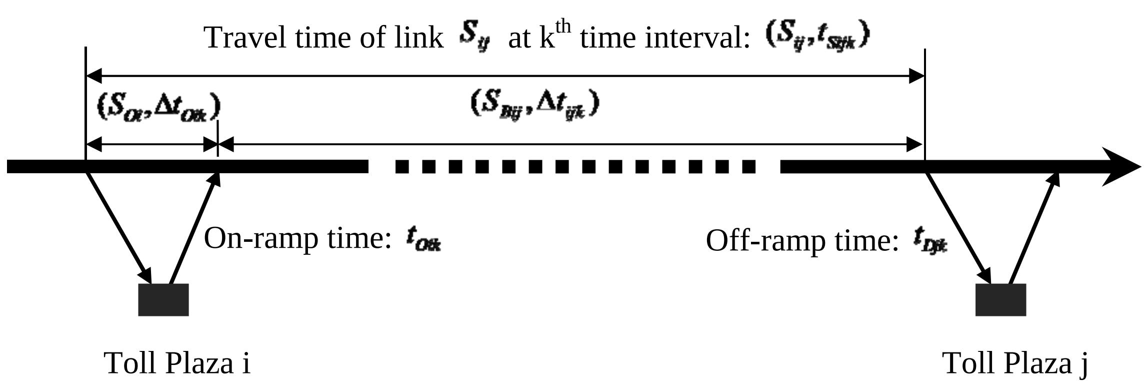


Figure 5.1 Schematic of travel time analysis between two toll plazas

As shown in Figure 5.1, the link travel time t_{Sijk} of the mainline section between entry toll plaza i and exit toll plaza j for vehicles entering at k^{th} time interval is consisted of two part: (a) the travel time Δt_{Oik} for the short segment between the off-ramp diverge area and the on-ramp merge area of toll plaza i and (b) the travel time Δt_{ijk} for the long segment between the on-ramp merge area of the entry toll plaza i and the off-ramp diverge area of the exit toll plaza j . t_{Sijk} can be represented by the following equation:

$$t_{Sijk} = \Delta t_{Oik} + \Delta t_{ijk} = \Delta t_{Oik} + \left(t_{ijk} - t_{Oik} - t_{Djk}\right) \tag{7}$$

Since there is no direct measurement for the travel time Δt_{Oik} of the short segment within an interchange, a linear expansion factor is assumed based on the length of the segments. The estimation of Δt_{Oik} is described as follows:

$$\Delta t_{Oik} = \Delta t_{ijk} \times \frac{S_{Oi}}{S_{Oi} + S_{:Bij}} = \left(t_{ijk} - t_{Oik} - t_{Djk}\right) \times \frac{S_{Oi}}{S_{Oi} + S_{Bij}} \tag{8}$$

where S_{Oi} is the length of the segment between the off-ramp diverge area and the on-ramp merge area of toll plaza i; S_{Bij} is the length of the segment between the on-ramp merge area of the entry toll plaza i and the off-ramp diverge area of the exit toll plaza j .

Based on equation (8), the link travel time t_{Sijk} of the mainline section between an entry toll plaza i and exit toll plaza j at k^{th} time interval shown in equation (7) is rewritten as

$$t_{Sijk} = \left(t_{ijk} - t_{Oik} - t_{Djk}\right) \times \left(1 + \frac{S_{Oi}}{S_{Oi} + S_{ij}}\right) \tag{9}$$

As the length of each segment is a constant value, only information about the travel time between two toll plazas and the corresponding on-ramp travel time and off-ramp travel time is needed to estimate the link travel time t_{Sijk} in equation (9).

The travel time between a toll plaza i and toll j can be simply estimated by the above equation (9). However, the results might not be representative for the target link between i and j . This is because the demand between toll plaza i and toll plaza j might be very low for certain periods, particularly at night. In addition, the demand can be very low if toll plazas i and j are very close and few vehicles prefer to pay to use this short link for their trip. As mentioned before, it is desirable to combine travel time information from vehicles associated with other OD pairs that cross the target link. Therefore, a data fusion procedure is developed. Figure 5.2 is used to illustrate the proposed data fusion procedure.

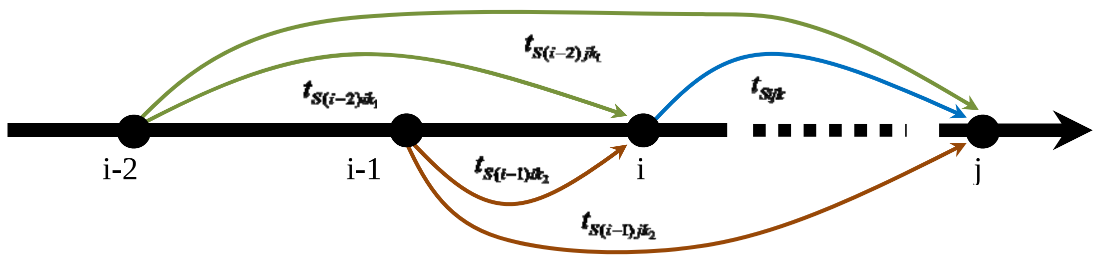


Figure 5.2 Estimate target link travel time between i and j based on other adjacent OD pairs

Let's assume that the objective is to estimate travel time t_{Sijk} for link ij at the k^{th} time step. Using equations 6 to 9, we can obtain a rough estimation of travel time for any OD pair that crosses the target link and have j as its destination. For instance, let's assume that there exist N toll plazas at the upstream of toll plaza i. Travel times between an upstream origin toll plaza $i-n$ $(n=1,2,...,N)$ and toll plaza i and toll plaza j measured based on equation (9) are denoted as $t_{S(i-n)ik_n}$ and $t_{S(i-n)jk_n}$, respectively. Thus, the travel time of the target link ij at the k^{th} time step can be calculated by equation (10). Since there will be delays due to vehicles traversing from one link to another, equation (11) is used to synchronize vehicles that enter the target link at the same time interval.

$$t_{Sijk} = t_{S(i-1)jk_1} - t_{S(i-1)ik_1} = t_{S(i-2)jk_2} - t_{S(i-2)ik_2} = ... = t_{S(i-n)jk_n} - t_{S(i-n)ik_n} \tag{10}$$

$$k = k_1 + t_{S(i-1)ik_1} = k_2 + t_{S(i-2)ik_2} = ... = k_n + t_{S(i-n)ik_n} \tag{11}$$

Once the travel time for the target link ij is derived based on equation (10) and equation (11), the final estimated travel time of $\hat{t}_{Sijk}$ can be calculated using equation (12).

$$\hat{t}_{Sijk} = \frac{1}{N}\sum_{n=1}^{N}\left(t_{S(i-n)jk_n} - t_{S(i-n)ik_n}\right) \tag{12}$$

Note that this equation assumes that the mean value of the derived travel time t_{Sijk} from different OD pairs is the final estimation. Instead of using the mean value, the median value can be another option for the final estimation of $\hat{t}_{Sijk}$. The estimated travel time $\hat{t}_{Sijk}$ can also be compared with the one that is directly derived based on equation (9) using the ETC data between toll plaza i and toll plaza j.

5.1.3. Probe Vehicle Based Travel Time Algorithm

When implementing the above proposed approach for travel time estimation, there are still two important questions that need to be answered. With equation (9) in mind, the first question is how to obtain the entry travel time t_{Oik} and exit travel time t_{Djk}. The second question is how to filter and aggregate ETC measurements of multiple probe vehicles to obtain a representative travel time estimation t_{ijk} for each time interval.

One way to obtain the entry and exit travel times is to assume that there is a constant travel time based on the fixed entry and exit distances and the corresponding speed limits. However, despite the relative short entry distances, the entry travel time t_{Oik} is closely related to the traffic conditions on the entry ramp as well as the mainline. Similarly, the exit travel time t_{Djk} is related to the traffic conditions at the exit ramp and the queues in the approach zone of the exit toll plaza. Depending on the traffic conditions, these two travel time values can vary. For instance, an assumption of constant entrance/exit times would not work when there is congestion along the mainline and exit toll plaza. In highway configurations, congestion along the mainline would block a vehicle’s access to the mainline whereas the congested exit toll plaza would delay the vehicle from leaving the toll plaza. Therefore, the constant travel time values calculated from the entry or exit distances and the posted speed limits cannot very accurately represent actual traffic conditions, particularly during peak periods. For instances where the historical travel time distributions for the entry section and the exit section are available, random samples of the corresponding time periods are preferable to using the assumed constant travel time values.

To obtain the representative travel time for each time interval based on observed probe vehicle travel time measurements, unrealistic observations (outliers) have to be eliminated. These individual outlier observations might be caused by vehicles stopping in rest areas or various other factors. In addition, for the periods with very few or no observations, interpolation should be made based on other available information. In other words, the travel time from the previous period and the free flow travel time can be considered when making an interpolation.

Table 5.1 shows an example of the algorithm used to filter and aggregate the observed travel time for obtaining the representative travel time.

Table 5.1 Pseudo code for filtering and aggregating travel time measurements obtained probe vehicles

At time interval k :

Assumption: there were N probe vehicle travel time observations $t_k^{obs,n}$ $(n = 1, 2, ..., N)$

Parameters: weight factors α_1 and α_2

Objective: filter outliers and estimate the travel time t_k^{est} based on $t_k^{obs,n}$

Step 1: check the number of probe vehicle measurements and found no observation

$$if\ (N = 0)\ \left\{ t_k^{est} = \alpha_1 \times t_{k-1}^{est} + (1-\alpha_1) \times t_{ff} \right\}$$

Step 2: check the number of probe vehicle measurements and found only one observation

$$\begin{array}{l} if\ (N = 1) \\ \{ \\ \quad if\ \left(t_k^{obs,i} \geq \dfrac{1}{\alpha_2} \times t_{k-1}^{est}\ \ \&\ \ t_k^{obs,i} \leq \alpha_2 \times t_{k-1}^{est} \right)\ \left\{ t_k^{est} = \alpha_1 \times t_{k-1}^{est} + (1-\alpha_1) \times t_k^{obs,i} \right\} \\ \quad else\ \left\{ t_k^{est} = \alpha_1 \times t_{k-1}^{est} + (1-\alpha_1) \times t_{ff} \right\} \\ \} \end{array}$$

Step 3: check the number of probe vehicle measurements and found two observations

$$\begin{array}{l} if\ (N = 2) \\ \{ \\ \quad \text{Subset } M \text{ observations }\ t_k^{obs,m} \in \left(\dfrac{1}{\alpha_2} \times t_{k-1}^{est},\ \ \alpha_2 \times t_{k-1}^{est} \right),\ \ m = 1, 2, ..., M\ \&\ M \leq N \\ \quad if\ (M = 0)\ \ \left\{ t_k^{est} = \alpha_1 \times t_{k-1}^{est} + (1-\alpha_1) \times t_{ff} \right\} \\ \quad if\ (M > 0)\ \ \left\{ t_k^{est} = \alpha_1 \times t_{k-1}^{est} + (1-\alpha_1) \times median\left(t_k^{obs,m}\right) \right\} \\ \} \end{array}$$

Step 4: check the number of probe vehicle measurements and found three or more observations

$$\begin{array}{l} else \\ \{ \\ \quad \text{Subset } M \text{ observations }\ t_k^{obs,m} \in \left(\dfrac{1}{\alpha_2} \times t_{k-1}^{est},\ \ \alpha_2 \times t_{k-1}^{est} \right),\ \ m = 1, 2, ..., M\ \&\ M \leq N \\ \quad if\ (M = 0)\ \ \left\{ t_k^{est} = \alpha_1 \times t_{k-1}^{est} + (1-\alpha_1) \times t_{ff} \right\} \\ \quad if\ (M > 0)\ \ \left\{ t_k^{est} = \alpha_1 \times median\left(t_k^{obs,m}\right) + (1-\alpha_1) \times t_{k-1}^{est} \right\} \\ \} \end{array}$$

Iteration: $k = k + 1$

5.1.4. *Case Studies*

The proposed travel time estimation method is applied to the New Jersey Turnpike (NJTPK). The studied highway is a closed tolling system that collects tolls through both a traditional ticket system and a ETC collection system at the toll plazas. Despite the availability of the time stamps for all vehicles entering and exiting the toll plazas, only EZ-Pass users were considered as probe vehicles because other cash users may be delayed when picking up the tickets at an entry toll plaza, returning tickets, or paying cash at an exit toll plaza. Empirical EZ-Pass transaction data from 2011 were obtained. The case study section is limited to the eight links between Interchange 9 and Interchange 5 as shown in Figure 5.3.

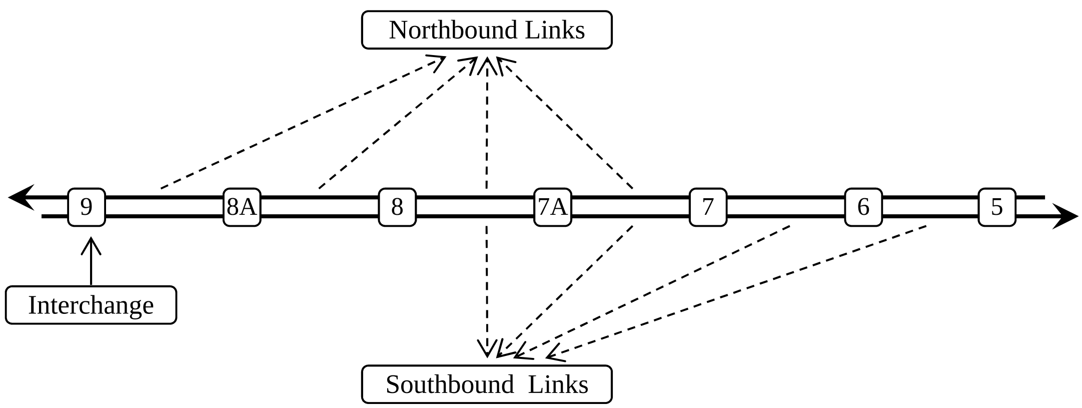


Figure 5.3 Analyzed links in selected section between Interchange 9 and Interchange 5

When implementing the proposed travel time estimation approach, three time intervals are considered: 5-minute, 10-minute, and 15-minute. The 5-minute interval is considered to be the minimum update interval to follow the traffic conditions that would evolve quickly (e.g. incident conditions). The proposed method is tested using data of multiple days randomly selected from 2011. The estimated link travel times based on different time intervals were compared through root mean square percentage error (RMSPE). RMSPEs are computed by comparing the observed and estimated travel times using the following equation:

$$RMSPE = \sqrt{\frac{1}{M}\sum_{a=1}^{A}\sum_{b=1}^{B}\left(\frac{\hat{t}_{est\,a} - t_{obs\,a,b}}{t_{obs\,a,b}}\right)^2} \tag{13}$$

where $\hat{t}_{est\,a}$ is estimated travel time at a^{th} period, $a = 1,2,...,A$; $t_{obs\,a,b}$ is the b^{th} observation in a^{th} period, $b = 1,2,...,B$; B that varies in each period is the total number of observations during a given time period; and M is the total number of observations during all analyzed periods.

Figure 5.4 and Figure 5.5 show two examples of travel time estimation for the link between interchange 08A and 009 in the northbound direction. Figure 5.4 shows the estimated travel time under normal conditions whereas Figure 5.5 illustrates the estimated travel time under incident conditions on the same weekday but from a different week.

