Measuring Non-Recurring Congestion in Small to Medium Sized Urban Areas

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UTCA

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The University of Alabama, The University of Alabama at Birmingham, and
The University of Alabama in Huntsville

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UTCA Theme: Management and Safety of Transportation Systems

University Transportation Center for Alabama

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16 Abstract

Understanding the relative magnitudes of recurrent vs. non-recurrent congestion in an urban area is critical to the selection of proper countermeasures and the appropriate allocation of resources to address congestion problems. Small to medium sized cities such as Birmingham, AL typically lack the extensive traffic sensor networks necessary to monitor and record traffic performance on a continuous basis. Alternative methods are needed to gain an understanding of the magnitudes of recurrent and non-recurrent congestion and implement proper countermeasures to reduce them. The objective of this study was to test methodologies for quantifying non-recurrent congestion in a small to medium sized urban area such as Birmingham which has limited traffic monitoring infrastructure. More specifically, the study investigated the potential use of commercially available vehicle probe data to quantify incident-related non-recurrent congestion on key interstate facilities in the Birmingham region. Archived GPS probe data collected in the Birmingham Region were analyzed and combined with accident reports from the State's ASAP (Alabama Service and Assistance Patrol) incident response system to test the effectiveness of measuring non-recurrent congestion in this manner.

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List of Abbreviations

GPS	Global Positioning System
ATR	Automatic Traffic Recording Devices
GIS	Geographic Information System
DoD	Department of Defense
I-65	Interstate 65
ASAP	Alabama Service & Assistance Patrol
PeMS	Performance Measurement System
CHP	California Highway Patrol
FSP	Freeway Service Patrol
DOT	Department of Transportation
SND	Standard Normal Deviate
TTI	Texas Transportation Institute
DOCC	Downstream Occupancy
OCCD	Spatial Difference in Occupancies
OCCRD	Relative Spatial Difference in Occupancies
DOCCTD	Relative Temporal Difference in Downstream Occupancy
ATMS	Advanced Traffic Management Systems
ATIS	Advanced Traveler Information Services

Executive Summary

Understanding the relative magnitudes of recurrent vs. non-recurrent congestion in an urban area is critical to the selection of proper countermeasures and the appropriate allocation of resources to address congestion problems. Small to medium sized cities such as Birmingham, AL typically lack the extensive traffic sensor networks necessary to monitor and record traffic performance on a continuous basis. Alternative methods are needed to gain an understanding of the magnitudes of recurrent and non-recurrent congestion and implement proper countermeasures to reduce them. The objective of this study was to test methodologies for quantifying non-recurrent congestion due to vehicle incidents in a small to medium sized urban area such as Birmingham. More specifically, the study investigated the potential use of vehicle probe data to quantify non-recurrent congestion on key interstate facilities in the Birmingham region. Archived GPS probe data collected in the Birmingham Region were analyzed and combined with accident reports from the State's ASAP (Alabama Service and Assistance Patrol) incident response system to develop meaningful measures of non-recurrent congestion.

The study found that a simple standard normal deviate (SND) procedure was able to detect a very high percentage of non-recurrent vehicle incidents (crashes, disabled vehicles, and lane closures) in an interstate test corridor. The procedure allowed users to scan historical speed data, identify congestion, and characterize it as either recurrent or non-recurrent. When combined with traffic volume data, this method could be used to calculate the magnitude of non-recurrent incident-related congestion at a relatively low cost and with good accuracy.

Keywords: Non-Recurrent Congestion, Incident Detection, ASAP data, Birmingham

1. Introduction

1.1 Problem Statement

With the growth of traffic volumes and congestion on roads, the performance of urban roadway networks is a concern to road users, transportation planners, and maintaining agencies. The U.S. Department of Transportation requires every metropolitan area with a population over 200,000 to implement and maintain a Congestion Management Process, the purpose of which is to enhance the mobility of people and goods within that area. A CMP is a comprehensive system for monitoring transportation system performance, identifying causes of congestion, implementing cost-effective actions, and evaluating the effectiveness of those actions. Critical to this process is monitoring and measuring congestion, of which there are two broad types: recurrent and non-recurrent. Recurrent congestion is typically caused when traffic demand exceeds available roadway capacity, leading to congestion that tends to recur at the same times and in the same places every day. Non-recurrent congestion, on the other hand, is typically caused by incidents or events that either temporarily reduce roadway capacity or increase traffic demand, such as crashes, construction zones, bad weather, or special events. The distinction between the two types of congestion is important because the measures deployed to address them can be very different. Measures to address recurrent congestion can include capacity improvements, signal timing, managed lanes, and demand management. Measures to address non-recurrent congestion may include incident detection and response, work zone management, variable message signs, and advisory radio.

To effectively allocate resources to address congestion, transportation managers need to better understand the relative magnitudes of recurrent vs. non-recurrent congestion in their region. Of the two, recurrent congestion is the easier to quantify; its predictable nature lends itself well to simulation modeling. Non-recurrent congestion is far more difficult to quantify. Some large U.S. cities (e.g., Los Angeles, San Francisco, and Seattle) have developed methodologies to quantify non-recurrent congestion on their roadway networks, but these methodologies are largely confined to freeway corridors and rely on extensive sensor networks already in place. In the small and medium sized cities common in the Southeast, these sensor networks simply don’t exist or are too expensive to implement on a wide scale. It leaves transportation managers in these areas with the difficult task of quantifying the extent of non-recurrent congestion with little data and no clear methodologies for doing so. This project attempted to fill that void by testing methodologies that rely on low-cost data collection and analysis techniques to estimate incident-related non-recurrent congestion on key facilities.

1.2 Project Approach

Congestion monitoring presents significant challenges for small and medium sized transportation agencies. Currently there is no universally accepted set of performance measures to be used by transportation professionals to monitor traffic system conditions. The evaluation of performance measures relies on the availability, accuracy, and reliability of collected traffic data. In order to accurately quantify non-recurrent congestion related to vehicle incidents on a roadway segment or network, extensive performance data are needed. These data include as a minimum free flow speeds, average speeds during different periods of the day, segment volumes at suitable resolutions, and information on any factors (incidents, construction, special events, and weather) that may have affected performance on the segment during the periods monitored. Such data are not easily collected without extensive performance monitoring systems in place. In large urban areas, speed and volume data have typically been gathered using freeway sensors, primarily inductive loop detectors but also video and microwave detectors. These sensors can provide accurate data on vehicle speeds and volumes at fine levels of resolution. From these data, free flow speeds can be determined and total congestion can be computed as the excess travel time (vehicle-hours) occurring below designated threshold speeds. Because freeway flow and congestion are highly variable, such data need to be analyzed over long periods (months) to provide statistically meaningful results for any one roadway segment.

In the Birmingham region, no extensive inductive loop network or similar monitoring system currently exists to provide spatial and temporal information for performing non-recurrent congestion analysis. While some traffic monitoring detectors exist, they are localized and lack spatial coverage. Also, using remote sensing imagery from satellites cannot provide continuous transportation information.

As part of an effort to test methodologies to quantify non-recurrent congestion related to vehicle incidents in Birmingham and other small to medium sized urban areas with limited traffic monitoring resources, this study investigated the use of Global Positioning System (GPS) probe vehicle data as a part of the traffic data collection system. GPS provides spatial and time specific measurements and has been increasingly used in conducting transportation studies. This method offers a low capital cost, a low installation cost, and a low data collection cost combined with a reasonably high location accuracy.

1.3. Goals and Objectives

The goal of this project was to evaluate a set of GPS probe vehicle data, which was collected by traffic services provider INRIX from freight vehicles in the Birmingham region, and use them to quantify non-recurrent congestion related to vehicle incidents. The specific objective of this project was to test a methodology for quantifying non-recurrent congestion that could then be used in similar urban areas. To accomplish this objective, archived freight data collected in the Birmingham Region by the Alabama DOT was combined with crash reports from the State's ASAP incident response system to develop and verify meaningful measures of non-recurrent congestion. Specific topics that are addressed in the following sections include:

- A discussion of different methodologies that can be used to detect and classify congestion into recurrent and non-recurrent congestion, based on a literature review;

- An analysis of the potential use of GPS data to identify incidents and quantify non-recurrent congestion;

- Appropriate methods to analyze historical GPS data obtained from freight vehicles;

- Data validation through comparison of incidents identified from the freight vehicle speed data with the ASAP service logs, and

- Calculation of non-recurrent congestion delay.

2. Literature Review

2.1 Traffic Congestion

Traffic congestion is a condition that arises as vehicle demand increases beyond the roadway capacity and is characterized by slower than free-flow speeds, delays in trip times, and vehicle queues. As discussed previously, congestion can be broadly classified into recurrent and non-recurrent congestion based on the circumstances that caused it. Recurrent congestion is typically caused when traffic demand exceeds available roadway capacity, leading to congestion that tends to recur at the same times and in the same places every day. Non-recurrent congestion is typically caused by incidents or events that either temporarily reduce roadway capacity or increase traffic demand, such as crashes, construction zones, bad weather, or special events. The focus of this study was specifically on non-recurrent congestion related to vehicle incidents.

In a study, Gall et al. (1989) tried to differentiate between recurrent and non- recurrent congestion based on downstream traffic conditions. The main logic behind their approach is the assumption that traffic operation downstream of a recurrent bottleneck is different than that observed due to an incident-caused (non-recurrent) bottleneck. More specifically, the method proposed by Gall et al. classifies operations of traffic on the freeway facility into four possible traffic states (Figure 1) on the basis of volume and % occupancy (1). The traffic operations upstream and downstream of the incident are considered. Though the upstream traffic operations of the bottleneck site will be in *State-3* for both the types of congestion, the downstream traffic operations differ. Under recurrent congestion, traffic operations downstream of the bottleneck will be in *State-4* (traffic flow will be at or close to capacity). On the other hand, downstream traffic operations in the presence of incident-induced congestion will be in *States-1 or 2*. The logic was put to test and the results showed that the recurrent congestion portion of the logic was confirmed; however, inconsistencies were observed when validating the incident congestion portion of the logic.

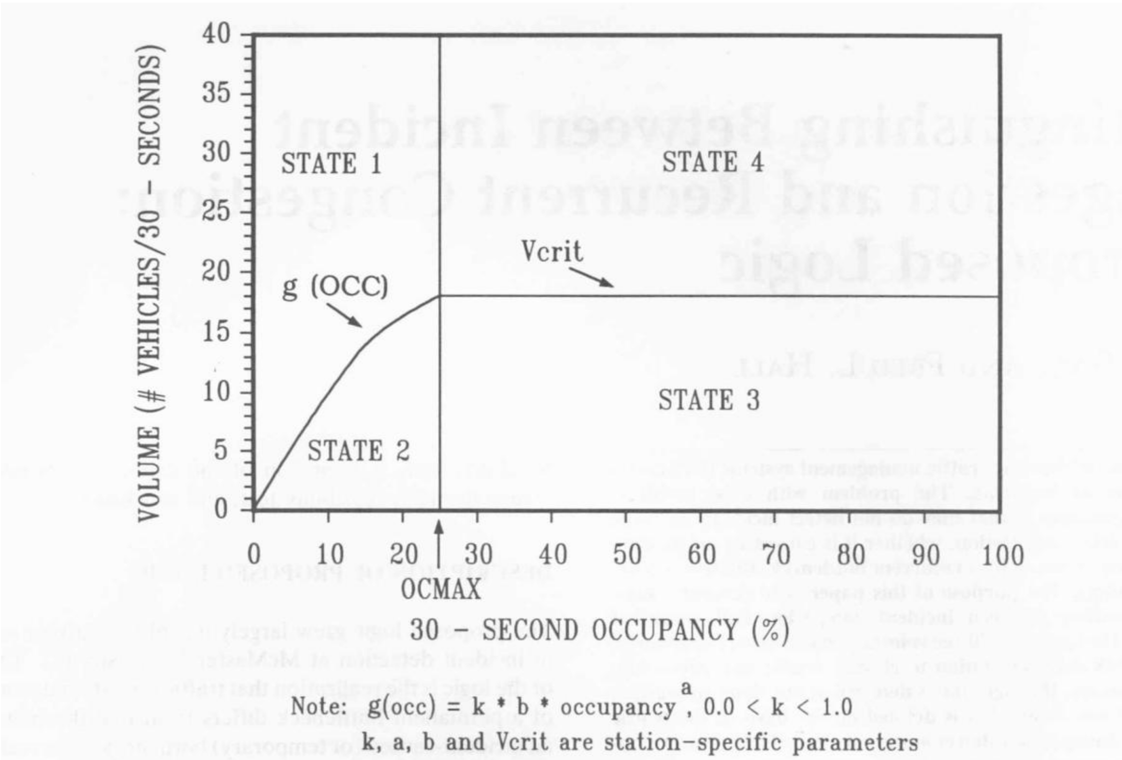


Figure 1. An illustration of the volume-occupancy template for traffic state classification (Source: Gall et al., 1989)

In another study, Skabardonis et al. in California developed a preliminary methodology for quantifying recurrent and non-recurrent congestion using data from the California Freeway Performance Measurement System (PeMS) and incident reports from the California Highway Patrol (CHP). The study was able to estimate both recurrent and non-recurrent congestion on selected freeway segments using these data and characterize non-recurrent delay as being the result of either incident or non-incident causes. The study also found that the portion of non-recurrent delay as a part of total delay on any segment was related to segment characteristics and the extent of recurrent congestion (Skabardonis et al., 2003).

2.2. Classification of Incident Detection Algorithms

Roadway incidents refer to non-recurring events which result in congestion and/or traffic disruptions. Incidents typically result in bottlenecks, which in turn restrict the normal capacity of the roadway, often leading to the formation of queues and traffic delays. Incidents have significant consequences for safety, congestion, pollution, and the cost of travel (Fonseca et al., 2011). This study identified incident detection algorithms that could allow us to review the historical probe vehicle speed data and identify incidents and their related congestion.

A number of incident detection algorithms have been proposed and are classified based on their approach into comparative, statistical, time series and filtering algorithms, traffic flow theory based, and advanced formulation based algorithms. The following paragraphs discuss the characteristics of each type, and further information can be obtained from the work of Fonseca et al. who have compiled a list of incident detection algorithms and their classification (2011).

Comparative incident detection algorithms evaluate the tracking variables against standard thresholds or against one another to identify any disruptions. Occupancy is the most common tracking variable. These types of algorithms are also referred to as pattern recognition algorithms. The California Algorithm is a good example of comparative algorithm (Fonseca et al., 2011).

In statistical algorithms, the standard traffic flow characteristics (i.e., traffic flow, average speed, and lane occupancy) are used as the indicators for any disruptions in traffic. The Standard Normal Deviate is a good example of a statistical algorithm.

Time series and filtering algorithms have also been introduced that treat the tracking variable as a time-series variable. Any deviation from the modeled time-series behavior serves as an indication of disrupted flow. The difficult task is to differentiate random variations from variations due to incidents.

Traffic theory-based algorithms depend on the relationship between the traffic variables for their analysis. For example, the McMaster Algorithm, which is based on catastrophe theory, determines the state of traffic based on its position in the flow-density-speed plot. It detects incidents based on the transition from one state to another (Fonseca et al, 2011).

In some cases, algorithms with advance mathematical formulation-based techniques, as well as algorithms that incorporate inexact reasoning and uncertainty into the detection logic, have been developed. Algorithms based on fuzzy logic are a good example of such advanced algorithms.

2.3. Incident Detection Algorithms

A good incident detection algorithm is a critical component for any incident management system. Some of the most commonly used incident detection algorithms are discussed here.

2.3.1. McMaster Incident Detection Algorithm

Persaud, Hall et al. (1990) adopted a proposed logic for incident detection which was suggested more than 20 years prior by Athol. The authors elaborated on a catastrophe theory model to describe the relationship between flow, occupancy, and speed. The essence of the logic is shown in Figure 2, which is a plot of 30-sec flow-occupancy data for the median lane of a freeway.

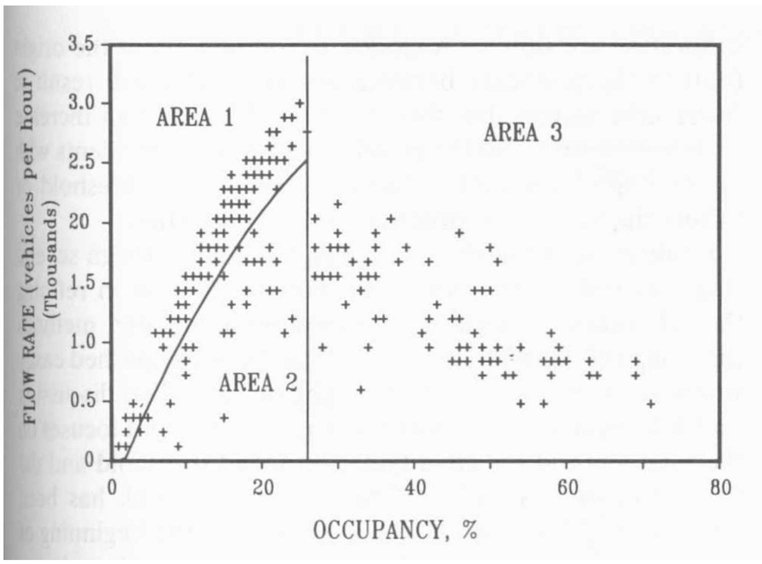


Figure 2. Three flow-occupancy areas shown with the 30-sec-data (Source: Persaud et al.,1990)

The principle of the basic version of the congestion detection logic is that a congestion flag can be indicated by either operations in Area 2 or 3 (divided on the flow rate vs. occupancy graph) or by a slow speed. Even if vehicles start accelerating after passing an incident, they might still be traveling slowly when they pass a downstream detection station. The downstream pattern depends on the distance of the incident to the detector station, but commonly the operation tends to have a speed drop and to move to Area 2 and lower volumes. The closer the incident is to the downstream station, the larger is the speed drop and the more to the right of Area 2 is the flow-occupancy value. The tests indicated that the algorithm can be used where congestion is mainly incident related (Persaud et al., 1990).

2.3.2. Standard Normal Deviate Algorithm

Cullip et al. (1997) studied different incident detection algorithms that are based on standard normal deviation. Some of them were:

- Volume or Occupancy Standard Deviation
- Occupancy Standard Normal Deviate, and
- Volume and Occupancy with Lower Bound of Uncongested Data

An effective algorithm would have a high incident-detection rate, a low mean time to detection, and a minimal number of false alarms. The volume and occupancy data based on signal cycles, rather than 20-sec counts, provided an improved basis for algorithm development because the fluctuations caused by the traffic signals were diminished. The approach that compared both volume and occupancy for the present cycle with their respective averages over the previous 3, 5, and 10 cycles was capable of detecting the incident at the affected stations with a minimal time to detection and no false alarms.

