MOUNTAIN-PLAINS CONSORTIUM

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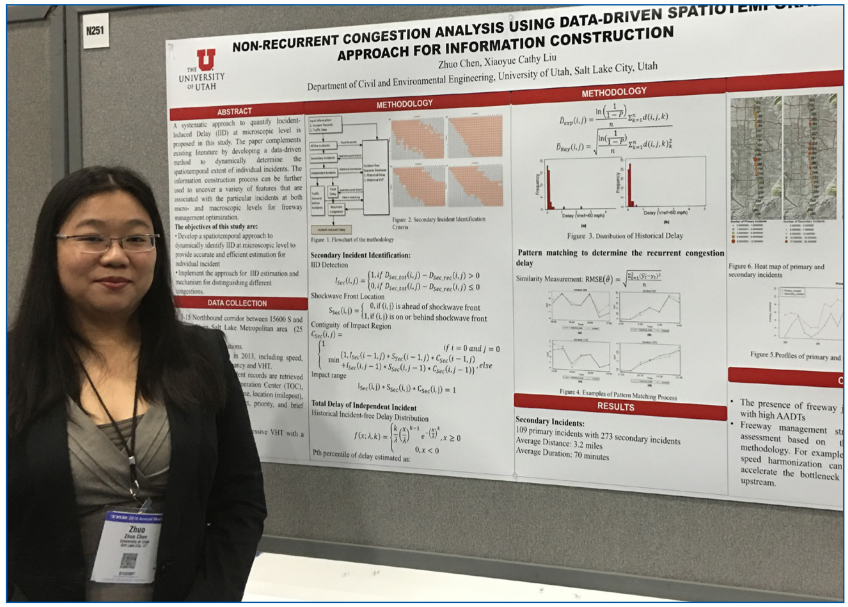
Data-Driven Freeway Performance Evaluation Framework for Project Prioritization and Decision Making



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MOUNTAIN-PLAINS CONSORTIUM REGION 8

Data-Driven Freeway Performance Evaluation Framework for Project Prioritization and Decision Making

Xiaoyue Cathy Liu
Assistant Professor
Department of Civil and Environmental Engineering
University of Utah
Salt Lake City, Utah, 84112
Phone: (801) 587-8858
Email: cathy.liu@utah.edu

Zhuo Chen
Graduate Student
Department of Civil and Environmental Engineering
University of Utah
Salt Lake City, Utah, 84112
Phone: (801) 300-8060
Email: zhuo.chen@utah.edu

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Disclaimer

ABSTRACT

This report describes methods that potentially can be incorporated into the performance monitoring and planning processes for freeway performance evaluation and decision making. Reliability analysis was conducted on the selected I-15 corridor by employing congestion frequency as the performance measure. Hot spots during peak hours were identified through sensitivity analysis. A data-driven algorithm combining spatiotemporal analysis and shockwave theory was developed to determine secondary incidents. Incident-induced delay was further quantified through spatiotemporal pattern recognition. The average delay induced by incidents aligns well with the incidents' severity and impact. Several hot spots suffered from higher delays and were explored in further detail. A statistical mechanism was developed to determine adverse weather impact on travel. Using the weather records in 2013 and mapping with the PeMS traffic database, volume and delay were estimated under normal conditions and compared with adverse weather conditions. The analysis of different roadway conditions reveals that the general parabolic pattern of speed and volume disappear under severe adverse weather condition. The mechanism was able to identify the causes for reduced volume under a variety of scenarios through empirical data, either due to roadway capacity reduction or travel demand reduction.

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EXECUTIVE SUMMARY

This study aims to develop a set of performance metrics and computational methodologies that can be incorporated into the operational management and planning process for investment decision making. This report details the work performed in the research project. The objectives of this project are to (a) quantify the impact of nonrecurring congestions, including incidents and weather; and (b) provide linkage between performance measures and decision making by using interpretative indicators to inform decisions.

Freeway performance measures often are considered in three dimensions: temporal aspect, spatial details, and source of congestion. This study studies these dimensions from a holistic view and strives to describe the roadway conditions in support of investment decisions. The study examines the freeway network as a whole, and determines its overall condition. Questions posed included where are the unreliable locations along a freeway corridor and how is reliability/unreliability determined? To answer these questions, a measure called congestion frequency was developed. It is intuitive and consistent with the speed reliability measurement currently used by UDOT. Congestion frequency is defined as the percentage of time that speed drops below a certain threshold. By extracting traffic information from historical archived data in PeMS, this indicator can be calculated and sensitivity analysis conducted to choose the proper threshold.

A methodological framework is developed to quantify the incident-induced delay and identify secondary incidents based on the empirical data collected. The framework acknowledges that each individual incident has a different impact on the roadway spatially and temporally due to varying traffic conditions, roadway geometries, and crash characteristics. Thus, a data-driven algorithm was developed to determine the impact region for each incident. By heuristically searching the historical database and performing pattern matching to find the historical traffic condition that matches the incident scenario, the incident-induced delay was calculated and secondary incidents were identified. There were 109 primary incidents and 240 secondary incidents identified on the selected I-15 Northbound corridor in 2013. From the distribution of secondary incidents, it was found that the occurrence of secondary incidents was highly related to weather condition. The incident-induced delay was influenced by severity, location, and time-of-day.

A statistical mechanism was developed to determine adverse weather impact on travel. Utilizing the weather/roadway information provided by Traveler Advisory Telephone System (TATS) and PeMS, an algorithm was developed to map traffic data with the weather database. It was concluded that during adverse weather, especially when the road is snow-covered, lower flow is associated with high delay during the peak period, indicating a reduction in speed. Also, the non-peak period had a significant reduction in delay compared with the historical travel pattern, which implies a reduction in demand.

1. INTRODUCTION

1.1 Background

The burgeoning development of the Intelligent Transportation System (ITS) over the past decades has resulted in intelligent and efficient management of current roadway networks. One concern of freeway performance management was congestion, which is attributed to recurring and nonrecurring causes. According to the 2012 Urban Mobility Report, urban congestion costs about $12.1 billion and a total of a 5.52 billion-hour delay in 2011 (Schrank, et al., 2012). Congestion has been growing over the past years, and transportation agencies actively seek ways to better monitor the traffic, identify bottlenecks, and respond efficiently and effectively to incidents. From an operations perspective, using a set of meaningful performance measures to obtain a comprehensive assessment of the roadway system is one of the most effective solutions for congestion management. It also is critical to decision making. The Moving Ahead for Progress in the 21st Century Act (MAP-21) establishes a performance-based transportation program to guide the transportation capital investment and development. Therefore, it enables the need to carry out a performance-based approach to evaluate the transportation system. Freeway networks play a critical role in providing accessibility to a many resources and serve as the backbone of a region's economic vitality. It also is the primary focus of operations agencies. Meanwhile, social and economic needs, and the rapid advancement of technology continue to shape the freeway network. It is imperative to develop a data-driven freeway performance assessment framework able to link the performance measures with investment decisions.

Freeway performance measures often are considered in three dimensions: temporal aspects, spatial details, and source of congestion. Attention to each varies, depending on the emphasis of specific agencies. For example, a senior leader would use a holistic view to evaluate performance and obtain overall freeway network conditions. Traffic engineers may need to provide instantaneous operation decisions based on the source of congestion and time of day. Transportation planners might consider developing plans for alleviating congestion bottlenecks that are most critical to the entire network. These three areas should be used to develop performance measures that will provide comprehensive and useful information to transportation agencies, and effectively describe roadway condition to support investment decisions. Recently, the transportation profession has acknowledged that performance measures should be viewed from both facility perspective, for monitoring and management purposes, and user perspective, for customer experiences. To address this, performance measures should focus on freeway congestion (facility perspective) and mobility (user perspective).

Seven potential sources contribute to travel unreliability, as identified by the FHWA SHRP 2 program: traffic incidents, weather, work zones, demand fluctuations, special events, traffic control devices, and inadequate base capacity. Incidents are one of the most critical contributors for traffic congestion and account for approximately 50-60% delay on U.S. highways (Bertini and McGill, 2003). To mitigate the impacts of incidents, it is crucial for the incident management program to develop strategies that can effectively estimate incident impact range and respond appropriately. The Traffic Incident Management (TIM) is a planned and coordinated process to detect, respond to, and remove traffic incidents and restore capacity as safely and quickly as possible. Accurate estimation of Incident-Induced Delay (IID) would assist with a better understanding of incident-related congestion and provide insights for effective TIM. Transportation agencies use information regarding IID for transportation planning purposes at different levels. Recently, the successful incorporation of reliability analysis into the planning and programming processes has demonstrated the importance of incident effects modeling (Cambridge Systematics, 2013). The estimation and prediction of IID can further be applied to traffic simulation calibration and validation. Accurate estimation of such delays can help identify appropriate decisions regarding incident response so limited monetary and labor resources can be allocated efficiently. The IID also is essential for development of active traffic management and integrated corridor management strategies. One critical step for the IID estimation is to determine impact range of incidents in both spatial and temporal domains, which also makes it feasible for identifying secondary incidents due to congestion caused by a previous incident. According to FHWA, secondary incidents account for 20% of all incidents, including not only crashes, but also engine stalls, overheating and running out of fuel scenarios where vehicles experience unexpected delay due to the primary incidents. Secondary incident is also used to evaluate effectiveness of TIM. According to Karlaftis et al. (1999), the likelihood of a secondary crash increases by 2.8% for every minute that the primary incident continues to be a hazard.

Another major source of non-recurring congestion is adverse weather, which leads to changes in driver behavior that affect traffic flow. Adverse weather conditions have a major impact on roadway safety and operations, which directly impacts vehicle performance, pavement friction, and roadway infrastructure. Due to reduced visibility and road friction, speeds are lowered and headways are increased when wet, snowy, or icy roadway surface conditions are present. To mitigate the impact of adverse weather (e.g. rain, snow, ice, and fog), transportation agencies implement roadway weather management strategies. For example, advisory strategies can provide information on predicted conditions. Control strategies can help restrict or regulate traffic flow through altering traffic control devices in operation. Treatment strategies can minimize weather impacts through the application of sand, salt, and anti-icing chemicals to increase pavement traction. Studies that explore the interaction between adverse weather and travel demand can benefit the weather management program to help it understand people's travel behavior and evaluate the effectiveness of these strategies.

1.2 Objectives

The primary objective of this research project is to quantify the impact of nonrecurring congestions. The nonrecurring sources in this study are focused on incidents and weather. IID is quantified through a data-driven algorithm. Previous research provided a general approach for the IID estimation, however, important features associated with incidents tend to be ignored in the estimation process, e.g. location-specific characteristics, congestion propagation and dissipation process in both spatial and temporal domains. Secondary incident identification is conducted by analyzing the congestion caused by a cluster of incidents via a binary contour method. The study also develops a mechanism to evaluate adverse weather impacts on the freeway network.

A secondary objective of this research project is to provide a link between performance measures and decision making by using interpretative indicators to inform decisions. The performance measures should be easily understood and have practical applications. The measures should tie to typical congestion levels, reliability, and freeway throughput to describe congestion/mobility performance of freeways. The measures should also be easily understood and relatable to the general public.

1.3 Scope

The following three major components were performed for this research: *freeway performance metrics development*, *IID analysis and secondary incident identification*, and *weather impact evaluation*. The specific tasks include:

- Develop a performance measure that can be used to describe the day-to-day variation of traffic conditions and is easily understandable by both practitioners and the general public.
- Develop a data-driven algorithm for secondary incident identification.
- Design an empirical methodological framework to quantify the IID on freeways, providing reference for incident management.

- Use pattern recognition to estimate non-recurrent congestion and demand reduction caused by adverse weather.

To conduct the above mentioned tasks requires the support of extensive historical and real time data from multiple sources and jurisdictions. The Performance Measurement System (PeMS) is a freeway performance measurement system used by the Utah Department of Transportation (UDOT) and other transportation agencies, which is based on a subscription to the Iteris PeMS database. It contains a rich pool of information about traffic data and provides an excellent platform to both transportation practitioners and researchers. The system integrates various traffic data sources including traffic detectors, incident logs, vehicle classification data, and roadway inventory, etc. These traffic data have been automatically collected and archived, and real-time information is updated from moe than 28,000 detectors. Meanwhile, UDOT maintains separate databases for vehicle incident tracking, weather conditions, and pavement conditions in the Traffic Operations Center (TOC). These datasets offer valuable information for modeling the impact of incidents and weather, and develop performance metrics for decision making purposes.

1.4 Outline of Report

The rest of the report is structured as follows. Section 2 summarizes literature on reliability performance analysis, incident and weather related modeling. Methodologies developed in this project, including secondary incident identification, IID quantification, and adverse weather impact analysis are presented in Section 3. Section 4 describes data sources used for the analysis, and Section 5 presents the analysis results. Section 6 presents the conclusion of this study and recommendations for future research.

2. LITERATURE REVIEWS

2.1 Overview

In recent years, the concept of data-driven performance evaluation has been gaining more and more popularity for traffic management. This section presents a literature summary on the three major components in this project: *performance metrics for reliability analysis*, *secondary incident identification and IID*, and *evaluation of adverse weather impact*.

2.2 Performance Metrics for Reliability Analysis

To quantify the roadway network performance, several standards are applied by the traffic operators. Travel time reliability has been widely used in different contexts to evaluate the performance of transportation facilities. In SHRP 2 L03 (2013), travel time reliability is defined as the level of consistency in travel conditions over time; while SHRP 2 L02 considers a system as reliable if each traveler's experienced actual time of arrival matches its desired time of arrival. Whichever definition is used, reliability is a critical measurement of congestion that users experience in a certain period of time. Various performance metrics are developed to describe travel time reliability, including Travel Time Index (TTI), Buffer Index (BI), Planning Time Index (PTI), Congestion Frequency, etc.

Several previous studies have demonstrated the accuracy, sensitivity, and correlations of the above performance metrics (Edwards and Fontaine, 2012; Mahmassani, *et al.*, 2012; Mehran and Nakamura, 2009; Guo, *et al.*, 2012; Tu *et al.*, 2012). Table 2.1 shows a list of reliability measures examined in the previous work.

Table 2.1 Travel time reliability measures from previous works

Travel Time Reliability Measure	Saberi and Bertini (2010)	Pu (2011)	Lyman and Bertini (2008)	Van Lint and Van Zuylen (2005)	Alvarez and Hadi (2012)
90th or 95th Percentile Travel Time		√	√		
Coefficient of Variation	√	√			
Travel Time Index	√	√	√		√
Buffer Index	√	√	√		√
Planning Time Index	√	√			√
Misery Index				√	√
Skew of travel time distribution		√			√
Width of travel time distribution				√	
Congestion Frequency	√	√			
Others		Failure rate			Failure-on-time

Alvarez and Hadi (2012) and Saberi and Bertini (2010) investigated the sensitivity of various reliability metrics in response to the variation of parameters of travel time distributions. Pu (2011) examined a number of reliability metrics assuming a log-normal distribution of travel time. He pointed out that for heavily right-skewed travel time distribution, the BI is not appropriate unless it is computed on the basis of the median rather than the mean. Saberi and Bertini (2010) reviewed existing methods that measure travel time reliability, including TTI, BI, PI, and Congestion Frequency. By comparing different reliability metrics in given segments, they concluded that BI and coefficient of variation (standard deviation of travel time divided by mean travel time) have a high consistency among other measures. Also, PI and Congestion Frequency appear to follow similar pattern.

