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16. Abstract

This guidebook provides methodologies and procedures for using incident data collected at Texas transportation management centers (TMCs) to perform two types of analysis – evaluation/planning analysis and predictive analysis. For the evaluation/planning analysis, this guidebook provides (1) guidelines for reporting incident characteristics, (2) methods for analyzing hot spots, (3) methodologies for estimating incident impacts, and (4) guidelines and procedures for calculating performance measures. For predictive analysis, this guidebook describes (1) methodologies for predicting incident duration using incident characteristics and (2) methodologies for predicting incident-induced congestion clearance time using combined historical and real-time traffic data. Examples of applications and results from the methodologies and procedures described are provided throughout this guidebook.

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A GUIDEBOOK FOR EFFECTIVE USE OF INCIDENT DATA AT TEXAS TRANSPORTATION MANAGEMENT CENTERS

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DISCLAIMER

This research was performed in cooperation with the Texas Department of Transportation (TxDOT) and the Federal Highway Administration (FHWA). The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official view or policies of the FHWA or TxDOT. This document does not constitute a standard, specification, or regulation.

This report is not intended for construction, bidding, or permit purposes. The researcher in charge of this project was Praprut Songchitruksa.

The United States Government and the State of Texas do not endorse products or manufacturers. Trade or manufacturers' names appear herein solely because they are considered essential to the object of this report.

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TABLE OF CONTENTS

Page

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION TO THE GUIDEBOOK

The objective of this guidebook is to provide the Texas Department of Transportation (TxDOT) with methodologies and procedures on how historical incident data can be used to support and/or evaluate incident management operations at transportation management centers (TMCs). It is envisioned that each module in this guidebook can be used as a stand-alone product. However, the links between the terms and methods used across multiple modules are sometimes inevitable. Appropriate references across modules are provided where necessary.

Module 1 provides a general introduction to the use of this guidebook. In Module 2, the guidebook provides an overview of intelligent transportation system (ITS) deployment at various Texas TMCs and existing data management. This module also summarizes what data are being collected from Texas TMCs. The remaining modules in this guidebook provide methodologies and procedures for using historical data to conduct two major types of analysis:

- evaluation/planning analysis and
- predictive analysis.

The corresponding modules for each type of analysis are summarized in Table 1-1. This guidebook addresses primarily the use of incident data for various applications. However, the traffic data are required for some types of analysis. Table 1-2 summarizes the data sources required for specific types of analysis.

Table 1-1: Using the Guidebook by Analysis Type.

Analysis Type	Evaluation/Planning	Predictive
• Reporting incident characteristics	Module 3	
• Analyzing hot spots	Module 4	
• Estimating incident impacts	Module 5	
• Calculating performance measures	Module 6	
• Predicting incident duration		Module 7
• Predicting incident-induced congestion clearance time		Module 8

Module 3 provides the analyst with the guidelines on what and how incident characteristics should be reported. This module addresses reporting considerations for common incident characteristics recorded at Texas TMCs. The complexity of the analysis of incident data for reporting increases with the number of levels of attributes used in the procedure.

Module 4 outlines methodologies and tools for the analysis of incident-prone locations or hot spots from incident databases. Hot spot identification methods can be selected based upon data availability at the TMCs and the objectives of the hot spot analyses. Suggestions on how the agencies can utilize hot spot analysis results are also provided.

Table 1-2: Data Requirement by Analysis Type.

Analysis Type	Incident Data	Traffic Data
• Reporting incident characteristics	Required	None
• Analyzing hot spots	Required	Optional
• Estimating incident impacts	Required	Required
• Calculating performance measures	Depends	Depends
• Predicting incident duration	Required	None
• Predicting incident-induced congestion clearance time	Required	Required

Module 5 provides methodologies to estimate incident-related impacts using historical traffic and incident data. This module is separated into three major sections:

- The first section provides an overview of incident impact estimation approaches ranging from deterministic models to simulation methods.
- The second section describes an approach for estimating incident delay using historical traffic and incident data.
- The third section proposes a comprehensive methodology using a profile-based method to quantify various incident-related impacts such as delay index and traffic recovery time.

Module 6 provides a list of performance measures that can potentially be used to describe and evaluate the existing operation condition. This list was assembled based upon a review of literature, data availability at Texas TMCs, and feedback received from the survey conducted in this project. This module also provides methodologies and procedures for calculating these performance measures.

Module 7 describes a set of guidelines and procedures for developing and applying models for predicting incident duration using incident characteristics available from incident databases. The methods discussed in this module mathematically capture incident characteristics that are statistically correlated with incident durations. The end users can use the models developed to predict the duration of an ongoing incident given its known characteristics. The predicted incident durations can be used to support the traffic control and advisory decisions of traffic managers during the incident management process.

Module 8 describes a proactive use of historical and real-time traffic data for estimating incident-induced congestion clearance times. The analyst can proactively predict the impact of traffic incidents based on the time that it will take for the traffic to return to normal after incident occurrence. Total incident-induced time requires two components to be estimated: incident duration and incident-induced congestion clearance time. The first component can be predicted using the incident duration models described in Module 7. This module describes a methodology to estimate the second component using a deterministic queuing diagram.

Examples from the methodologies and procedures developed are based on Houston TranStar’s data structure to maintain the continuity and consistency throughout this guidebook. These examples are intended to demonstrate the applications of the methodologies and present the results. The applications of the proposed methods and procedures are however not limited to just Houston's TranStar. These procedures are applicable to any Texas TMCs provided that the data sources required for the analysis are available.

The methodologies and procedures described in this guidebook were demonstrated and evaluated in a companion report 0-5485-1. This report also includes the results from case studies conducted at three Texas TMCs, which are Houston's TranStar, Austin's Combined Transportation and Emergency Communications Center (CTECC), and Fort Worth's TransVision. The users of this guidebook can find more information on the case study results and various applications of the proposed methodologies in this report.

2. OVERVIEW OF TEXAS TRANSPORTATION MANAGEMENT CENTERS

This module documents the current state of the practice in using and archiving incident data in traffic management centers in Texas. We examined different configurations in TMCs in Texas; assessed the availability, quantity, and quality of historical and real-time data in these TMCs; examined current incident detection and reporting procedures of these TMCs; and assessed current applications of historical data at these TMCs.

As shown in Table 2-1, there are nine TMCs currently operating in Texas. These nine management centers are in different stages of maturity. Several of these centers, such as Amarillo's Panhandle Electronic Guidance and Safety Information System (PEGASIS), Laredo's South Texas Regional Advanced Transportation Information System (STRATIS), and Texoma Vision, have been operating for less than five years, while several of the other centers (such as TranStar, TransGuide, and TransVision) have over 15 years of operating experience.

Table 2-1: List of Texas Transportation Management Centers.

City Population (2000 Census Data)	Transportation Management Center
Greater than 1 million	Houston's TranStar Dallas' DalTrans San Antonio's TransGuide
Between 500,000 and 1 million	Austin's CTECC Fort Worth's TransVision El Paso's TransVista
Less than 500,000	Amarillo's PEGASIS Laredo's STRATIS Wichita Falls' Texoma Vision

Through phone interviews with TxDOT and Texas Transportation Institute (TTI) contacts familiar with TMC deployment and data management, we collected the following information from each of these nine TMCs:

- ITS deployment status including closed-circuit television (CCTV) coverage, traffic and environmental sensors, and traveler information systems; and
- data management including real-time and historical data availability and data applications.

2.1. ITS Deployment and Data Management at Texas TMCs

2.1.1. Houston's TranStar

The Houston TranStar consortium is a partnership of four government agencies: TxDOT, Harris County, the Metropolitan Transit Authority of Harris County, and the City of Houston (*1*). TranStar operates 24 hours a day and 7 days a week. The Motorist Assistance Patrol (MAP) operates as a public/private partnership from 6AM to 10PM weekdays.

2.1.1.1. Deployment

TranStar has a total of 770 directional freeway miles with real-time traffic data collection. In addition, CCTV cameras cover 335 freeway centerline miles. With 87 ramp meters, Houston has the largest deployment of ramp metering in Texas. Traffic data collection at TranStar relies mostly on automated vehicle identification (AVI). This system determines travel speeds on 720 miles of Houston area freeways and 61 miles of high-occupancy vehicle (HOV) lanes by using 147 AVI reader stations with over a million AVI toll tags (transponders) to calculate travel times.

To provide traveler information, TranStar relies on 147 permanent and 5 portable dynamic message signs (DMSs), 12 fixed and 1 portable highway advisory radio (HAR) units covering 68 freeway centerline miles, a media outlet, and an Internet website (http://www.houstontranstar.org).

TranStar is one of the four TMCs in Texas that specifically implemented a mobile version of its Internet website for travelers with wireless devices. The mobile version is accessible at http://traffic.houstontranstar.org/mobile. The information available on its mobile webpage includes speed maps, travel times, camera snapshots, incident information, construction closures, and message signs.

Houston TranStar has established a multimedia partnership with the major news outlets in Houston, Texas (the 11th largest media market in the country). Houston TranStar's CCTV images and AVI speed data can be seen on ABC, CBS, NBC, FOX, and Univision 7 days a week, 365 days a year. Houston TranStar also provides other outlets, including Metro Traffic Network, Traffic Pulse Networks, and the Houston Chronicle, with traffic- and weather-related information.

The MAP is a partnership between the Harris County Sheriff's Department, Metropolitan Transit Authority of Harris County (METRO), the Texas Department of Transportation, the Houston Automobile Dealers Association, and Verizon Wireless telephone company. The MAP assists motorists with changing flat tires, provides fuel or water, assists with minor engine repairs, jump-starts vehicles, and transports motorists to safe locations.

Houston TranStar was the first management center in the nation to establish a partnership with the Washington, D.C.-based Operation Respond Institute for the use of the Operation Respond Emergency Information System (OREIS). The OREIS enables Houston area emergency response personnel to quickly access information concerning hazardous loads traveling on Houston's freeways. With this system, Houston TranStar can access information on hazardous materials by container number, trailer number, or carrier name. In the event of an accident, responding emergency personnel can quickly identify the materials at hand, the safety precautions they must employ, and the correct methods to contain the hazardous situation.

2.1.1.2. Data Management

TranStar's transportation management software operates on an Oracle database. TranStar has been archiving 15-minute aggregated AVI travel time and speed data since October 1993, freeway incident data since May 1996, emergency road closure data since August 2001, and construction lane closure data since May 2002 (*2*).

Traffic Data

TranStar currently collects and archives traffic data from two sources: AVI and microwave detection. The AVI system collects vehicle tag IDs and their corresponding time stamps each time vehicles are passing the checkpoints. An example of raw AVI data is shown in Table 2-2. Note that actual tag IDs are not displayed here for privacy reasons. These data are used to determine a travel time for each vehicle traveling on the segment. Table 2-3 shows an example of 15-minute aggregated AVI data.

Table 2-2: Example of TranStar's Raw AVI Data.

Tag_ID	Antenna_ID	Checkpoint_ID	Time_ID
HCTR00000001	5103	159	11/12/2006 00:00:45
HCTR00000002	8021	216	11/12/2006 00:00:59
HCTR00000003	4111	106	11/12/2006 00:00:59
HCTR00000004	4076	229	11/12/2006 00:00:59
HCTR00000005	8043	219	11/12/2006 00:01:00
HCTR00000006	1200	351	11/12/2006 00:00:59
HCTR00000007	4203	63	11/12/2006 00:01:00
:	:	:	:

Table 2-3: Example of 15-Minute Aggregated AVI Data.

ReadDate	TimeInSecond	StartChkPt	EndChkPt	Freq	TravelTime	Speed
10/1/2006	0	122	123	15	190.00	62.53
10/1/2006	900	122	123	8	187.88	63.23
10/1/2006	1800	122	123	13	190.92	62.22
10/1/2006	2700	122	123	7	175.71	67.61
10/1/2006	3600	122	123	9	179.67	66.12
10/1/2006	4500	122	123	9	192.44	61.73
10/1/2006	5400	122	123	5	172.60	68.83
10/1/2006	6300	122	123	3	189.00	62.86
10/1/2006	7200	122	123	7	190.86	62.25
10/1/2006	8100	122	123	4	189.25	62.77
10/1/2006	9000	122	123	10	189.00	62.86
10/1/2006	9900	122	123	7	181.00	65.64
10/1/2006	10800	122	123	6	183.67	64.68
:	:	:	:	:	:	:

Houston TranStar recently installed Wavetronix microwave detection systems, shown in Figure 2-1, at a number of locations. The Wavetronix SmartSensor uses a 10.525 GHz frequency modulated continuous wave (FMCW) radar to provide traffic detection. The radar sensor is installed aboveground and can measure vehicle volume, occupancy, speed, and classification in up to eight lanes of traffic simultaneously *(3)*. Table 2-4 shows an example of 30-second Wavetronix data. In addition, TranStar also has EIS Remote Traffic Microwave Sensor (RTMS) units installed on IH-10, IH-45, and SH-71.

Incident Data

Incident detection relies mostly on police dispatch monitoring, MAP calls, commercial traffic services, and CCTV camera scanning. TranStar has an incident detection algorithm that compares and detects changes in segment speeds versus historical speed values. However, relatively few incidents were detected in this manner, due largely to the long distance between consecutive AVI readers that prolongs the time for incident signals to reach AVI readers.

Figure 2-1: Wavetronix SmartSensor.

Table 2-4: Example of 30-Second Wavetronix Data.

ID	Time Stamp	Lane #	Volume	Speed	Occupancy	Small	Medium	Large
1077	09/10/2006 00:00:00	1	3	59	3	2	1	0
1077	09/10/2006 00:00:00	2	3	70	2	2	1	0
1077	09/10/2006 00:00:00	3	3	63	2	3	0	0
1077	09/10/2006 00:00:00	4	2	69	2	0	2	0
1077	09/10/2006 00:00:00	5	2	73	3	0	0	2
1077	09/10/2006 00:00:00	99	13	66	2	7	4	2
1077	09/10/2006 00:00:30	1	2	59	1	2	0	0
1077	09/10/2006 00:00:30	2	4	75	5	0	3	1
1077	09/10/2006 00:00:30	3	5	61	4	3	2	0
1077	09/10/2006 00:00:30	4	3	72	3	1	2	0
1077	09/10/2006 00:00:30	5	1	73	1	0	1	0
1077	09/10/2006 00:00:30	99	15	67	3	6	8	1
1077	09/10/2006 00:01:00	1	2	63	1	2	0	0
1077	09/10/2006 00:01:00	2	5	76	5	2	2	1
1077	09/10/2006 00:01:00	3	4	59	2	3	1	0
1077	09/10/2006 00:01:00	4	5	79	4	1	2	2
1077	09/10/2006 00:01:00	5	0	0	0	0	0	0
1077	09/10/2006 00:01:00	99	16	71	2	8	5	3
:	:	:	:	:	:	:	:	:

Operators at TranStar verify incidents using CCTV cameras; then they decide on appropriate responses, such as posting messages on the DMSs. Incident-related information is entered into the database through the Regional Incident Management

System (RIMS) interface. There are four main time points used to record an evolution of an incident: detected, verified, moved, and cleared.

"Detected" refers to the time an operator, including the MAP dispatcher, creates an incident record in the database. This time may or may not coincide with the actual detection time. "Verified" refers to the time the operator confirms the incident with the CCTV camera. "Moved" refers to the time when emergency services remove lane-blocking vehicles from traveled lanes. This time stamp is not always recorded depending on the type of incident and service required. "Cleared" refers to the time the appropriate response units clear the incident.

TranStar provides incident information and updates its status in real time through its website (http://www.houstontranstar.org). Screenshots of incident information and its related information are shown in Figure 2-2.

2.1.1.3. Data Applications

The Houston TranStar Traffic Alarm Application was developed by TTI for TxDOT and Houston TranStar. The application uses travel time and speed data from Houston's AVI system to graphically alert users to areas of extraordinary congestion and potential incidents on Houston area freeways.

The application is currently run in a web browser and is only accessible to operators at TranStar at this time. The system compares real-time speed data with last year's averages. The averages exclude weekends and holidays. Screenshots of this application are shown in Figure 2-3 and Figure 2-4.

Once every minute, the system compares the current 15-minute speed average with the historical averages. An alarm is generated when the real-time speed average falls below the 97th percentile of the compiled historical averages. To minimize false alarms, the system performs a simple consistency check by requiring an alarm to be generated twice before it is plotted on the map. In other words, this feature requires the speed to remain below the threshold for at least two minutes before an alarm is generated. The alarm remains active until the speed moves above the 97th percentile threshold.

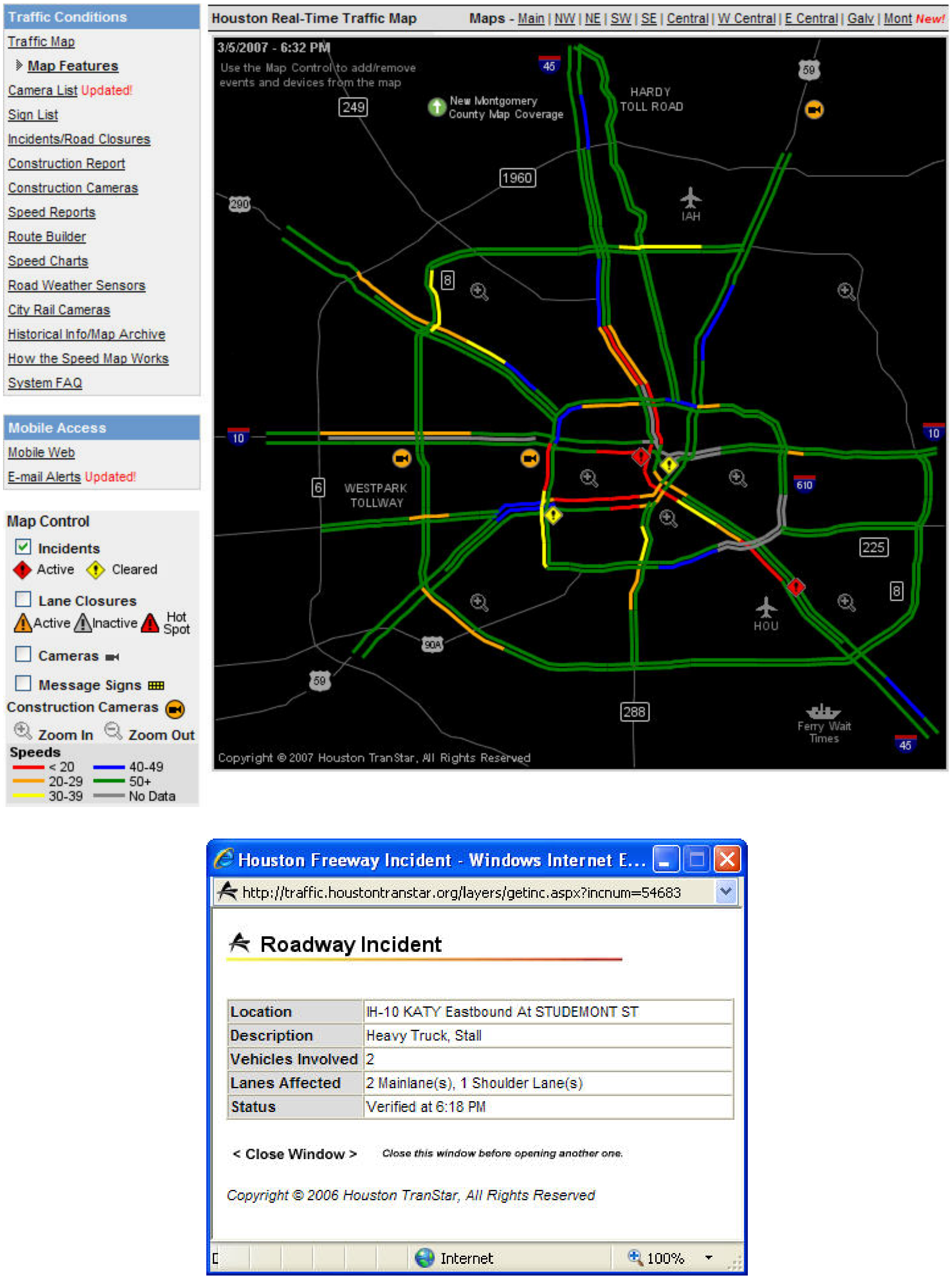


Figure 2-2: Incident Information on Houston's TranStar Website.

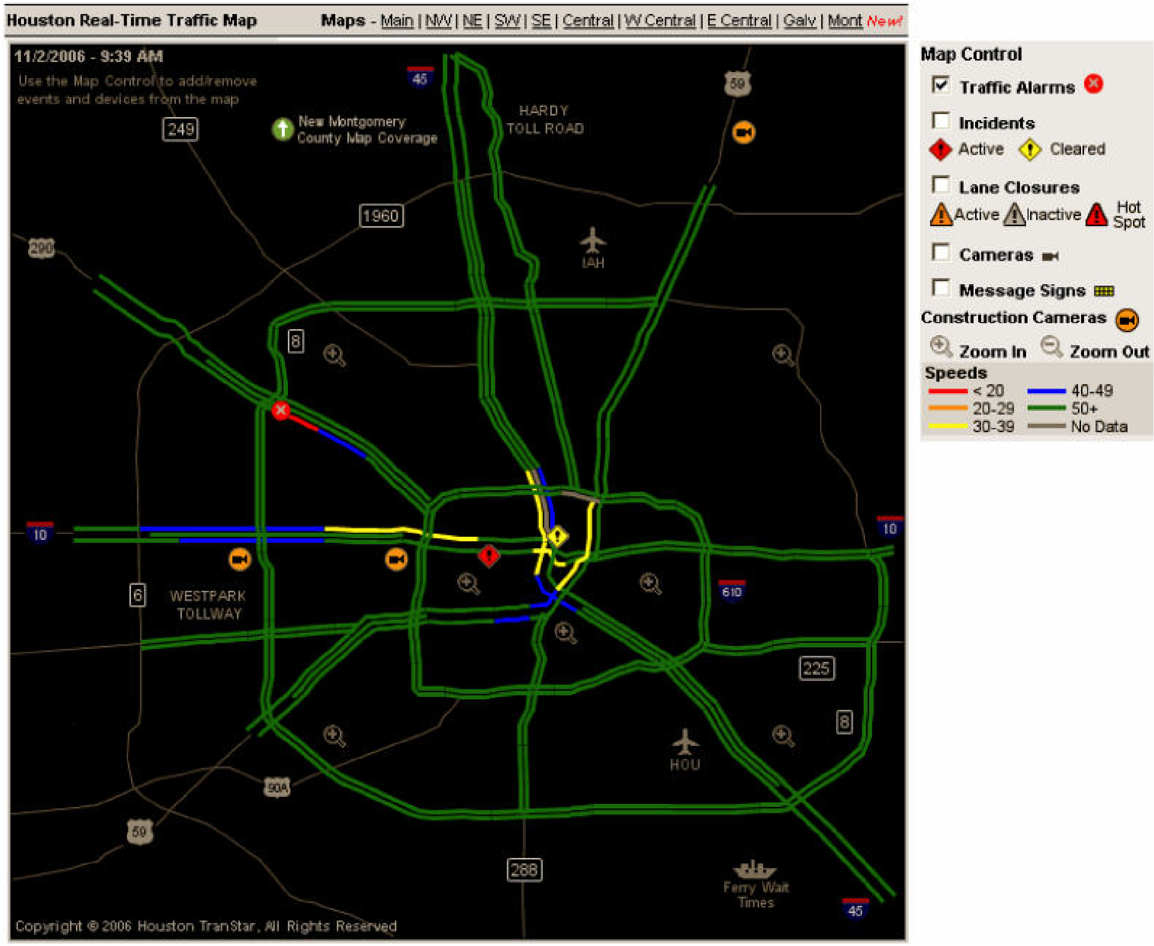
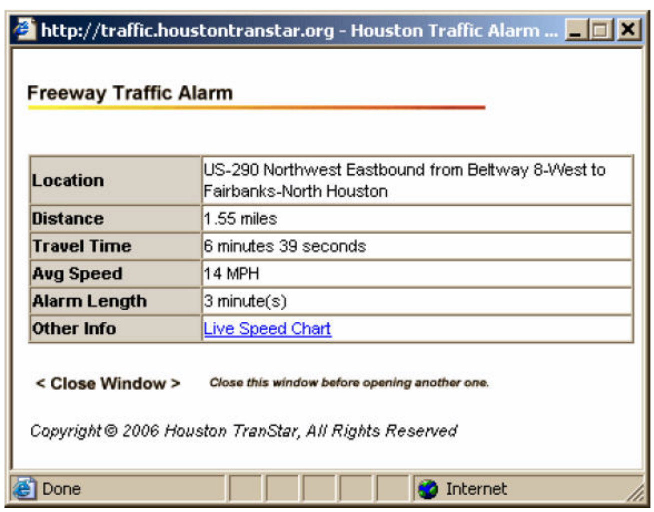


Figure 2-3: TranStar's Traffic Alarm Map.



http://traffic.houstontranstar.org - Houston Traffic Alarm ...

Freeway Traffic Alarm

Location	US-290 Northwest Eastbound from Beltway 8-West to Fairbanks-North Houston
Distance	1.55 miles
Travel Time	6 minutes 39 seconds
Avg Speed	14 MPH
Alarm Length	3 minute(s)
Other Info	Live Speed Chart

< Close Window > *Close this window before opening another one.*

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Done Internet

Figure 2-4: TranStar's Traffic Alarm Details.

2.1.2. Dallas' DalTrans

A new DalTrans TMC was recently completed in 2007. The grand opening of the $10 million facility was held on January 23, 2008. The new 54,000-square-foot facility expands DalTrans' capabilities to monitor traffic operations in the Dallas area, which includes more than 1,000 square miles and more than 30 cities. DalTrans has interfaces for a number of external systems to enable data exchange with other centers such as Fort Worth's TransVision, City of Dallas, City of Richardson, City of Plano, and Dallas County. DalTrans implemented a standard center-to-center (C2C) interface with TransVision to enable system status data exchange and system device control.

2.1.2.1. Deployment

DalTrans' CCTV and traffic sensor deployment includes:

- CCTV cameras – approximately 200 cameras along more than 100 miles of roadway;
- loop detectors (currently a large percentage of them are not working);
- 34 Autoscope cameras covering approximately 26 miles of freeway; and
- 59 microwave sensors.

Currently, DalTrans is no longer using loop detectors to collect traffic data since a large percentage of them are damaged. Each Autoscope camera uses up to six virtual detectors that continuously capture volume, occupancy, speed, and vehicle classification data. The system polls camera data every 10 seconds *(2)*. The microwave detection system is a primary source for traffic data collection at DalTrans.

DalTrans provides traveler information via the following methods:

- dynamic message signs – 37 existing, 6 in the construction phase, and 12 in the design phase;
- Dallas traffic information website accessible at http://dfwtraffic.dot.state.tx.us or alternatively http://www.daltrans.org. Camera snapshots are automatically updated at roughly every eight minutes;
- incident notification system allowing subscribers to be notified of freeway incidents via email. The service is currently limited to TxDOT and related transportation personnel; and
- media outlets.

DalTrans is one of the four TMCs in Texas that implemented a mobile version of its traffic information website. Travelers with web-enabled wireless devices can access the mobile webpage at the same Uniform Resource Locator (URL) (http://www.daltrans.org). The devices are automatically detected, and the mobile version is brought up automatically. Alternatively, the users can specifically access the mobile version of the webpage at one of these two URLs: http://www.daltrans.org/mobile and http://dfwtraffic.dot.state.tx.us/mobile. DalTrans also shares its mobile website with Fort Worth's TransVision, although the scope of traffic information available is slightly different. The information available through DalTrans' mobile webpage includes speed and incident map, incident information, lane closures, and camera snapshots.

2.1.2.2. Data Management

DalTrans' central management software is a proprietary system developed internally to support DalTrans' initial and short-term ITS deployment needs. DalTrans relies on a Microsoft Access® database. The current prototype DalTrans software is a distributed and modular system whose components interact with one another using real-time Transmission Control Protocol/Internet Protocol (TCP/IP) messaging (*4*).

Traffic Data

DalTrans developed a Universal Detector Data Archive (UDDA) to include the data from Autoscope video detectors, inductive loops, and SmartSensor side-fire microwave detectors. The new archive transfers data from multiple sources using Hypertext Transfer Protocol (HTTP) and Simple Object Access Protocol (SOAP) to access a web service that writes to the archive (*2*). The archive can be accessed via the Internet at http://ttidallas.tamu.edu/detectordataarchive. The archived data are in a comma-delimited format consisting of average speed, volume, and occupancy at five-minute aggregated intervals (see Table 2-5).

Table 2-5: Example of DalTrans' Detector Archive Data.

```
2006-12-04 17:52:07Z, EB IH635@Welch EBHOV, 10043 3282, 0, 46, 63, 3, 0
2006-12-04 17:52:07Z, EB IH635@Welch EBL1of4, 10043 3295, 0, 16, 52, 3, 0
2006-12-04 17:52:07Z, EB IH635@Welch EBL2of4, 10043 3308, 0, 18, 56, 4, 0
2006-12-04 17:52:07Z, EB IH635@Welch EBL3of4, 10043 3321, 0, 19, 68, 4, 0
2006-12-04 17:52:07Z, EB IH635@Welch EBL4of4, 10043 3334, 0, 22, 71, 4, 0
2006-12-04 17:52:07Z, EB IH635@Welch EBMNL, 10043 3347, 0, 21, 247, 4, 0
```

Detector data are archived using a comma-delimited 8-bit Unicode Transformation Format (UTF-8) text format. Each data row contains the following fields separated by a comma:

- date and time – the end of the collection period is recorded for the associated data;
- detector name;
- detector number;
- detector status where 0 = normal, 1 = error, 2 = out of service, 3 = no data, and 4 = incomplete;
- average speed for the collection interval;
- total volume for the collection interval;
- average occupancy for the collection interval; and
- percent truck for the collection interval.

DalTrans also has an algorithm to compute travel time based on three-minute rolling averages of speed data and segment length. Computed travel times are not archived.

Incident Data

Incident detection at DalTrans relies mainly on operators, cameras, and scanning of data feeds from Dallas 911 and Metro Traffic. Other sources include police radio scanning and courtesy patrol. Every five minutes, DalTrans receives an updated list of incidents from the City of Dallas 911 system. The software then filters out incidents that are not freeway related.

Incident data are archived using a Microsoft Access database. An example of DalTrans' incident record is shown in Table 2-6. DalTrans' incident table includes the following fields for each incident record:

- Latitude – cross street's latitude.
- Longitude – cross street's longitude.
- Road – the name of a roadway where an incident occurs.
- Cross Street – the name of a cross street.
- Cross Street Proximity – indicates the location of an incident on the roadway with respect to the cross street (At/Departing/Approaching).
- Incident Status Change Times – the time when an incident is detected, verified, and cleared. DalTrans also has the disregarded time for an incident that was disregarded rather than cleared. An operator might disregard an incident as a false alarm, as an operator error, or for several other reasons.
- Affected Lanes – indicates the lanes affected by the incident. This field is encoded as an integer, which requires a bit mask, shown in Table 2-7, to determine the affected lanes.
- Incident Types – DalTrans collects five types of incidents, which are Accident, Stalled Vehicle, Debris, Undetermined, and Others.
- Notified – indicates the units that have been notified of an incident. This field is encoded as an integer, which requires a bit mask, shown in Table 2-8, to interpret the value.
- Detection Mode – Courtesy Patrol, Camera, Call-In, Police/Fire, Unknown, and Others.
- Associated DMS – indicates DMSs associated with the affected incident location.
- Camera – indicates the key of the nearest camera.
- Operators – names of operators who detect and/or modify the status of an incident.
- Number of vehicles involved in an incident.

From the example of incident records, the "Affected Lanes" field value is 8224, which is equivalent to the following binary bits:

0010 0000 0010 0000

Comparison of the above bits with the bit masks from Table 2-7 indicates that Lane 1 and HOV Lane are affected by the incident.

Conversely, if the Entrance Ramp, Lane 4, and Lane 5 are affected by the incident, the "Affected Lanes" would be equivalent to 0x0004 + 0x0100 + 0x0200 = 4 + 256 + 512 = 772.

Table 2-6: Example of DalTrans' Incident Records.

```
Fieldnames:

Key, GUID, Latitude, Longitude, Road, CrossStreet, CrossStreetProximity,
Comments, PrivateComments, DetectedTime, DisregardedTime, VerifiedTime,
ClearedTime, Status, AffectedLanes, Type, Notified, DetectionMode,
AssociatedDMSs, Camera, VerifiedBy, DetectedBy, DisregardedBy, ClearedBy,
EstimatedClearTime, LastModifiedByFullAccessUser, CourtesyPatrolVehicleKeys,
NumVehicles

Incident Records:

25362, {B4BE681B-F830-423C-BD65-8918FD46389B}, 32.92458, -96.76327, IH 635,
US 75, At, , , 11/25/2003 10:44:22 AM, 12:00:00 AM, 11/25/2003 10:46:12 AM,
11/25/2003 10:46:15 AM, Cleared, 32, Debris, 0, Call-In, 24 27 28 29, 270,
April Shortridge, Joe Hunt, , April Shortridge, , Yes, , 0

906, {5EF73855-2309-11D7-9A99-000255A016CF}, 32.91071, -96.88166, IH 635,
Josey Ln, At,  , , 1/15/2003 6:38:32 PM, 12:00:00 AM, 1/15/2003 6:38:32 PM,
1/15/2003 6:56:32 PM, Cleared, 8224, Accident, 0, Camera, 24 27 28 29 25 26,
129, Rick Edwards, Rick Edwards, , Rick Edwards, , Yes, , 2
```

Table 2-7: DalTrans' Bit Masks for "Affected Lanes" Field.

Description	Hexadecimal Bit Mask (with "0x" Prefix)	Equivalent Binary Bit Mask
Left Shoulder	0x0001	0000 0000 0000 0001
Right Shoulder	0x0002	0000 0000 0000 0010
Entrance Ramp	0x0004	0000 0000 0000 0100
Exit Ramp	0x0008	0000 0000 0000 1000
Connector	0x0010	0000 0000 0001 0000
Lane 1	0x0020	0000 0000 0010 0000
Lane 2	0x0040	0000 0000 0100 0000
Lane 3	0x0080	0000 0000 1000 0000
Lane 4	0x0100	0000 0001 0000 0000
Lane 5	0x0200	0000 0010 0000 0000
Lane 6	0x0400	0000 0100 0000 0000
Lane 7	0x0800	0000 1000 0000 0000
Lane 8	0x1000	0001 0000 0000 0000
HOV	0x2000	0010 0000 0000 0000

Table 2-8: DalTrans' Bit Masks for "Notified" Field.

Description	Hexadecimal Bit Mask (with "0x" Prefix)	Equivalent Binary Bit Mask
Police	0x01	0000 0001
Courtesy Patrol	0x02	0000 0010
Maintenance	0x04	0000 0100
Public Information Office (PIO)	0x08	0000 1000
Affected City	0x10	0001 0000

Other Data

DalTrans also archives DMS logs in an Access database. DMS messages are recorded in an Extensible Markup Language (XML) format. Each DMS log contains the information about DMS key, user name, date and time, and displayed messages. An example of a travel time message in an XML format is shown in Table 2-9.

Table 2-9: Example of XML Messages.


```
<DMSMessage><ID>dc43fa94-86dc-49da-a8d5-
465d91811f03</ID><Priority>1</Priority><Phases><Phase><Duration>2200</Duratio
n><Lines><Line><Alignment>2</Alignment><Text>TRAVEL
TIME</Text></Line><Line><Alignment>2</Alignment><Text>TO GARLAND
RD</Text></Line><Line><Alignment>2</Alignment><Text>19 TO 21
MINUTES</Text></Line></Lines></Phase><Phase><Duration>2200</Duration><Lines><
Line><Alignment>2</Alignment><Text>TRAVEL
TIME</Text></Line><Line><Alignment>2</Alignment><Text>TO
IH30</Text></Line><Line><Alignment>2</Alignment><Text>25 TO 28
MINUTES</Text></Line></Lines></Phase></Phases><LastUpdated>7/10/2006 5:30:10
PM</LastUpdated><LastUpdatedBy>*Travel Time DMS Message
Manager</LastUpdatedBy><BeaconStatus>2</BeaconStatus><DisplayedDate>1/1/2001<
/DisplayedDate></DMSMessage><Description>635 EB Preston  Added this message
(*Travel Time DMS Message Manager)</Description>
```


The above XML example is updated by a travel time DMS message manager, which can be translated to the alternate displays (two phases) on the DMS as shown in Figure 2-5.

TRAVEL TIME
TO GARLAND RD
19 TO 21 MINUTES

TRAVEL TIME
TO IH30
25 TO 28 MINUTES

Figure 2-5: Example of DMS Message Display.

2.1.2.3. Data Applications

Travel Time Application

DalTrans is currently using three-minute rolling averages of mainlane speed data and segment length to compute travel time. Speed data are obtained from Autoscope and a side-fire radar detection system. Travel time calculations are configurable by TxDOT. Travel time is recalculated every time there is a change in one of the constituent detector values.

Travel Time DMS Message Manager (TTMM) is a TMC component that automatically posts travel time messages on DMSs. Travel time messages are composed of text and variables. Variables express the values of associated detectors. "Detector" values for DalTrans are not necessarily coming from detectors. They can actually be any numeric value. The travel time application takes the incoming speed data from actual detectors and then injects the computed travel times back into the system as additional "Detector" data.

Multiple variables can be inserted into each line of a DMS message, and each variable can be given a bias. For example, to create an "X to X+4" message, two variables would be inserted into a single line. Both variables have their values derived from the same detector, but the second variable is given a bias of 4.

Message variables also support thresholds and alternate messages. When the value of a detector moves below or above the specified thresholds, an alternate message can be displayed. This enables messages such as "TRAVEL TIME LESS THAN 5 MINUTES" to be displayed when travel time drops below five minutes. The upper threshold can be used to display messages such as "TRAVEL TIME GREATER THAN 20 MINUTES" when travel time exceeds the upper threshold.

For single-phase DMS messages, if the status of any detector that is tied to a constituent variable is not normal (i.e., error, out of service, or no data), then the message is removed from the DMS. For multi-phase DMS messages, only the phase or phases that contain abnormal variables are removed. If all of the phases of a multi-phase DMS message contain abnormal variables, then the entire message is removed.

The TTMM configuration is controlled by means of an XML file. The TTMM will automatically recognize when the configuration file has been modified, and it will update the system and the DMSs accordingly.

2.1.3. San Antonio's TransGuide

The Texas Department of Transportation's "smart highway" project called TransGuide became operational on July 26, 1995. TransGuide's intelligent transportation system was designed to provide information to motorists about traffic conditions, such as accidents, congestion, and construction. TransGuide can detect travel times and respond rapidly to accidents and emergencies. Partners in the TransGuide project include TxDOT, the City of San Antonio (police/fire/emergency medical service [EMS]/traffic), and VIA Metropolitan Transit *(5)*.