The Standard Normal Deviate (SND)-based algorithm which was first proposed by Dudek et al. (1974) was developed by the Texas Transportation Institute (TTI). The SND of a variable is computed as the difference of the given variable from its mean, divided by the standard deviation of the data set. One can set up a limiting value for the SND of 1.5 or more, to indicate a disruptive flow or an incident. By doing so, Dudek et al. (1974) reported a 92% detection ratio with a 1.3% false alarm rate during peak periods. The time to detect incidents was 1.1 minutes on average.

2.3.3. The California Algorithms

The California Department of Transportation and its associates developed several algorithms for freeway incident detection in the 1970s that are collectively known as California algorithms. As many as ten variations of these algorithms were developed, all of which use the lane occupancy values at one or two adjacent stations as inputs and compare them with preselected thresholds to characterize the state of the traffic flow (Karim and Adeli, 2002).

The algorithms use 20- and 30-second occupancies and volumes averaged over all lanes at a particular station. Several variables are derived based on the occupancy values at the concerned station and the station downstream at different time points. Some of the most prominent variables are Downstream Occupancy (DOCC), Spatial Difference in Occupancies (OCCD), Relative Spatial Difference in Occupancies (OCCRD), and Relative Temporal Difference in Downstream Occupancy (DOCCTD). These derived variables are evaluated at every time-step at each station in the concerned section of roadway and compared to thresholds at different points in a decision tree to determine whether an incident has occurred in the system (Fonseca et al., 2011).

The logic behind the California algorithms is shown in Figure 3 below. At each step, the occupancies are compared with a predetermined standard threshold. The first step in this algorithm compares the difference in occupancy between the downstream and upstream stations with the threshold value (Ozbay and Kachroo, 1999). The next two steps look at the relative temporal and spatial differences of occupancies. An incident is signaled if all three thresholds are exceeded. The decision tree for California algorithm #7 is shown in Figure 4 below.

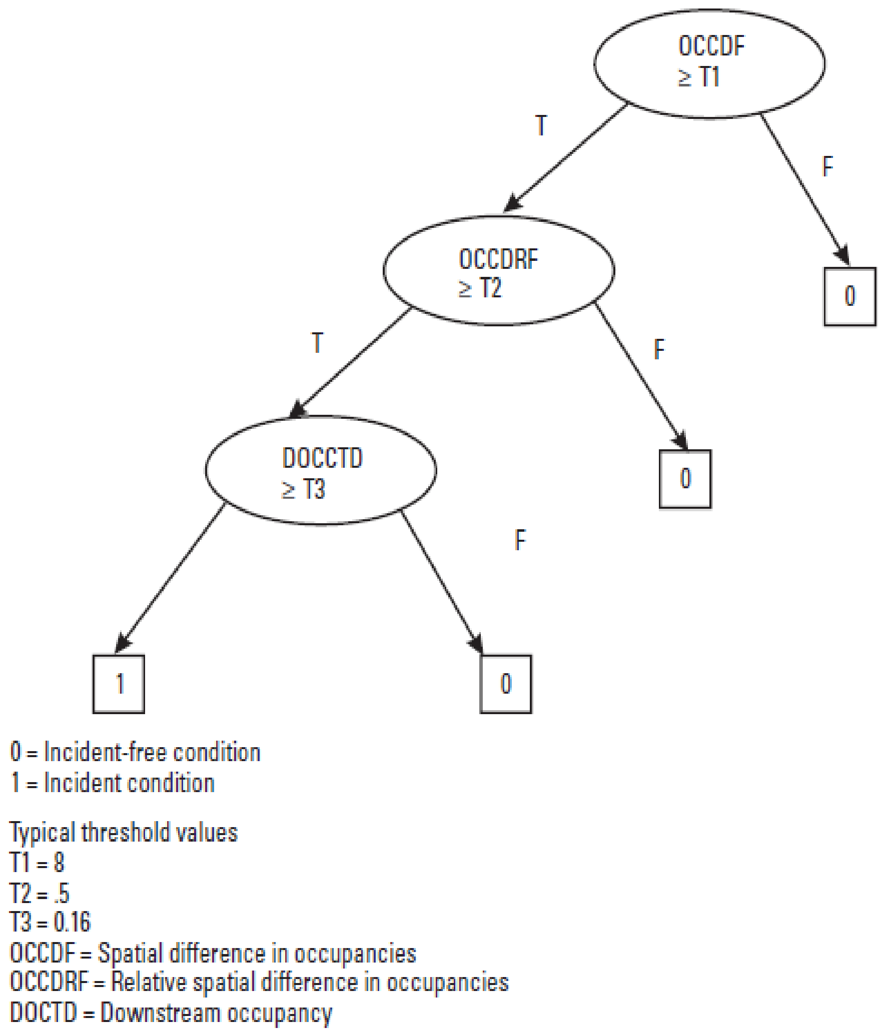


Figure 3. Basic California Algorithm (Source: Payne et al., 1976)

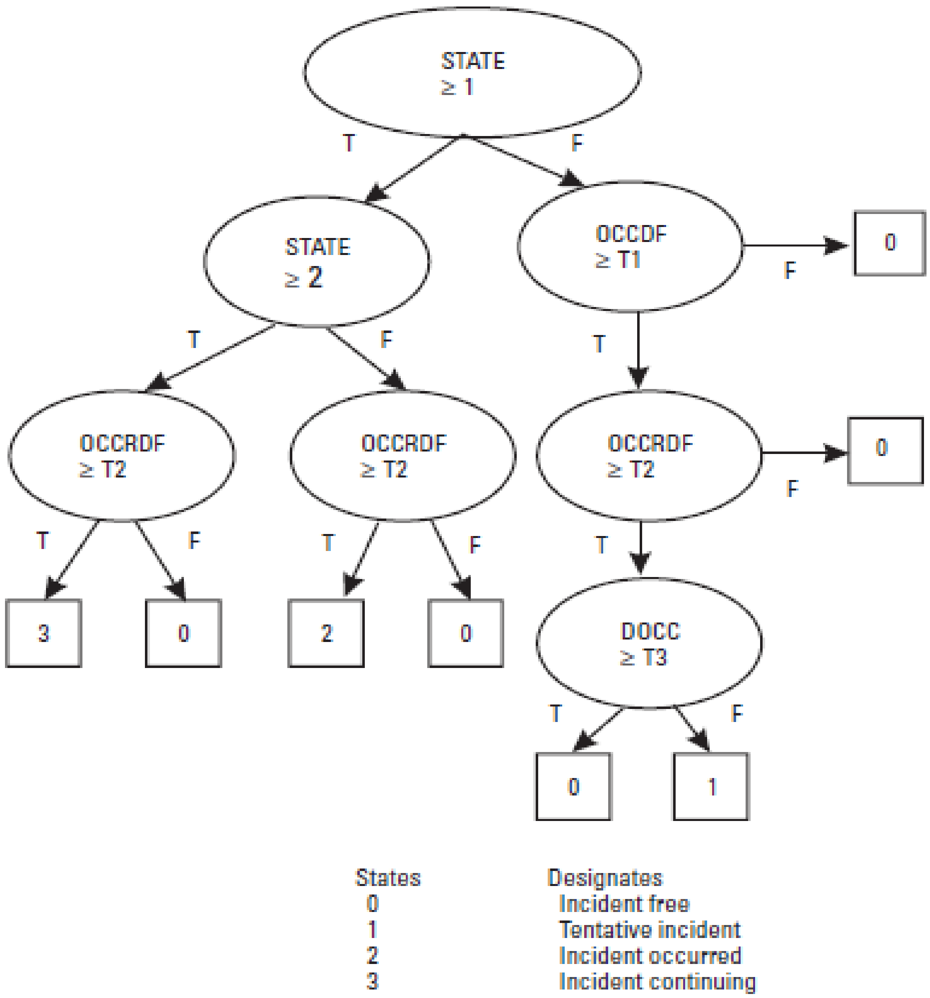


Figure 4. Decision tree for California algorithm #7 (Source: Payne et al., 1976)

2.3.4. Bayesian-based Algorithm

A Bayesian probability theory based algorithm was developed by the Illinois DOT. This approach is generally used along with any other algorithm to decrease the false alarm rate of incident detection. A Bayesian network is created with a set of parameters using upstream and downstream detector stations. The variables include two traffic events (incident: Inc1_1, congestion: Con1_1) and seven traffic parameters (volumes: Vol1_1 and Vol2_1, occupancies: Occ1_1 and Occ2_1 speeds: Spd1_1 and Spd2_1, and the occupancy difference between upstream and downstream: D_occ1). At each detection interval, a traffic case is loaded from the data processing module, and available states of the traffic parameters are propagated through the network.

The concept is shown in Figure 5 below. The updated probability distributions of both incident and congestion at current detection interval are used to estimate the current incident probability for incident report, and the estimated incident probability of the previous two detection intervals are taken into account at each interval (Zhang and Taylor, 2005).

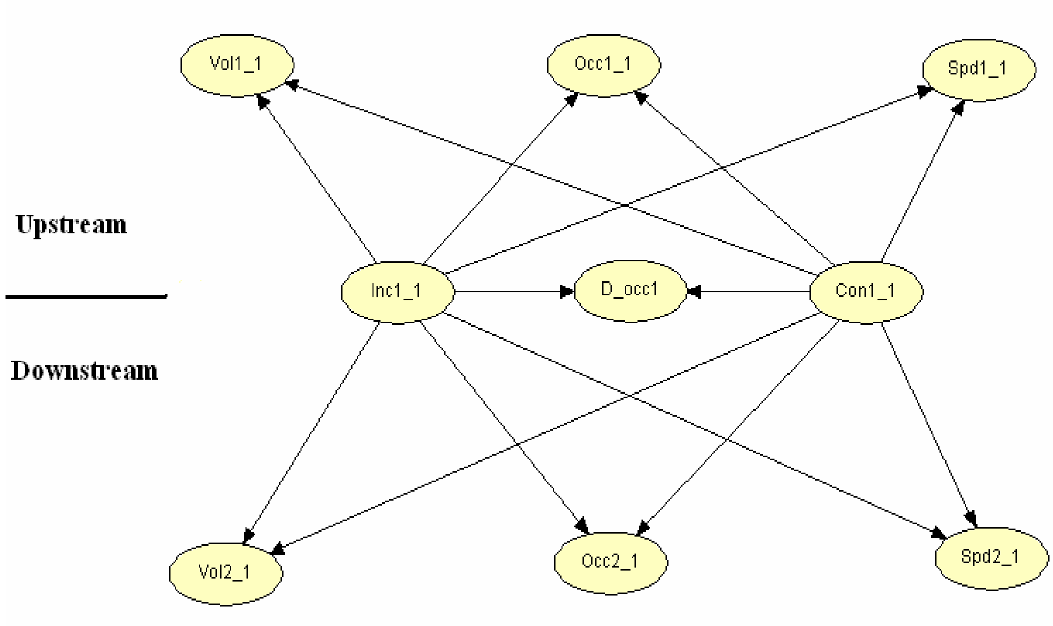


Figure 5. A Bayesian network for freeway incident detection (Source: Zhang and Taylor, 2005)

A summary of the most prevalent incident detection algorithms -- compared based on detection rate, false alarm rate and average detection time -- is shown below in Table 1. Among those algorithms listed, the Standard Normal Deviate appears to be the most promising for utilization in small and medium size areas with limited data collection means as it requires only speed and travel time inputs. Occupancy measurements required by the other methods necessitate distributed network detectors that are often not available in medium and small urban areas.

Table 1. Summary of the evaluation results of the most commonly used algorithms (Source: Ozbay and Kachroo, 1999)

Algorithm Type	Detection Rate (%)	False Alarm Rate (%)	Average Detection Time (secs)
Basic California	82	1.73	0.85
California #7	67	0.134	2.91
California #8	68	0.177	3.04
Standard Normal Deviate	92	1.3	1.1
Bayesian	100	0	3.9
Time Series (Autoregressive Integrated Moving Average)	100	1.5	0.4
Exponential Smoothing	92	1.87	0.7
Low-Pass Filter	80	0.3	4.0
Modified McMaster	68	0.0018	2.2
Multi Layer Feed Forward Neural Networks	89	0.01	0.96
Probabilistic Neural Networks	89	0.012	0.9
Fuzzy Sets	Good	Good	Up to 3 minutes quicker than conventional algorithms

2.4. Traffic Data Collection Methods

There are a number of traffic data collection techniques available to agencies for the purpose of monitoring network performance and quantifying congestion. Among the data typically collected are volumes, speeds, occupancy, and classification. A brief summary of the different collection methods follows.

2.4.1. Manual data collection

This method can provide a classification of vehicle by type, size, and occupancy. Also, queue lengths and delays can be observed and recorded. One of its major limitations is that it requires a lot of manual labor, and thus, is not appropriate for a long time period data collection for a specific road location (Tong 2004). Due to its nature, manual data collection is not an appropriate method for incident detection and congestion characterization.

2.4.2. Automatic data collection

Automatic data recording techniques are used when extended counts (day, week, and month) are needed. Single-trap loop detectors which only measure volume and occupancy are used in many systems. Automated systems provide a baseline for traffic data collection. However, they are fixed counting stations, and thus cost limitations often restrict their application, which limits the ability to provide all traffic counts needed in an urban area for congestion and incident management purposes. Also, these detectors often require intrusive installation in the roadbed. In addition, loop detectors are not able to measure certain useful traffic data parameters, such as turning movement counts, or complex weaving movements. Such limitations have led to the introduction of numerous non-intrusive traffic data collection devices utilizing a variety of recently emerged technologies, such as video, radio, and bluetooth detection. These offer greater capabilities and flexibility than loop detectors but still require extensive installations to provide the amount of data necessary for network-wide congestion detection.

2.4.3. Cellular Phones

Cell phone reports can serve as good sources of data for incident detection. Motorists can make calls from cellular phones to report any kind of incidents on the freeway. These reports may vary in detail and effectiveness and may not be placed in a timely manner or report the precise location of the incident. Therefore, the utilization of cellular phones for incident detection is typically viewed as a secondary source of information as far as network monitoring is concerned (though they still serve as a primary source of information for emergency responders).

Cell phone reports detect up to 38% of incidents and 1% of the other events. This is most probably because incidents which block lanes and affect the flow of traffic are likely to get more attention from fellow motorists. Other events like breakdowns on the shoulder, which actually are more frequent events, often go unreported by cellular phone users. The false alarm rate of cellular phones is about 7% for all incidents (verified by the freeway patrol) and it goes up to 32% for other events which do not hinder the flow of traffic (21).

Another limitation of cellular phone reporting is in providing information on when the flow of traffic is back to normal. Skabardonis et al. (2003) have compared the detection rates and false alarm rates for different sources like cellular phones, California Highway Patrol (CHP) reports, Freeway Service Patrols (FSP), any public entity, and a call box, and their findings are summarized in Table 2.

Table 2. Comparison of different incident detection sources based on detection rate (%) and false alarm rate (%) (Source: Skabardonis et al., 2003)

DETECTION SOURCE	DETECTION RATE		FALSE ALARM RATE	
	Incidents	Other Events	Incidents	Other Events
CELLULAR PHONE	**37.9**	1.2	7.4	32.0
CHP	25.0	4.3	0.0	0.0
FSP	17.1	4.9	0.0	0.0
PUBLIC ENTITY	13.3	0.6	5.4	11.1
CALL BOX	4.5	3.6	0.0	7.1

2.4.4 GPS Techniques

GPS has been accepted by the transportation industry because the technology can provide useful real-time information about vehicle and facility locations. The GPS receivers automatically record the changes in position of a person or vehicle, along with the time information. The basic output from a receiver is the latitude, longitude, altitude coordinates and the time for a moving or stationary object, at possible update rates on the order of once per second. By integrating over time and space, additional information becomes available, such as travel distances, more precise travel times, travel velocities and route information with GPS receivers. Based on this information, traffic system performance can be analyzed.

GPS has a spatial coverage advantage over other traffic data-capture techniques. Also, GPS does not require sensors to be installed in the road infrastructure, with an obvious reduction in upfront and maintenance costs. Furthermore, GPS provides the capability to easily integrate the resulting travel time data with geographic information system (GIS)-based databases.

In a research effort, Zito et al. (2000) examined the basic characteristics of vehicle position and speed data using GPS and demonstrated its usefulness for collecting travel data. The study results show that overall GPS demonstrates a good ability to provide good location data in various parts of an urban area environment. However, signal blockage or multipath errors in downtown areas or the central business district of a city were detected, especially where high-rise buildings of various materials, such as concrete and steel, are located.

Sethi et al. (1995) developed incident detection algorithms for street networks using data from fixed detectors and GPS probe vehicles. The proposed incident algorithms can be generalized to a variety of link types and to periods of higher or lower traffic volumes by comparing current traffic flow measures to historic values under non-incident conditions for the corresponding day (e.g., weekday, weekend) and time period. The current values were reported from fixed detectors and/or probe vehicles. In the probe vehicle algorithm, the current link travel time and travel speed derived from a probe vehicle were compared to the historic average travel time and travel speed for the corresponding link, day, and time period to infer the presence of incidents.

Generally speaking, travel time can be used to quantify congestion and evaluate corridor performance. Quiroga and Bullock (1998) described a methodology for performing travel time studies using GPS and GIS technologies (17). They presented a spatial and mathematical model based on the GPS speed data to generate the travel time information on the road segments. More than 180,000 segment travel time and speed records were derived between 1995 and 1996 from nearly three million GPS data points collected on 30,000 miles of travel runs along 300 miles of urban highways in three metropolitan areas – Baton Rouge, Shreveport, and New Orleans, Louisiana.

D’Este et al. (1999) explored and tested ways in which GPS can be used to derive useful quantitative measures of congestion. They developed congestion indicators of travel time, average speed of the journey, congestion index, time moving, proportion of stopped time, acceleration noise and velocity gradient using GPS data. Their results demonstrated that GPS can provide reliable data for the calculation of congestion parameters, even with such variables as acceleration noise and velocity gradient, which require speed data information. Furthermore, GPS can deliver the data in real time with regular observations at high frequency. This is ideal for developing a real-time congestion monitoring system, for supporting Advanced Traveler Information Systems (ATIS), and for enhancing incident detection and management.
In conclusion, among the various traffic data collection techniques considered, GPS appears to provide the best and most cost-effective way for data collection in the absence of extensive traffic detection instrumentation. Thus, GPS techniques will be further investigated in this research, and details on freeway performance analysis using data collected by GPS probe vehicles will be discussed in the following sections.

2.4.5. Vehicle Probes
Vehicle probe technology has emerged as a useful means to observe flow of traffic, providing both the travel time and speed information in support of the data requirements of advanced traffic management systems (ATMS) and advanced traveler information services (ATIS)

applications. Vehicle probe data can support many transportation agency requirements, including impacts assessment of construction activities, planning, and engineering. Meanwhile, the steep cost of installing fixed-point loop detectors and also maintaining them is pushing the transportation authorities to consider outsourcing traffic monitoring and also finding new detection techniques, which creates new opportunities for vehicle probe data to be used for congestion measurement and monitoring applications.