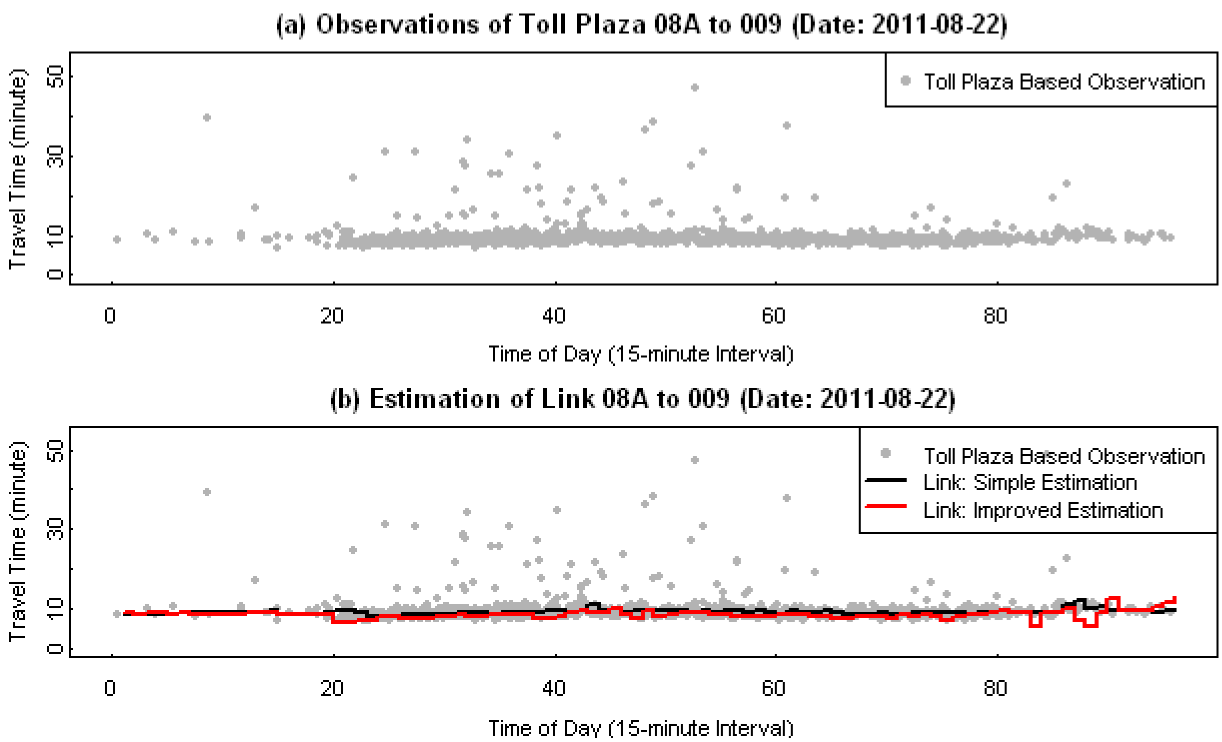


Figure 5.4 Travel time estimation under normal conditions

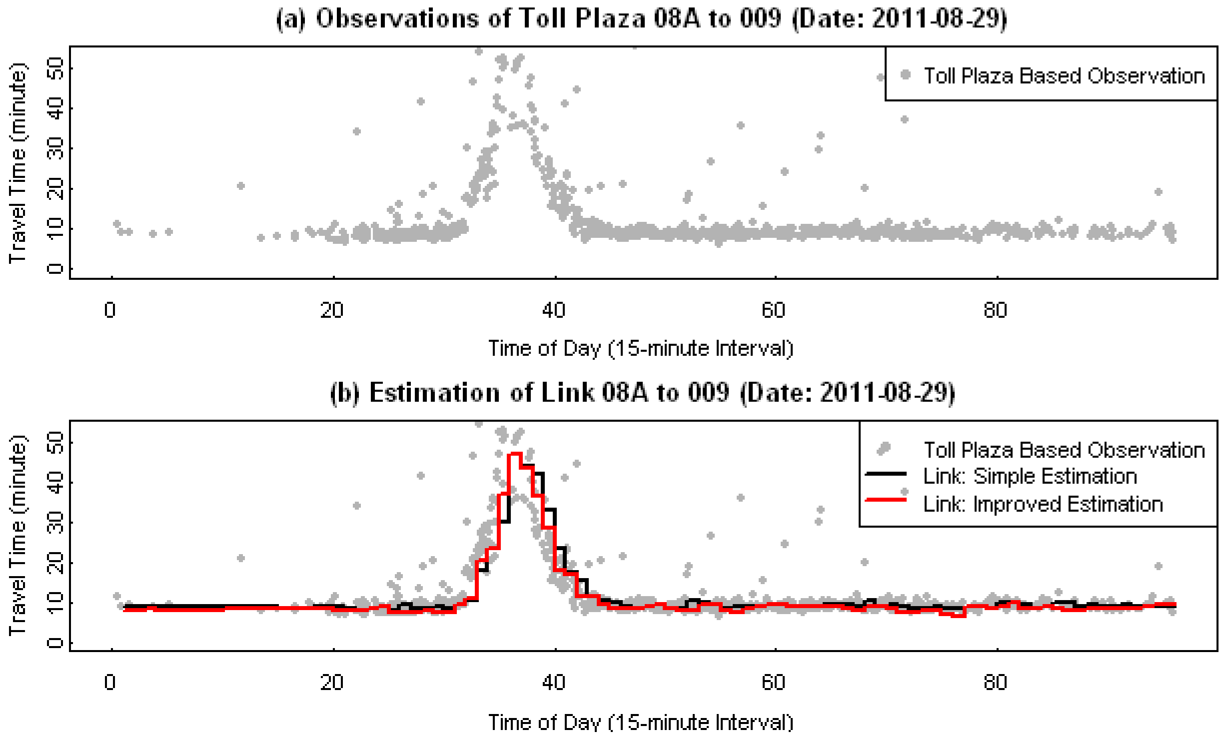


Figure 5.5 Travel time estimation under incident conditions

The estimations shown in Figure 5.4 and Figure 5.5 are based only on the probe data collected through OD pairs associated with the target link. In contrast, the improved estimations represent the results based on the additional probe data from OD pairs associated with the target link as well as adjacent OD pairs.

To further examine the performance of the improved method, RMSPEs errors were computed for travel time estimations for both different days and conditions. Table 5.2 shows the computed RMSPEs. The results show that using 5-minute time interval produces relatively larger RMSPEs compared with RMSPEs found with longer time intervals. The 10-minute interval and 15-minute time intervals produce similar results. To improve computational efficiency, 15-minute interval will be used for deriving related performance measures.

Table 5.2 Comparison of travel time estimations based on different time intervals

Analyzed Links	RMSPE (Day: 4/17/11)			RMSPE (Day: 9/22/11)			RMSPE (Day: 4/11/11)		
	5-min	10-min	15-min	5-min	10-min	15-min	5-min	10-min	15-min
8 to 7A	0.341	0.141	0.143	0.286	0.200	0.200	0.257	0.194	0.177
7A to 7	0.427	0.325	0.295	0.378	0.293	0.285	0.398	0.711	0.389
7 to 6	1.058	0.183	0.186	1.147	0.306	0.308	1.125	0.306	0.306
6 to 5	0.331	0.250	0.265	0.338	0.162	0.183	0.343	0.138	0.142
7 to 7A	0.634	0.213	0.217	0.326	0.302	0.297	0.414	0.431	0.461
7A to 8	0.400	0.181	0.185	0.269	0.194	0.194	0.265	0.172	0.177
8 to 8A	0.274	0.184	0.162	0.584	0.718	0.240	0.314	0.253	0.251
8A to 9	0.231	0.120	0.121	0.255	0.150	0.151	0.256	0.151	0.152

5.1.5. *Travel Time Comparisons*

The estimated travel times based on probe vehicle data are compared with the measured travel time based on RTMS data. The RTMS data from 2011 from the NJ Turnpike were collected. Travel time for each short link was calculated. The travel time between two interchanges was then calculated by summing these individual link travel times. This summation represents the instantaneous travel time. The travel time estimation based on the probe vehicle data represents the experienced travel time, which is closer to the actual travel time for a vehicle traveling from one interchange to another. Of course, when the traffic is operating under a free flow condition, travel times based on the RTMS and ETC data should be relatively close. However, if there is congestion on a certain link, the RTMS downstream of the congested link may report free flow travel time since no vehicle would have crossed that location due to the upstream bottleneck. Thus the instantaneous travel time will not reflect the actual travel time. Figure 5.6 shows an example of the travel time obtained from different data sources. Figure 5.6(a) and Figure 5.6(b) show that under non-congested conditions travel time based on the RTMS data is similar to the estimated travel time based on the probe vehicle. Figure 5.6(c) and Figure 5.6(d) show that the travel time based on the RTMS data is obviously different than the ETC estimates during the congested period. Thus, if the RTMS data were used to quantify travel time-based performance measures (e.g., travel time reliability measures), the results will be biased, particularly when congestion occurs. It is advised then, to use experienced travel times instead of instantaneous travel times to develop travel time related performance measures.

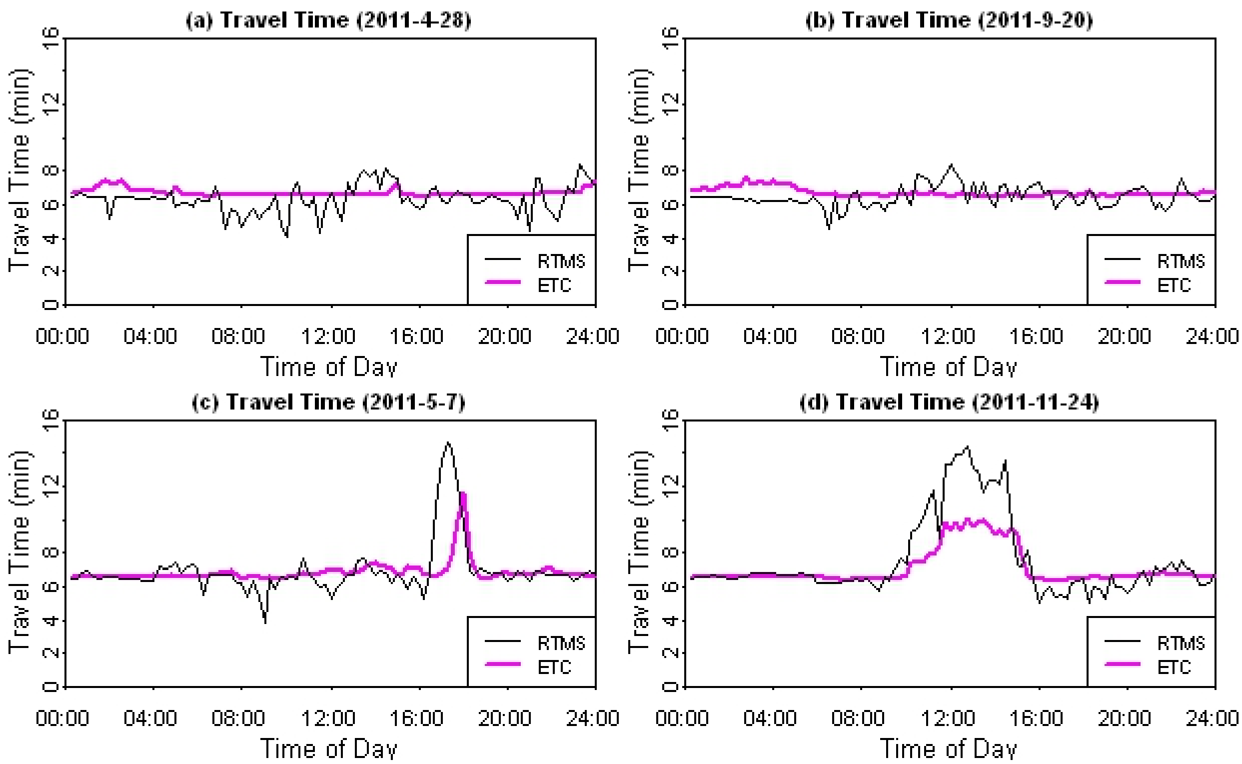


Figure 5.6 Comparisons between travel times based on RTMS and probe vehicles (7A to 8)

5.1.6. *Summary*

The primary purpose of this section is to provide accurate travel time estimates using probe data collected by the ETC system instead of other sensors specifically deployed for traffic monitoring. This dual use of toll readers for travel time estimation can be an attractive approach since it eliminates the burdensome additional costs incurred for deploying and maintaining infrastructure sensors. However, this approach can also present a significant challenge of achieving a high level of estimation accuracy when readers are not located on the main roadway but only on the ramps. To break down path travel times into link travel times, an improved estimation method is developed. Results showed that the proposed improved method clearly outperforms the simple estimation method, and 15-minute update periods provide the best results for the highway segment in this report. Thus case study segment is long enough to achieve a proper demand level and short enough to respond to rapid changes in the network. Our results, based on the real data, show that it is possible to use vehicles with electronic toll tag data as probes to provide reasonably accurate estimations of link travel times to track traffic conditions.

5.2. Assessing Travel Time Reliability

In this section, the estimated travel time based on the travel time estimation methodology presented in the previous section has been used to develop travel time reliability measures. These travel time reliability measures for the eight links shown in Figure 5.3 are reported. As mentioned before, travel time reliability can be aggregated by different applications. Table 5.3 shows an example of computed travel time measures based on one-year travel time information for each link. The free-flow travel time (FFTT) indicates the travel time based on a speed limit of 65 mph for each link. The mean travel time (MTT) represents an annual average of estimated travel time for all time periods. 95th percentile travel time (95th PTT), buffer index (BI), planning time index (PTI), and congestion frequency index (CFI) were derived based on the definition in Chapter 4. The last four travel time indices (TTI) were considered for the purposes of showing the variation of travel time reliability during the AM peak period and PM period on different days.

Table 5.3 Annual reliability measures for transportation performance evaluation

Link	FFTT (min)	MTT (min)	95th PTT (min)	BI (%)	PTI	CFI (%)	Weekday AM TTI	Weekday PM TTI	Weekend AM TTI	Weekend PM TTI
(1S) 8-7A	6.55	7.14	9.92	38.9	1.515	5.2	1.015	1.100	1.001	1.099
(2S) 7A-7	6.18	6.49	8.12	25.1	1.314	2.8	0.984	1.058	0.989	1.072
(3S) 7-6	2.77	3.53	4.75	34.6	1.715	11.1	1.096	1.227	1.148	1.291
(4S) 6-5	6.00	5.59	6.59	17.9	1.098	0.7	0.948	0.932	0.948	0.925
(1N) 7-7A	6.2	7.34	12.96	76.6	2.09	8.1	1.097	1.232	1.081	1.390
(2N) 7A-8	6.47	7.17	11.28	57.3	1.743	7.2	0.996	1.176	0.992	1.261
(3N) 8-8A	6.00	6.38	8.11	27.1	1.352	2.7	1.054	1.077	1.031	1.103
(4N) 8A-9	8.77	8.52	9.86	15.7	1.124	1.0	0.934	0.973	0.926	0.979

If the BI is used to rank the links, the link between interchange 7 and interchange 7A in the northbound direction with a BI of 76.6 percent is ranked as the highest. In other words, when crossing this link, travelers should incorporate more time cushion into their travel plans. Similarly, the PTI for this link is the highest, with a PTI value of 2.09. To ensure 95% on-time crossing, the total travel time needed is more than twice that of the link's free-flow travel time. Assuming the congestion frequency is increased every time when the travel time exceeded the 1.5 times of free-flow travel time, we found that the link between interchanges 7 and 6 in the southbound lanes were more frequently subject to congestion as the CFI was 11.1 percent of the total number of periods This is followed by the link between interchanges 7 and 7A in the northbound direction. Overall, the TTI of AM periods during both weekdays and weekends were less than that of PM periods. This result indicates that the travel time during the PM periods is higher than that of the morning peak period.

Since travel time reliability measures can be aggregated according to different criteria, transportation agencies need to define their specific goals. For instance, if they are interested in understanding the change of the reliability measures by time, they should develop weekly, monthly, and seasonal measures. Figure 5.7 shows an example of monthly analyses of the weekday travel time reliability measures. It can be seen that all measures fluctuated according to the months. More importantly, the months with a higher travel time, buffer index, planning time index and congestion frequency index are easy to understand visually. Based on these characteristics of the travel time reliability measures, transportation agencies can implement necessary countermeasures to maintain the optimal performance of their facilities.

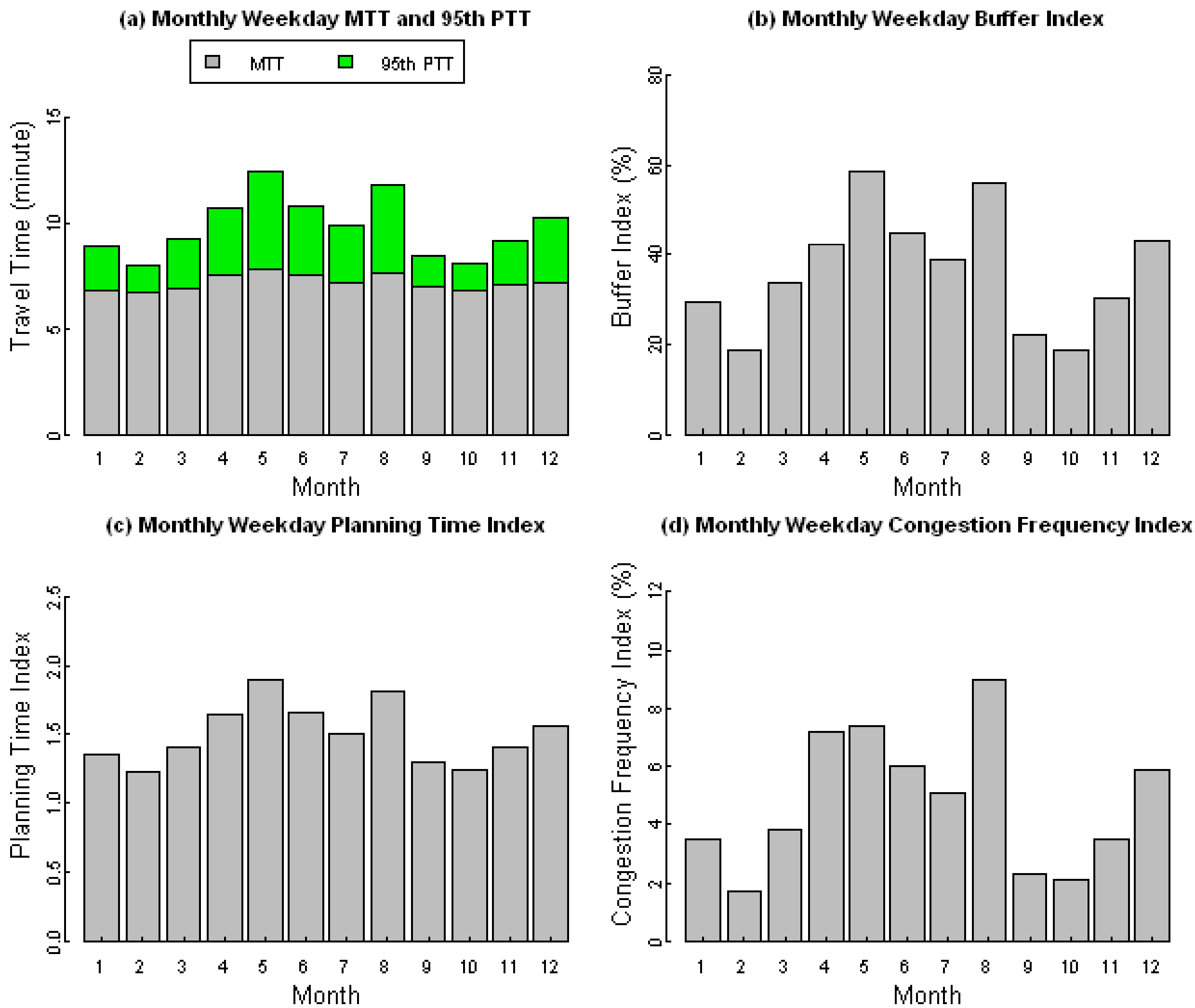


Figure 5.7 Variations of travel time reliability measures by month

5.3. Incident Duration Estimation

The development of a practical model for traffic incident management is investigated through Bayesian Networks (BNs) in this section. BNs are capable of accurately predicting incident durations and can be easily incorporated into the incident management activities of Traffic Management Centers to improve their real-time decision-making processes.