Some researchers focused on developing new measures of travel time reliability to overcome disadvantages of existing measures (Emam and AI-Deek, 2006; Van Lint and Van Zuylen, 2005; Liu, *et al.*, 2007), e.g., the reliability is insensitive to geographical locations, or the reliability is estimated as a constant while it varies by departure time. Emam and AI-Deek (2006) proposed a new travel time reliability performance metric. The travel time reliability $R(T)$ is in response to a well-defined reliability engineering function $\lambda(T)$, namely failure rate function. The relationship between the reliability and failure rate function is expressed as $R(T) = e^{-\int_0^T \lambda(t)dt}$, where $\lambda(t) = f(t)/R(T)$ and $f(t)$ is the probability distribution function. Compared with existing methods, the new method has more emphasis on users' perception of travel experience, and has strong potential in estimating travel time reliability as a function of departure time. Van Lint and Van Zuylen (2005) proposed two reliability metrics based on 10^{th}, 15^{th}, and 90^{th} precentile of the day-to-day travel time distribution for a given route based on Day-of-Week Time-of-Day (DOW- TOD) considering that mean and variance tend to obscure important features of reliability distribution under certain circumstances. They used skewness and width of travel time distribution as indicators, and concluded that metrics can effectively identify unreliability of travel times for a given DOW-TOD period.

2.3 Secondary Incident Identification and Incident-Induced Delay

The challenge of IID quantification lies in the extraction of IID from total delay, which is the result of compounding effect of recurrent and non-recurrent congestion. Recurrent delay is defined as congestion caused by routine traffic operation in a typical setting. Non-recurrent congestion is the unexpected or unusual congestion caused by an event that is transient relative to other similar days (Hallenbeck *et al.*, 2003). Seven potential sources were identified for non-recurrent congestion by FHWA in SHRP 2: incidents, extreme weather, work zones, demand fluctuations, special events, traffic control devices, and inadequate base capacity. Kwon *et al.* (2006) found that congestion caused by incidents is 3 to 5 times that of the ones caused by special events and weather. Also considering that incident is more common than other unreliability sources, IID estimation should be performed in an effort to quantify the non-recurrent congestion impact.

Numerous studies have been conducted to quantify IID. The most widely-used methodologies are: including deterministic queueing theory (Li, *et al.*, 2006; Wang, *et al.*, 2008; Runze Yu *et al.*, 2014), shockwave theory (Mongeot and Lesort, 2000; Chandana Wirasinghe, 1978), and statistic method (Skabardonis, *et al.*, 2003). Deterministic Queuing Theory (DQT) is implemented in the Highway Capacity Manual (HCM) for estimating delay. In DQT, delay is calculated as the area enclosed by the arrival and departure curves, requiring key parameters, such as arrival rate, departure rate, incident duration, and capacity, to be determined before the calculation. The parameters are either assumed or via stochastic method, and estimation accuracy is compromised when applied to individual incident (Li, *et al.*, 2006). Some of the parameters are difficult to determine for predicting incident delay in dynamic networks. Yu *et al.* (2014) proposed a modified DQT method and avoided the parameters estimation using short-term traffic flow forecasting. However, the method yields unsatisfying results when the incident happens during unstable traffic conditions (e.g. oversaturated condition downstream). Shockwave-based algorithms are developed on the basis of traffic flow theory, treating incidents as flow perturbations. The algorithm suffers from mathematical complications, and is difficult to be implemented in the existing performance measurement infrastructure. In Mongeot *et al.* (2000), the algorithms is fulfilled with first-order macroscopic traffic flow model. The study assumed that the traffic flow is in equilibrium status constantly, which further ignored the speed and volume reduction due to the queuing phenomenon. Statistical models also were applied in the previous research to estimate congestion. Compared with the other two methods, it is easier to be implemented and has loose constraints on the quality of sensor data (Skabardonis, *et al.*, 2003). However, the methods are not capable of estimating delay at microscopic level.

One challenge needed to quantify IID is to rule out the impact induced by secondary incidents. Secondary incidents are considered stochastic events induced by traffic congestion originated from the primary incident. A loose assumption regarding secondary incident identification is that secondary incidents happen in certain spatial and temporal range of primary incidents. To simplify the identification procedure, the majority of previous studies have used fixed spatial and temporal boundaries, assuming that the selected boundaries are applicable to all types of incidents. Khattak, et al. (2009) provides a summary on the previous work, most of which used spatial and temporal boundaries up to two miles and 120 minutes. Since incident impact varies with the geometric characteristics of the road, periodic characteristics of traffic, and incident type, the general assumption of fixed spatiotemporal boundary lacks universality. To accommodate the varying spatiotemporal boundaries, Chung (2013) and Yang, et al., (2013) presented data-driven dynamic methods to estimate primary incidents' impact based on traffic features and incident data.

Yang, et al. (2013) believed that one location is under the impact of previous incidents if the speed at this location is lower than the historical speed value. They constructed spatiotemporal binary speed plots of each incident by comparing speed value against the historical incident-free speed profile at the same location. They also developed an algorithm to identify whether the incidents that followed were within the spatiotemporal impact range of the previous incident. Under ideal conditions, the impact range demonstrates continuous stripe pattern stretching upstream spatially and downstream temporally. However, due to loop detector errors and bias in estimating incident-free speed, there were interrupting structures (bubbles) in the actual impact range (Chung, 2013). To eliminate effects of the interrupting structures, they proposed three criteria for impact range identification: the spatiotemporal progression of the incident shockwave is uninterrupted, the boundary of the spatiotemporal progression of the incident shockwave is upstream, and the entire boundary of the affected region is contiguous.

2.4 Evaluation of Adverse Weather Impact

Another major source for non-recurring congestion is adverse weather, which leads to changes in driver behavior that affect traffic flow. Many studies focused on the adverse weather's impact on crash occurrence and the overall traffic condition (Bergel-Hayat et al., 2013; Yu et al., 2013; El-basyouny et al., 2014; Ahmed et al., 2014; Brijs et al., 2008). Yu et al. (2013) studied real-time weather effect on crash frequency by adding seasonal weather-related random factor to Bayesian random effect model. El-basyouny *et al.* (2014) investigated the impact of weather elements, especially sudden extreme snow or rain weather, on crash type using Bayesian multivariate Poisson lognormal model.

Numerous efforts have been performed by researchers to study weather effects on traffic condition, e.g. traffic flow, speed, and non-recurrent congestion (Datla and Sharma, 2008; Maze et al., 2006; Thakuriah and Tilahun, 2012; Keay and Simmonds, 2005; Chung, 2012). Keay and Simmonds (2005) investigated the relationship between weather variables and traffic flow at different time-of-day by performing regression analysis. Chung (2012) used the spatiotemporal analysis to quantify the congestion caused by precipitation events.

2.5 Summary

This section summarized key findings from the literature search. Three main topics of focus in this project include performance metrics for reliability analysis, secondary incident identification and IID, and evaluation of adverse weather's impact. Previous studies have focused on addressing these issues with theoretical modeling and statistical methods. In the following sections, data-driven solutions are presented for these problems.

3. RESEARCH METHODS

3.1 Overview

To conduct data-driven performance evaluation on a freeway corridor, high resolution traffic data must be collected to assist with analysis. I-15 was chosen as the study corridor for this project. I-15 stretches 401.07 miles long in the State of Utah and connects the vast majority of the state's population and employment centers. For demonstration purposes, the corridor segment from MP 285 to MP 310 on I-15 Northbound was chosen to illustrate the performance analysis process. This segment lies in the Salt Lake City metropolitan area where the majority of accidents are observed, with 60 valid stations. Figure 3.1 is a map of the selected segment of the I-15 corridor. In the subsequent analysis, interpolation was applied for a finer time resolution and for incidents located between stations.

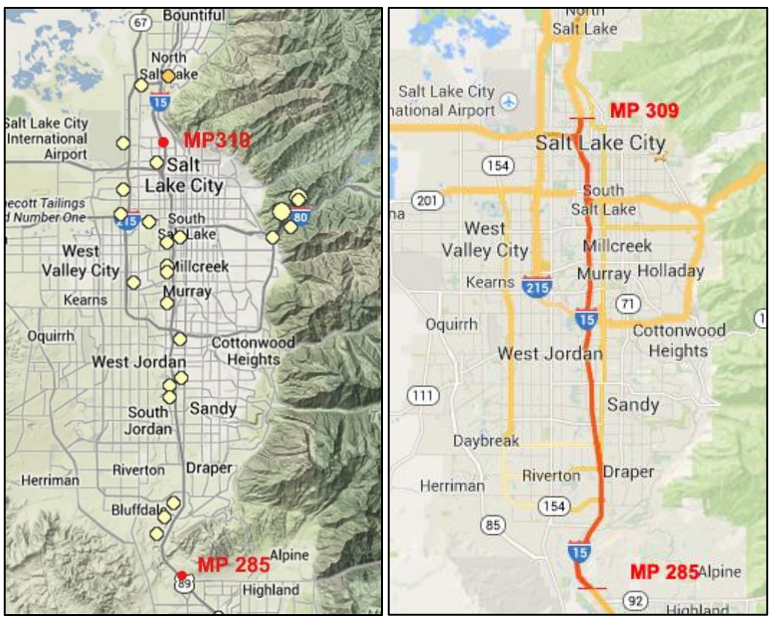


Figure 3.1 I-15 study corridor

3.2 Performance Metrics for Reliability Analysis

UDOT currently is using speed profile to describe travel reliability along the I-15 corridor. Speed measure (mean, 15^{th} and 85^{th} speed percentile) is intuitive and interpretative for both practitioners and the general public. Figure 3.2 displays this reliability measure along the I-15 corridor. However, it would be desirable to develop an easily comprehended unified measure to describe the same speed variation. Congestion Frequency is recommended as a measure of reliability by FHWA. It is typically expressed as the percentage of days or time that travel times exceed X minutes or travel speeds fall below Y mph. It is relatively easy to compute given the availability of traffic data, and typically reported for weekdays during peak periods.

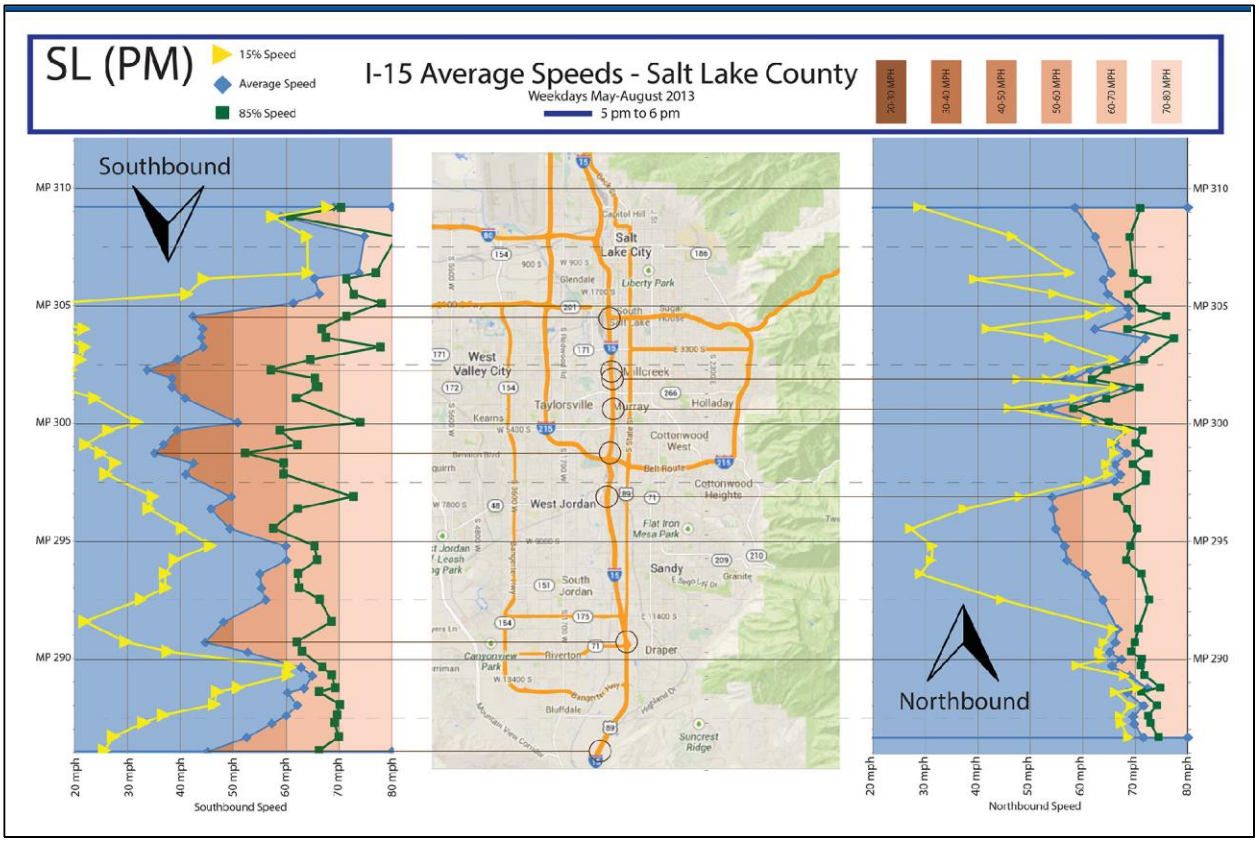


Figure 3.2 Speed profile at 15th, 50th, and 85th percentiles across study corridor

The speed threshold below which the roadway condition is considered congested is critical in congestion frequency measurement. In Pu's (2011) work, congestion is defined as the condition when speed is less than or equal to 50% of the free-flow speed, or equivalently, travel time is more than or equal to twice of the free-flow travel time. In Pu (2011), $Travel\ Time\ Index = 1.3$ is used as a criterion to define congestion. In this study, traffic breakdown (congestion criterion) is identified via speed-flow relationship along the I-15 corridor. Figure 3.3 shows the speed-flow scatter plot using the empirical data collected on I-15. Traffic breakdown occurs around 50-55 mph. Thus, 55 mph is adopted in this study as the speed threshold in the Congestion Frequency measure. This is also consistent with Lyman and Bertini's (2008) definition, where using the average speed at midnight as the free-flow speed (69 mph on I-15), the speed threshold is estimated at 53 mph ($1.3 * FFS$).

Figure 3.4 shows the sensitivity analysis of the Congestion Frequency measure under different speed thresholds. The result of the analysis is illustrated as heat maps where the spatial and temporal pattern of Congestion Frequency can be observed. It is noted that at MP 292-293, it is congested during the entire morning peak hour. As the congestion threshold increases (from 30 mph to 55 mph), more and more regions are identified as congested.