Vehicle probe technology includes two basic methods: GPS data obtained from freight or other vehicles and geo-location schemes that leverage cellular phone infrastructure. Research work at the University of Maryland focused on real-time traffic operations data collection using vehicle probe technology and characterized different types of vehicle probe technologies available including Cell-based Probes, Automated Vehicle Location Services, Toll-Tag Technology, and Probe-based Technology Markets (Young 2007). The author found that lower class roadways have shown less success toward implementation of vehicle probe data collection methods. Other issues relate to the difficulty cell-based probes have differentiating traffic between closely spaced facilities, such as between frontage roads and an adjoining freeway. It should also be noted that the main limitation of cell phone data is that they lack the accuracy and resolution of inductive loop or video detector data. Inductive loops are able to measure both speed and volume with great accuracy and can be placed at regular intervals to monitor roadway segments of any length desired. Cell phone probes, on the other hand, can record only average speeds across a roadway segment and their spatial resolution is limited by the location of cell towers. Furthermore, cell phone systems can infer but cannot directly measure vehicle volumes on any given segment.

3. Data Collection

This study used an interstate corridor in Alabama to demonstrate the feasibility of using GPS fleet probe data to measure recurrent and non-recurrent congestion. The corridor chosen for the study was I-65 in Birmingham, between Walker Chapel Road to the north and the Shelby/ Jefferson County line to the south. The study corridor is shown in Figure 6. Table 3 shows the study links along with their length (in miles) for both directions. Table 4 lists the links according to milepost number.

The study used speed data collected by INRIX, a leading provider of traffic information. The data were collected from GPS-equipped freight vehicles over a three month period including February, March, and April of 2010. Speed data from the AM peak hours and the PM peak hours on Mondays, Tuesdays, Wednesdays, and Thursdays were used for our analysis, because these days are considered typical weekdays for traffic analysis purposes. Public holidays, if any, were excluded from the data base. The morning peak hours were assumed to be from 6:00 AM to 10:00 AM, while the afternoon peak hours were assumed to be from 3:00 PM to 7:00 PM.

Travel times and speeds were calculated by subtracting the segment entering time from the segment exit time. The speed was averaged over five minute intervals for further calculations in order to smooth out any anomalies in the data. A sample of the data provided by INRIX is shown below in Table 5, along with sample calculations of average speeds and travel times.

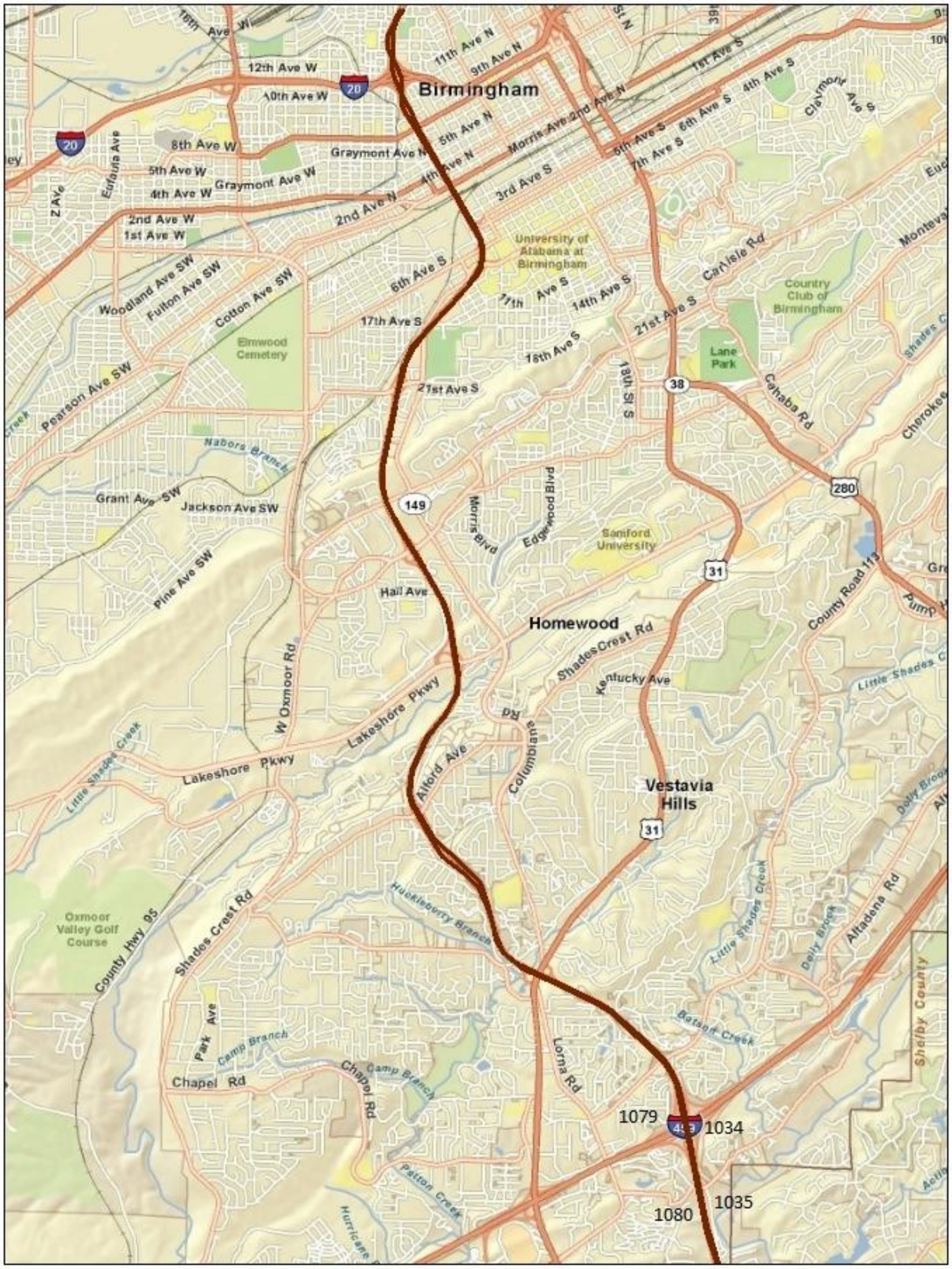


Figure 6. Study corridor location

Table 3. Study corridor links and characteristics

NB Link	SB Link	Link ID	Length(miles)	
			NB	SB
1001	1046	I-65N WalkerChapelRd(Exit267)	0.58	0.74
1002	1047	I-65N WalkerChapelRd(Exit267)	0.98	1.28
1003	1048	I-65N Hwy31(Exit266)	0.68	0.48
1004	1049	I-65N Hwy31(Exit266)	1.36	1.43
1005	1050	I-65N 41stAve(Exit264)	0.27	0.51
1006	1051	I-65N 41stAve(Exit264)	0.49	0.26
1007	1052	I-65N 32ndAve/33rdAve(Exit263)	0.63	0.46
1008	1053	I-65N 32ndAve/33rdAve(Exit263)	0.3	0.31
1009	1054	I-65N FinleyBlvd(Exit262B)	0.33	0.37
1010	1055	I-65N FinleyBlvd(Exit262B)	0.45	0.4
1011	1056	I-65N 16thSt(Exit262A)	0.26	0.25
1012	1057	I-65N 16thSt(Exit262A)	0.31	0.34
1013	1058	I-65N I-20/I-59(Exit261)	0.48	0.51
1014	1059	I-65N I-20/I-59(Exit261)	0.24	0.25
1015	1060	I-65N 6thAve(Exit260)	0.28	0.26
1016	1061	I-65N 6thAve(Exit260)	0.07	0.07
1017	1062	I-65N 3rdAve(Exit260B)	0.21	0.21
1018	1063	I-65N 3rdAve(Exit260B)	0.43	0.32
1019	1064	I-65N 4thAve(Exit259B)	0.07	0.12
1020	1065	I-65N 4thAve(Exit259B)	0.09	0.09
1021	1066	I-65N 6thAve(Exit259A)	0.02	0.09
1022	1067	I-65N Hwy149/UnivBlvd(Exit259)	0.29	0.12
1023	1068	I-65N Hwy149/UnivBlvd(Exit259)	0.77	0.84
1024	1069	I-65N GreenSpringsAve(Exit258)	0.44	0.43
1025	1070	I-65N GreenSpringsAve(Exit258)	0.97	0.93
1026	1071	I-65N OxmoorRd(Exit256)	0.56	0.53
1027	1072	I-65N OxmoorRd(Exit256)	0.62	0.44
1028	1073	I-65N LakeshoreDr(Exit255)	0.4	0.32
1029	1074	I-65N LakeshoreDr(Exit255)	0.95	1.19
1030	1075	I-65N AlfordAve(Exit254)	0.54	0.49
1031	1076	I-65N AlfordAve(Exit254)	1.44	1.27
1032	1077	I-65N US-31/MontgomeryHwy(Exit252)	0.23	0.16
1033	1078	I-65N US-31/MontgomeryHwy(Exit252)	1.07	1.37
1034	1079	I-65N I-459(Exit250)	1.03	1.04
1035	1080	I-65N I-459(Exit250)	1.05	1.05
1037	1081	I-65N Shelby/JeffersonCountyLine	0.86	0.81

Table 4. Corridor links by milepost

Milepost	NB Link	SB Link
249	1037	1081
250	1034,1035	1079,1080
251	1033,1034	1078,1079
252	1032,1033	1077,1078
253	1031,1032	1076,1077
254	1030,1031	1075,1076
255	1028,1029	1073,1074
256	1026,1027	1071,1072
257	1025,1026	1070,1071
258	1024,1025	1069,1070
259	1019,1020,1021,1022,1023	1064,1065,1066,1067,1068
260	1015,1016,1017,1018	1060,1061,1062,1063
261	1013,1014	1058,1059
262	1009,1010,1011,1012	1054,1055,1056,1057
263	1007,1008	1052,1053
264	1005,1006	1050,1051
265	1004,1005	1049,1050
266	1003,1004	1048,1049
267	1001,1002	1046,1047

Table 5. A sample of speeds averaged over five minutes

<table>
<tr><th>Date</th><th>Time</th><th>LinkID</th><th>Travel Time (s)</th><th>Speed (mph)</th><th>Average Travel Time (s)</th><th>Average Speed (mph)</th></tr>
<tr><td>3/8/2010</td><td>9:20:00 AM</td><td>1010</td><td>30</td><td>54</td><td rowspan="5">29.6</td><td rowspan="5">54.4</td></tr>
<tr><td>3/8/2010</td><td>9:21:01 AM</td><td>1010</td><td>29</td><td>55</td></tr>
<tr><td>3/8/2010</td><td>9:22:00 AM</td><td>1010</td><td>29</td><td>55</td></tr>
<tr><td>3/8/2010</td><td>9:23:01 AM</td><td>1010</td><td>30</td><td>54</td></tr>
<tr><td>3/8/2010</td><td>9:24:00 AM</td><td>1010</td><td>30</td><td>54</td></tr>
<tr><td>3/8/2010</td><td>9:25:01 AM</td><td>1010</td><td>31</td><td>52</td><td rowspan="5">31.0</td><td rowspan="5">51.8</td></tr>
<tr><td>3/8/2010</td><td>9:26:00 AM</td><td>1010</td><td>31</td><td>52</td></tr>
<tr><td>3/8/2010</td><td>9:27:01 AM</td><td>1010</td><td>31</td><td>52</td></tr>
<tr><td>3/8/2010</td><td>9:28:00 AM</td><td>1010</td><td>31</td><td>52</td></tr>
<tr><td>3/8/2010</td><td>9:29:01 AM</td><td>1010</td><td>31</td><td>51</td></tr>
</table>

Using traffic data described above and incident data from ASAP daily reports, estimates of non-recurrent congestion were developed, and the spread of congestion during lane closures was quantified as described in Chapter 4.

4. Study Methodology

This chapter presents the methodology used in this study for identifying the presence of vehicle incidents and related congestion on the basis of vehicle probe speed data. This was done using the GPS generated data (i.e., travel times and average speeds) and the Standard Normal Deviate (SND) method, which was discussed in the literature review chapter. Incident reports from the Alabama Service and Assistance Patrol (ASAP) were used to compare and verify the results of the methodology.

Specifically, 2010 freight vehicle GPS data were used to calculate average speeds on a link-by-link basis during AM and PM peak periods of typical work days. It was found that the probe speed data included some dropouts in the data, particularly during early morning periods most likely due to low truck volumes. The periods with data dropouts were removed from our analysis as they were incomplete and might later affect the analysis.

4.1 Speed Analysis

The procedure followed in this study for the speed analysis followed 4 steps as described below:

Step 1. The speed was first averaged over 5 minute periods as shown in Table 6. This was done to smooth out any anomalies in the data.

Table 6. Sample speeds averaged for every five minutes

Date	Time	LinkID	Travel Time (s)	Speed (mph)	Avg Speed (mph)
4/5/2010	6:00:00 AM	1001	32	65	65.4
4/5/2010	6:01:01 AM	1001	32	65	
4/5/2010	6:02:00 AM	1001	32	65	
4/5/2010	6:03:01 AM	1001	32	66	
4/5/2010	6:04:00 AM	1001	32	66	
4/5/2010	6:05:01 AM	1001	32	66	66.0
4/5/2010	6:06:00 AM	1001	32	66	
4/5/2010	6:07:01 AM	1001	32	66	
4/5/2010	6:08:00 AM	1001	32	66	
4/5/2010	6:09:01 AM	1001	32	66	

Step 2. The average speeds calculated in the previous step were all tabulated side by side, so that all the speeds collected over the three months, for a specific time period were shown in a single row (Table 7).

Table 7. Link speeds tabulated with respect to time and date

Time	LinkID	Speed (mph)				
		02/01	02/02	02/03	02/04	02/05
6:04:01 AM	1001	66.0	68.8	69.4	63.2	65.0
6:09:01 AM	1001	66.0	63.8	67.8	63.2	61.6
6:14:01 AM	1001	61.6	60.0	66.0	62.2	50.6
6:19:01 AM	1001	61.6	64.6	66.0	63.4	55.0
6:24:01 AM	1001	62.4	67.2	67.0	66.8	68.8
6:29:01 AM	1001	67.0	62.2	68.0	66.0	73.4
6:34:01 AM	1001	63.4	61.8	67.8	69.0	69.0
6:39:01 AM	1001	65.2	68.6	66.4	67.6	66.2
6:44:01 AM	1001	66.8	61.6	66.0	69.0	66.0
6:49:01 AM	1001	70.0	58.4	66.0	71.0	70.0
6:54:01 AM	1001	69.8	59.0	68.6	64.0	68.6
6:59:01 AM	1001	69.6	63.2	71.4	62.0	62.4

Step 3. The averages and standard deviations of each row (for a particular time) were then calculated as shown in Table 8.

Table 8. Speed averages and standard deviations for specific time periods

Time	LinkID	Speed 02/01 (mph)	Speed 02/02 (mph)	------	Avg (mph)	Std Dev
6:04:01 AM	1001	66.0	68.8		66.85581	3.146071
6:09:01 AM	1001	66.0	63.8		67.15814	3.693897
6:14:01 AM	1001	61.6	60.0		66.04186	5.109572
6:19:01 AM	1001	61.6	64.6		66.07907	5.163635
6:24:01 AM	1001	62.4	67.2		66.25581	5.116235
6:29:01 AM	1001	67.0	62.2		66.74884	4.634877
6:34:01 AM	1001	63.4	61.8		67.75349	3.517531
6:39:01 AM	1001	65.2	68.6		68.21395	2.996632
6:44:01 AM	1001	66.8	61.6		67.73488	2.854811
6:49:01 AM	1001	70.0	58.4		66.61395	4.241158
6:54:01 AM	1001	69.8	59.0		67.23256	3.796974
6:59:01 AM	1001	69.6	63.2		67.62791	3.155519

Step 4. Finally, the Standard Normal Deviate (SND) for each speed (i.e., for a particular day and time) was calculated as shown in Equation 1, and sample results are displayed in Table 9 below.

$$(\mathrm{SND})\mathrm{ij} = \frac{[(\mathrm{Speed})\mathrm{ij} - (\mathrm{Avg\ Speed})\mathrm{i}]}{(\mathrm{Std\ Deviation})\mathrm{i}} \quad \text{Equ. (1)}$$

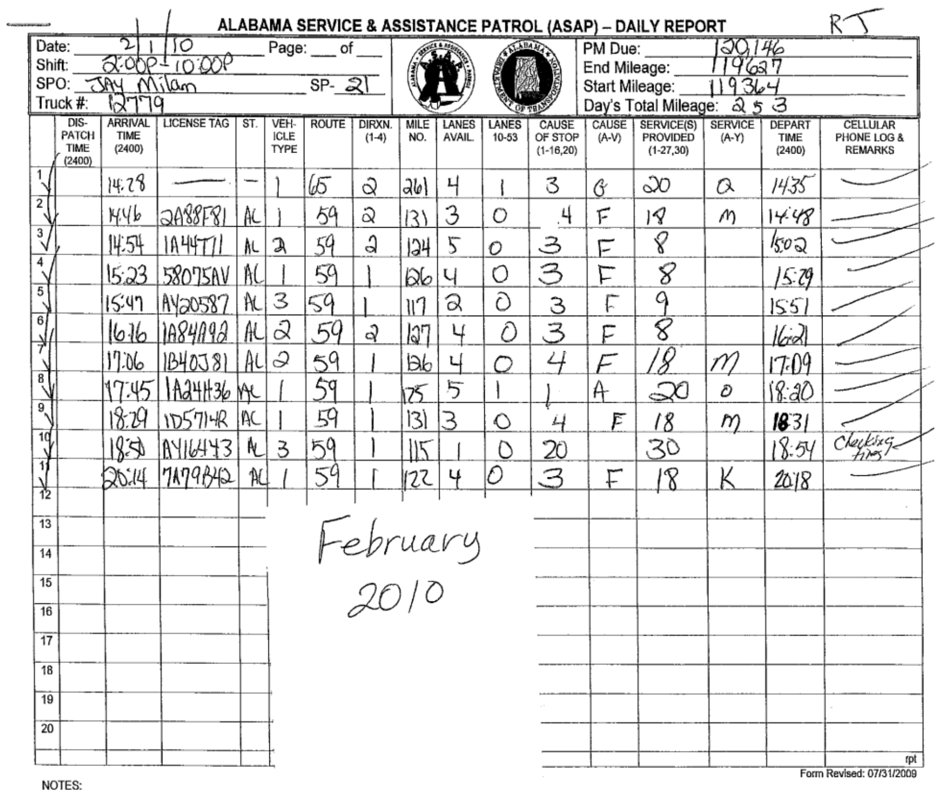
Where:
SND = Standard Normal Deviate
i/j = number of row/column respectively.