5.3.1. Problem Definition

Incidents, such as accidents, disabled vehicles, and other unusual events significantly contribute to traffic congestion and delays in urban freeways. If incidents are not responded to and cleared in a timely manner, secondary crashes may also take place. To minimize the effects of incident-induced congestion and to prevent secondary accidents, an effective incident management tool that can reliably predict incident durations in real-time is of the utmost importance. Real-time duration predictions can also provide useful information to travelers for decision-making (e.g. route diversion) as well as reduce uncertainty regarding their travel times [34].

At the early stages of an incident evaluation, reliable estimates of incident durations may improve incident response operations, which, in turn, have the potential to mitigate the effects of incidents considerably. At this point, Bayesian Networks (BNs) could be a good alternative to the traditional incident duration estimation models as it is possible to use BNs with uncertain conditions. A BN is essentially a graphical model in which nodes represent variables and arcs represent dependencies among the nodes. Since the problem domain is modeled as a whole by constructing a joint probability distribution over different combinations of the variables in BNs, they can be used for solving both classification and regression problems [35].

Figure 5.8 shows how BNs can be utilized for real-time incident management operations. First, an incident occurs and it is either detected by traffic sensors or reported by travelers after its occurrence. At this stage, information about the details of the incident can be limited to the location and the number of vehicles involved in the incident. Even though this information is limited, a Bayesian network-based incident duration prediction model can be utilized to provide expected incident durations. Based on the first prediction using partial information, an initial response strategy can be determined and emergency vehicles can be dispatched. Later, when additional information is received from emergency teams and/or additional real-time reports, the input to the prediction model can be updated to obtain a new and more accurate prediction. Then, the response strategy can be re-evaluated and necessary changes can be made.

The flexibility of the BN model stands in stark contrast to the models in the literature that call only for a single estimation using an initial dataset, thus lacking an appropriate mechanism for adapting to the changing incident conditions [36, 37]. The absence of such a learning mechanism within the model can also result in a decreased performance over time. This can be avoided, however, by incorporating an adaptive learning mechanism within the BNs that utilizes newly added data and maintains a high level of prediction performance.

Below are this section's major objectives.

1. Identify the best ways to estimate BNs so that they provide more accurate predictions of incident durations given the known difficulties with using traditional parametric prediction methods. Different structure learning algorithms are tested to construct a BN structure for incident duration prediction using 2005 New Jersey incident data.
2. Clearly quantify and discuss the predictive power of the BNs based on a cross validation method and Bayesian Information Criterion (BIC) statistic. The best performing model is picked based on the prediction accuracy and BIC statistic.
3. Demonstrate the adaptive learning performance of the Bayesian model for future data. First, 2011 incident durations are predicted with the model using only 2005 New Jersey incident data. Then, the model is updated with 2011 New Jersey incident data for the same locations in a monthly and quarterly basis. The six-year difference between training and prediction data can demonstrate how the model performance changes over time; it can also indicate if the model is still valid after a substantial period of time after its initial estimation.

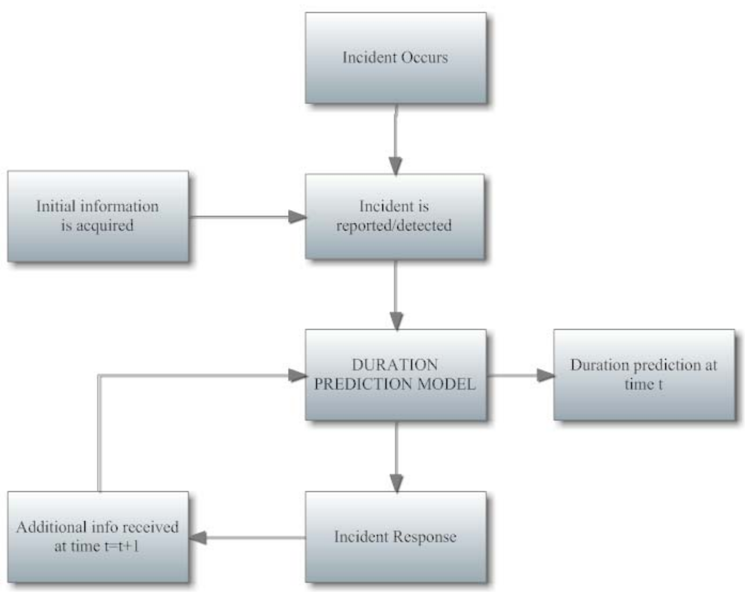


Figure 5.8 Use of BNs for real-time incident duration prediction

5.3.2. Modeling Background

5.3.2.1 Bayesian Networks and Inference

A BN is also known as a directed acyclic graph (DAG). Figure 5.9 depicts an example of a simple DAG with 5 nodes. If an arc is not present between two nodes in a DAG, then these two nodes are said to be conditionally independent. While nodes represent variables that can be either discrete or continuous, arcs between the nodes stand for conditional dependency between variables. Each variable X_i is independent of its child nodes given the values of its parents in the graph. The joint probability distribution P of the variables in the example DAG is equal to the product of its conditional distributions of all nodes given values of their parents; it is written as follows:

$$P\left(X_1, X_2, X_3, X_4, X_5\right) = P\left(X_5 \mid X_3, X_2\right) P\left(X_4 \mid X_2\right) P\left(X_3 \mid X_1\right) P\left(X_2 \mid X_1\right) P\left(X_1\right) \tag{14}$$

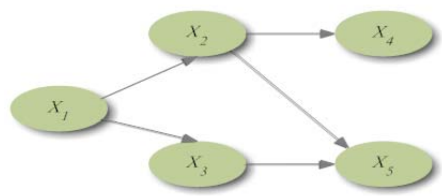


Figure 5.9 Example BN

If the conditional probabilities on the right side of the equation exist (i.e. conditional dependencies between nodes) then the above equation can also be written in the factorized form as follows:

$$P(X_1, ..., X_n) = \prod_{i=1}^{n} P(X_i \mid pa(X_i)) \tag{15}$$

where $pa(X_i)$ is the set of parents of X_i in the DAG. The assigned value of a variable will be propagated through the network and will update the marginal posterior distributions of all nodes. The details of belief propagation in BNs can be found in a previous study [38].

5.3.2.2 Structure Learning for Automatically Building Bayesian Networks

When expert knowledge is available, the BN structure can be easily created by defining the dependencies between variables. However, if it is unknown, it is still possible to learn the network structure automatically from the data. Bayesian Information Criterion (BIC) is a widely used measure for model selection in structure learning. The measure includes a goodness of fit term and a penalty term to account for model complexity [39]:

$$BIC = \log L - \frac{d}{2} \log N \tag{16}$$

where L is the sum of likelihood of parameters , d is the dimension of BN and N is the sample size. To evaluate the BIC score of a BN, first, the maximum likelihood of the parameters of the model is estimated. If the data is complete, this part can be reduced to frequency counting. Then, probability for each case in the data can be computed using the estimates.

The problem in finding the best scoring model is known to be NP-hard (i.e. computationally intractable) due to the complexity of the search space of all possible graphs [40]. Hence, the structure learning algorithms use search heuristics to limit the size of the search space. They use operators such as arc-insertion or arc-deletion to explore the graph space and local score to minimize the computational effort to the score variation between two neighboring graphs. Now, we will briefly discuss the structure learning algorithms that are evaluated in this study.

Naïve Bayes classifier is a simple probabilistic classifier where all the parameters are assumed to be independent given the class variable (node). Class variable is the parent of all other variables in a Naïve Bayes classifier and other variables do not have any other parent in a Naïve Bayes classifier. Even though the independence assumption is violated in most cases, Naïve Bayes classifiers are shown to work well within many classification problems. To learn and use the dependencies between variables other than class variable, one can override the independence assumption in Naïve Bayes using an augmented Naïve Bayes classifier (TAN) [41]. Chow and Liu [42] proposes an estimation method derived from the maximum weight spanning tree algorithm (MWST). This method associates a weight to each edge which can then be either the mutual information between two variables [42] or the score variation when one node becomes a parent of the other [43]. The K2 algorithm proposed by Cooper and Herskovits [44] limits the search space to a subset of all possible networks based on the ordering of the variables. Since the processing of the K2 algorithm depends on the given enumeration order, this order needs to be pre-defined by a heuristic method if it has not already been defined by experts. As Andrieu et al. [45] proposes, the oriented tree obtained with the MWST algorithm can be used to generate this order.

5.3.2.3 Parameter Estimation for Adaptive Learning in Bayesian Networks

Provided that the data is complete (a value provided for each of the variables for each record), the parameters in a BN can be estimated using batch learning. For each record *d* in the data *D*, the probability $P(d \mid M)$ is called the likelihood of model *M* given *d*. For a DAG, the conditional probability distribution can be estimated using either maximum likelihood or maximum a posteriori. Then, the log-likelihood of *M* given *d* is

$$L(M \mid D) = \sum_{d \in D} \log_2 P(d \mid M) \tag{17}$$

To estimate the conditional probabilities among the possible models M_θ that have the same structure but different parameters, θ, one must select a parameter estimate $\hat{\theta}$ that maximizes the likelihood:

$$\hat{\theta} = \arg\max_{\theta} L(M_\theta \mid D) \tag{18}$$

However, when new data is acquired sequentially, it is necessary for the model to adapt to new cases. Hence, the conditional probabilities need to be updated since the new records will increase the uncertainty in the accuracy of the conditional probabilities. This can only be achieved by modifying certain parameters in a BN structure. As the new records are acquired, the goal is to learn from the new records. Although we are certain of the network structure, the conditional probabilities will vary depending on each new case. Thus it is essential to develop a model that can automatically adapt to new cases. For a BN structure such as the one in Figure 1, the variable X_5 is influenced by X_2 and X_3, and the conditional probability can be modeled as $P(X_5 \mid X_2, X_3)$. The uncertainty in the conditional probability can be explicitly modeled by introducing a new parent *Y* for X_5. To represent each possible result of X_5, a prior distribution, P(*Y*), can be defined for *Y*. When a new case, r, is entered to the BN, the propagation will result in a new distribution $P^*(Y)= P(Y|r)$ and this way the change in the distribution will reflect what is learned from the case. For the additional cases $P^*(Y)$ can be used in the same way and when i^{th} case is acquired, the corresponding variables will be instantiated and $P^*(Y) = P(Y|r_1,\ldots,r_{i-1})$ will be updated to $P(Y|r_1,\ldots,r_i)$) [46].

5.3.3. Case Study

Incident duration prediction using BNs approach is applied to incidents along the New Jersey Turnpike (NJTPK).

5.3.3.1 Description of Data

The data in this study is created by using individual incident logs and New Jersey Department of Transportation crash records from 2005 and 2011. An incident log is used to obtain the duration and the number of vehicles involved in an incident. The second dataset also includes the same crashes with a different set of parameters such as direction, weather conditions, and vehicle type. Since these two datasets are coming from different sources, even for the same incident, there exists a small discrepancy between them, which requires the utilization of a matching procedure. The data is combined using a simple matching algorithm. The steps are as follows:

For Each Record in Incident Database(I)
Search for Matching Record in Accident Database(II) with following conditions
Date(I) = Date (II)
|MILEPOST(I) – MILEPOST(II)| <= 0.2 miles
|STARTTIME(I) – STARTTIME(II)| <= 15 minutes
Then match RECORD(I) to RECORD(II)

As a result of the above process, 2221 records in 2005 and 1951 records in 2011 from incident logs are matched with the accidents in the NJDOT crash database. The outliers in the records in 2005 dataset, which later will be used in model development, are discarded using the method explained in a previous study [47]. In this method, the distance of a data from k^{th} (k=5) nearest neighbor is calculated and then the points are ranked by the distance from its k^{th} nearest neighbor and the top n points are identified as outliers (n = 247, 10% of the data). The description of parameters in the combined dataset is given in Table 5.4. Since BNs work with tabular nodes, prior to model development, incident durations are discretized into 4 separate categories

1) Low: incidents lasting less than 30 minutes.
2) Medium: incidents lasting between 30 to 60 minutes.
3) High: incidents lasting between 60 to 90 minutes.

4) Very High: incidents lasting more than 90 minutes.

Table 5.5 shows the frequency of the records in those categories and summary statistics for incident duration data. As Table 5.5 shows, the distribution of the incident duration in 2005 and 2011 are quite similar. Accessibility measures that indicate the distance of the incident location from the nearest exit are also discretized by rounding up the distance to the nearest integer value.

The data used in the study incorporate incident specific parameters such as incident duration, number of injuries and incident type as well as the parameters related to environmental and roadway conditions. One advantage of predicting incident duration using this data might be the ease of initial estimation as some of the parameters like weather conditions are known as soon as the incident has been reported. However, parameters such as the number of injuries, number of fatalities, or roadway damage are unknown until after the incident has occurred.

Table 5.4 Description of the model variables

Parameter	Description	State description
Month	Month of year	0-12
DayofWeek	Day of week	(1) weekday; (2) weekend
TimeofDay	Time of day	(1) morning peak (6-9 a.m.); (2) afternoon off-peak (9 a.m.-4 p.m.); (3) evening peak (4-7 p.m.); (4) evening off-peak (7 p.m. - 6 a.m)
NumFat	Number of fatalities	0, 1, 3
NumInj	Number of injuries	0-12
CrshType	Type of crash	(1) rear end; (2) side swipe (same direction); (3) right angle; (4) head-on; (5) side swipe (opposite direction); (6) struck parked vehicle; (7) left/u turn; (8) backing; (9) encroachment; (10) overturned; (11) fixed-object; (12) animal; (13) pedestrian; (14) pedalcyclist; (15) non-fixed object
VehNo	Number of vehicles involved	1-6
Pavement	Pavement conditions	(1) dry; (2) wet; (3)snowy; (4) icy
Light	Lighting conditions	(1) daylight; (2) dawn; (3) dusk; (4) dark (street lights off); (5) dark (no lights); (6) dark (continuous lighting)
Weather	Weather conditions	(1) clear; (2) rain; (3) snow; (4) fog/smog/smoke
Roadway Damage	Presence of roadway damage	0,1 (binary)
NumTrkInv	Number of trucks involved	0-4
Location	Link on which incident occurred (interchange to interchange)	1-28
Distance	Distance from the closest exit (in miles)	0-6.6
Duration	Duration of incident	3-762

Table 5.5 Summary statistics of the incident duration data

	Frequency				Duration (minutes)			
Year	**0-30 min**	**30-60 min**	**60-90 min**	**90+ min**	**Min**	**Max**	**Mean**	**St. Dev.**
2005	**13.4%**	**51.9%**	**23.0%**	**11.7%**	**3**	**762**	**62.4**	**57.5**
2011	**13.5%**	**52.2%**	**22.7%**	**11.6%**	**5**	**615**	**60.8**	**48.7**

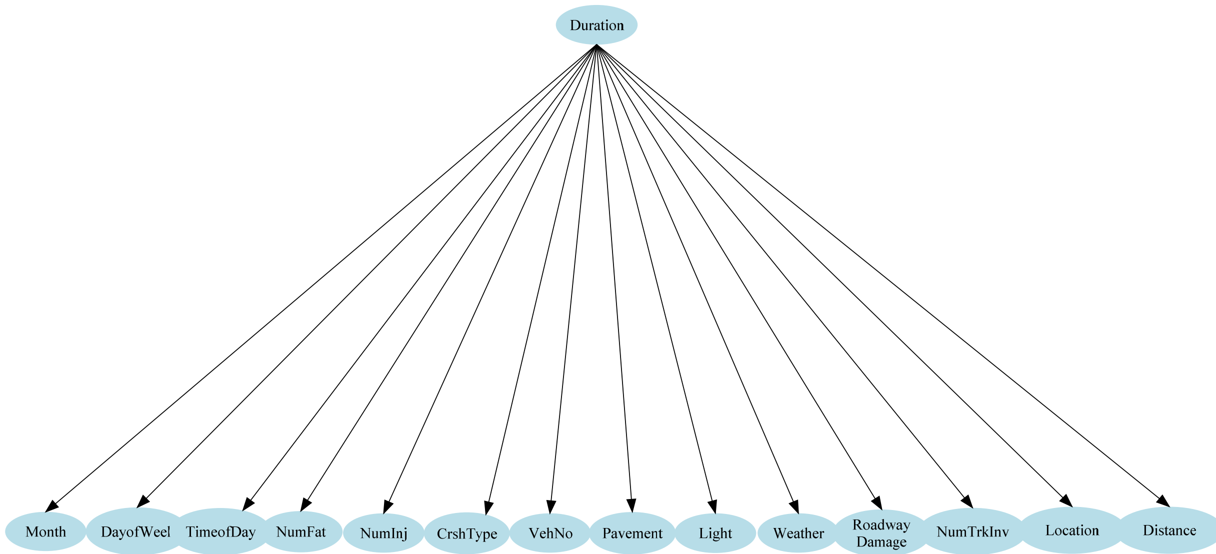
5.3.3.2 Structure Learning and Model Estimation

In this section, three structure learning algorithms, namely Naïve Bayesian classifier, Tree Augmented Naïve Bayes (TAN) and K2, are tested to determine the best BN to use for an incident duration model using the integrated incident dataset. Development of the BNs in this study requires the use of software packages such as Bayes Net Toolbox (BNT) [48] and Structure Learning Package (SLP) for BNT. These software packages are used because SLP for BNT complements BNT by offering additional structure learning algorithms while using the basic functions of BNT [49]. The combination of these software packages can handle algorithms used in the study as they have been already implemented in the packages as built-in functions. Using the built-in functions of the software packages mentioned above, the following BNs (see Figure 5.10) are estimated:

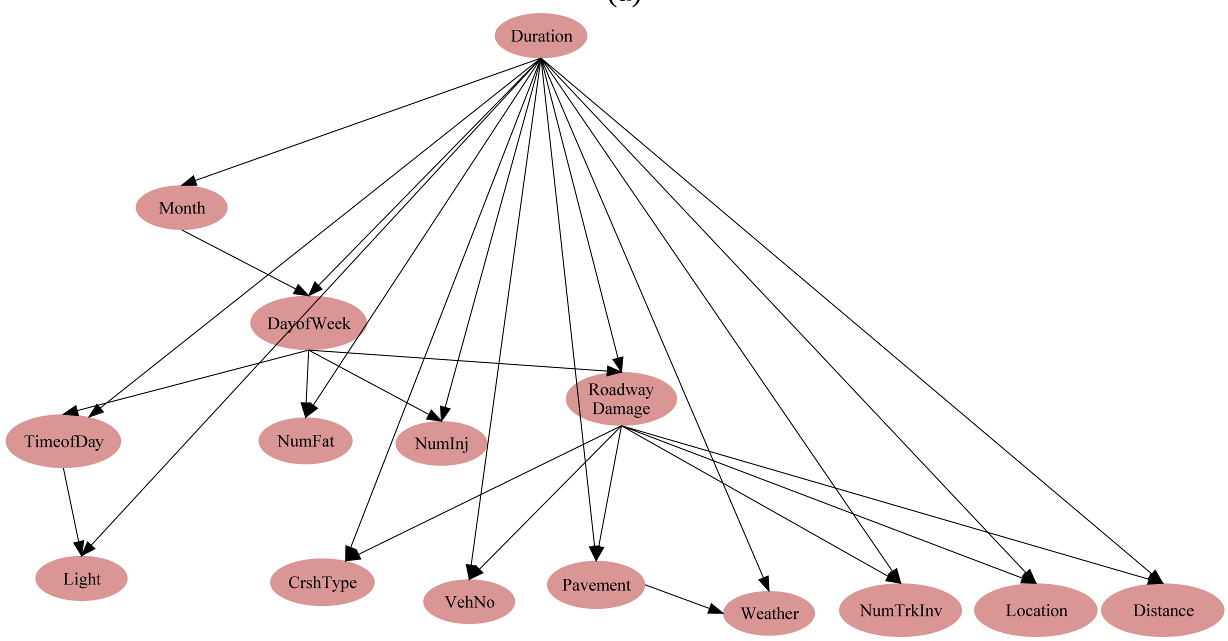
Naïve Bayes Model: This model has a fixed structure around the class node. Therefore, for this algorithm, the structure learning is minimal as long as the class node, which in our case is incident duration, is defined. When the only requirement of the algorithm (defining a class node) is supplied, the other nodes have a one-to-one connection to the class node. The resulting BN structure is shown in Figure 5.10 (a). According to this structure incident characteristics are conditionally independent of each other given the value of incident duration. In other words, in this model, it is assumed that the presence (or absence) of information on a particular variable (node) of a class node (incident duration) is unrelated to the presence (or absence) of information on any other variable. For example, the model will predict the duration of an incident if only VehNo, CrshType and Light variables are known. Although these variables might be related to each other or other variables, the model considers all of these variables to independently contribute to the probability of the incident duration. Even though the Naïve Bayesian classifier is an over simplistic model due to the very simplistic assumption of complete independence between class variables, it has shown superior performance to other classifiers in complex real world problems [50].

TAN (Tree Augmented Naïve Bayes) Model: The TAN model is simply a modified version of the Naïve Bayes model where the relationships between variables are recovered using a structure learning algorithm. In our case, the mutual relationships between incident characteristics are recovered using a MWST algorithm. The resulting undirected tree can be oriented around any chosen root node except the class node (incident duration). In Figure 5.10 (b), it can be seen that the tree structure is oriented randomly around Day-of-Week but note that any other node would result in the same structure as the MWST algorithm initially produces an undirected tree. As explained before, the relationships between variables are recovered by using mutual information (where mutual information is variable pairs of, say, X and Y, with the measure for the amount of uncertainty being removed from X by knowing the state of Y and vice versa). Therefore, the BN structure generated based on this algorithm may not necessarily show causality between the variables, as the better mutual information between variables does not always necessitate a cause-effect relationship.

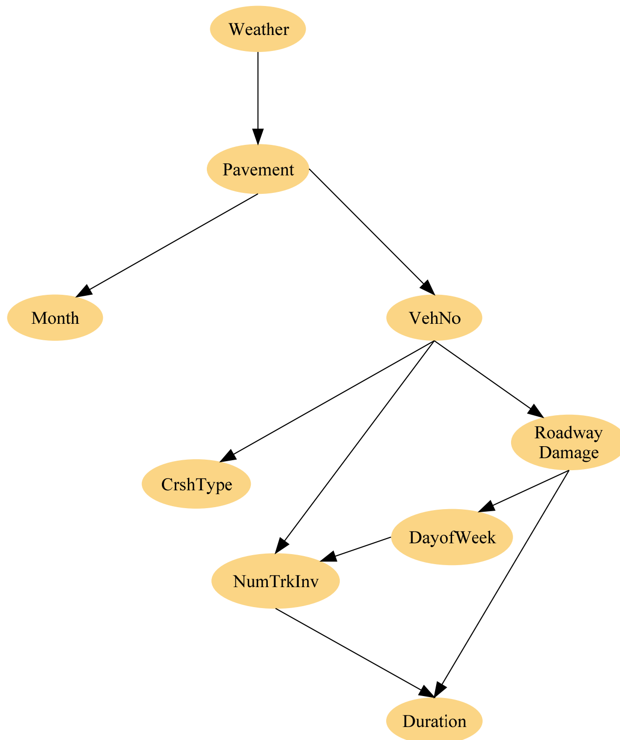
<u>K2 Model:</u> K2 algorithm limits the search space to a subset of all possible networks based on the ordering of the variables. Since no expert opinion is assumed in this study, the initial search for ordering the variables is obtained by using the MWST algorithm. According to the output of MWST, the initial ordering of variables is as follows: Duration > Location > Distance > Light > TimeofDay > CrshType > NumTrkInv > DayofWeek > Roadway Damage > VehNo > NumInj > Month > Pavement > Weather > NumFat where Duration variable accepts the most and NumFat accepts the least number of variables as parents. This algorithm searches all DAG space (limited by variable order) and also gives room for additional input, mainly expert knowledge for variable ordering. Therefore, it may perform very well especially if expert knowledge is available. Figure 5.10 (c) shows the BN created by the K2 algorithm. It can be observed from the figure that this BN is less complex than the previous BNs (less number of edges) and six variables are excluded from the pool of all variables. It is found that Light depends on TimeofDay and Distance depends on Location. NumFat and NumInj variables are found to be independent of the other variables in the BN. It is worth noting that although these variables are in fact considered in the model development stage, they are not shown in Figure 5.10 (c) as the algorithm excluded the variables from the BN structure.


Duration
Month
DayofWeel
TimeofDay
NumFat
NumInj
CrshType
VehNo
Pavement
Light
Weather
Roadway Damage
NumTrkInv
Location
Distance

(a)


Duration
Month
DayofWeek
TimeofDay
NumFat
NumInj
Roadway Damage
Light
CrshType
VehNo
Pavement
Weather
NumTrkInv
Location
Distance

(b)



(c)

Figure 5.10 BN structures from (a) Naïve Bayes, (b) TAN and (c) K2

5.3.3.3 Model Validation

To determine the best BN among these three BN structures, their BIC scores are calculated and shown in Table 5.6. The Bayesian Information Criterion (BIC) assesses the overall fit of a model and facilitates the comparison of BN models. For example, if we have two different models and there is no prior information on which model performs better, BIC identifies the model that is more likely to have generated the observed data. The smaller the value of the statistic (or the more negative the value is) the better is the fit of the model.

When BIC scores of the models are considered, Naïve Bayes algorithm results in a network with the lowest BIC score compared to the other structure learning algorithms, which are TAN and K2. The BIC scores also suggest that:

- Although complete independence among the variables is assumed, the Naïve Bayes model ranks the best among the three algorithms.

- When relaxing the independence assumption of Naïve Bayes, a better representation of the data cannot be achieved (TAN model).
- K2 achieves the worst representation of the data by employing a simpler structure and excluding the many variables that might help better represent the data.

Table 3 gives the prediction accuracy of each model. Here, prediction accuracy is defined as the number of correctly predicted incident durations by the model; expressed as a percentage of the total number of samples in the data. Prediction accuracy of the models is computed using a 10-fold cross-validation method, in which incident durations are randomly partitioned to 10 equal size subsamples and one of the subsamples is kept for validation. Other samples are used for model estimation. This process is then repeated 10 times to produce prediction accuracy for the models in Table 5.6.

For our dataset, Naïve Bayes model predicts, on average, 63.1% of the incidents accurately. The prediction accuracy of TAN and K2 model are also calculated as 61.4% and 60.9%, respectively. Although the best performing BN was found previously using BIC scores, these values again confirmed that the Naïve Bayes model represents the data best among all the models estimated using other "structure learning algorithms" tested in this study.

Table 5.6 BIC scores and accuracies of prediction models

Structure Learning Algorithm	BIC	Prediction Accuracy (%)
Naïve Bayes	-39037	63.1±3.6
TAN	-37365	61.4±5.6
K2	-34281	60.9±4.9

Thus, BN estimates using the Naïve Bayes algorithm are selected for the prediction of incident durations. This structure makes it possible to predict incident duration even in the cases where just a single parameter is known since any evidence provided in a node will result in an update of the probability distributions of connected nodes. It's worth pointing out that traditional methods such as classification trees require a-priori knowledge of sequential information. Moreover, missing information in the sequence would result in the failure of estimating incident duration due to hierarchy involved in their structure.

Classification trees are constructed in such a way that only one variable of interest can be estimated from the tree as opposed to the flexible dynamic representation capability of a BN. As the probabilistic relationships between multiple variables are captured by BNs, there is no need to define a classification variable [44]. For example, a Naïve Bayes model can be used to predict the conditional probability distribution of the number of injuries in an incident, which ultimately produces the values of parameters that are conditionally dependent on the number of injuries.

5.3.3.4 Real-time Prediction Performance and Adaptive Learning using 2011 Data

One of the main problems in using the real-time incident duration prediction models is that most are estimated using a particular dataset and the prediction performance of the model is only tested using a subsample of this data. Even if the subsample is not used in estimating the model, the data used in testing still belongs to the same sample and the same timeframe from when the data has been collected.

Hence, to evaluate the real performance of a BN model for future data, it is important to predict future incident durations using the model. In this study, 2011 NJ incident data is used for the prediction of incident durations. Since the model is estimated using 2005 incident data, there is a considerable time difference between training and prediction data. Therefore, the prediction data may reveal how the model can be expected to behave in the relatively distant future.

Another related problem in the real-time incident duration prediction is that the data acquired from the system evolves over time. However, most models are static and they can only provide estimation based on archived data. Generally, it is not easy to tune model parameters by using data acquired after the model has been developed. This may lead to a decrease in model performance over time since the model cannot adapt to the continuously changing incident conditions and durations.

In this study, an adaptive learning scheme is introduced into the BN model, to overcome the problems listed above. Figure 5.11 demonstrates how adaptive learning occurs in the proposed BN prediction model. At t=0, the adaptive model is initialized by using the parameters of the base model. At the end of first time interval t, the data is received and the adaptive model learns the new data. The scheme also keeps track of another instance of the model without learning the data for the current time interval t. At the end of next time interval t+1, both instances are used to predict incident durations in time interval t+1. If the learning in the previous time interval helped improve the model performance (prediction accuracy), the parameters of the model are updated. The updated model is then used for the next time interval and so on. Note, though, that if the learning data in the previous time interval does not improve prediction accuracy then the parameters of the model are kept the same for the next time interval. Figure 5.12 shows the prediction results for 2011 data provided by the base model and by the adaptive learning scheme using the new data. First, month-to-month prediction accuracy performance of the base model and the model with adaptive learning is compared. For adaptive learning the model is fed with monthly data and the model parameters are automatically adjusted. If the learning criteria is met for the base model, the predictions are estimated without changing the initial parameters.

The same performance analysis is done once again by dividing the data into quarters.

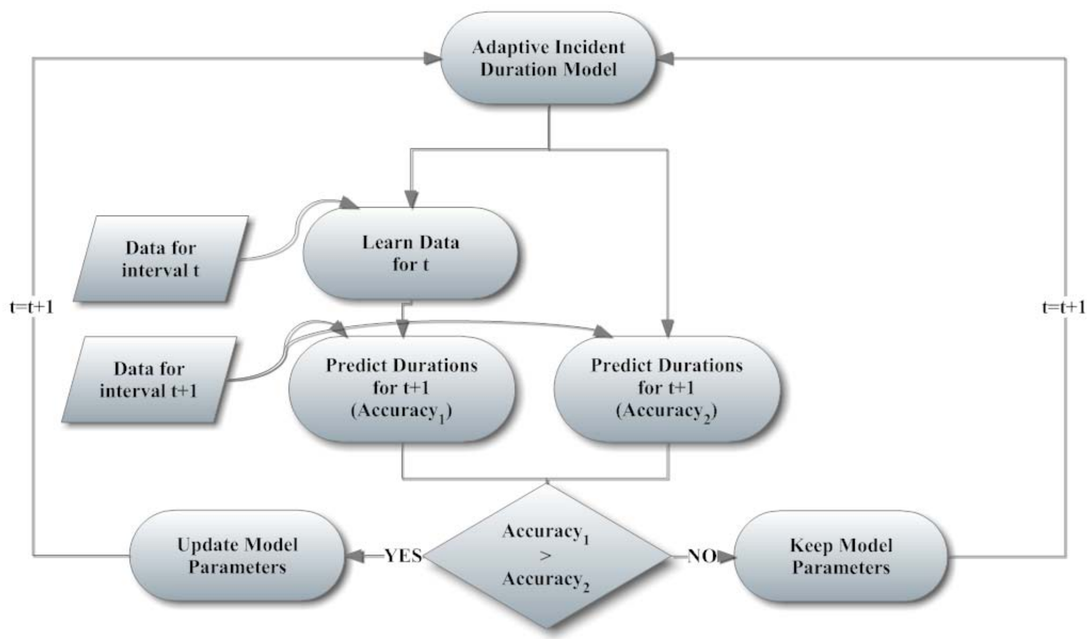


Figure 5.11 Adaptive learning mechanism in the BN model

The results indicate that:

- Adaptive learning can improve the prediction of the model by adjusting the model parameters when the new data is acquired. It can be clearly seen from Figure 5.12 that the prediction accuracy of the base model is significantly improved after introducing adaptive learning to the base model.

- Even without adaptive learning and 6 years after the development of the model, BN models can still produce reasonably accurate predictions.

If the data is fed to the model monthly, the results appear to fluctuate more than when the data is fed quarterly.

5.3.4. Summary

In this section, three different “structure learning algorithms” are used to develop a BN for predicting incident durations. Although all of the algorithms provided promising results, the BN generated using a Naïve Bayes algorithm is selected since it is observed to be the best representation of the data according to its BIC score and cross-validation results. Then, the prediction performance of the chosen model with and without adaptive learning is examined using 2011 incident data.

It is found that the model performance in predicting future incident durations significantly improves if the proposed adaptive learning scheme is employed. This improvement occurs because the model can adjust its parameters based on the new data to consider time-dependent changes. Based on the prediction results of the model for 2011 data with and without learning from the future data, it is shown that the developed BN has the capability to automatically adapt itself by learning the emerging patterns of new incident durations (see Table 5.7).

BNs can also be considered good candidates for real time incident duration prediction because of their flexibility in adjusting to future conditions. Moreover, BNs can also deal effectively with missing data, creating a suitable tool for real-time incident management applications. Another advantage of BNs over the classification tree and other regression-based models is that it makes its predictions in the form of a probability distribution of possible outcomes instead of fixed outcomes like a point estimate. The probability of outcomes other than the one predicted can also be evaluated and more informed decisions can be made about a response strategy based on the variability of the outcome.

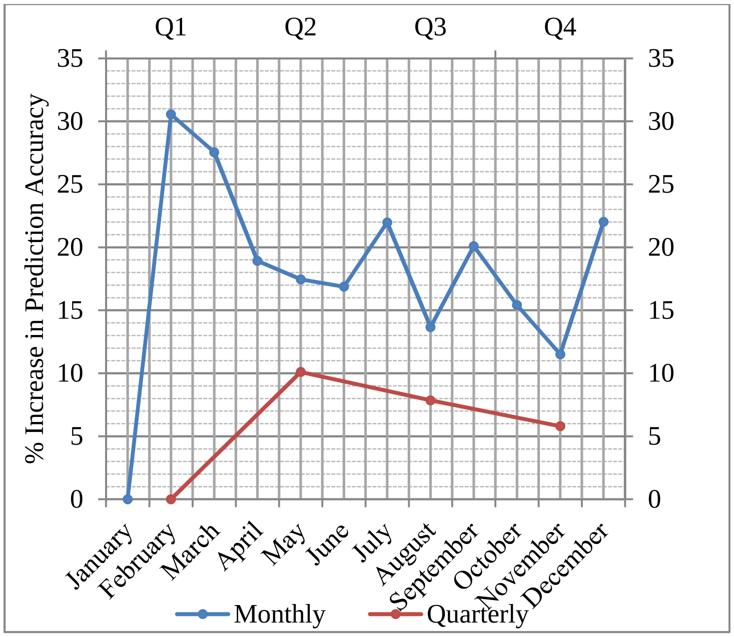


Figure 5.12 Percent increase in prediction accuracy of the model with adaptive learning with monthly and quarterly 2011 data

Table 5.7 Performance of the model for 2011 data with adaptive learning

	% Improvement in Prediction Accuracy								
	Q2			Q3			Q4		
	April	May	June	July	August	September	October	November	December
Monthly	18.9	17.5	16.9	22.0	13.7	20.1	15.4	11.5	22.0
Quarterly	10.1			7.9			5.8		

5.4. Identification of Secondary Crashes

Highway agencies have been using inductive-loop detectors since the 1960's for data collection and traffic surveillance. Much is known about their operation, advantages and disadvantages. As the technology has improved, new and more efficient traffic detection and surveillance devices have also emerged (e.g., video image detectors, microwave radar sensors, and passive acoustic sensors). Today many freeway corridors are equipped with these surveillance units that continuously monitor and archive traffic data (e.g., PeMS in California [51]). In addition, state DOTs keep and maintain a crash database that includes detailed data such as time, location, severity, number of vehicles involved, gender, age and vehicle type. The proposed methodology aims to combine these rich data sources and to fully account for the dynamic spatio-temporal impact of an incident under the prevailing circumstances. The proposed methodology consists of following major components:

(1) Defining secondary crashes.