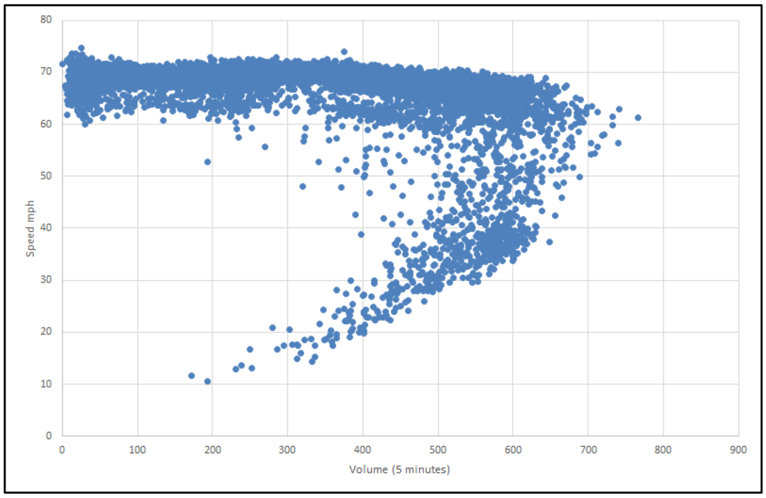


Figure 3.3 Speed-flow relationship using empirical data collected

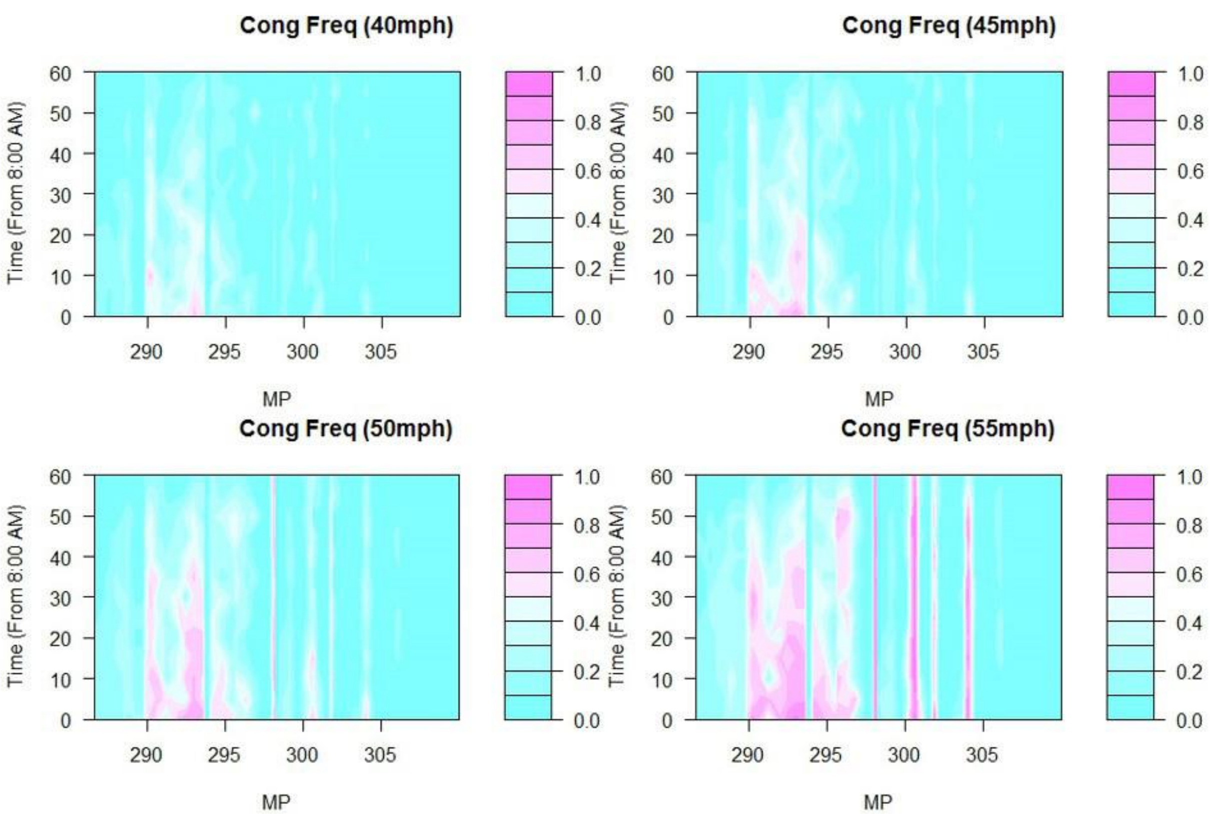


Figure 3.4 Congestion frequency heat map under different speed thresholds

3.3 IID

IID quantification at individual incident level enables further analysis on delay-based behavior modeling and inspires follow-up research on exploring relationships between the incident itself and associated features (e.g., severity, lane blockage, or traffic conditions). The proposed algorithm in this study starts by ruling out the influence of secondary incidents, as subsequent events occurring in spatiotemporal domain can result in an overestimation of the primary incident impact. This is achieved by mapping cascading incidents onto the spatiotemporal extents of the potential primary incidents. The total delay induced by each individual incident is then dynamically calculated using a spatiotemporal clustering approach. Recurrent congestion can be eventually determined through heuristically searching in the historical database for pattern matching. The methodology is data-driven in nature and algorithm is easily transferable to any traffic operation system that has access to the sensor data at corridor level.
The algorithm for IID estimation follows a three-component scheme: secondary incident identification, spatiotemporal extent determination (total delay), and recurrent congestion identification. The detailed explanation for each component is presented in this section.

3.3.1 Secondary Incident Identification

Due to the cascading effect of secondary incidents, delays can be elongated substantially. To separate the delay induced by primary and secondary incidents, a method that considers spatiotemporal effects of primary incidents is required. As mentioned in Chung (2013), the secondary incident identification should be fulfilled by defining the primary incident impact area. Delay induced by an incident, defined as the excess Vehicle Hours Traveled (VHT) with a reference speed of 60 mph as an example, can be visualized in a spatiotemporal contour map, as shown in Figure 1. In this figure, spatiotemporal impact extent is established on the basis of three criteria: IID detection, shockwave front location, and contiguity of impact region. Any cascading incidents occurring within the spatiotemporal extent are identified as secondary incidents. Specific explanation of the criteria follows.

IID Detection

Let $D_{Sec\_tot}(i,j)$ be the representative of total delay at location i with Time-of-Day Day-of-Week (TOD DOW) j induced by an incident, $D_{Sec\_rec}(i,j)$ be the representative of corresponding recurring delay, and $d_{Sec}(i,j,k)$ be the historical delay under incident-free scenario at the same location i with TOD DOW j, but at different week k. The *incident-free scenario* is defined as no incident occurring within five hours prior to the time stamp and within 10 miles upstream of the location. The recurring delay $D_{Sec\_rec}(i,j)$ is estimated with $d_{Sec}(i,j,k_1)$, $d_{Sec}(i,j,k_2), \dots, d_{Sec}(i,j,k_n)$, where $k_1, k_2, \dots, k_n$ are the weeks under incident-free scenario. The spatiotemporal extent based on the difference between total and recurrent delays, in which any new incident occurred, offers a sense of existence of secondary incidents. In case a secondary incident appears, its impact extent would be connected with one of the primary incidents, expanding on the original spatiotemporal range. As a result, a secondary incident would never appear at the boundary of a spatiotemporal impact region. Using fixed percentiles of historical delay to represent recurring congestion (e.g., 80 percentile), a binary contour map for detecting existence of IID can be generated by subtracting $D_{Sec\_rec}(i,j)$ from $D_{Sec\_tot}(i,j)$:

$$I_{Sec}(i,j) = \begin{cases} 1, if\ D_{Sec\_tot}(i,j) - D_{Sec\_rec}(i,j) > 0 \\ 0, if\ D_{Sec\_tot}(i,j) - D_{Sec\_rec}(i,j) \leq 0 \end{cases} \quad ((1)$$

where $I_{Sec}$is the indicator of IID existence. $I_{Sec}(i,j) = 1$, suggesting that IID exists at spatiotemporal location (i,j), otherwise $I_{Sec}(i,j) = 0$.

Shockwave Front

Considering random factors that may influence delay after an incident occurs (e.g., adverse weather, work zone), $I_{Sec}(i,j) = 1$ does not necessarily mean that the delay is purely incident-induced. To rule out such possibilities, shockwave front location method is used to filter out other non-recurrent delays. As soon as an incident occurs, a shockwave is triggered. The shockwave is originated from the incident and spread spatially backward and temporally forward. Therfore, an incident impact region should coincide with the spatiotemporal area behind the front of shockwave. The spatiotemporal contour map can be broken down into two parts:

$$S_{Sec}(i,j) = \begin{cases} 0, if\ (i,j)\ is\ ahead\ of\ shockwave\ front \\ 1, if\ (i,j)\ is\ on\ or\ behind\ shockwave\ front \end{cases} \quad ((2)$$

where S_{Sec} is the indicator for determining whether the location *(i, j)* is behind the shockwave front.

The shockwave effect is a complicated process and varies based on traffic volume, density, and severity of incidents. The shockwave front location is defined with a dynamic threshold as developed in Yang and Recker (2005): the sensor station whose traffic density is greater than twice the density at the upstream station and the sensor station whose average speed is greater than twice the speed at the downstream station. Therefore, if a delay is detected ahead of the shockwave front in the spatiotemporal context, it is not considered to be induced by the incident.

Contiguity of Impact Region

The propagation of congestion is unidirectional in spatial and temporal domains. Thus, the IID at spatiotemporal location (i,j) (if any) must be inherited from a prior location that is spatially forward or temporally backward. The contiguity of impact region suggests that if IID exists at (i,j), it must also exist in either $(i-1,j)$ or $(i,j-1)$, or both. Mathematically, this can be expressed as:

$$C_{Sec}(i,j) = \begin{cases} 1 & if\ i = 0\ and\ j = 0 \\ \min\{1, I_{Sec}(i-1,j) * S_{Sec}(i-1,j) * C_{Sec}(i-1,j) + I_{Sec}(i,j-1) * S_{Sec}(i,j-1) * C_{Sec}(i,j-1)\}, & else \end{cases} \quad (3)$$

where C_{Sec} is the indicator for contiguity. $C_{Sec}(i,j) = 1$ suggests the criterion of contiguity is met, otherwise $C_{Sec}(i,j) = 0$.

Based on the aforementioned criteria, every spatiotemporal cell within the impact range of an incident must satisfy:

$$I_{Sec}(i,j) * S_{Sec}(i,j) * C_{Sec}(i,j) = 1 \quad (4)$$

Therefore, any incident that falls within the impact range of a prior incident would be considered secondary [*1-zone* in Figure 3.5 (d)]. Figure 3.5 (a)-(c) demonstrates the results of applying the IID detection, shockwave front, and contiguity of impact region criteria to the spatiotemporal profile of delay after incident. Cells marked as 1 represent the spatiotemporal units that meet the criterion in each plot. Figure 3.5 (d) is the conjunction plot based on the three criteria. Note that the spatiotemporal impact extent due to a cascading incident would be much greater than those of independent incidents. If a delay is calculated based on such overlapping effects, it would significantly overestimate IID, especially for locations with high secondary incident frequency. With the primary incidents and secondary incidents identified, attention is directed to total delay and recurrent delay quantification, which are spatiotemporal-sensitive.

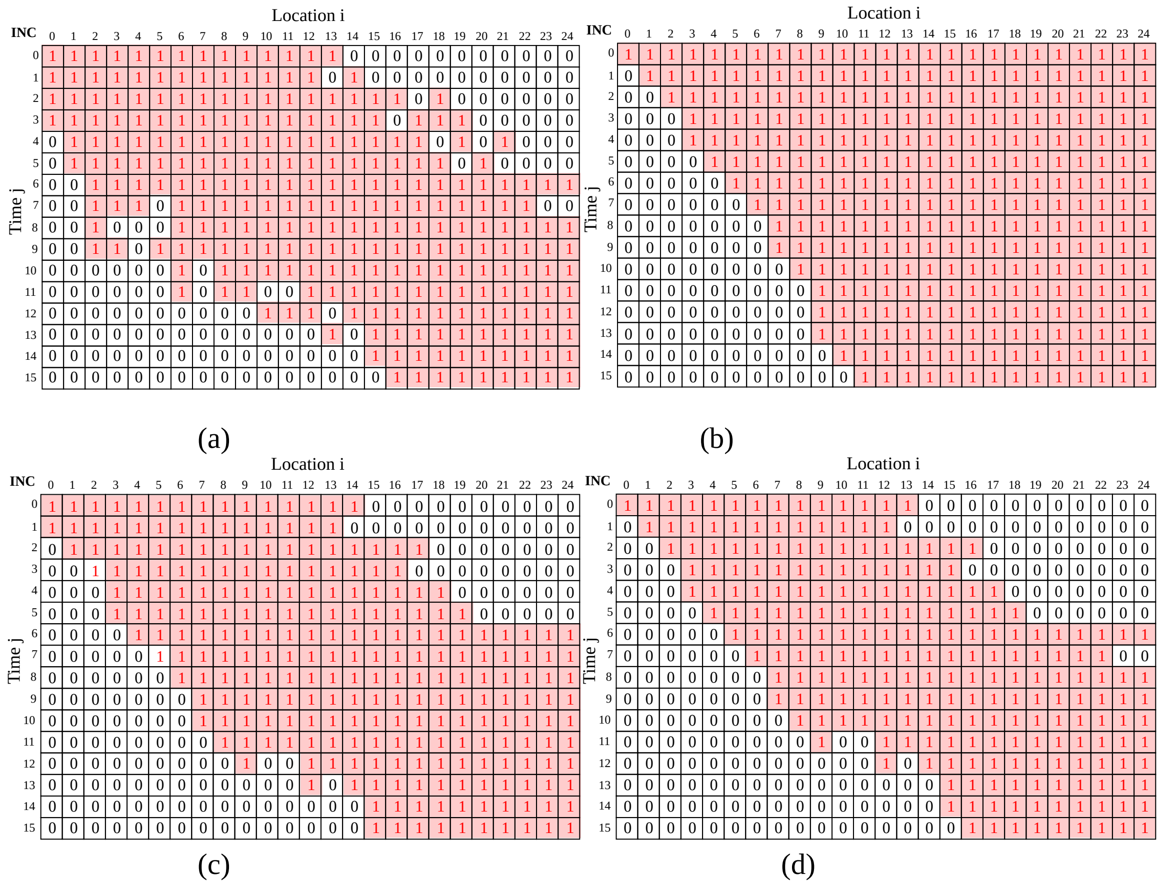


Figure 3.5 Illustration of secondary incident identification process: spatiotemporal profile of (a) function I.; (b) function S; (c) function C; and (d) function I*S*C

3.3.2 Total Delay of Independent Incident

The total delay of an incident refers to the accumulated delay augmented in its spatiotemporal impact extent. Compared to secondary incident identification, total delay quantification is more sensitive to the spatiotemporal range. The same spatiotemporal clustering analysis applies here with the exception of fixed percentile threshold for defining "normal condition." Instead, a statistical model, which can be trained with empirical data, is used to provide a more reasonable threshold.

To implement the threshold estimation, 1,000 TOD DOW and locations were randomly chosen, and histograms of the delay occurring during those periods were constructed. Two typical patterns of delay frequency emerged, as shown in Figure 3.6. Non-parametric estimation determined that the incident-free delay followed Weibull distribution, whose probability density function is expressed as:

$$f(x;\lambda,k) = \begin{cases} \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-\left(\frac{x}{\lambda}\right)^{k}}, x \geq 0 \\ 0, x < 0 \end{cases} \quad (5)$$

where k is the shape parameter. When $k = 1$ or $k = 2$, the distribution becomes Exponential Distribution or Rayleigh Distribution. The Cumulative Distribution Functions (CDF) are:

$$k = 1, F(x;\lambda) = 1 - e^{-\lambda x}\ (x \geq 0)\ \text{(Exponential Distribution)}$$
$$k = 2, F(x) = 1 - e^{-\frac{x^2}{2\sigma^2}}\ (x \geq 0)\ \text{(Rayleigh Distribution)} \tag{6}$$

The parameters can be estimated as:

$$\hat{\lambda} = \frac{n}{\Sigma_{k=1}^{n} d(i,j,k)}$$
$$\hat{\sigma} = \sqrt{\frac{1}{2n}\Sigma_{i=1}^{n} x_i^2} \tag{7}$$

Let $d(i,j,k)$ refer to the historical delay under incident-free scenario at location i, TOD DOW j, and week k. With distribution parameters known, the P^{th} percentile of delay can be estimated as:

$$\widehat{D}_{exp}(i,j) = \frac{\ln\left(\frac{1}{1-P}\right)}{n} \Sigma_{k=1}^{n} d(i,j,k) \tag{8}$$

$$\widehat{D}_{Ray}(i,j) = \sqrt{\frac{\ln(\frac{1}{1-P})}{n} \Sigma_{k=1}^{n} d(i,j,k)_k^2} \tag{9}$$

where $\widehat{D}_{Exp}$ and $\widehat{D}_{Ray}$ are the estimated threshold when delay follows Exponential and Rayleigh Distribution, respectively. The distribution of historical delay varies by TOD DOW, so instead of exploring the distributions for any TOD DOW, the minimum of $\widehat{D}_{exp}$and $\widehat{D}_{Ray}$ was used as the threshold.