The TransGuide transportation operations center operates 24 hours a day and 7 days a week. TransGuide no longer has its own courtesy patrol program.

2.1.3.1. Deployment

TransGuide's traffic monitoring and sensor deployment includes approximately 144 CCTV cameras installed on IH-10, IH-35, LP-410, south side of US-90, and northwest of LP-1604; approximately 200 stations of inductive loop detectors; 325 sensor locations of sonic detectors; and about 20 Autoscope detection systems.

TransGuide provides pre-trip and en-route travel information through several channels including:

- 155 dynamic message signs,
- 180 lane control signals,
- Internet website (http://www.transguide.dot.state.tx.us), and
- local media outlets.

In early 2003, TransGuide began to transmit a live video feed to local television stations through an external access video switch. The television stations, which include three local network affiliates and one local cable news channel, can pick and choose which camera will be shown during morning and afternoon traffic updates. This allows them to spend as much time as is needed on one or two cameras to discuss an accident or other situation that would affect the motorists' travel time. Up to 20 channels of video can be broadcast to the stations at any time.

2.1.3.2. Data Management

TransGuide's central management software operates as a client/server-based system that runs on Sun workstations in a Unix Solaris environment. The system includes multiple subsystems such as alarm incident handler (AIH) subsystem, CCTV subsystem, lane control signal (LCS) subsystem, and others. The details of the TransGuide subsystems were documented in a previous TTI research report *(2)*.

TransGuide uses a Sybase database to archive data describing ITS equipment characteristics and operations data to support day-to-day activities at the TMC. TransGuide maintains a long-term data repository in compressed file format, including traffic detector and event data. Scenario logs are maintained in Sybase, which includes a scenario header table and a scenario execution table.

A scenario process is a predefined incident response program used by TransGuide. TransGuide operators create "scenarios" based on the incident location, the lanes affected, the type of incident, and whether the demand exceeds capacity for every lane mile covered by the TransGuide system *(6)*.

Traffic Data

TransGuide archives volume, occupancy, and speed data for all freeway lanes at 20-second intervals. The 20-second traffic data are also aggregated at 15-minute intervals using 2-minute running averages. The 15-minute data set also includes local control units (LCU) poll data, alarm/incident assignments, and manager/operator changes, as well as scenario execution, commands, and cancellations.

TransGuide's traffic data are available on a public domain. TransGuide maintains data on a File Transfer Protocol (FTP) server, which can be accessible through any conventional FTP software or a web browser using the URL ftp://www.transguide.dot.state.tx.us/lanedata.

An example of TransGuide's 20-second lane data is shown in Figure 2-6. Each record contains date and time stamp, detector address, speed, volume, and percent occupancy. TransGuide does not archive vehicle classification information (i.e., percent trucks). The speed value is recorded as –1 for non-trap detectors typically installed at entrance and exit ramps.

```
07/15/2006 00:02:29 EN1-0010W-574.621  Speed=56 Vol=006 Occ=008
07/15/2006 00:02:29 EN2-0010W-574.621  Speed=45 Vol=002 Occ=003
07/15/2006 00:02:29 EN3-0010W-574.621  Speed=49 Vol=001 Occ=001
07/15/2006 00:02:29 EX1-0010E-574.624  Speed=-1 Vol=001 Occ=002
07/15/2006 00:02:29 EX2-0010E-574.624  Speed=-1 Vol=003 Occ=004
07/15/2006 00:02:29 L1-0010W-574.623   Speed=69 Vol=001 Occ=001
07/15/2006 00:02:29 L2-0010E-574.623   Speed=68 Vol=002 Occ=002
07/15/2006 00:02:29 L2-0010W-574.623   Speed=00 Vol=000 Occ=000
07/15/2006 00:02:29 L3-0010E-574.623   Speed=67 Vol=001 Occ=001
07/15/2006 00:02:30 EN1-0010W-575.259  Speed=-1 Vol=000 Occ=000
07/15/2006 00:02:30 EX1-0010E-575.259  Speed=-1 Vol=000 Occ=000
07/15/2006 00:02:30 EN1-0010E-576.246  Speed=-1 Vol=000 Occ=000
07/15/2006 00:02:30 EX1-0010W-576.287  Speed=-1 Vol=000 Occ=000
07/15/2006 00:02:30 L1-0010E-576.264   Speed=00 Vol=000 Occ=000
07/15/2006 00:02:30 L1-0010W-576.264   Speed=00 Vol=000 Occ=000
07/15/2006 00:02:30 L2-0010W-576.264   Speed=65 Vol=001 Occ=001
07/15/2006 00:02:30 L3-0010E-576.264   Speed=00 Vol=001 Occ=000
```

Figure 2-6: Example of TransGuide's 20-Second Lane Data.

The detector address has three fields separated by a dash:

- Detector location and lane designation – "L" represents main lane, "EN" represents entrance ramp, and "EX" represents exit ramp. The number represents the lane numbering starting with the lane closest to the median.
- Freeway number and direction – For example, 0010E represents IH-10 E.
- Mile marker.

Incident Data

Incidents are detected based on a combination of detector-based alarms and 911-based alarms (through the AIH subsystem), CCTV camera scanning, San Antonio Police Computer-Aided Dispatch (SAP CAD) system, and media outlets. The majority of incidents are detected by police CAD.

TransGuide does not directly archive incident data. However, both alarms from the incident detection algorithm and scenarios deployed by operators are recorded in an event data archive. TransGuide's event data include 30 different major record types. An example of an event data archive is shown in Figure 2-7.

```
2301    cms_master 2006/12/15 19:10:43 1166231443 CMS CMS2-0035S-169.575 Display Return: msgID=2507  text='TRAVEL TIME TO|LP410 UNDER 5
MINS|IH37 12-14 MINS|||'
2301    cms_master 2006/12/15 19:11:44 1166231504 CMS CMS2-0035S-171.127 Display Return: msgID=2507  text='TRAVEL TIME TO|LP410 UNDER 5
MINS|IH37 14-16 MINS|||'

2303    cms_master 2006/12/15 20:58:02 1166237882 CMS2-0090E-571.426 Conflict: Current msgID=2569, text='MAJOR ACCIDENT ON|IH-35 NORTH|UPPER
LEVEL CLOSED|||', New msgID=2572, text='MAJOR ACCIDENT ON|IH-35 S UPPER LVL|USE CAUTION|||'
2303    cms_master 2006/12/15 20:58:02 1166237882 CMS2-0010W-574.304 Conflict: Current msgID=2569, text='MAJOR ACCIDENT ON|IH-35 NORTH|UPPER
LEVEL CLOSED|||', New msgID=2572, text='MAJOR ACCIDENT ON|IH-35 N UPPER LVL|USE CAUTION|||'

3303    lcs_master 2006/12/15 17:29:55 1166225395 LCS4-0410E-026.668 Conflict: Current msgID=2538,
sig='YellowDown|YellowDown|GreenDown|GreenDown||', New msgID=2538, sig='YellowDown|YellowDown|GreenDown|YellowDown||'
3303    lcs_master 2006/12/15 17:45:03 1166226303 LCS4-0410E-026.656 Conflict: Current msgID=2538,
sig='YellowDown|YellowDown|GreenDown|YellowDown||', New msgID=2538, sig='YellowDown|YellowDown|GreenDown|GreenDown||'

5301    aih_back 2006/12/15 22:20:01 1166242801 332 'PDLN-0010W-558.864' 'DE ZAVALA RD   IH 10 W       ' 'Northwest' 'Minor Accident'
'ToBeAssigned' 0.005 'MinorAlarm' 'CCTV-0010E-558.502'.1 'ToBeAssigned' 'mbarker' '' '' 1166242801 0 0 0
5301    aih_back 2006/12/15 22:56:07 1166244967 333 'PDEN-0035N-153.860' '00304 GIVENS AV              ' 'Central' 'Minor Accident'
'ToBeAssigned' 0.060 'MinorAlarm' 'CCTV-0035S-153.878'.1 'ToBeAssigned' 'mbarker' '' '' 1166244967 0 0 0

5302    aih_back 2006/12/15 20:05:42 1166234742 314 'PDLN-1604E-050.000' 'N FM 1604 E    NACOGDOCHES RD' 'Northeast' 'Minor Accident'
'Canceled' 0.024 'Normal' ' '.1 'ToBeAssigned' 'jpaniag' '' '' 1166234320 0 0 0
5302    aih_back 2006/12/15 20:05:42 1166234742 313 'PDEX-1604W-033.560' 'EB IH 10       N FM 1604 W   ' 'Northwest' 'Minor Accident'
'Canceled' 0.013 'Normal' ' '.1 'ToBeAssigned' 'jpaniag' '' '' 1166234320 0 0 0

5303    aih_back 2006/12/15 23:20:12 1166246412 339 'PDLN-0010W-558.864' 'DE ZAVALA RD   IH 10 W       ' 'Northwest' 'Minor Accident'
'Canceled' 0.005 'Normal' 'CCTV-0010E-558.502'.1 'Canceled' 'mbarker' '' '' 1166246227 0 0 1166246412
5303    aih_back 2006/12/15 23:30:18 1166247018 338 'PDLN-0281N-149.000' 'US 281 N       EB LOOP 410 NE' 'Traffic' 'Major Accident'
'Canceled' 0.006 'Normal' ' '.1 'Canceled' 'mbarker' '' '' 1166246227 0 0 1166247018

5304    aih_back 2006/12/15 16:00:02 1166220002 133 'L3-0010W-557.843' 'SECT-0010W-557.843' 4 21 28 'MinorAlarm' 'CCTV-0010W-557.547'.1
'ToBeAssigned' 'jpaniag' '' '' 1166216847 0 0 0
5304    aih_back 2006/12/15 16:00:24 1166220024 170 'L1-0410W-015.079' 'SECT-0410W-015.079' 1 17 32 'MajorAlarm' ' '.1 'ToBeAssigned'
'jpaniag' '' '' 1166219902 0 0 0

8352    scm_master 2006/12/15 20:59:15 1166237955 2569 None 0 CMS2-0U35N-155.190 MAJOR ACCIDENT| |USE OPEN LANES| | |
8352    scm_master 2006/12/15 21:03:27 1166238207 2569 None 0 CMS3-0U35N-155.054 RAMP CLOSED|DO NOT ENTER| | | |
8352    scm_master 2006/12/15 21:05:13 1166238313 2571 None 0 CMS2-1604E-028.988 STALLED VEHICLE|RIGHT LANE CLOSED|1 MILE| | |
8352    scm_master 2006/12/15 21:08:36 1166238516 2572 None 0 CMS2-0U35N-155.190 MAJOR ACCIDENT|RIGHT LANE CLOSED|USE LEFT LANE| | |
8352    scm_master 2006/12/15 21:29:44 1166239784 2571 None 0 CMS2-1604E-028.988 STALLED VEHICLE|RIGHT LANE CLOSED|1 MILE| | |
8352    scm_master 2006/12/15 21:29:44 1166239784 2571 None 1 LCS3-1604E-029.286 2 4 2 0 0 0
8352    scm_master 2006/12/15 21:29:44 1166239784 2571 None 1 LCS2-1604E-029.929 2 1 0 0 0 0
8352    scm_master 2006/12/15 21:44:31 1166240671 2574 None 0 CMS3-0410W-016.154 STALLED AUTO|ON HIGHWAY| |ENTER WITH|CAUTION|
8352    scm_master 2006/12/15 21:47:29 1166240849 2573 None 0 CMS2-0010E-561.242 MINOR ACCIDENT|RIGHT LANE CLOSED|AT VANCE JACKSON| | |
```

Figure 2-7: Example of TransGuide's Event Data Archive.

Originally, this event data archive was to serve as a debugging tool for an advanced transportation management system (ATMS). Nevertheless, over time, the archive has become a very extensive data repository. Of particular interest related to the incident data are the following record types:

- 2301, 2303 – messages displayed on the DMS;
- 5301, 5302, and 5303 – contain incident data records; and
- 8352 – contains DMS and LCS scenario data records.

The detailed procedure to extract and analyze TransGuide's incident data was described in previous TTI research reports (*2, 7, 8*).

2.1.3.3. Data Applications

Incident Detection Algorithm

Detector-based alarms are generated from the algorithm using speed data for speed-trap detectors (on main lanes) and occupancy data for non-trap detectors (on entrance and exit ramps). LCUs continuously poll and relay the detector data to the AIH subsystem every 20 seconds. For speed-trap detectors, if a two-minute rolling average of speed drops below 25 mph, the AIH subsystem automatically triggers a minor (yellow) alarm. If a two-minute speed average drops below 20 mph, the AIH subsystem triggers a major (red) alarm. For non-trap detectors, the default occupancy thresholds are set at 25 and 35 percent occupancy for minor and major alarms, respectively.

Travel Time Application

TransGuide's algorithm takes the speed data from point-based detectors (i.e., loops and video detection) and the segment length covered by each to estimate travel times from a DMS to major intersections and/or interchanges. TransGuide's algorithm defines a segment as a portion of a freeway between two sensor locations. The algorithm assigns the lower speed of the upstream and downstream average speeds to the segment. The travel time displayed on the DMS is the summation of segment travel times from the DMS to the major interchange or intersection for which the travel time is given. The freeway segments for travel time calculation are illustrated in Figure 2-8.

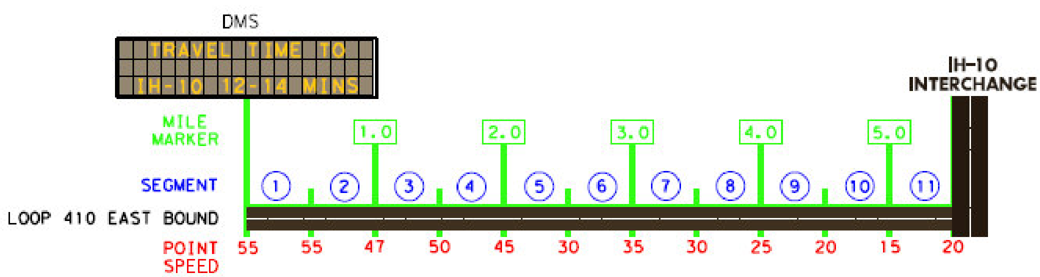


Figure 2-8: Illustration of Segments for TransGuide's Travel Time Algorithm (6).

In this diagram, there are 11 segments defined by 12 sensor locations where all segments are assumed to be exactly half a mile in length. The segment travel time computation is shown in Table 2-10. The total travel time for over 5.5 miles (11 segments) is equal to 12.2 minutes.

Table 2-10: TransGuide's Travel Time Calculation.

	Segment	
Segment	Speed (mph)	Travel Time (minutes)
1	55	0.5
2	47	0.6
3	47	0.6
4	45	0.7
5	30	1.0
6	30	1.0
7	30	1.0
8	25	1.2
9	20	1.5
10	15	2.0
11	15	2.0
Total		***12.2***

The travel times displayed on DMSs are shown as a range due to the variability in vehicle speeds. The travel time display is as follows:

- If total travel time is less than 5 minutes, the display is shown as "under 5 minutes."
- If total travel time is in the range of 5-20 minutes, the travel time is displayed in a 2-minute range.
- If total travel time is in the range of 20-30 minutes, the travel time is displayed in a 3-minute range.
- If total travel time is greater than 30 minutes, the travel time is always displayed as "over 30 minutes." However, the travel time of this range is rarely displayed. It is unusual to take 30 minutes or more to travel a 10-mile section unless there is an incident. The incident-related messages will override the travel time messages.

The estimated travel times will be rounded down and then added with two or three minutes depending on the range. Therefore, for the example in Table 2-10, the travel time to IH-10 will be displayed as 12-14 minutes.

TransGuide's travel time process is fully automated. The existing TransGuide scenario process is used to display travel time messages. Travel time scenarios were created for each freeway with DMSs installed. The process extracts speed data from the existing speed subsystem and calculates travel times. The travel times are then inserted into the travel time scenarios and the messages displayed. The DMS travel times are automatically recalculated and updated every minute. When the travel time process is activated, the travel times are displayed throughout the day with no further actions required by the operators *(6)*.

2.1.4. Austin's CTECC

Austin's CTECC is part of a multi-agency (City of Austin, Travis County, TxDOT, and the Capital Metropolitan Transportation Authority) emergency communications project called the 911 Radio, Computer-Aided Dispatch, Mobile Data, and Transportation (911-RDMT) project.

CTECC has been established since January 2003 and has operated 24 hours a day and 7 days a week since July 5, 2006. CTECC has its own courtesy patrol program known as the Highway Emergency Response Operations (HERO) program, which operates weekdays from 6AM to 10PM. CTECC is currently working on contracting private companies to provide additional response units during peak hours.

2.1.4.1. Deployment

CTECC has CCTV cameras covering approximately 37 freeway centerline miles. CCTV spacings are not uniform, with most cameras located at intersections and congestion-prone locations. CTECC's current sensor deployment includes loop detector stations covering some 37 freeway centerline miles, with detectors located roughly every half a mile. Speed-trap detectors are used for main lane and frontage roads, and non-trap detectors are used for entrance and exit ramps.

To provide travelers with traffic information, CTECC has 16 DMSs and 44 LCSs installed under sign bridges at roughly every 3 miles. CTECC has installed three highway advisory radio (HAR) stations covering about 118 freeway miles. Motorists can tune into 530AM and 800AM for pre-trip and en-route traffic information. CTECC also shares video feeds with four major television networks.

CTECC also provides camera snapshots on the Internet via http://ausits.dot.state.tx.us (see Figure 2-9). The web application was developed by TxDOT Information Services Division (ISD). ISD maintains and handles the web/Internet details to provide the same look and feel. Smaller Texas TMCs can benefit from the web application while avoiding the need to find additional resources to maintain the website. As of now, the ISD web applications are deployed at Austin's CTECC, Amarillo's PEGASIS, and Wichita Falls' Texoma Vision. The primary function now is to provide video snapshots to the public. The snapshots are updated approximately every two seconds for CTECC's cameras.

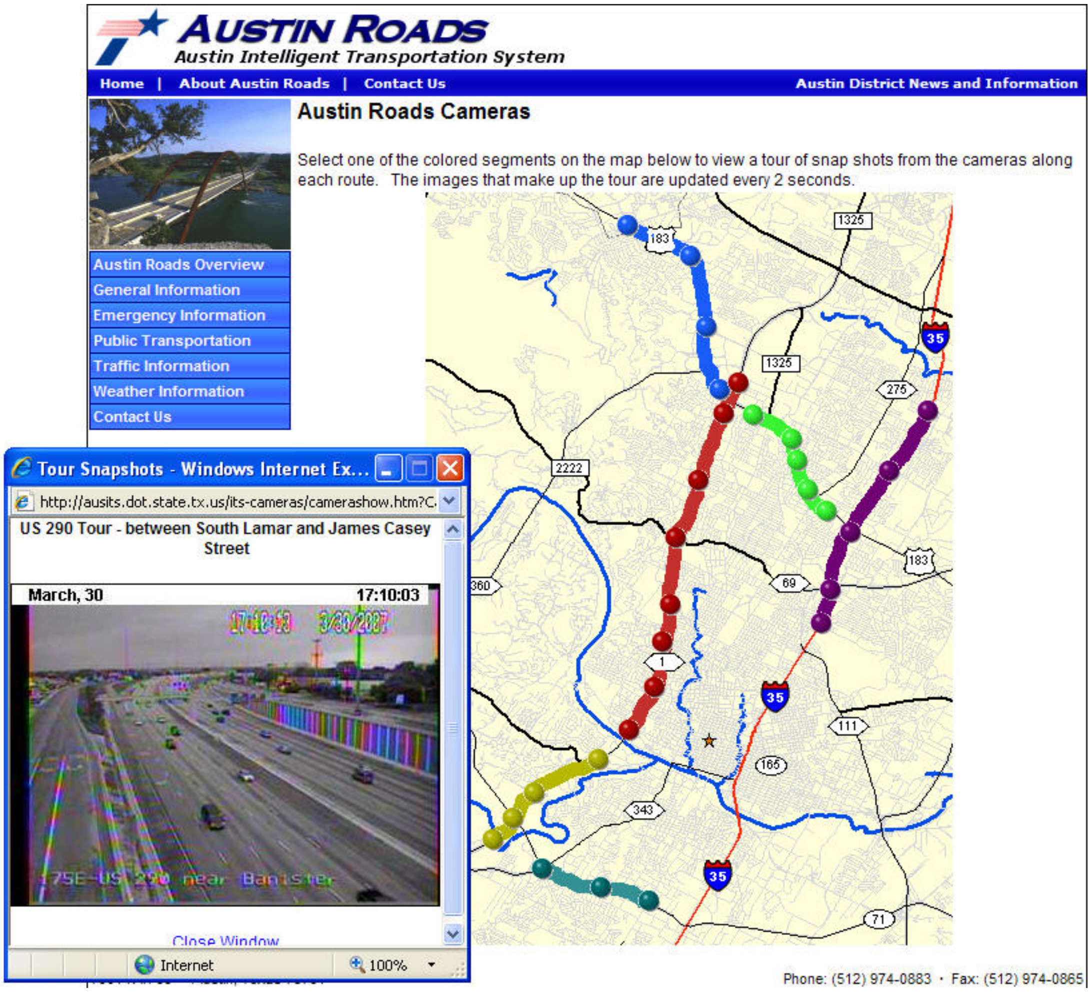


Figure 2-9: CTECC's CCTV Camera Locations and Example Snapshots.

CTECC receives email alerts from local flood detectors owned by the City of Austin Office of Emergency Management (OEM) as well as weather alerts from the National Oceanic and Atmospheric Administration (NOAA) subscription service. Operators can take appropriate actions upon receiving these alerts. CTECC also implemented an incident notification system in which subscribers are notified of freeway incidents and stalls via a pager system.

2.1.4.2. Data Management

Austin's CTECC uses TxDOT's ATMS software and relies on Sybase as the main data repository.

Traffic Data

CTECC relies on loop detectors as a main source of traffic data. LCUs poll the traffic data every 20 seconds, and the data are aggregated at one-minute intervals. The one-minute lane-by-lane traffic data archive includes volume, occupancy, speed, and percent truck along freeway main lanes and at selected locations along frontage roads. Archived data also include volume and occupancy on most entrance and exit ramps.

CTECC maintains archived traffic data files by days and freeway segments (IH-35, LP-1, US-290, and US-183). Each archived file contains a file header and detector data. Each file header contains information about the total number of detectors, detector number, and cross street and lane descriptions. An example of a file header is shown in Figure 2-10. From this example, "258" represents the total number of detectors. The lane designation is represented by a two-digit alphanumeric code following a cross street description. The first digit is either F, E, or X, which signifies freeway main lanes, entrance ramps, and exit ramps, respectively. The second digit is the lane number where 1 is the lane nearest to the median.

```
258,2000411,Guadalupe St     F1            ,2000412,Guadalupe St     F2
,2000413,Guadalupe St     F3            ,2000415,Guadalupe St     E1
,2000421,Guadalupe St     F1            ,2000422,Guadalupe St     F2
,2000423,Guadalupe St     F3            ,2000427,Guadalupe St     X1
,2000511,Chevy Chase Dr     F1          ,2000512,Chevy Chase Dr     F2
,2000513,Chevy Chase Dr     F3          ,2000515,Chevy Chase Dr     E1
,2000521,Chevy Chase Dr     F1          ,2000522,Chevy Chase Dr     F2
,2000523,Chevy Chase Dr     F3          ,2000527,Chevy Chase Dr     X1
,2001011,Carver Ave     F1              ,2001012,Carver Ave     F2
,2001013,Carver Ave     F3              ,2001015,Carver Ave     E1
,2001021,Carver Ave     F1              ,2001022,Carver Ave     F2
,2001023,Carver Ave     F3              ,2001027,Carver Ave     X1, …
```

Figure 2-10: Example of File Header from CTECC's Archived Detector Data.

An example of loop detector data is shown in Figure 2-11. Each data record begins with a time stamp (e.g., 14:40:27, 14:41:27), followed by a sequence of detector-by-detector traffic data in a comma-delimited format (detector number, volume, occupancy, speed, and percent truck).

Loop detector data quality continues to be a major concern for CTECC. Two major types of data problems are erroneous and missing data. Erroneous data problems include data values beyond the expected range and detector-data shuffling/mismatching. Missing and erroneous data flagged by the basic checking algorithm (mostly threshold checking) at the System Control Unit (SCU) are recorded as –1.

```
144027,2000411,11,4,66,0,2000412,23,10,54,4,2000413,16,9,51,18,
2000415,12,6,45,0,2000421,5,2,64,0,2000422,11,5,62,0,2000423,
22,10,55,9,2000427,14,6,52,0,2000511,12,4,47,0,2000512,
25,11,38,4,2000513,0,0,0,0,2000515,27,10,33,0,2000521,7,2,49,0,
2000522,16,6,46,0,…
144127,2000411,13,5,64,7,2000412,27,13,51,3,2000413,18,10,51,11,
2000415,4,2,48,0,2000421,10,4,65,10,2000422,12,5,62,0,2000423,
19,9,54,5,2000427,17,9,49,11,2000511,3,1,47,0,2000512,10,3,42,0,
2000513,0,0,0,0,…
```

Figure 2-11: Example of CTECC's Archived Traffic Data from Loop Detectors.

Incident Data

In Exhibit B of the CTECC agreement (*9*), an incident is defined as any condition in which traffic flow is not normal. As an example, abnormal traffic flow could be caused by debris in the road or by non-recurring congestion, such as onlookers to an accident, construction, or roadway maintenance. The duration of the incident shall be considered complete once traffic flow has returned to normal and any TxDOT and/or emergency service personnel and vehicles have departed from the incident scene.

Incident detection at CTECC relies heavily on a combination of loop detector-based incident alarms, CCTV camera scanning, police radio scanning, and courtesy patrols. The majority of incident detection is calls to CTECC. Upon receiving emergency calls, 911 operators usually take approximately 30-90 seconds to evaluate the situation and identify appropriate responders. The 911 operators notify TMC operators if the incident is traffic related.

The current incident detection algorithm compares a three-minute moving average of percent occupancy values against a threshold and generates an alarm if the moving average exceeds the threshold. The system supports different threshold profiles for different days and conditions. Operators can use these visual alerts from the incident detection algorithm to check if any incident is ongoing.

Incident locations are identified by:

- the coordinates of cell phones through the Enhanced 911 (E911) wireless system,
- visual identification by the operators (click on the map to get the coordinates), and
- the coordinates of cross streets for detector-based alarms used in conjunction with the field “At/Before/After.”

E911 service allows a wireless or mobile telephone to be located geographically using some form of radio location from the cellular network or by using a global positioning system (GPS) built into the phone itself.

CTECC has been archiving incident data since 1999. Nine incident types are supported in the ATMS incident report page, which are: collision, congestion, overturn, stall, abandonment, vehicle on fire, road debris, hazardous material spill, and public emergency. Accident, congestion, and stall make up more than 90 percent of all incident types recorded at CTECC. An example of a CTECC incident record is displayed in Figure 2-12 in a comma-delimited data format.

CTECC collects the following time points for each incident record in the database:

- incident detected/reported time (logged_datetime),
- incident clearance time (cleared_datetime), and
- incident last detected time (last_detected_datetime) – recorded when the alarm threshold has been exceeded more than once.

Incident detected/reported times can be recorded in three different manners:

- the time when an operator enters incident information into the database,
- the time when detector-based alarm thresholds are exceeded, or

- the time when the incident message is received by the ATMS system from C2C communications.

The C2C protocol allows subscribers to share incident-related messages based on ITS national standards.

```
24305,9,Southbound,IH 0035,-10,,51st Street,,,,after,5100,Collision,"TxDOT
ATMS Operations, Media",29-Jul-05,29-Jul-05,,JG.. cam 139.. collision
blocking lane 1 just past 51st.. LCS's and DMS's posted.. HERO en
route..,Freeway,Lane 1,,,Dry,No Defects,,Dawn,Clear/Cloudy,Courtesy
Patrol,Possible injuries,2,"Passenger car,
Truck",,JGOLD,10086089.52,3124167.018,237,,0.998,,,

24306,1,Southbound,IH 0035,-10,,St. Johns
Ave,,,,before,7200,Abandonment,,28-Jul-05,29-Jul-05,,JG..cam 132.. small
white honda in R shoulder just past the entrance connector from US 183.. not
blocking..,Freeway,Right
Shoulder,,,,,,,,,,,,JGOLD,10094585.26,3125914.945,239,,0.651,,,

24307,15,Southbound,US 0183 Frontage Road,-10,,,Chevy Chase Dr.X1 exit
ramp,,,at,500,Congestion,,29-Jul-05,29-Jul-05,,Routine Traffic,Freeway,Lane
1,,,,,,,,,,,,1,,10097547.32,3126417.38,0,,,,,
```

Figure 2-12: Example of CTECC's Archived Incident Records.

CTECC defines incident clearance time as the time traffic has returned to normal conditions, which essentially is the time when the scene has returned to the same condition as it was prior to the incident occurrence. For example, if there is a vehicle left on a shoulder as a result of an incident, the incident status will not be cleared until this vehicle is removed from the scene.

2.1.4.3. <u>Data Applications</u>

CTECC implemented automated incident detection using three-minute rolling averages of lane occupancy data. The alarms are generated once the occupancy data exceed a threshold profile configured by TxDOT. TxDOT implementation allows up to six thresholds and corresponding time periods for a given day.

Thresholds can be set at any level of occupancy, and time intervals can be established at any point throughout the 24 hours of a day. The 24 hours of a typical profile start at 12:00AM and end at 11:59PM. There can be at most six non-overlapping time intervals in a profile. Multiple profiles can be configured for different situations, such as weekdays, weekends, special events, and inclement weather (*10*). A typical threshold graph for the TxDOT incident detection algorithm is shown in Figure 2-13.

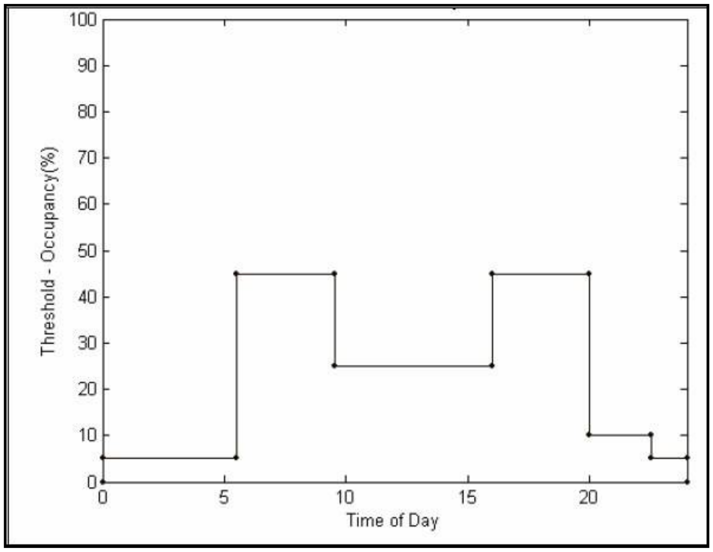


Figure 2-13: Typical Thresholds for TxDOT's Incident Detection Algorithm (*10*).

Since occupancy thresholds are configurable by TxDOT, a change in these thresholds can affect the number of alarms generated by the algorithm in the incident database. For instance, a significant increase in the number of detector-based congestion alarms from 2003 to 2004 in the CTECC data archive is due in large part to the change in threshold configurations inside the TxDOT algorithm.

2.1.5. Fort Worth's TransVision

Fort Worth's TMC has been established since 1992 to manage and coordinate traffic operations in the district. A new facility for Fort Worth's TransVision was opened in June 2000. The 29,622-square-foot TMC and initial system software were implemented at a cost of $8.4 million. The current TMC operating hours are from Monday to Friday, 6AM to 6PM, with remote access provided 24 hours a day and 7 days a week. The courtesy patrol in the Dallas-Fort Worth area is operated by TxDOT. The area covered by the courtesy patrol is shown in Figure 2-14.

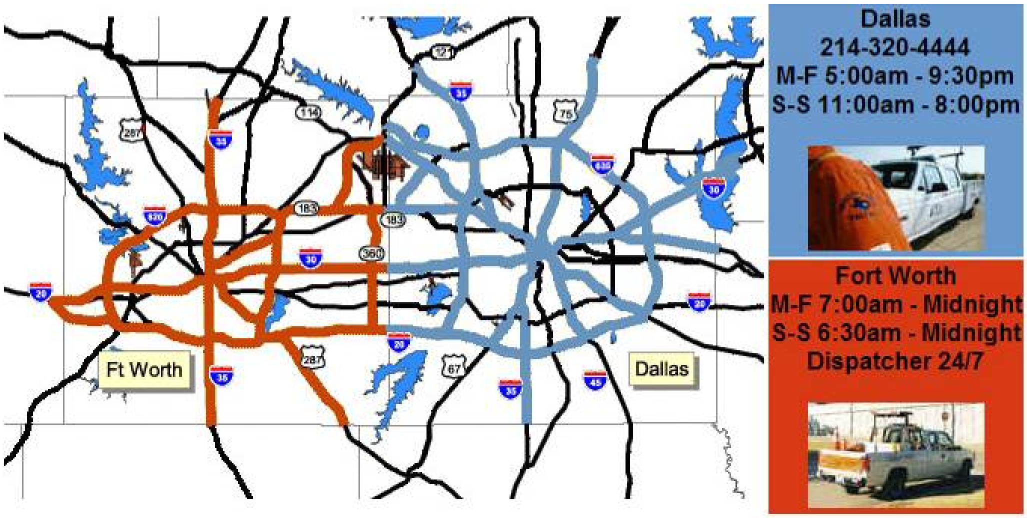


Figure 2-14: Dallas-Fort Worth Courtesy Patrol Coverage.

2.1.5.1. Deployment

As of 2007, Fort Worth's TransVision has approximately 100 freeway centerline miles with real-time traffic data collection technologies and five ramp metering systems (*11*). The CCTV coverage is also approximately 100 freeway centerline miles. The camera locations are available on the web-based map (http://dfwtraffic.dot.state.tx.us). Real-time traffic data are collected by loop detectors and side-fire radar detection. TransVision is currently replacing damaged loop detectors with side-fire radar detection units.

To disseminate travel-related information, TransVision relies on 64 DMSs and a traffic information website (http://dfwtraffic.dot.state.tx.us). TransVision shares its video feeds with all local television stations, Fort Worth public cable television, North Central Texas Council of Governments (NCTCOG), City of Fort Worth Emergency Operations Center, traffic service providers (traffic.com and MetroNet), and the Tarrant County 911 Center. TransVision also shares real-time traffic conditions with traffic service providers and with subscribers to TransVision's incident email listserver (*12*).

TransVision and DalTrans share their traffic information website. The URLs for both TMCs are directed to the same webpage (i.e., http://www.daltrans.org and http://dfwtraffic.dot.state.tx.us). TransVision is also one of the four TMCs in Texas that implemented a mobile version of its traffic information webpage. Wireless devices are automatically detected, and users are directed to the mobile webpage from the same URLs. Information available on the mobile version is similar to DalTrans' except that the speed and incident map is unavailable for TransVision's.

2.1.5.2. Data Management

The TransVision management software is a combination of legacy codes originally developed by Lockheed Martin and software modules developed under the Statewide

Development and Integration (SDI) program. TransVision relies on a database structure in Sybase that is modified from Houston's TranStar system, as well as Microsoft SQL Server. The latter is used by SDI subsystems for CCTV and DMS.

Real-time traffic data are available primarily from the side-fire radar detection system. Available traffic data include volume, occupancy, speed, and percent truck. TransVision does not archive these data on a regular basis although it has a capability to do so. Therefore, the availability of archived traffic data at TransVision is very limited. Occupancy data, in particular, are continuously used for the automated incident detection module.

Incident detection at TransVision relies on CCTV cameras, police dispatch monitoring, courtesy patrol calls, and commercial traffic services. The system also shares the incident information with DalTrans through the implemented C2C technology. The incident data have been archived since 2000.

TransVision collects the following time points for each incident record:

- incident reported/detected time,
- incident verification time,
- incident moved time,
- incident clearance time, and
- queue clearance time.

Queue clearance time is the time when the queue built up as a result of a lane-blockage incident has dissipated. The queue and incident clearance times are the same if the incident neither obstructs travel lanes nor creates a queue.

2.1.5.3. Data Applications

TransVision currently uses occupancy data as inputs to its occupancy-based incident detection algorithm. TransVision also has a travel time estimation module, which takes point-based speed data and segment lengths to compute segment travel time.

2.1.6. El Paso's TransVista

El Paso's TMC TransVista has been fully operational since November 2000. Overseen by TxDOT, TransVista manages 75 centerline miles of roadway with less than 25 TMC employees. TransVista currently operates Monday through Friday, 6AM to 8PM. TransVista operates a courtesy patrol program known as HERO from 8AM to 11PM. TTI is currently developing a TMC draft operator's guide for TransVista, which includes general operating policies and traffic management operating procedures (*13*). Most monetary funding for TransVista comes from the federal Congestion Mitigation and Air Quality (CMAQ) Improvement Program. TxDOT, however, provides funds to cover ITS maintenance costs for El Paso area state highways.

2.1.6.1. Deployment

TransVista monitors and controls freeway operations in the El Paso area, which includes the use of CCTV cameras, DMSs, lane control signals, and vehicle data collection. The TMC also provides network connection to the City of El Paso for traffic signal interconnection. TransVista recently installed a highway advisory radio system, but the system was not operational as of January 2007. It also has plans to replace its inducted loop detectors with a side-fire microwave vehicle detection system (MVDS) on area freeways. Figure 2-15 shows the ITS equipment map for El Paso's TMC. The sensor and DMS deployment on LP-375 is shown in Figure 2-16.