Table 9. Respective SNDs tabulated for all the links

Time	LinkID	Speed 02/01	Speed 02/02	-------	SND 02/01	SND 02/02	-----
6:04:01AM	1001	66	68.8		-0.27203	0.617973	
6:09:01 AM	1001	66	63.8		-0.31353	-0.9091	
6:14:01 AM	1001	61.6	60.0		-0.86932	-1.18246	
6:19:01 AM	1001	61.6	64.6		-0.86743	-0.28644	
6:24:01 AM	1001	62.4	67.2		-0.75364	0.184547	
6:29:01 AM	1001	67.0	62.2		0.05419	-0.98144	
6:34:01 AM	1001	63.4	61.8		-1.23765	-1.69252	
6:39:01 AM	1001	65.2	68.6		-1.00578	0.128827	
6:44:01 AM	1001	66.8	61.6		-0.32748	-2.14896	
6:49:01 AM	1001	70.0	58.4		0.798378	-1.93672	
6:54:01 AM	1001	69.8	59.0		0.676181	-2.16819	
6:59:01 AM	1001	69.6	63.2		0.624966	-1.40323	

According to the methodology, negative values of SND that are greater than a selected threshold would indicate congestion beyond average levels and likely non-recurrent congestion. Thus, after calculating the SNDs, the task at hand was to set a threshold for the deviation. A threshold value of (-1.5) was selected according to the literature and confirmed through a sensitivity analysis performed in Section 5.1. SND values which deviated by more than -1.5 were indicative of non-recurrent congestion speeds and used to detect the presence of incidents along with their occurrence times and locations.

For verification purposes, the incidents detected with this method were then compared with the Alabama Service and Assistance Patrol (ASAP) service logs. The ASAP data consist of a daily report of incidents (accidents, breakdowns, or any events) that take place on interstate highways, as shown in Figure 7. The report indicates the location based on the mile post and direction of travel. It also records the number of lanes available for travel during the incident, the number of lanes blocked, and the type of services provided by the patrol. It should be noted that not every vehicle incident will trigger an ASAP response, so there were likely many minor incidents detected by the methodology that could not be verified using the ASAP logs.



ALABAMA SERVICE & ASSISTANCE PATROL (ASAP) – DAILY REPORT

RT

Date: 2/1/10 Page: ___ of ___
Shift: 2:00P – 10:00P
SPO: JAY Milam SP- 21
Truck #: 12779

PM Due: 120,146
End Mileage: 119627
Start Mileage: 119364
Day's Total Mileage: 253

	DIS-PATCH TIME (2400)	ARRIVAL TIME (2400)	LICENSE TAG	ST.	VEH-ICLE TYPE	ROUTE	DIRXN. (1-4)	MILE NO.	LANES AVAIL.	LANES 10-53	CAUSE OF STOP (1-16,20)	CAUSE (A-V)	SERVICE(S) PROVIDED (1-27,30)	SERVICE (A-Y)	DEPART TIME (2400)	CELLULAR PHONE LOG & REMARKS
1		14:28	—	—	1	65	2	261	4	1	3	G	20	Q	1435	
2		14:46	2A88F81	AL	1	59	2	131	3	0	4	F	18	M	14:48	
3		14:54	1A44T71	AL	2	59	2	124	5	0	3	F	8		1502	
4		15:23	58075AV	AL	1	59	1	126	4	0	3	F	8		15:29	
5		15:47	AY20587	AL	3	59	1	117	2	0	3	F	9		15:51	
6		16:16	1A84A92	AL	2	59	2	127	4	0	3	F	8		16:21	
7		17:06	1B40J81	AL	2	59	1	126	4	0	4	F	18	M	17:09	
8		17:45	1A24H36	AL	1	59	1	125	5	1	1	A	20	O	18:20	
9		18:29	1D5714R	AC	1	59	1	131	3	0	4	F	18	M	1831	
10		18:50	AY16443	AL	3	59	1	115	1	0	20		30		18:54	Checking tires
11		20:14	7A79B42	AL	1	59	1	122	4	0	3	F	18	K	2018	
12																
13																
14																
15																
16																
17																
18																
19																
20																

February 2010

rpt

NOTES:

Form Revised: 07/31/2009

Figure 7. A sample report from the ASAP service logs

Each result matrix contains speed (or SND data) for all the study links (NB and SB) and all 43 data collection days (15 days in February, 17 in March and 11 in April, 2010). For each link, forty-eight 5-min periods were considered, representing the 4 peak hours of interest (either AM or PM peak) versus all data collection days over the three months (tabulated horizontally). Each final matrix had 3,456 rows and 43 columns, and two such matrices were produced (i.e., one for AM and one for PM speed analysis). Overall, the amount of data is very large and thus cannot be presented in its entirety. Two snapshots of the SND values calculated for over 11 days in April during AM peak (link 1017) and PM peak (link 1034) are presented in Tables 10 and 11 respectively.

Table 10. Sample of SND values calculated for link 1017 for April 2010 (AM) peak

Time (AM)	Link ID	SND 04/05	SND 04/06	SND 04/07	SND 04/08	SND 04/13	SND 04/14	SND 04/15	SND 04/19	SND 04/20	SND 04/21	SND 04/22
6:29:01	1017	-1.63	0.27	-0.61	-0.31	-0.80	-0.22	-1.19	-0.02	3.68	-1.43	0.17
6:34:01	1017	-0.72	-0.72	-0.56	0.06	-2.12	1.40	0.22	-0.56	2.79	-0.61	0.61
6:39:01	1017	-0.75	-0.46	-0.71	0.36	-1.49	-0.05	1.55	-0.46	0.85	-0.05	0.77
6:44:01	1017	-0.58	-0.27	1.17	0.47	-0.76	0.40	1.35	-0.55	0.65	0.65	0.93
6:49:01	1017	-1.06	1.17	0.55	0.55	-0.73	-0.23	0.63	-1.10	1.38	0.68	0.80
6:54:01	1017	0.27	0.88	0.53	-1.90	-0.35	-0.79	-0.06	-0.23	1.35	0.76	0.97
6:59:01	1017	0.28	0.39	1.10	-0.88	0.39	-0.88	-0.29	0.33	1.41	0.53	1.49
7:04:01	1017	0.64	0.07	1.25	-0.86	0.88	-1.94	-0.54	0.75	1.34	0.88	0.80
7:09:01	1017	1.24	0.79	1.24	-0.16	0.66	-0.19	0.08	0.62	0.52	0.45	0.69
7:14:01	1017	0.84	1.20	1.06	-0.15	0.26	0.44	1.15	-1.22	-0.01	-0.32	0.53
7:19:01	1017	-1.99	-1.12	0.90	0.42	-0.19	0.16	0.86	-0.77	-0.50	0.07	0.73
7:24:01	1017	-0.98	-0.36	1.22	-0.85	-0.72	-0.01	0.74	-0.54	-0.45	0.87	0.12
7:29:01	1017	0.91	1.42	-2.46	-0.88	-0.61	-0.54	1.05	-0.27	0.07	0.91	0.04
7:34:01	1017	-1.01	1.20	-2.16	-0.74	-1.81	-0.61	0.30	0.11	0.32	0.70	0.40
7:39:01	1017	-0.78	0.93	0.06	-0.50	-0.67	-0.57	0.91	0.25	0.19	0.23	0.27
7:44:01	1017	0.94	1.14	0.85	0.24	0.53	-0.29	0.90	0.44	-1.95	-0.39	0.40
7:49:01	1017	0.41	0.72	1.04	0.41	0.52	-0.31	0.72	0.62	-3.59	-0.48	0.43
7:54:01	1017	-0.65	0.73	-0.21	-0.65	0.28	0.70	0.49	0.98	-4.26	-0.49	0.23
7:59:02	1017	-0.40	0.98	-0.96	-1.02	0.05	0.81	0.59	1.01	-3.87	0.14	0.53
8:04:02	1017	0.12	0.92	0.06	-1.00	-0.97	0.92	-0.59	0.77	-1.09	0.06	0.77
8:09:01	1017	-0.20	0.74	0.35	-1.03	-0.29	0.76	-0.95	0.29	-0.73	-0.23	0.90
8:14:01	1017	-0.54	-1.51	0.15	-0.85	0.18	0.99	-1.10	0.12	-0.32	-0.29	0.99
8:19:01	1017	-0.62	-0.60	0.64	0.20	-0.13	0.92	-1.00	0.20	-0.80	-0.60	0.79
8:24:01	1017	-0.52	0.30	1.02	0.12	-0.29	1.07	-1.21	0.46	-1.00	-0.75	0.61

Note: Critical SND values are shown in pink; incidents from the ASAP database (highlighted with grey) superimposed over the SND values.

Table 11. Sample of SND values calculated for link 1034 for April 2010 (PM) peak

Time (PM)	Link ID	SND 04/05	SND 04/06	SND 04/07	SND 04/08	SND 04/12	SND 04/13	SND 04/14	SND 04/19	SND 04/21	SND 04/22
3:59:01	1034	1.03	-0.47	0.79	0.01	-2.21	0.79	-0.05	0.55	-0.71	1.51
4:04:01	1034	0.23	-0.19	0.65	-0.38	0.23	0.51	0.04	0.46	-0.38	1.17
4:09:01	1034	-0.15	1.28	-0.20	0.49	1.44	0.49	-0.15	-0.10	-0.42	1.60
4:14:01	1034	-0.33	0.94	1.00	1.75	1.35	0.42	-1.14	-0.10	-0.62	0.83
4:19:01	1034	-0.07	-2.49	0.43	1.91	-0.01	-0.40	-0.84	0.70	-0.78	0.70
4:24:01	1034	0.15	-0.71	-0.04	0.58	-0.96	0.09	-2.24	0.46	-1.08	0.95
4:29:01	1034	0.03	0.20	-0.38	0.20	-0.79	0.61	-2.35	0.32	0.55	1.07
4:34:01	1034	-0.47	0.05	-0.12	0.01	1.83	0.05	-2.73	0.09	0.14	0.66
4:39:01	1034	-0.52	0.07	0.07	0.03	1.75	-0.98	-2.66	0.07	0.70	-1.57
4:44:02	1034	0.36	-0.13	0.30	0.41	2.46	-1.05	-2.18	-0.13	0.84	-1.81
4:49:01	1034	1.47	-0.24	1.41	1.09	0.13	-1.15	0.93	-0.13	0.24	-0.29
4:54:01	1034	0.43	-1.19	1.32	0.97	-0.35	-0.17	1.03	0.91	-0.47	0.79
4:59:01	1034	-1.45	1.26	0.54	-1.09	0.72	0.12	1.26	1.50	-0.54	1.26
5:04:01	1034	-1.53	2.17	-0.21	-0.87	0.45	-1.20	-0.14	0.92	-0.94	0.65
5:09:01	1034	-0.78	2.20	-1.05	-0.30	-0.30	-1.86	-0.98	0.44	-1.39	0.37
5:14:01	1034	-0.31	1.63	-3.10	-1.12	0.29	-1.04	-1.00	0.78	-0.84	0.33
5:19:01	1034	-0.39	1.35	-2.32	-0.64	-1.63	-0.74	-0.54	0.90	-0.88	-0.29
5:24:01	1034	0.33	0.26	-0.44	-1.08	-1.29	-1.01	0.12	1.24	-2.20	0.61
5:29:01	1034	0.47	0.21	0.01	-1.07	-1.17	-0.66	0.52	-0.50	-1.33	0.57
5:34:01	1034	0.27	0.15	-0.47	-1.21	-1.55	-0.93	0.10	-0.59	-0.30	0.27
5:39:01	1034	-0.36	0.05	-2.09	-0.87	-0.72	-0.21	-0.01	-0.01	-0.72	1.17
5:44:01	1034	0.12	-0.14	-1.79	-0.27	-1.84	-0.27	-0.70	0.43	-0.23	-0.97
5:49:01	1034	0.44	-0.47	0.07	-1.30	0.82	0.07	-0.92	1.52	-0.05	-2.83
5:54:01	1034	0.33	-0.37	0.33	-2.32	1.12	0.93	-1.16	1.16	-0.97	-1.30

Note: Critical SND values are shown in pink; incidents from the ASAP database (highlighted with grey) superimposed over the SND values.

4.2 Travel Time Analysis

Travel time was analyzed in the same way as travel speed. The travel times were obtained from truck GPS records by dividing the length of the link by the speed on that link at that time. The travel times represent the time taken to travel through a particular link (in seconds), at a specific time of the day and a particular day of the year. These travel times were averaged over 5 minutes in a similar fashion to the speed analysis, to smooth out any anomalies in the data.

The AM travel times and PM travel times for each direction were tabulated in separate excel sheets resulting in two additional 3,456 by 43 matrices. If the observed travel time was greater than the average link travel time by a specified threshold value, then the difference between the two was considered the average link delay (in seconds). By dividing the link delays by the link length we can obtain average link delays per unit length (in seconds/mile) and compare those to threshold values to determine delay presence. Furthermore, the link delays can be considered as the non-recurrent congestion delay for the links that have speeds with SND less than a threshold value.

From the link delay, we then calculated the total average delay as the sum of all delay values in the delay table over the three months, for a specific 5-min time slot and location. The results helped us determine if and when congestion appears on each link and then use the information to identify links that experience the most severe congestion and the times it occurs.

5. Results and Discussion

5.1 Results of the Sensitivity Analysis for SND Threshold

The SND values were calculated for eleven data collection days in the month of April 2010, and different threshold SND values were considered to determine incident detection rates based on the threshold value. According to Equation 1, the higher absolute value of SND threshold implies a larger speed drop required to trigger the detection of non-recurrent congestion. The results of the analysis are summarized in Table 12 below. It can be seen that the detection rate for a threshold of -1.5 was 88.0% for incidents resulting in a lane closure but dropped to 76.0% if a threshold value of -1.7 or -1.9 was used. No improvement in the detection rate was observed if a 1.3 threshold value was used (instead of -1.5). The -1.5 threshold appears to be a reasonable choice for our corridor.

Table 12. Sensitivity of SND Threshold

SND Threshold Value	-1.3	-1.5	-1.7	-1.9
	AM			
Actual number of incidents	14	14	14	14
Incidents confirmed	12	12	10	10
Detection rate (%)	85.71	85.71	71.43	71.43
	PM			
Actual number of incidents	11	11	11	11
Incidents confirmed	10	10	9	9
Detection rate (%)	90.10	90.10	81.80	81.80
	Total			
Actual number of incidents	25	25	25	25
Incidents confirmed	22	22	19	19
Detection Rate (%)	**88.00**	**88.00**	**76.00**	**76.00**

5.2 Results of the Speed Analysis

The comparison of SND results and ASAP data showed that, for the most part, the SND method was suitable for identifying the congestion associated with lane-closure incidents, as the SND values reported were above the threshold value of -1.5 and thus identified incident occurrence and the presence of non-recurrent congestion.

However, in some instances incidents listed in ASAP service logs were not confirmed by the SND methodology. A likely reason is that the incident might have caused very little to no congestion due to its type (e.g., vehicle breakdowns or debris on the shoulder) or due to the fact that enough reserve capacity was available to absorb the impacts of a minor incident without any disturbance to traffic operations. An in-depth analysis was performed excluding minor incidents, i.e. those that did not include any lane closures. As part of this analysis, a total of 25 incidents recorded in April 2010 (20 resulting in 1-lane closure and 5 resulting in 2-lane closures) were considered in detail. The results are summarized in Table 13. Note that periods with significant GPS data errors were removed (i.e., 4/12/10 AM, 4/15/10 PM, and 4/20/10 PM).

Table 13. Analysis of incidents resulting in lane closures (April 2010)

			NB		SB	
			Lanes Closed		Lanes Closed	
			1	2 or more	1	2 or more
			Incidents		Incidents	
			Actual (Matched)	Actual (Matched)	Actual (Matched)	Actual (Matched)
4/5/2010	Mo	AM	1(1)	-	1(0)	-
4/6/2010	Tu	AM	1(1)	-	-	-
4/7/2010	We	AM	1(0)	-	1(1)	-
4/8/2010	Th	AM	1(1)	-	3(3)	-
4/13/2010	Tu	AM	-	-	-	-
4/14/2010	We	AM	-	-	-	-
4/15/2010	Th	AM	-	-	-	-
4/19/2010	Mo	AM	-	-	-	-
4/20/2010	Tu	AM	1(1)	3(3)	-	-
4/21/2010	We	AM	-	-	-	-
4/22/2010	Th	AM	-	-	1(1)	-
4/5/2010	Mo	PM	-	-	2(2)	1(1)
4/6/2010	Tu	PM	-	-	1(1)	-
4/7/2010	We	PM	-	-	2(2)	-
4/8/2010	Th	PM	-	-	-	-
4/12/2010	Mo	PM	-	-	1(0)	-
4/13/2010	Tu	PM	-	-	-	-
4/14/2010	We	PM	-	-	-	-
4/19/2010	Mo	PM	-	-	-	-
4/21/2010	We	PM	1(1)	-	1(1)	1(1)
4/22/2010	Th	PM	-	-	1(1)	-
Total			6(5)	3(3)	14(12)	2(2)
Detection Rate (%)			83.30	100.00	85.71	100.00
Total incidents detected			25(22) → 88.00%			

The findings in Table 13 clearly show that the method was able to detect congestion resulting from a lane closure 88.0% of the time (or 22 out of 25 incidents). The detection rate for 1-lane closure incidents was 85.0% (17 out of 20 incidents detected) and for 2-lane closures was 100% (5 out of 5). These results are very encouraging and show that the method holds promise for identifying incident-induced congestion. The incidents with 1-lane closures that went undetected are listed in Table 14 below. During the AM peak there is heavy traffic in the NB direction from the Shelby/Jefferson County line to the downtown Birmingham area, and in the SB direction for the corridor between US-31 (north of downtown) and the downtown area (inbound). During the PM peak there is heavy traffic in the opposite directions (outbound). The first incident listed below was during a low traffic period and hence went undetected even with a lane closure (the roadway had enough capacity to handle the traffic at that time with a lane closed). The second lane closure incident went undetected mostly because it was cleared very quickly, resulting in no congestion. Although the third incident occurred during heavy traffic, it went undetected and the reasons are not clear, although it may have also been cleared before significant congestion could occur.

Table 14. Incidents not detected by the SND methodology (April 2010)

Day	AM/PM	Direction	Incident Time	Milepost	In the peak direction?
04/05/2010	AM	SB	8:20AM – 8:30 AM	259	No
04/07/2010	AM	NB	8:43 AM – 8:44 AM	259	Yes
04/12/2010	PM	SB	5:25PM – 5:30 PM	260	Yes

Furthermore, the SND values were used to study the intensity as well as the extent of congestion in space and time for all study dates in April 2010 that also had ASAP incident reports. The results are reported in a series of color coded time-space diagrams displayed in Figures 8 through 31. The actual incidents reported through ASAP are also shown, and the number of lane closures resulting from the incident is denoted.

Inspection of Figures 8 through 31 provides useful information regarding the number of downstream links that are affected by an incident, the intensity of incident-induced congestion, and the time that it takes the congestion to clear from the affected links. Also, likely secondary incidents can be identified, as is the case in Figure 15. The space time analysis also showed the congestion caused in the opposing direction when there was a major incident in one direction. An example can be identified through the observation of Figures 20 and 21. Overall, the time-space diagram analysis demonstrates another useful application of the SND method toward quantifying incident-induced congestion.