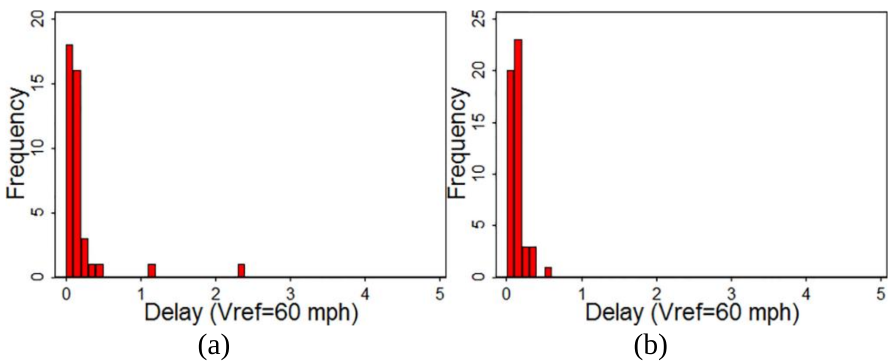


Figure 3.6 Typical patterns of delay distributions: (a) Exponential Distribution (b) Rayleigh Distribution

Let $D_{Ins}(i,j)$ be the representative of instantaneous delay at location i and TOD DOW j after an incident and D_{Tot} denote the total delay of an incident. The spatiotemporal extent of an incident's impact is defined as:

$$I(i,j) = \begin{cases} 1, if\ D_{Ins}(i,j) - \min\{\widehat{D}_{exp}(i,j), \widehat{D}_{Ray}(i,j)\} > 0 \\ 0, if\ D_{Ins}(i,j) - \min\{\widehat{D}_{exp}(i,j), \widehat{D}_{Ray}(i,j)\} \leq 0 \end{cases} \tag{10}$$

$$D_{Tot} = \Sigma_i \Sigma_j I(i,j) * D_{Ins}(i,j) \tag{11}$$

where I is the congestion indicator,$I(i,j) = 1$ indicates that it is congested at location (i,j), otherwise $I(i,j) = 0$.

The congestion threshold estimation is performed in both *Secondary Incident Identification* and *Total Delay Determination*. Compared to the fixed percentile method in secondary incident identification, applying the statistical distribution model can avoid bias due to limited sample size and outliers. Yet the selection of thresholds can be risky. A lower threshold may incorporate any possible delay into the total delay, but also significantly expand the spatiotemporal impact range and then compromise the accuracy of the method. Though rarely observed, for extreme incident cases where the spatiotemporal extent is unreasonably long (e.g., more than 5 hours), a fixed spatiotemporal extent should apply.

3.3.3 Recurrent Delay Determination by Pattern Matching

Generally, recurrent delay is defined as congestion caused by routine traffic operations in a typical setting. Yet traffic conditions vary on a daily basis, even for recurrent congestion. When predicting the recurrent delay for an incident scenario, the "background congestion" from historical record requires special attention. The "typical recurrent congestion" determined from statistical models in previous studies often is not applicable to every incident scenario. This is remedied through a pattern matching process, where recurrent delay is considered a function of location, TOD DOW, traffic condition, and other miscellaneous factors can be expressed as:

$$d_{Rec^*} = F(i, j, T, \dots) \tag{12}$$

where d_{Rec^*} is the accumulated delay within the incident's impact extent if there was no incident, i is the location, j is the TOD DOW, and T is background traffic condition.

Other variables have marginal effects and were not considered part of the equation. When considering incident scenario, it is impossible to infer what the recurrent congestion would be if the incident did not occur, but recurrent delay can still be deduced through matching traffic conditions from historical data. For any historical traffic scenario T_{his}, if there exists $|T - T_{his}| < \epsilon$, where ϵ is a threshold for the difference of traffic condition. It is reasonable to assume that:

$$|d_{Rec^*} - d_{his}| < \epsilon' \tag{13}$$

where d_{his} is the recurrent delay of the matching historical scenario, and ϵ' is threshold for the difference of recurrent delay.

The sensitivity analysis of thresholds ϵ and ϵ' will be investigated in future work. Previous research compared three pattern matching techniques (DOW, cluster, KNN) with different weighting methods (Habtemichael and Cetin, 2015). Yet without knowing the relationship between delay, location, time, and traffic condition, any weighting attempt is susceptible to questioning as it lacks validation. In this study, pattern matching was performed based on TOD-DOW. Quantifying the recurrent congestion becomes equivalent to identifying the best-matched historical traffic scenario at the same location and TOD-DOW. The performance measure for pattern matching is VHT, which can best describe speed and volume and is easily obtained from traffic sensors. It is critical that the historical matching scenarios be incident-free, therefore filtration should be applied to the database (no incident within a five-hour span at the same location and TOD-DOW). Statistical performance indicator Root-Mean-Square-Error (RMSE) is used for choosing the matching scenario:

$$RMSE = \sqrt{\frac{\Sigma_{t=1}^{2}\left(\widehat{V}_t - V_t\right)^2}{n}} \tag{14}$$

where $\widehat{V}_t$ is VHT for historical incident-free scenario, V_t is VHT for traffic scenario prior to the incident, and n is the number of observations.

The pattern matching process is conducted on traffic conditions within a 30-minute time frame prior to the incident. The number of observations is determined by interval selection and aggregation level of sensor data. The pattern matching essentially is a heuristic search on historical database until the matching traffic scenario with the least RMSE is found. The recurrent delay in the incident's impact extent can be estimated as the accumulated delay from the matching scenario at the same location i and TOD DOW j but a different week K, expressed as:

$$D_{REC} = \Sigma_{j=1}^{J} \Sigma_{i=s_{m,j}}^{s_p} d_{his}(i, j, K) \tag{15}$$

Pattern matching based on single VHT for the same TOD DOW at the same location may be subject to inaccuracy when providing a holistic view of traffic conditions. To compensate, the K-Nearest Neighbor (KNN) method was applied in the pattern matching process to determine the closest incident-free scenarios that can be used to describe recurrent congestion. KNN is a classification method that offers a nonparametric procedure for assigning a class label to the input pattern based on the K-closest neighbors of the vector (Keller et al., 1985). In this study, similarity (RMSE) of the K-closest neighbors (historical scenarios) was used as the means of classification. The delay at matching scenario is calculated as:

$$d_{his}(i, j)_{KNN} = \frac{1}{K} \Sigma_{k=1}^{K} d_{his}(i, j, W_k) \tag{16}$$

where $d_{his}(i, j)_{KNN}$ is the mean of KNN recurrent delay, and W_k is the week when the KNN traffic scenario occurred. The robustness of VHT as measurement and value of K in KNN method are discussed in the next section.

The entire algorithm, deconstructed into three major components as described above, is depicted in Figure 3.7. Note that the congestion threshold estimation used in both Secondary Incident Identification and Total Delay Determination might bear two types of errors for incident spatiotemporal extent determination. First, when the actual recurrent delay is higher than the threshold, the incident spatiotemporal extent and the total delay would both be over-estimated. However, over-estimated spatiotemporal extent also would cause recurrent delay over estimation. The overall effect is canceled when estimating IID. Second, when the actual recurrent delay is less than the threshold, the spatiotemporal extent is under-estimated. But in the region near the boundary of spatiotemporal extent, the impact of the incident is almost dismissed. Therefore, the delay in such a region is negligible.

For implementation purposes, incident records, including location, date, time, and traffic sensor data, which contain speed, volume, and density, must be obtained. The following section presents finer details of the algorithm implementation on the I-15 corridor in Salt Lake City, Utah.

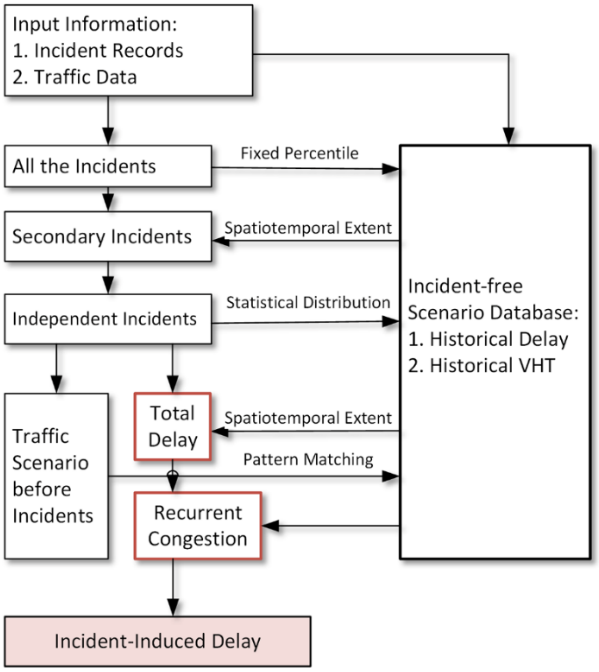


Figure 3.7 Illustration of proposed IID quantification framework

3.4 Evaluation of Adverse Weather Impact

In this project, weather impact on traffic condition along the freeway corridor is examined. Although traffic condition degradation under adverse weather was observed in many studies, none has quantitatively explored the relationship between adverse weather and degraded traffic conditions, which may be caused by many reasons (e.g. slippery road surface, vehicle performance degrade, and impaired visibility). Of particular interest to this study is the interaction between weather and delay. During adverse weather, people tend to rearrange or cancel trips to avoid suffering longer travel time or higher risk of incidents. Since it is nearly impossible to measure actual demand along a corridor, a mechanism was developed to model the impact of adverse weather on throughput and delay.

To measure adverse weather impact on throughput and delay, historical traffic data (volume and delay) were retrieved from PeMS at the same DOW-TOD at the same location for each weather record. Data filtering process ensures that historical records under the impact of incidents are ruled out. Let $\mathrm{D_{Wea}}(m,t,s,w)$ be the delay when the adverse weather is reported, where m is the location, t is the TOD, d is the DOW, and w is the week. Historical delay at the same location and time stamp is represented using $d_{Wea}(m,t,s,u)$, where $u = 1,2,\dots,54$, $u \neq w$, and $I_{Inc}(m,t,s,u) = I_{Inc}(m,t,d,w) = 0$. The same data retrieval performed on throughput (volume), and $F_{Wea}(m,t,s,w)$ and $f_{Wea}(m,t,s,u)$ represent the flows under adverse weather and historical normal days, separately. For the historical delay records, if flow difference (under normal day vs. adverse weather day) falls below a certain threshold, then delay under the normal day is counted as a sample representative for further analysis. This can be expressed as:

$$\widehat{\mathrm{D}}_{\mathrm{Weaf}}(m,t,s,w) = \frac{1}{\mathrm{n}}\Sigma_{\mathrm{i=1}}^{\mathrm{n}} d_{Wea}(m,t,s,u_i),$$
$$if\ \left(abs\left(F_{wea}(m,t,s,w) - f_{Wea}(m,t,s,u_i)\right)\right) \leq \text{Flow Threshold} \qquad (16)$$

The threshold is chosen as 10% of the values during the adverse weather. Similarly, for historical flow records, if delay difference (between normal day vs. adverse weather day) falls below a certain threshold, flow under the normal day is counted as a sample representative for further analysis:

$$\hat{F}_{Weaf}(m,t,s,w) = \frac{1}{n}\Sigma_{i=1}^{n} f_{Wea}(m,t,s,u_i),$$
$$if\ \left(abs\left(D_{wea}(m,t,s,w) - d_{Wea}(m,t,s,u_i)\right)\right) \leq \text{Delay Threshold} \tag{17}$$

Subsequently $\Delta\mathrm{D}_{\mathrm{wea}}(m,t,s,w)$ and $\Delta\mathrm{F}_{\mathrm{wea}}(m,t,s,w)$ can be calculated to quantitatively measure the impact of adverse weather on delay and traffic throughput, where:

$$\Delta\mathrm{F}_{\mathrm{wea}}(m,t,s,w) = \hat{F}_{Weaf}(m,t,s,w) - F_{wea}(m,t,s,w) \tag{18}$$
$$\Delta\mathrm{D}_{\mathrm{wea}}(m,t,s,w) = \widehat{D}_{Weaf}(m,t,s,w) - D_{wea}(m,t,s,w) \tag{19}$$

3.5 Summary

In this section, methodologies for reliability analysis, IID and secondary incident identification, and weather impact evaluation were presented. Congestion frequency was considered as a comparable measure to the speed percentile for describing freeway reliability, yet it was easy to interpret. The IID and secondary incident identification adopted spatiotemporal analysis at individual incident level and heuristically searched from the historical traffic database to match the recurrent delay. A simplified estimator was developed to model weather impact in terms of traffic volume and delay. In the following sections, the methodologies developed will be applied to the data collected through PeMS, incident and weather databases to demonstrate the performance evaluation result.

4. DATA COLLECTION

All traffic data used in this project are from PeMS (Freeway Performance Measurement System), hosted and managed by Iteris in the Cloud. Data was designed to collect, filter, process, aggregate, and examine traffic data provided by UDOT. The system contains a rich pool of information about real-time and historical traffic dat,a and provides an excellent platform to both transportation practitioners and researchers. The system integrates various traffic data sources including loop detectors, incident logs, vehicle classification data, and roadway inventory, etc. These traffic data have been automatically collected and archived from more than 28,000 detectors every 30 seconds, which totals 46 billion data samples per year. Meanwhile, UDOT maintains separate databases for vehicle incident tracking in TOC. These datasets offer details regarding incident ID, time, location, duration, severity, priority, impact, and brief description. For IID and secondary incident identification, the incident database was obtained for the year 2013, with 9,302 incident records. Of those, 1,377 of them were used for modeling purpose, since they occurred along I-15 Northbound between MP 285 to 309. Weather data used in this project were obtained from the Traveler Advisory Telephone System (TATS) database. These data were collected by trained citizen reporters, who can be UDOT employees, law enforcement, truck drivers, plow drivers, experienced commuters, or other volunteers, to report on the current road conditions along specific segments across Utah. The dataset from November 2013 to March 2014 was obtained, including road condition, sky condition, date and time, reporter, and route segment ID. More than 190,000 records exist on freeways and arterials throughout the state, and more than 3,000 records on the selected corridor in the Salt Lake Metropolitan Area. Weather data is categorized by road condition as dry, wet, slushy, patchy snow, icy spots, and snow covered, and by sky condition as rain, mixed rain and snow, blowing snow, and snow.