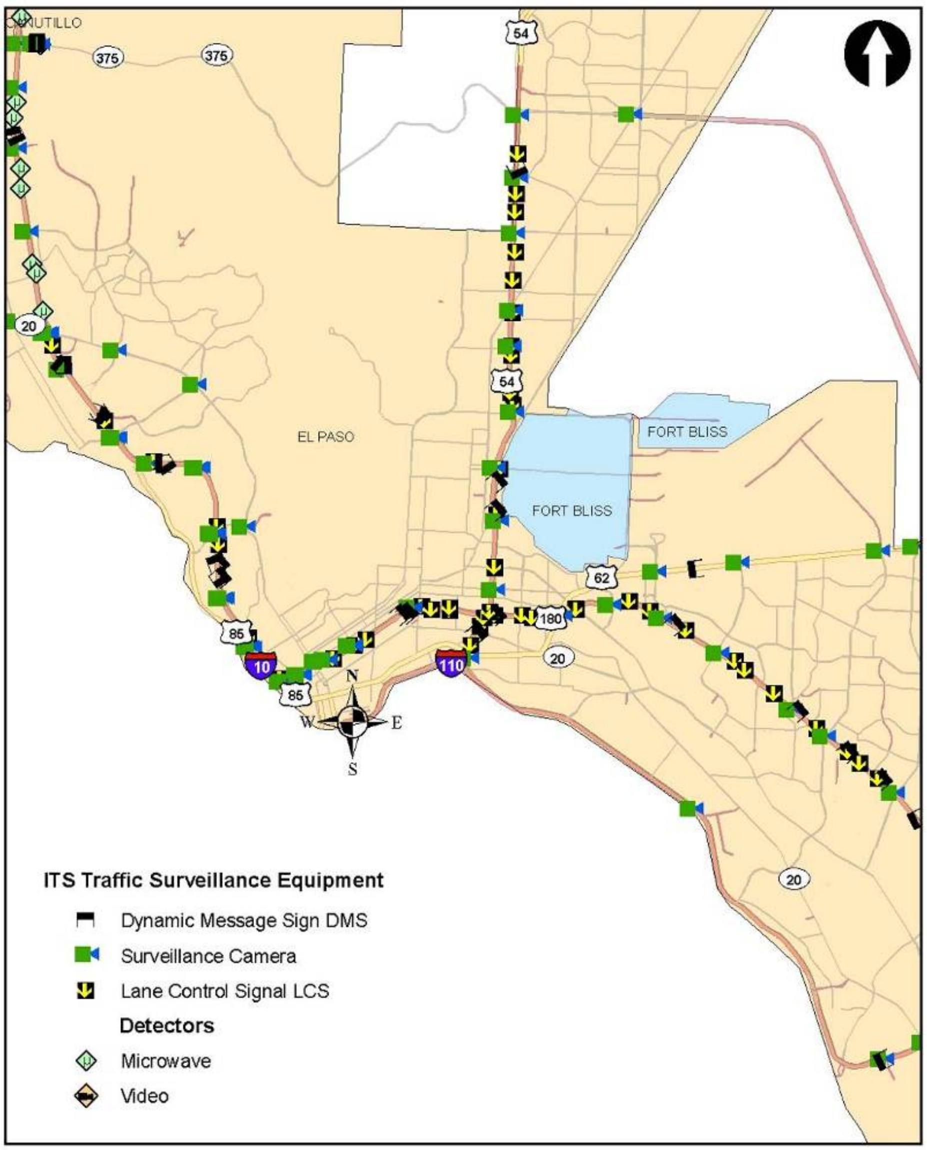


Figure 2-15: TransVista's ITS Equipment Map.

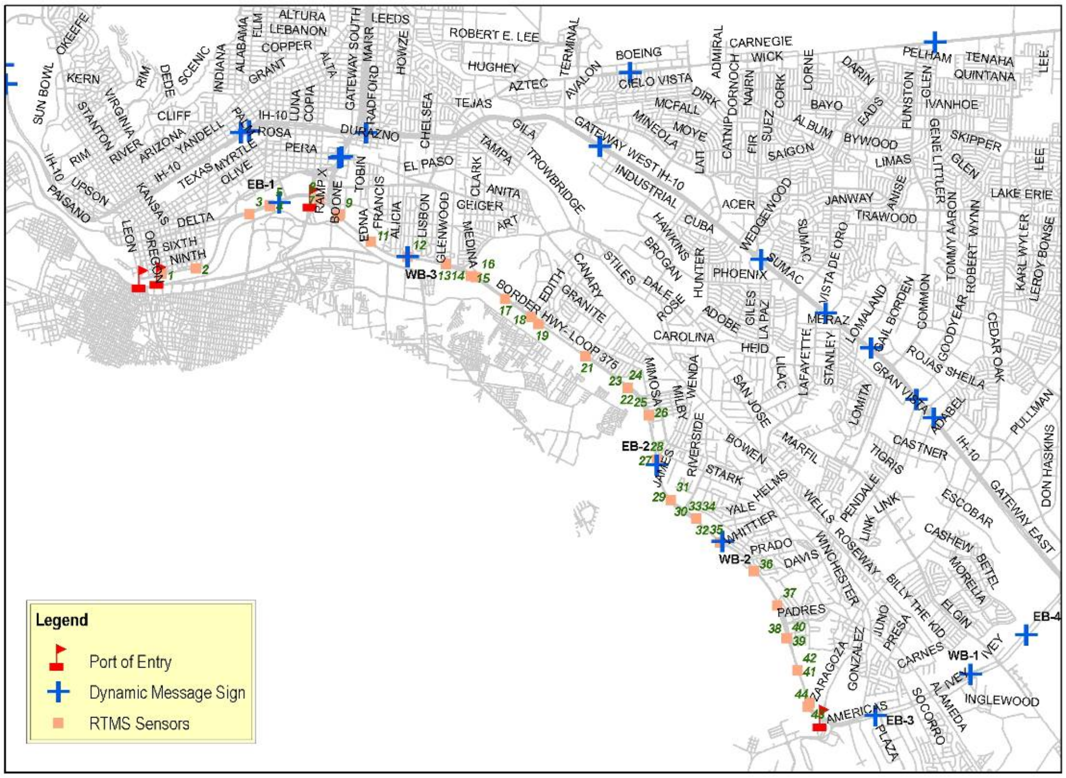


Figure 2-16: TransVista's ITS Deployment on LP-375.

TransVista's CCTV coverage, sensor, and DMS/LCS deployment broken down by freeway segment is summarized in Table 2-11. TransVista also has two ramp metering systems located on IH-10.

Table 2-11: TransVista's CCTV, Sensor, DMS, and LCS Deployment.

Segment	Miles Covered	CCTV Cameras	Loops	DMSs	LCSs	Radar
Montana	13	5	0	2	0	0
Airway	4	1	0	0	0	0
IH-10	36	35	684	21	110	Yes*2
US-54	9	14	294	5	45	Yes*2
LP-375	10	23	24	4	0	Yes*2
Mesa (SH-20)	NA*1	5	0	0	0	0
Zaragosa (FM-659)	NA*1	1	0	0	0	0
Total	***72***	***84***	***1002***	***32***	***155***	***--***

Notes: *1 – No data available; *2 – Exact figure is unavailable.

In addition, several ITS deployment projects are currently in the construction phase for TransVista, including installation of 17 CCTV cameras, 7 DMSs, loop detectors to cover an additional 16 miles on LP-375, and a traffic signal synchronization project.

TransVista provides traffic and other information on the Internet at http://www.transvista.dot.state.tx.us. The website provides camera snapshots updated every minute, traffic alerts, border waiting times, and road closure information. TransVista also shares CCTV video and control with other TMCs, emergency personnel (fire, police, etc.), and local media outlets.

2.1.6.2. Data Management

TransVista relies on TxDOT ATMS software with a Sybase database to provide four primary operations components: traffic monitoring, incident assessment and reporting, environmental sensing of road conditions, and traffic management.

Traffic Data

TransVista is capable of collecting and archiving traffic data from loop detectors. However, these data are not used currently due to data quality concerns. TransVista relies on a side-fire radar detection system as its main source of traffic data. TransVista collects and archives volume, occupancy, speed, and truck percentage data from the radar detection system on a lane-by-lane basis. Figure 2-17 shows sample traffic data from the side-fire radar detection system aggregated at 30-second intervals. Each data column represents the data from a specific lane at each detection station.

Incident Data

Incidents are detected by the HERO program, police radio scanning, scanning of police reports via the Internet, and communications with the police department. The majority of incidents are detected from scanning of police reports. Incident data are currently collected but not archived. The HERO program maintains a separate archive for its patrol operations.

TransVista routinely archives DMS messages as well as field maintenance/equipment data. An example of DMS logs is shown in Figure 2-18. LCS data are available in real time and archived in a separate database.

```
14 05 2006 00:07:20
MESSAGE NO. 232      VOLUME:   0   2   1   1   3   1   0   0
                   LONG VEH:   0   0   0   0   0   0   0   0
STATION ID. 37    OCCUPANCY:   0   1   1   1   3   2   0   0
FWDLK SPEED-?   SIDEFRD SPD:   ?   56  64  54  57  38  ?   ?
14 05 2006 00:07:37
MESSAGE NO. 169      VOLUME:   4   2   0   0   0   0   0   0
                   LONG VEH:   0   0   0   0   0   0   0   0
STATION ID. 16    OCCUPANCY:   3   1   0   0   0   0   0   0
FWDLK SPEED ?   SIDEFRD SPD:   45  54  ?   ?   ?   ?   ?   ?
14 05 2006 00:07:37
MESSAGE NO. 169      VOLUME:   4   2   0   0   0   0   0   0
                   LONG VEH:   0   0   0   0   0   0   0   0
STATION ID. 17    OCCUPANCY:   1   1   0   0   0   0   0   0
FWDLK SPEED-?   SIDEFRD SPD:   60  60  ?   ?   ?   ?   ?   ?
14 05 2006 00:07:38
MESSAGE NO. 169      VOLUME:   1   1   0   0   0   0   0   0
                   LONG VEH:   0   0   0   0   0   0   0   0
STATION ID. 18    OCCUPANCY:   1   1   0   0   0   0   0   0
FWDLK SPEED-?   SIDEFRD SPD:   58  57  ?   ?   ?   ?   ?   ?
14 05 2006 00:07:42
MESSAGE NO. 169      VOLUME:   2   1   0   0   0   0   0   0
                   LONG VEH:   0   0   0   0   0   0   0   0
STATION ID. 22    OCCUPANCY:   1   1   0   0   0   0   0   0
FWDLK SPEED-?   SIDEFRD SPD:   50  57  ?   ?   ?   ?   ?   ?
```

Figure 2-17: Example of TransVista's Traffic Data.

```
01-Nov-06 17:43:03  SL_INFO      DMS Main     ELP-ITS-ATMS  SYSTEM 1020   DMS
Main2663     Send Message Response     New message placed on 10E - Mesa. New
message is:
[pt25o0][jl3]SIGN[nl][jl3]UNDER[nl][jl3]TEST[np][pt25o0][jl3][nl][jl3]TESTING
, owner is: , duration is 1:0, priority is neutral, beacons are off, pixel
service is off

01-Nov-06 17:43:13  SL_INFO      DMS Main     ELP-ITS-ATMS  SYSTEM 1017   DMS
Main2667     Send Sequence Message     Sequence message sent to 10E - Mesa.
Sequence ID is: Advisories\Mesa_trucks center lane. Message is:
[pt30o0][jl3]TRUCKS[nl][jl3]USE[nl][jl3]CENTER
LANE[np][pt30o0][jl3]NEXT[nl][jl3]5 MILES

01-Nov-06 17:43:16  SL_INFO      DMS Main     ELP-ITS-ATMS  SYSTEM 1020   DMS
Main2667     Send Message Response     New message placed on 10E - Mesa. New
message is: [pt30o0][jl3]TRUCKS[nl][jl3]USE[nl][jl3]CENTER
LANE[np][pt30o0][jl3]NEXT[nl][jl3]5 MILES, owner is: DMS Main, duration is
18:50, priority is neutral, beacons are off, pixel service is off

01-Nov-06 17:43:49  SL_INFO      DMS Main     ELP-ITS-ATMS  SYSTEM 1020   DMS
Main2671     Send Message Response     New message placed on 10E - Mesa. New
message is: [pt30o0][jl3][np][pt30o0][jl3], owner is: , duration is 0:0,
priority is neutral, beacons are off, pixel service is off

01-Nov-06 17:43:57  SL_INFO      DMS Main     ELP-ITS-ATMS  SYSTEM 1017   DMS
Main2675     Send Sequence Message     Sequence message sent to 10E - Mesa.
Sequence ID is: Advisories\Mesa_trucks center lane. Message is:
[pt30o0][jl3]TRUCKS[nl][jl3]USE[nl][jl3]CENTER
LANE[np][pt30o0][jl3]NEXT[nl][jl3]5 MILES
```

Figure 2-18: Example of TransVista's DMS Logs.

2.1.6.3. Data Applications

While TransVista does not have any data applications at this time, TTI currently compiles an annual internal report, which is provided to TransVista and shared with the Federal Highway Administration (FHWA), TxDOT, emergency personnel, and other TMCs. TransVista also provides certain traffic data, such as number of incidents and incident clearing time, to TTI as part of its pollution study.

2.1.7. Amarillo's PEGASIS

Amarillo's PEGASIS is the TMC for the panhandle region. PEGASIS was established in 2001 with the installation of the first phase of ITS equipment completed in the fall of 2002. The camera usage is strictly to monitor the traffic and weather conditions. The video is neither recorded nor used by any agency for other purposes. PEGASIS' current operating hours are Monday through Friday, from 8AM to 5PM, with remote access 24 hours a day and 7 days a week. PEGASIS does not have a courtesy patrol program. PEGASIS' interior is shown in Figure 2-19 (*14*).

Figure 2-19: Amarillo's TMC – PEGASIS.

2.1.7.1. Deployment

PEGASIS ITS equipment deployment includes 10 CCTV cameras (7 cameras on IH-40 and 3 cameras on US-287) and 8 DMSs. PEGASIS plans to install an additional 6 CCTV cameras and 5 DMSs by the end of 2007. PEGASIS provides travel-related information via DMS, HAR system, and Internet. Currently, PEGASIS has one HAR station operational and plans to install one more station in the near future. PEGASIS has a traffic information website, which is accessible at http://amaits.dot.state.tx.us. Currently, only camera snapshots are updated in real time on the website every two seconds and eight seconds for broadband and dial-up connections, respectively. A screenshot of PEGASIS' traffic information webpage is shown in Figure 2-20. PEGASIS has no sensors deployed for real-time traffic data collection at this time.

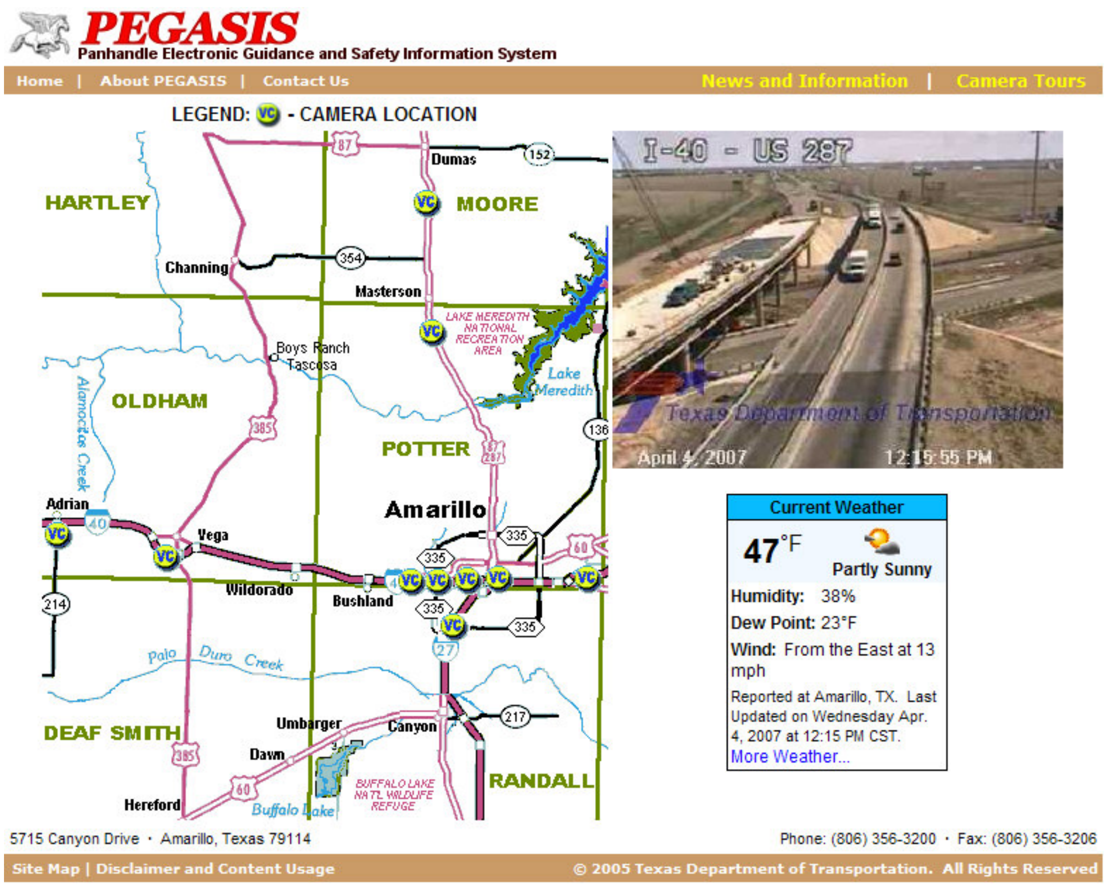


Figure 2-20: PEGASIS Traffic Information Webpage.

PEGASIS also specifically provides a mobile version of its webpage for wireless devices. The mobile webpage can be accessed at http://amaits.dot.state.tx.us/mobile/. Currently, only the real-time CCTV camera snapshots are available to the public. Users can specify which cameras they want to watch. The snapshots are not automatically updated for the mobile version.

2.1.7.2. Data Management and Applications

PEGASIS uses the TxDOT ATMS as its central management software. Currently, neither traffic nor incident data are collected or archived at the TMC. The level of ITS deployment at PEGASIS is still in the early stage. Since PEGASIS does not collect any data currently, there is no application of either real-time or historical data at this time.

2.1.8. Laredo's STRATIS

Laredo's STRATIS was established in 2004 to support traffic monitoring and management in the Laredo region. The Laredo region is located just south of the Texas Hill Country on the north bank of the middle Rio Grande River. The ITS stakeholders defined the regional boundaries to correspond with the Rio Grande River and the counties that surround or include the City of Laredo. The initial phase of ITS infrastructure in the Laredo region consists of DMSs, video surveillance cameras, traffic sensors, HAR, and a central management software system. The primary functions of the TxDOT system are to provide congestion management, incident management, and traveler information for motorists (*15*).

Figure 2-21 shows the interior of Laredo's STRATIS (*14*). The TMC's current operating hours are Monday through Friday, from 8AM to 5PM. Currently, there is only one operator staffing the facility. STRATIS does not have its own courtesy patrol program.

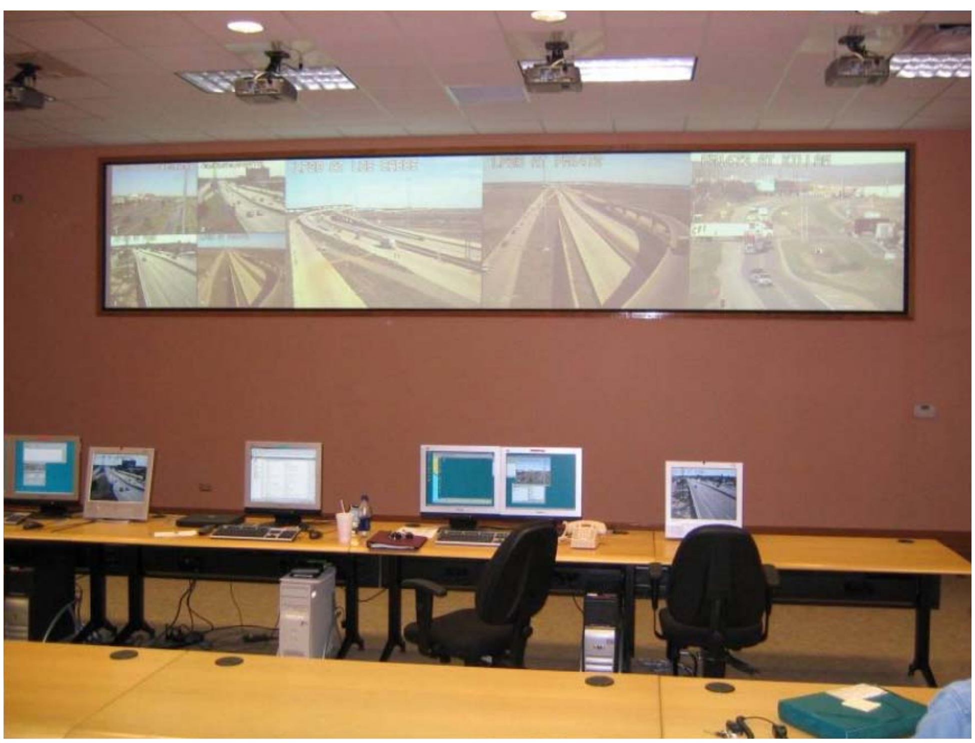


Figure 2-21: Laredo's TMC – STRATIS.

2.1.8.1. Deployment

The video surveillance and traffic sensor deployment at Laredo's STRATIS include:

- CCTV cameras on IH-35 (mile marker 1-10), FM-1472 (2 miles), and LP-20 (11 miles);
- inductive loop detectors on LP-20 and FM-1472 covering approximately 5 miles; and
- microwave radar detection on IH-35 (mile marker 1-7).

STRATIS has five stations of flood detection system installed in Del Rio. The flood data are integrated into the TMC through datawide servers. STRATIS also implemented a railroad crossing monitoring system using wireless doppler radar.

STRATIS relies on DMS, LCS, and HAR to provide traveler information to motorists. As of February 2007, 12 DMSs are operational, 2 additional DMSs are to be installed by August 2007, and 4 more will be installed by the end of 2008. There are 11 LCS stations with a total of 32 LCS heads. Two HAR stations have been deployed for the region. Motorists can tune into 530AM for railroad crossing status (so motorists can take alternative routes to avoid delay) and 1610AM for other general traffic and incident information.

Currently, the TMC website development is in progress, but no exact operational date was provided. Information to be provided to the public will include CCTV camera snapshots, work zone and construction information, lane closures, and DMS messages. In addition, STRATIS is developing a system to automatically detect approaching trains at the railroad crossing over IH-35 and display messages on DMSs.

STRATIS shares the video feeds only with the police department (PD) at this time. The PD cannot control the cameras directly but can request camera adjustment verbally.

2.1.8.2. Data Management and Applications

STRATIS uses the TxDOT ATMS as its central management software system and Sybase for its database structure. Traffic data, which include volume, occupancy, and speed, are collected in real time and archived every minute from both loop detectors and a radar detection system.

Incident detection at STRATIS relies primarily on 911 callers and CCTV cameras. While the ATMS subsystem is capable of collecting and archiving incident data, STRATIS neither collects nor archives incident information on a regular basis at present.

Similar to other smaller Texas TMCs (e.g., those in Amarillo and Wichita Falls), STRATIS is still in its early stage of ITS deployment and does not have any applications using either real-time or historical data at this time.

2.1.9. Wichita Falls' Texoma Vision

Wichita Falls' Texoma Vision has had many of the individual components that make up the intelligent transportation system in place for years. The process began in September 2003 when a group of local stakeholders met to develop the Wichita Falls Regional ITS Architecture and Development Plan. The individual components were officially brought together as a system with the construction of the Texoma Vision Traffic Management Center at the TxDOT Wichita Falls District Office that began in March 2004 (*16*).

The TMC is the focal point of the system due to the ability to have a visual aid through camera locations placed along the IH-44 corridor. The TMC is monitored by TxDOT and the Wichita Falls Police Department. Hours of operation at the TMC are Monday through Friday, from 8AM to 5PM. Hours of operation at the 911 Wichita Falls Police Dispatch are 24 hours a day, 7 days a week.

2.1.9.1. Deployment

Texoma Vision has nine CCTV cameras installed on the IH-44/US-287 corridor covering approximately 10 miles of freeway. The TMC monitors traffic for the Texoma area on two 52-inch plasma screen TVs at the TxDOT office on Southwest Parkway. The Police Station 911 Center also has a 48-inch plasma screen TV to monitor traffic movements from their location at 710 Flood Street (Figure 2-22). The cameras can be controlled from either location. Currently, all cameras are located along the IH-44/US-287 corridor. Emphasis was placed on this particular corridor due to high traffic volumes in this specific area of the district (*16*).

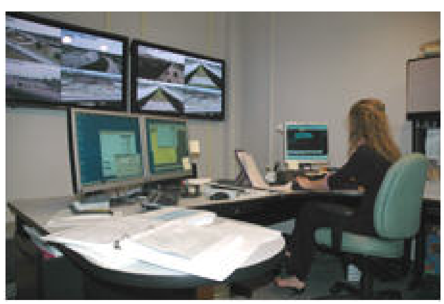


Figure 2-22: Texoma Vision Traffic Management Center.

Texoma Vision provides travel information to motorists through four DMSs and a traffic information website. CCTV camera snapshots updated every two seconds are provided to the public over the Internet at http://wfsits.dot.state.tx.us/its-trafficinfo. Users can visually check current traffic conditions within CCTV coverage areas by selecting the cameras they want to watch from a web-based map, as shown in Figure 2-23.

The TMC also has flood sensors, ice sensors, and full weather stations deployed for the region. The readings from the flood sensors are used to determine if and when the frontage roads need to be closed. Texoma Vision is one of the two TMCs (another one is

PEGASIS) in this study that have no sensors for collecting real-time traffic data at this time.

The Texoma Vision TMC shares information with the Oklahoma Department of Transportation to aid motorists that travel between Oklahoma and Texas.

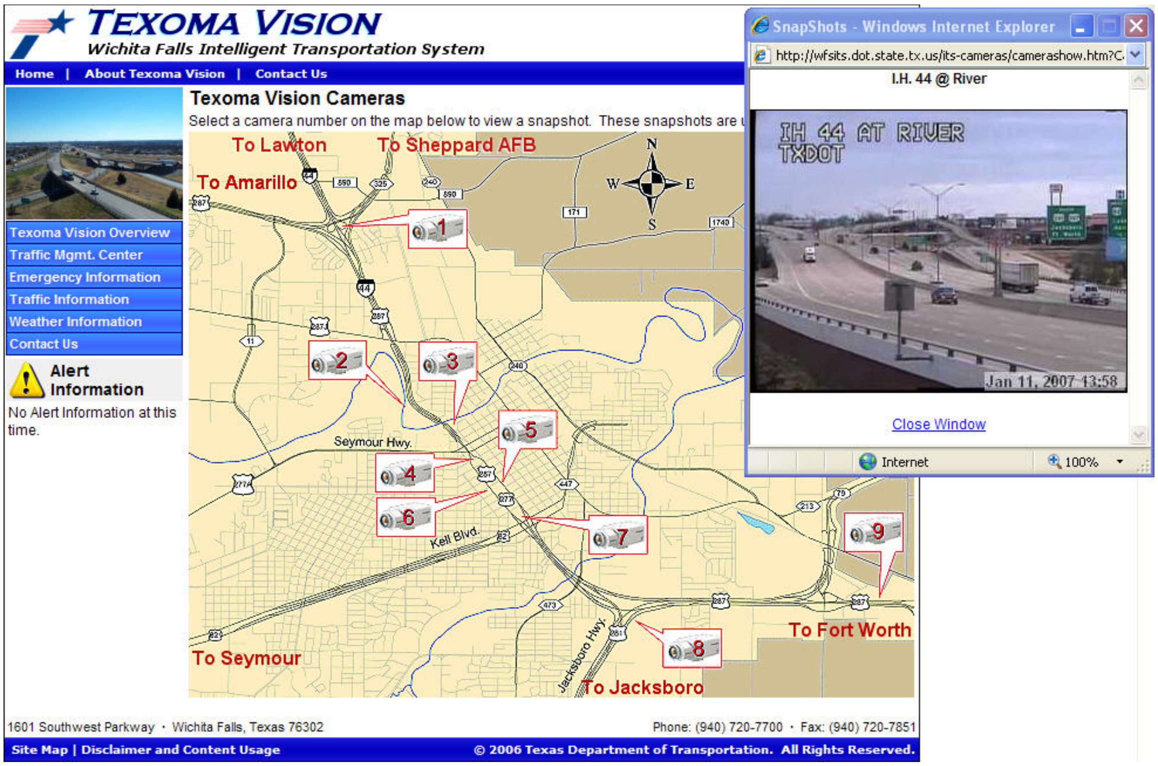


Figure 2-23: CCTV Snapshots from Texoma Vision Website (*16*).

2.1.9.2. Data Management and Applications

Texoma Vision implemented the TxDOT ATMS as its central management software system. The Skyline software system is used to manage DMS operations. Currently, there are no traffic sensors deployed in the region, and thus no traffic data are being collected.

Texoma Vision utilizes TxDOT's automated weather stations to help determine the need to close roads or advise travelers of high winds or roadway hazards. Flood sensors are an effective way to monitor roads without human eyes gauging a need to close the road due to water over the roadway. United States Geological Survey (USGS) flood sensor data are monitored to evaluate when rivers and creeks are at dangerous levels, and a road closure can be issued if necessary. Ice detection enables TxDOT to provide faster response to developing ice conditions and post winter weather advisories (*16*).

2.2. Summary and Comparison of Texas TMCs

The information about ITS deployment and data management gathered from the survey of nine Texas TMCs is summarized in tabular form in Tables 2-12 through 2-19.

Table 2-12: General TMC Information.

TMCs	General TMC Information	Courtesy Patrol	Central Management Software and Database
Houston - TranStar	Established in April 1996. Operates 24/7.	MAP operates as a public/private partnership from 6AM-10PM on weekdays.	Proprietary developed software. TranStar uses Oracle database.
Dallas - DalTrans	Established in 2001. Operates M-F 5AM-9PM.	Operates 5AM-9:30PM M-F and 11AM-8PM weekends.	Proprietary software developed and maintained by TTI. DalTrans uses Microsoft Access database.
San Antonio - TransGuide	Established in 1995. Operates 24/7.	Terminated.	TransGuide's ATMS operates as a client-server-based system that runs on Sun workstations in a Unix Solaris environment. TransGuide uses Sybase database.
Austin - CTECC	Established in January 2003. Operates 24/7 since July 5, 2006.	Known as HERO program. Operates weekdays 6AM-10PM. Currently CTECC is working on contracting private companies to provide additional response units during peak hours.	TxDOT ATMS with Sybase database.
Fort Worth - TransVision	Established in 1992. Moved into a new facility in 2000. Operators on site M-F 6AM-6PM. Remote access 24/7.	Operates M-F 7AM to midnight and weekends 6:30AM to midnight.	TransVision's software is a combination of legacy codes originally developed by Lockheed Martin and software modules developed under SDI program. TransVision uses Sybase and Microsoft SQL Server. The latter is used by SDI subsystems for CCTV and DMS.
El Paso - TransVista	Operates M-F 6AM-8PM.	Known as HERO (Highway Emergency Response Operation) program. Operates 8AM-11PM daily.	TxDOT ATMS with Sybase database.
Amarillo - PEGASIS	Established in 2001. Operates from M-F 8AM-5PM. Remote access 24/7.	None.	TxDOT ATMS.
Laredo - STRATIS	Established in 2004. Operates M-F 8AM-5PM. One operator.	None.	TxDOT ATMS with Sybase database.
Wichita Falls - Texoma Vision	Established in 2004. Operates M-F 8AM-5PM. One operator.	None.	TxDOT ATMS is used but no data are archived. Skyline software is used to manage DMS messages.

Table 2-13: CCTV and Real-Time Traffic Sensors.

TMCs	CCTV	Freeway Traffic Sensors				
		Inductive Loop Detectors	**Video Image Vehicle Detection Systems (VIVDS)**	**Probe Vehicle System**	**Radar Detectors**	**Sonic/Acoustic Detectors**
Houston - TranStar	Over 400 operational CCTV sites covering more than 335 freeway centerline miles as well as arterials. Plan to have more coverage on arterials.	Currently used only for detection at ramp meters. Long-term plan is to remove all and replace with radar sensors.	Terminated.	Main source for travel time data. Antenna located approximately every 1-5 miles.	Approximately 40 microwave radar sensors have been installed on I-10, I-45, US-290, and hurricane evacuation route.	None.
Dallas - DalTrans	Operational. Camera locations are available from the web-based map on www.daltrans.org.	Terminated.	Operational (Autoscope). Concern with data quality.	Terminated.	Side-fire radar detection. Primary source for DalTrans' traffic data.	None.
San Antonio - TransGuide	Approximately 144 CCTV cameras are used to monitor traffic on IH-10, IH-35, LP-410, south side of US-90, and northwest of LP-1604.	Major source of traffic data. Approximately 200 stations are installed roughly every half a mile.	Approximately 20 VIVDS are operational.	Terminated.	None.	Terminated.
Austin - CTECC	Covers 37 freeway miles.	Covers 37 freeway miles with loops located approximately every half a mile. Currently considering replacing damaged loops with magnetic detectors.	Autoscope Solo Pro and Iteris Vantage detectors on IH-35.	None.	Side-fire radar sensors as part of a testbed on IH-35.	Acoustic sensors as part of a testbed on IH-35.
Fort Worth - TransVision	Covers approximately 100 freeway miles. Camera locations are available from the internet (dfwtraffic.dot.state.tx.us).	Operational. Currently replacing damaged loops with side-fire radar.	None.	None.	Side-fire radar detection covers approximately 100 freeway miles.	None.
El Paso - TransVista	35 cameras on IH-10, 14 cameras on US-54, 23 cameras on LP-375, and 5 cameras on SH-20.	Operational. Problems with data quality.	None. City of El Paso uses Autoscope for signal operations.	None.	MVDS installed on LP-375, US-54, and part of IH-10.	None.
Amarillo - PEGASIS	7 cameras on IH-40 and 3 cameras on US-287. Plan to install 6 more by the end of 2007.	None.	None.	None.	None.	None.
Laredo - STRATIS	Operational on IH-35 (10 miles), FM-1472 (2 miles), and LP-20 (11 miles).	5-mile coverage on LP-20 and FM 1472.	None.	None.	Microwave detection installed on IH-35 (7 miles). Future plan is moving toward more detection of this type.	None.
Wichita Falls - Texoma Vision	Nine cameras on the IH-44/US-287 corridor covering approximately 10 miles. Live video is not recorded.	None.	None.	None.	None.	None.

Table 2-14: Environmental Sensors and Other ITS Deployment.

TMCs	Environmental Sensors			Other ITS Deployment	Comments
	Flood Sensors	Ice Detection	Full Weather Station		
Houston - TranStar	19 road flood gauges.	9 sensors.	18 stations on evacuation route.	Ramp metering. Galveston ferry wait times available on the Internet. Regional Computerized Traffic Signal System (RCTSS) allows operators to modify timing plans. Rail-grade crossing monitoring provides frequent snapshots from 19 cameras at critical rail-grade crossings.	None.
Dallas - DalTrans	None.	None.	None.	Implement C2C technology with TransVision.	None.
San Antonio - TransGuide	Five low-water crossing stations are currently operational.	None.	None.	TransGuide operates the Advance Warning for Railroad Delays (AWARD) in which three railroad crossings are being monitored. Warning signs are displayed when trains are passing.	TxDOT is transferring the control of 190 of its signals to City of San Antonio (CoSA) which in turn will upgrade these signals and share its signal data with the TMC.
Austin - CTECC	None.	None.	None.	Ambient temperature sensors installed locally on DMS cabinet. Data can be downloaded on-site and are not integrated into ATMS system.	Austin used to have two ramp meters during the 1970s-1980s.
Fort Worth - TransVision	One high-water station was installed as part of frontier technology demonstration project.	One ice detection station was installed as part of frontier technology demonstration project.	Currently plan to install six full weather stations to be used mainly for ice prediction.	Implement C2C technology with DalTrans. TransVision also has 5 individual ramp meters.	Currently, there is a plan to incorporate vehicle classifications (based on 13 FHWA categories) into the data repository of the system.
El Paso - TransVista	Three pump stations located on IH-10 next to embankment are used to monitor water level.	None.	None.	None.	None.
Amarillo - PEGASIS	None. Plan to install one high water detection in the near future.	None.	None.	None.	None.
Laredo - STRATIS	5 stations of flood detection system are installed in Del Rio.	None.	None.	Railroad crossing monitoring using wireless doppler radar. Currently working on automating train detection and display of DMS messages near railroad crossing over IH-35.	Currently plan to increase the number of sensors, DMSs, and LCSs deployed.
Wichita Falls - Texoma Vision	Operational.	5 ice sensors.	5 stations collecting wind speed/direction, temperature, humidity, and precipitation.	None.	None.

Table 2-15: Traveler Information Systems.

TMCs	Traveler Information System						
	Dynamic Message Signs (DMS)	**Lane Control Signals (LCS)**	**Highway Advisory Radio**	**Internet**	**Flood Alert / Road Weather Information Systems (RWIS)**	**Personal Alert Notification System**	**Others**
Houston - TranStar	Approximately 150 DMSs.	Operated by METRO for HOV lanes.	Motorists can tune into 1610AM or 1680AM depending on locations.	http://www.houstontranstar.org. Mobile versions is also available at http://traffic.houstontranstar.org/mobile.	Rainfall data and bayou water elevations are available in real time at http://hcoem.houstontranstar.org/txdot.	Subscribers receive personal alerts of incidents, traffic, and emergency info via their web-enabled PDA, cell phones, and computers.	Partnership with media outlets and with private sectors which use traffic data for commercial purposes e.g. traffic.com, trafficgauge.com, Inrix.
Dallas - DalTrans	37 DMSs. 6 in construction phase and 12 in design phase.	Terminated.	None.	http://www.daltrans.org. Shared website with TransVision. Mobile version is also available at the same website (mobile device is automatically detected) or http://www.daltrans.org/mobile.	None.	Subscribers are notified of freeway incidents via email. The service is limited to TxDOT and related transportation personnel.	Media outlets. All television stations in Dallas have access to video feeds.
San Antonio - TransGuide	155 DMSs	180 LCSs	TransGuide has an active project to install HAR at two locations. They are expected to be operational next year.	http://www.transguide.dot.state.tx.us provides camera images, traffic conditions, incident information, lane closure information, railroad crossing status, DMS displays, and segment travel time.	Five low-water crossing stations are currently operational. Real-time data are fed to district maintenance office.	None.	Since 1996, TransGuide has shared video with the local media and the general public by broadcasting live video using a 1,000-watt low-power Television (LPTV) transmission.
Austin - CTECC	16 DMSs.	44 LCSs installed under sign bridges at roughly every 3 miles. Typically 3 heads per station.	Three HAR stations covering 118 freeway miles. Motorists can tune into 530AM and 800AM for traffic info.	http://ausits.dot.state.tx.us provides CCTV camera snapshots updated approximately every 2 seconds.	CTECC receives email alerts from local flood detectors owned by City of Austin OEM office and weather alerts from NOAA service.	Pager system pages information about freeway incidents/stalls to subscribers.	Media outlets. CTECC shares video feeds with all four major television networks.
Fort Worth - TransVision	64 DMSs.	Operational for some sections (limited use).	None.	http://dfwtraffic.dot.state.tx.us. Shared website with DalTrans.	None.	Implemented TransVision's incident email listserver.	Media outlets also provide traveler information.
El Paso - TransVista	45 DMSs.	179 LCSs (traffic control for work zones and incidents).	13 HAR stations were installed recently. Not yet operational as of January 2007.	http://www.transvista.dot.state.tx.us provides camera snapshots, traffic alerts, border waiting times, and road closure information.	Alert messages are manually put on DMSs in case of flood alerts (from flood sensors).	Paging system. Subscribers are notified of freeway incidents via email.	Video feed sharing with police (full access) and local media (watch only).
Amarillo - PEGASIS	8 DMSs. Plan to install 5 more by the end of 2007.	None.	1 HAR station. 1 more station to be installed.	http://amaits.dot.state.tx.us provides video snapshots updated every 2 seconds for broadband and 8 seconds for dial-up. Mobile version is also available at http://amaits.dot.state.tx.us/mobile.	None.	None.	None.
Laredo - STRATIS	Currently 12 DMSs are operational. 2 additional DMSs will be installed by August 2007, and 4 more by the end of 2008.	11 LCSs. 9 stations with 3 heads. 1 station with 1 head. 1 station with 4 heads.	2 HAR stations. 530AM advises motorists on railroad crossing status. 1610AM provides other general traffic information.	Development in progress. Website is expected to be launched by August 2007. Information to be provided includes CCTV snapshots, workzone info, lane closure, and DMS messages.	None.	None.	Video feed sharing with police (watch only). PD can request verbally for camera adjustment.
Wichita Falls - Texoma Vision	4 DMSs.	None.	None.	http://wfsits.dot.state.tx.us provides snapshots from CCTV cameras updated every 1-2 seconds.	Readings from flood sensors are used by operators to determine if frontage roads need to be closed.	None.	None.