SND>-4.5	-4.5<SND<-4.0	-4.0<SND<-3.5	-3.5<SND<-3.0	-3.0<SND<-2.5	-2.5<SND<-2.0	-2.0<SND<-1.5

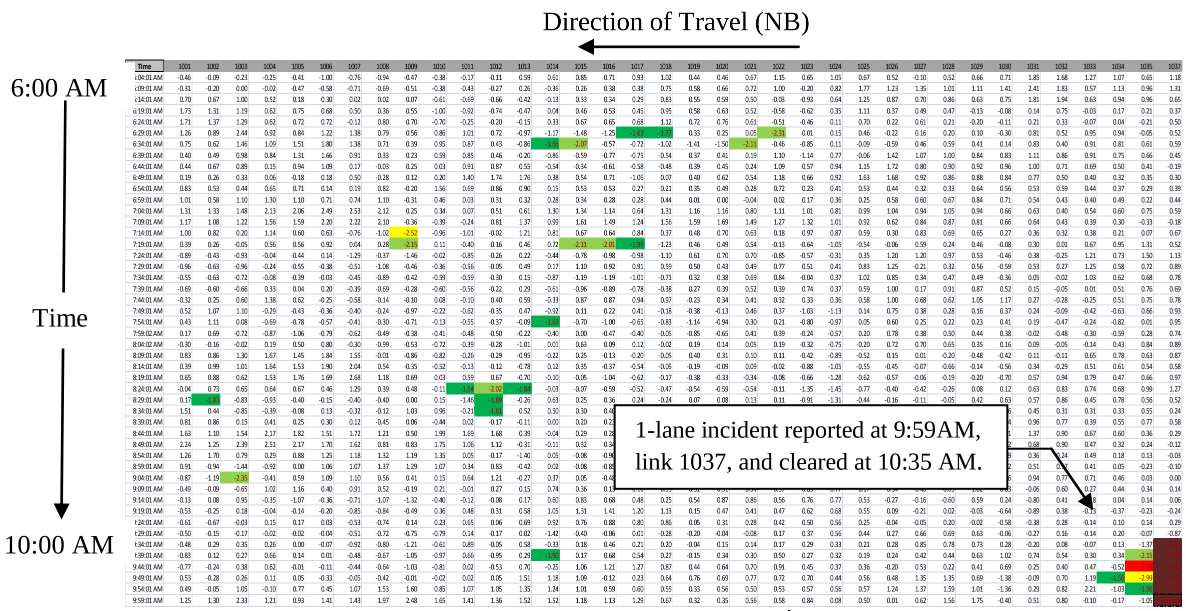


Figure 8. Time-Space Diagram, Monday, April 5th, 2010 AM (NB)
(One 1-lane incident: matched)

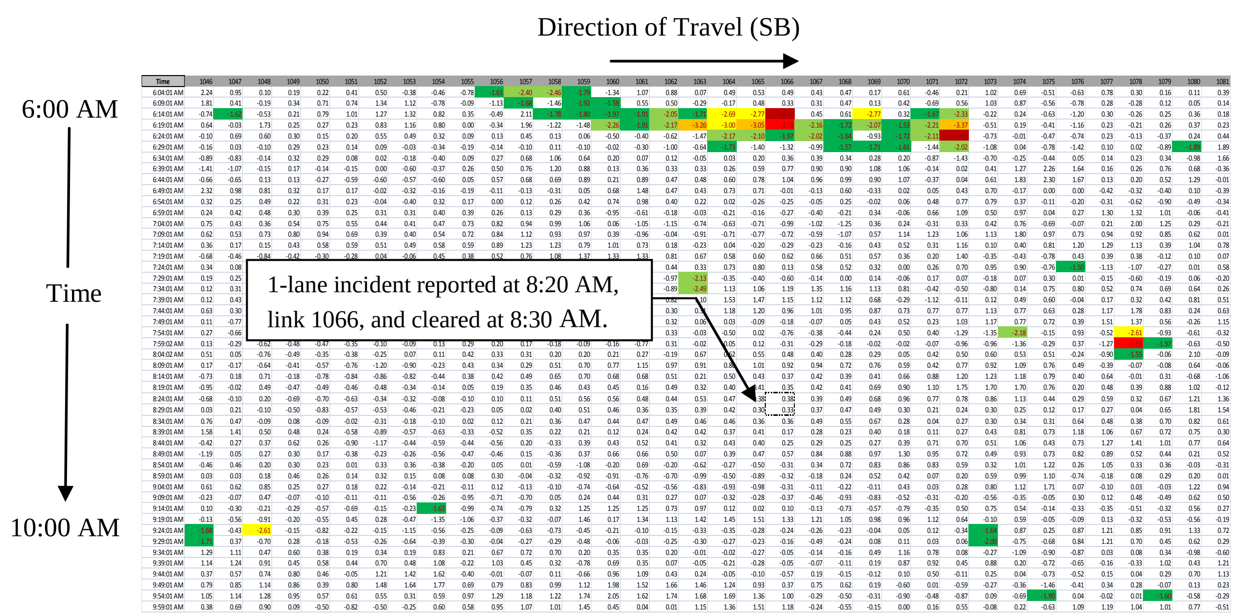


Figure 9. Time-Space Diagram, Monday, April 5th, 2010 AM (SB)
(One 1-lane incident: missed)

SND>-4.5	-4.5<SND<-4.0	-4.0<SND<-3.5	-3.5<SND<-3.0	-3.0<SND<-2.5	-2.5<SND<-2.0	-2.0<SND<-1.5

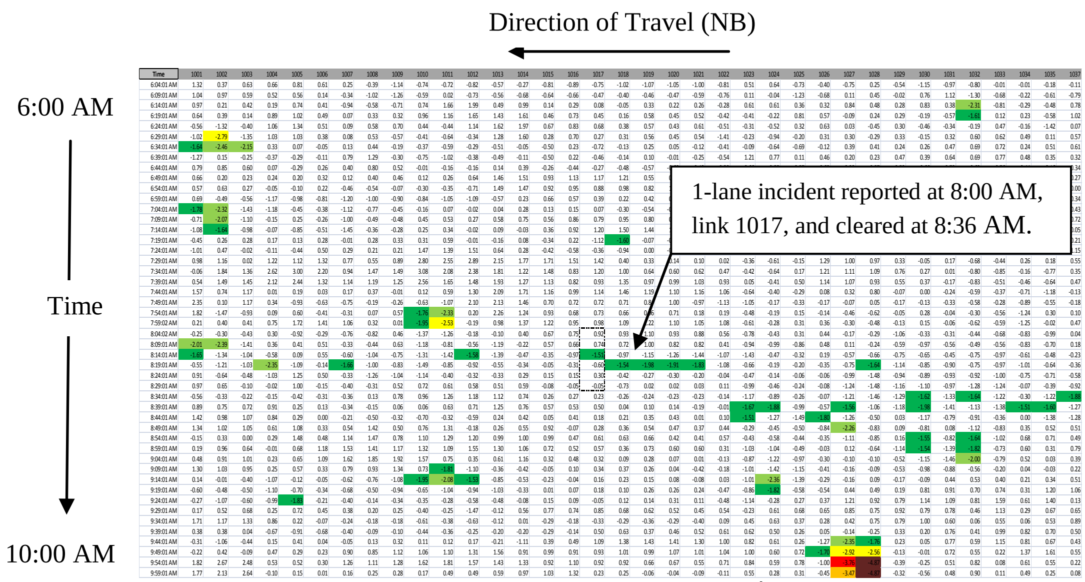


Figure 10. Time-Space Diagram, Tuesday, April 6th, 2010 AM (NB) (1-lane incident: matched)

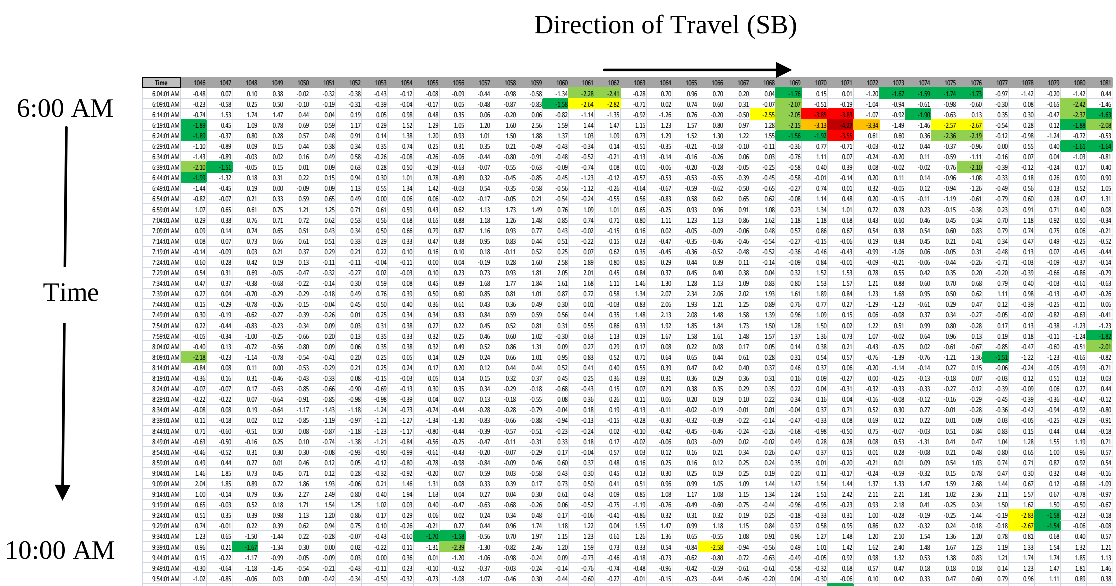


Figure 11. Time-Space Diagram, Tuesday, April 6th, 2010 AM (SB)

SND>-4.5	-4.5<SND<-4.0	-4.0<SND<-3.5	-3.5<SND<-3.0	-3.0<SND<-2.5	-2.5<SND<-2.0	-2.0<SND<-1.5

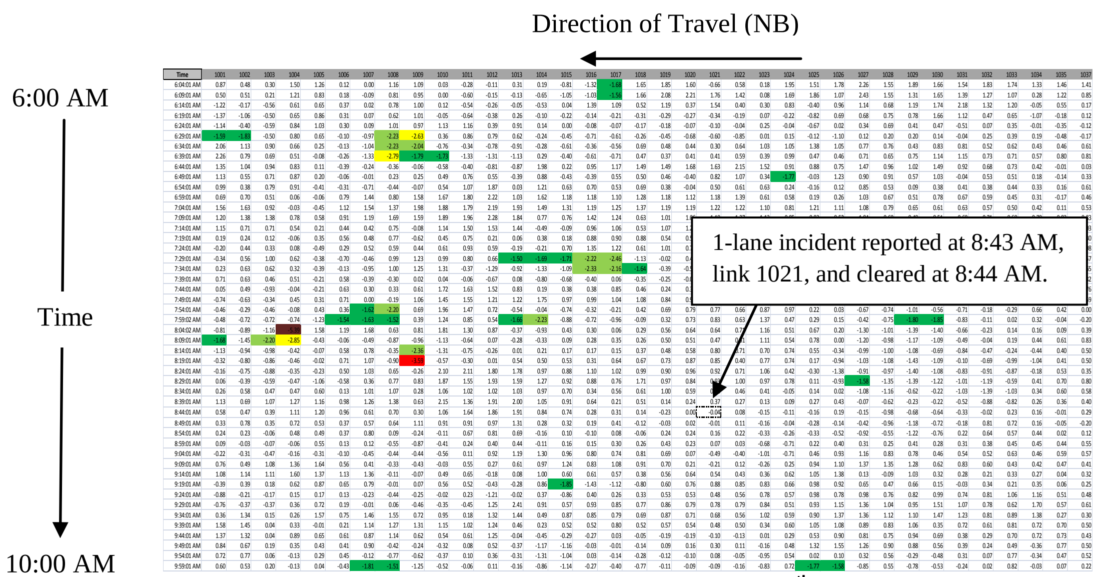


Figure 12. Time-Space Diagram, Wednesday, April 7th, 2010 AM (NB) (1-lane incident: missed)

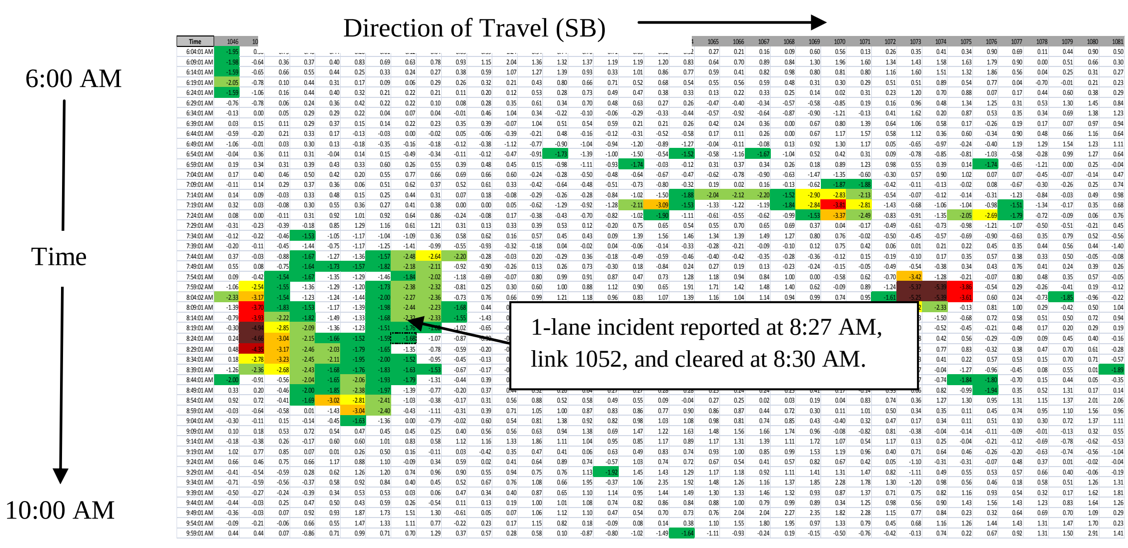


Figure 13. Time-Space Diagram, Wednesday, April 7th, 2010 AM (SB) (1-lane incident: matched)

SND>-4.5	-4.5<SND<-4.0	-4.0<SND<-3.5	-3.5<SND<-3.0	-3.0<SND<-2.5	-2.5<SND<-2.0	-2.0<SND<-1.5

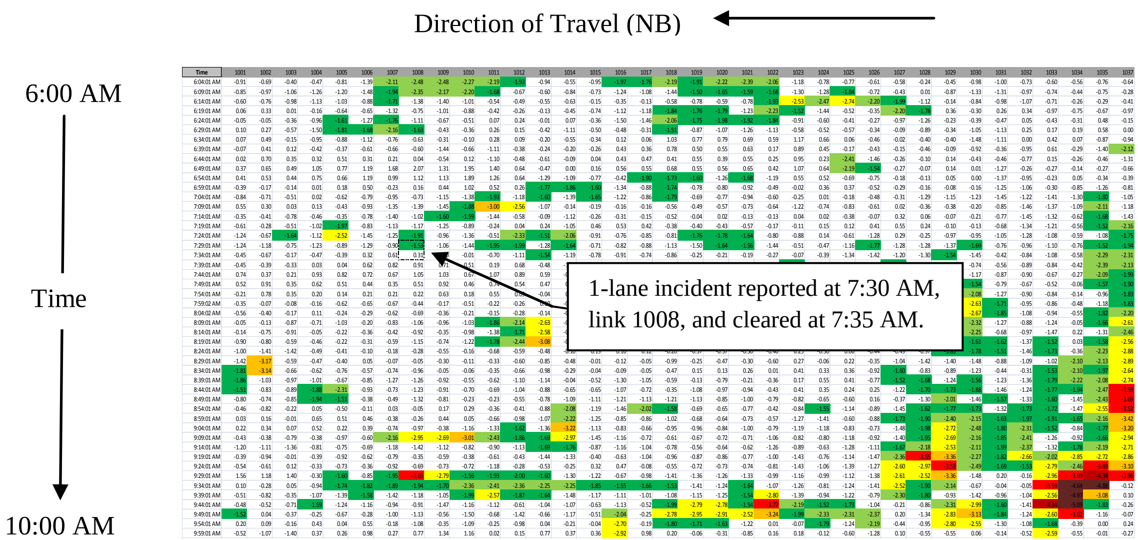


Figure 14. Time-Space Diagram, Thursday, April 8th, 2010 AM (NB) (1-lane incident matched)

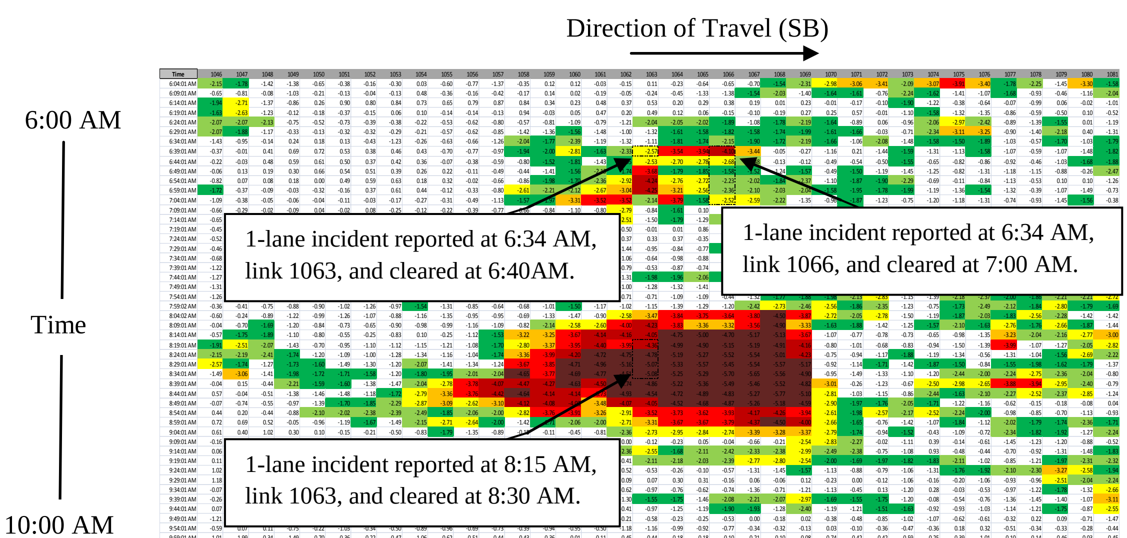


Figure 15. Time-Space Diagram, Thursday, April 8th, 2010 AM (SB) (Three 1-lane incidents matched)