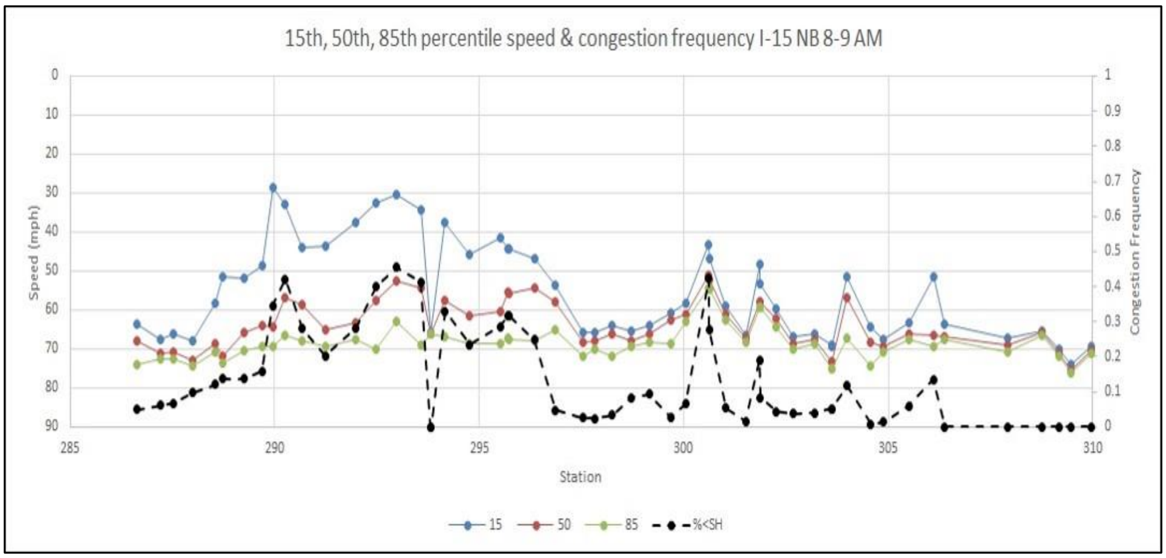
5. DATA ANALYSIS

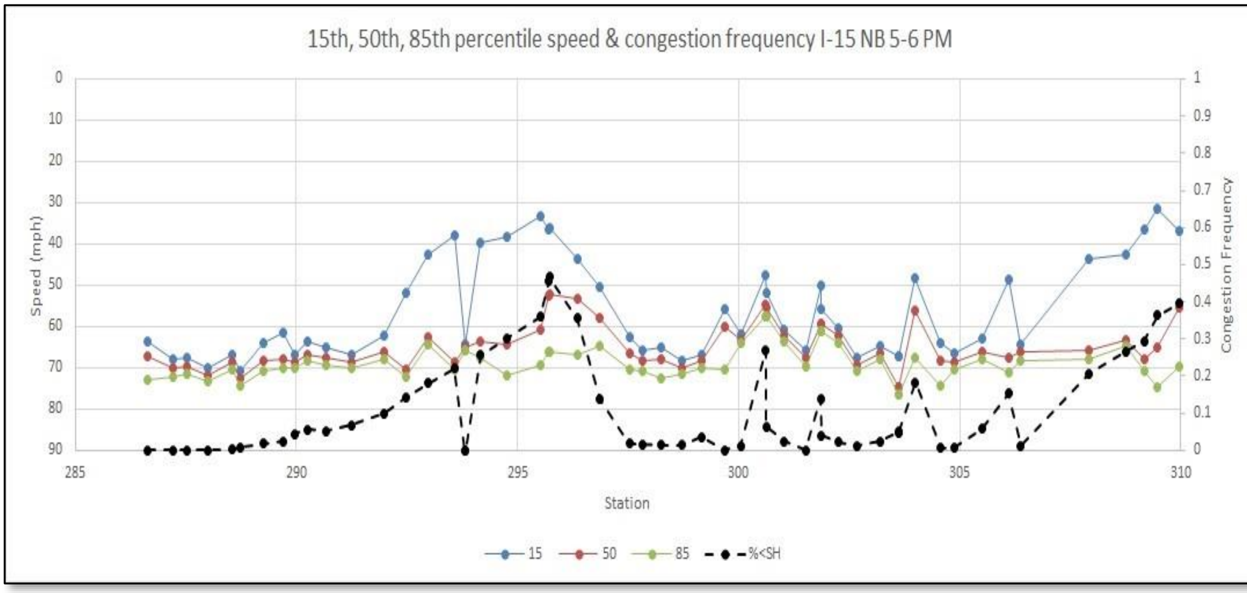
5.1 Overview

In this Section, methodologies presented in Section 3 were applied to data collected in the State of Utah. Analysis shows the performance evaluation at corridor level and location level. Results demonstrate strong policy implications that potentially will lead to incorporation of the measures/algorithms into the roadway traffic management and assist with project prioritization.

5.2 Performance Metrics for Reliability Analysis

Congestion frequency is computed using traffic condition data from 2013 with 55 mph as the threshold for this I-15 study corridor. Figure 5.1 shows congestion frequency and speed profile along I-15 for morning and afternoon peak hours. Two measures demonstrate a consistent pattern. Congestion frequency is in the range of 0 to 1 and can be translated into the probability that travelers will experience certain traffic conditions. A congestion frequency of 1 suggests that if the user drives to the location during that time period, he/she will be sure to experience a speed less than 55 mph. Figure 5-1 shows that during morning peak hour there is a high probability of speed less than 55 mph at MP 290 and MP 301 on Northbound I-15, and at MP 301 and MP 309 on Southbound I-15. During the evening peak hour, there is a high probability of speed less than 55 mph at MP 296 and MP 309 on Northbound I-15, and at MP 286, MP 301, and MP 304 on Southbound I-15.




15th, 50th, 85th percentile speed & congestion frequency I-15 NB 5-6 PM
Speed (mph)
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50
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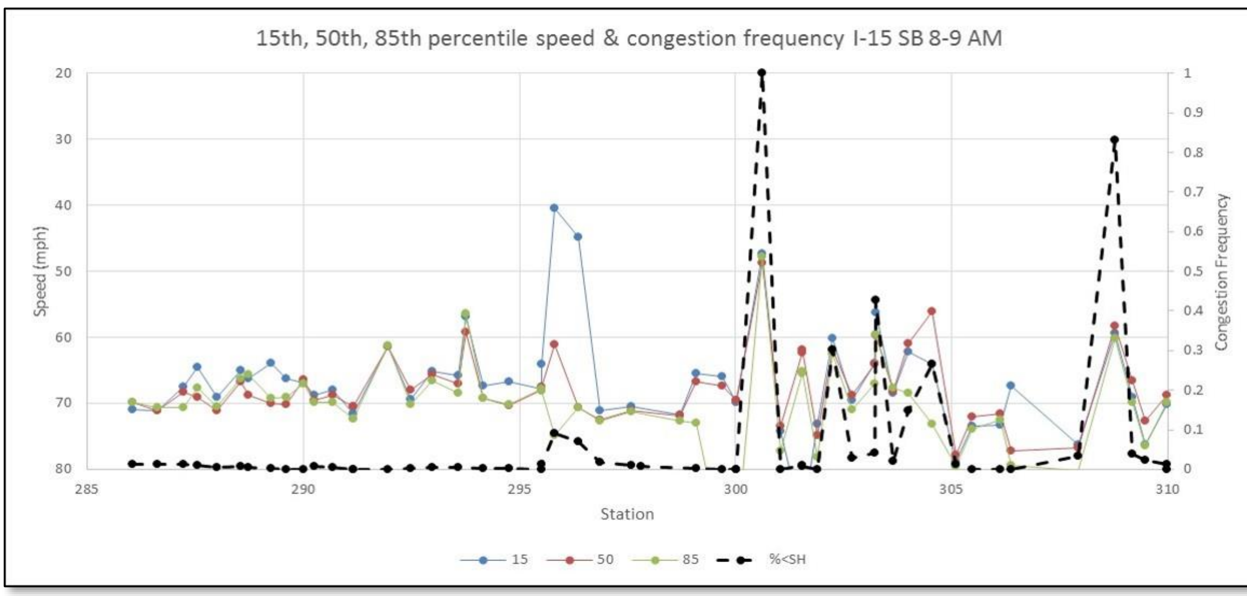
15th, 50th, 85th percentile speed & congestion frequency I-15 SB 8-9 AM
Speed (mph)
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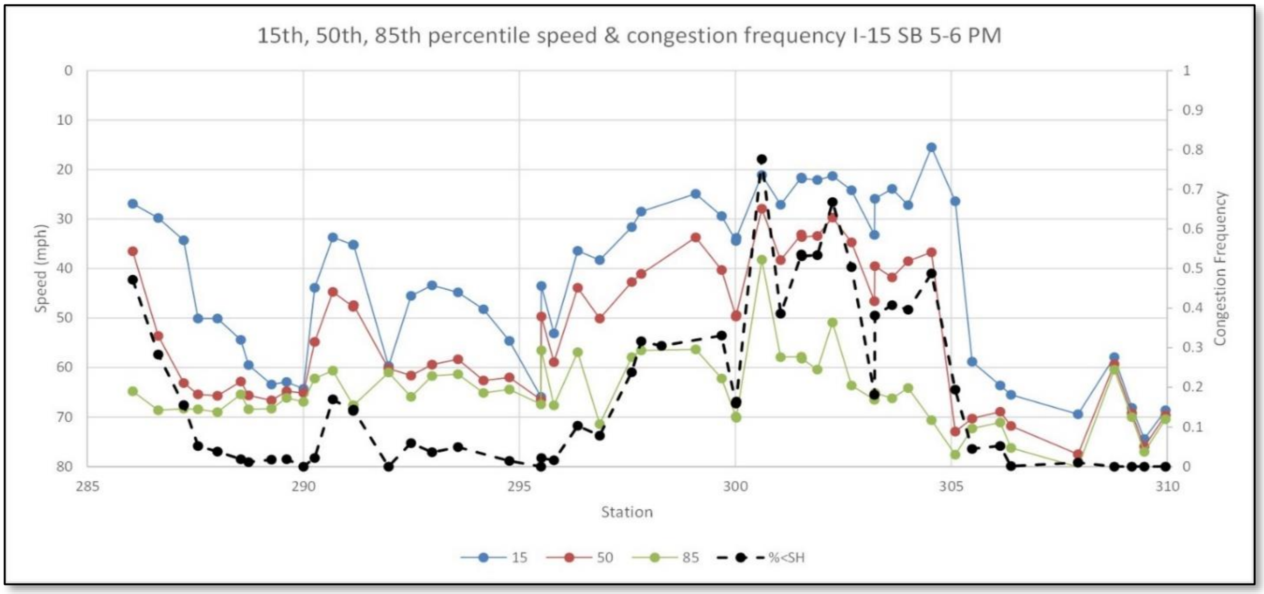


Figure 5.1 Congestion frequency and speed profile at 15th, 50th, and 85th percentiles across I-15 study corridor

5.3 Secondary Incident Identification

Applying the data-driven algorithm described in Section 3.3.1 to the 2013 incident database, we identified 240 secondary incidents as a result of 109 (7% of the total incidents) primary incidents along the I-15 northbound study corridor during year 2013.

Figure 5.2 shows a histogram of the number of secondary incidents caused by each primary incident. Figure 5.3 shows distribution of secondary incidents by month, and demonstrates a pronounced seasonal pattern, with December having the most secondary incidents. This implies that precipitation and slippery road conditions increase the probability of secondary incident occurrence.

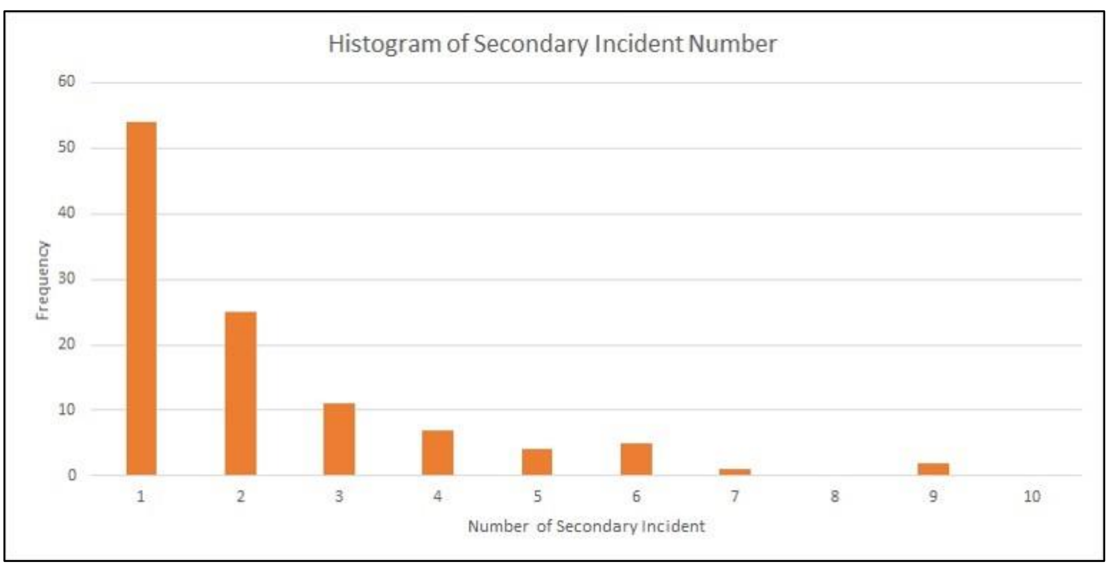


Figure 5.2 Histogram of secondary incident induced

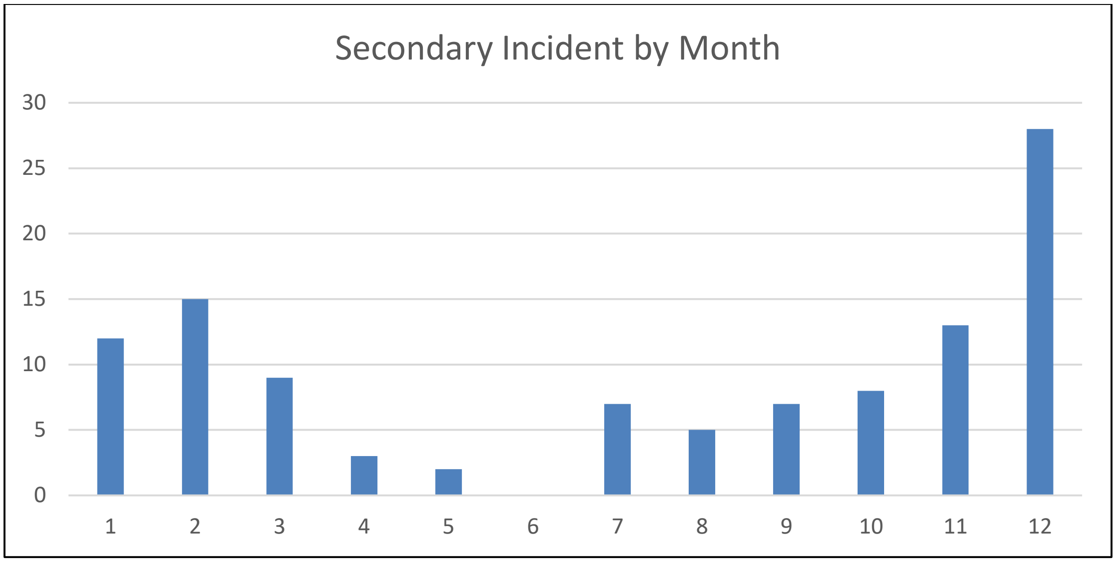


Figure 5.3 Secondary incident distribution by month

5.4 IID

To validate the robustness of VHT as a measurement index for traffic scenarios in pattern matching, effectiveness of different measures was compared, including VHT, speed, and volume, in predicting recurrent delay. To accomplish pattern matching for each incident, a dataset of traffic pattern spans was built, which are incident-free at the same TOD DOW as the incident scenarios for each incident. One span was randomly chosen from the database as the span whose traffic pattern was to be predicted. The remaining spans were used as candidates for matching. A dataset with 800 incidents was used for the validation, i.e., prediction. VHT, speed, and volume were used as determination variables separately for different K-values ($K < 10$). The RMSEs of delays were calculated to measure robustness of different indicators. Table 5.1 shows the sum of RMSEs with different K values for KNN. It shows that KNN is more reliable than single value, since the sum of RMSEs decreases as K increases. At lower K-value, speed outperforms the other two measures. With higher K-value, VHT is slightly better than speed, and both outperform volume. Overall, using relatively high K-value KNN and VHT as determination variable can best predict recurrent delay. Therefore, VHT was used as determination variable and KNN method with $K = 9$ when processing pattern matching.