Table 2-16: Operations Data.

TMCs	Operations Data					Comments
	Volume	Occupancy	Speed	Vehicle Classification	Travel Time	
Houston - TranStar	Lane data is available in 30-sec interval both real-time and archived from radar detectors.	Lane data is available in 30-sec interval both real-time and archived from radar detectors.	Lane data is available in 30-sec interval both real-time and archived from radar detectors. Segment speed is also calculated from AVI travel time, available in 15-minute interval both real-time and archived.	Lane data is available in 30-sec interval both real-time and archived from radar detectors.	Obtained from AVI system. 15-minute average is available in both real-time and archived.	AVI data is used to provide travel time information.
Dallas - DalTrans	Lane data is available in 30-sec interval in real-time and archived every 5 minutes from radar and Autoscope.	Lane data is available in 30-sec interval in real-time and archived every 5 minutes from radar and Autoscope.	Lane data is available in 30-sec interval in real-time and archived every 5 minutes from radar and Autoscope.	Lane data is available in 30-sec interval in real-time and archived every 5 minutes from radar and Autoscope.	Computed from speed data. Not archived.	None.
San Antonio - TransGuide	Lane data is available in 20-sec interval both real-time and archived.	Lane data is available in 20-sec interval both real-time and archived.	Lane data is available in 20-sec interval both real-time and archived.	None.	Computed from speed lane data. Not archived.	City of San Antonio will share its real-time signal operation data with TransGuide.
Austin - CTECC	Lane data is available in 1-minute interval both real-time and archived from loop detectors.	Lane data is available in 1-minute interval both real-time and archived from loop detectors.	Lane data is available in 1-minute interval both real-time and archived from loop detectors (trap only).	Percent truck is available in 1-minute interval both real-time and archived from loop detectors (trap only).	None but would like to have in the future.	Data shuffling problem with loop detectors from Feb-Oct 2006. MPO currently looks at volume and % truck data for congestion management studies.
Fort Worth - TransVision	Available in 1-minute interval from sidefire radar. Not archived.	Available in 1-minute interval from sidefire radar. Not archived. Occupancy data is currently used in the automated incident detection module.	Available in 1-minute interval from sidefire radar. Not archived.	Available in 1-minute interval in terms of percent trucks. Not archived.	Computed from speed data. Not archived.	Would like to have signal timings and special event data e.g. posted messages, area affected. Traffic data can be archived upon request.
El Paso - TransVista	Lane data is available in 30-sec interval both real-time and archived from radar detectors.	Lane data is available in 30-sec interval both real-time and archived from radar detectors.	Lane data is available in 30-sec interval both real-time and archived from radar detectors.	Lane data is available in 30-sec interval both real-time and archived from radar detectors.	None.	Loop data are not used currently due to data quality concern.
Amarillo - PEGASIS	None.	None.	None.	None.	None.	None.
Laredo - STRATIS	Available every 1 minute in real-time and archived from loop and radar.	Available every 1 minute in real-time and archived from loop and radar.	Available every 1 minute in real-time and archived from loop and radar.	None.	None but would like to have in the future.	None.
Wichita Falls - Texoma Vision	None.	None.	None.	None.	None.	None.

Table 2-17: Explanatory Data.

TMCs	Explanatory Data						
	Weather Data	Flood Data	Work Zone	DMS Logs	Lane Closure	Courtesy Patrol	Others
Houston - TranStar	Data logs from rainfall, temperature, and wind sensors. Also available from incident database but not always recorded.	Available from flood sensors in real-time and archived.	Available from incident database. Not always recorded.	Separate DMS logs in Oracle database. Real-time and archived.	Lane closure logs. Real-time and archived.	Archived in MAP database.	
Dallas - DalTrans	None.	None.	Real time and archived in Access format.	Real time and archived in Access format.	None.	Maintained as a separate archive.	None.
San Antonio - TransGuide	None.	Data are collected from five low-water crossings. Not archived.	Scheduled lane closure data are available in real-time via TransGuide website. This data are also archived.	Displayed DMS messages as part of scenario database are available in real time and archived in event data.	Entered by operators. Archived.	None.	LCS scenario logs (available in real time and archived in event data); scenario data (available in real-time and archived, logged by operators, deployed in response to abnormal events); ITS equipment inventory (available off-line, not archived; GIS-based inventory also exists); future plan with CoSA to share real-time signal data with TransGuide.
Austin - CTECC	ATMS software has a capability to record this into an incident table (both real-time and archived) but rarely used. Required if command of traffic control device is needed.	None.	Can be archived by ATMS software but rarely used. Handled through road closure list.	Available in real time and archived in a separate SQL database table.	Archived.	Manually archived monthly in a separate database.	LCS data are available in real-time and can be logged for only the first 300 lines. Maintenance logs contain error logs from LCUs such as communication failure and data polling timeout.
Fort Worth - TransVision	Available from incident records.	None.	None.	Archived.	Entered by operators. Archived.	None.	None.
El Paso - TransVista	None.	Water level data are archived in a separate subsystem.	None.	Real-time and archived using proprietary protocol.		Archived from HERO patrol (Excel).	LCS data are available in real-time and archived in a separate database.
Amarillo - PEGASIS	None.	None.	None.	None.	None.	None.	None.
Laredo - STRATIS	None.	Available in real-time and archived.	None.	Available in real-time and archived through ATMS subsystem.	Archived through ATMS subsystem.	None.	None.
Wichita Falls - Texoma Vision	Available from weather sensors in real-time and archived.	Available from flood sensors in real-time and archived.	None.	None.	None.	None.	None.

Table 2-18: Incident Data.

TMCs	Incident Detection	Incident Data	Collected Incident Time Points				
			Reported	Verified	Moved	Cleared	Others
Houston - TranStar	Incidents are detected by CCTV cameras, incident detection algorithm, police radio scanning, MAP, police dispatch monitoring, and commercial traffic service. Primary source for detection is CCTV cameras.	Collected and archived since the beginning of the TMC operation. Incident locations are referenced to nearest cross street.	Collected.	Collected.	Collected.	Collected.	Incident entry time, i.e., the time that an operator enters an incident into a database.
Dallas - DalTrans	Incidents are primarily detected by operators, cameras, and scanning of data feeds from Dallas 911 and Metro Traffic. Other sources include police radio scanning and courtesy patrol.	Collected and archived since 2001 in Access format. Incident locations are referenced to nearest cross street.	Collected.	Collected.	None.	Collected. Operators could either use the time when all lanes are opened or when responders left the scene.	DalTrans collects incident status change times which also include incident disregarded time.
San Antonio - TransGuide	Incidents are detected by alarms from incident detection algorithm, operators, San Antonio Police Computer-Aided Dispatch system (SAP CAD), and media outlets. Majority of incidents are detected by police CAD.	Incident data are collected but not archived. Both alarms from incident detection algorithm and scenarios deployed by operators are archived, however.	Collected.	None.	None.	None.	Scenario log starting time can be used to indicate when incident was verified.
Austin - CTECC	Incidents are detected by video cameras, police radio scanning, HERO patrol, and alerts from automated incident detection alarms.	Collected and archived. Incidents can be located by cell phones (E911), operators (visually identify and click the location on the map), and coordinates of a cross street for detector-based alarms.	Collected.	None.	None.	Collected. Defined as the time the traffic returns to normal condition as it was before an incident.	Last detected date/time is recorded when the alarm threshold has been exceeded more than once.
Fort Worth - TransVision	Incidents are detected by video cameras and commercial traffic service.	Collected and archived since 2000. Incident locations are referenced to nearest cross street.	Collected.	Collected.	Collected.	Collected.	Queue clearance time. Incident and queue clearance times are the same if there is no queue.
El Paso - TransVista	Incidents are detected by HERO program, police radio scanning, scanning of police reports via internet, and communications with PD. Majority of incidents are detected from scanning of police reports.	Collected but not archived. HERO patrol data are collected and archived separately.	None.	None.	None.	None.	None.
Amarillo - PEGASIS	No incident management program. Incidents are primarily detected by being called, e.g., police, TxDOT personnel, fire department.	Not collected.	None.	None.	None.	None.	None.
Laredo - STRATIS	No incident management program. One operator. Incidents are primarily detected by 911 callers and video cameras.	Incidents are not collected on a regular basis although current ATMS subsystem is capable of doing so.	None.	None.	None.	None.	None.
Wichita Falls - Texoma Vision	No incident management program. One operator. PD can control and monitor the CCTV cameras.	Not collected.	None.	None.	None.	None.	None.

Table 2-19: Data Applications at Texas TMCs.

TMCs	Data Applications		
	Automated Incident Detection	**Travel Time Estimation**	**Others**
Houston - TranStar	Speed-based algorithm compares real-time speed data with historical averages and generates alarms if the current speed falls below certain thresholds.	Obtained from AVI system. Segment travel times are averaged every 15 minutes.	None.
Dallas - DalTrans	None.	Real-time 3-minute rolling averages of speed data are used to compute travel time.	None.
San Antonio - TransGuide	Operational. Real-time 2-minute moving average of speed lane data is used for incident detection on mainlanes while occupancy is used on entrance and exit ramps.	Real-time speed lane data are used to compute travel time. The outputs are not archived.	None.
Austin - CTECC	Loop-detector-based alarm thresholds using occupancy values. Threshold profiles are configured by the ATMS system administrator.	None.	Currently, TTI is working on IAC to develop an Access/Excel-based tool to help evaluate the correlation between weather and incident data.
Fort Worth - TransVision	Operational. Occupancy-based algorithm.	Speed-based algorithm.	None.
El Paso - TransVista	None.	None.	None.
Amarillo - PEGASIS	None.	None.	None.
Laredo - STRATIS	None.	None.	None.
Wichita Falls - Texoma Vision	None.	None.	None.

3. REPORTING INCIDENT CHARACTERISTICS

Currently, several Texas TMCs routinely collect and archive incident data from daily operations. These data are currently used at some TMCs to produce annual performance reports. The purpose of this module is to provide the analyst with information on what and how incident characteristics being collected should be reported. Common reporting formats are tables, graphs, and pie charts. The list of reports provided in this module is intended to serve as a guideline for the analyst to customize and build his or her own list of standard reports in order to meet the analysis and reporting objectives of the agencies.

The following list consists of commonly collected incident data attributes at Texas TMCs:

- incident type,
- detection method,
- verification method,
- severity,
- weather/environmental conditions,
- vehicles involved – the number and types of vehicles involved,
- incident responders, and
- lane blockage characteristics – the number and types of lanes blocked.

In addition, the following time points are commonly collected to represent the progress of the incident management process at the TMCs:

- incident detection time and
- incident clearance time.

The analyst can use these data attributes to produce standard incident characteristics reports. Three major types of analyses can be used to produce these reports (in the order of increasing complexity):

- frequency analysis (single attribute),
- cross-attribute analysis, and
- derived attribute analysis.

Frequency analysis is the most common type of analysis involving the study of the distributions of incident data attributes. Cross-attribute analysis is the study of the distributions of two or more attributes concurrently. Derived attribute analysis involves specific calculations to retrieve certain characteristics from the database. This could be a single attribute or cross-attribute analysis of parameters that are not directly recorded in the incident database (e.g., number of lanes blocked, incident duration, etc.).

3.1. Frequency Analysis of Incident Attributes

Frequency distribution is the most common type of reporting incident characteristics. The analyst can query the incident database to produce frequency distributions for each data attribute. This type of frequency reporting can be performed on various time scales such as monthly, quarterly, and annually depending on the objectives of the agency (e.g., short-term versus long-term performance monitoring).

When frequency distributions are analyzed over time, they can reveal the trends and changes in occurrence patterns of specific incident data attributes. The choice of time scale in the frequency analysis depends on the objectives of the agencies. For operations planning, shorter time scales such as time of day or day of week can provide meaningful results for the frequency analysis. A longer time scale such as quarterly or annually is more suitable for long-term performance monitoring. Table 3-1 provides suggested time scales for the frequency analysis of incident data attributes.

For example, the distributions of lane blockage should be reported either quarterly or annually for long-term monitoring, but the same analysis would not be particularly useful when analyzed by either time of day or day of week. On the other hand, the distribution of incident frequency by incident types would be useful at all ranges of time scale and thus could be used for both short- and long-term monitoring and planning.

Table 3-1: Suggested Time Scale for Frequency Analysis.

Common Incident Data Attributes	Time Scale				
	Time of Day	Day of Week	Monthly	Quarterly	Annually
Incident Types	x	x	x	x	x
Detection Method	x	x			x
Verification Method	x	x			x
Responders	x	x		x	x
Severity	x	x		x	x
Weather Conditions				x	x
Vehicles Involved	x	x			x
Lane Blockage				x	x

3.1.1. Reporting Format

There are several alternatives to present the results from the analysis. Tabular formats are generally recommended for data archival purposes. However, graphical reporting formats are usually better for communicating the results across various groups of audiences. The general guideline for selecting the graphical reporting format is as follows:

- If the percentage sum of the figures from all categories being analyzed is equal to 100 percent, use pie charts or relative bar charts with a fixed height. This format is suitable for incident attributes that are mutually exclusive. For example, the distribution of incident severity is mutually exclusive because there can be only one level of severity recorded per incident (see Figure 3-1). However, this option is recommended only if the number of levels being represented in a bar is no more than four. For a greater number of levels, use the second alternative (separate bar charts) instead to avoid visual cluttering of information.

- If the percentage sum of the figures from all categories being analyzed is not equal to 100 percent, use separate bar charts for each category. For example, Figure 3-2 shows the distribution of incident responders by year. There can be multiple responders recorded per incident, and thus the percentage sum of all the figures in each year can be greater than 100 percent.
- Use line charts to represent the counts, frequencies, or rates of incidents over time. For example, Figure 3-3 shows incident counts on a monthly basis for selected types of incidents.

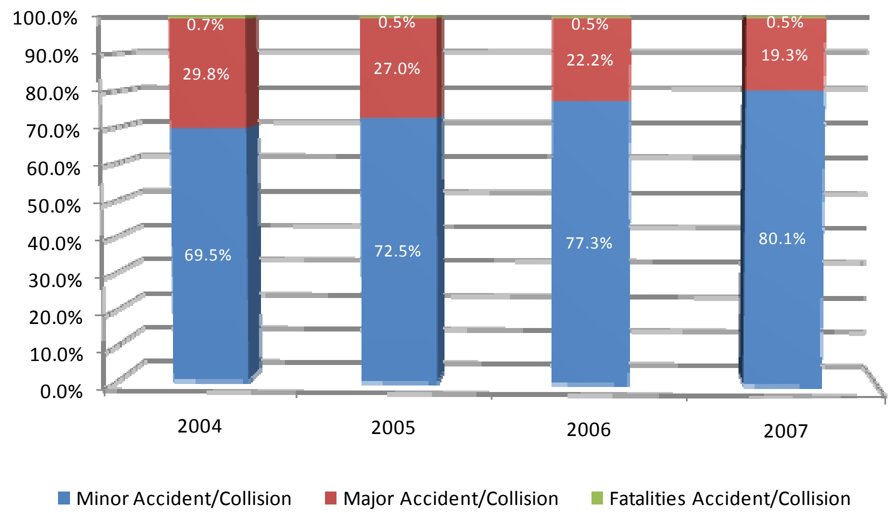


Figure 3-1: Yearly Distribution of Incident Severity (Houston).

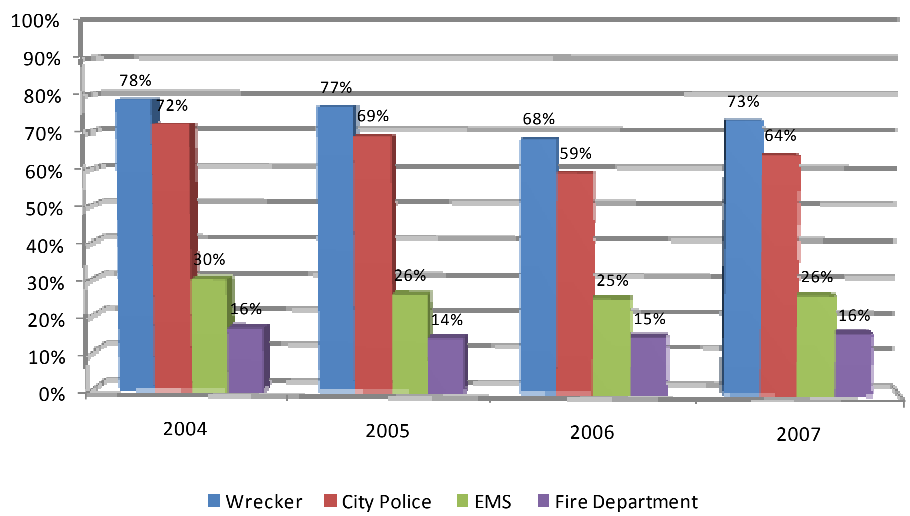


Figure 3-2: Yearly Distribution of Major Incident Responders (Houston).

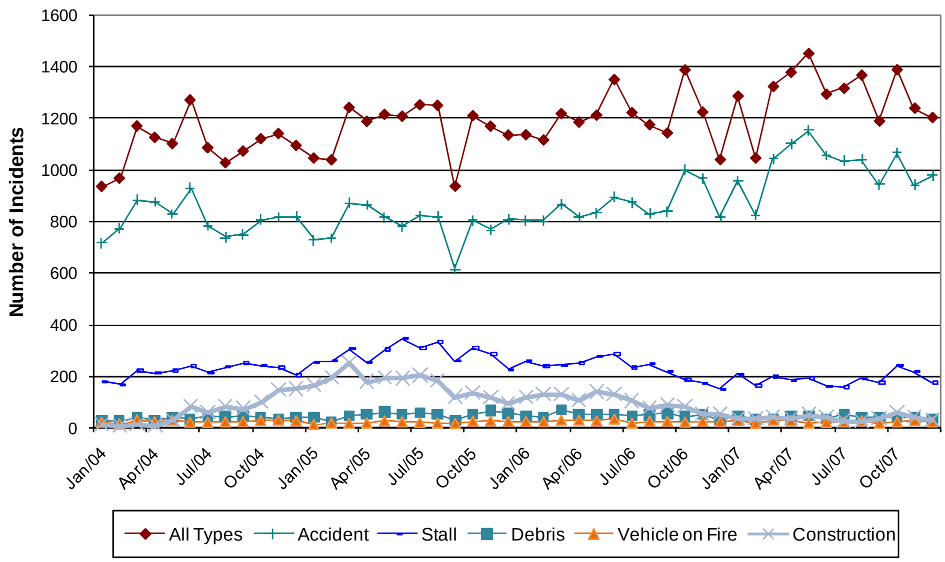


Figure 3-3: Monthly Incident Counts for Major Incident Types (Houston).

3.1.2. Reporting Time Scale

The time scale used to produce frequency distribution reports should be selected based upon the objectives of the analysis. The general guideline is as follows:

- operations evaluation/short-term monitoring – time of day, day of week, and monthly; and
- before-after evaluation/long-term monitoring – quarterly and annually.

The analyst may also consider other time scales as seasonality or weekday/weekend effects to address specific objectives of the analysis. It is important to ensure that the incident rates being compared are normalized by appropriate exposure. For example, when the incident frequency is analyzed by time of day, the number of hours included in AM peak, PM peak, and midday periods can vary. Incident rates must be calculated by dividing incident counts with the same unit time (e.g., 1,000 hours). Figure 3-4 shows the distribution of selected incident types by time of day. In this case, the weekday data were classified into different time periods, and the weekend counts were aggregated altogether regardless of time of day. The number of incident counts for each time period was normalized by the appropriate number of hours.

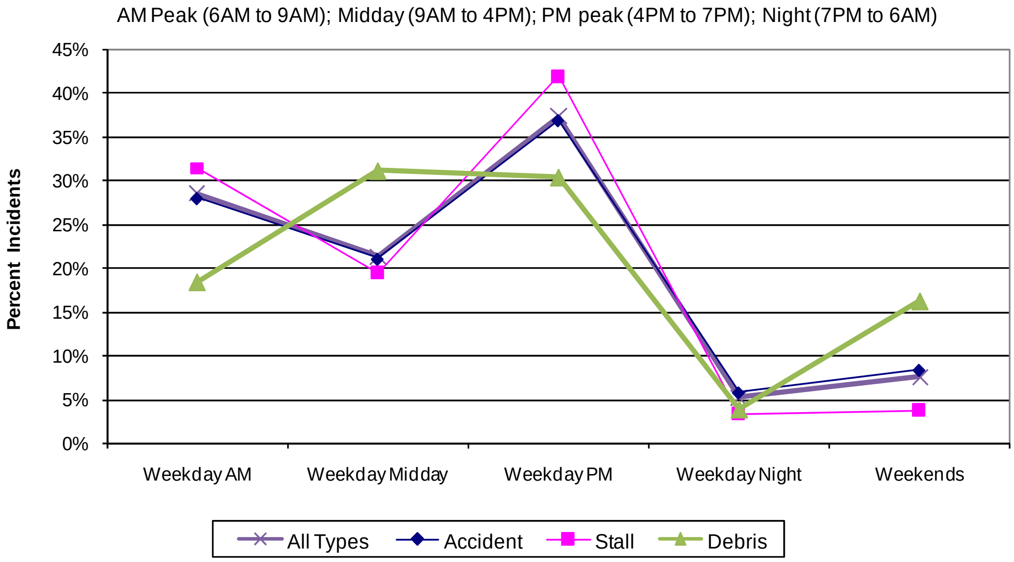


Figure 3-4: Distribution of Selected Incident Types by Time of Day (Houston).

3.2. Cross-Attribute Analysis

Frequency analysis in the previous section relies on a single incident data attribute. The analyst can study frequency distributions taking into account two or more data attributes simultaneously in the analysis. The incident reports produced from the analysis in this manner are referred to as “cross-attribute” analysis.

The cross-attribute analysis, while usually more complicated, can provide a greater insight into occurrence patterns of specific combinations of incident data attributes. For example, a frequency distribution of incident severity by type can be used to identify the types of incidents with relatively higher rates of injuries and fatalities. Two-level cross-attribute analysis refers to the type of distribution report based on two attributes concurrently (e.g., incident severity by type, number of lanes blocked by incident severity, etc.). When more than two attributes are used simultaneously, the distribution analysis becomes multi-level cross-attribute analysis. Theoretically, there is no upper limit on the number of attributes that the analyst can include. However, the results from multi-level cross-attribute analysis can quickly become confusing due to the excessive number of potential combinations. Moreover, the results of multi-level distribution reports can be difficult for the agency to synthesize internally or communicate to the public.

Table 3-2 summarizes the suggested two-level cross-attribute analysis of incident data. The “x” in the table indicates a scenario where cross-attribute analyses can produce meaningful results. The analyst can use this matrix to create a customized list of desirable reports from cross-attribute analysis that suits the needs and/or requirements of the agency.

Table 3-2: Suggested Two-Level Cross-Attribute Analysis of Incident Data.

	Incident Types	Detection Method	Verification Method	Incident Responders	Severity	Weather Conditions	Vehicles Involved	Lane Blockage
Incident Types				x	x	x	x	x
Detection Method						x		
Verification Method						x		
Incident Responders					x			
Severity						x	x	x
Weather Conditions								
Vehicles Involved								x
Lane Blockage								

The considerations for reporting format and time scale for cross-attribute analysis are similar to those of single attribute analysis. Figure 3-5 shows the distribution of major responders by incident types. A distribution of all responders was first examined to identify the types of major responders. Then, a cross-attribute analysis by incident types was performed on major responders to examine specific distributions of responders by incident types.

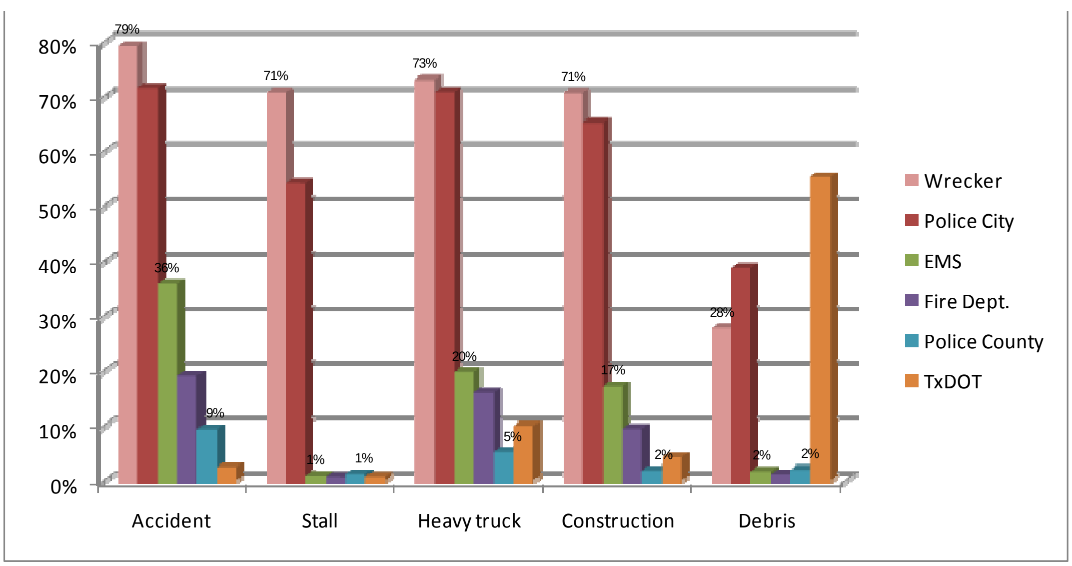


Figure 3-5: Distribution of Selected Responders by Incident Types (Houston).

3.3. Derived Attribute Analysis

Derived attributes are the characteristics that are not directly recorded but can be computed or extracted from the incident database. The level of complexity involved in retrieving these attributes varies and depends on the structure and format of the incident data archive. Examples of derived attributes are summarized in Table 3-3.

Table 3-3: Examples of Derived Attributes.

Attribute	**Calculation**
Categorical Attribute	
First Responder	• If arrival times by responders are recorded in the database, use the earliest arrival time among all the responders.
Number of Lanes Blocked	• If lane number is recorded for each lane block, add up all the lanes recorded by types (e.g., main lane, frontage lane, ramp lane).
Continuous Attribute	
Incident Duration	• If both incident detection and clearance times are recorded, obtain the incident duration by computing the difference between the detection and clearance times.
First Responder Response Time	• Calculate the difference between incident detection time and first responder arrival time, if available.
Total Response Time	• Calculate the difference between incident detection time and last responder arrival time, if available.

3.3.1. Validity Check

It is recommended that data validity checks be performed prior to any subsequent analyses. The most common types of validity checks can be classified as follows:

- Missing data – For example, incident duration cannot be computed if the clearance time is missing.
- Erroneous data – For example, incident durations cannot be negative values.
- Invalid data – Examples of logical checks for invalid data include minimum and maximum of duration data such as incident duration and first responder response time.

3.3.2. Reporting Continuous Derived Attribute

Considerations for reporting formats and time scales in this case are similar to all the previous analyses. Categorical variables can be analyzed and reported using frequency distributions grouped by either single or multiple attributes. However, for continuous derived attributes such as duration data, the frequency method will no longer apply. The following types of statistics are recommended for reporting continuous values:

- Mean – Mean value should only be used for data that are symmetrically distributed. Asymmetrically distributed data can give a biased estimate of mean value. When the distribution is symmetrical, the mean and median will be approximately the same. The advantage of the arithmetic mean over the median is that it is simpler and more efficient to calculate in computer software (e.g., spreadsheet based or database software).
- Median – Median value is recommended for most duration data observed in the incident database. Median value is not affected by extremely low or high values in the data set and thus suitable for calculating averages of asymmetrically distributed data.
- Specific percentile values – Percentile value is recommended for calculating the upper and lower ranges of the data set. To illustrate, 95th percentile of incident duration would represent the duration value at which only 5 percent of all incident data will exceed. Percentile values are preferred to minimum and maximum values for establishing the lower and upper ranges of the observed attribute values since they are less likely to be affected by outliers.
- Exceedance rate – The rate at which the specified threshold is exceeded. This measure is useful when the agency is interested in analyzing specific situations. For example, in addition to obtaining incident duration, the analyst can also compute the rate at which the incident duration is greater than two hours by time of day.

Figure 3-6 shows the example of incident duration statistics classified by incident types. In this case, the analyst can determine the average duration of specific incident types based on the median values and the corresponding upper duration threshold by the 85th percentile values. The duration data were displayed on a log scale in order to capture a wider range of duration values in the same chart.

Figure 3-7 displays another example of derived attribute analysis. The incident data from Fort Worth were used to identify the major types of first responders and then compute the median and 95th percentile values of first responder response times. The data were also displayed in a log scale as in the case of incident durations.

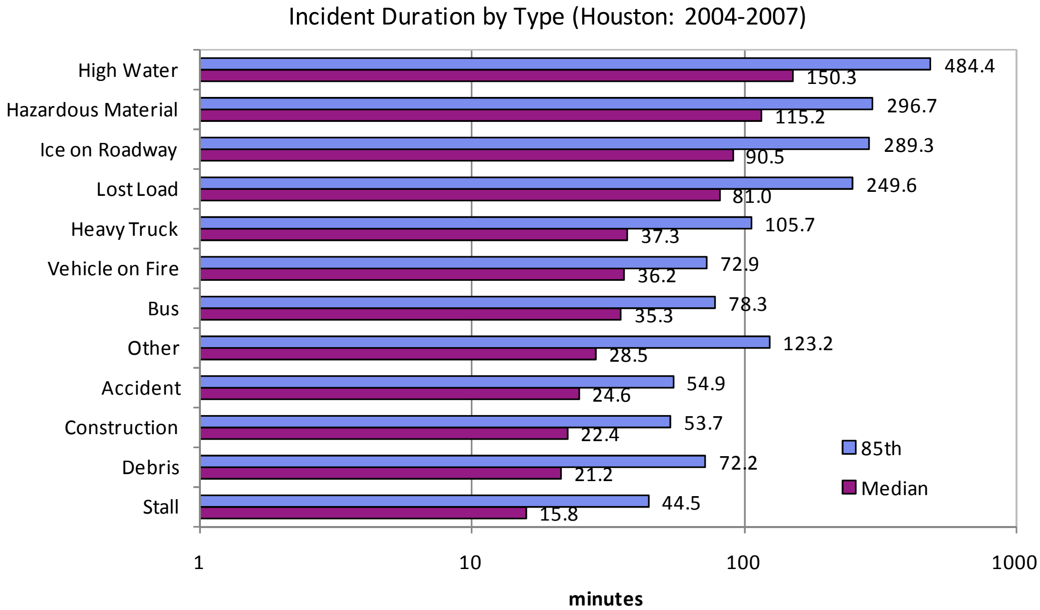
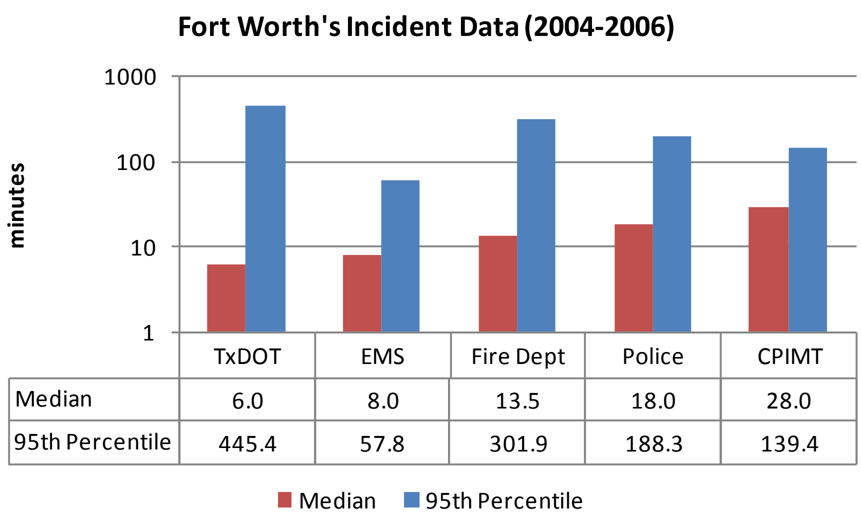


Figure 3-6: Incident Duration Statistics by Incident Types (Houston).



	TxDOT	EMS	Fire Dept	Police	CPIMT
Median	6.0	8.0	13.5	18.0	28.0
95th Percentile	445.4	57.8	301.9	188.3	139.4

Figure 3-7: First Responder Response Time Statistics (Fort Worth).

3.4. Considerations for Reporting Incident Characteristics

Producing routine reports on incident characteristics is time consuming and requires technical expertise to do the job accurately. Incident characteristics are worth reporting if they are used to make informed decisions. The following considerations should be taken into account in producing these reports:

- What are the objectives of the reports?
- The objectives of the reports should determine the appropriate time scale for the analysis.
- What types of characteristics should be reported?
- Are the data sufficient and valid for producing the reports?
- Who will be the audiences?
- What are the most effective presentation methods to communicate the results to the audiences?
- Consider automating the calculation and reporting procedures if the reports are needed on a regular basis.
- Incident characteristics are based on what has happened and by themselves are not predictions of what will happen.

Table 3-4 outlines some of the possible advantages and disadvantages to the frequency of reporting.

Table 3-4: Regular Monitoring Report Considerations – Modified from (*17*).

Frequency of Regular Monitoring Reports	Possible Advantages	Possible Disadvantages
Quarterly	• Better connection to strategic agency goals and decisions. • An active reporting system improves the visibility of performance improvement. • Improves communication between various stakeholders. • If formatted for public view, it also can be a good public information and accountability tool. • Encourages improvements in data organization and quality. • Builds internal agency support and accountability. • Regular reporting establishes a routine, helping to instill performance measurement into agency culture and daily activities.	• Slow data reporting and processing may limit the value of a quarterly report. • Personnel resources required may exceed those available. • Measures driven by data availability may not be suitable for quarterly reporting. • Measures related to critical agency objectives may be difficult to report on frequent basis. • High “yawn” factor if conditions do not change quarterly.
Annually	• Greater ability to track historic trends. • Longer time period to collect data. • If formatted for public view, good public relations and accountability tool. • Able to provide in-depth coverage of agency’s performance.	• Data availability and consistency. • Limited personnel resources. • Vulnerable to changes in administration or leadership (if not routinely visible and valued by top-level management).

4. ANALYZING HOT SPOTS

Historical incident data archived at the TMCs can be used to help identify incident-prone locations or hot spots. This module describes the analytical methods and tools for this application.

This module outlines procedures to evaluate spatial and temporal patterns in the distribution of incidents for Texas TMCs and to use this information to develop strategies for improving incident management operations such as improving detection/response times. The main idea of this analysis is to perform incident data mining to determine whether there was evidence of spatial and temporal effects in the distribution of incidents. TMC managers can use such information as decision support tools for designing and improving their incident management strategies. Examples of hot spot applications include the assignment of patrol vehicles around freeway segments with high incident frequencies, identifying hazardous freeway segments for improved traffic sensors, and allocating control center operators for different work shifts.

4.1. Overview of Hot Spot Identification Methods

Depending on data availability, two methods can be used for identifying hot spots:

- the frequency-based method and
- the attribute-based method.

First, the frequency-based identification method relies mainly on the frequency and location of incidents regardless of their characteristics. This method considers locations experiencing high rates of incidents as hot spots. The advantage of this method is that it is simple and requires minimal incident data attributes. However, the weakness of this method is that it treats all the incidents equally regardless of their characteristics. The impacts of the incidents are not incorporated into the analysis.

Second, in addition to incident frequency, incident characteristics such as incident duration can potentially be used as a proxy of incident impacts to identify hot spots. To utilize such information, the analyst may consider using the attribute-based identification method. The attribute-based method combines the information about the locations, frequencies, and certain attributes of incidents to identify hot spots. This method can help TMC managers pinpoint the locations of concern through effective use of the information available in the incident database. However, this also increases the complexity and data requirement of hot spot analysis procedures.

4.2. Data Requirement

The first step prior to the hot spot analysis is to check if the incident data attributes are sufficient for the analysis. As noted, characterization of incident data entails evaluating temporal and spatial patterns in the distribution of incidents. Two types of data attributes are generally required for analyzing incident-related statistics and hot spot locations:

- Temporal attributes – This attribute is typically collected as time logs for various events in an incident timeline. The most critical temporal element is the incident occurrence time. The incident detection or notification time is often used to signify the incident starting time since the actual occurrence time can be difficult to obtain.
- Spatial attributes – This attribute is used to identify the incident locations on the freeway. There are many ways to spatially reference incidents. Examples include geographical coordinates (longitude and latitude), roadway sector address, names of closest intersecting roads, street address, and highway name and milepost. The analyst could use any of these methods to map incident information. Nevertheless, the easiest method would be geographic coordinates.

In addition to the required attributes, the supplemental attributes collected in the incident database are often very useful for this analysis. For instance, the analyst can examine high-incident locations classified by incident types where such attributes are available. These supplemental attributes are generally collected along each incident record at Texas TMCs. Examples of these attributes include:

- incident type;
- incident severity;
- weather conditions;
- incident responders;
- blockage characteristics, e.g., number of lanes blocked, duration, and types of lanes blocked; and
- number and type of vehicles involved.

To suit various analysis objectives, the specific data requirement should be further tailored based on data availability at individual TMCs because the approaches for generating and archiving incident data vary from agency to agency.

For example, TranStar maintains a comprehensive incident archive with over 70 incident data attributes generally collected. In contrast, San Antonio's TransGuide archives a much simpler log of incidents with only several incident data elements; nevertheless, TransGuide also archives all messages displayed on its DMSs. Smaller TMCs, such as Laredo's STRATIS, do not archive any of their incident information. TMCs also vary in how they geographically reference their incident data. For instance, TranStar uses the following incident location identifiers: main road name, direction, cross street name, and a qualifier (at, before, and after), in addition to longitude/latitude coordinates. TransGuide, on the other hand, geographically references its incidents using a sector address, which has three components separated by a dash: the letters SECT, representing roadway sector; freeway number; and mile marker. TransGuide has a GIS-based database identifying the location of these sectors. Mapping incident locations is crucial for the spatial analysis of the incidents.