SND>-4.5	-4.5<SND<-4.0	-4.0<SND<-3.5	-3.5<SND<-3.0	-3.0<SND<-2.5	-2.5<SND<-2.0	-2.0<SND<-1.5

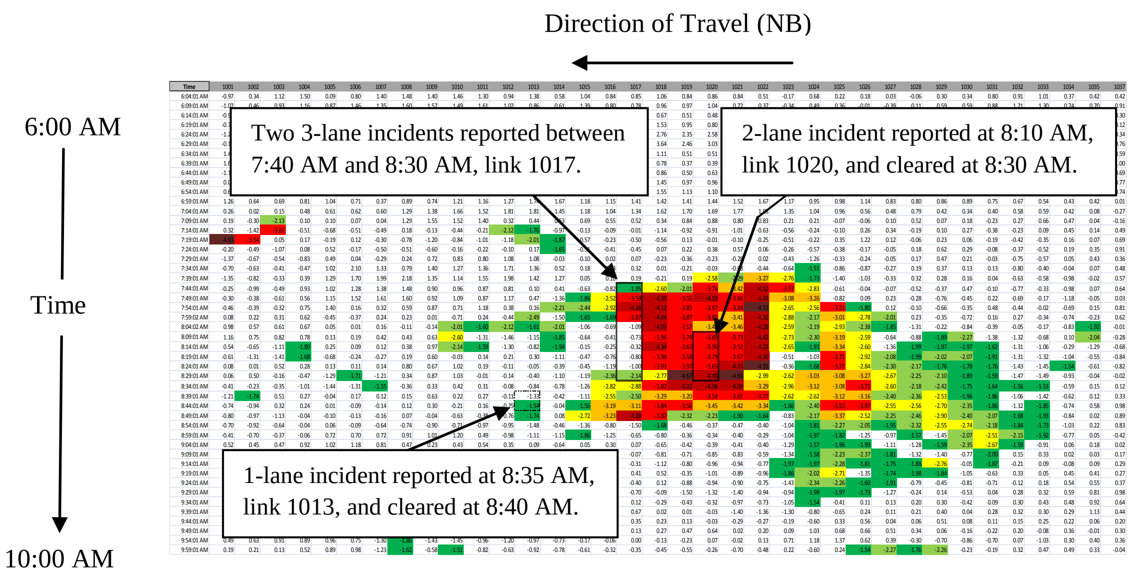


Figure 16. Time-Space Diagram, Tuesday, April 20th, 2010 AM (NB) (1-lane incident matched and three 2-lane (or more) incidents matched)

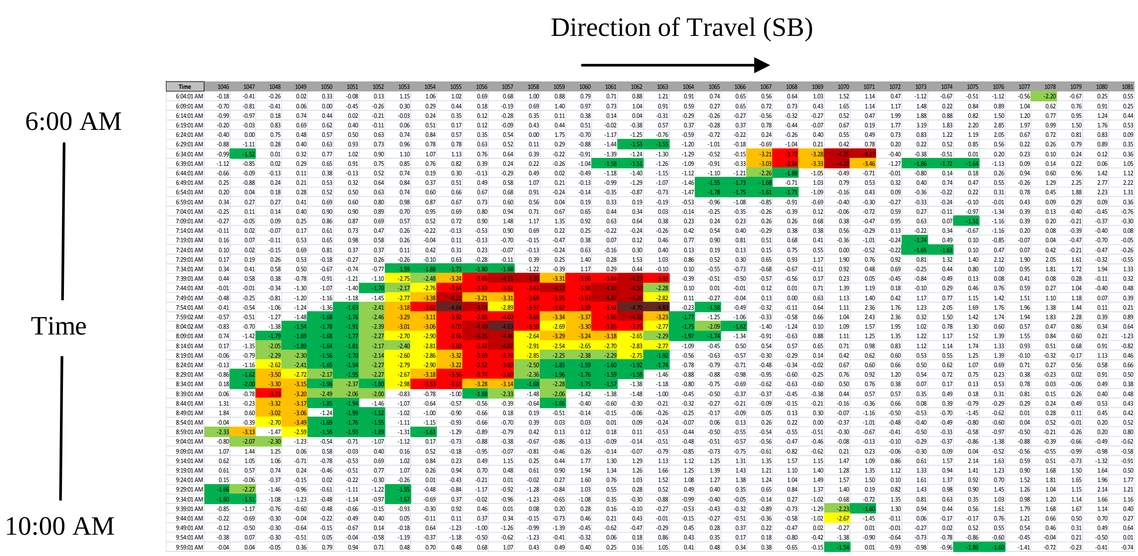


Figure 17. Time-Space Diagram, Tuesday, April 20th, 2010 AM (SB)

SND>-4.5	-4.5<SND<-4.0	-4.0<SND<-3.5	-3.5<SND<-3.0	-3.0<SND<-2.5	-2.5<SND<-2.0	-2.0<SND<-1.5

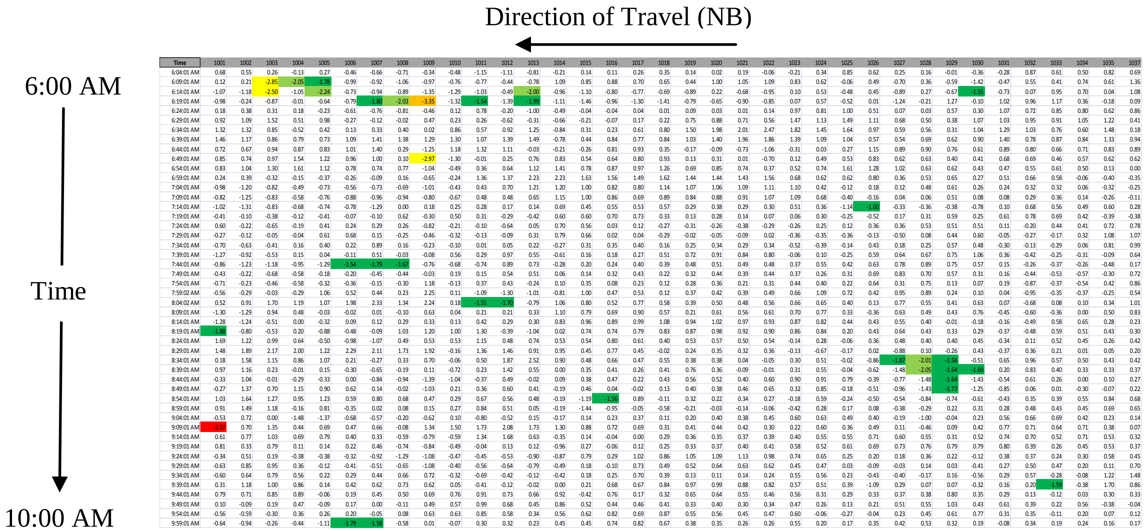


Figure 18. Time-Space Diagram, Thursday, April 22nd, 2010 AM (NB)

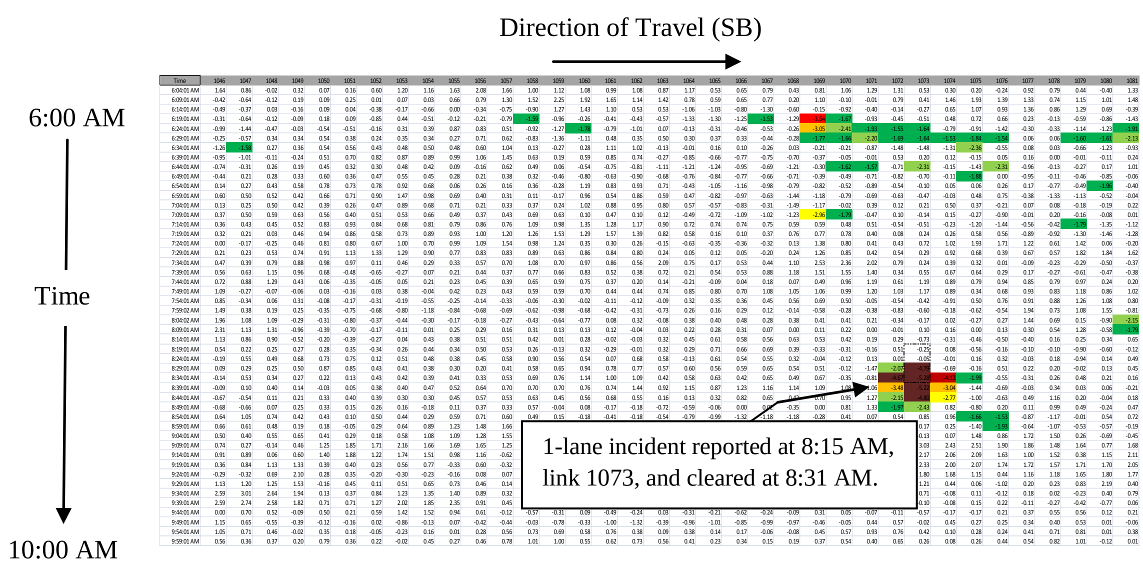


Figure 19. Time-Space Diagram, Thursday, April 22nd, 2010 AM (SB) (1-lane incident matched)

SND>-4.5	-4.5<SND<-4.0	-4.0<SND<-3.5	-3.5<SND<-3.0	-3.0<SND<-2.5	-2.5<SND<-2.0	-2.0<SND<-1.5

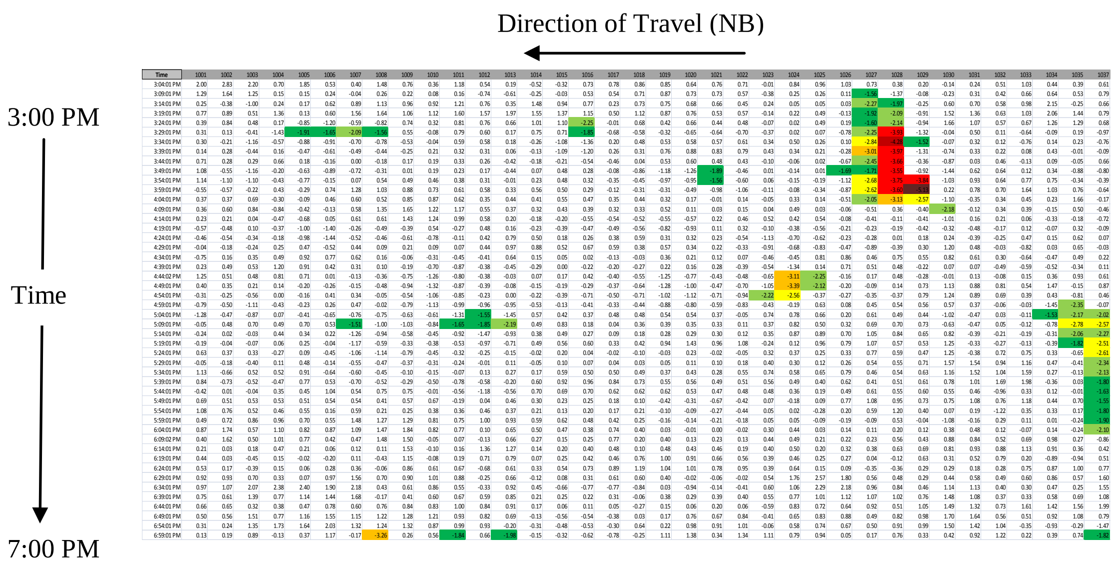


Figure 20. Time-Space Diagram, Monday, April 5th, 2010 PM (NB)

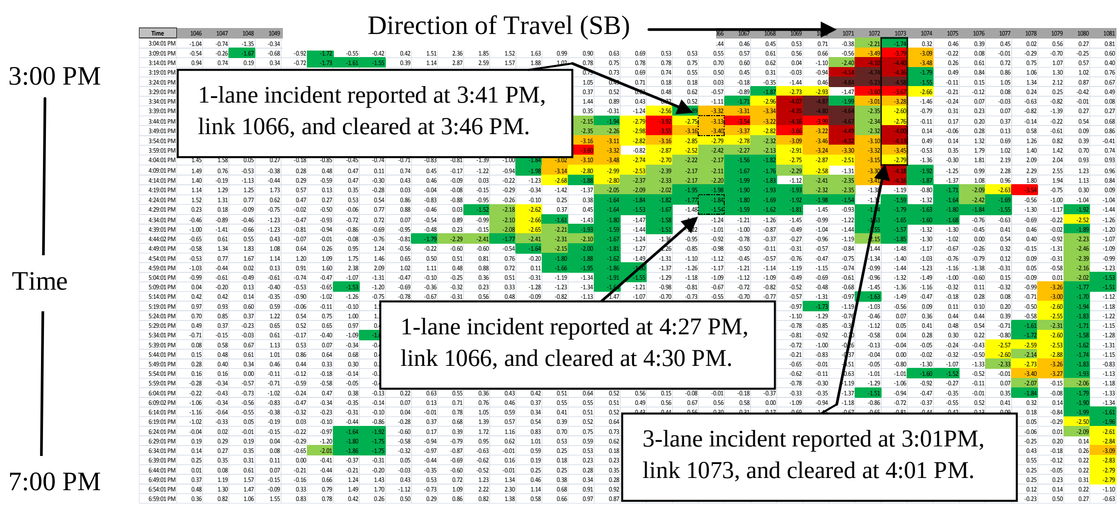


Figure 21. Time-Space Diagram, Monday, April 5th, 2010 PM (SB)
(Two 1-lane incidents matched and one 2-lane (or more) incident matched)

SND>-4.5	-4.5<SND<-4.0	-4.0<SND<-3.5	-3.5<SND<-3.0	-3.0<SND<-2.5	-2.5<SND<-2.0	-2.0<SND<-1.5

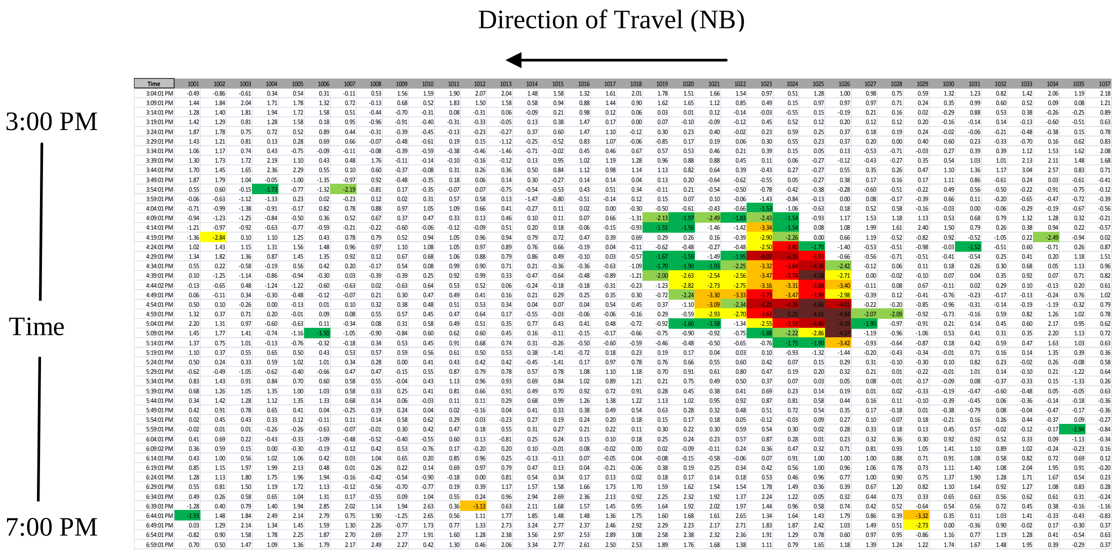


Figure 22. Time-Space Diagram, Tuesday, April 6th, 2010 PM (NB) (1-lane incident matched)

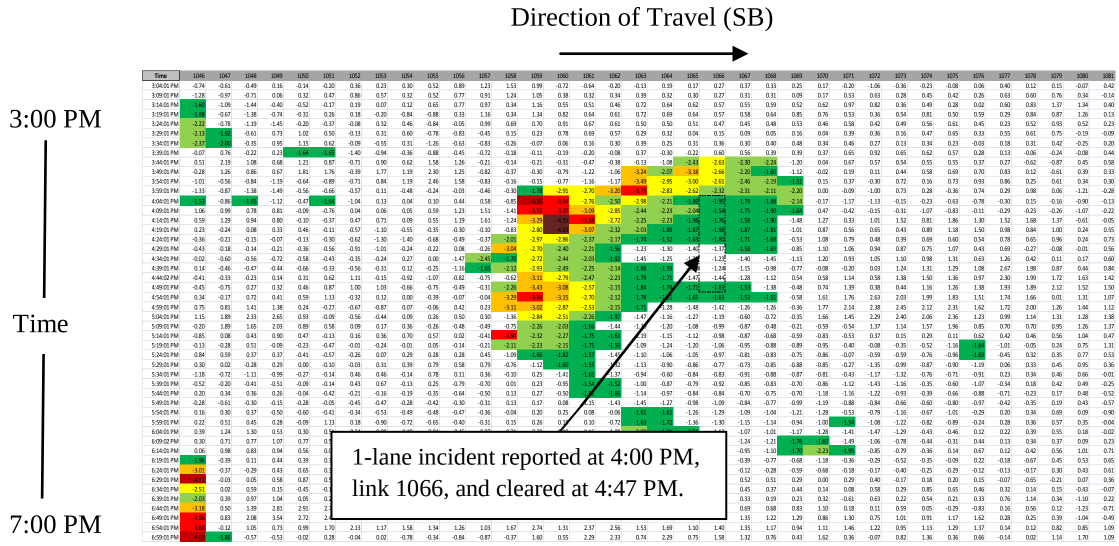


Figure 23. Time-Space Diagram, Tuesday, April 6th, 2010 PM (SB) (1-lane incident matched)

SND>-4.5	-4.5<SND<-4.0	-4.0<SND<-3.5	-3.5<SND<-3.0	-3.0<SND<-2.5	-2.5<SND<-2.0	-2.0<SND<-1.5

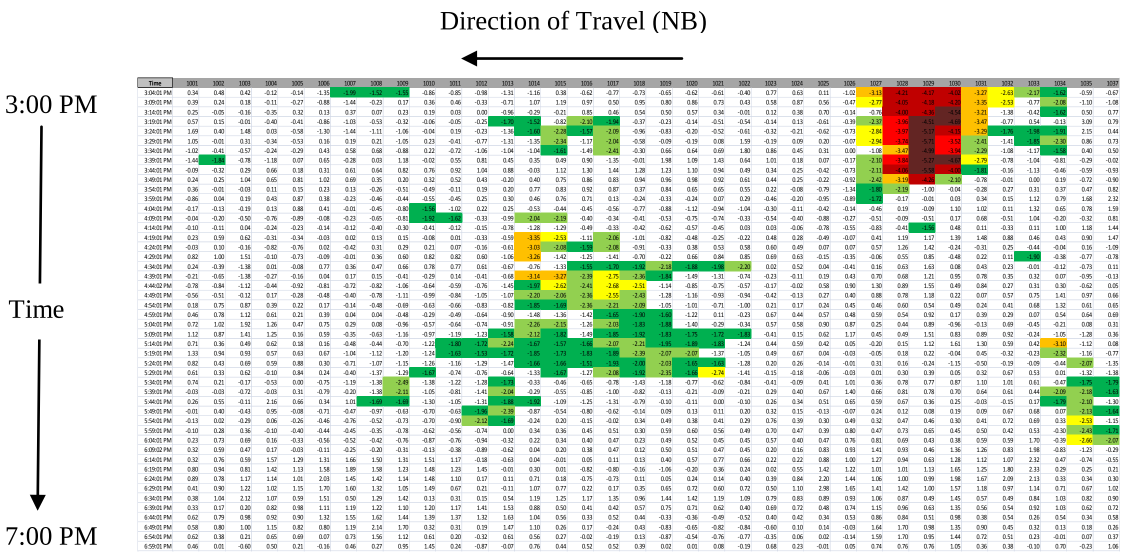


Figure 24. Time-Space Diagram, Wednesday, April 7th, 2010 PM (NB) (Two 1-lane incidents matched)