(2) Detecting the impact range of a primary incident using archived traffic sensor data.

(3) Identifying secondary crashes within the spatio-temporal impact range of the primary incident.

5.4.1. Secondary Crash Definition

Secondary crashes are stochastic events mainly induced by the impact of a prior incident. Figure 5.13 describes the potential occurrence of secondary crashes under different scenarios. The first scenario describes a case where a secondary crash B occurs as a result of the queue caused by the prior incident A. Similarly, the second scenario indicates a case where the prior incident A causes a queue and multiple secondary crashes (B and C) occur as a result. It should be mentioned that these multiple secondary crashes could sometimes be interdependent. For instance, if an upstream secondary crash (C) occurs after another secondary crash (B), both the primary crash (A) and the earlier secondary crash (B) could be the cause of a third crash C. Scenarios 1 and 2 represent typical cases where a prior incident results in a bottleneck and negatively affects roadway mobility and safety. The third scenario shown in Figure 5.13 describes the prior incident A causing a secondary crash B, although there is no queue formation. This represents a number of minor incidents that do not seriously impede traffic flow but still induce crashes. For instance, an off-road crash that does not cause an obvious queue formation may distract some drivers passing the incident scene and cause a secondary crash. It is assumed that such secondary crashes can only occur close to the onset time of a primary incident and also within a short upstream distance . The last scenario shown in Figure 5.13 depicts a case where the secondary crash B is caused by the rubbernecking effect. This describes the incurred crashes in the opposite direction of the prior incident A.

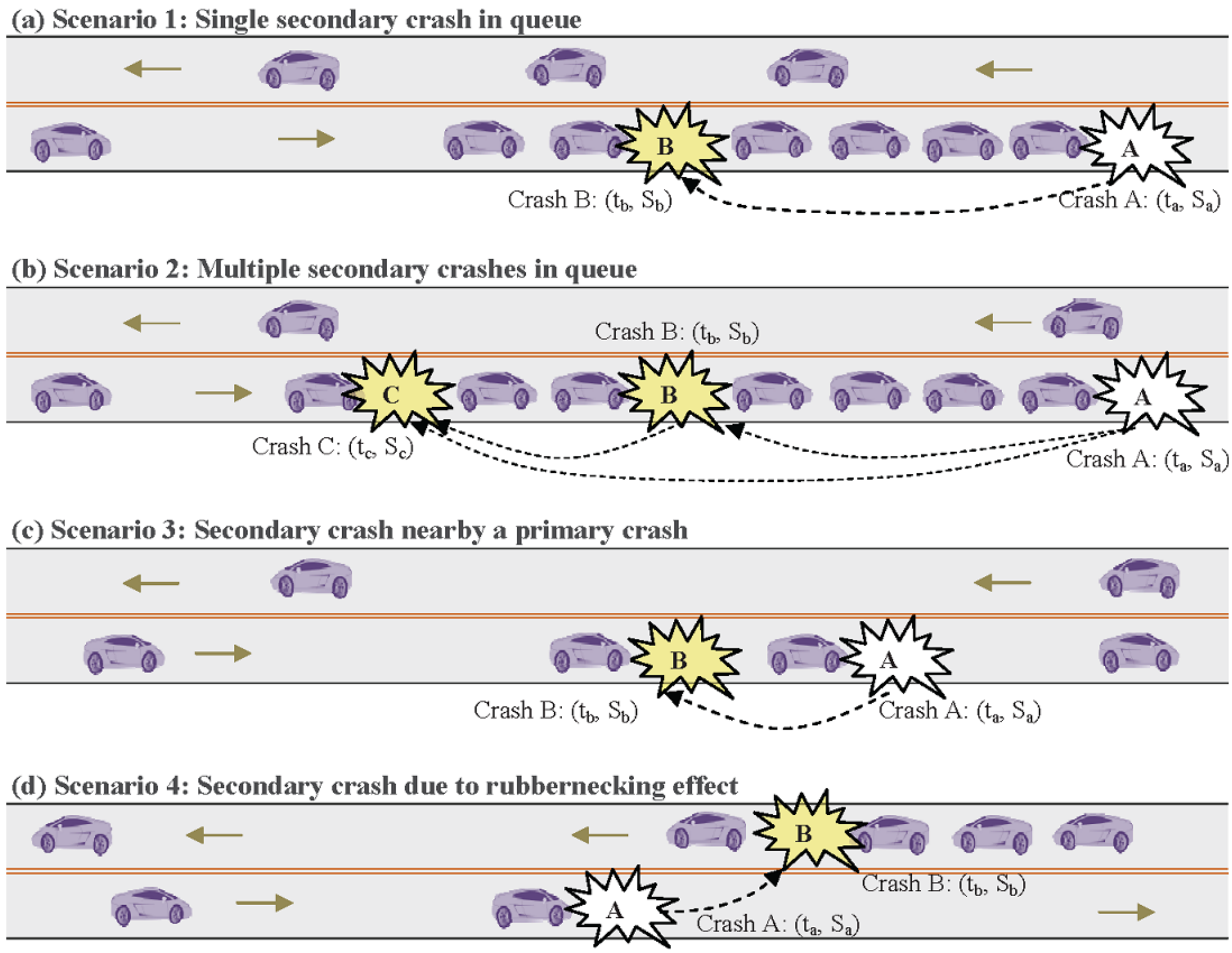


Figure 5.13 Defining secondary crashes under some typical conditions [52]

5.4.2. *Impact Range of Primary Incidents*

The impact range is the vehicle queue caused by a primary incident measured in time and space. As noted previously, the previous studies estimated vehicle queues either by assuming fixed queue length and duration or by relying on simple queuing modeling techniques. Instead, this study takes advantage of archived traffic sensor data and develops a new methodology to accurately capture the impact range of primary incidents. The following steps describe the proposed data-driven methodology.

Step 1- Constructing Speed Contour Plots: The impact of each incident on traffic mobility can be visualized through a series of speed contour plots (SCP) over time and space. Figure 5.14 (a) shows an example of a SCP of a freeway under normal traffic condition. The x and y axes represent time and the roadway length, respectively. Each cell in Figure 5.14 (a) represents a speed measurement $V(t,s)$ by traffic sensor s at t^{th} time interval, $\forall s=1,2,\ldots,S$ and $\forall t=1,2,\ldots,T$. Traffic speed is color coded. Figure 5.14 (b) shows a slice of a typical SCP when a crash occurs on the same freeway but on another day. It can be seen that a clear congestion pattern forms soon after crash A.

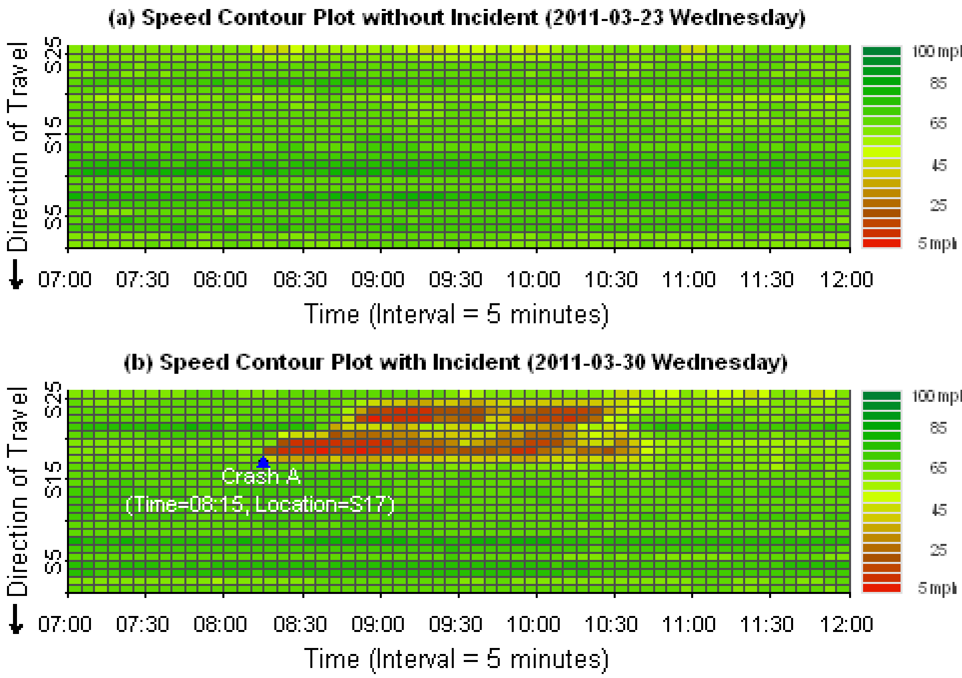


Figure 5.14 Speed contour plots: (a) without incident, (b) with incident

Step 2- Constructing a representative speed contour plot: In order to determine what speed range constitutes a queue formation, an average baseline speed range needs to be estimated. Historical sensor data for the days when no incident occurred are used to create a representative speed contour plot (RSCP). Specifically, the p^{th} percentile speed $V_{i,p}(t,s)$ is used as the representative speed measured at detector s and time period t, where $i=1,2,\ldots,7$ is analogous to the day of the week from Monday to Sunday. For instance, we can create a RSCP that represents normal Wednesday traffic conditions on a freeway based on data collected every five minutes during all other Wednesdays in a calendar year. Specifically, the representative speed $V_{i,p}(t,s)$ of the RSCP is obtained by using the following sub-steps:

(a) Create a subset of historical speed measurement $V_i^d(t,s)$ from detector s at each time period t on i^{th} day of each week, where d means d^{th} sample, $\forall d=1,2,\ldots,D$; D is the total number of all sampled days that belong to the i^{th} category. For instance, if $i=3$, D represents the total number of Wednesdays during a period (e.g., a calendar year) for which historical data are available;

(b) Sort the historical speed measurements $V_i^d(t,s)$ in ascending order. Denote $V_i^j(t,s)$ as the sorted speed measurement at j^{th} place, $\forall j=1,2,..,D$; and

(c) Let k be an integer such that $k=Int[p\times D]+1$, where $Int[x]$ denotes an integral part of a number x. Find the $V_{i,p}(t,s)$ such that $V_{i,p}(t,s)=V_i^k(t,s)$.

If there is recurring traffic congestion at a specific section of the freeway, the corresponding representative speeds shown in RSCP should be low (e.g., red cells in RSCP). In contrast, if there is no recurring congestion, the RSCP should reflect very smooth traffic conditions (e.g., most of measurements are high speed (green cells) in RSCP). Identifying the recurring congestion is very useful as the incident-induced congestions can be separated from the recurrent congestion. However, it should be mentioned that serious recurrent congestion at some sections could lead to long queues formed upstream. Primary-secondary crash pairs occurring within the queue cannot be practically determined. This is because the recurrent queue covered the congestion caused by the prior incident. In this case, it is difficult to clearly judge whether a later crash was caused by the prior incident or caused by the recurrent congestion. Thus, such confounded cases are excluded in the following step.

Step 3- Constructing a binary speed contour plot (BSCP)**:** Compare $V(t,s)$ of SCP in step 1 with the corresponding $V_{i,p}(t,s)$ in RSCP generated in step 2. If $V(t,s)<\omega\times V_{i,p}(t,s)$, the speed measurement $V(t,s)$ in the original SCP is converted into $\hat{V}(t,s)=1$. Otherwise, it is denoted as $\hat{V}(t,s)=0$. This constraint defines the abnormal traffic condition if the measured speed is below the threshold $\omega\times V_{i,p}(t,s)$. Here ω is a user defined weighting factor between 0 and 1. It assumed that a $(1-\omega)\times 100$ percent reduction in the representative (normal) speed indicates the occurrence of congestion. A small ω suggests an aggressive threshold to define congestion whereas a large ω implies a conservative threshold. To reflect the consistency of speed measurements in short time periods, the speed measurement at the t^{th} time period will be changed to $\hat{V}(t,s)=1$ if $\{\hat{V}(t-1,s)=1, \hat{V}(t,s)=0 \; and \, \hat{V}(t+1,s)=1\}$. After conversion, the original SCP will be represented by a

BSCP. Figure 5.15 shows an example of converting the original SCP into a BSCP based on the RSCP of 50th percentile historical speeds. In BSCP, a red cell indicates that $\hat{V}(t,s)=1$ and a green cell means $\hat{V}(t,s)=0$. Each cluster of red cells visualizes non-recurring traffic congestion associated with an incident [e.g., crash A in Figure 5.15 (b)].

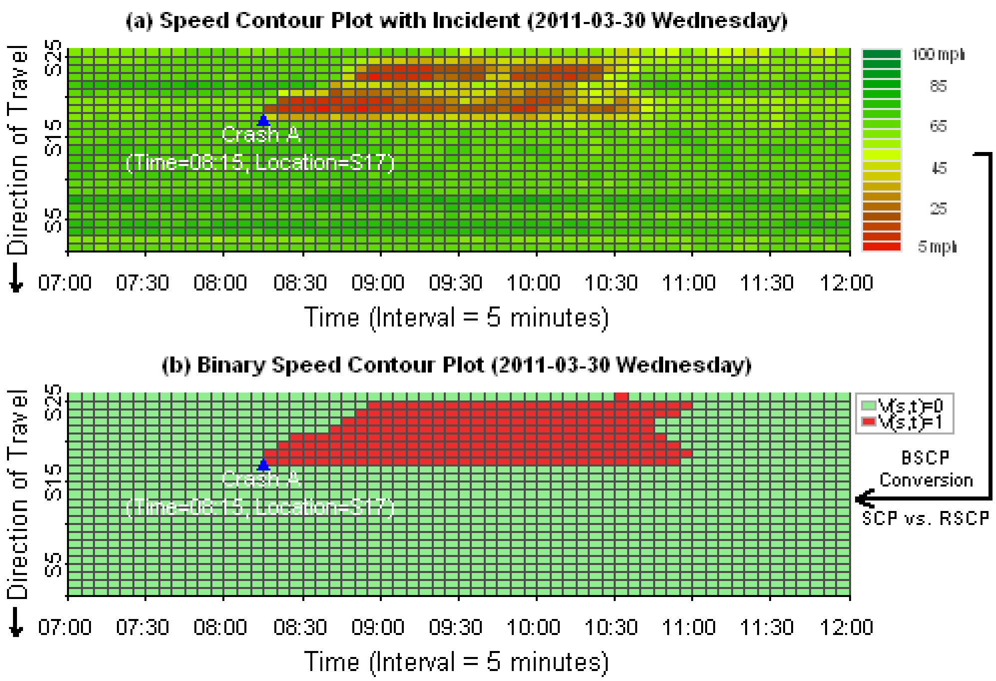


Figure 5.15 Converting SCP into a binary speed contour plot

5.4.3. *Identifying Secondary Crashes*

We can identify the queue that has been caused by incidents by using the steps described in the previous section. The next task is to identify whether a crash is associated with a prior incident. Let us recall the BSCP generated in Figure 5.15, and assume that there are two more crashes B and C that happened on the same day after the first crash A. The time and location of each crash are shown in Figure 5.16. The task is to determine whether B and C are secondary crashes related to the first crash A. If we use the static method or queue-based method that assumes the maximum temporal and spatial impact range as thresholds, both crash B and C have to be classified as secondary crashes. However, crash C should not be a secondary crash as the queue triggered by crash A $(t=08:15, s=S17)$ has not reached the location of crash C at the time when it occurred $(t=08:28, s=S23.5)$. In contrast, when crash B occurred $(t=09:37, s=S21.6)$ it was in the queue. Therefore, only crash B should be classified as a secondary crash.

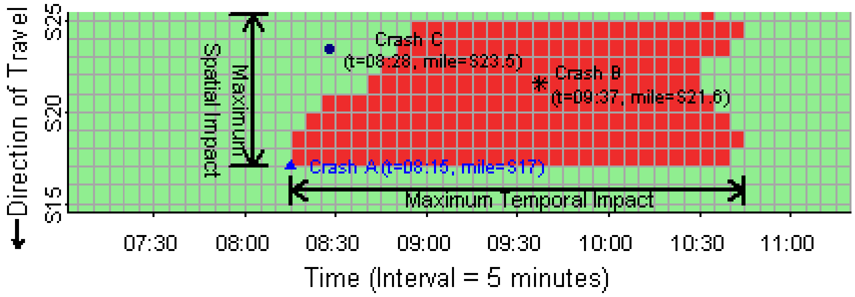


Figure 5.16 Binary speed contour plot with multiple crashes

However, it is time consuming to identify secondary crashes visually as it has been done above. Therefore, we have developed an algorithm that automatically identifies secondary crashes within the impact range. The algorithm is described as follows:

Step 1- Estimate the Equation of a Straight Line between a Pair of Crashes: Using the coordinates of the prior incident and a potential secondary crash, a line that links the two crashes is formed. Using Figure 5.17 as an example, the line AB and line AC can be represented using the following equations:

Line AB: $s_X = \frac{(s_B - s_A)}{(t_B - t_A)} \times (t_X - t_A) + s_A$ Line AC: $s_X = \frac{(s_C - s_A)}{(t_C - t_A)} \times (t_X - t_A) + s_A$

where (t_A, s_A), (t_B, s_B), and (t_C, s_C) are coordinates (in terms of time and distance) of crash A, crash B, and crash C, respectively. The pair (t_X, s_X) represents the coordinate of any point X on an estimated line (i.e., line AB).