Table 5.1 Sum of RMSE of delay with volume, speed, VHT as determination variable when K=1,2,…,9

K	1	2	3	4	5	6	7	8	9
Volume	413.1	242.8	228.4	217.6	196.0	161.5	146.5	132.0	123.4
Speed	245.6	238.3	202.4	161.0	145.3	131.0	119.4	109.5	98.8
VHT	378.9	287.0	222.5	165.8	136.2	119.3	112.8	102.3	97.4

Using the 2013 incident database (1,377 incidents in total) for the study corridor, a total of 109 primary incidents were identified with 270 secondary incidents. 778 incidents were independent incidents, and 220 incidents (16%) were censored by the spatiotemporal boundary. These 220 incidents' spatiotemporal extents were beyond the 5-hour 10-mile maximum boundary set forth by the algorithm.

On average, the primary and secondary incidents were 3.2 miles and 70 minutes apart. Note that multiple consecutive secondary incidents all are considered to be traced from the original primary incident, thereby resulting in an elongated time span. Figure 5.4 illustrates a secondary incident (23:40, MP 304, marked as 1) that occurred three miles upstream from the primary incident (23:19, MP 307, marked as P). Notice that another incident (23:32, MP 305, marked as 2) also appears in the vicinity. However, according to the spatiotemporal analysis, causality is not inferred. Figure 5.5 shows the heat map and profiles of primary and secondary incidents along the study corridor. The profiles exhibit similar trends with few exceptions, and the distribution of secondary incident is upstream-skewed due to the hysteresis nature. Lag between the two ranges from one to four miles, which is consistent with the average distance reported. A reverse pattern appears in the segment between MP 298 and 300, where denser secondary incidents are induced by fewer primary incidents. This is to be expected as a freeway junction exists between I-15 and I-215 that triggers more intensive weaving with an AADT of 77,000 vehicle/day. This can be contrasted with another junction between I-15 and I-80 with an AADT of 54,000 vehicle/day, which had an aligned incident occurrence pattern.

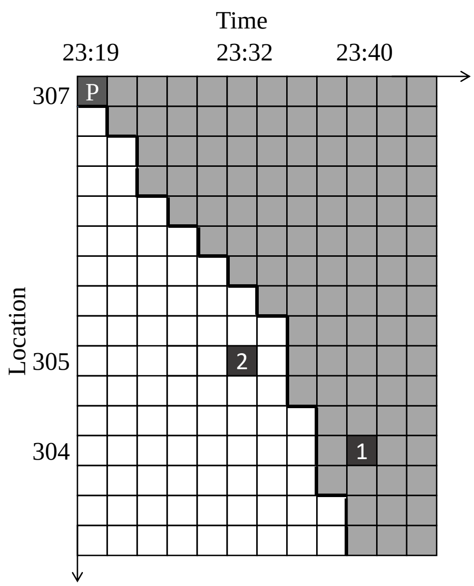


Figure 5.4 Example of secondary incident identification
(P: primary incident, 1: secondary incident,
2: independent incident, grey: spatiotemporal extent)

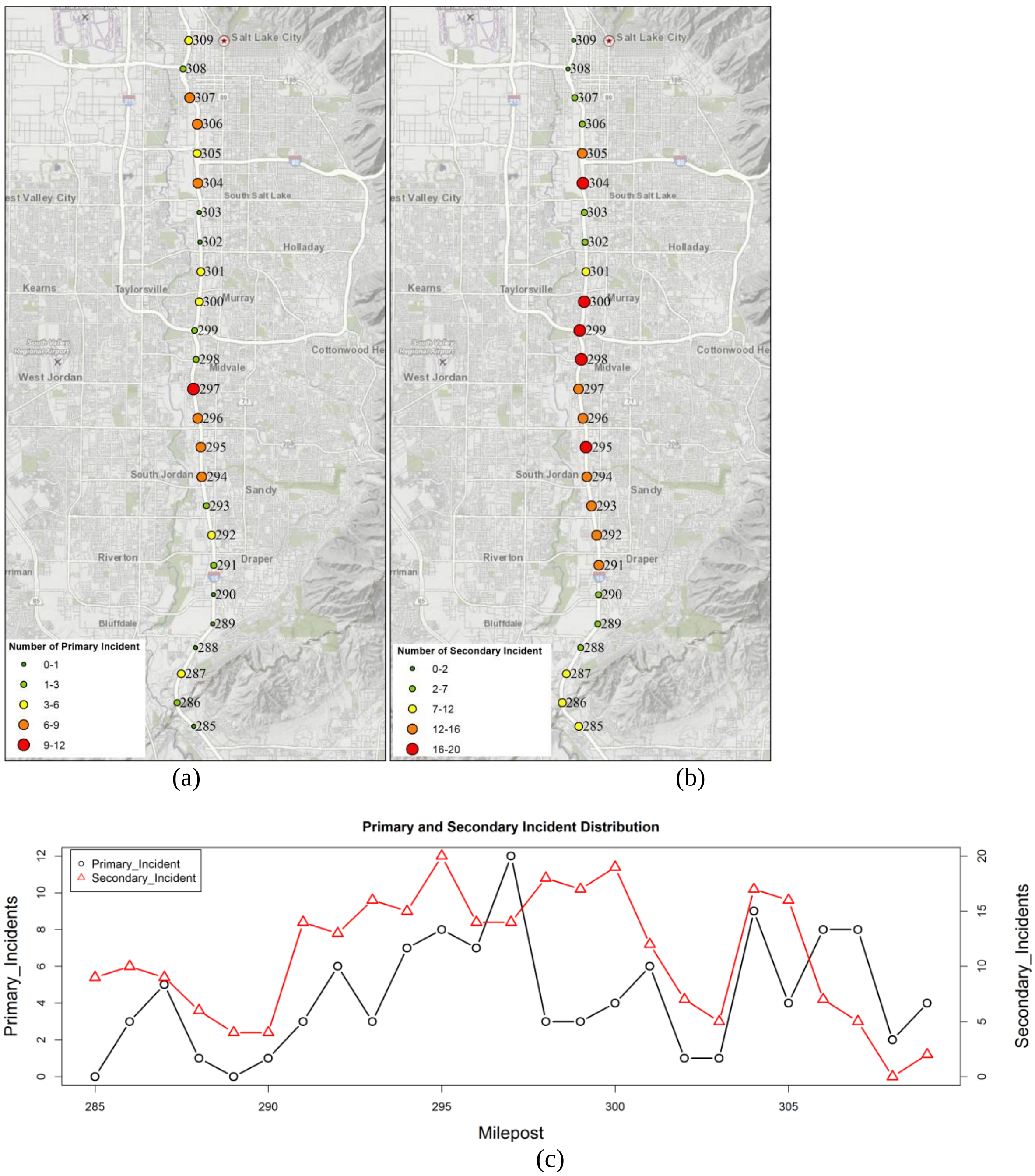


Figure 5.5 Heat map (a) (b) and profile of primary and secondary incidents (c) along the I-15 corridor

Table 5.2 shows the IID statistics of major incident types. Due to the large amount of incidents that did not cause much extra VHT, e.g. incidents during midnight or non-peak hours, the distributions of IIDs are positive skewed. This induces high standard deviations. Incidents involving vehicles on fire tend to cause higher IID because the clearance of such incidents usually requires longer time and tends to cause rubbernecking.

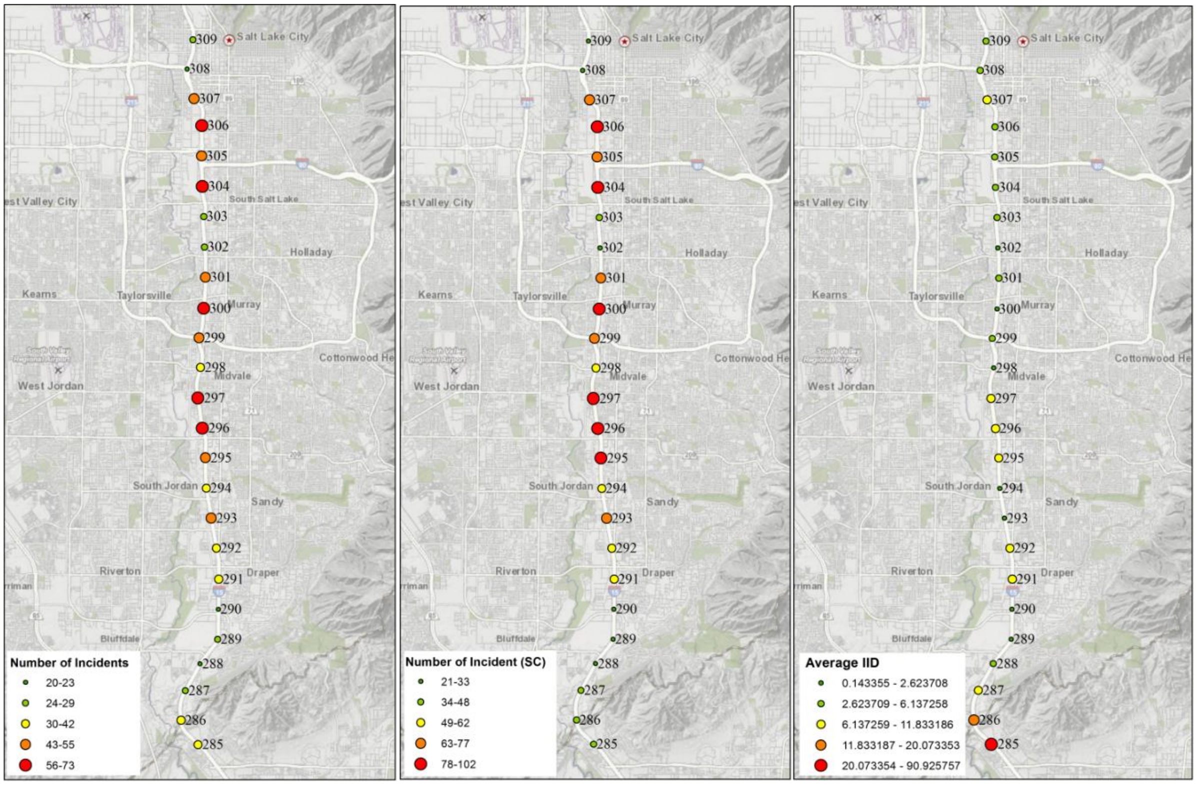
Table 5.2 IID statistics by incident type

Feature	Mean (vehicle*hour)	Standard Deviation (vehicle*hour)
Vehicle on Fire	18.33	32.09
Debris	0.01	0.15
Stalled Vehicle	10.58	5.40
Police Incident	0.23	0.70
Lane Closure	11.2	31.85
Other Crash	10.72	37.07

The average IID is 43 vehicle-hours. IID distribution is right-skewed, indicating a small portion of incidents with extremely high IID. For freeway management purposes, IID should be jointly studied to trace the reason behind their occurrence and for effective incident mitigation strategies. To this end, hot spot analysis is used to observe incident frequency along the corridor. Note that incident occurrence is usually not an isolated event. For example, Ord and Getis (1995) proposed a spatial statistic based on the weighted spatial autocorrelation between incidents. A similar concept was applied to the hot spot analysis: not only was the number of incidents at the spot considered, but also the number of incidents associated to the spot. At each location, the occurrence of an incident is weighted by its independence. For example, an independent incident has the lowest weight since occurrences of independent incidents are random. A secondary incident has higher weight since it carries on the influence from primary incidents. A primary incident has the highest weight since it tends to induce more congestion and damage. Thus, each incident is weighted by the number of incidents it is associated with (including itself). For comparison purposes, the top five locations from each method were identified as hot spots. Figure 5.6 (a) and (b) show the hot spots identified by incident frequency with or without considering the weighting. They yield quite similar results with hot spots identified at two freeway junctions and between MP 295 and 297. However, when illustrating the spatial profile of IID as shown in Figure 6 (c), hot spots are clustered between MP 285 and MP 287, which is distant from the freeway junctions.

Several factors might contribute to this phenomenon. First, the existence of bottleneck might exacerbate the impact of incident, which may be one of the contributing factors for extremely high IID. MP 285 is at the on-ramp of I-15 from a major arterial (Timpanogos Highway) where severe congestion is observed frequently. Evidence from a closer scrutiny of the spot validates that assumption. Most of the incidents happened during peak periods, which greatly impeded the queue clearance. Another reason might be the way IID is calculated as it solely considers the delay induced by independent incidents for accurately identifying their spatiotemporal extent. This might downplay the delay effect of cascading incidents. Therefore, two hotspots analysis methods in this study complement each other and can be jointly used for decision making on incident mitigation. Note that the segment between MP 295 and 297 is identified as a hot spot in both methods. This may be due to the convoluted effects of multiple causes. This segment has an AADT as high as 100,000 vehicles/day and is located upstream of the spaghetti junction where triggered secondary incidents introduce great disturbances in traffic. Also the segment between MP 295 and 297 has the shortest distance between curvatures along the corridor. TTwo curvatures are less than three miles apart, which may cause instability in the traffic flow. This aligns with Zhang and Khattak's (2010) finding that short segments are prone to secondary incidents.

Based on the analysis, it is further concluded that locations with higher IID are prone to be bottlenecks with severe recurrent congestion. When incidents occur at freeway junctions under heavy traffic volume, a significant increase in IID with induced secondary incidents upstream may occur. Freeway management strategies might be especially ripe for assessment based on this result. For example, when an incident occurs at a bottleneck, speed harmonization, such as variable speed limit, can be implemented upstream to accelerate bottleneck clearance and create a uniform speed upstream.



(a) (b) (c)

Figure 5.6 Hot spots identification analysis with (a) incident frequency method without spatial-correlation; (b) incident frequency method with spatial-correlation; and (c) average IID method

5.5 Adverse Weather's Impact

To analyze the impact of adverse weather on demand and capacity reduction, weather data is first categorized by road and sky conditions. Figure 5.7 shows the histogram of weather record by road condition. Wet is the most frequently occurring road condition under adverse weather (60%), and slushy road condition accounts for approximately 15% of all the records. Figure 5.8 shows the histogram of sky condition from all the weather records. Snow is the most frequently occurring sky condition, since weather data was collected from November to December.