Table 4-1 shows an example of incident data attributes used to perform hot spot analysis based on Houston's TranStar incident data specifications.

Table 4-1: Example of Incident Data Attributes Used for Hot Spot Analysis.

ROADWAY	CROSS_STREET	DIRECTION	LATITUDE	LONGITUDE	Incident Duration	Day of Week	Hour	Time of Day
IH-10 KATY	IH-610 WEST LOOP	Westbound	29.7805	-95.4539	17.0	Wed	20	Night
US-59 SOUTHWEST	KIRBY DR	Northbound	29.7305	-95.4187	18.0	Thu	2	Night
US-59 SOUTHWEST	IH-610 WEST LOOP	Northbound	29.7288	-95.4606	153.4	Thu	4	Night
IH-10 EAST	US-59 EASTEX	Eastbound	29.7697	-95.3413	164.6	Thu	4	Night
IH-45 GULF	LOCKWOOD	Northbound	29.72789	-95.33644	11.6	Thu	5	Night
IH-45 GULF	EL DORADO BLVD	Southbound	29.5536	-95.154	21.0	Thu	5	Night
IH-45 NORTH	WEST RD	Northbound	29.91512	-95.41241	40.2	Thu	6	AM Peak
US-59 EASTEX	IH-45 GULF	Southbound	29.74448	-95.36276	32.4	Thu	6	AM Peak
US-59 EASTEX HOV	MT HOUSTON RD	Southbound	29.8909	-95.3183	18.3	Thu	6	AM Peak
SH-225	SH-146	Eastbound	29.6886	-95.031	33.0	Thu	6	AM Peak
US-290 NORTHWEST HOV	PINEMONT DR	Eastbound	29.8415	-95.4926	98.0	Thu	7	AM Peak
IH-10 EAST	HARDY/MCKEE ST	Eastbound	29.76999	-95.35217	1.3	Thu	7	AM Peak
IH-610 EAST LOOP	SHIP CHANNEL	Northbound	29.7249	-95.2666	2.8	Thu	7	AM Peak
IH-610 WEST LOOP	MEMORIAL DR	Southbound	29.7733	-95.4559	24.2	Thu	8	AM Peak
IH-610 WEST LOOP	IH-10 KATY	Southbound	29.7806	-95.4536	20.8	Thu	8	AM Peak
IH-610 EAST LOOP	CLINTON DR	Southbound	29.7383	-95.2654	5.0	Thu	8	AM Peak
US-59 SOUTHWEST	SH-288	Southbound	29.73405	-95.37128	15.4	Thu	8	AM Peak
IH-610 NORTH LOOP	KELLEY ST	Eastbound	29.8094	-95.3071	2.3	Thu	9	Midday
IH-610 NORTH LOOP	HOMESTEAD RD	Eastbound	29.8073	-95.3018	72.2	Thu	9	Midday
US-59 EASTEX	TIDWELL RD	Northbound	29.8488	-95.3339	7.9	Thu	9	Midday
US-59 SOUTHWEST	IH-610 WEST LOOP	Northbound	29.7288	-95.4606	92.7	Thu	9	Midday
IH-610 SOUTH LOOP	IH-45 GULF	Eastbound	29.6975	-95.2886	21.6	Thu	10	Midday
IH-45 NORTH	IH-610 NORTH LOOP	Southbound	29.81483	-95.37582	5.9	Thu	11	Midday

4.3. Analysis Tools

Geographic information system tools are particularly useful for an analysis of this type where required database queries are specifically related to mapping queried results as features on the base map. A typical database program such as Microsoft Access can also be used, but it provides limited functionalities in visualizing the results in a map-based format. The analyst can use a combination of Microsoft Access and ESRI ArcGIS to perform the hot spot analysis. Access is used mainly to manipulate and query the incident data. Most queries can be performed using Access unless spatial relationships are to be considered. Examples of spatial queries are locating the incidents that occurred within the proximity of loop detectors or locating the incidents that occurred within the proximity of each other. Spatial queries will require a GIS-based tool to carry out the analysis.

4.4. Preliminary Evaluation of Incident Data

The second step prior to conducting a hot spot analysis on the data is to conduct a preliminary evaluation on historical incident data. There are two major tasks in this evaluation:

- data validation – check the incident data for any errors or abnormalities and
- distribution analysis – identify any noticeable temporal or spatial incident patterns for the specific locations or areas of interest.

4.4.1. Data Validation

Incident data can be invalid for hot spot analysis for a number of reasons. Common errors observed in the incident database are:

- Missing geographic reference information – Missing data fields such as road names, cross streets, and directions can lead to wrong placement of incident locations and thus produce incorrect analysis results. Only incident records with complete geographic reference information should be retained.

- Non-unique coordinate data – Multiple coordinates may exist for a single location based on the description of the cross street and roadway name. In cases where multiple coordinates are located within the proximity of the others, the one with highest incident counts should be considered the correct one. To avoid this problem, it is advisable to generate a table of unique location information to which individual incidents can be mapped.
- Invalid incident duration – Incident duration is a derived attribute and also a good indicator for flagging invalid incident records. There are several forms of invalid duration value. For example, in Houston's incident database, negative incident durations were occasionally observed; in Austin's incident database, missing incident clearance times and unrealistically short incident durations are more common. These records should be excluded if the analyst intends to incorporate an incident duration component into the analysis, e.g., calculating average duration values. Otherwise, they can be left intact in the database as long as they do not significantly alter the frequency distributions of incident data.
- Duplicate/invalid incident data entries – Some incident records appear more than once in the database. This type of error can occur when more than one operator is handling the same incident. This type of error may be detected by a pattern of very close start and end times and exactly the same characteristics such as response unit and detection methods. Though they are not easily identifiable, they do not represent a significant portion of the data based on our observation.

4.4.2. Distribution Analysis

Due to variations in generating and archiving incident data among Texas TMCs, preliminary analysis of the incident data must be conducted differently. In general, the analyst will need to develop queries that are specific to the agency's incident database. The query outputs are in the same format for the same type of analysis. The implementation of the queries, however, varies depending on the specification of the incident database.

Three major types of queries can be performed during the preliminary analysis for the identification of hot spots:

- temporal distribution of incidents,
- spatial distribution of incidents, and
- distribution of incidents customized by supplemental attributes.

4.4.2.1. Temporal Distribution of Incidents

First, the analyst can develop queries to evaluate temporal patterns in the distribution of incidents from the sample incident data. Examples include the following categories:

- distribution of incidents by month and if needed by season (summer season versus school-in-session season);

- distribution of incidents by day of week and weekday versus weekend days; and
- distribution of incidents by time of day (AM peak, midday, PM peak, and night and early-morning hours).

For each of these time periods, the average number of incidents per time period and the corresponding relative distribution percentages can be computed. Such statistics will provide a number of performance measures that could be used to improve incident management practices. Produced incident rates can also provide simple incident-frequency forecasts, which can be used for optimizing TMC operator staffing and freeway courtesy patrol fleet scheduling and routing.

The analyst can use the temporal trends of incidents to determine if and how the hot spots should be identified. For example, if the analyst observes distinct patterns of incident distribution by specific times of day or specific days of the week, the hot spots during those particular conditions should be separately identified for incident management purposes.

Figure 4-1 shows an example of incident count distribution by months using TranStar's incident database.

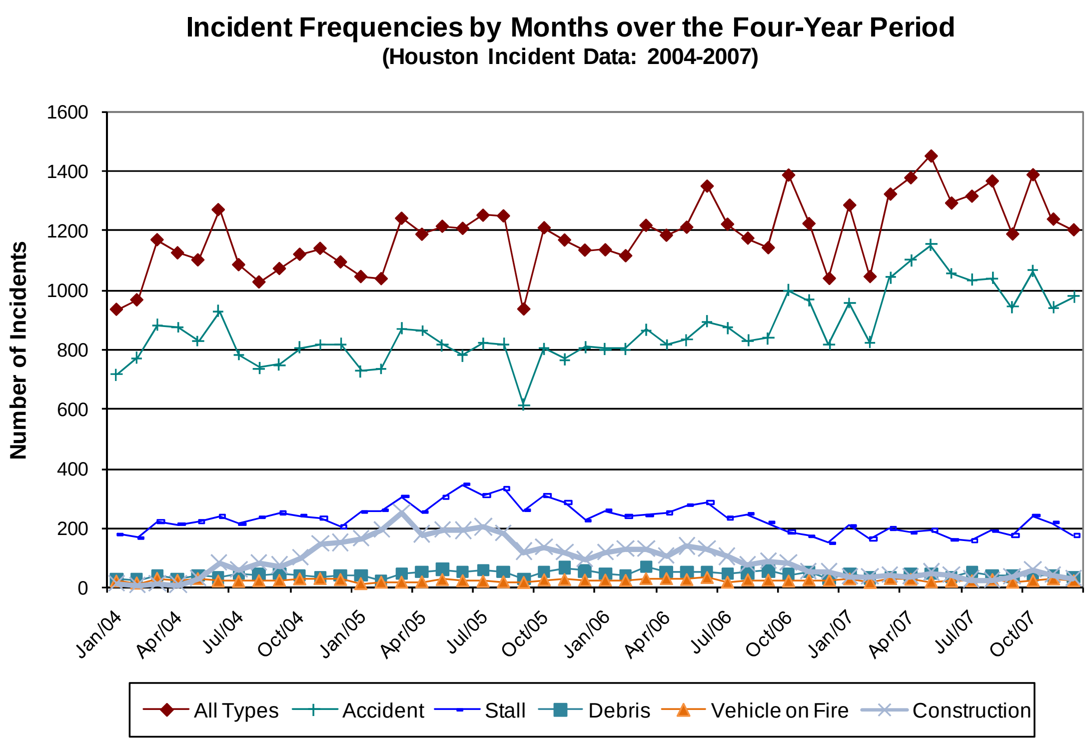


Figure 4-1: Example of Monthly Incident Frequency over Time (Houston).

4.4.2.2. <u>Spatial Distribution of Incidents</u>

This procedure focuses on evaluating spatial patterns in the distribution of incidents from the sample incident data. Maps showing the incident information corresponding to different time periods can be generated. The spatial analysis will be used to identify incident hot spots, i.e., areas with higher-than-normal incident rates. For example, the information about the higher-than-normal incident locations and time periods can be used to develop appropriate surveillance strategies for TMC operators to help improve incident detection capabilities.

A more aggregate, corridor-level spatial analysis can be done by dividing the city's network into roughly homogeneous corridors. For each corridor, the analyst can determine a number of performance measures such as average number of incidents per weekday, average number of incidents per weekday per mile, average number of incidents per million vehicles, and average number of incidents per million vehicle miles traveled (VMT). The rankings of the corridors based on each of the aforementioned performance measures can also be determined.

To examine spatial distributions of incidents, each incident record must contain the location information. The most common and convenient form is the coordinate data in latitude and longitude format. Texas TMCs typically use the coordinates of the nearest cross street to identify the locations of incidents. Additional location qualifiers (at/before/after) are also used to describe the incident locations with respect to the locations of the cross street.

Microsoft Access can be used to perform queries for spatial distributions. However, GIS is particularly useful in displaying the query results in a map-based format. Most coordinate data recorded in an incident database can be easily projected onto the map using GIS. In this manner, the analyst can quickly examine the results and identify the potential locations of concern.

Figure 4-2 shows an example of spatial distribution of incidents using TranStar's incident database. The query was first performed in Microsoft Access using Structured Query Language (SQL), and then the results were imported and displayed on the GIS-based map. The analyst can customize the map symbols based on different ranges of incident frequencies.

4.4.2.3. Distributions of Incidents Customized by Supplemental Attributes

Various incident characteristics can be used to further disaggregate the incident distributions, for instance, by type or by severity. The analyst may also wish to examine the temporal-spatial distribution of incidents, which can be obtained by developing queries using a combination of both temporal and spatial attributes.

For example, the analyst can combine the temporal and spatial attributes of incidents and perform the queries to:

- identify locations with high incident frequency on an hourly basis or specific time of day (e.g., AM peak, PM peak, night); and
- identify locations with high incident frequency by month or seasonality.

In addition to the temporal-spatial distributions of incidents, the analyst can also customize incident distributions using supplemental attributes from the incident database. Examples of these supplemental attributes include:

- Incident severity – TranStar, for example, classifies the incident severity into three categories based on visual assessment of its impact on freeway traffic. These three categories are minor, major, and fatalities accident/collision.
- Incident types – Examples of incident types typically recorded in Texas TMCs include accident, disablement/stall, and congestion. Note that the congestion type is included in the incident database for certain Texas TMCs, such as Austin's CTECC. Congestion incidents in the CTECC database are the results of detector alarms when the occupancy exceeds the pre-specified thresholds.

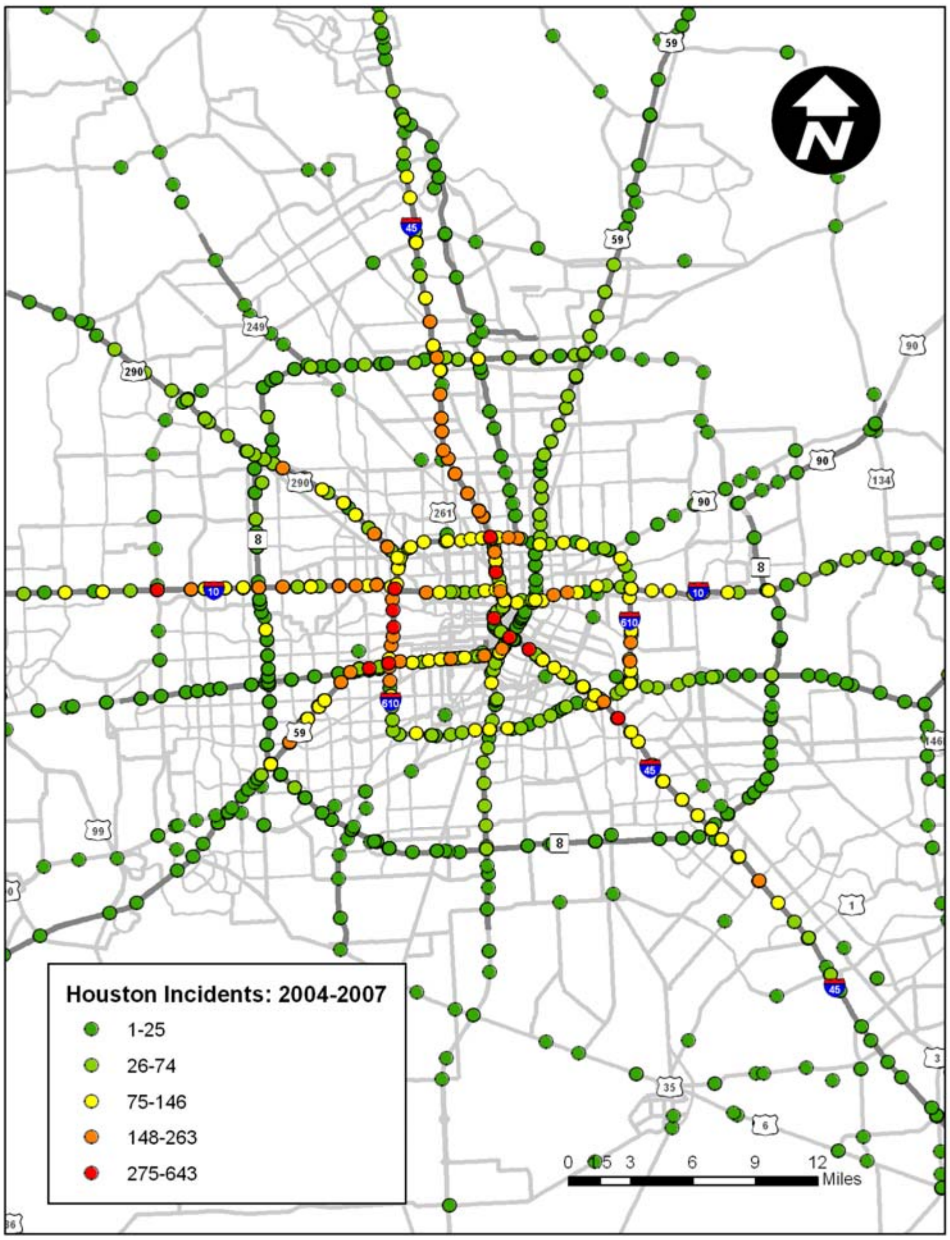


Figure 4-2: Example of Spatial Distribution of Incidents (TranStar).

4.5. Frequency-Based Hot Spot Analysis

The frequency-based hot spot identification method defines hot spots as the locations that experience above-normal incident rates. Incident rates are the number of incidents divided by the time period over which the incidents occurred. An upper threshold must be specified to determine if a particular location has unusually high incident rates.

4.5.1. Procedures for Frequency-Based Hot Spot Analysis

The procedures to identify hot spots using the frequency-based method can be summarized as follows:

- Conduct a preliminary analysis to identify any temporal/spatial patterns of incident distributions. The analyst can use this information to determine how the hot spot identification should be conducted. For example, based on our examination of Austin's incident database, it was found that the hot spot analysis should be conducted based on different times of day. There was no distinct trend to conduct the analysis on a monthly basis.
- Conduct queries that group incidents by their locations and other characteristics. For example, the analyst can query the spatial distribution of incidents by times of day. Similarly, the analyst can also examine particular types of incidents, such as collision, stall, etc. The query results should contain locations, counts or frequencies, and other specific characteristics (e.g., time of day, type of incident).
- Normalize the incident counts by appropriate exposure. The concept of incident exposure is analogous to that of safety analysis. The rate at which incidents occur should be proportional to their exposure. The exposure for traffic incidents could be as simple as time period or traffic volume. It could also be more complicated, such as conflicting flows designed to capture specific types of conflicting traffic streams. It is important that the selected exposure has a logical relationship with incident occurrence. We recommend the use of time exposure (e.g., 1,000 hours) for this method due to its simplicity and error-free measurement.
- Specify the threshold for hot spots. For example, 90th percentile of incidents per year can be set as a hot spot threshold. The locations that experience incident rates higher than the threshold are designated as hot spots. The threshold can be increased or decreased to balance the number of identified hot spots with available incident management resources.
- Plot the identified hot spots on the map. A GIS-based map is a very useful and convenient tool for displaying the hot spot results. Only coordinate data of the hot spot locations are needed for the map display. For incident data, the coordinates of nearest cross streets are commonly used to give approximate locations of incidents.

4.5.2. Defining Thresholds for Frequency-Based Hot Spots

The analyst may consider three alternatives for threshold specification. First, if available, the threshold may be specified according to TMC policies. Second, specific percentile values of incident rates can be established based on all historical incident data. Third, the specific number of top hot spot locations can be specified by the agency (e.g., top 20 hot spot locations), and then the threshold can be established such that it yields the specified number of hot spots.

The thresholds may be adjusted based on available incident management resources. A higher threshold would allow fewer locations to be qualified as hot spots, and vice versa for a lower threshold. For example, a lower threshold may be adopted if there are sufficient monitoring resources (e.g., center operators) for all locations identified as potential hot spots.

4.5.3. Recommended Frequency-Based Hot Spot Analysis

There are several alternatives for conducting frequency-based hot spot analysis for the agency such as frequency by time of day or by incident type. It is recommended that, at the minimum, the following analyses should be performed for the agency:

- weekday AM peak frequency-based hot spots,
- weekday midday frequency-based hot spots,
- weekday PM peak frequency-based hot spots,
- weekday night frequency-based hot spots,
- weekend frequency-based hot spots, and
- all frequency-based hot spots (using all incidents regardless of time of day).

The rule of thumb for safety evaluation requires three years worth of crash data in the analysis to ensure that hot spot results are reliable. It is possible to use less data in this analysis because incident data for all types are more frequent than the accident type alone. However, when analyzing hot spots for specific types of incidents, the analyst should be aware of the potential regression-to-mean effect, which is the case where safe locations are mistakenly notified as unsafe locations due to the randomness of incident occurrences.

4.5.4. Example of Frequency-Based Hot Spot Results

Figure 4-3 shows an example of hot spots identified using the frequency-based method during the AM peak period in Houston. Table 4-2 lists the locations of hot spots ranked by average number of incidents per 1,000 hours. In this case, incident data archived from 2004 to 2007 in the Houston TranStar's incident database were used. Then, the top 20 locations with the highest incident rates were selected as hot spots. Other alternative thresholds, such as percentile of total number of locations or certain value of incident rates, can be used to designate hot spots as well.

The hot spot queries were first conducted using Microsoft Access SQL, and then the results were customized and displayed using a GIS-based map. The maps can be customized to display the name of the cross streets and the freeway directions associated with the hot spots as well.

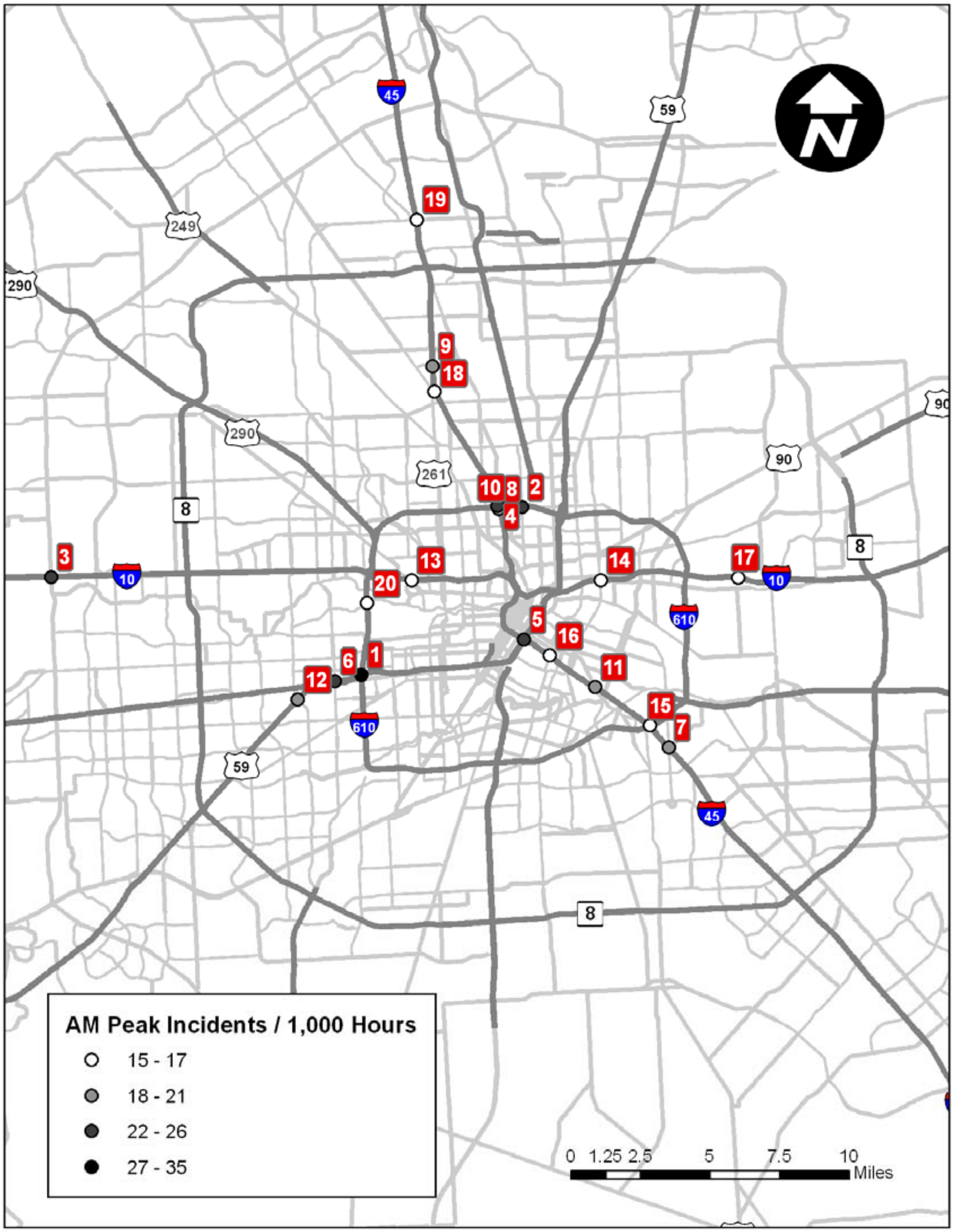


Figure 4-3: Houston AM Peak Frequency-Based Incident Hot Spots.

Table 4-2: Locations of Houston AM Peak Frequency-Based Incident Hot Spots.

Rank	Roadway	Cross Street	Direction	Total	Avg*
1	US-59 SOUTHWEST	IH-610 WEST LOOP	Northbound	111	35
2	IH-610 NORTH LOOP	IRVINGTON BLVD	Westbound	82	26
3	IH-10 KATY	SH-6	Eastbound	80	26
4	IH-45 NORTH	IH-610 NORTH LOOP	Southbound	75	24
5	IH-45 GULF	US-59 EASTEX	Northbound	72	23
6	US-59 SOUTHWEST	CHIMNEY ROCK RD	Northbound	69	22
7	IH-45 GULF	BROADWAY ST/PARK PLACE	Northbound	67	21
8	IH-610 NORTH LOOP	IH-45 NORTH	Westbound	63	20
9	IH-45 NORTH	GULF BANK RD	Southbound	62	20
10	IH-610 NORTH LOOP	FULTON	Westbound	61	19
11	IH-45 GULF	TELEPHONE RD	Northbound	55	18
12	US-59 SOUTHWEST	HILLCROFT AVE	Northbound	55	18
13	IH-10 KATY	WASHINGTON AVE/WESTCOTT ST	Westbound	54	17
14	IH-10 EAST	LOCKWOOD DR	Westbound	51	16
15	IH-45 GULF	IH-610 SOUTH LOOP	Northbound	48	15
16	IH-45 GULF	SCOTT ST	Northbound	48	15
17	IH-10 EAST	HOLLAND AVE/JOHN RALSTON RD	Westbound	47	15
18	IH-45 NORTH	N SHEPHERD DR	Southbound	46	15
19	IH-45 NORTH	RANKIN RD	Southbound	46	15
20	IH-610 WEST LOOP	WOODWAY DR	Northbound	46	15

Note: * Incident counts in respective locations are normalized by time exposure (1,000 hours).

4.6. Attribute-Based Hot Spot Analysis

The frequency-based identification method primarily uses only location and time of incident occurrences to identify hot spots. Though the frequency-based method is simple and easy to implement, several other potentially useful attributes collected in the database are not fully utilized. The attribute-based hot spot identification method aims to address this shortcoming by incorporating more attributes from the incident database into the identification of hot spots.

The attribute-based identification method can be viewed as a supplemental technique to the frequency-based method. The analyst can use any appropriate incident attribute for the analysis as long as attributes have logical causations to the distribution of incidents. Typical examples of incident attributes include incident duration, incident type, incident delay, lane blockage characteristics, incident severity, and so forth. Discrete attribute values can be recoded using numeric values and then rescaled to appropriate ranges.

The attributes used in the attribute-based hot spot analysis must possess the following characteristics:

- The attribute value must be ordinal and numeric.
- The increase and decrease in the attribute value should have a logical causal relationship with incident impacts. For example, the locations with high incident durations on average are more critical than the locations with lower average durations.

Examples of attributes other than incident duration that meet these requirements include incident clearance time, traffic volume (requires separate data source), number of lanes blocked, and number of vehicles involved.

The following sections describe the methods for producing:

- basic attribute-based hot spots and
- advanced attribute-based hot spots using Getis-Ord spatial statistics.

The advanced attribute-based identification method requires the use of the *spatial analyst* toolbox in ArcGIS to conduct the analysis.

4.6.1. Basic Attribute-Based Hot Spot Analysis

Basic attribute-based hot spot analysis identifies the locations with high attribute value as hot spots. The attribute values are calculated using descriptive statistics derived from all the incidents corresponding to each unique location.

Among all incident attributes, incident duration is one important attribute that can be incorporated into the analysis. Incident duration can be easily calculated from the incident database if incident occurrence and clearance time logs are available. Incident duration can be viewed as a good proxy of incident impact measured on a continuous scale. For example, by incorporating duration characteristics, the analyst can define hot spots as the locations that tend to experience long-duration collisions. Several factors can be attributed to its long duration, such as the distance between incident sites and response units, freeway congestion at the time of collision, lack of CCTV coverage, etc. By incorporating the duration attribute into the hot spot analysis, the analyst can map out the locations where high-duration collisions are more likely to occur.

4.6.1.1. Procedures for Basic Attribute-Based Hot Spot Analysis

In this section, the duration attribute and median statistics are used as an example to describe the procedure. Other incident attributes with continuous values can be directly applied using appropriate aggregation statistics such as median, mean, maximum, etc. The procedures to identify hot spots using the median duration method can be summarized as follows:

- Conduct a preliminary analysis to identify a logical correlation between the selected incident attribute and other incident characteristics. For example, based on the preliminary analysis of incident data in Houston, it was found that incident types have significant influence on incident duration. Also, the implication of long incident duration can differ by incident type. Accidents with long incident duration generally are high-impact ones. Non-lane-blocking stalls with long incident duration are typically those abandoned on shoulders, which do not require immediate response.
- Create queries to retain only incident records with valid data attributes (i.e., incident duration).

- Check the sample size for each location for calculating median durations. First, query the incident counts grouped by locations and directions throughout the analysis period; then sort and rank incident counts in a descending order. Retain only the locations with sufficient incident counts for the median calculation. For Houston data, it is recommended that the top 25 percent of all locations (in terms of incident counts) are retained for the analysis, which is equivalent to the minimum of six incidents per unique location over the four-year period 2004 to 2007.
- Calculate median durations for all the locations retained from the previous step. Median statistics can effectively minimize the potential bias from data that are heavily skewed. In this manner, the extremely high or low duration values (outliers) will affect the average duration calculated by using median statistics.
- Specify the threshold for hot spots. As discussed in Section 4.5.2, three alternatives can be used to establish the threshold.
- Plot the identified hot spots on the map using the GIS-based tool. Similar to the frequency-based maps, only the coordinate data of the hot spot locations are required for the map display.

The analyst should be mindful of the fact that median statistics require sufficient data points for the calculation. Setting a minimum threshold for incident frequency prior to the median analysis can help prevent a situation where locations with a few high-duration incidents could be mistakenly identified as hot spots. For Houston's example, the top 25 percent of locations with high incident frequency still retain approximately 80 percent of all incident records. Depending on the characteristics of incident data at the TMCs, different thresholds may be applied.

4.6.1.2. Defining Thresholds for Hot Spots

Similar to the methods for specifying thresholds for frequency-based hot spot analysis, three methods can be considered for establishing a threshold based on the calculated attribute value for each unique location:

- agency-established threshold (e.g., median incident duration of 30 minutes or longer);
- percentile-based threshold (e.g., 95th percentile of incident duration); and
- target-based threshold (e.g., a duration threshold which yields 20 hot spots).

4.6.1.3. Recommended Basic Attribute-Based Hot Spot Analysis

There are a number of combinations to perform the attribute-based hot spot analysis ranging from the choice of attribute to the set of selected characteristics (e.g., incident type, time of day, etc.) Incident duration attribute should be considered as one candidate for the routine attribute-based hot spot analysis. The following analyses are recommended for basic duration-based analysis:

- median duration hot spots by incident type and
- median duration hot spots by incident severity.

Attributes other than incident duration can be considered as well. Incident response time, for example, measures the performance of response units to incidents, and it can be influenced by factors such as response units, incident type, and time of day. If the agency wishes to prioritize hot spots by those with long response times, the analyst can perform the following analyses:

- median response time hot spots by major responders and
- median response time hot spots by major responders for common types of incidents.

In addition to attributes available from the incident database, external data sources can be considered in the attribute-based analysis as well. Examples include traffic volume and occupancy data from either loop detectors or radar sensors. These external data must be matched with incident records using incident detection times as a reference point. This data matching procedure can be complex in some cases.

4.6.1.4. Example of Duration-Based Hot Spot Analysis

Figure 4-4 shows the example results of attribute-based hot spot analysis using the median incident duration. The top 20 locations with high median duration are listed in Table 4-3. Only accidents from 2004 to 2007 recorded at Houston TranStar were used in the analysis regardless of time of day. The corresponding duration-based hot spot map is shown in Figure 4-4.

4.6.2. Getis-Ord (Gi*) Spatial Statistics

Gi* spatial statistics are a hot spot analysis tool implemented in ArcGIS software. Gi* spatial statistics can be used to find the locations of spatial clusters of either high or low attribute values. Let us consider the duration attribute as an example. Gi* statistics can be used to locate sites where above-average and below-average duration values tend to be found clustered. This tool can be run to calculate Gi* statistics corresponding to each incident record. Then, the analyst can specify a threshold for Gi* statistics to identify the locations that have clusters of incidents with high incident durations. This tool allows the analyst to test if those patterns of high/low attribute values are statistically significant. The appropriate level of statistical significance can be specified and adjusted to balance the number of hot spots identified with available incident management resources.

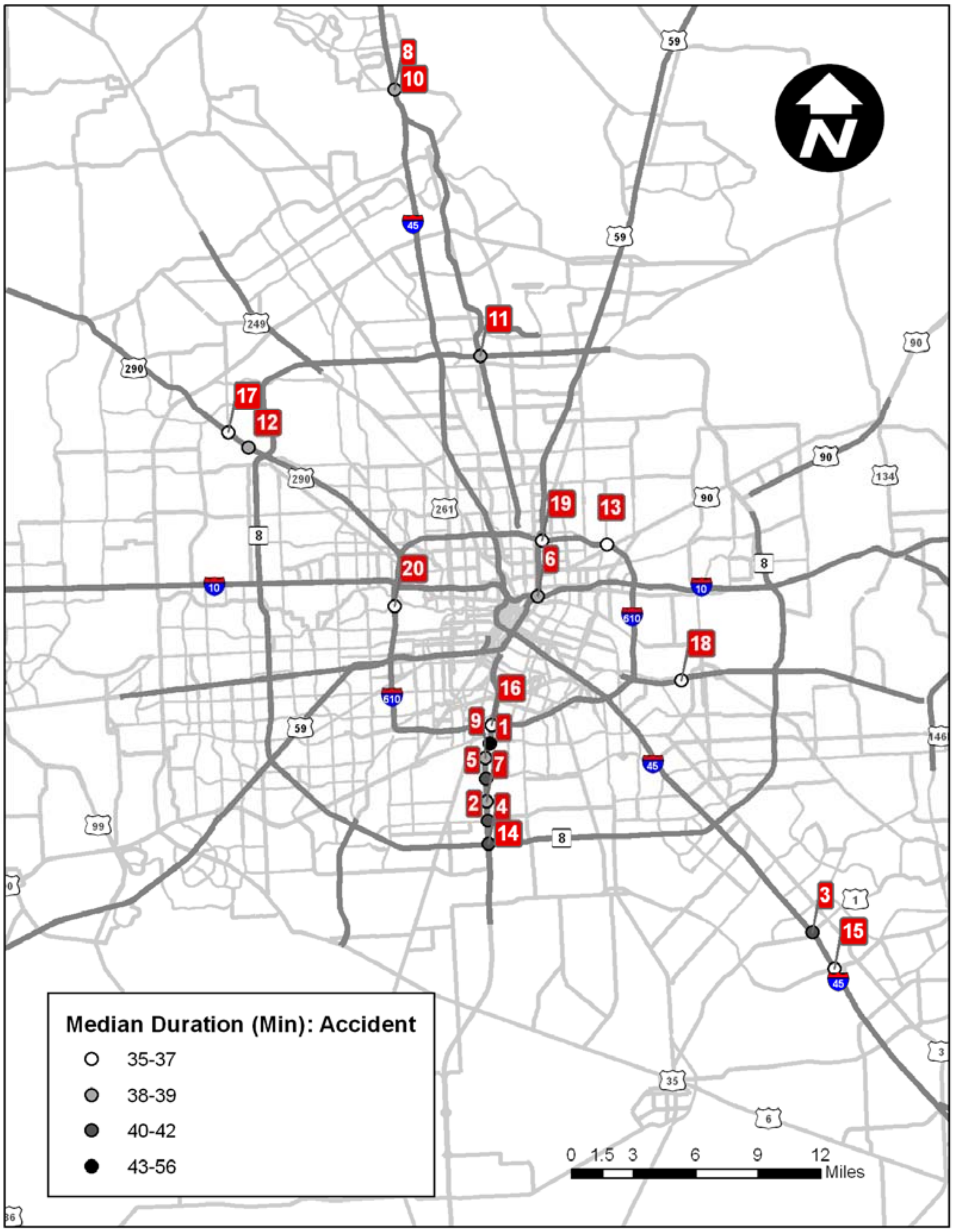


Figure 4-4: Basic Attribute-Based Hot Spot Identification (Median Duration).

Table 4-3: Locations of Hot Spots Using Basic Attribute-Based Analysis.

Rank	Roadway	Cross Street	Direction	Median Duration (min)	# of Incidents
1	SH-288	BELLFORT BLVD	Northbound	56.2	31
2	SH-288	ALMEDA-GENOA RD	Northbound	42.5	55
3	IH-45 GULF	FM-528/W NASA ROAD ONE	Northbound	42.3	48
4	SH-288	SAM HOUSTON TOLLWAY	Southbound	41.2	47
5	SH-288	AIRPORT BLVD	Northbound	41.1	34
6	US-59 EASTEX	IH-10 EAST	Southbound	39.4	37
7	SH-288	OREM	Northbound	39.3	36
8	IH-45	RAYFORD RD/SAWDUST RD	Southbound	38.9	29
9	SH-288	REED RD	Southbound	38.7	29
10	IH-45	RAYFORD RD/SAWDUST RD	Northbound	37.8	34
11	BELTWAY 8-NORTH/SAM HOUSTON TOLL	HARDY TOLL	Westbound	37.7	83
12	US-290 NORTHWEST	FM-529	Eastbound	37.5	44
13	IH-610 NORTH LOOP	WAYSIDE DR	Eastbound	37.1	36
14	SH-288	SAM HOUSTON TOLLWAY	Northbound	37.1	61
15	IH-45	FM-518	Southbound	36.9	43
16	IH-610 SOUTH LOOP	SH-288	Eastbound	36.6	97
17	US-290 NORTHWEST	JONES RD	Eastbound	36.6	44
18	SH-225	SCARBOROUGH LN	Westbound	35.5	37
19	IH-610 NORTH LOOP	US-59 EASTEX	Eastbound	35.4	72
20	IH-610 WEST LOOP	WOODWAY DR	Southbound	35.2	75

Note: * Total incidents in respective locations are normalized by time exposure (1,000 hours).