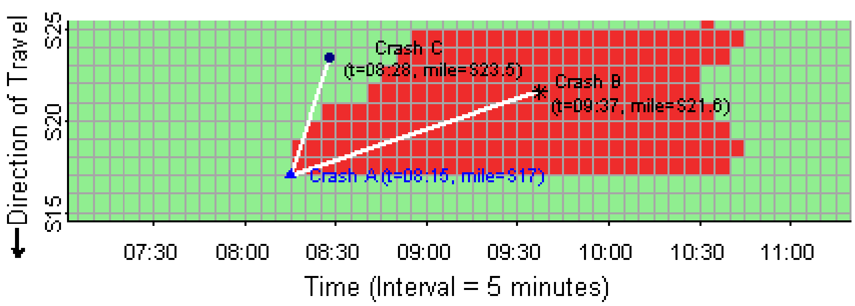


Figure 5.17 Estimate lines between a prior crash and a possible secondary crash

Step 2- Make Two Types of Predictions Using the Estimated Line Equation in Step 1: Type 1 -- given $t_X = t_{m+1}, t_{m+2}, \ldots, t_n$, predict s_X, assuming that $t_m \le t_a < t_{m+1}$ *and* $t_n \le t_b < t_{n+1}$. Type II -- given

$s_X = s_{h+1}, s_{h+2}, ..., s_u$, predict t_X , assuming that $s_h \le s_a < s_{h+1}$ *and* $s_u \le s_b < s_{u+1}$. Figure 5.18 (a) and Figure 5.18 (b) show the examples of these two types of predictions, respectively.

Step 3- Calculate the Coordinates of Middle Points: The midpoint of any two adjacent points predicted in step 2 is calculated. Figure 5.18 (c) illustrates an example of Q middle points $M_1, M_2, ..., M_q, M_{q+1}, ..., and\, M_Q$ that have to be calculated. The coordinate of each middle point is denoted by (t_q, s_q) .

Step 4- Check Binary Speed Measurements $\hat{V}(t,s)$ ***of the Cells that Enclose Middle Points:*** Let $t_R < t_q < t_{R+1}$ *and* $s_L < s_q < s_{L+1}$, where t_R is the R^{th} time interval in BSCP and s_L is the location of the L^{th} sensor. We can easily find the cell that contains the q^{th} middle point based on the information of the coordinates of the point [see Figure 5.18 (d) as an example]. Assume the binary speed measurement of the identified cell is $\hat{V}_q(t_R, s_L)$, where $\hat{V}_q(t_R, s_L) = 1$ indicates congestion and $\hat{V}_q(t_R, s_L) = 0$ means normal condition.

If the binary speed measurements of all corresponding middle points are equal to 1 [i.e., Figure 5.18 (e)], we have $\sum_{q=1}^{Q} \hat{V}_q(t_R, s_L) = Q$. This condition indicates that the line between the prior incident and a later crash is located in the impact range of the prior incident. Once we confirm that the line is located within the impact range, the later crash is identified as a secondary crash [e.g., crash B in Figure 5.18 (e)]. However, if a part of the line is not located in the impact range of the prior incident, we have $\sum_{q=1}^{Q} \hat{V}_q(t_R, s_L) < Q$. In other words, the later crash is not affected by the prior one if a portion of the line is out of the impact range. Thus the later crash is not classified as a secondary crash [e.g., crash B in Figure 5.18 (f)].

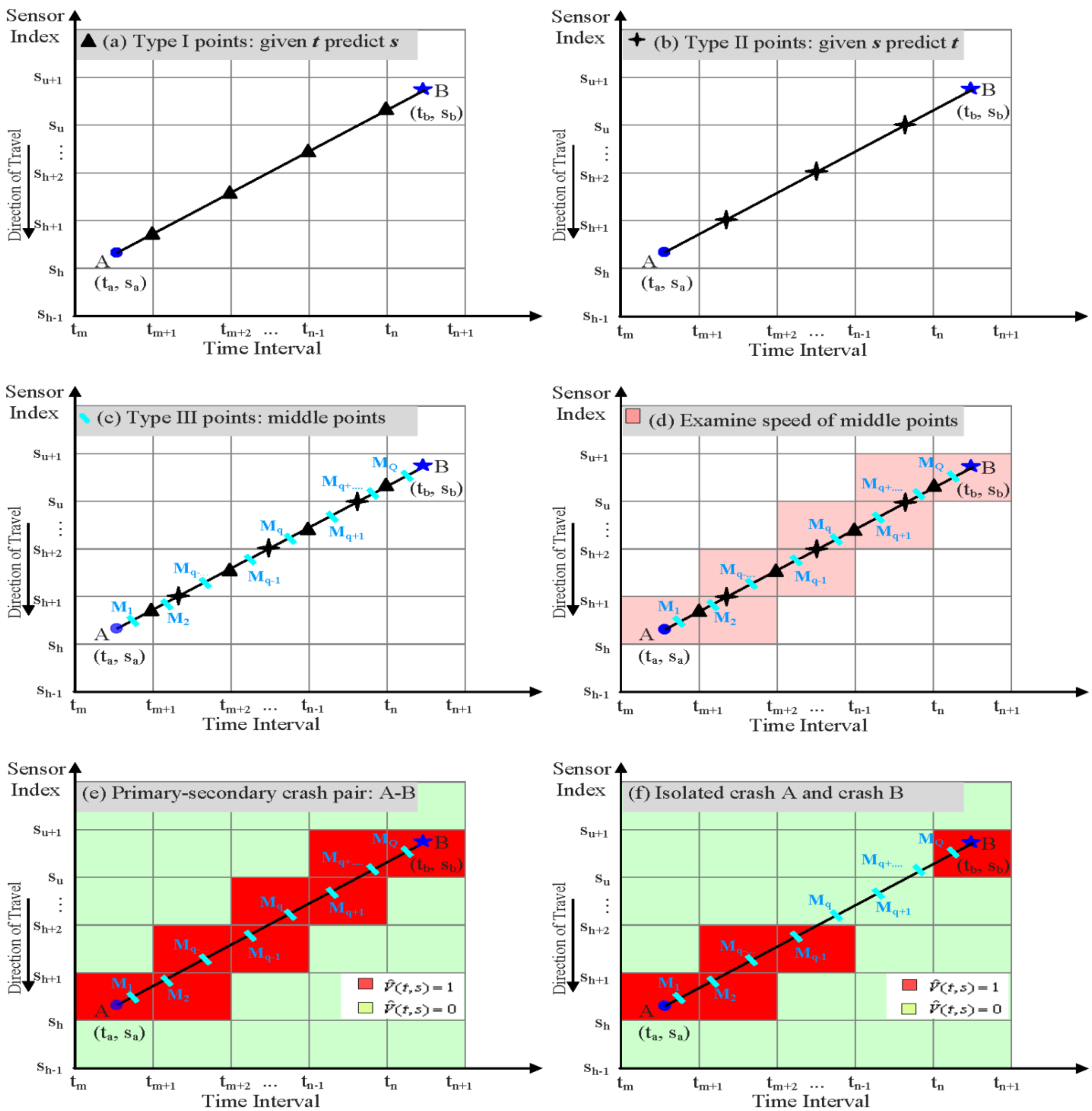


Figure 5.18 Visual depiction of the proposed algorithm that determines the relationship between two crashes

5.4.4. *Case Study*

The proposed methodology is used to identify secondary crashes on a 27-mile section of a major highway in New Jersey.

5.4.4.1 Data Description

A section of New Jersey Turnpike located between interchanges 5 and 9 was used as the case study. Figure 5.19 shows the site map. The study section is about 27 miles. It has 25 traffic sensors placed approximately every one mile of the mainline. There are 3 lanes between mileposts 48 and 72.5 and 5 lanes beyond milepost 72.5 in the northbound direction, as shown in Figure 5.19. The posted speed limit of the section is 65 mph. Traffic data collected by each traffic sensor in 2011 are used for the analyses. The data include volume, speed, and occupancy measured at different time intervals at each sensor station. The data aggregated in 5-minute intervals is extracted to develop the speed contour plots using the proposed method.

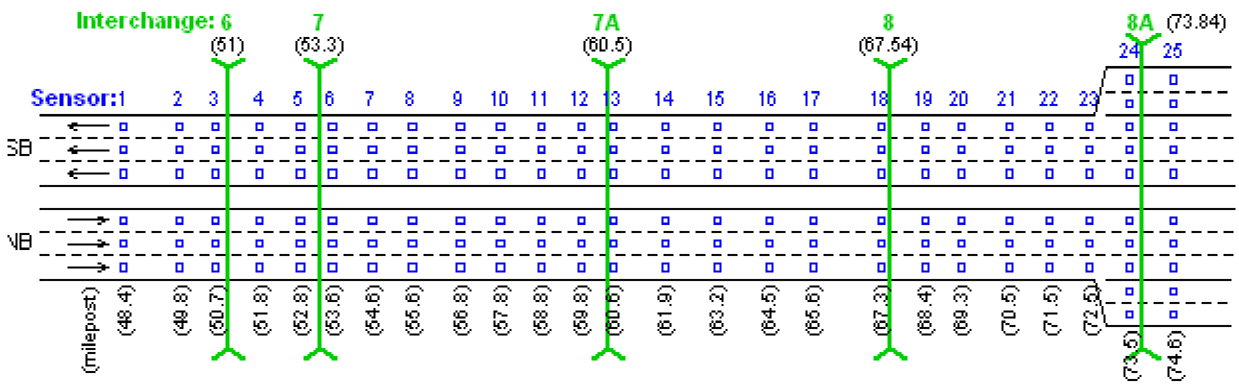


Figure 5.19 Schematic of the studied freeway section.

The corresponding crash records in 2011 are obtained from the online crash database of the New Jersey Department of Transportation (NJDOT) [53]. The records include detailed crash characteristics such as date, time, location, crash type, number vehicles involved, vehicle characteristics, and crash severity. After the exclusion of two ramp crashes and another 24 ceashes with unknown direction, the remaining data consist of a total of 1,188 crash records for the studied section (Southbound: 575 crashes; Northbound: 613 crashes).

5.4.4.2 Implementation of the Proposed Methodology

To identify the potential secondary crashes on a given day, the corresponding SCP, RSCP, and BSCP need to be generated. The daily SCP is created based on the speed measurements from the traffic sensors. The 50th percentile value of the historical speed data is used to create the RSCP based on the proposed method. It is assumed that the weighting factor is $\omega = 0.7$ when converting the SCP to BSCP. In other words, a 30 percent reduction in the representative (normal) speed is identified as the traffic congestion. This weighting factor is based on previous studies related to congestions and/or bottlenecks analysis on freeways [54-57]. Based on the SCP, RSCP, and the selected weight factor, the BSCP for each day is generated. The observed crashes are also superimposed on the BSCP. Then the BSCP, together with the proposed identification algorithm, is used to identify the major types of secondary crashes shown in Figure 5.13 (a) and Figure 5.13 (b). The third type of secondary crash shown in Figure 5.13 (c) was assumed to be crashes that occurred within 30 minutes and 0.5 miles upstream of the prior incident. The fourth type of secondary crash is defined as a crash that occurred in the opposite direction within one hour and one mile upstream of the prior incident. In addition to the spatial and temporal criteria, the potential secondary crash in the opposite direction has to be in a queue to be considered as a secondary crash due to rubbernecking.

For comparison purposes, secondary crashes are also identified using the static method. Sixteen types of fixed spatio-temporal boundaries ranging from 0.5 to 2 miles and from 0.5 to 2.0 hours are identified as secondary crashes in the same direction of a prior incident. For possible secondary crashes in the opposite direction of a prior incident, the same criteria as described in the previous paragraph are used.

Both the proposed method and the static approach are coded and implemented in the statistical software package R. The results are summarized in the following section.

5.4.4.3 Results and Discussion

The secondary crashes are identified using both the static and the proposed methods. The static method identified 42 out of 1,188 crashes (3.5 percent) as secondary crashes based on the maximum spatio-temporal boundaries of two miles and two hours. If the spatio-temporal thresholds of 0.5 miles and 0.5 hours are used the static method identifies only 18 secondary crashes. If the static thresholds were increased, the static method can capture more secondary crashes. However, the false identifications will also increase. As mentioned earlier, the selection of spatio-temporal criteria is subjective and the static method cannot account for different types of incidents that have a varying impact range (in time and space). For instance, Figure 5.20 (b) shows a crash (time= 17:30) occurred within two miles upstream of the prior crash (time=15:37). If the static method were used, the crash would have been classified as a secondary crash.

However, the original speed contour plot in Figure 5.20 (a) clearly suggests that the prior crash (time=15:37) had no notable impact on overall traffic flow. In addition, it was not the scenario described in Figure 5.20 (c) where the later crash is in the vicinity of a prior crash. Thus, the later crash (time= 17:30) was unlikely to be caused by the prior incident.

In contrast, the proposed method individually examines the impact of each incident and identified 100 secondary crashes as a result of 71 primary crashes. For a sensitivity analysis, if we use an aggressive weighting factor $\omega = 0.65$, 80 secondary crashes are identified. In contrast, if ω is increased to 0.75, 116 secondary crashes are identified. The variations of the results suggest that a reasonable weight factor should be used based on the highway operators' definitions of normal and congested traffic. Despite the variation, all the numbers are twice or more than the number (42 crashes) identified by the static method. The large difference between the findings of the two methods is expected because the static method cannot capture many of the primary incidents that impact traffic beyond the defined boundaries. For instance, a major crash such as a multi-vehicle collision blocking multiple lanes can create multiple hours and/or miles of disruption of traffic [27, 28, 51]. Thus, many secondary crashes that occurred beyond the defined boundaries are not identified by the static method but by the proposed method (see Figure 5.20 (b) for an example).

Twenty-three of the secondary crashes identified by the static method are also classified as secondary crashes by the proposed method. The remaining 19 (like the one identified by the static method in Figure 5.20 (b)) are successfully excluded by the proposed method. Figure 5.20 (c) and Figure 5.20 (d) illustrate the case when both methods identified the same secondary crashes. In this case, the secondary crash is not only within the pre-defined spatio-temporal boundaries of a prior crash but also in the queue that caused it. Other than the single primary-secondary crash pair, the proposed method can also determine multiple secondary crashes in relation to a primary one. For instance, Figure 5.20 (e) and Figure 5.20 (f) illustrated that a crash (at 14:57) in the northbound side of the studied freeway induced two secondary crashes (at 15:58 and 16:26) at the end of the long queue, which was far beyond the spatial boundary of the static method.

In summary, the static method can only identify 42 secondary crashes whereas the proposed method can identify 100 secondary crashes based on the assumed weighting factor. These results indicate that the proposed method not only reduces the incorrect classifications but also captures more secondary crashes missed by the static method. Another advantage of the proposed method is its computational efficiency. Our case study showed that it only took two to three minutes to process the 24-hour archived sensor data and complete the identification.

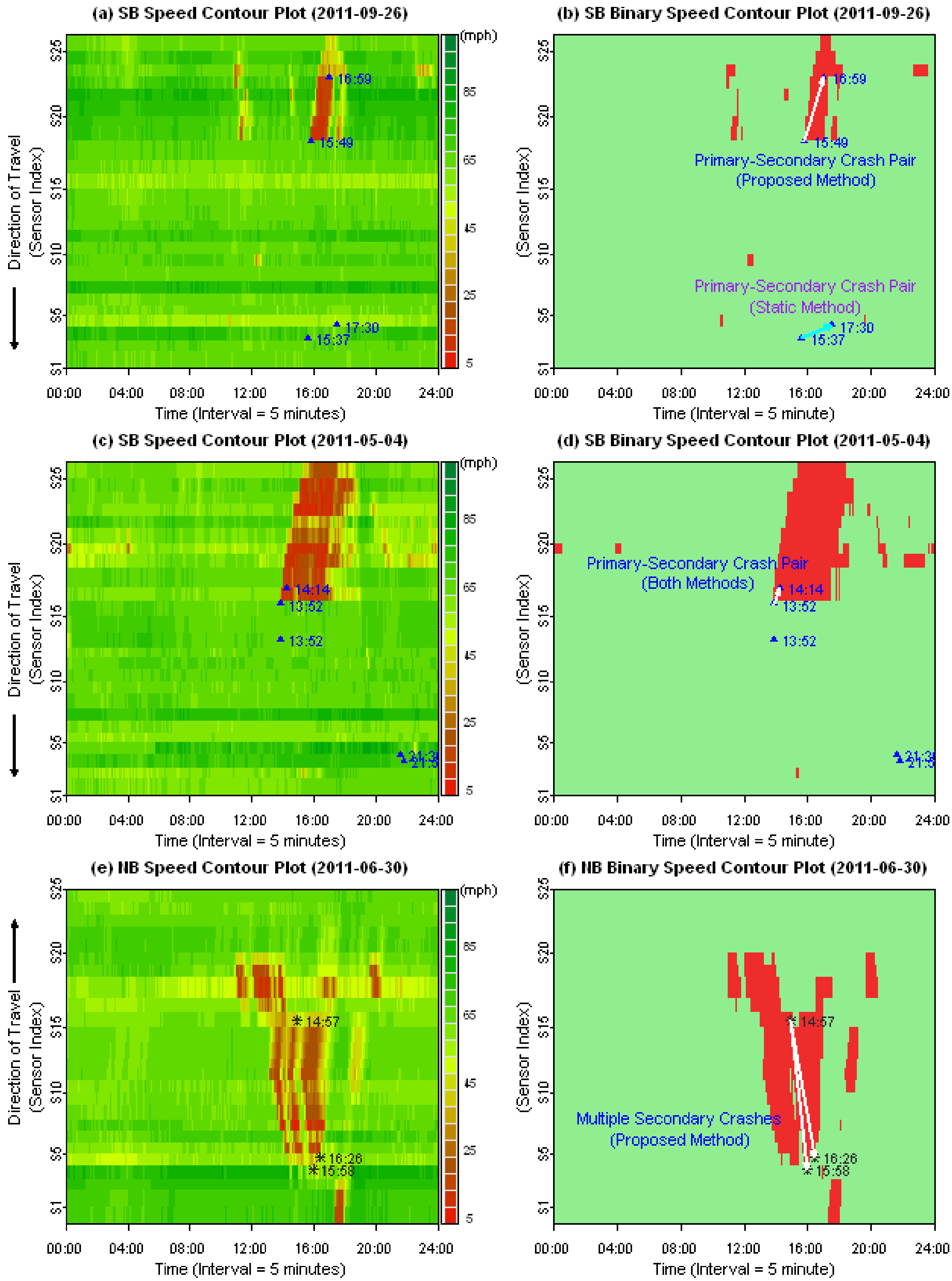


Figure 5.20 Identified secondary crashes using different methods.