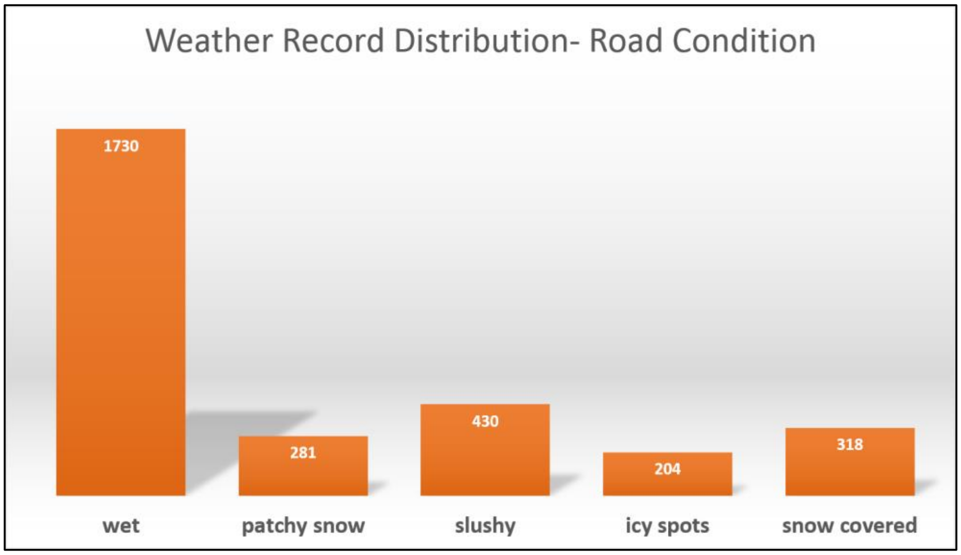


Figure 5.7 Histogram of weather observations by road condition

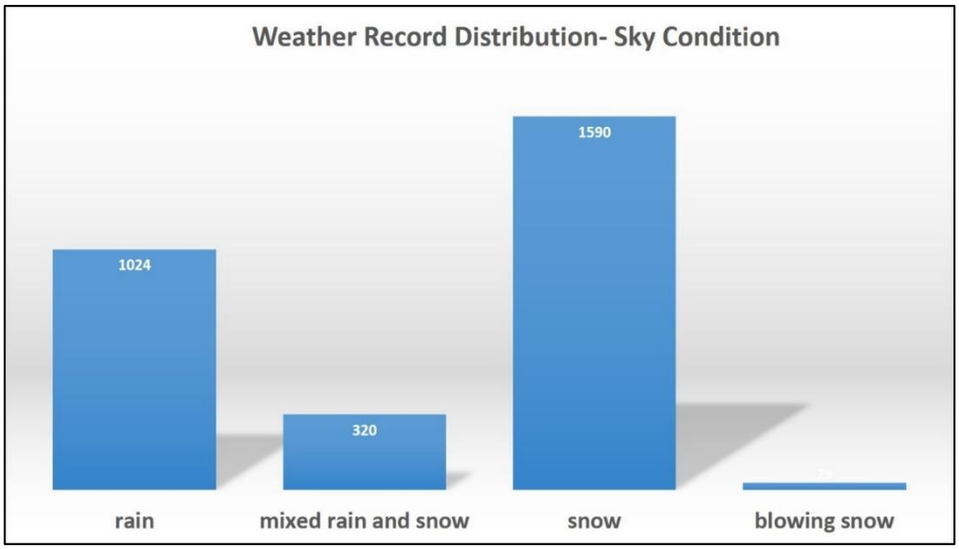


Figure 5.8 Histogram of weather observations by sky condition

Each weather record was linked to the PeMS traffic database by extracting speed, volume, and delay data in an effort to observe traffic pattern. Figure 5.9 shows the plots of speed-flow data under different road conditions. It is noted that speed-flow pattern can demonstrate the severity of different weather and its impacts on the traffic. For example, when the roadway is wet, speed flow pattern still follows the general parabolic curve where distinctions between congested and uncongested regimes are observable. However, as the roadway condition gets worse, the normal pattern would become blurred and data are more randomly congregated. The scattered plot breaks down into two clusters, particularly when the road is covered by snow.

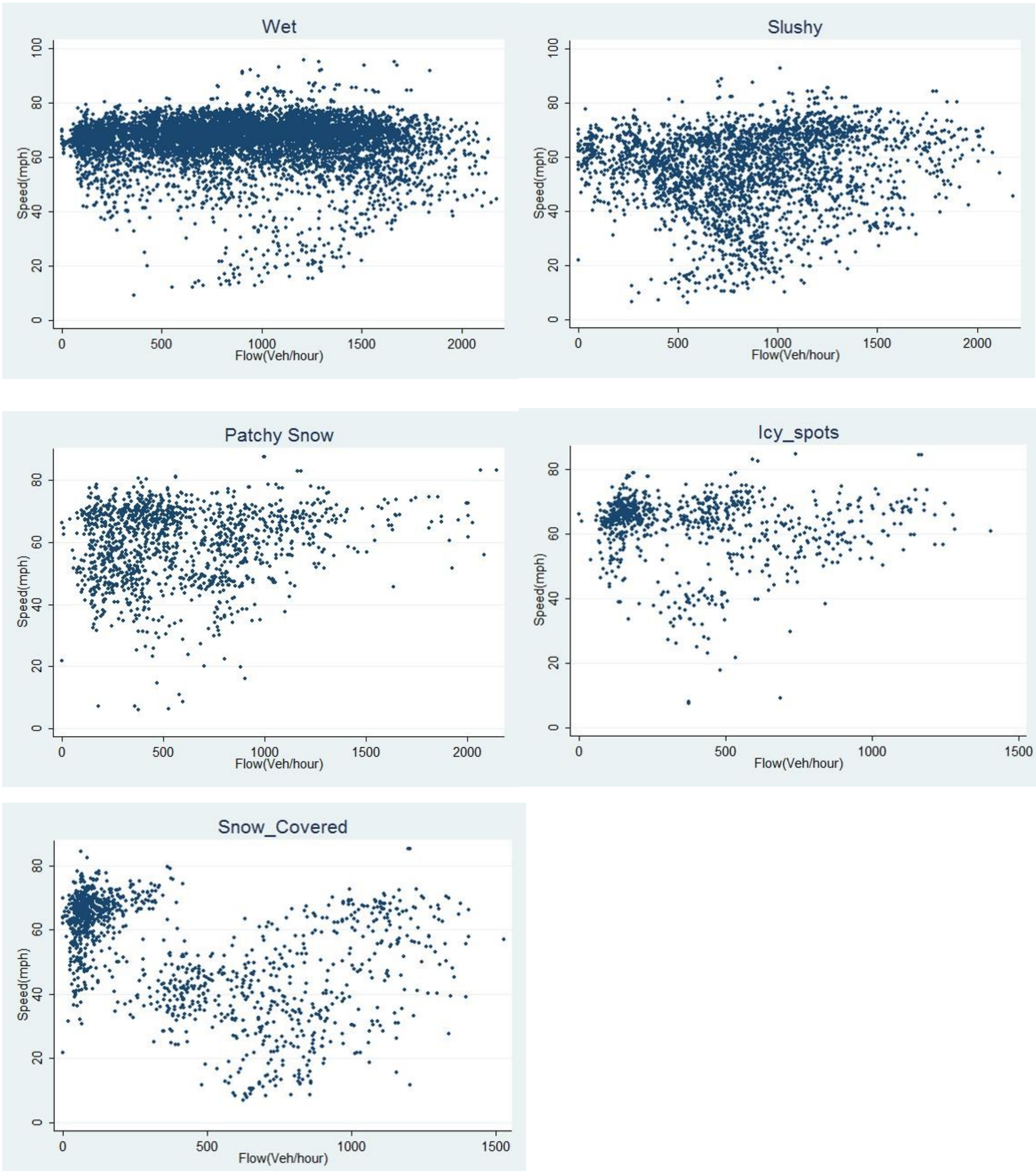


Figure 5.9 Traffic flow vs. speed plots under different road conditions

To quantitatively analyze the impact of adverse weather, the mechanism presented in Section 3.4 is applied to the dataset collected. Since $\Delta D_{Wea}(m,t,s,w)$ and $\Delta F_{Wea}(m,t,s,w)$ represent the delay and flow difference between the adverse weather and normal weather, they can be used to classify the impact into different categories (expressed as ΔD and ΔF in the following section).

If $\Delta F > 0$ and $\Delta D > 0$, both volume and delay under normal conditions are higher than under adverse weather conditions, suggesting a demand reduction during adverse weather. If $\Delta F > 0$ and $\Delta D < 0$, volume under normal conditions is higher than under adverse weather, yet delay under normal conditions is lower than under adverse weather. It is caused by freeway capacity reduction during adverse weather.

When $\Delta F < 0$ and $\Delta D > 0$, volume under normal conditions is lower than under adverse weather, and delay under normal conditions is higher than adverse weather. This situation would be quite counterintuitive and rarely should be observed in reality. When $\Delta F < 0$ and $\Delta D < 0$, both volume and delay under normal conditions are lower than under adverse weather, which means that the adverse weather does not have obvious impact on the freeway performance. In the following discussion, the four scenarios are referred as C1, C2, C3, and C4, separately. Table 5.3 shows the signs of ΔF and ΔD for each combination.

Table 5.3 Signs of $\boldsymbol{\Delta F}$ and $\boldsymbol{\Delta D}$ for combinations of C1, C2, C3, C4

	C1	C2	C3	C4
ΔF	+	+	-	-
ΔD	+	-	+	-

Figure 5.10 shows the scattered ΔF and ΔD distribution under adverse weather during peak hours and non-peak hours. During peak hours, distribution is more scattered than during non-peak hours. This demonstrates that the traffic during peak hours is more sensitive to disturbance than during non-peak hours, and any potential non-recurrent congestion source for is likely to induce higher fluctuations on both traffic volume and delay.

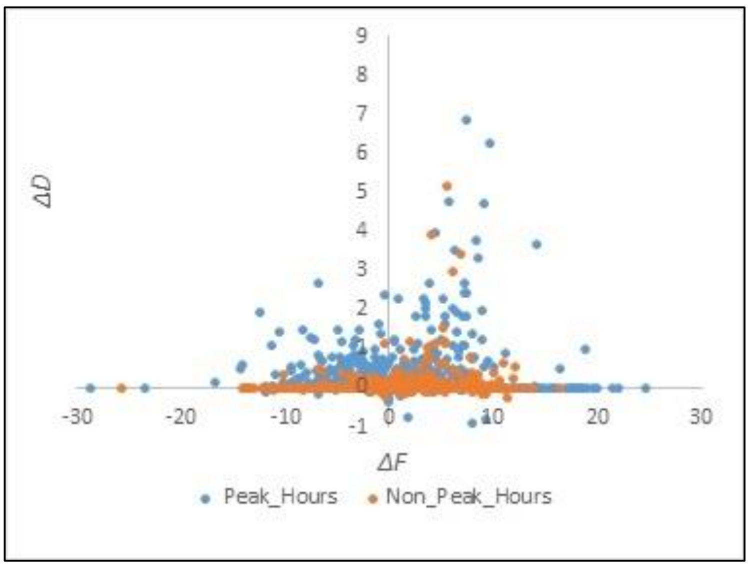


Figure 5.10 Scatter plots of $\boldsymbol{\Delta F}$ vs. $\boldsymbol{\Delta D}$ during peak and non-peak hours

Figure 5.11 shows pie charts of the four ΔF and ΔD combinations during peak hours and non-peak hours. For both scenarios, C1+C2 accounts for more than 90% of the cases, indicating volume under adverse weather is lower compared with the normal days. C1 is the most frequently appeared situation, which shows that demand reduction is a major cause for lower volume under adverse weather.

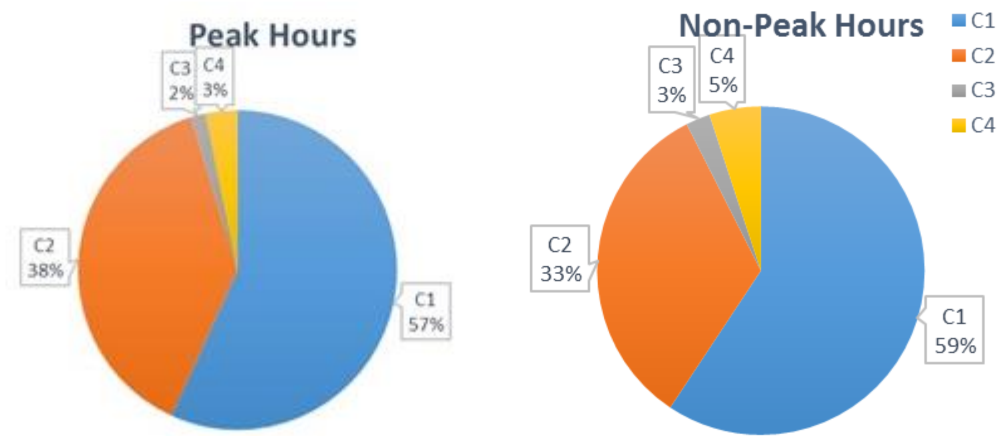


Figure 5.11 Comparison of Pie Charts during Peak and Non-Peak Hours

Figure 5.12 shows pie charts for different road conditions during peak hours. As the road condition gets worse, the fractions of C1 increase, from 52% (wet road) to 71% (patchy snow). This is consistent with the fact that people trend to rearrange or cancel their trips when the weather worsens.

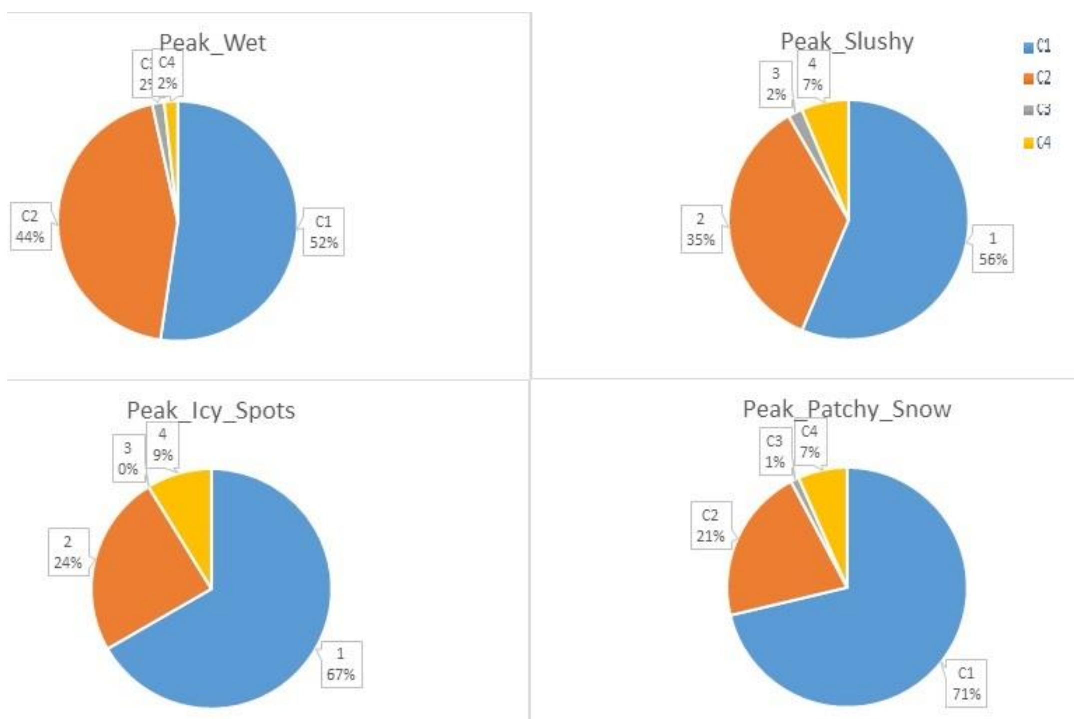


Figure 5.12 Combination Frequency during Peak Hours under Different Road Conditions

5.6 Summary

In this section, in-depth analysis of the three major tasks was performed using data collected along the I-15 study corridor. The reliability analysis using congestion frequency allowed hot spots to be easily identified for different time periods. The congestion frequency index can be translated into the probability that a user will experience certain speed when he/she travels through a specific location. The unified measure is easy to interpret and implement for operational management. IID and secondary incident identification results also were presented in this section. During 2013, 7% of incidents that happened on the selected I-15 corridor were secondary incidents, which is lower than the 20% estimates given by FHWA. The occurrence of secondary incidents is highly related to adverse weather, where December has the highest number of the secondary incidents. The IID algorithm was applied to the 2013 incident dataset, and in general, it was found that high severity incidents would cause more delay with several exceptions due to the geometries of the roadway characteristics. The mechanism for quantifying the adverse weather impact was presented. Delay and volume estimators were applied to the 2013 winter adverse weather records. Two major causes exist for the low volume during adverse weather. One is the freeway capacity reduction caused by lowered speed, the other is the demand reduction. The general parabolic curve of speed and volume does not hold when weather gets worse.