4.6.2.1. Procedures for Hot Spot Analysis

This analysis requires the hot spot analysis tool implemented in the ArcGIS software. The duration attribute is used to describe the procedure. It should be noted that other incident attributes with continuous values can be directly applied without any modifications. In addition, some categorical incident attributes can be converted to continuous numeric values as long as the original implications of the attributes remain. The primary steps to prepare the data for the GIS-based hot spot analysis can be summarized as follows:

- Perform queries to create a data table that comprises the following fields: incident time logs, coordinate data, and selected attribute values (e.g., duration).
- Remove locations with insufficient incident records from the analysis. The analyst can specify thresholds based upon the distribution of incident counts at each location. For Houston's example, the observed median count was used as a cut-off value (i.e., six incidents per four years).
- Remove locations with unrealistically low and high attribute values from the analysis. For Houston's duration data, incidents longer than one day were excluded from further analysis to prevent the effects of outliers on the computed Gi* statistics.
- Transform the duration values using a natural logarithm. This step is optional for attributes other than duration data. The purpose of log transformation is to account for the scaling effects. For example, consider an increase of incident duration by 30 minutes from the base durations of 30 minutes versus 300 minutes.

Logically, a 30-minute increase at a 30-minute duration should be considered more critical. However, without log transformation, such an increase will be weighed equally in the analysis. Log transformation will neutralize these effects so that the hot spot analysis results are not biased by the incidents with unusually long duration values.

- Import the data table into the base map. The feature "Add XY…" in the ArcMap can be used to facilitate the process. The coordinate data are used for plotting incidents on the base map. Depending on the data sources, the coordinate systems used may be different. The analyst must check if the coordinate system of the incident database and that of the base map are matched to ensure that the results are plotted properly. The imported incident data will be created as a layer on the base map.
- Export the created layer as a feature class. This class will be used as a data source for Gi* hot spot analysis.

The procedures for calculating Gi* spatial statistics using duration attribute in ArcGIS are summarized as follows:

- Open the Gi* Hot Spot Analysis module in ArcGIS. The dialog box as shown in Figure 4-5 will be displayed. Specify the location of a feature class (data source) created from the previous steps.
- Specify the input field. The input field is the numeric attribute, which in this case is the log-transformed duration.
- Specify the output feature class. This class will receive the calculated outputs (Gi* z score statistics).
- Specify the conceptualization of spatial relationships as "zone of indifference." This method considers any incidents within a critical distance (to be specified next) as part of the analysis. Once this critical distance is exceeded, the level of impact quickly drops off.
- Specify the distance method as "Euclidean Distance." Euclidean distance is a straight-line distance between two points.
- Specify the distance band or threshold distance. To determine the appropriate distance band, we conducted an evaluation using a high/low clustering technique and searched for a critical distance that gives the highest z score (statistical significance). Based on the analysis results, it is recommended that 30 feet be used as a threshold distance.
- Click OK to start the hot spot analysis. The Gi* statistics will be calculated for each incident and then stored in the output feature class.

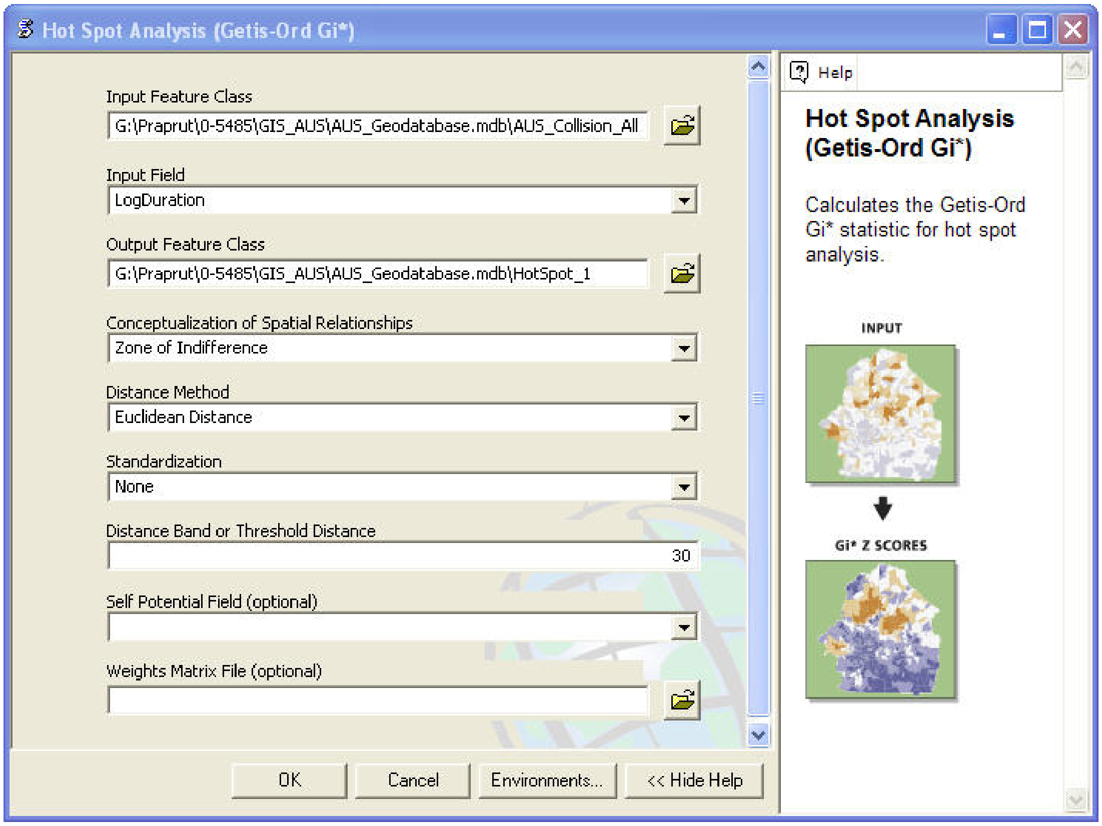


Figure 4-5: Hot Spot Analysis (Getis-Ord Gi*) Tool in ArcGIS.

4.6.2.2. Defining Threshold for Gi* Spatial Statistics

The Gi* spatial statistics are essentially a z score. The higher the z score is, the higher the statistical significance of the clusters with high attribute values is. The same interpretation applies for the low z score.

The z score is a test of statistical significance that the analyst can use to help decide whether or not to reject the null hypothesis. Z scores are measures of standard deviation. For example, if a tool returns a z score of +2.5, it is interpreted as "+2.5 standard deviations away from the mean." Z score values are associated with a standard normal distribution. This distribution relates standard deviations with probabilities and allows significance and confidence to be attached to z scores.

In order to reject or accept the null hypothesis, the analyst must make a subjective judgment regarding the degree of risk one is willing to accept for being wrong. This degree of risk is often given in terms of critical values and/or confidence level.

For example, if the analyst would like to limit the probability of selecting the wrong sites as hot spots (having unusually high incident durations) at 5 percent, this corresponds to the use of 95 percent confidence level. If the z scores are between –1.96 and +1.96, the analyst cannot reject the null hypothesis at 5 percent significance; or in other words, the probability that the observed patterns of clusters of incidents with high durations may be a result of randomness is greater than 5 percent.

Below is the basic guideline of the use of Gi* z scores. First, the analyst must specify the appropriate level of confidence of the hot spot identification. Then, the threshold for Gi* statistics can be established as follows:

- At 95 percent confidence level, define Gi* > 1.96 as hot spots.
- At 90 percent confidence level, define Gi* > 1.64 as hot spots.
- At 85 percent confidence level, define Gi* > 1.44 as hot spots.

Next, the analyst can use the identified hot spots to define the hazardous freeway segments. Hazardous segments are defined as those segments within the vicinity of the hot spots. The next section describes the procedure to define hazardous segments.

4.6.2.3. Using Hot Spots to Define Hazardous Segments

Since the hot spots are geographically referenced to the nearest cross streets in the incident database, the exact locations of incidents may be difficult to determine. Using hot spot information alone may leave out adjacent freeway segments that could be of high risk otherwise. These segments can potentially be frequently monitored by control center operators to improve incident detection and response times. To address this issue, the analyst may wish to create a distance buffer around the identified hot spots to include freeway segments in the proximity of the hot spots. GIS spatial queries can be used to perform this task. The freeway segments adjacent to the hot spots derived from the GIS query analysis are referred to as "hazardous segments."

The procedure to define hazardous segments from the identified hot spots using GIS is described below:

- Use "Select by Attributes…" to select the hot spots. For example, if hot spots are defined by those incidents with Gi* > 1.96, the analyst can use the Gi* attribute to specifically select the sites of hot spots.
- Use "Select by Locations…" to select the road segments within the distance buffer of hot spots. For example, the analyst can select the features from a freeway segment layer that are within a distance of 0.5 mile of the selected hot spot locations (defined from the previous step).
- Depending on how the data layers are constructed in the GIS base map, the analyst may need to refine the current selection to keep only the freeway portion selected. In this case, the analyst may need to perform one more query using "Select by Attributes…" to select only the road segments from the current selection that are classified as freeways (i.e., using the roadway type attribute).

4.6.2.4. Example of Advanced Attribute-Based Hot Spot Results

Table 4-4 and Figure 4-6 show the example results of hot spot analysis using the advanced attribute-based identification method. Accident incidents from Houston TranStar were used for the hot spot analysis. In addition to basic data validation, incident records at locations with fewer than 1.5 accidents per year and those with durations longer than one day were excluded from the analysis. Logarithmic transformed duration values were used as an attribute for the calculation of Getis-Ord Gi* spatial statistics. Using a 99 percent confidence level, hot spots are identified as shown on the map in Figure 4-6. These hot spot locations are likely to have clusters of collisions with long durations. In addition, the specified confidence level also implies that the chance that these clusters occurred by random is less than 1 percent.

In the Figure 4-6, the GIS spatial queries were used to define hazardous freeway segments within the proximity of the hot spots. A buffer distance of 1 mile was used to designate hazardous segments. The analyst can also modify this buffer value based upon examination of the results.

Table 4-4: List of Accident Hot Spots Using Gi* Statistics (Houston).

Rank	Roadway	Cross Street	Direction	Gi* Score
1	IH-10 EAST	US-59 EASTEX	Eastbound	7.29
2	IH-10 EAST	US-59 EASTEX	Westbound	7.29
3	US-59 EASTEX	IH-10 EAST	Northbound	7.29
4	US-59 EASTEX	IH-10 EAST	Southbound	7.29
5	US-59	SWEETWATER BLVD	Northbound	5.39
6	US-59	SWEETWATER BLVD	Southbound	5.39
7	IH-610 SOUTH LOOP	SH-288	Westbound	5.34
8	SH-288	IH-610 SOUTH LOOP	Northbound	5.34
9	SH-288	IH-610 SOUTH LOOP	Southbound	5.34
10	SH-288	ALMEDA-GENOA RD	Northbound	4.83
11	SH-288	ALMEDA-GENOA RD	Southbound	4.83
12	US-59	BRAZOS RIVER	Northbound	4.31
13	US-59	BRAZOS RIVER	Southbound	4.31
14	SH-225	SH-134 BATTLEGROUND	Eastbound	3.93
15	SH-225	SH-134 BATTLEGROUND	Westbound	3.93
16	IH-45	SH-6/SH-146	Northbound	3.78
17	IH-45	SH-6/SH-146	Southbound	3.78
18	IH-610 NORTH LOOP	WAYSIDE DR	Eastbound	3.72
19	IH-610 NORTH LOOP	WAYSIDE DR	Westbound	3.72
20	SH-288	BELLFORT BLVD	Northbound	3.71
21	SH-288	BELLFORT BLVD	Southbound	3.71
22	IH-10 KATY	BARKER CYPRESS RD	Eastbound	3.67
23	IH-10 KATY	BARKER CYPRESS RD	Westbound	3.67
24	SH-225	PRESTON	Eastbound	3.61
25	SH-225	PRESTON	Westbound	3.61
26	SH-225	CENTER ST	Eastbound	3.46
27	SH-225	CENTER ST	Westbound	3.46
28	IH-45	SH-242	Northbound	3.36
29	IH-45	SH-242	Southbound	3.36
30	US-59 EASTEX	IH-610 NORTH LOOP	Northbound	3.32
31	US-59 EASTEX	IH-610 NORTH LOOP	Southbound	3.32
32	US-59	SH-99 GRAND PARKWAY/CRABB RIVER RD	Northbound	3.30
33	US-59	SH-99 GRAND PARKWAY/CRABB RIVER RD	Southbound	3.30
34	IH-45	FM-1488	Northbound	3.22
35	IH-45	FM-1488	Southbound	3.22
36	SH-146	IH-45	Southbound	3.22
…	…	…	…	…

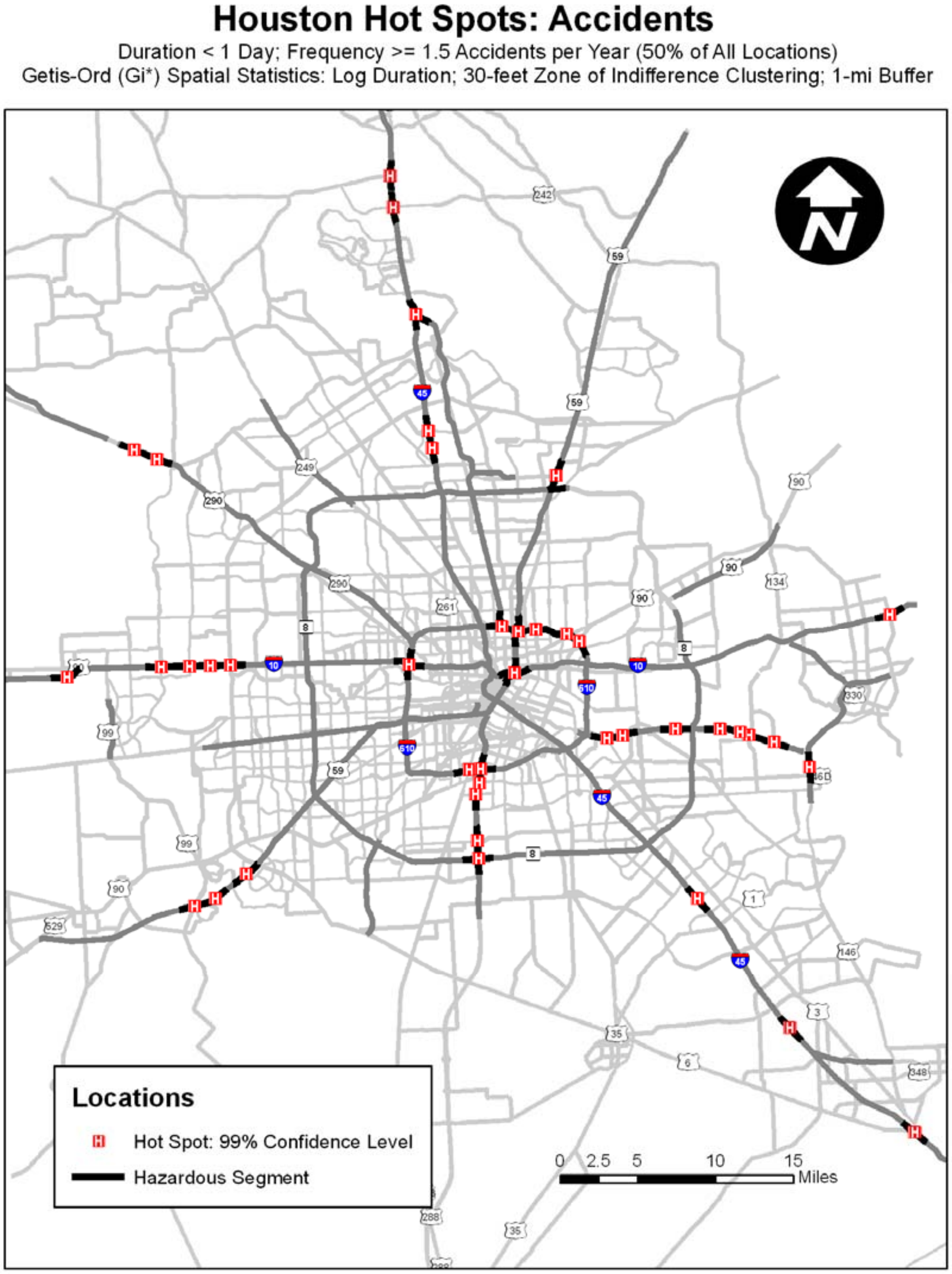


Figure 4-6: Hot Spots and Hazardous Segments Using Gi* Spatial Statistics.

4.7. Selecting Hot Spot Analysis Method

Frequency-based and attribute-based hot spot analyses were described in the previous sections. Selecting the appropriate analysis method requires the following considerations:

- availability and sufficiency of incident data, and
- objectives of the analyses.

Frequency-based hot spot analysis is essentially a spatial distribution of cumulative incident counts. Its implementation is simple, and the results are easy to display graphically. Explanation of the results is also straightforward. However, it does not take into account the impact of the incident, which could be otherwise measured by specific data attributes. The analyst should consider this method if:

- only incident detection times and locations are available in the database; and/or
- the agency's priority is to reduce the frequency of incident occurrences.

Basic attribute-based hot spot analysis accounts for meaningful relationships among various incident data attributes. The analyst can tailor the attribute-based analysis to meet the needs and analysis objectives of the agencies. The attribute-based method effectively utilizes data attributes commonly available in the incident database. The analyst should consider this method if:

- attribute data are available, valid, and sufficient (e.g., at least six valid incident records for calculating median duration);\ and/or
- the agency's priority is to evaluate and improve the incident management performance of relevant entities based on the attributes of interest (e.g., reducing the incident duration, improving incident response time, etc.).

Advanced attribute-based hot spot analysis simultaneously accounts for the frequency and the attribute value of incidents using Gi* spatial statistics. Only locations with repeated occurrences of high-impact incidents shall be defined as hot spots in this analysis. When using incident duration as an attribute, the hot spots are those locations that experience high frequency of high-duration incidents. This approach is more complicated and requires more resources than the other approaches. The analyst should consider this approach if:

- the incident data and the attribute of interest are available, valid, and sufficient and/or
- the agency's priority is to reduce the frequency of high-impact incidents (e.g., high duration).

4.8. Using Hot Spot Analysis Results

Based on temporal-spatial distributions of incidents, high-incident locations with respect to temporal factors (e.g., time of day, months, seasonality) and various incident characteristics can be determined. It is suggested that this information be presented in a map-based format. A GIS-based map is a potential tool to facilitate the presentation of this information. Using the results from GIS-based database queries, TMC managers can identify which corridors are subject to higher incident rates at a specific time period and may use this information as a decision support or to adjust strategic incident management activities as needed.

The analyst can perform several variations of hot spot analyses depending on the objectives of the analysis and the availability and accuracy of the historical incident database. Below is a list of examples of comprehensive hot spot analysis with different objectives:

- locations and time period with high frequency of incidents,
- locations and time with high frequency of fatalities,
- locations with high frequency of truck accidents,
- locations and time period with high frequency of long incident duration, and
- locations and time period with long incident response time.

For example, if the analyst wishes to examine the historical incident database to help improve the incident response time, the analyst can follow the steps below to achieve this objective:

- First, examine the historical incident data to determine if the incident response time is collected in the database on a regular basis.
- Second, use the attribute-based identification method to incorporate the incident response time into hot spot analysis and statistically determine the locations that are more likely to experience a long response time.
- Third, the analyst can use GIS-based tools to represent the identified locations onto the map and then visually examine the results from the analysis.

Once the analysis is completed, a catalogue of strategic activities may be considered for improving incident detection and response times. Examples of these strategies along with their pros and cons are summarized in Table 4-5.

Table 4-5: Strategies for Improving Incident Detection and Response Times.

Strategies	Descriptions	Pros	Cons
Roving Courtesy Patrols/ Service Patrols	This strategy involves the use of a specially equipped vehicle to provide emergency repairs and rapid clearance of stalled or disabled vehicle from the roadway. Vehicle can be either pre-positioned at strategic locations or rove in traffic stream based on hot spot results.	• Permits the rapid detection and clearance of minor incidents. • Provides assistance and minor repairs for stalled/disabled vehicles. • Provides positive public relation image for agency. • Can provide traffic control for emergency responders. • Service can be contracted to private provider.	• When patrol is busy with event, it cannot rapidly respond to secondary incident that may occur. • Requires specially equipped vehicles. • Operators may require special training and certification. • Congestion in work zone may prevent patrol from rapidly reaching incident.
Closed Circuit Television/ Video Surveillance Cameras	This strategy involves the use of closed circuit television or video surveillance cameras to assist in the rapid detection and verification of incident location and severity through visual inspections. Operators can adjust the rotation of cameras to frequent the hot spots. Additional camera installations can be considered at the hot spot locations to improve surveillance coverage.	• Allows visual detection and confirmation of incident location and severity prior to initiating response. • Allows assessment of impacts of incidents on traffic operations. • Allows operators in control center to adjust operational strategies as incident conditions change.	• Requires an individual to monitor video surveillance cameras, usually at a traffic management center. • Requires special technical skills to keep camera and communications system operational. • Can be costly to install and maintain during life of construction project.
Stationary Observers	This involves the use of specially trained spotters or observers who can provide information about incident locations via radio or cell phone to TMC or other emergency dispatch center. The observed locations can be strategically assigned based on the hot spot locations.	• Volunteers can be used as observers.	• Must contact someone else to initiate clearance functions. • Volunteer may not always be dependable. • May require special agency personnel to manage observers.
DMS Messages/ Locations	This strategy involves routine posting of call-in numbers that motorists can use to report traffic incidents. The hot spot results can be used to identify specific locations for this strategy. The locations of new installation of DMS can be based on hot spot analysis as well.	• Can be incorporated as part of construction-related information dissemination/511 system. • Allows motorists to communicate directly with highway agency.	• Most motorists are likely to use E911 services to report incidents. • Motorist may have difficulty remembering special call-in number. • May require specially trained call takers.
ITS Traffic Sensors	This strategy involves the use of traditional traffic detection and sensing technologies (such a loop detectors, radar detectors, video image detection system, etc.) to detect unusual pattern of traffic flows. Usually requires the use of automatic detection algorithms to locate incidents. Hot spot results can be used to plan the locations of new traffic sensors or where to improve the sensor coverage.	• Transportation operators generally familiar with technology and techniques. • Traffic data collected can be used in many applications such as incident impact estimation or before-after evaluation study.	• Detection algorithms prone to high false alarm rates and slow detection times, especially in highly congested locations.
Improved Milepost Markers/ Location Referencing System	This strategy involves improving or augmenting the traditional milepost marking system to provide incident response personnel and citizens with more accurate information. This can be accomplished by spacing markers more closely (e.g., 10th of a mile on freeways) or improving visibility of markers (e.g., oversizing) based on the hot spot results.	• Improves communication between citizens and response personnel. • Relatively inexpensive. • Provides motorist with location information for getting help quickly. • Helpful in managing traffic records and subsequent analysis.	• May be difficult to keep signs visible/clean all the time. • Requires skilled motorists to understand referencing system.

5. ESTIMATING INCIDENT IMPACTS

This module provides methodologies to estimate incident-related impacts using historical traffic and incident data. Availability of historical data collected at the TMCs allows us to quantitatively assess and predict the impacts of various events on traffic conditions.

This module is separated into four major sections:

- The first section provides an overview of incident impact estimation approaches ranging from deterministic models to simulation methods.
- The second section proposes an approach for estimating incident impacts in terms of traffic delay using historical traffic and incident data. Traffic delay has been widely used as a measure for the quality of travel. The analyst can use the approach described in this section to evaluate incident delays. The proposed method is intended for after-the-fact assessment.
- The third section proposes a comprehensive methodology for evaluating impacts from specific incidents using historical incident and traffic data. The analyst can use this approach to estimate the time it takes for the traffic to return to normal conditions for any given incidents.
- The fourth section describes how the measured incident impacts can be viewed from both system and travelers perspectives.

5.1. Overview of Incident Impact Estimation

An incident is defined as any occurrence that affects a roadway's capacity, either by obstructing travel lanes or by causing gawkers to block traffic (*18*). Incidents include accidents, vehicle breakdowns, temporary maintenance and construction activities, and other random events that cause congestion. Incident-induced delay is one of the most important indicators for measuring the impacts on traffic operations. Incident-induced delay is determined by many factors, such as incident severity, roadway conditions, traffic conditions, and incident duration (*19*). There are two types of delay:

- recurring delay – a delay caused by an increase in traffic demand, typically in a recurring pattern such as specific time of day and
- non-recurring delay – a delay caused by unusual events such as traffic incidents, weather events, and construction zones.

This section provides an overview of methods available for evaluation of the second type of delay. Several approaches have been developed in the past for estimating incident-induced delay, which includes the deterministic queuing models (*20-27*), stochastic models (*19, 28*), difference-in-travel-time method (*2, 29-33*), and simulation method (*17*). These methods are summarized in this section.

5.1.1. Deterministic Queuing Model

The deterministic queuing model is often depicted using a basic deterministic queuing diagram, which is shown in Figure 5-1. Figure 5-1 illustrates cumulative vehicle arrivals and departures during the congestion. In this model, traffic demand (q), incident duration (r), freeway capacity (s), and bottleneck capacity (s_1) are assumed to be known and constant. The parameters in the diagram are defined as follows: q = traffic flow rate (vehicles per hour [vph]); r = incident duration (minutes); s = freeway capacity (vph); s_1 = reduced freeway capacity during the incident (vph); t_c = traffic-return-to-normal time; l = queue size at time t (vehicles [veh]); and d = the incident delay of the vehicle with arrival time t.

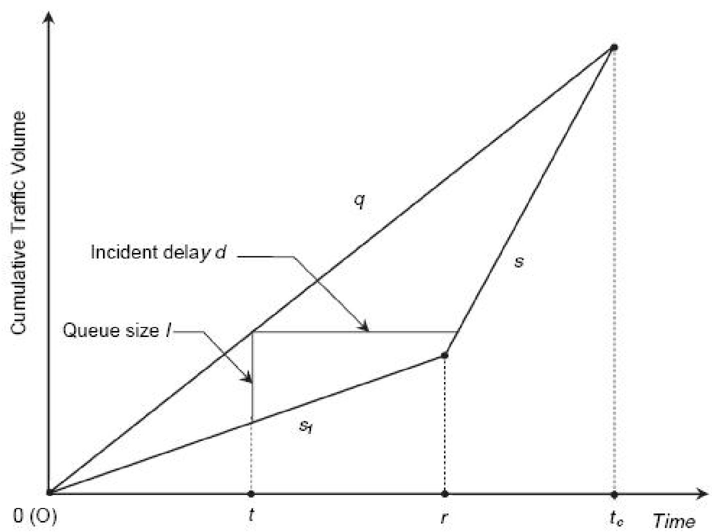


Figure 5-1: Typical Deterministic Queuing Diagram.

Figure 5-2 shows the queue size (l) and the incident delay (d) versus vehicle arrival time after the onset of the incident, in which rs_1 / q represents the arrival time of the vehicle that experiences the highest delay. The maximum queue length happens when the incident is cleared. According to Figure 5-2, the incident delay (d) and the queue size (l) can be expressed by the following equations:

$$d(t|r,s_1) = \begin{cases} (q/s_1 - 1)\cdot t & \text{if } 0 \le t \le r\cdot s_1/q,\ 0 \le s_1 < q \\ (q/s - 1)\cdot t + (1 - s_1/s)\cdot r & \text{if } r\cdot s_1/q \le t < t_c,\ 0 \le s_1 < q \\ 0 & \text{if otherwise} \end{cases} \quad (5\text{-}1)$$

$$l(t|r,s_1) = \begin{cases} (q - s_1)\cdot t & \text{if } 0 \le t \le r,\ 0 \le s_1 < q \\ (s - s_1)\cdot r + (s - q)\cdot t & \text{if } r \le t < t_c,\ 0 \le s_1 < q \\ 0 & \text{if otherwise} \end{cases} \quad (5\text{-}2)$$

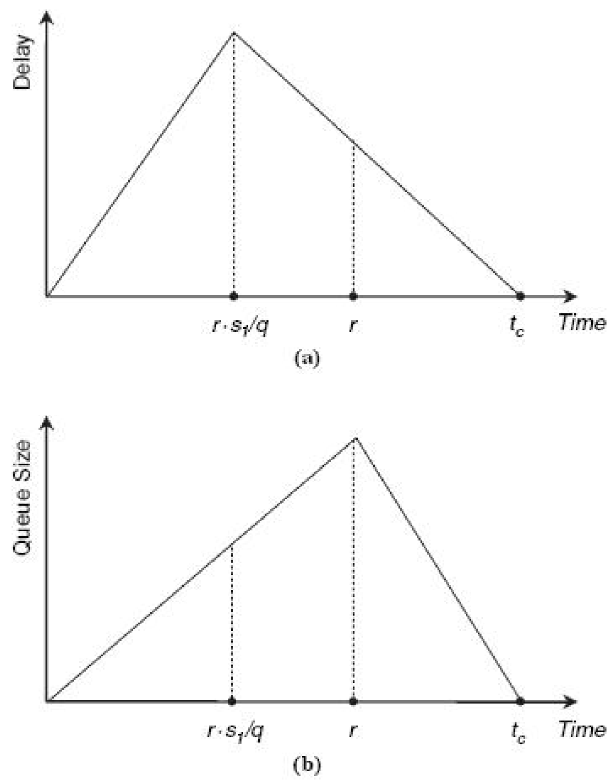


Figure 5-2: Schematic Diagrams of (a) Incident Delay and (b) Queue Size.

In the deterministic queuing diagram, the area of the triangle formed by the curves of q, s, and s_1 denotes the total delay (TD) of the traffic stream induced by the incident. The TD can be calculated through Equation (5-3). It can be seen that the TD is a convex function of incident duration (r).

$$TD = \frac{(s - s_1) \cdot (q - s_1) \cdot r^2}{2(s - q)} \tag{5-3}$$

During the congestion, the total number of vehicles affected by the incident is:

$$N = s_1 \cdot r + s \cdot (t_c - r) = \frac{q(s - s_1)}{(s - q)} \cdot r\,. \tag{5-4}$$

Thus, the average delay for all vehicles affected by the incident can be calculated by:

$$\bar{d} = \frac{TD}{N} = \frac{(q - s_1)}{2 \cdot q} \cdot r \tag{5-5}$$

In the deterministic queuing model, the incident duration and the reduced capacity are the two parameters that are difficult to estimate with reasonable accuracy. In practice, the reduction in capacity can be specified based on Exhibit 22-6 of the *Highway Capacity Manual* (*34*), where the remaining capacities (percent of the original capacity) are shown as a function of the number of travel lanes blocked, the number of travel lanes, and incident severity. For example, for a three-lane freeway section with one lane blocked by the incident, the remaining capacity is 49 percent of the original capacity.

Incident duration is the sum of detection, verification, response, and clearance times. The incident duration depends on several factors, such as incident location and incident type, and on the incident management systems in operation, such as the Freeway Service Patrol (FSP). The default incident duration sometimes can be taken from available records (*17*). The duration is also commonly estimated based on incident characteristics as discussed in the previous task of this project.

Note that the incident clearance process could be a multistage one that takes an extended period of time. During such a clearance process, the available capacity may increase as more lanes are open to traffic. In a deterministic queuing analysis, this process will be reflected by different values of capacity S^i at different stages of the clearance process.

5.1.2. Stochastic Incident Delay Model

The deterministic queuing model assumes that traffic demand, capacity reduction, and incident duration can be identified. Thus, this method may be adequate for the after-incident evaluation, but it is insufficient for real-time incident delay estimation because incident duration and reduced capacity are unknown. The stochastic model was hence developed to estimate delay with the consideration of the randomness of incident duration and/or reduced capacity, which are modeled as random variables rather than deterministic values. The stochastic model is able to estimate the probability distribution of incident delay, from which the mean and variance of delay can be derived (*19, 28*).

To illustrate the stochastic model, let the incident duration be the random variable under consideration (other variables are kept constant). Then, the probability distribution of delay depends on the probability distribution pattern of the incident duration. Suppose the probability density function (PDF) of the incident duration has two parameters, the mean $\bar{r}$ and the variance σ_r^2; then the mean delay can be expressed by:

$$E[d(t,r|s_1)] = \int_0^\infty E[d(t,r|s_1)] \cdot f(r) \cdot dr = \frac{(q-s_1)\cdot\bar{r}}{2\cdot q} \qquad (5\text{-}6)$$

The variance of delay and the expected total delay can be also calculated by the following two equations, respectively:

$$\text{var}[d(t,r|s_1)] = E\{\text{var}[d(t,r|s_1)]\} + \text{var}\{E[d(t,r|s_1)]\} = \frac{(q-s_1)^2\sigma_r^2}{3q^2} + \frac{(q-s_1)r^2}{12q^2} \qquad (5\text{-}7)$$

$$E[TD(t,r|s_1)] = \int_0^\infty \frac{(s-s_1)(q-s_1)r^2}{2(s-q)} f(r)dr = \frac{(s-s_1)(q-s_1)(r^2+\sigma_r^2)}{2(s-q)} \qquad (5\text{-}8)$$

It can be seen that the expected total delay in Equation (5-8) is larger than that in Equation (5-3), with the consideration of the probability distribution of incident duration. In addition to the mean delay, the variance of delay, and the expected total delay, the incident delay of a vehicle with a certain arrival time to the link can be calculated also through the stochastic model.

The stochastic model requires information on the probability distributions of the random variables. For instance, the mean and standard deviation of the incident duration are needed if incident duration is considered as a two-parameter random variable. The study by Sullivan *(35)* provides the means and standard deviations of incident durations under different incident types, incident management systems in operation, and incident locations.

Boyles and Waller *(36)* proposed a stochastic delay prediction model for predicting delay incurred by an ongoing incident. This model was a part of a research project sponsored by TxDOT (0-5422). The model uses a probabilistic-based approach to account for uncertain incident duration in predicting delay. The accuracy of delay prediction depends heavily on incident duration and demand profile characteristics. However, no specific guidelines were given in this study on how to establish realistic demand profiles in order to use the proposed method.

It is important to note that using a single expected value of incident duration will always underestimate delay in the presence of uncertainty. This effect can be traced to Jensen's inequality where $E[f(X)] \geq f(E[X])$ if f is convex and X is a random variable. Here, let f and X be an incident delay function and a random variable representing incident duration, respectively. Because f is proportional to the square of X, $f(X)$ is strictly convex; thus the expected incident delay must be greater than delay that would result from an incident of expected duration *(36)*.

From the geometry of queue polygon, the total delay induced by a stationary incident can be expressed as:

$$D = \frac{1}{2}\tau^2 \frac{(q_r - q_c)(q_i - q_c)}{(q_r - q_i)} \tag{5-9}$$

where D is the total delay, τ is incident duration, q_i is initial flow rate, q_c is congested flow rate, and q_r is recovery flow rate. Boyles and Waller *(36)* derived delay functions where uncertainty in incident duration (τ) is represented by different probability distributions. One common assumption is a lognormal-distributed incident duration calibrated using regression techniques. If τ follows a lognormal distribution with parameters μ and σ^2, the expected total delay becomes:

$$E[D] = \frac{1}{2} e^{2(\mu+\sigma^2)} \frac{(q_r - q_c)(q_i - q_c)}{(q_r - q_i)}. \tag{5-10}$$

5.1.3. Difference-in-Travel-Time Method

The difference-in-travel-time method was developed based on the identification of travel times under normal and incident conditions and the quantification of the amount of traffic affected by incidents. Thus, delay (moving delay) is the extra travel time to traverse a freeway segment under incident conditions in contrast to the travel time under incident-free conditions. Depending on TMC configurations, travel time can be calculated using either:

- spot speed data collected from point-based sensors at regular spacings or
- section or link travel times using probe-vehicle data.

Given the length of the freeway segment, prevailing traffic volume, and travel times (either directly observed or converted from speed data), delay can be calculated by the following equation. Note that converting travel times from speeds will require the speeds to be different from zero.

$$D = \sum_{i=1}^{T} V_i \cdot (t_i - t_0) \qquad (5\text{-}11)$$

where D = delay (veh-hour); i = time interval for the delay calculation (e.g., 5-minute or 15-minute interval); T = time period under incident-induced congested condition (in multiples of i); t_i = actual average travel time for interval i; and t_0 = average travel time under prevailing incident-free conditions.

Previous studies using this method derived travel times from speed data observed through loop detectors at close spacings, such as 0.3 mile on I-880 in a San Francisco Bay Area study (*31*) and 0.5 mile on I-35 in a San Antonio study (*2*). The freeway segment is divided into sectors according to the placement of loop detectors. In this method, speed and volume data collected from dual loop detectors are used for delay estimation. Figure 5-3 shows sampled 20-second speed data on a freeway segment impacted by an incident (*2*). This figure also shows three conceptual reference speed profiles for the calculation of incident delay: free-flow speed, incident-free historical average speed, and a hypothetical "incident-free" average speed.

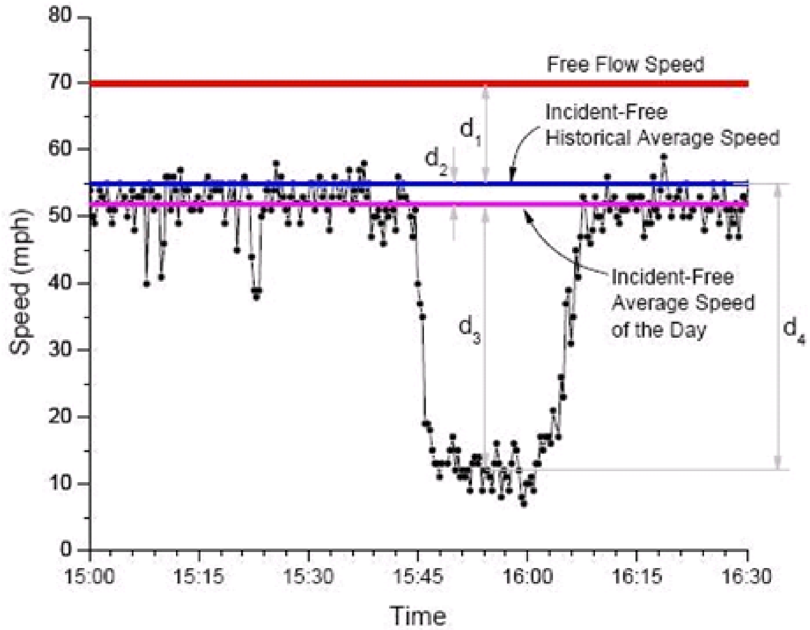


Figure 5-3: Typical Incident Lane Speed Profile (2).

With the conceptual reference speeds provided, delay can be calculated for each lane and further for each sector. The total incident delay is the sum of delays on all affected sectors:

$$D = \sum_{j=1}^{m} d_j = \sum_{j=1}^{m}\sum_{k=1}^{p} d_{jk} = \sum_{j=1}^{m}\sum_{k=1}^{p}\sum_{i=1}^{n} d_{ijk} = \sum_{j=1}^{m} L_j \cdot \sum_{k=1}^{p}\sum_{i=1}^{n} V_{ijk}\left(\frac{1}{S_{ijk}} - \frac{1}{R_{ijk}}\right) \qquad (5\text{-}12)$$

where d_j = delay per sector j; d_{jk} = delay per sector j and time interval k; d_{ijk} = delay per lane i, sector j, and time interval k; L_j = length of sector j; V_{ijk} = number of vehicles passing over the detector during time interval k on lane i and sector j; S_{ijk} = speed per lane i, sector j, and time interval k, which is the average speed of all vehicles passing over the detector during time interval k; and R_{ijk} = incident-free historical average speed per lane i, sector j, and time interval k.