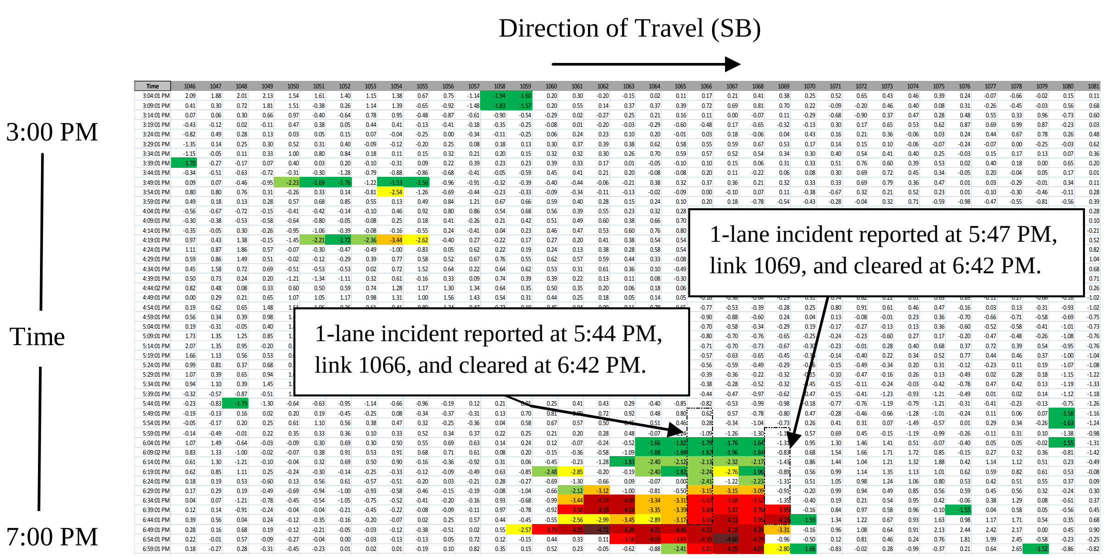


Figure 25. Time-Space Diagram, Wednesday, April 7th, 2010 PM (SB) (Two 1-lane incidents matched)

SND>-4.5	-4.5<SND<-4.0	-4.0<SND<-3.5	-3.5<SND<-3.0	-3.0<SND<-2.5	-2.5<SND<-2.0	-2.0<SND<-1.5

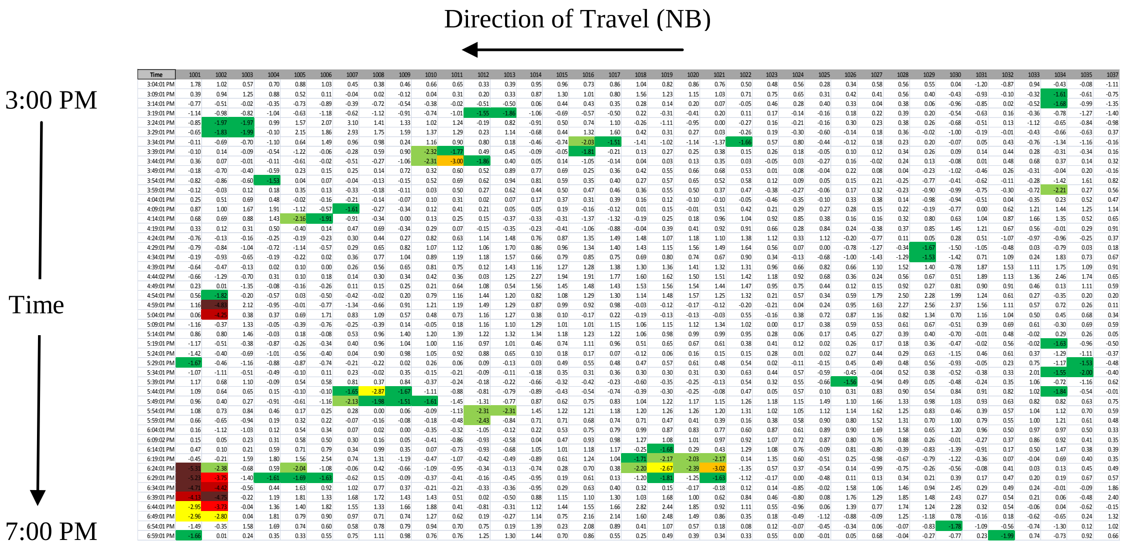


Figure 26. Time-Space Diagram, Monday, April 12th, 2010 PM (NB)

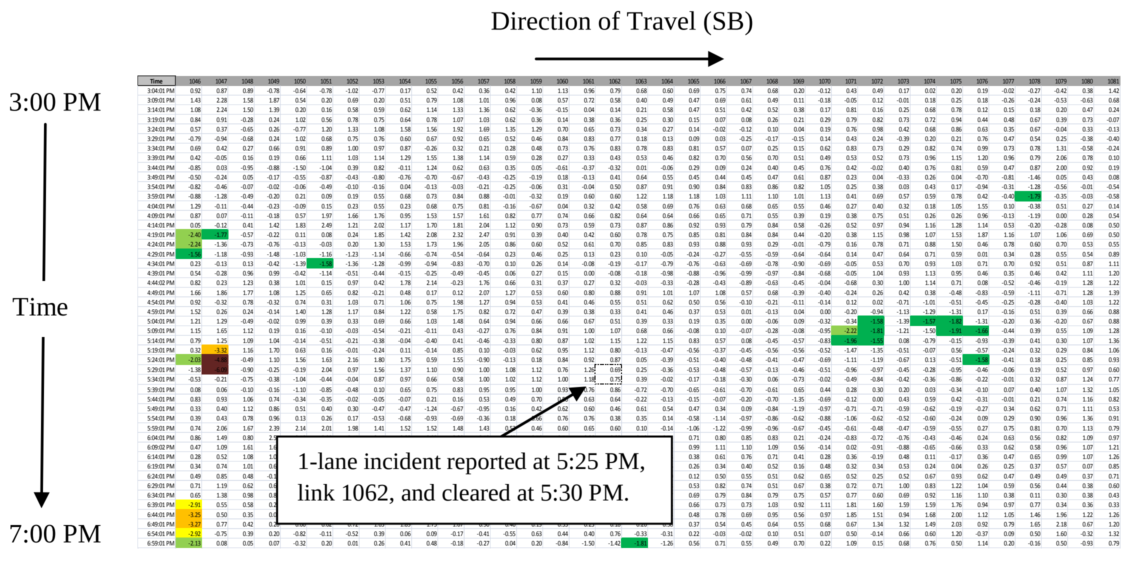


Figure 27. Time-Space Diagram, Monday, April 12th, 2010 PM (SB)
(1-lane incident missed)

SND>-4.5	-4.5<SND<-4.0	-4.0<SND<-3.5	-3.5<SND<-3.0	-3.0<SND<-2.5	-2.5<SND<-2.0	-2.0<SND<-1.5

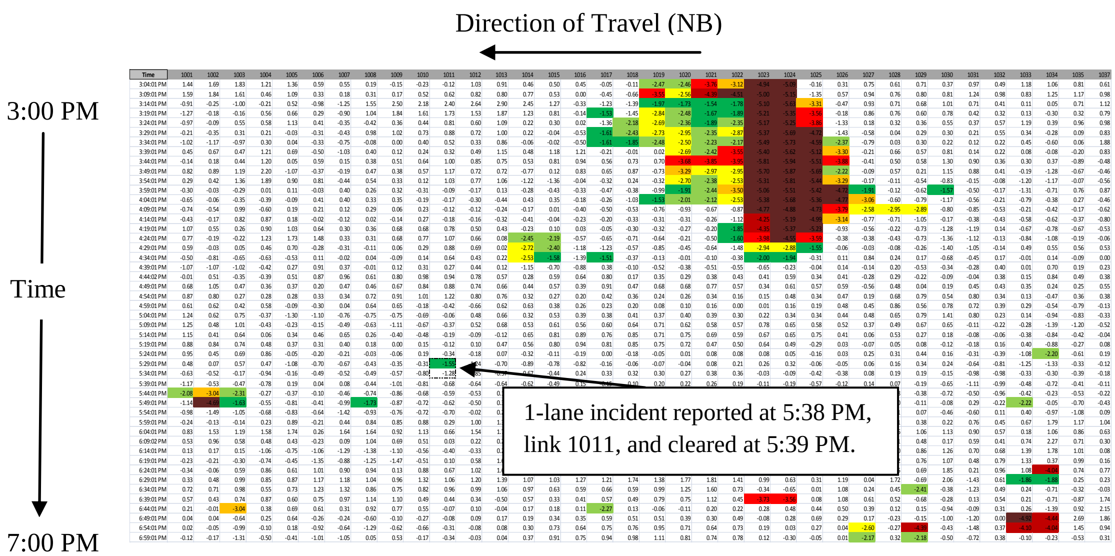


Figure 28. Time-Space Diagram, Wednesday, April 21st, 2010 PM (NB) (1-lane incident matched)

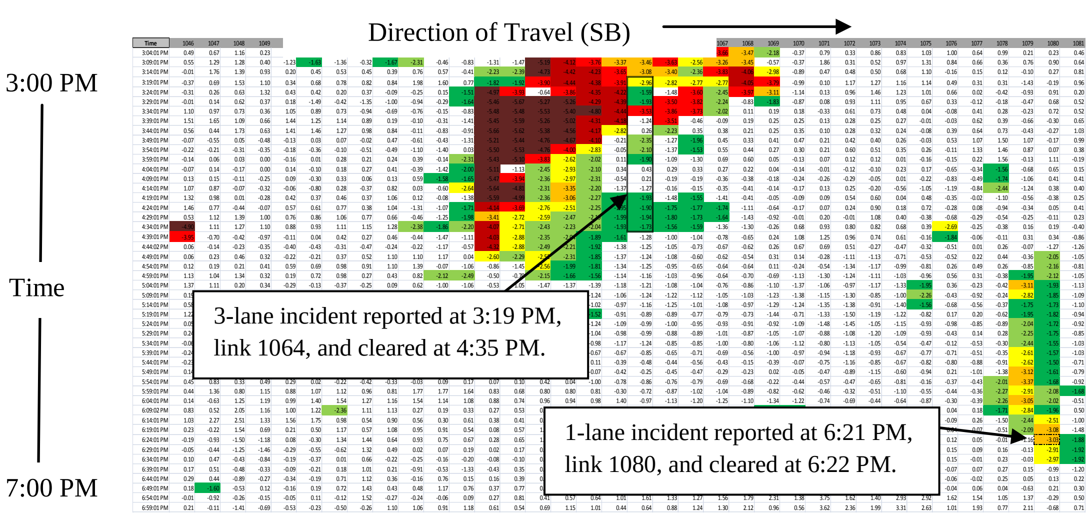


Figure 29. Time-Space Diagram, Wednesday, April 21st, 2010 PM (SB) (1-lane incident and 2-lane (or more) incident matched)

SND>-4.5	-4.5<SND<-4.0	-4.0<SND<-3.5	-3.5<SND<-3.0	-3.0<SND<-2.5	-2.5<SND<-2.0	-2.0<SND<-1.5

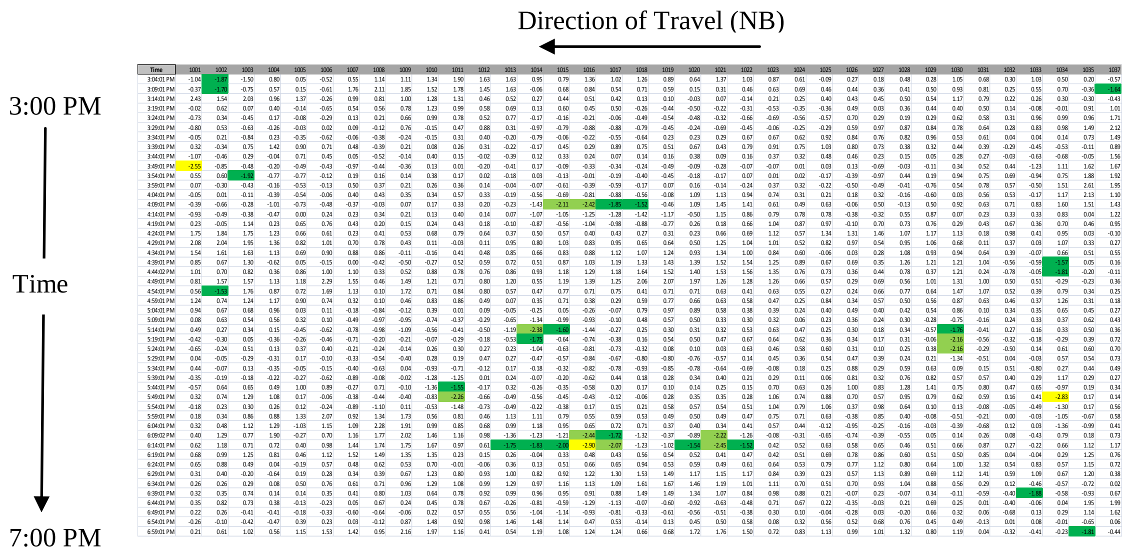


Figure 30. Time-Space Diagram, Thursday, April 22nd, 2010 PM (NB)

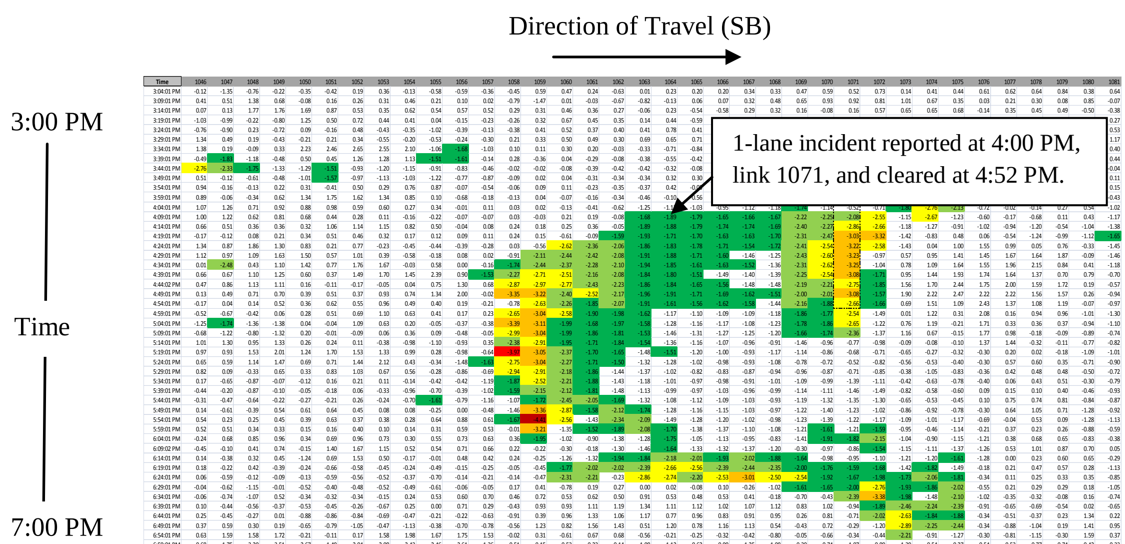


Figure 31. Time-Space Diagram, Thursday, April 22nd, 2010 PM (SB) (1-lane incident matched)

5.3 Results of the Travel Time Analysis

The travel times obtained in this study were used to determine average delays on selected links. The analysis of records considered the entire data base representing 3 months of typical day AM and PM peak periods. Here, some links were selected for demonstration purposes and link delays were plotted and interpreted.

Example 1. Link 1001 was selected and non-recurrent delays plotted for the 6:00 AM time period over the course of all 43 days of GPS data. The delay is plotted on the vertical axis and is expressed in seconds. The horizontal axis shows the 43 days of data collection. It can be easily observed that link delays are negligible (less than 2.5 sec) for link 1001 during this early morning period, as would be expected.

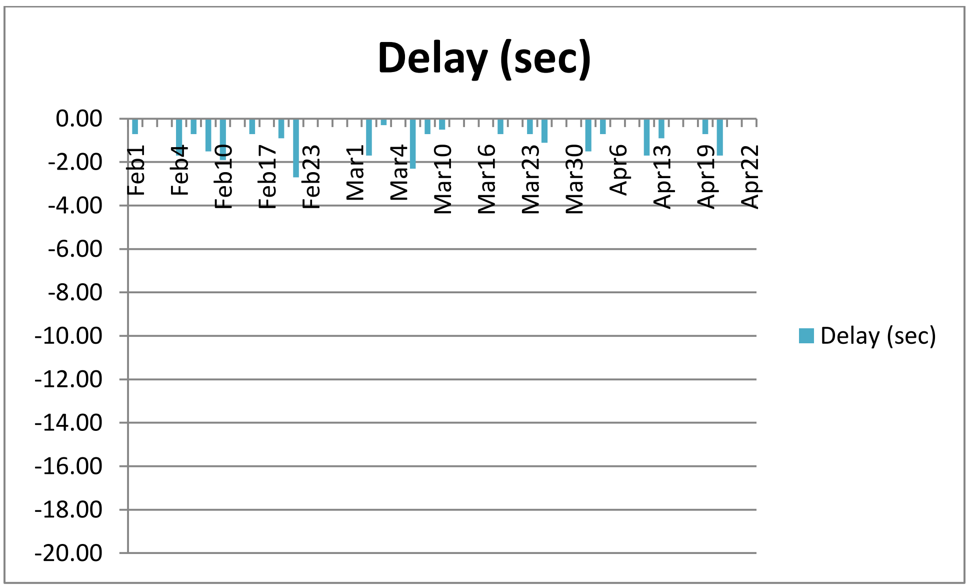


Figure 32. Delay on different days over the three months for link 1001 at 6:00 AM

Example 2. Link 1031, a link with known non-recurrent congestion presence on some days, as selected and link delays (in secs) were plotted for 8:20 AM as shown in Figure 33.