5.4.5. *Summary*

This section extended the previous research on identifying secondary crashes. A new methodology that takes advantage of archived traffic data from traffic sensors is presented. Instead of assuming fixed spatio-temporal thresholds, the proposed methodology uses the concept of the Binary Speed Contour Plot (BSCP) to capture the evolution of an actual traffic queue induced by a primary incident. Based on the detected impact range of each primary crash, the proposed identification method automatically examines potential secondary crashes caused by the prior incident. It should be mentioned that the proposed framework also integrated the static method to cover cases when no queue exists. Step-by-step descriptions of the proposed approach provide a readily deployable data analysis tool for transportation agencies to identify secondary crashes through archived sensor data and existing crash databases.

A case study to test the performance of the proposed methodology is also presented. The secondary crashes induced by primary crashes are identified. The results show that the proposed methodology can identify twice the number of secondary crashes than the static method based on fixed spatio-temporal thresholds. This is because the proposed methodology successfully captures crash impacts far beyond the pre-defined spatio-temporal thresholds of the static method. In addition, 45 percent of secondary crashes identified by the static method are excluded by the proposed method as there is a weak evidence to link them with prior incidents. Although the case study demonstrates the secondary crashes identified by primary crashes, the same approach can be used to examine secondary crashes caused by other non-crash incidents given the availability of the incident data. The proposed methodology reduces biases (overestimation and underestimation) associated with the subjective thresholds used by the static method. In addition to the superior performance of the proposed identification approach, it only takes a short time period to aggregate the daily sensor data and crash information to identify whether a primary incident caused secondary crashes. With the availability of real-time sensor data, this kind of computational efficiency enables the proposed method to conduct a faster identification of secondary crashes. Given the access to real-time sensor data, the proposed methodology can be easily implemented to conduct on-line identification of secondary crashes. More studies with high-quality sensor data to investigate the capability of the proposed approach are suggested.

5.5. On-Line Scalable Analysis of Performance Measures

Before using the derived measurements from virtual sensors the data quality has to be examined. The derived speed measurements from virtual sensors have to be consistent with the other known reference data such as the infrastructure-based sensor output. As a case study, multiple remote traffic microwave sensor (RTMS) stations deployed along the New Jersey Turnpike are selected and corresponding virtual sensors are created on the Bing Maps. A customized API is developed to derive speed measurements from virtual sensors on the Bing Maps. The speed estimations from the virtual sensors are then compared with the outputs from the RTMS. Comparisons are conducted for different weekdays, incidents, and work zone conditions. Figure 5.21 illustrates the speed data collected by both types of sensors. The Wilcoxon signed-rank test is applied to examine the two-paired samples (The null hypothesis H_0 is that the two data sets are equivalent). The corresponding p-values for all the scenarios were greater than 0.05. Thus, it is concluded that the speed measurements derived from the virtual sensors are consistent with the measurements from infrastructure-based sensors. Like the RTMS data, the virtual sensor measurements can be used to identify the events that disrupt the normal traffic.

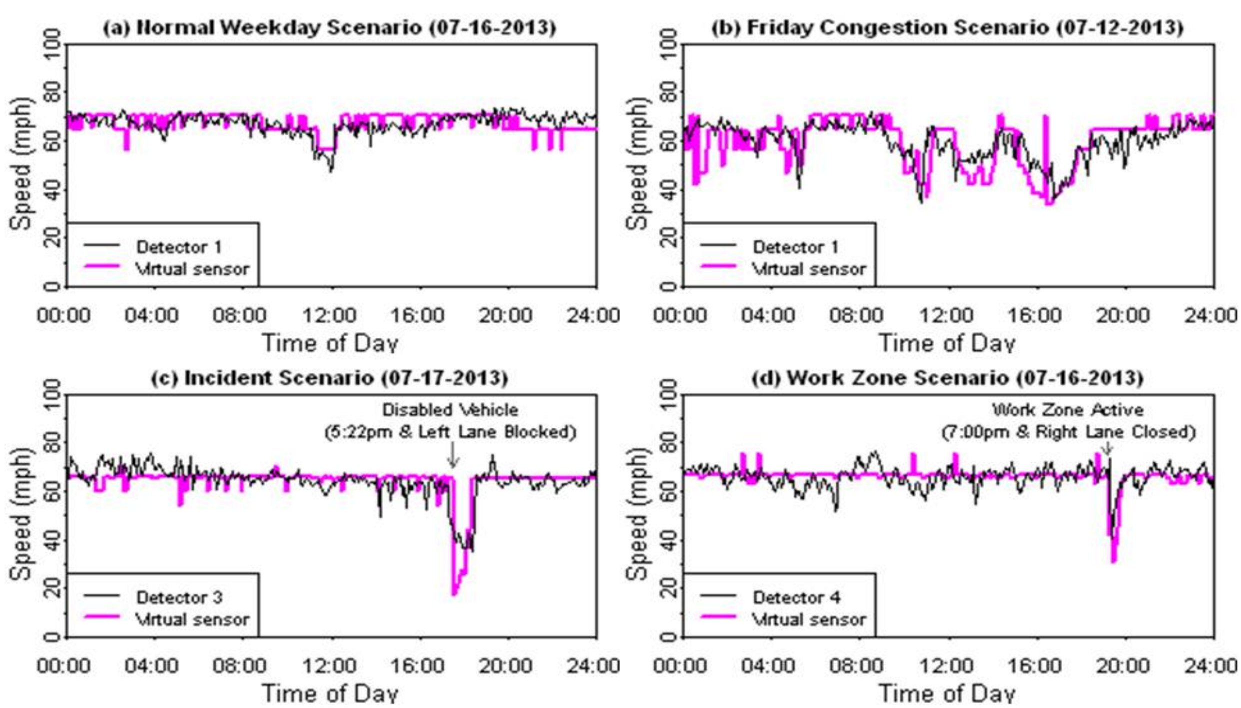


Figure 5.21 Virtual sensor speed versus infrastructure-based sensor output.

Despite the relatively acceptable performance of virtual sensors, users need to recognize that the accuracy of their information is often affected by the penetration rate of smartphone users with their GPS enabled. For instance, the penetration rate might be too low to generate reliable speed estimates for highways in a rural area. In addition, the performance of the undisclosed algorithms used by the map service providers also affects the quality of the results. With increasing penetration rate of smartphone users with their GPSs enabled and more open source data, the quality of the virtual sensor measurements is expected to improve. Given the availability of these open source data, researchers are enabled to conduct on-line scalable analyses of different performance measures for large networks.

5.5.1. *Travel Time Reliability Application Example*

As an example, the travel time reliability measures of a 78-mile section between interchanges 2 and 11 on the NJTPK is developed using collected virtual sensor data. There are eleven sub-sections which are exit-to-exit segments along the facility and for each subsection reliability measures are calculated separately. Buffer index (BI) is used as the reliability parameter, which represents the extra time (or time cushion) that most travelers add to their average travel time when planning trips to ensure on-time arrival. It is calculated as the ratio of the difference between the 95th percentile travel time and mean travel time (MTT). For a specific route trip and time period, the buffer index is computed using the equation (2) presented in Chapter 4.

The results are shown in Figure 5.22. We collected one-week real-time data using virtual sensor methodology from both Bing Maps and MapQuest and then compared the reliability parameters using heat maps. The vertical axis shows the road sections and the horizontal axis shows the time-of-day. Buffer index is a parameter between zero and one and increasing values mean lower reliability or higher variability in travel times. As seen for both northbound and southbound segments, real-time data from both sources yield similar results in terms of the subsections' travel time reliability. For the northbound segment, most unreliable travel times are observed during afternoon peak hours (i.e. between 4:00 pm and 8:00 pm). For the southbound segment, in addition to afternoon peak hours, unreliable travel times are also observed during the midday period (i.e. around 12 pm). Subsections with higher travel time variability can also be identified using the proposed methodology; for example, subsections 4 to 8 have comparably higher travel time variability during the afternoon peak for the northbound segment.

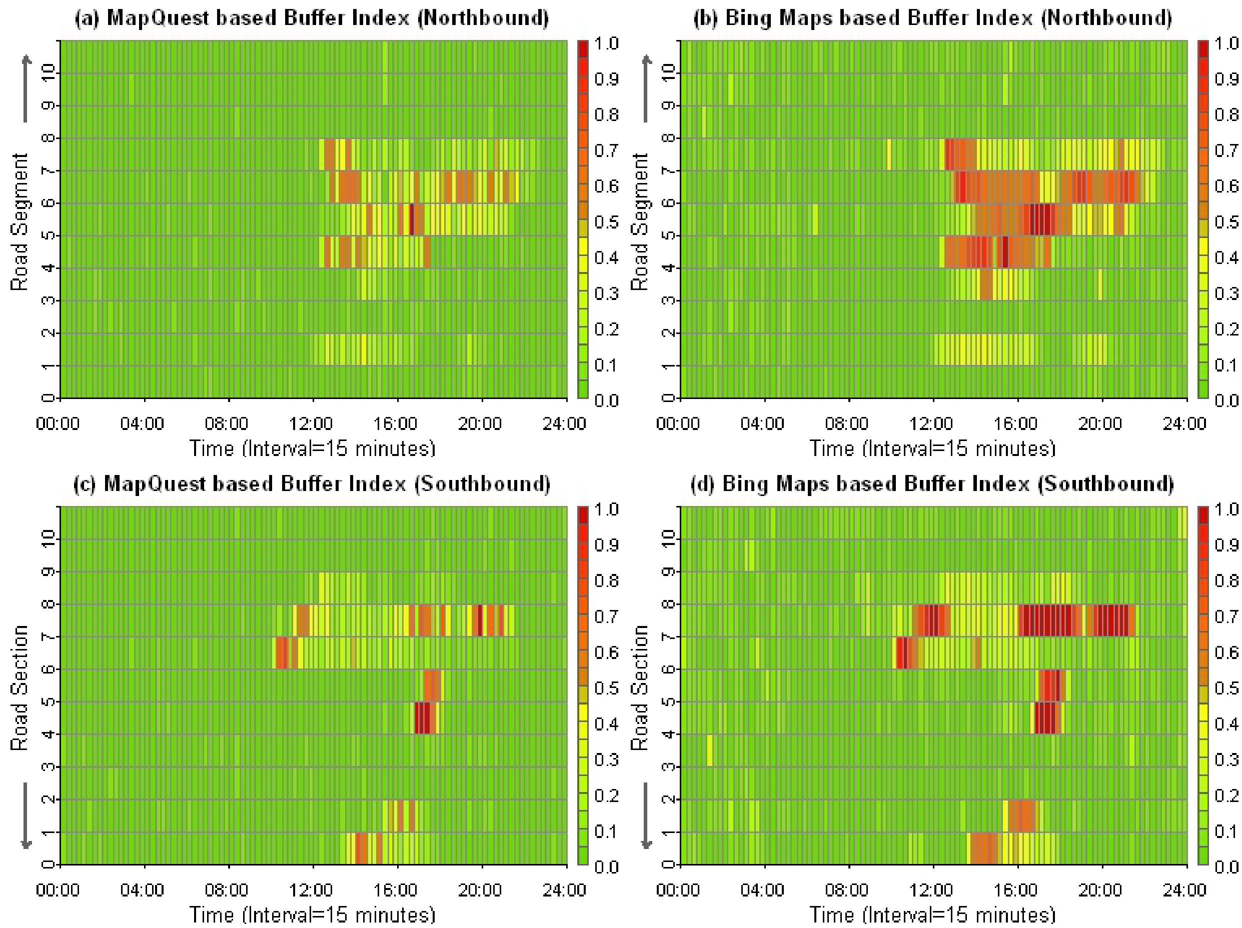


Figure 5.22 Buffer index analysis using virtual sensor data.

5.5.2. *On-Line Scalable Identification of Secondary Crashes*

The development of a scalable approach for identifying secondary crashes involves two major tasks: (a) large-scale traffic data acquisition and (b) development and implementation of a new identification algorithm. Instead of using data from infrastructure-based sensors such as loop detectors, this study proposes utilizing traffic information from open sources such as Bing Maps, Google Maps, and MapQuest. Combining the obtained traffic information and the identification algorithm enables practitioners to identify secondary crashes quickly and at a large scale. Figure 5.23 shows the methodological framework of the proposed approach. The following sub-sections describe the proposed approach in detail.

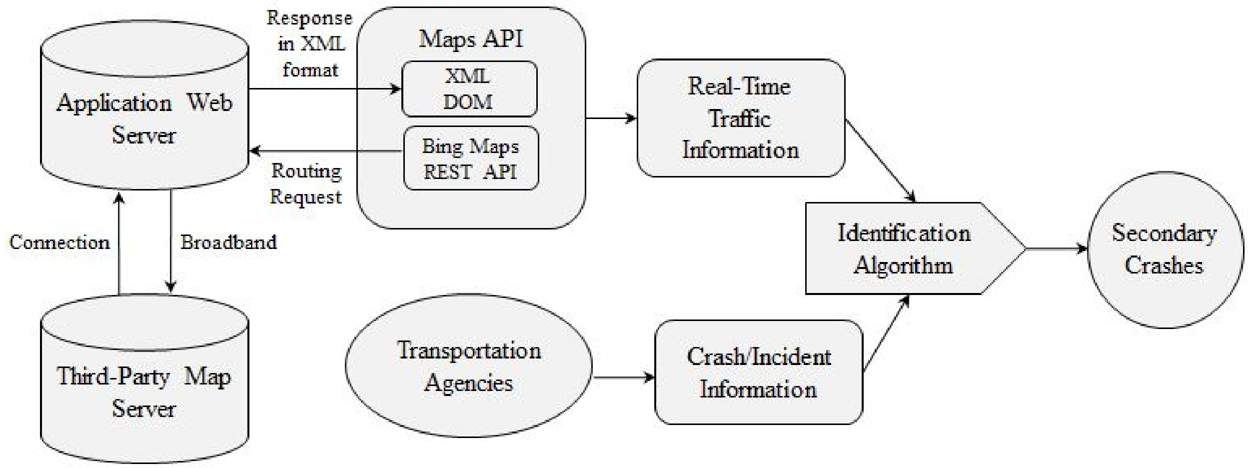


Figure 5.23 Framework of using virtual sensor data for identifying secondary crash.

As an example, Figure 5.24 shows a potential primary-secondary crash pair on New Jersey's 511 interactive map on July 19, 2013. Crash A had occurred earlier on southbound I-95 and induced congestion due to left lane blockage. Then crash B had occurred upstream just 9 minutes after the first crash A. In order to identify whether or not crash B is a secondary crash, the major task is to examine the impact area of the prior incident A. The impact area is described by temporal and spatial constraints. If a simple static threshold 1 shown in Figure 5.24 was used as the spatiotemporal criterion, crash B will not be identified as a secondary crash. However, if another static threshold 2 with longer spatial and temporal limits was used, crash B will be classified as a secondary crash. The difficulty is to determine an appropriate threshold to capture the progression of the actual impact of crash A. This is because each crash will have a different impact on traffic. Figure 5.25 shows an example of the impact progression of a severe crash on July 30, 2013 on the New Jersey Turnpike. It can be seen that the queue length reached as long as 10 miles and the queue presented more than 3 hours. Thus any static thresholds cannot capture the queuing evolution process.

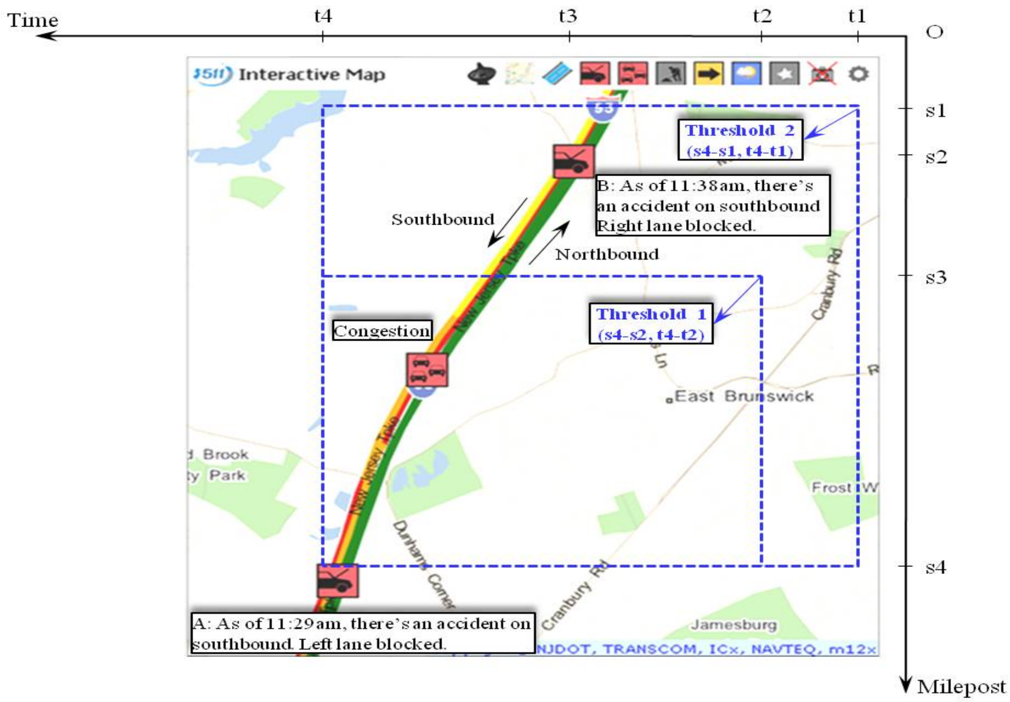


Figure 5.24 Example of potential primary-secondary crashes shown on 511NJ map.