5.1.4. Simulation Method

Macroscopic simulation packages provide an alternative approach to estimating incident delay (34). In the simulation of incident scenarios, several incident characteristics should be defined, such as:

- number of freeway lanes,
- volume-to-capacity ratio,
- incident rate,

- incident duration, and
- presence of usable shoulders.

Simulation models have the flexibility of modeling the entire incident clearance process and its impact on travel flow in a larger network. However, calibration of simulation models under incident scenarios has not been researched enough since the logic of simulation is mainly developed for normal vehicle movements. Also, depending upon whether the simulation model is macroscopic or microscopic in nature, the simulation calibration process is completely different.

5.2. Estimating Incident Delay

Given that historical traffic and incident data are available, the difference-in-travel-time method is the most suitable approach for routine estimation of incident delay. This method calculates directly from the measured traffic data and requires minimal assumptions for prevailing incident-free traffic conditions. The limitation of this method is that it can be used only for after-the-fact evaluation of incident management operations and traffic impacts. There is no predictive component that TMC managers could potentially use to support incident management activities during the incident.

Delay is easily understood by the public and can be aggregated to provide summary statistics for the corridor, area, or region. The numerical units or travel segments reported are critical components of information being conveyed to the audience. Similarly, specific delay statistics (e.g., total incident-induced delay during morning peak period on US-290 at LP-610) can be used as input to very specific operational or capital planning studies. These might be either operational or short-range applications. Delay easily translates into monetary values, and thus it is often used when conducting benefit/cost analyses.

5.2.1. Data Requirement

The following data elements are required for calculating delay using the difference-in-travel-time method:

- incident data – at the minimum, the incident record should contain the incident occurrence or notification time and geographic reference for the locations;
- travel time data – either observed through an AVI system or converted from continuously recorded speed data from closely spaced point-based sensors (e.g., loop detectors, radar system); and
- traffic volume – collected for specific freeway segments and time periods during both incident and incident-free conditions.

5.2.1.1. <u>Selecting Data Sources</u>

Travel time data are a critical input for incident delay calculation. Travel time data from probe-vehicle-based systems such as Houston's AVI should be used whenever possible.

For TMCs with predominantly point-based detection systems, the sensors upstream of the incident location should be used for the analysis. In general, the travel time data either obtained directly from the probe-vehicle system or converted from speed data are not exactly the same. For comparative evaluation, a freeway segment in Houston with both types of systems installed was selected. First, the travel time data were retrieved from the AVI database and then converted to speed. Then, the speed data were obtained from three different radar sensors within the selected AVI segment using the same aggregation interval. The speed data were used to compare the data from both types of systems since they are independent of the segment length. Figure 5-4 shows the diagram of the example freeway segment. The AVI segment is defined based on the tag reader location, which in this case is 2.45 miles in length from 34th Street (origin checkpoint #30) to Pinemont Street (destination checkpoint #31). Three radar sensors were installed within this segment to collect traffic volume, occupancy, speed, and vehicle classification data on a lane-by-lane basis.

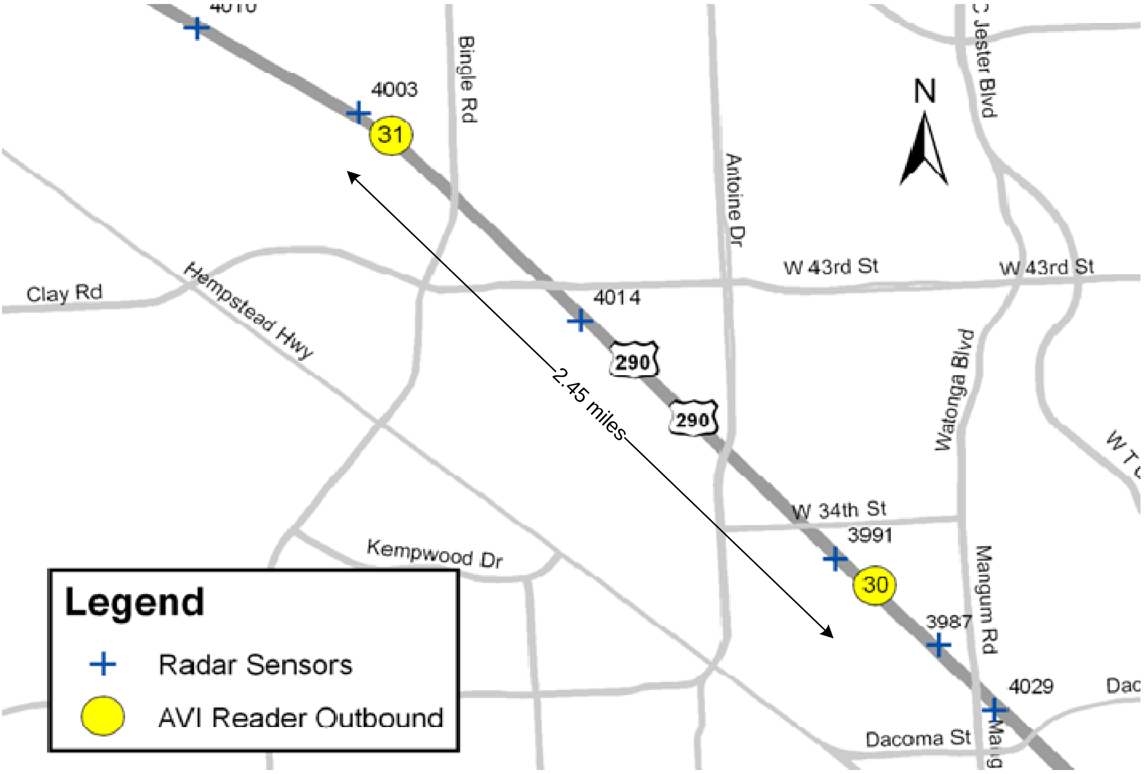


Figure 5-4: AVI Travel Time Segment and Radar Sensor Locations.

Figure 5-5 compares the speed data obtained from both types of systems on a typical incident-free day. Root mean square of errors (RMSE) was used to quantify the differences between the speed profiles from radar sensors and the AVI-based profile. The RMSE values calculated for all the profiles are approximately the same ranging from 6.9 to 7.6 mph. When the traffic conditions are not affected by the incident, the travel time data obtained from point-based sensors located within the travel time segment of interest are not substantially different from those obtained from the probe-vehicle system. In other words, the locations of point-based sensors do not have a significant impact on the travel time data during incident-free conditions. Incident-free conditions can be represented by any point-based sensors within the segment of interest.

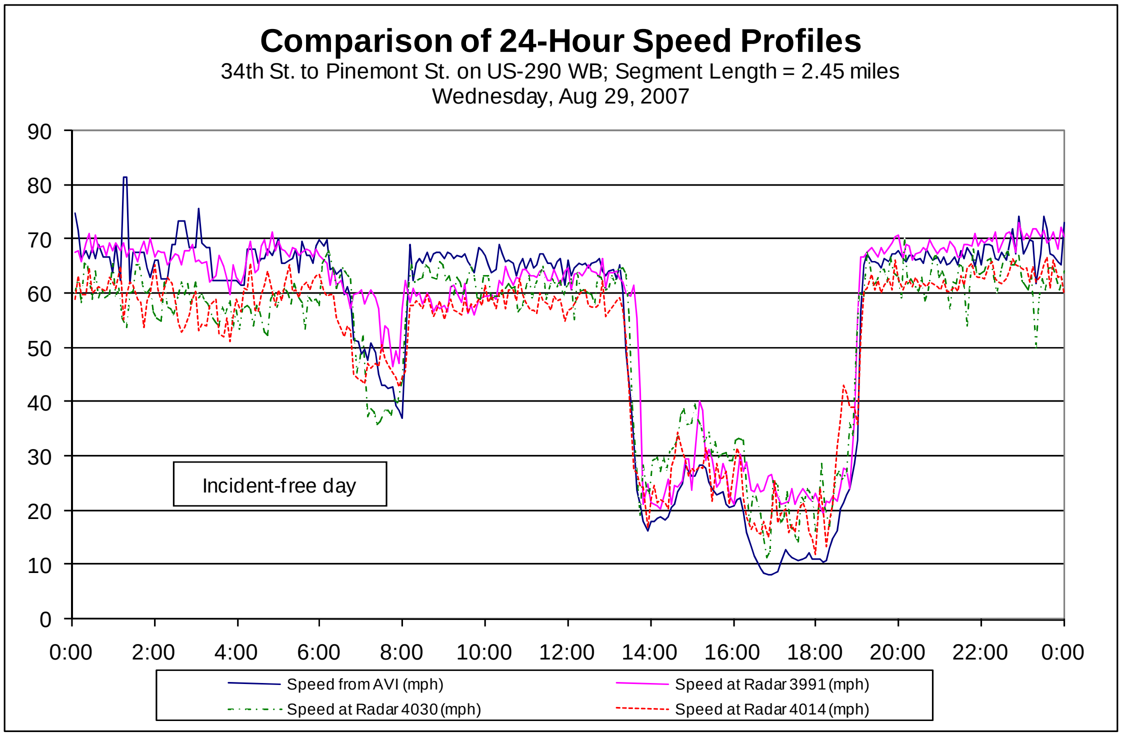


Figure 5-5: AVI-Based (Probe-Vehicle) versus Radar-Based (Point-Based) Data.

However, under incident conditions, the traffic data observed from the point-based sensors will depend on the relationship between the sensors and incident locations. For the purpose of travel time calculation, the sensors upstream of incident locations should be used for the analysis. Figure 5-6 shows the effects of incidents on speed profiles obtained from radar sensors at different locations within the travel time segment of interest.

The first incident occurred in the morning hours between sensor ID 3991 and ID 4030. In this scenario, ID 3991 is located upstream of the incident location, and ID 4030 and ID 4014 are downstream. The profiles obtained from the sensor upstream of the incident location and the AVI system generally follow the same pattern. However, for the sensors downstream of an incident, the speed profiles did not drop until the incident was removed, which was when the traffic accumulated upstream was released all at once, causing the sudden drop in speed.

The second incident in this profile occurred at Hollister Road. Therefore, all three sensors shown in Figure 5-6 are upstream of the incident location. In this case, there is no noticeable lag in speed drop as in the case of the first incident. However, the extent to which the speed profiles drop depends on shock wave characteristics and traffic diversion rates.

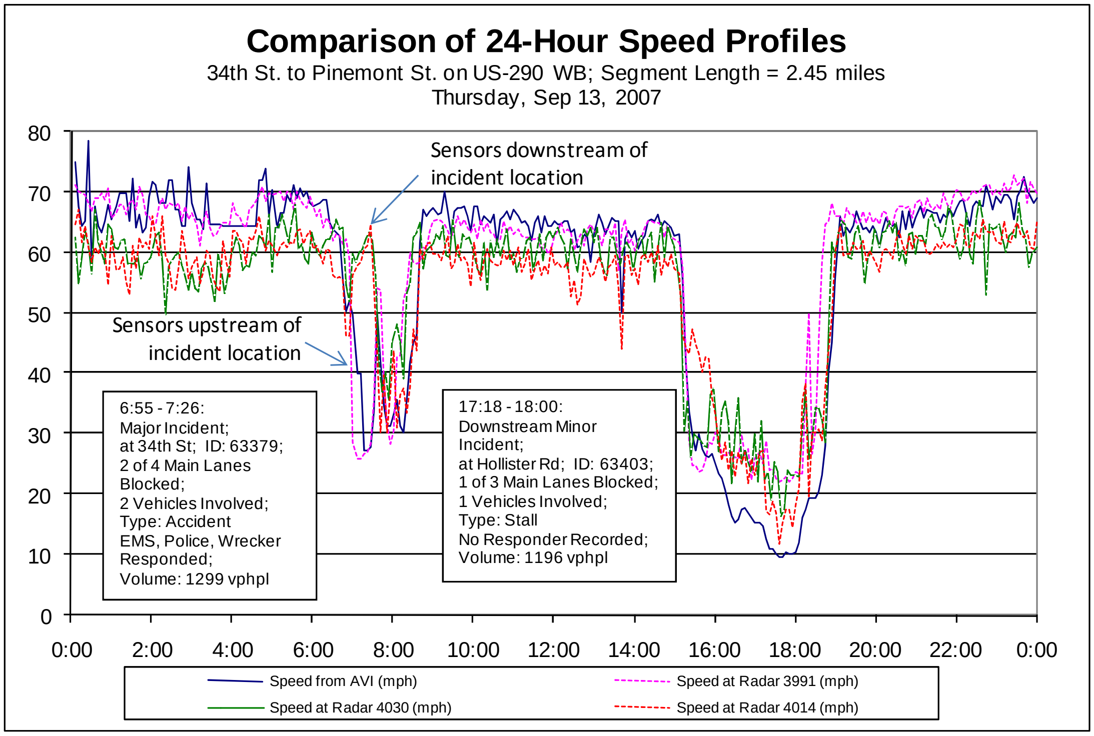


Figure 5-6: Comparison of Speed Profiles under Incident Conditions.

5.2.2. Calculation Procedures

There are four important steps in calculating incident delay using the difference-in-travel-time method:

- Identify the scope for the analysis. Define the scope based on the objective of the analysis, whether it is to evaluate the impacts from specific incidents, freeway segments, and/or time periods.
- Establish prevailing incident-free traffic conditions during the same period. This step would require some assumptions on how historical traffic data could be used to represent traffic conditions if the incident had not occurred.
- Establish prevailing traffic conditions during incident-induced congestion. Identify the duration in which the traffic conditions are affected by the incident.
- Calculate the delay using the difference-in-travel-time method.

5.2.2.1. Define the Scope for the Analysis

The objective of the analysis dictates the scope and the data requirement for the analysis. To evaluate the delay for a particular incident, the analyst would require only incident location and traffic data at that location. If the objective is to evaluate the incident impacts for a specific freeway segment during a peak period, the analyst will have to identify all the incidents that occurred on that segment during the peak period.

The analyst will also have to define the extent for the delay analysis. First, it is logical to define the segments based on sensor configuration and deployment at the TMCs. For example, a freeway can be segmented by the locations of AVI readers or the locations of main lane loop detectors. Then, the analyst may combine multiple segments upstream of the incident location to define the extent of the delay analysis.

5.2.2.2. Determine Prevailing Background Traffic Conditions

Prevailing background or incident-free traffic conditions are the traffic conditions that travelers would have experienced if there were no incidents. Historical traffic data are required to develop realistic prevailing incident-free traffic conditions. It should be noted that a congested condition may already exist even if there is no incident. Several factors, in addition to incidents, such as peak-period traffic demand, inclement weather conditions, and bottlenecks, may contribute to freeway congestion. Prevailing incident-free traffic conditions can be specifically defined by the analyst to capture all the sources of congestion except for the incident being examined.

Incident-free traffic conditions can be defined using either speed or travel time profile. Travel time is, however, the final input used for calculating incident delay. Unless freeways are instrumented with a probe-vehicle system, the speed data observed through point-based detection must be converted to travel time for delay calculation using the following relationship:

$$\text{Travel Time (minutes)} = \frac{\text{Segment Length (miles)}}{\text{Average Speed (mph)}} \times 60 \qquad (5\text{-}13)$$

Incident-Filtered Method for Establishing Background Traffic Conditions

If incident data are available and easy to retrieve, the analyst should consider the following options in establishing prevailing incident-free traffic conditions:

- Incident-free traffic data from the previous week during the same time on the same day of the week – Use the traffic data from prior weeks if the data from a week ago are invalid for the calculation (e.g., affected by incidents or unavailable). Figure 5-7 shows an example of a one-day historical lane speed profile aggregated from 30-second traffic data observed through the SmartSensor radar system on US-290 at Huffmeister Road.
- Average of incident-free traffic data from several weeks on the same days of the weeks – More historical data must be available and valid for this alternative. The advantage of this method is that averaging data reduces the chance of unusual daily traffic variations.
- Weighted average method – This is the average of incident-free historical traffic data adjusted by different weighting factors. Similarly, the historical data used for averaging should be obtained from the same days of the weeks. However, in contrast to the previous alternatives, this method can give more weight to the most recent data in establishing prevailing incident-free traffic conditions. This method should be considered when sufficient historical data are available for calibrating

weighting factors such that the output can reasonably reflect the expected incident-free traffic condition.

Properly calibrated weighting factors can be used for combining historical speed data from multiple days. Formally, the combined speed profile can be expressed as:

$$\bar{v} = \sum_{i=1}^{n} \alpha_i v_i ; \ \sum_{i=1}^{n} \alpha_i = 1; \ \alpha_i \geq 0 \qquad (5\text{-}14)$$

where $\bar{v}$ is the expected incident-free speed profile, v_i is the historical speed profile from week i on the same day of the week, n is number of weeks used in the calculation, and α_i is a weighting factor for historical speed profile v_i.

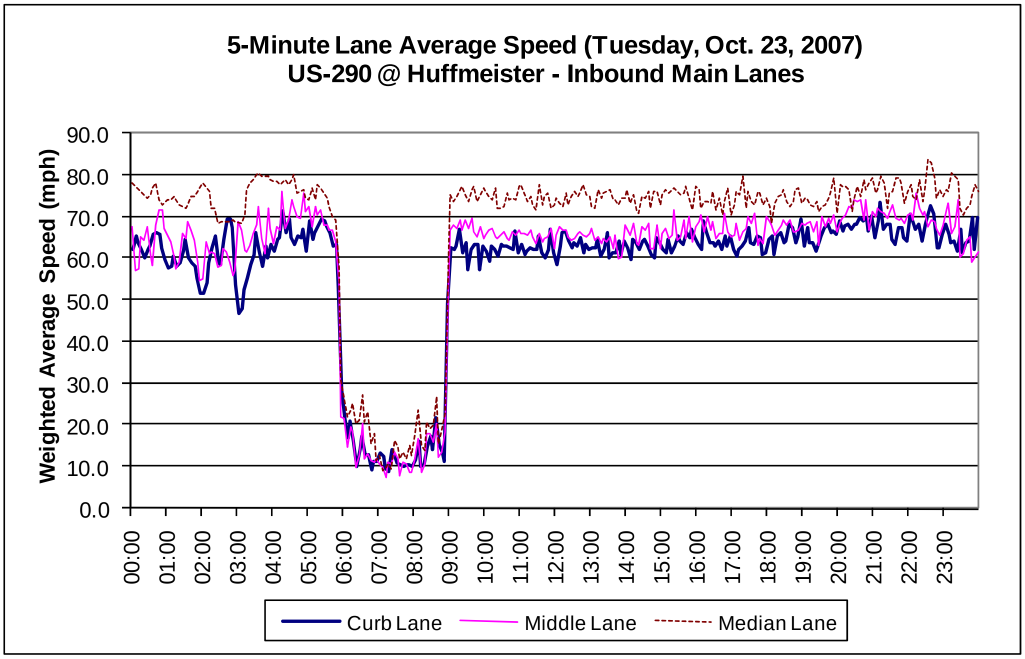


Figure 5-7: Example of Incident-Free Speed Profile Using SmartSensor Data.

From Equation (5-14), the analyst can place more emphasis on the most recent historical data by assigning higher weighting factors to more recent speed profiles. The analyst can calibrate the parameters using regression techniques and determine the optimal value for the parameter n. If travel time is directly observed from a probe-vehicle system, the speed profile in this equation can be replaced with the travel time profile directly. Note that the averaging method described in the second option is a special case of the weighted average where $\alpha_i = 1/n$ for $i = 1, 2, \ldots, n$.

Median-Based Method for Establishing Background Traffic Conditions

All the previous methods for establishing incident-free or background traffic conditions assume that the analyst has incident data available to filter traffic data for only incident-free days. This may not always be practical since traffic and incident data are often logged independently and thus require the analyst to manually integrate both data sources in order to construct appropriate background traffic conditions. The whole process could be very time consuming and still unable to fully remove incident traffic conditions, particularly if the incidents occur upstream or downstream of the freeway segments of interest. In order to address this problem, a simplified method for establishing background traffic conditions when incident data are limited or unavailable is described below.

Instead of taking averages of incident-free traffic data (e.g., speed, travel time, flow), the analyst can choose multiple days of traffic data regardless of the traffic conditions and then calculate the median values for each interval in order to derive a background profile. The method is referred to as the “median-based profile approach.” The median-based profile relies on the following assumptions:

- Incident traffic conditions generally substantially deviate from normal incident-free traffic conditions during the same time period.
- For every time interval, the data used to derive the profile consist of at least one interval of background traffic data. This condition is typically met when the sample size is sufficiently large since normal traffic conditions represent a much greater proportion of overall traffic conditions.

The median-based profile approach requires only traffic data from the same time period. For example, to derive a background travel time profile for Monday traffic, the analyst should use multiple Mondays of traffic data from the same segment for best results. The procedure to obtain a median-based travel time profile under incident-free conditions is as follows:

- Obtain at least four intervals of the data for at least one interval of the profile (4:1) to be constructed. For instance, if the incident-free travel time profile for Monday is to be constructed, the analyst should obtain at least four Mondays of travel time data for this purpose. Our evaluation of this technique indicated that the use of 4:1 to 8:1 ratios will generally produce reliable background profiles.
- Calculate the median value for each time interval (e.g., 5-minute, 15-minute). A series of median values over the analysis period is a travel time profile under incident-free traffic conditions.

Median statistics simply remove extreme traffic conditions generally experienced under incident conditions or inclement weather events. Provided that the sample size is large enough, the remaining data in the mid-range of all the data represent the values that one would observe under normal traffic conditions.

To illustrate this approach, a freeway segment on US-290 westbound from 34th Street to Pinemont Street was selected for the analysis. Figure 5-8 shows an example of incident-free segment travel time profiles obtained from the AVI system for three Thursdays in 2007. Houston’s incident data were queried to identify a list of incidents that occurred on the segment as well as the segment downstream. In this manner, we can mitigate the effect of incident-induced congestion that could potentially propagate from the downstream segment. Nevertheless, irregular spikes in the travel time profiles are still noticeable but relatively less obvious than those observed in the incident-affected profiles shown in Figure 5-9.

Thursday data were retrieved with and without incidents for four days each to perform the median-based analysis. Figure 5-10 shows the effects of sample size used to construct the profile. The number of days used was varied from three to eight Thursdays, and the days were randomly selected regardless of incident impacts. Irregular spikes or trends in the background profiles diminish as the number of days increases, thus indicating a positive correlation between the effectiveness of the method and the sample size.

Figure 5-11 provides a comparison of background speed and travel time profiles obtained from incident-free data versus all data including incident-affected days. In this particular example, the speed profile was converted directly from the travel time data obtained from the AVI system. The median-based background profiles obtained from all data start to converge to the profile obtained from incident-free data as the number of days increases. It was found that using four to eight days of data is generally sufficient for weekday profiles. Fewer days (approximately three to six) are needed for weekend profiles in most cases. This approach is quite efficient and robust to irregularities observed in the data sources.

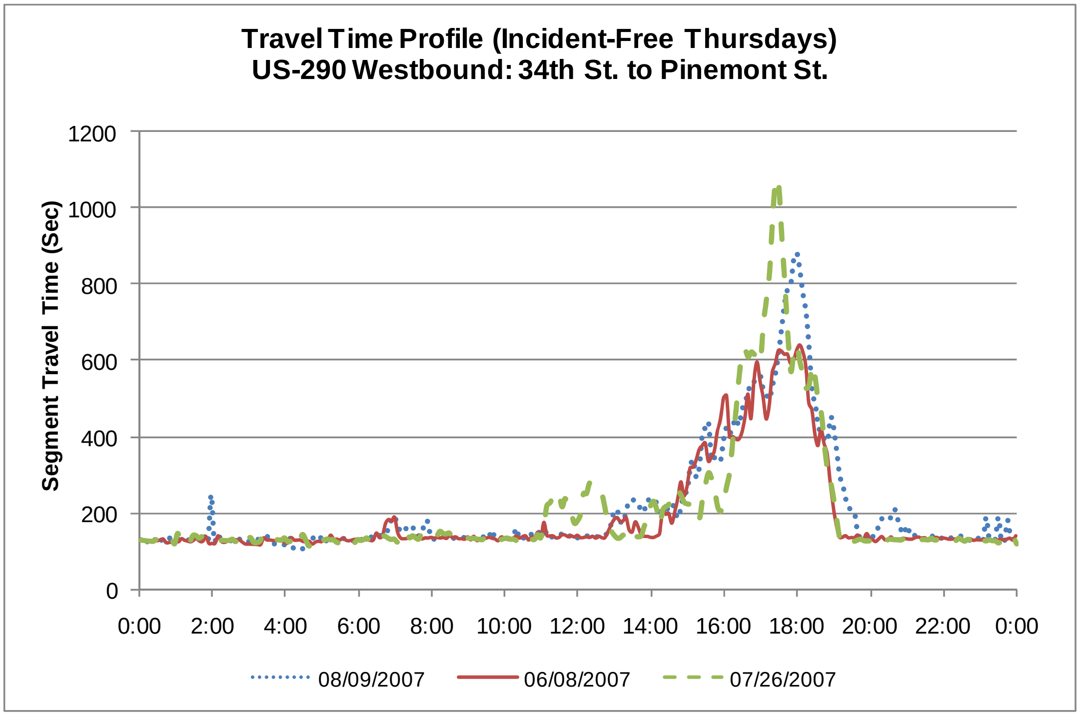


Figure 5-8: Example of Incident-Free Travel Time Profiles.

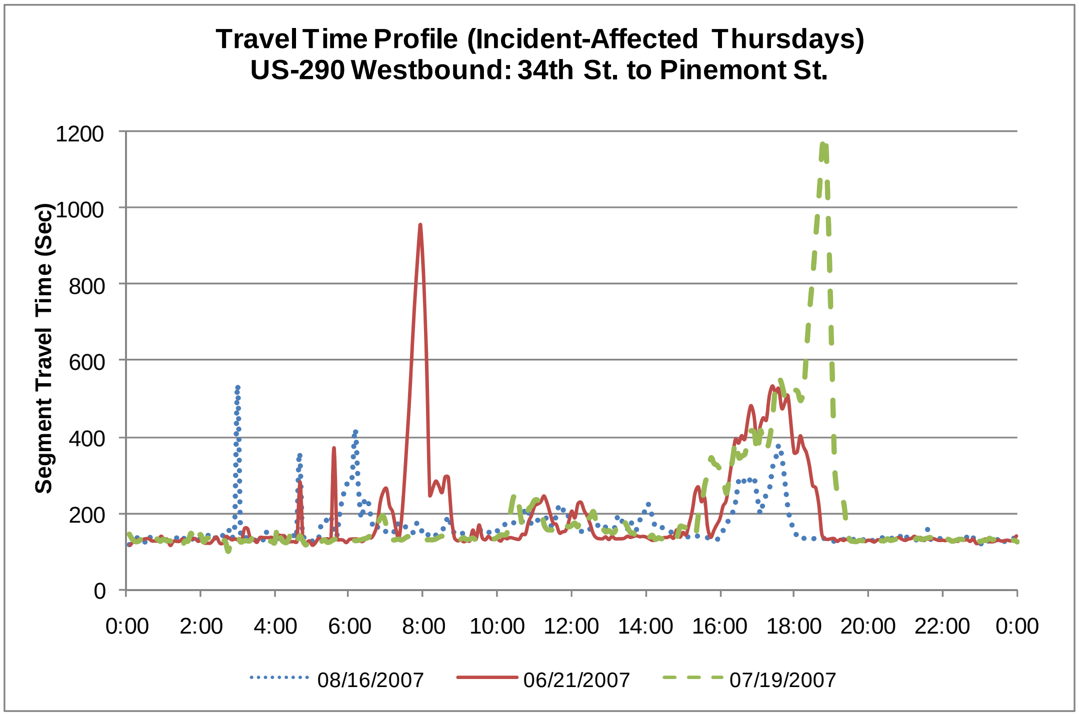


Figure 5-9: Example of Incident-Affected Travel Time Profiles.

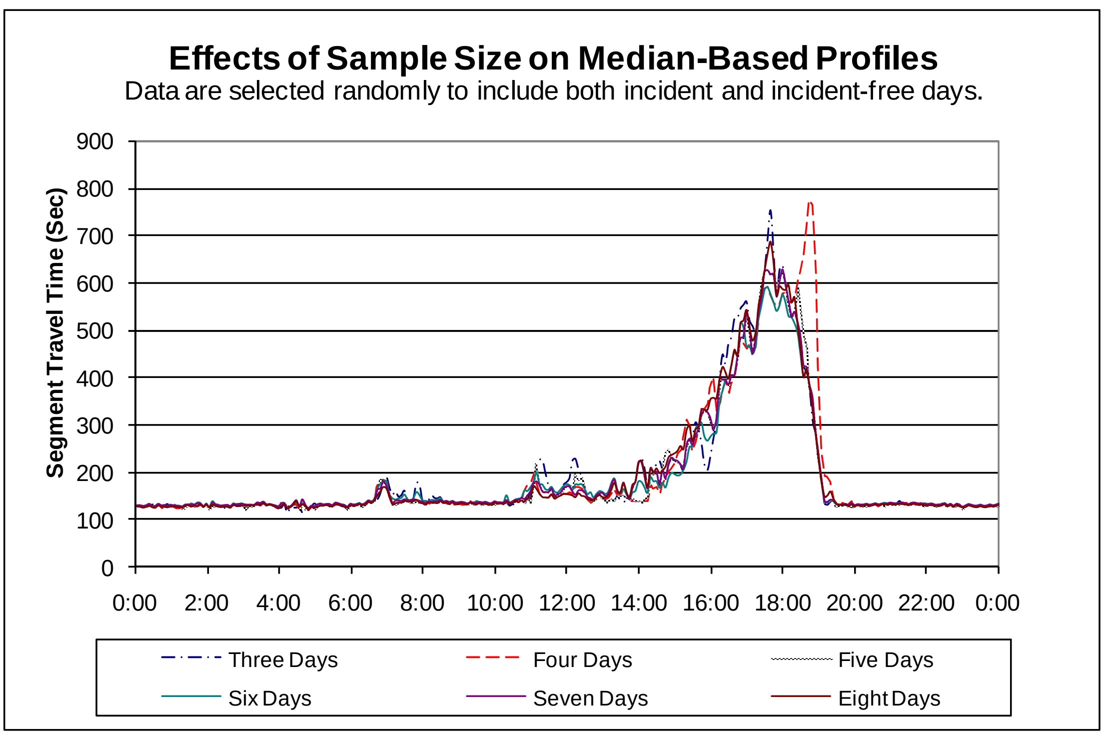


Figure 5-10: Effects of Sample Size on Median-Based Background Profiles.

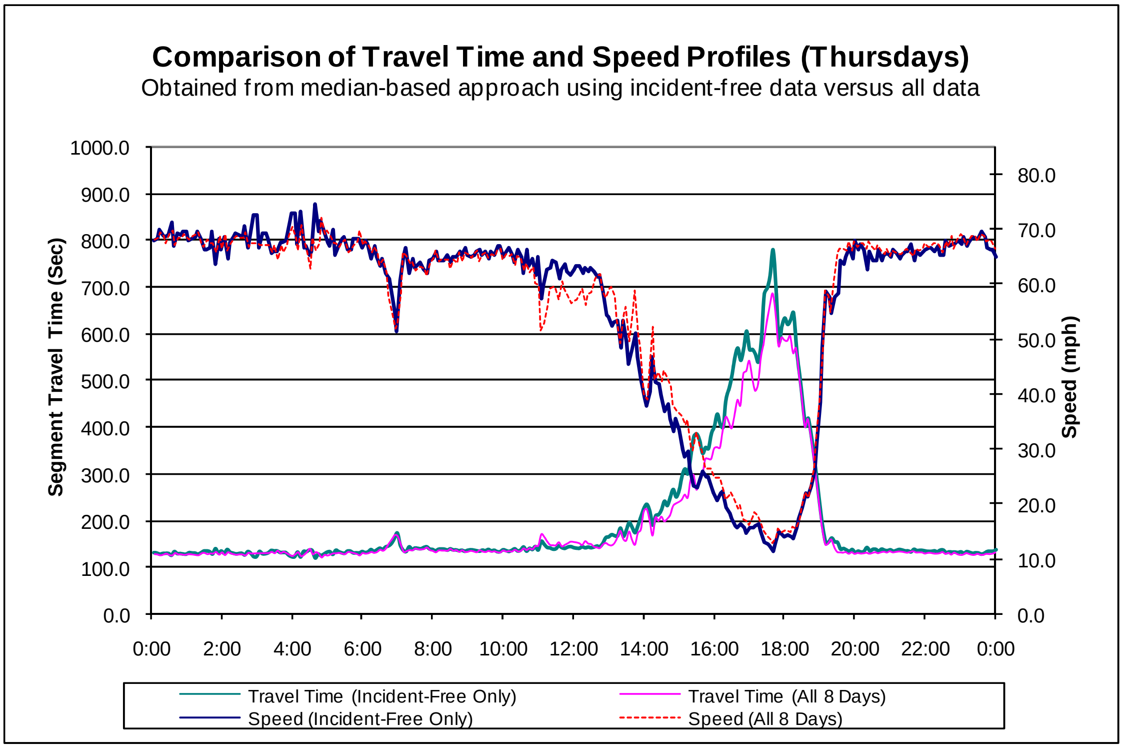


Figure 5-11: Median-Based Profiles Using Incident-Free versus All Data.

5.2.2.3. Determine Prevailing Incident-Induced Traffic Conditions

Traffic data observed from both a probe vehicle system and point-based sensors can be used to derive prevailing incident traffic conditions. There are two key components that need to be determined in this step: the duration and the extent of the incident impact. Visual assessment of speed profiles is particularly helpful for identifying the duration of incident-induced congestion. For TMCs with an AVI system, the analyst can examine the speed profiles of the segment affected by the incident. For TMCs with point-based detection, the analyst can examine the speed profiles observed through the sensors downstream of the incident.

The analyst can compare the speed profiles between incident-induced and incident-free traffic conditions (see previous section) and then determine the total incident-induced duration, which is defined by the time period in which the speed profiles are lower than those of incident-free traffic conditions.

Then, the analyst must obtain the current travel time profiles (converted from the speed) for the freeway segments within the extent of the delay analysis. In the next step, these incident-induced travel time profiles will be compared with the incident-free counterparts obtained from the previous step.

5.2.2.4. Calculate Delay Using the Difference-in-Travel-Time Method

In the final step, the total incident delay can be estimated by adding the incident delay for each segment over the period of analysis. Figure 5-12 shows the example of hypothetical freeway segmentation for the delay analysis. Let us assume that segments $j = 1,\ldots,\ell$ are affected by the incident for a total of time period T. Let k be the time interval of size Δ (e.g., five minutes) where $k = 1,\ldots,m$ and $m = \lceil T / \Delta \rceil$. Delay is then defined by the summation of products of traffic volume and average difference in travel time across all m time intervals and ℓ segments.

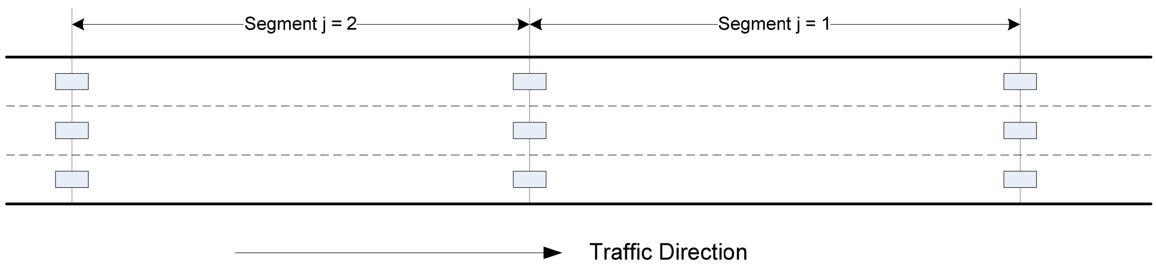


Figure 5-12: Freeway Segmentation Based on Detector Locations.

Mathematically, expanding the concept of delay calculation using the difference-in-travel-time method in Equation (5-11) gives:

$$D = \sum_{j=1}^{\ell} \sum_{k=1}^{m} V_{jk} d_{jk}; \; d_{jk} = \begin{cases} t_{jk} - \overline{t}_{jk} \text{ if } t_{jk} > \overline{t}_{jk} \\ 0 \text{ if otherwise} \end{cases} \tag{5-15}$$

where D = total incident delay (veh-hours); V_{jk} = traffic volume on j^{th} segment during k^{th} interval; t_{jk} = average travel time for j^{th} segment during k^{th} interval; and $\overline{t}_{jk}$ = expected incident-free travel time for j^{th} segment during k^{th} interval.

Total incident delay can be presented specifically for an individual incident or on a larger scale such as a freeway corridor or a region. Area-wide total incident delay can also be used to measure the effectiveness of an incident management program, as well as various freeway management strategies. It is important that the scope of the delay analysis be defined properly in the first step to ensure that the objective of the analysis is achieved.

5.3. Quantifying Detailed Incident-Related Impacts

Multiple data types are typically archived at the TMCs after an incident. This section describes a methodology to analyze a combination of traffic and incident data to measure various incident-related impacts for specific incidents in addition to delay-related components. The results from this methodology would serve as supplemental measures for characterizing and evaluating specific incident impacts in addition to the incident delay (see Section 5.2). This methodology would enable the analyst to answer several questions related to a particular incident, such as:

Incident Management Perspective

- How long does it take for the traffic to return to normal conditions after the incident has been cleared?
- What is the total delay caused by an incident?
- When does the total delay peak after the beginning of an incident?

Travelers' Perspective

- What is the worst average (per-vehicle) delay experience to the travelers with respect to their anticipation? When does it take place after the beginning of an incident?
- How much additional time do those travelers actually spend in traffic congestion as the result of an incident?
- How do the changing traffic conditions affect the delay experienced by the travelers?

5.3.1. Data Requirement

The following data elements are required for calculating detailed incident-related impacts:

- travel time data,
- traffic volume data, and
- incident data.

The travel time data can be obtained either directly (probe-vehicle system) or converted from speed data (point-based detection system such as radar and loop detectors). The travel time data are used to construct both incident-affected and background travel time profiles.

Traffic volume data during the incident-affected period are needed to calculate the total delay from the incident. For a point-based detection system, data retrieved from detectors upstream of incident locations should be used for the analysis.

Incident data records, at a minimum, should contain incident detection and clearance times. The incident details, if available, are useful for describing the causal relationships between incident characteristics and their related impacts. In addition, the impacts of incidents sharing similar characteristics can be compared and evaluated across multiple locations or over different time periods. Any changes in the incident management strategies can also be evaluated provided that the data are available.