6. CONCLUSIONS

6.1 Summary

The focus of freeway performance measurements and monitoring is to describe congestion and mobility of the roadway networks. Congestion levels are not the same every day. Under the impact of nonrecurring congestion sources, e.g. incident, work zone, and adverse weather, the associated congestion and its extent should be diagnosed with special attention. This study provides data-driven solutions for evaluating freeway performance under various scopes to assist with project prioritization and decision making. Freeway performance measures are often considered in three dimensions: temporal aspects, spatial details, and source of congestion. This study addresses all three dimensions simultaneously. A performance measure was developed, which is easy to understand and has practical implications. The measure, congestion frequency, ties to typical congestion levels and reliability to describe congestion/mobility performance of freeways, yet can be easily comprehended and related to by the general public, based on their everyday experience. Once unreliable locations were identified through the corridor performance analysis, close scrutiny was paid to reasons for the unreliability. Incidents and adverse weather are considered as the main sources for nonrecurring congestion. Data-driven algorithms were developed to calculate IID and identify secondary incidents. The algorithms utilize spatiotemporal analysis to determine the impact range of each incident on the microscopic level, along with pattern matching and background subtraction methods to determine the recurrent congestion impact. To quantify the impact of adverse weather, a mechanism was developed by evaluating volume and delay changes under both normal days and days with adverse weather. It was quantitatively proven that under snow-covered conditions, travel demand is decreased significantly.

6.2 Findings

The findings for the three major components carried through this project are summarized as follows.

6.2.1 Congestion Frequency Index

Congestion Frequency was presented as the measurement of performance reliability. Hot spots were identified on the I-15 corridor in morning and evening peak hours from May to August 2013. Its pattern is consistent with speed percentiles, which is the current reliability measure used at TOC.

6.2.2 Secondary Incident Occurrence

Secondary incidents refer to those that resulted from congestion caused by previous incidents, including not only crashes, but also engine stalls, overheating, and running out of fuel scenarios. With the data-driven algorithm developed in this project, 240 secondary incidents were identified, which were caused by 109 primary incidents on the selected I-15 corridor during 2013. The occurrence of secondary incidents follows a distinct seasonal pattern, where months with high precipitation (from November to March) have higher frequency of secondary incidents, while there were no secondary incidents identified for June, which was the driest month reported in Utah for the Years 1895-2013, according to the National Climate Data Center. Reduced road friction and impaired visibility might be the main contributors for secondary incidents.

6.2.3 Hotspots on I-15 Corridor

The IID is not only determined by the severity of incident, but also dependent on the location and time of day. Locations with high incident frequency generally suffer from higher IID than the locations with low incident frequency. Exceptions happened at MP 284, MP 296, and MP 309 on Northbound I-15, where fewer incidents are observed with relatively high IID. These hotspots usually are located before off-ramps or after on-ramps connecting I-15 and arterials.

6.2.4 Mechanism of Adverse Weather Impacting Traffic

The results of adverse weather impact analyses indicates that under the influence of adverse weather travel demand decreases, which is the case for more than 50% of scenarios. A conclusion was made that in 2013 the adverse weather forecasting system succeeded in alerting the public and preventing severe traffic breakdowns. As roadway condition worsen, traffic demand shows a more significant reduction pattern.

6.3 Recommendations

The data-driven performance-based approach presented in this study is effective in quantitatively evaluating the freeway mobility/reliability, incident and adverse weather impact. The objectives of this project align well with the goal set forth by MAP-21, which is to establish performance-based transportation programs to guide the transportation capital investment and development. The algorithm developed can be integrated into the operational analysis to identify hotspots along the freeway corridor, and assist with project prioritization and decision making. Future work involves evaluating the impact of other nonrecurring congestion sources identified by SHRP 2, including work zone, demand fluctuations, special events, traffic control devices, and inadequate base capacity. Also, since pattern matching algorithms are used in analysis for determining the recurrent congestion from historical data, i a web-based platform should be developed to allow operators/researchers to customize duration of the historical data window to assist with interactively transportation analytics.

REFERENCES

Ahmed, Mohamed M, Mohamed Abdel-aty, Jaeyoung Lee, and Rongjie Yu. 2014. "Real-Time Assessment of Fog-Related Crashes Using Airport Weather Data : A Feasibility Analysis." *Accident Analysis and Prevention* 72: 309–317. doi:10.1016/j.aap.2014.07.004. http://dx.doi.org/10.1016/j.aap.2014.07.004.

Alvarez, Patricio, and Mohammed Hadi. 2012. "Time-Variant Travel Time Distributions and Reliability Metrics and Their Utility in Reliability Assessments." *Transportation Research Record: Journal of the Transportation Research Board* 2315: 81–88. doi:10.3141/2315-09. http://trb.metapress.com/openurl.asp?genre=article&id=doi:10.3141/2315-09.

Bergel-Hayat, Ruth, Mohammed Debbarh, Constantinos Antoniou, and George Yannis. 2013. "Explaining the Road Accident Risk: Weather Effects." *Accident Analysis and Prevention* 60: 456–465. doi:10.1016/j.aap.2013.03.006. http://dx.doi.org/10.1016/j.aap.2013.03.006.

Bertini, Robert L, and Galen E McGill. 2003. "Getting Traffic Moving Again." *Public Roads* 67 (2): 14–17.

Brijs, Tom, Dimitris Karlis, and Geert Wets. 2008. "Studying the Effect of Weather Conditions on Daily Crash Counts Using a Discrete Time-Series Model." *Accident Analysis and Prevention* 40: 1180–1190. doi:10.1016/j.aap.2008.01.001.

Cambridge Systematics. 2013. "Incorporating Reliability Performance Measures into the Transportation Planning and Programming Processes."

Chandana Wirasinghe, S. 1978. "Determination of Traffic Delays from Shock-Wave Analysis." *Transportation Research* 12 (5) (October): 343–348. doi:10.1016/0041-1647(78)90010-2. http://www.sciencedirect.com/science/article/pii/0041164778900102.

Chung, Younshik. 2012. "Assessment of Non-Recurrent Congestion Caused by Precipitation Using Archived Weather and Traffic Flow Data." *Transport Policy* 19 (1): 167–173. doi:10.1016/j.tranpol.2011.10.001. http://dx.doi.org/10.1016/j.tranpol.2011.10.001.

Chung, Younshik. 2013. "Identifying Primary and Secondary Crashes from Spatiotemporal Crash Impact Analysis." *Transportation Research Record: Journal of the Transportation Research Board* 2386 (-1) (December 1): 62–71. doi:10.3141/2386-08. http://trb.metapress.com/openurl.asp?genre=article&id=doi:10.3141/2386-08.

Datla, Sandeep, and Satish Sharma. 2008. "Impact of Cold and Snow on Temporal and Spatial Variations of Highway Traffic Volumes." *Journal of Transport Geography* 16: 358–372. doi:10.1016/j.jtrangeo.2007.12.003.

Edwards, Matthew B., and Michael D. Fontaine. 2012. "Investigation of Travel Time Reliability in Work Zones with Private-Sector Data." *Transportation Research Record: Journal of the Transportation Research Board* 2272: 9–18. doi:10.3141/2272-02.

El-basyouny, Karim, Sudip Barua, and Tazul Islam. 2014. "Investigation of Time and Weather Effects on Crash Types Using Full Bayesian Multivariate Poisson Lognormal Models." *Accident Analysis and Prevention* 73: 91–99. doi:10.1016/j.aap.2014.08.014. http://dx.doi.org/10.1016/j.aap.2014.08.014.

Emam, Emam, and Haitham AI-Deek. 2006. “Using Real-Life Dual-Loop Detector Data to Develop New Methodology for Estimating Freeway Travel Time Reliability.” *Transportation Research Record* 1959 (1959): 140–150. doi:10.3141/1959-16.

Guo, Feng, Qing Li, and Hesham Rakha. 2012. “Multistate Travel Time Reliability Models with Skewed Component Distributions.” *Transportation Research Record: Journal of the Transportation Research Board* 2315 (-1) (December 1): 47–53. doi:10.3141/2315-05. http://trb.metapress.com/openurl.asp?genre=article&id=doi:10.3141/2315-05.

Hallenbeck, Mark E, John M Ishimaru, Jennifer Nee, and Toby D Rickman. 2003. “Measurement of Recurring Versus Non-Recurring Congestion.”

Keay, Kevin, and Ian Simmonds. 2005. “The Association of Rainfall and Other Weather Variables with Road Traffic Volume in Melbourne, Australia.” *Accident Analysis and Prevention* 37: 109–124. doi:10.1016/j.aap.2004.07.005.

Khattak, Asad, Xin Wang, and Hongbing Zhang. 2009. “Are Incident Durations and Secondary Incidents Interdependent?” *Transportation Research Record: Journal of the Transportation Research Board* 2099 (-1) (January 1): 39–49. doi:10.3141/2099-05. http://trb.metapress.com/openurl.asp?genre=article&id=doi:10.3141/2099-05.

Kwon, Jaimyoung, Michael Mauch, and Pravin Varaiya. 2006. “Components of Congestion: Delay from Incidents, Special Events, Lane Closures, Weather, Potential Ramp Metering Gain, and Excess Demand.” *Transportation Research Record* 1959 (1) (January 1): 84–91. doi:10.3141/1959-10. http://trb.metapress.com/openurl.asp?genre=article&id=doi:10.3141/1959-10.

Li, Jibing, Chang-jen Lan, and Xiaojun Gu. 2006. “Estimation of Incident Delay and Its Uncertainty on Freeway Networks.” *Transportation Research Record: Journal of the Transportation Research Board*: 37–45.

Liu, Henry X., Xiaozheng He, and Will Recker. 2007. “Estimation of the Time-Dependency of Values of Travel Time and Its Reliability from Loop Detector Data.” *Transportation Research Part B: Methodological* 41 (4) (May): 448–461. doi:10.1016/j.trb.2006.07.002. http://linkinghub.elsevier.com/retrieve/pii/S0191261506000890.

Lyman, Kate, and Robert L. Bertini. 2008. “Using Travel Time Reliability Measures to Improve Regional Transportation Planning and Operations.” *Transportation Research Record: Journal of the Transportation Research Board* 2046 (-1) (December 1): 1–10. doi:10.3141/2046-01. http://trb.metapress.com/openurl.asp?genre=article&id=doi:10.3141/2046-01.

Mahmassani, Hani S., Tian Hou, and Jing Dong. 2012. “Characterizing Travel Time Variability in Vehicular Traffic Networks.” *Transportation Research Record: Journal of the Transportation Research Board* 2315 (-1) (December 1): 141–152. doi:10.3141/2315-15. http://trb.metapress.com/openurl.asp?genre=article&id=doi:10.3141/2315-15.

Maze, Thomas, Manish Agarwai, and Garrett Burchett. 2006. “Whether Weather Matters to Traffic Demand, Traffic Safety, and Traffic Operations and Flow.” *Transportation Research Record* 1948: 170–176. doi:10.3141/1948-19.

Mehran, Babak, and Hideki Nakamura. 2009. “Implementing Travel Time Reliability for Evaluation of Congestion Relief Schemes on Expressways.” *Transportation Research Record: Journal of the*

Transportation Research Board 2124 (-1) (December 1): 137–147. doi:10.3141/2124-13. http://trb.metapress.com/openurl.asp?genre=article&id=doi:10.3141/2124-13.

Mongeot, Hélène, and Jean-Baptiste Lesort. 2000. “Analytical Expressions of Incident-Induced Flow Dynamics Perturbations: Using Macroscopic Theory and Extension of Lighthill-Whitham Theory.” *Transportation Research Record: Journal of the Transportation Research Board* 1710 (1): 58–68.

Pu, Wenjing. 2011. “Analytic Relationships Between Travel Time Reliability Measures.” *Transportation Research Record: Journal of the Transportation Research Board* 2254 (1) (December 1): 122–130. doi:10.3141/2254-13. http://trb.metapress.com/openurl.asp?genre=article&id=doi:10.3141/2254-13.

Saberi, Meead, and Robert L Bertini. 2010. “Beyond Corridor Reliability Measures : Analysis of Freeway Travel Time Reliability at the Segment Level for Hotspot Identification” 514 (July 2009): 1–13.

Skabardonis, Alexander, Pravin Varaiya, and Karl F Petty. 2003. “Measuring Recurrent and Nonrecurrent Traffic Congestion.” *Transportation Research Record: Journal of the Transportation Research Board* 1856 (1): 118–124. doi:10.3141/1856-12.

Thakuriah, Piyushimita (Vonu), and Nebiyou Tilahun. 2012. “Incorporating Weather Information into Real-Time Speed Estimates: Comparison of Alternative Models.” *Journal of Transportation Engineering* (April): 121001063128003. doi:10.1061/(ASCE)TE.1943-5436.0000506.

Tu, Huizhao, Adam J. Pel, Hao Li, and Lijun Sun. 2012. “Travel Time Reliability During Evacuation.” *Transportation Research Record: Journal of the Transportation Research Board* 2312 (-1) (December 1): 128–133. doi:10.3141/2312-13. http://trb.metapress.com/openurl.asp?genre=article&id=doi:10.3141/2312-13.

Van Aerde, Michel, and Hesham Rakha. 1995. “Multivariate Calibration of Single Regime Speed-Flow-Density Relationships.” In *Proceedings of the 6th 1995 Vehicle Navigation and Information Systems Conference*, 334–341.

Van Lint, J., and H. Van Zuylen. 2005. “Monitoring and Predicting Freeway Travel Time Reliability: Using Width and Skew of Day-to-Day Travel Time Distribution.” *Transportation Research Record* 1917 (1) (January 1): 54–62. doi:10.3141/1917-07. http://trb.metapress.com/openurl.asp?genre=article&id=doi:10.3141/1917-07.

Wang, Yinhai, Patikhom Cheevarunothai, and Mark Hallenbeck. 2008. “Quantifying Incident-Induced Travel Delays on Freeways Using Traffic Sensor Data.”

Yang, Hong, Bekir Bartin, and Kaan Ozbay. 2013. “Use of Sensor Data to Identify Secondary Crashes on Freeways.” *Transportation Research Record: Journal of the Transportation Research Board* 2396 (-1) (December 1): 82–92. doi:10.3141/2396-10. http://trb.metapress.com/openurl.asp?genre=article&id=doi:10.3141/2396-10.

Yang, and Will Recker. 2005. “Simulation Studies of Information Propagation in a Self-Organizing Distributed Traffic Information System.” *Transportation Research Part C: Emerging Technologies* 13 (5-6) (October): 370–390. doi:10.1016/j.trc.2005.11.001. http://linkinghub.elsevier.com/retrieve/pii/S0968090X05000550.

Yu, Rongjie, Mohamed Abdel-Aty, and Mohamed Ahmed. 2013. “Bayesian Random Effect Models Incorporating Real-Time Weather and Traffic Data to Investigate Mountainous Freeway Hazardous

Factors." *Accident Analysis and Prevention* 50: 371–376. doi:10.1016/j.aap.2012.05.011. http://dx.doi.org/10.1016/j.aap.2012.05.011.

Yu, Runze, Yunteng Lao, Xiaolei Ma, and Yinhai Wang. 2014. "Short-Term Traffic Flow Forecasting for Freeway Incident-Induced Delay Estimation." *Journal of Intelligent Transportation Systems* 18 (3) (May 23): 254–263. doi:10.1080/15472450.2013.824757. http://dx.doi.org/10.1080/15472450.2013.824757.