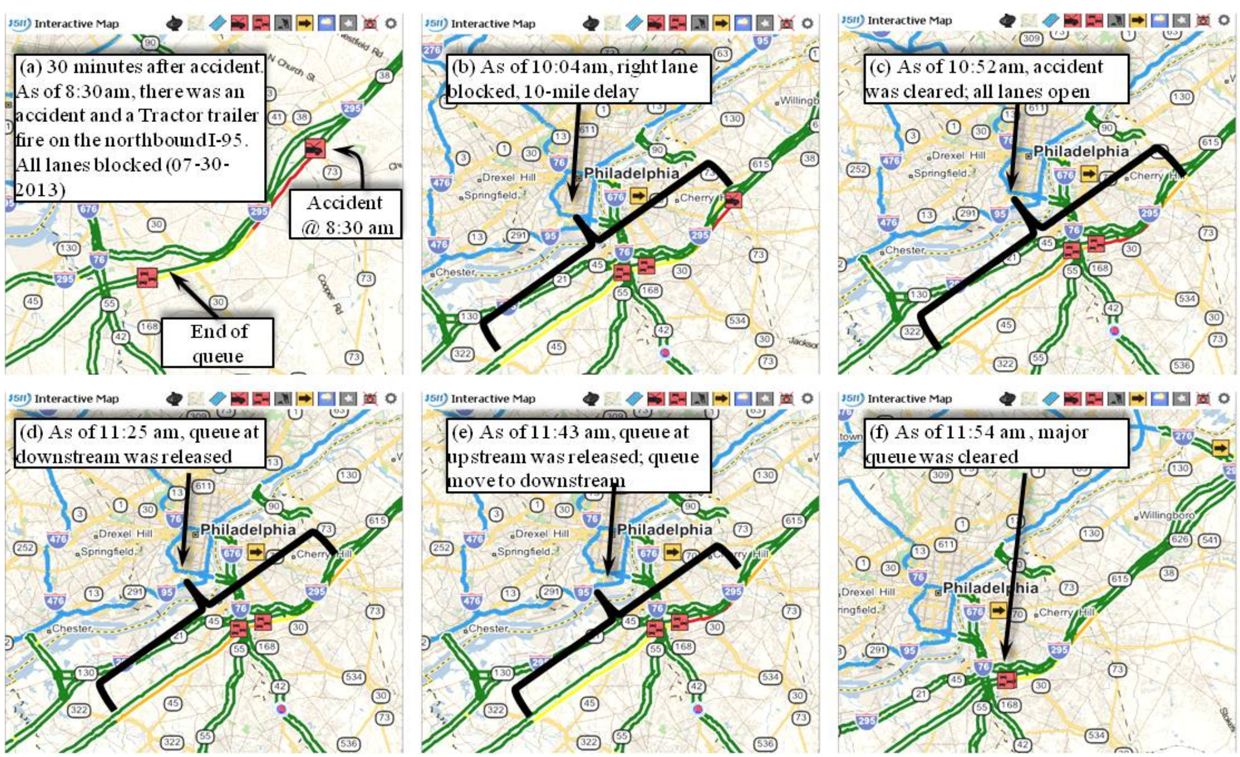


Figure 5.25 A crash with significant impact (10-mile maximum queue; queue presented 3+ hours).

Instead of using fixed thresholds or simplified queuing models, the developed identification approach uses virtual sensor data to explore secondary crashes on a larger scale. With the increased penetration of smartphones and GPS use among travelers, the quality of these third-party data is also expected to increase. These traffic data in turn can support extensive investigation of secondary crashes on highways with limited or no infrastructure-based sensors. With the developed algorithm, the identification process will be automated and the identification performance will be improved as the real-time traffic information becomes ubiquitous. In practice, many existing traffic and transportation information systems can extend their functions to conduct real-time identifications of secondary crashes using the developed approach. For example, the New Jersey's 511 system shown in Figure 5.24 already displays live traffic speed and traffic incidents on its interactive map. In that figure, the first crash at 11:29 am causes notable congestion and then another crash occurs in the queue at 11:38 am. Consequently, these two crashes are independently recorded in the police reports (and shown on the map). If the system had implemented the proposed identification approach based on the live traffic speed and crash information from the interactive map, it would have detected the two incidents to be a primary-secondary crash pair in real time and alerted travelers.

6. CONCLUSION AND SUMMARY

This research explores the tactical performance measures based on a number of transportation data sources. The major performance measures associated with traffic congestion, traffic reliability, and traffic safety are studied. The travel time, travel time reliability, incident duration, and secondary crashes are of particular interest than many conventional, easily-derivable performance measures such as traffic counts and crash counts. The potential of using various data sources to develop these performances is also demonstrated.

First, an improved algorithm is developed to estimate the travel time using electronic toll collection data. This adds additional value to the archived toll transaction data and develops the useful information to monitor the highways' operational performance. More reliable performance measures such as traffic delays and travel time reliability can be derived given the improved travel time estimation.

Second, structure learning algorithms are used to develop the Bayesian Networks for predicting incident duration, which is one of the key performance measures for traffic incident management programs. The proposed approaches help understand the exact mechanism of incident duration with respect to incident characteristics by examining incident logs and crash records obtained from the New Jersey Department of Transportation.

Third, secondary crashes are identified by exploring sensor data and historical crash records. Traditionally, it is very difficult to identify secondary crashes caused by prior incidents/crashes. However, archived traffic data from sensors such loop detector and RTMS enable us to develop a practical new algorithm to identify secondary crashes. The value of these sensor data has not been fully explored before to help understand the secondary crash issues. The data driven approach and associated crash records provide us a better view of the safety impact of the both primary and secondary crashes.

Considering the fact that not all highways are installed with traffic sensors, an on-line scalable approach has been developed to acquire real-time traffic data from the third-party traffic services providers such as the Bing map and Google map. A large amount of traffic data can be obtained from the transportation network through the developed virtual sensors. This enables us to identify the operational performance of traffic and impact of secondary crashes for many roadways without traffic sensors.

The data-driven methodologies proposed in the study provide valuable insights for the understanding of how some of the key performance measures important for transportation agencies can be used to improve their systems. The success of these performance measures relies on the availability of appropriate data sources. This research project also shows that by mining existing data sources, the performance measures can be more efficiently and accurately quantified without major expenditures for the deployment of new sensors.

7. REFERENCES

1. Poister, T.H., *NCHRP Synthesis of Highway Practice 238: Performance Measurement in State Departments of Transportation*, 1997, Transportation Research Board, National Research Council: Washington, D.C.
2. Cambridge Systematics, Inc., *A Guidebook for Performance-Based Transportation Planning, NCHRP Report 446*, 2000, Transportation Research Board, National Research Council: Washington D.C.
3. Cambridge Systematics, Inc., *Multimodal Transportation: Development of a Performance-Based Planning Process, NCHRP Project 8-32(2)*, 1999, Transportation Research Board, National Research Council: Washington D.C.
4. Poister, T.H., *NCHRP Synthesis 326: Strategic Planning and Decision Making in State Departments of Transportation: A Synthesis of Highway Practice*, 2004, Transportation Research Board of the National Academies: Washington, D.C.
5. Cambridge Systematics, Inc., *Performance Measures and Targets for Transportation Asset Management, NCHRP report 551*, 2006, Transportation Research Board, National Research Council: Washington D.C.
6. AASHTO, *Measuring performance among state DOTs*, 2006, American Association of State Highway and Transportation Officials (AASHTO) Standing Committee on Quality.
7. Baird, M.E. and R.E. Stammer Jr., *Measuring the Performance of State Transportation Agencies Three Perspectives.* Transportation Research Record, 2000. **1729**: p. pp. 26-34.
8. Vandervalk-Ostrander, A., R. Margiotta, and J. Meunier, *Performance Measures for Small Communities - Final Report*, in *Report No. FHWA-OP-03-080*2003, Federal Highway Administration, U.S. Department of Transportation.
9. MacDonald, D., et al., *Transportation Performance Measures in Australia, Canada, Japan and New Zealand*, in *Report No. FHWA-PL-05-001*2004, Federal Highway Administration, U.S. Department of Transportation.
10. Poister, T.H. *Performance Measurement in Transportation: State of the Practice*. in *Second National Conference on Performance Measures*. 2005. Irvine, California.
11. Haas, R., G.L. Felio, Z., and L. Cowe Falls, *Measurable Performance Indicators for Roads: Canadian and International Practice*, in *2009 Annual Conference of the Transportation Association of Canada - - Transportation in a Climate of Change*2009: Vancouver, British Columbia.
12. Moore, D., et al., *Performance Measures For Metropolitan Planning Organizations*, in *Research Report SWUTC/12/161004-1*2012, Texas Transportation Institute
13. NJDOT. *Roadway Information and Traffic Counts*. [cited 2012 Nov. 5]; Available from: http://www.state.nj.us/transportation/refdata/roadway/.
14. NYSDOT. *Traffic Data Viewer*. [cited 2012 Nov. 5]; Available from: www.dot.ny.gov/tdv.
15. Bing. *Bing Maps Now Using Nokia Backend Services for Traffic and Geocoding*. 2013 [cited 2013 June 10]; Available from: http://www.bing.com/blogs/.
16. Google. *The Bright Side of Sitting in Traffic: Crowdsourcing Road Congestion Data*. 2013 [cited 2013 May 18]; Available from: http://googleblog.blogspot.com/2009/08/bright-side-of-sitting-in-traffic.html.
17. Microsoft. *Bing Maps REST Services*. 2013 [cited 2013 April 03]; Available from: http://msdn.microsoft.com/en-us/library/ff701713.aspx.

18. Google. *Google Maps JavaScript API v3*. 2013 [cited 2013 April 06]; Available from: https://developers.google.com/maps.
19. MapQuest. *MapQuest Traffic API,*. 2013 [cited 2013 May 02]; Available from: http://developer.mapquest.com/web/products/dev-services/traffic-ws.
20. Yang, H., et al., *Development of an On-line Scalable Approach for Identifying Secondary Crashes.* Transportation Research Record: Journal of the Transportation Research Board, 2014 (Paper ID: TRB14-1689, forthcoming), 2014.
21. Morgul, E.F., et al., *Virtual Sensors: A Web-based Real-Time Data Collection Methodology for Transportation Operation Performance Analysis.* Transportation Research Record: Journal of the Transportation Research Board, 2014 (Paper ID: TRB14-4119, forthcoming), 2014.
22. FHWA, *Travel Time Reliability: Making It There On Time, All The Time*, 2006, U.S. Department of Transportation, Federal Highway Administration (FHWA): Washington, D.C.
23. FHWA, *Traffic Incident Management Handbook*, 2000, Federal Highway Administration Office of Travel Management.
24. Tedesco, S.A., et al. *Development of a Model to Assess the Safety Impacts of Implementing IVHS User Services*. in *4th Annual Meeting of IVHS America*. 1994. Atlanta, Georgia.
25. Karlaftis, M.G., et al., *ITS Impacts on Safety and Traffic Management: An Investigation of Secondary Crash Causes.* Journal of Intelligent Transportation Systems, 1999. **5**(1): p. 39–52.
26. Lari, A., D. Christianson, and S. Porter, *I-35 Incident Management and the Impact of Incidents on Freeway Operation*, in *Report No.: FHWA/MN/TE-82/04*1982, Minnesota Department of Transportation.
27. Raub, R.A., *Secondary Crashes: An Important Component of Roadway Incident management.* Transportation Quarterly, 1997. **51**(3): p. 93–104.
28. Raub, R.A., *Occurrence of Secondary Crashes on Urban Arterial Roadways.* Transportation Research Record: Journal of the Transportation Research Board, 1997. **No. 1581**: p. 53–58.
29. O'Laughlin, J. and A. Smith. *Operational Issues Discussion Paper on "Incident Management Operations: Top Five Issues"*. in *National Conference on Traffic Incident Management: A Road Map to the Future*. 2002.
30. Owens, N., et al., *2010 Traffic Incident Management Handbook Update*, in *Report No.: FHWA-HOP-10-013*2010, Federal Highway Administration, Office of Transportation Operations.
31. Zhan, C., et al., *Understanding the Characteristics of Secondary Crashes on Freeways*, in *Presented at 87th Annual Meeting of the Transportation Research Board*2008: Washington, D.C.
32. Latoski, S.P., R. Pal, and K.C. Sinha, *Cost-Effectiveness Evaluation of Hoosier Helper Freeway Service Patrol.* Journal of Transportation Engineering, 1999. **125**(5): p. 429-438.
33. Moore, J.E., G. Giuliano, and S. Cho, *Secondary Accident Rates on Los Angeles Freeways.* Journal of Transportation Engineering, 2004. **130**(3): p. 280–285.
34. Khattak, A.J., J.L. Schofer, and M. Wang, *A Simple Time Sequential Procedure for Predicting Freeway Incident Duration.* I V H S Journal, 1995. **2**(2): p. 113-138.
35. Myllymäki, P., *Advantages of Bayesian Networks in Data Mining and Knowledge Discovery*. BayesIT, 2010.

36. Ozbay, K. and N. Noyan, *Estimation of Incident Clearance Times Using Bayesian Networks Approach.* Accident Analysis & Prevention, 2006. **38**(3): p. 542-555.
37. Boyles, S., D. Fajardo, and S.T. Waller, *A Naïve Bayesian Classifier for Incident Duration Prediction*, in *86th Annual Meeting of the Transportation Research Board*2007: Washington, D.C.
38. Pearl, J., *Probabilistic Reasoning in Intelligent Systems*1988, San Mateo, CA: Morgan Kaufmann.
39. Schwarz, G., *Estimating the Dimension of a Model.* Annals of Statistics, 1978. **6**(2): p. 461-464.
40. Chikering, D.M., *A Transformational Characterization of Equivalent Bayesian Network Structures*, in *In Proceedings of 11th Conference on Uncertainty in Artificial Intelligence*1996: San Francisco, CA.
41. Keogh, E. and P. M. *Learning Augmented Bayesian Classifiers: A Comparison of Distribution-based and Classification-based Approaches*. in *7th International Workshop on Artificial Intelligence and Statistics*. 1999.
42. Chow, C. and C. Liu, *Approximating Discrete Probability Distributions with Dependence Trees.* IEEE Transactions on Information Theory, 1968. **14**(3): p. 462-467.
43. Heckerman, D., D. Geiger, and M. Chickering. *Learning Bayesian Networks: The Combination of Knowledge and Statistical Data*. in *10th Conference on Uncertainty in AI*. 1994. CA.
44. Cooper, G.F. and E. Herskovits, *A Bayesian Method for the Induction of Probabilistic Networks from Data.* Machine Learning, 1992. **9**(4): p. 309-347.
45. Andrieu, C., et al., *An Introduction to MCMC for Mach Learning.* Machine Learning, 2003. **50**(1-2): p. 5-43.
46. Jensen, F.V. and T.D. Nielsen, *Bayesian Networks and Decision Graphs Second Edition*2007: Springer.
47. Ramaswamy, S., R. Rastogi, and K. Shim. *Efficient Algorithms for Mining Outliers from Large Data Sets*. in *The 2000 ACM SIGMOD International Conference on Management of Data*. 2000. New York.
48. Murphy, K.P., *The Bayes Net Toolbox for Matlab.* Computing Science and Statistics:Proceedings of Interface, 2001. **33**.
49. Leray, P. and O. Francois, *BNT Structure Learning Package: Documentation and Experiments*, in *Technical Report Laboratoire PSI*2006, Université et INSA de Rouen.
50. Zang, H., *The Optimality of Naïve Bayes*, in *17th International FLAIRS Conference*2004: Miami Beach, FL.
51. Varaiya, P., *Freeway Data Collection, Storage, Processing, and Use*, in *Presented at Transportation Research Board Workshop: The Roadway INFOstructure*2002: Irvine, CA.
52. Yang, H., B. Bartin, and K. Ozbay, *Identifying Secondary Crashes on Freeways Using Sensor Data.* Transportation Research Record: Journal of the Transportation Research Board, 2013((In Press)).
53. NJDOT. *Crash Records*. 2012 [cited 2012 June 10]; Available from: http://www.state.nj.us/transportation/refdata/accident/.
54. Chen, C., A. Skabardonis, and P. Varaiya, *Systematic Identification of Freeway Bottlenecks.* Transportation Research Record: Journal of the Transportation Research Board, 2004. **1867**: p. 46–52.

55. Wu, Y.-J., et al., *Evaluation of Arterial and Freeway Interaction for Determining the Feasibility of Traffic Diversion.* Journal of Transportation Engineering, 2011. **137**(8): p. 509–519.
56. Bham, G.H. and S.H. Khazraee, *Missouri Work Zone Capacity: Results of Field Data Analysis*, in *Report No.: FHWA MO-2011-00X, Smart Work Zone Deployment Initiative*2011, Iowa State University.
57. Ullman, G.L., T.J. Lomax, and T. Scriba, *Primer on Work Zone Safety and Mobility Performance Measurement*, in *Report No.: FHWA-HOP-11-033*2011, U.S. DOT, Federal Highway Administration.

University Transportation Research Center - Region 2
Funded by the U.S. Department of Transportation

Region 2 - University Transportation Research Center
The City College of New York
Marshak Hall, Suite 910
160 Convent Avenue
New York, NY 10031
Tel: (212) 650-8050
Fax: (212) 650-8374
Website: www.utrc2.org