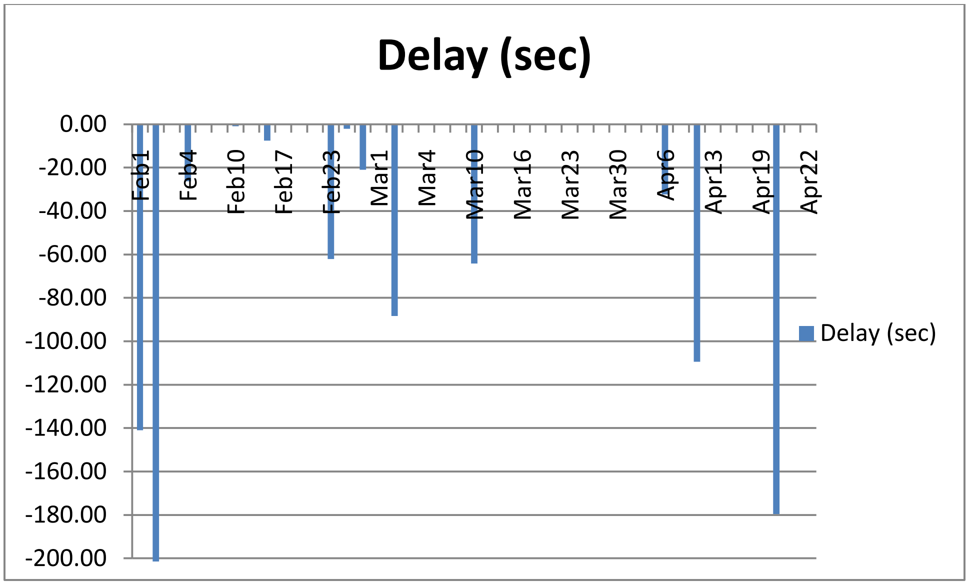


Figure33. Delay on different days over the three months for link 1031 at 8:20 AM

The plot shows abnormally high delays were observed on link 1031 on selected days at that time of day (8:20AM) which are indicative of presence of non-recurrent congestion. Some of these delays ranged from 60 sec/veh to 200/veh sec for the link.

To calculate the total non-recurrent congestion delay for each link at a particular time, we summed all the negative values in the delay table which have corresponding speed SNDs < -1.5 as shown in Table 15. As we repeated this procedure for each link, we identified the times of the day that each link experienced the highest delays. For instance, for link 1001 (Figure 34), total delay varied from 2 to 25 seconds, whereas for link 1031 (Figure 35) total delay varied from 20 to 1005 seconds and becomes maximum during 8:20 AM and 8:50 AM time intervals.

Table 15. Total delay over the study period, Link 1001 (6:04-6:44 AM).

	Link 1001 Delays									
Time (AM)	02/01	02/02	---	03/01	03/02	---	04/05	04/06	---	Total Delay
6:04										-2.71
6:09										-9.83
6:14										-19.07
6:19										-21.36
6:24										-19.23
6:29										-19.12
6:34		-2.83						-3.03		-5.86
6:39										-2.24
6:44		-3.26								-9.17

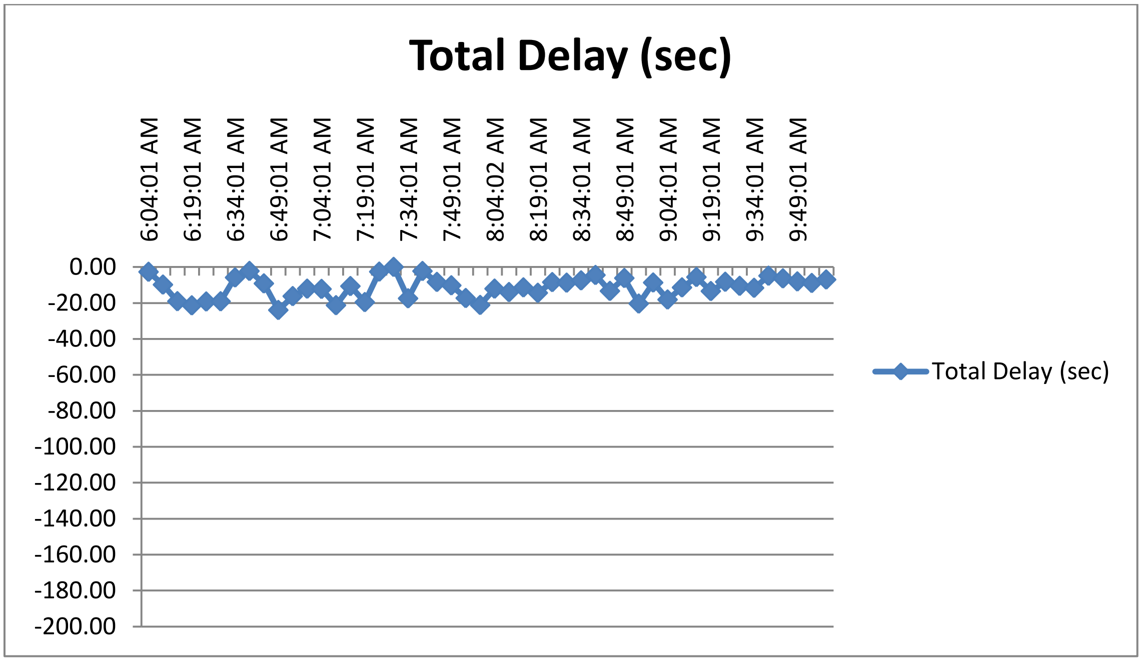


Figure 34. Total delay for Link 1001 over the study period (AM)

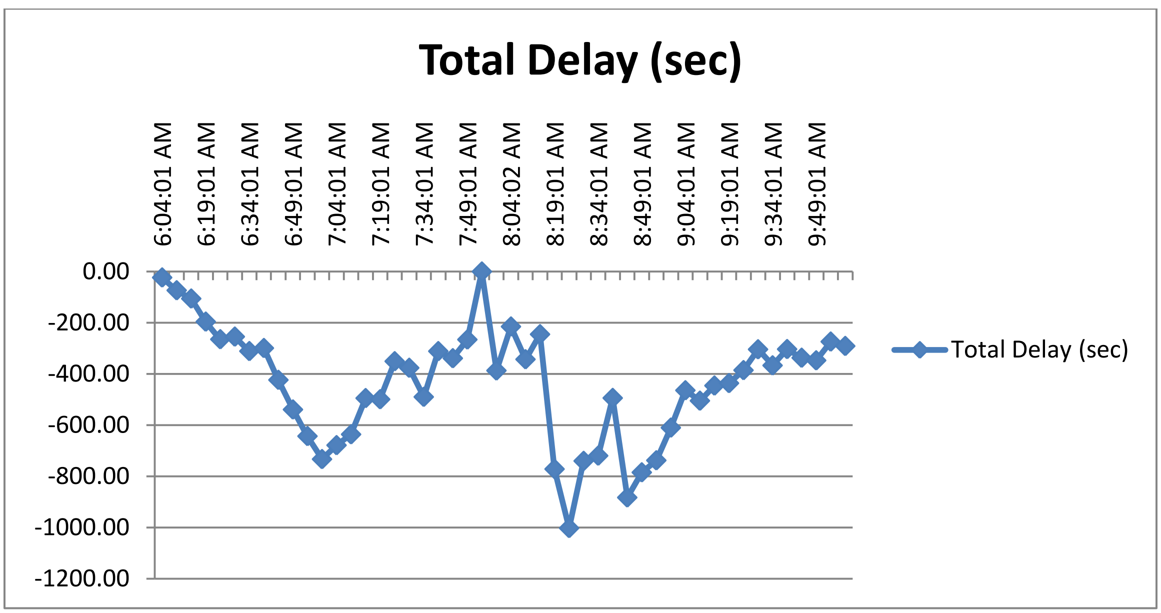


Figure 35. Total delay for Link 1031 over the study period (AM)

Further analysis of the remaining AM records shows that severe non-recurrent congestion was found at the links 1031, 1033, and 1049 at various times. Table 16 shows the times at which the links had the most amount of non-recurrent congestion (i.e., data with total delay more than

750 seconds over the three months was considered as the cut-off point). In a similar fashion the PM records were analyzed, and the links 1069, 1079, and 1080 experienced the most severe non-recurrent congestion (total delay more than 600 seconds) during the PM peak (Table 17). The findings can be used by transportation agencies to better understand congestion patterns and potential contributing factors on those links and consider countermeasures to address them.

Table 16. Links with severe non-recurrent congestion (AM)

Time	LinkID	Total Delay
8:19:01 AM	1031	-771.65
8:24:01 AM	1031	-1002.53
8:44:01 AM	1031	-882.93
8:49:01 AM	1031	-784.78
6:49:01 AM	1033	-894.58
6:59:01 AM	1033	-815.30
7:04:01 AM	1033	-941.45
7:09:01 AM	1033	-968.17
7:14:01 AM	1033	-955.92
8:24:01 AM	1033	-1153.33
8:29:01 AM	1033	-1169.73
8:34:01 AM	1033	-1207.56
8:39:01 AM	1033	-1039.73
8:44:01 AM	1033	-1094.75
8:49:01 AM	1033	-1086.36
8:54:01 AM	1033	-1085.11
8:59:01 AM	1033	-846.07
8:34:01 AM	1034	-897.94
8:39:01 AM	1034	-893.80
7:54:01 AM	1035	-857.08
7:54:01 AM	1037	-931.60
7:59:02 AM	1037	-806.96
7:04:01 AM	1047	-856.92
7:09:01 AM	1047	-833.13
6:34:01 AM	1049	-1054.74
6:39:01 AM	1049	-1243.27
6:44:01 AM	1049	-1059.00
6:49:01 AM	1049	-1131.53
6:54:01 AM	1049	-1278.04
6:59:01 AM	1049	-1424.03
7:04:01 AM	1049	-1116.85
7:09:01 AM	1049	-779.74
7:14:01 AM	1049	-950.88
7:19:01 AM	1049	-775.93
8:19:01 AM	1049	-992.70
8:24:01 AM	1049	-1070.72
8:29:01 AM	1049	-1292.45
8:34:01 AM	1049	-1062.13
8:39:01 AM	1049	-902.13
8:44:01 AM	1049	-883.14
6:24:01 AM	1077	-1042.26
6:29:01 AM	1077	-1058.43

Table 17. Links with severe non-recurrent congestion (PM)

Time	LinkID	Total Delay
6:59:01 PM	1001	-683.48
6:04:01 PM	1025	-610.15
6:29:01 PM	1029	-618.85
3:09:01 PM	1031	-674.74
5:39:01 PM	1037	-685.00
4:24:01 PM	1063	-617.53
4:04:01 PM	1069	-632.50
4:19:01 PM	1069	-603.54
4:39:01 PM	1069	-709.16
3:49:01 PM	1071	-652.76
3:54:01 PM	1071	-636.54
5:24:01 PM	1079	-611.68
5:29:01 PM	1079	-646.84
5:34:01 PM	1079	-607.96
5:59:01 PM	1079	-603.11
5:04:01 PM	1080	-763.24
5:09:01 PM	1080	-752.88
5:14:01 PM	1080	-906.44
5:19:01 PM	1080	-976.23
5:24:01 PM	1080	-1156.91
5:29:01 PM	1080	-1289.81
5:34:01 PM	1080	-1020.98
5:39:01 PM	1080	-1163.32
5:44:01 PM	1080	-1196.63
5:49:01 PM	1080	-920.40
5:54:01 PM	1080	-796.18
6:04:01 PM	1080	-762.53
6:09:02 PM	1080	-903.94
6:14:01 PM	1080	-969.42
4:59:01 PM	1081	-618.40
5:04:01 PM	1081	-825.60
5:09:01 PM	1081	-818.43

6. Conclusions and Recommendations

This study examined methods to analyze historical speed data to identify congestion associated with vehicle incidents and measure non-recurrent congestion in a test corridor. The project investigated the effectiveness of using GPS data for identifying incidents and measuring non-recurrent congestion in locations where loop detectors or similar infrastructure based sensors are unavailable.

Fleet GPS data obtained from trucks traveling along the I-65 corridor in Birmingham, Alabama over a 3 month period were used in the analysis. The data were analyzed using the Standard Normal Deviate method which proved to be a very convenient method to use for GPS data analysis. Link speeds were aggregated over 5 minute periods, then average speeds and standard deviations were calculated using link data obtained at the same time interval over all days of observation, and then those were used to determine the Standard Normal Deviate (SND) that shows deviation from the mean. Links with a SND less than a threshold value of -1.5 indicated speeds below normal congestion levels and were therefore considered as having non-recurring congestion.

The results were verified using ASAP service records for the corridor compiled during April 2010. When minor incidents were excluded (i.e., those that did not result in lane closures) the method was able to detect congestion associated with at least 88.0% of the incidents (or 22 out of 25 incidents resulting in lane closures). The detection rate for congestion caused by1-lane closure incidents was found to be at least 85.0% (17 out of 20 incidents detected) and the detection rate for 2-lane closure incidents was 100% (5 out of 5). These results are very encouraging and show that the method holds promise for identifying incident-induced congestion. It is possible that the remaining incidents which went undetected did not result in significant congestion, meaning there was little congestion to detect, and thus the method may have detection rates even higher than those shown above.

Determining the rate at which the method detects "false positives" is more difficult, since not every incident which causes congestion generates a police or ASAP response. There were numerous cases where congestion was detected in the data that did not correspond to any known ASAP call. Such incidents could have been the result of unreported minor crashes, temporarily stalled vehicles, road construction or repair, or even weather. A more detailed study will be required to determine how effective this method is for quantifying non-recurrent congestion due to these causes and whether or not the method tends to over- or underestimate non-recurrent congestion.

Furthermore, using time-space diagrams, the SND indices were used to determine the intensity and extent of congestion over space and time. Such information is very valuable in quantifying non-recurrent congestion impacts as well as providing insights regarding the occurrence of secondary incidents and their impacts on traffic operations.

Although some valuable insights regarding the location and extent of congestion related to incidents can be gained by this work, further refinement of the procedure is needed in the future to increase its reliability and improve the detection rate. The base average data which is used for comparison can be refined further by removing data from any severe incidents from the averages. This would help to avoid the possibility of an unusually severe incident skewing the data and hindering the detection of minor incidents during the same time period on some other day. Consideration of CARE database records as a substitute for or a supplement to the ASAP records is recommended for future work.

Overall, the GPS database was easy to use and provided very useful information about speeds, travel times, and delays changes across space and time. This study concludes that GPS fleet speed data is a valuable source of information for congestion studies, and it is recommended for future use in other corridors in Birmingham and/or other small to medium-sized urban areas with limited traffic collection resources.

References

Gall A. and Hall F. (1989), "Distinguishing between Incident Congestion and Recurrent Congestion: A Proposed Logic", Transportation Research Record 1232.

Persaud N., Hall F. and Hall L. (1990), "Congestion Identification Aspects of the McMaster Incident Detection Algorithm", Transportation Research Record 1287.

Fonseca D., Moynihan G., and Fernandes H. (2011), "The Role of Non-Recurring Congestion in Massive Hurricane Evacuation Events", Recent Hurricane Research - Climate, Dynamics, and Societal Impacts.

Payne H.J., E.D. Helfenbein, and H.C. Knobel (1976), "Development and Testing of Incident Detection Algorithms": Volume 2- Research Methodology and Detailed Results, Report No. FHWA-RD-76-20, Washington, D.C., Federal Highway Administration.

Ozbay K., and Kachroo P. (1999), "Incident Management in Intelligent Transportation Systems", ISBN 978-0-89006-774-1.

Zhang K. and Taylor M. (2005), "Towards Transferable Incident Detection Algorithms": Volume 6- Journal of the Eastern Asia Society for Transportation Studies, pp. 2263 – 2274.

Young S. (2007), "Real-Time Traffic Operations Data Using Vehicle Probe Technology", 2007 Mid-Continent Transportation Research Symposium, Ames IA.

Cullip M. and Hall F. (1997), "Incident Detection on an Arterial Roadway", Transportation Research Record 1603.

Karim A. and Adeli H. (2002), "Comparison of Fuzzy-Wavelet Radial Basis Function Neural Network Freeway Incident Detection Model with California Algorithm", Journal of Transportation Engineering, Vol. 128, No. 1, January/February 2002, pp. 21-30.

Dudek, C., Messer C., and Nuckles N. (1974), "Incident Detection on Urban Freeways", *Transportation Research Record 495*, TRB, National Research Council, Washington, D.C.

Middleton D., Gopalakrishna D., and Raman M. (2003), "Advances in Traffic Data Collection and Management", Report for Office of Policy, Federal Highway Administration, Washington, D.C.

Parkany E. and Xie C. (2005), "A Complete Review of Incident Detection Algorithms & Their Deployment: What Works and What Doesn't", Report for the New England Transportation Consortium (NETCR37).

Guin A., Williams B., and Daiheng Ni. (2004), "Assessment of the Current Status of Incident Detection Algorithms: Results of a Nationwide Survey", Proceedings of the 2004 Summer Computer Simulation Conference (SCSC 2004), the Society for Modeling and Simulation International. pp. 412-417. 2004.

D'Este G., Zito R., and Taylor M. (1999), "Using GPS to Measure Traffic System Performance", Computer-Aided Civil and Infrastructure Engineering, Volume 14: 255-265.

Martin P., Perrin J., and Hansen B. (2001), "Incident Detection Algorithm Evaluation", Prepared for Utah Department of Transportation.

Hallenback M., Ishimaru J., and Nee J. (2003), "Measurement of Recurring Versus Non-Recurring Congestion: Technical Report", Washington State Transportation Center and University of Washington.

Quiroga C. and Bullock D. (1998), "Travel time studies with global positioning and geographic information systems: an integrated methodology", Transportation Research Part C (6), 101-127.

Tong D. (2004), "Deriving Transportation Information from GPS Probe Vehicle Data Integrated with a GIS", A Project for the Ohio State University.

Ryder B. (2003), "Congestion Monitoring Using GPS on Freeways and Arterials in the Baltimore Region: A Comparison of Travel Speeds in 1998 & 2002", Task Report 03-11, Baltimore Metropolitan Council.

Zito R., D'Este G., and Taylor M. (2000), "Global positioning systems in the time domain: How useful a tool for intelligent vehicle-highway systems", Transportation Research, Volume 3-Part C(4).

Skarbardonis A., Chira-Chavala T., and Rydzewski D. (1998), "The I-880 Field Experiment: Effectiveness of Incident Detection Using Cellular Phones", California PATH Research Report, UCB-ITS-PRR-98-1.

Sethi V., Bhandari F., Koppelman F., and Schofer J. (1995), "Arterial incident detection using fixed detector and probe vehicle data", Transportation Research Part C- 3(2): 99-112.

Skabardonis A., Varaiya P., and Petty K. (2003), "Measuring Recurrent and Non-Recurrent Traffic Congestion", 82nd Annual TRB Meeting, Washington, D.C.

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