5.3.2. Methodology

The methodology to derive incident-related impacts is based on two critical profiles:

- travel time profile under incident condition or incident-affected profile and
- travel time under normal incident-free condition or background profile.

By superimposing the incident-affected profile onto the background profile, the analyst can obtain the delay profile from the differences between both profiles. This delay profile represents average delay (also known as per-vehicle delay) or additional delay experienced by travelers at a given point in time. It is the delay measured against background travel times, which in turn are a proxy of travelers' anticipation. In other words, if travelers expect to take 5 minutes to traverse a specific freeway segment at 7:00AM and they actually spend 12 minutes, this implies that the additional delay experienced by travelers is 7 minutes on average at 7:00AM. It is important to note that travelers' anticipation can differ by time of day and day of week as represented by the background profile. The actual traveling conditions would be represented by the travel time profile under incident conditions. Hence, the average delay experience would also vary over time as the incident clearance process and traffic conditions evolve.

The methodology to calculate detailed incident-related impacts for a specific incident is described step by step in the subsequent sections.

5.3.2.1. Derive Average Delay Profile

Average delay is an average delay per vehicle experienced by travelers for a particular freeway segment at a given time interval. It is the difference between actual travel time under incident conditions and background travel time under incident-free conditions. The average delay at any given interval becomes zero when actual travel time drops below the background travel time. Background travel time alternatively can be viewed as the expected travel time for motorists to traverse a freeway segment of interest. The average delay profile represents changes in average delay over time for a particular freeway segment. The analyst needs to prepare two profiles for deriving the average delay profile:

- the travel time profile under incident condition and
- the background travel time profile (normal incident-free condition).

The smaller time intervals such as three to five minutes are recommended for building the profiles. The higher resolution will provide more flexibility in the analysis and increased capability in detecting critical time points as the incident event progresses.

It is recommended that the 24-hour travel time profile be obtained for the incident day. However, if the data for an entire day are not available, the travel time data at least 30 minutes before an incident and 3 hours after an incident should be obtained for the analysis. Figure 5-13 shows an example of travel time and speed profiles obtained on an incident day. The travel time data in the example are extracted from Houston's AVI database. The vertical lines indicate the time from which the incident was detected until it was cleared. There were two incidents noted in this diagram. The first one occurred at approximately 7AM within the travel time segment. The second one occurred at 5:18PM in another travel time segment downstream of this one. The second incident was noted in this figure in order to illustrate how the delay profile can capture the impact of an incident-related lane closure downstream of the segment of interest.

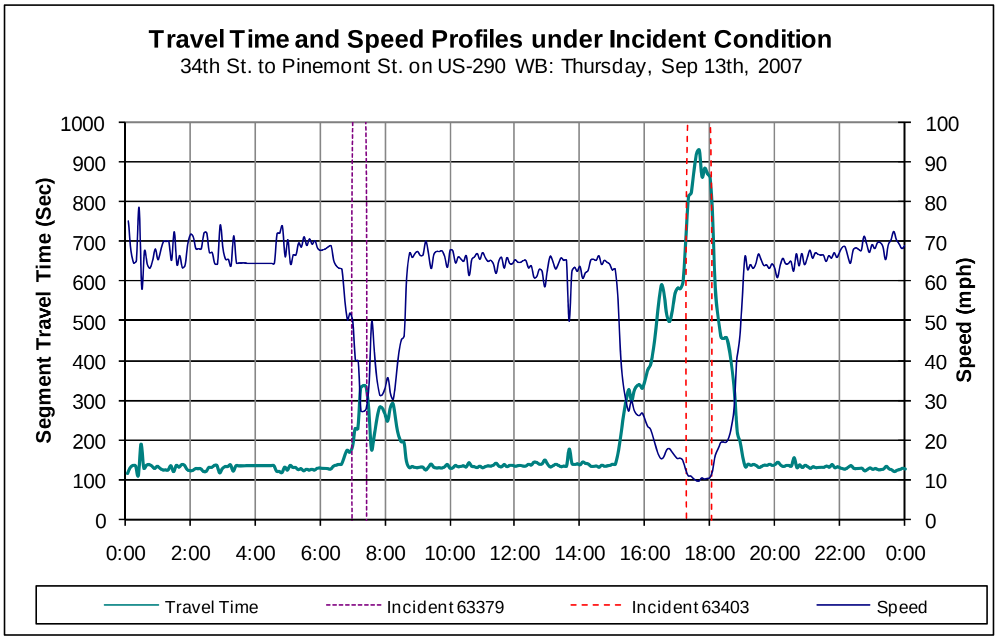


Figure 5-13: Travel Time and Speed Profiles under Incident Condition.

To derive the corresponding background profile, we used traffic data from eight Thursdays to build a profile using a median-based approach as described in Section 5.2.2.2. The resulting background profile is shown in Figure 5-14. The background profile reveals a pattern of recurrent congestion in the PM peak and to a lesser degree during the AM peak. It should be noted that, from the profile in Figure 5-13 alone, it is difficult to determine whether the AM and PM peaks in travel time are caused by an incident or merely recurrent congestion.

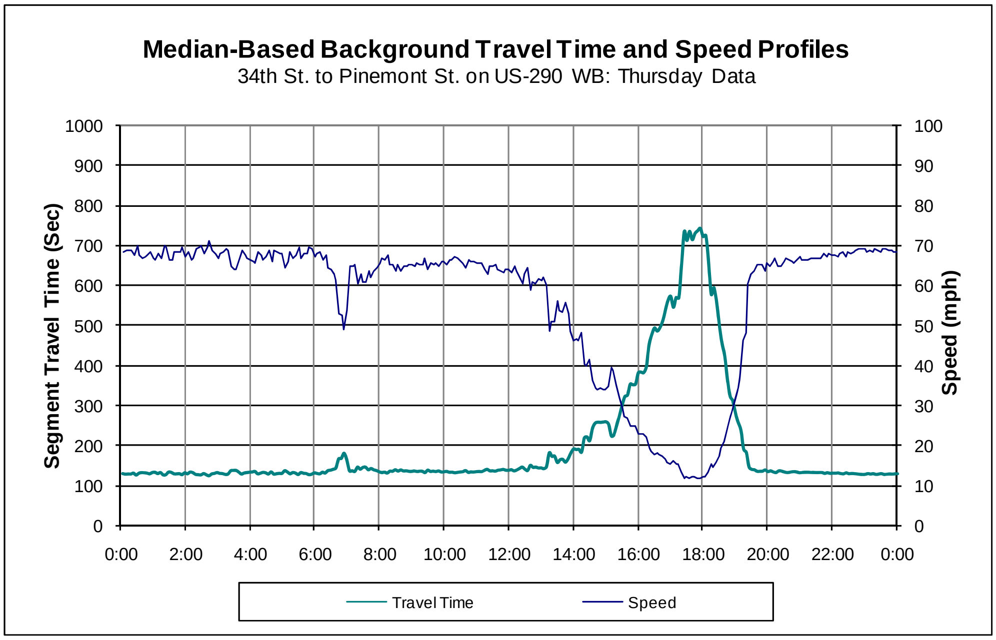


Figure 5-14: Background Travel Time and Speed Profiles.

Now, the average delay profile can be obtained by superimposing the profile in Figure 5-13 onto the background profile in Figure 5-14. The average delay per vehicle is the difference between these two travel time profiles. The resulting average delay profile and the corresponding traffic volume on the incident day are shown in Figure 5-15.

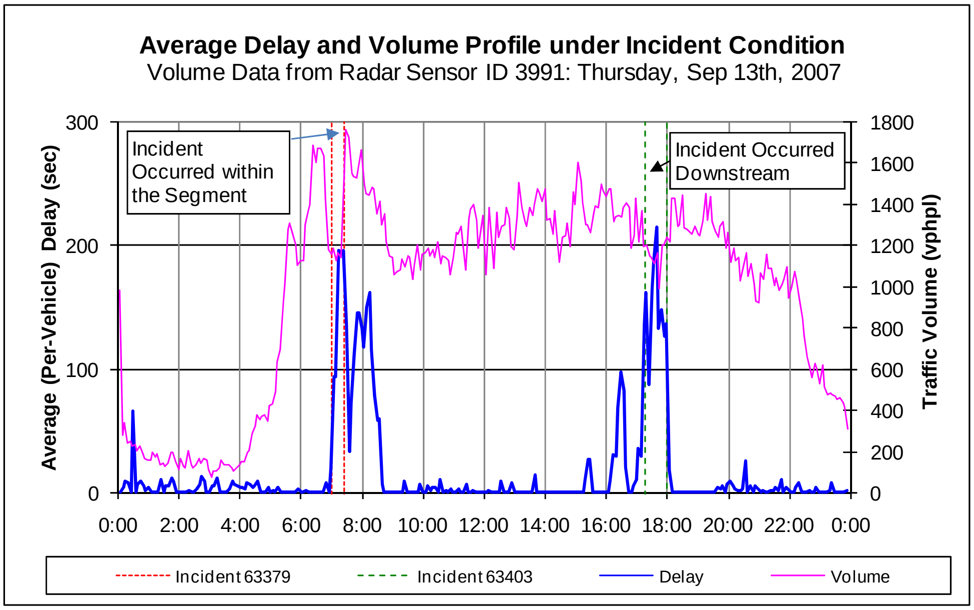


Figure 5-15: Average Delay and Traffic Volume Profiles.

Several incident-related impacts can be derived from the average delay profile shown in Figure 5-15. The next section describes various incident-related impacts measurable from the profiles derived.

5.3.2.2. Calculate Incident-Related Impacts from Average Delay Profile

From the average delay profile, several incident-related impacts can be determined as shown in Figure 5-16, which are:

- Profile-based incident start time – the time at which the impact of incident on traffic conditions is first observed. This time may not exactly coincide with the recorded incident detection time, but the difference is generally in the range of 5-30 minutes. This difference is noticeably smaller for major incidents.
- Peak delay per vehicle – the maximum amount of delay caused by an incident. This is also the maximum delay experienced by travelers from this incident.
- 85th percentile of delay per vehicle – the 85th percentile of observed average delay values. This measure is a better representation of incident impacts on travelers and can be used to compare the impacts of multiple incidents since it is less affected by a single unusual peak in delay per vehicle.
- Peak delay time point – the time point at which average delay per vehicle is the highest. It should be noted that this delay is measured against background travel time, and therefore the time at which the delay is peaked may not be the same as the time at which the segment travel time is the highest.

- Time to peak delay – the time it takes from the beginning of an incident to the time at which the peak delay is observed (peak delay time). This also indicates that the travelers who arrive at this freeway segment after the time to peak delay has passed would experience the highest amount of delay. It is recommended that the profile-based incident start time be used for this calculation if it does not coincide with the incident detection time recorded in the incident database. When incident clearance time is unavailable, the time to peak delay can serve as a good proxy for incident clearance time.
- Lane blockage duration – this duration is approximated by the time elapsed from the profile-based incident start time to the peak delay time point. In general, this duration should be close to the time to peak delay.
- Traffic recovery time (traffic-return-to-normal time) – the time elapsed from the moment at which the incident has been removed to the traffic-return-to-normal time. This is the time that it takes for the traffic to return to normal conditions after the incident has been removed, which in many cases can be longer than the incident duration itself. If the incident clearance time is unavailable, the peak delay time can be used to substitute this value.
- Incident-induced congestion duration – the total duration in which an incident has caused additional traffic delay. This duration is measured from the profile-based incident start time to the traffic-return-to-normal time (the end of incident impact). The incident-induced congestion duration is equal to a sum of lane blockage duration and traffic recovery time when the profile-based incident start time and peak delay time point are used to define the lane blockage duration.

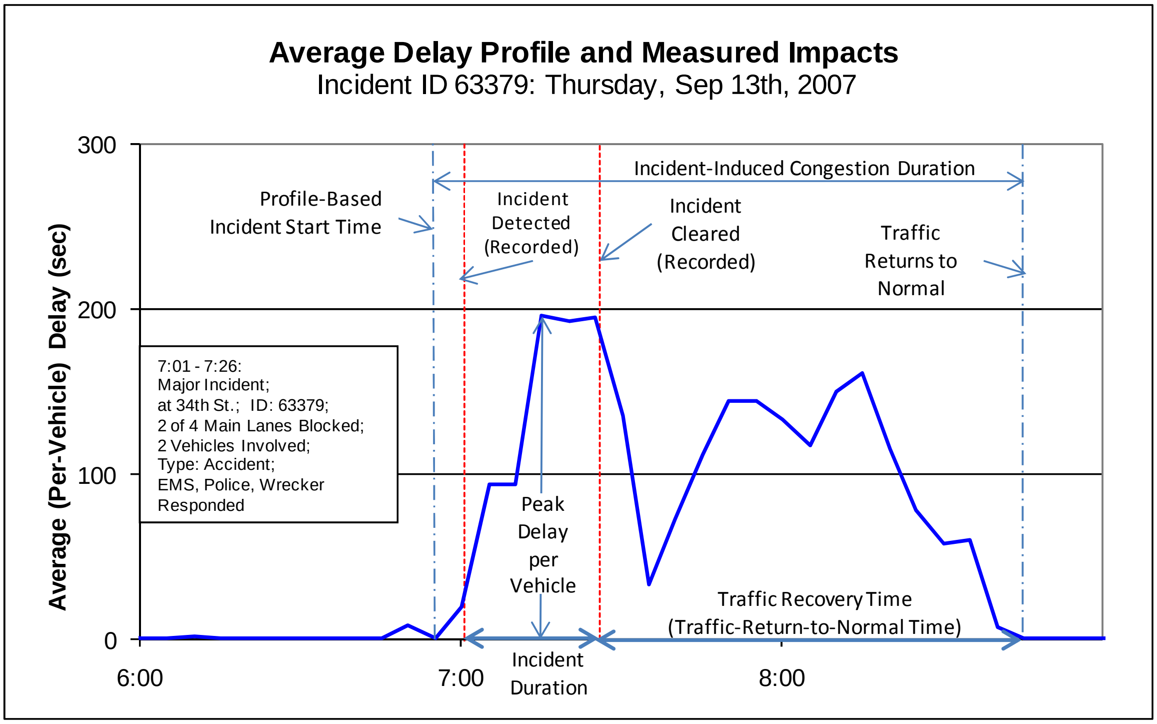


Figure 5-16: Measurable Impacts from Average Delay Profile.

5.3.2.3. Calculate Delay Index

One shortcoming of average delay per vehicle is that it does not fully account for the travel time anticipated by the travelers. For example, a traveler would be dissatisfied with a delay of one minute per vehicle during the off-peak period more than the peak period. This is because a traveler would anticipate a much shorter travel time during the off-peak period. In order to address this problem, a delay index can be used instead of average delay per vehicle to estimate the amount of travelers' delay relative to their anticipation. A delay index is defined by:

$$\text{Delay Index} = \frac{\text{Average Delay per Vehicle}}{\text{Background Travel Time}} \times 100 \,. \tag{5-16}$$

Since the average delay per vehicle is always zero or greater, the delay index will always be equal to or greater than zero. The higher delay index means more inconvenience to the travelers. For example, delay indices of 20 percent and 120 percent indicate that travelers would need to spend 20 percent and 120 percent more than their anticipated travel time to travel this freeway segment, respectively.

The delay index relates the amount of traffic delay to travelers' anticipation, thus making it suitable for quantifying the degree of customer satisfaction. A delay index profile as shown in Figure 5-17 can be used to assess the degree of travelers' satisfaction over the course of an incident event and compare travelers' attitudes toward multiple incidents at different times of day and locations.

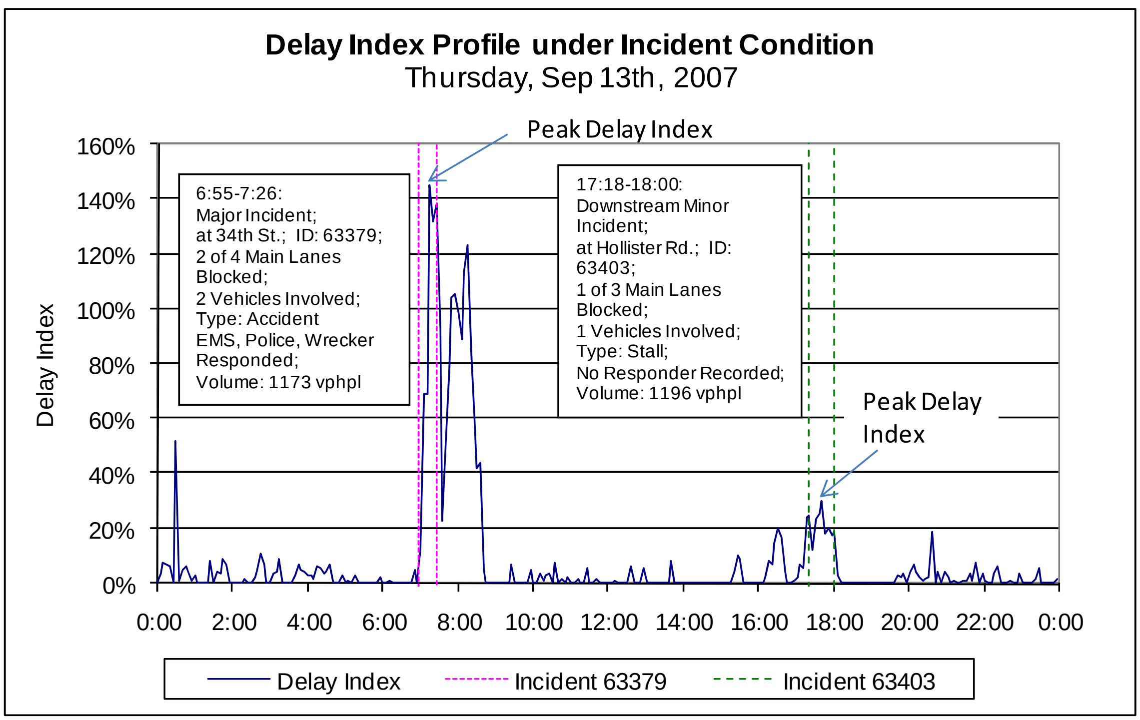


Figure 5-17: Delay Index Profile.

From Figure 5-17, the delay index peaks during the morning rush hours as a result of an accident blocking two main lanes. The delay index was also higher in the evening as a result of another downstream lane-blockage stall. It is interesting to note that the maximum average delays per vehicle caused by these two incidents are approximately the same (see Figure 5-15). However, when travelers' anticipation is taken into consideration through the delay index, it is obvious that the road users would feel more impacts from the morning delay. This is because they anticipated a much faster travel time for the outbound direction in the morning for this freeway segment.

5.3.2.4. Calculate Total Delay

The previous profile looks at the average delay for individual travelers. However, from the system viewpoint, the amount of traffic flow traversing a freeway segment must also be incorporated. The total delay represents the amount of delay caused by an incident to all vehicles, which can be calculated by multiplying delay per vehicle with traffic volume for the interval. The traffic volume should be obtained from the sensor upstream of an incident location. The time interval used to aggregate the volume data should be consistent with the time interval used to calculate the average delay profile. The per-interval total delay profile can be constructed by calculating total delays for every interval during the incident-induced congestion period. The total delay should be reported in vehicle-hours or vehicle-minutes. From the volume and vehicle delay profiles shown in Figure 5-15, the per-interval total delay profile for the first incident can be derived as shown in Figure 5-18.

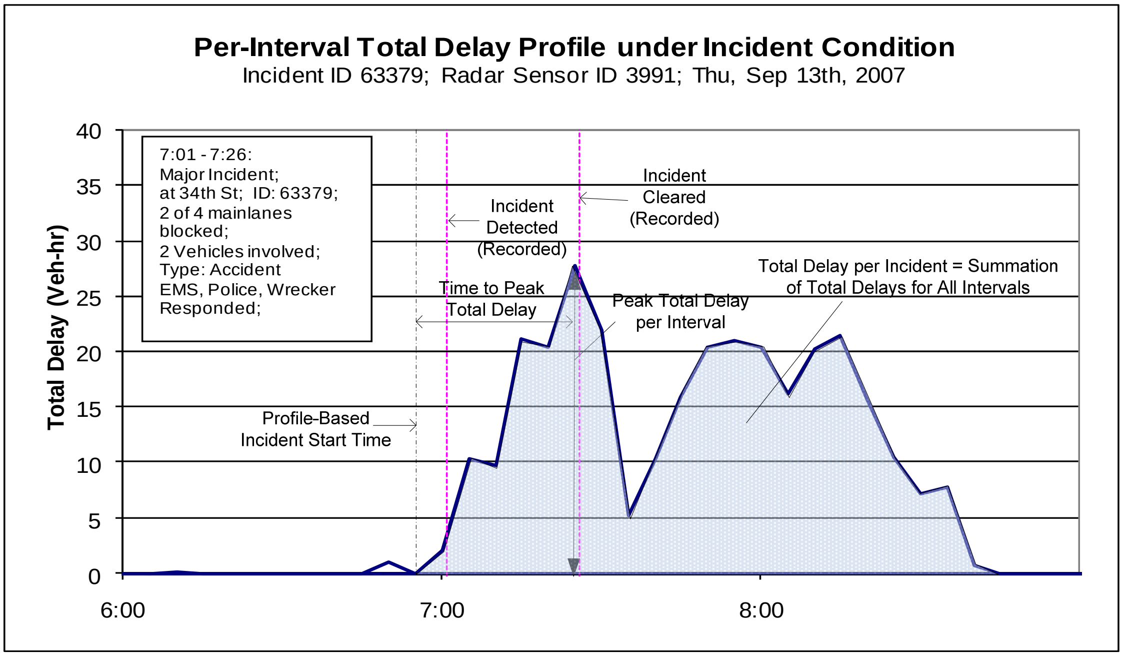


Figure 5-18: Per-Interval Total Delay Profile.

The following incident-related impacts can be extracted from the per-interval total delay profile:

- Peak total delay per interval – the maximum amount of total delay per interval caused by an incident. The time at which the total delay per interval reaches its peak may not be the same as that of average delay because the total delay also accounts for the amount of traffic flow arriving at the incident location. The total delay is a better measure from an incident management perspective, while the delay per vehicle better represents the travelers' perception of incident impacts.
- Time to peak total delay – the time it takes from the beginning of an incident to reach the time interval in which the peak total delay is observed.
- 85th percentile of total delay per interval – the 85th percentile value of total delay per interval. This value is more suitable for comparing the impacts of multiple incidents.
- Total delay per incident – calculated by summing the total delays for all intervals during the incident-induced congestion period. This measure represents an overall impact of an incident on traffic.

5.4. Using the Measured Incident Impacts

The methodology described in this module can be used to evaluate incident impacts from both the system and travelers' perspectives. From a system perspective, the analyst can apply this method to quantify the amount of traffic delay caused by an incident or to determine when the traffic flow resumes normal conditions. In addition, the analyst can relate the impact of incidents to travelers' experience through the derivation of average delay and delay index profiles. In this manner, the analyst can use measures such as peak delay per vehicle, time to peak delay, and peak delay to evaluate the magnitude of delay as perceived by travelers as well as the time at which the worst condition took place. Usage perspectives in relation to various incident-related impact measures are summarized in Table 5-1.

The analyst can use these measures as part of incident management performance monitoring and evaluation efforts such as:

- evaluate the impacts of a specific incident from both the system and travelers' perspectives,
- evaluate the degree of travelers' satisfaction,
- compare the incident delays from multiple incidents (spatially and temporally),
- evaluate the effectiveness of different incident management strategies using incident delay and recovery time, and
- determine the spatial and temporal extent of the incident impact on freeway segments using a delay profile.

From the example profiles shown in Figure 5-16 through Figure 5-18, the incident-related impacts can be measured as summarized in Table 5-2. The results are grouped by the profile from which the measures were extracted.

Table 5-1: Use of Incident-Related Impacts.

Impact Measures	System Perspective	Travelers' Perspective
Average Delay Profile		
Incident-Induced Congestion Duration	x	
Traffic Recovery Time	x	
Peak Delay per Vehicle		x
85th Percentile of Delay per Vehicle		x
Time to Peak Delay per Vehicle		x
Delay Index Profile		
Peak Delay Index		x
85th Percentile of Delay Index		x
Time to Peak Delay Index		x
Per-Interval Total Delay Profile		
Peak Total Delay per Interval	x	
85th Percentile of Total Delay per Interval	x	
Time to Peak Total Delay per Interval	x	
Total Impact		
Total Incident Delay	x	

For this example, the incident duration (from detection to clearance) as recorded in the database is 25 minutes. There were two vehicles involved in this accident, and two out of four main lanes were blocked (50 percent capacity reduction). The beginning of the incident impact as observed from the delay profile (i.e., profile-based incident start time) is close to the recorded incident detection time. The average delay per vehicle reaches its peak 25 minutes after the beginning of an incident, which is around the same time when the incident was cleared. The flow rate during the entire incident-induced congestion period is higher than the flow rate immediately before the incident. This implies that the traffic flow rate is increasing during this period. Since the volume is on the rise during this period (morning rush hour), the traffic takes as long as 69 minutes to recover to normal traffic conditions.

From the travelers' perspective, the maximum average delay was 196 seconds, which took place around the time when the incident was just cleared as indicated by the time to peak delay per vehicle of 25 minutes. The 85th percentile of average delay was 162 seconds, indicating that approximately 15 percent of the time the travelers had to spend at least 162 seconds more than what they had expected. Using the delay index to account for their anticipation, the worst perception of delay occurred 20 minutes into an incident where the index peaked at 145 percent. This implies that the travelers spend 145 percent more time to travel through this segment than what they anticipated.

From the system perspective, the total delay profile reaches its peak around the same time when the incident was cleared or 30 minutes after the beginning of an incident. This also indicates the worst traffic condition from an incident management viewpoint, which may not necessarily be the same as that from the travelers' perspective. The total impact from this incident on the freeway segment as measured by the total segment delay was 307 veh-hours.

Table 5-2: Example of Measured Incident Impacts.

Incident Characteristics	
ID	63379
Incident Detection Date & Time	Thu 9/13/2007 7:01
Incident Duration (Min)	25
Type	Accident
Severity	Major Accident/Collision
Number of Lanes Blocked	2 of 4
Vehicles Involved	2
Traffic Volume Data	
Average 10-minute Volume before the Start of the Incident (vphpl)	1299
Average 10-minute Volume after the Start of the Incident (vphpl)	1173
Average Volume throughout the Incident-Induced Congestion Period (vphpl)	1431
Per-Vehicle Delay Profile	
Profile-based Incident Start Time	Thu 9/13/2007 6:55
Lane Blockage Duration (min)	31
Incident Recovery Time (min)	69
Total Incident-Induced Congestion Duration (min)	100
Time to Peak Delay per Vehicle (min)	30
Max Delay per Vehicle (sec)	196
85th Percentile of Delay per Vehicle (sec)	162
Max Delay per Vehicle during Lane Blockage (sec)	196
Max Delay per Vehicle during Recovery Period (sec)	162
Delay Index Profile	
Time to Peak Delay Index (min)	20
Max Delay Index	145%
85th Percentile of Delay Index	123%
Max Delay Index during Lane Blockage	145%
Max Delay Index during Recovery Period	123%
Per-Interval Total Delay Profile	
Time to Peak Total Delay per Interval (min)	30
Max Total Delay per Interval (veh-hr)	28
85th Percentile of Total Delay per Interval (veh-hr)	21
Max Total Delay per Interval during Lane Blockage (veh-hr)	28
Max Total Delay per Interval during Recovery Period (veh-hr)	22
Total Impact	
Total Delay per Incident (veh-hr)	307

* All the time-to-peak values are measured from the profile-based incident start time.

6. CALCULATING PERFORMANCE MEASURES

Previously, Module 5 described methodologies to obtain a comprehensive set of incident-related impacts for each incident using a combination of traffic and incident data. This module describes a broader range of performance measures calculable from existing historical databases. The performance measures covered in this module were assembled based upon a review of literature, data availability, and feedback received from the surveys conducted at Texas TMCs. These measures are also easier to automate, and thus more convenient for regular monitoring as part of agencies' routines (e.g., performance reports).

6.1. Overview of Performance Measures

The analyst can use multiple metrics derived from historical data to describe the performance of the facilities and operations at TMCs. Table 6-1 summarizes various types of performance metrics that can be derived from historical data archived at the TMCs and their potential usage. Potential uses of performance metrics can be classified into major categories as follows:

- traveler information – The objective is to inform travelers of current traffic conditions so that they can make decisions on route choice (en route) or delay/cancel the trips (pre-trip),
- operations evaluation,
- resource allocation,
- safety evaluation,
- monitoring,
- land use/planning, and
- customer satisfaction – Customer satisfaction is difficult to measure since it is somewhat qualitative by nature. Surveys or questionnaires are common methods used to gauge customer satisfaction. However, it is possible that some metrics derivable from historical data can be a good proxy for customer satisfaction.

Literature on performance measurement suggested a distinction be made between output and outcome types of measures as follows:

- Output measures relate to the physical quantities of items: levels of effort expended and scale or scope of activities. Output measures are sometimes called "efficiency" measures. The National Cooperative Highway Research Program (NCHRP) 3-68 report (*17*) suggested the term "activity based" for this category of measures.
- Outcome measures relate to the nature and extent of the services provided to transportation users. The term "quality of service" was suggested for this type of measure (*17*).

Table 6-1: Performance Metrics and Potential Uses.

		Potential Usage						
Performance Metrics	**Definition**	**Traveler Information**	**Operations Evaluation**	**Resource Allocation**	**Safety Evaluation**	**Monitoring**	**Land Use/Planning**	**Customer Satisfaction**
Congestion Conditions								
Travel Time	The average time consumed by vehicles traversing a fixed distance of freeway.	•	•			•	•	•
Travel Time Index	The ratio of the actual travel rate to the ideal travel rate. Travel rate is the inverse of speed, measured in minutes per mile. The ideal travel rate is the rate that occurs at the free-flow speed of a facility (unconstrained conditions).		•			•	•	•
Average Speed	The average speed of vehicles traversing a fixed point on the freeway.	•	•		•	•	•	•
Delay per Vehicle	The excess travel time used on a trip, facility, or freeway segment beyond what would occur under ideal conditions.		•	•		•	•	
Total Delay	Total freeway delay divided by the number of vehicles using the freeway.		•	•		•	•	
Reliability								
Buffer Index	The difference between the 95th percentile travel time and the average travel time, normalized by the average travel time.					•	•	•
Planning Time Index	The 95th percentile travel time index.					•	•	•
Throughput								
Vehicle Throughput	Number of vehicles traversing a freeway.		•	•	•	•	•	
Vehicle Miles of Travel	The product of the number of vehicles traveling over a length of freeway times the length of the freeway.			•	•		•	
Safety								
Collision Frequency	Freeway crashes as defined by the state.			•	•			
Collision Rates	Total freeway crashes divided by freeway VMT for the time period			•	•			
Incident Characteristics								
Number of Incidents by Type and Extent of Blockage	Number of incidents classified by its types and lane blockage characteristics (e.g., number of main lanes blocked, number of shoulder lanes blocked, etc.).		•	•	•			
Incident Duration	The time elapsed from the notification of an incident to when the last responder has left the incident scene.	•	•	•	•			•
Blockage Duration	The time elapsed from the notification of an incident to when all evidence of the incident (including responders' vehicles) has been removed from the travel lanes.		•	•	•			•
Lane-Hours Loss Due to Incidents	The number of whole or partial freeway lanes blocked by the incident and its responders, multiplied by the number of hours the lanes are blocked.		•	•	•			
Incident Management								
First Responder Response Time	Time difference between when the incident was first detected by an agency and the on-scene arrival of the first responder.		•			•		
Notification Time	Time difference between when the incident was first detected and when the last agency needed to respond to the incident was notified.		•			•		
Total Response Time	Time difference between when the incident was first detected by an agency and the on-scene arrival of the last responder.		•			•		
Clearance Time	Time difference between when the first responder arrived on the scene and blockage of a travel lane was removed.		•			•		
On-Scene Time	Time difference between when the first responder arrived and the last responder left a scene; also may be computed for individual responders.		•			•		

6.2. Spatial and Temporal Scales for Data Analysis

There are several different spatial and temporal scales for performance analysis and reporting. The usage and intended audience in general will determine the appropriate spatial and temporal scales in performance reporting. The NCHRP guidebook (*17*) describes spatial scales to be considered for the analysis of most archived traffic operations data as follows:

- by lane – point location;
- direction – all functional lanes combined; sometimes referred to as a "station";
- link – typically between access points or entrance/exit ramps, same direction;
- segment/section – a collection of contiguous links;
- corridor – multiple adjacent sections/segments in approximately parallel directions. Examples include multiple types (e.g., freeway and arterial streets) and multiple modes (e.g., arterial street and rail line);
- subarea – a collection of several sections or corridors within defined boundaries; and
- area-wide/regional – a collection of several sections or corridors within a larger political boundary.

Figure 6-1 shows a schematic demonstrating how traffic data collected from loop detectors can be aggregated at various levels of spatial scales for travel time estimation.

Temporal scales are another important factor to be considered in the data analysis. Examples of temporal scales commonly used in the calculation of performance metrics include:

- peak hour;
- peak period – Three-hour periods in both the morning and afternoon as peak periods are recommended for most freeways (*17*). Two-hour and four-hour periods alternatively can be considered for smaller and larger urban areas, respectively;
- midday;
- weekday versus weekend;
- seasonality; and
- annual statistics.

Intended use of performance metrics will determine appropriate spatial and temporal scales for the data analysis.

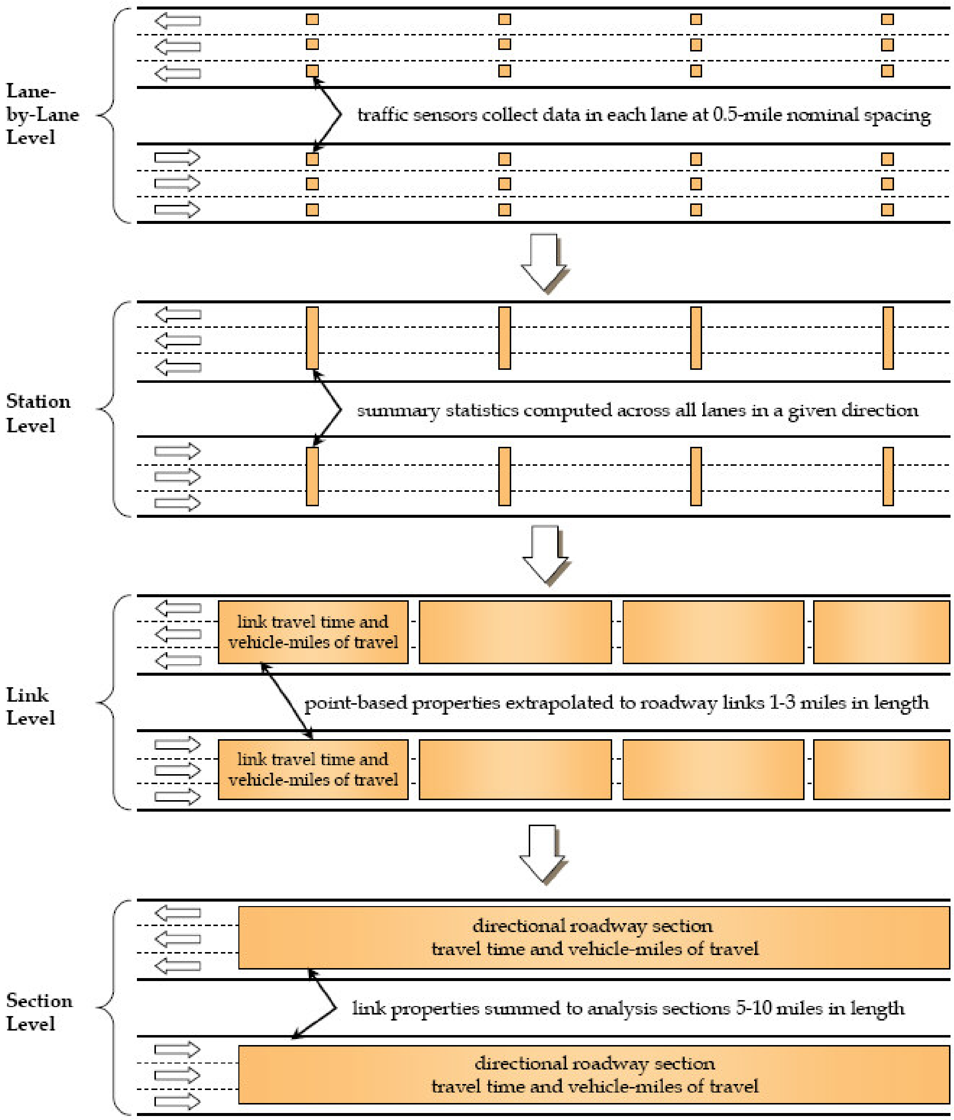


Figure 6-1: Different Spatial Scales for Aggregating Sensor Data *(37)*.

6.3. Calculation Procedures

This section describes detailed calculation procedures for performance metrics summarized in Table 6-1.

6.3.1. Congestion Conditions

6.3.1.1. Travel Time

Data Requirement

Depending on TMC configurations, travel time can be calculated using either:

- spot speed data collected from point-based sensors at regular spacings or
- section or link travel times using probe-vehicle data.

Calculation Procedures

There are two possible methods for calculating travel times from point-based sensors: snapshot method and vehicle trajectory method (*17*). The snapshot method sums all link travel times for the same period, regardless of whether vehicles traversing the freeway section will actually be in that link during the snapshot time period. The vehicle trajectory method traces the vehicle trip in time and applies the link travel time corresponding to the precise time in which a vehicle is expected to traverse the link.

The first method can be used for real-time application, but it does not give an accurate estimate of actual vehicle travel time. The second method provides the better estimate of vehicle travel times, but it can be used only after the fact. When traffic conditions are changing, the trajectory method tends to give a more accurate estimation of travel times. The snapshot method will underestimate section travel time when traffic is building and overestimate section travel time when traffic is clearing.

The accuracy of field data collected by a freeway surveillance system depends heavily on:

- sensor spacing and density and
- the reliability of the individual detectors, data communication, and storage system.

The errors tend to increase with larger detector spacing and sparser detectorization. Multiple detectors can also serve as data quality crosschecks for each other. Two closely spaced detectors can be compared to evaluate the quality and consistency of the data collected.

6.3.1.2. Travel Time Index

The travel time index is commonly used as a measure of the degree of congestion on freeways. The higher index implies more congested traffic conditions, which may lead to less predictable travel time. Planners may use this information to evaluate the congestion problem and/or benchmark their freeway performance with other comparable metropolitan areas. This index may also be one good proxy for road users' satisfaction. The degree of satisfaction is expected to have an inverse relationship with the travel time index.

Data Requirement

The following data elements are required for calculating the travel time index:

- section travel times during peak times,
- section travel times during light traffic or free-flow conditions, and
- VMT by sections (weighting factor for combining multiple travel time indices).

Calculation Procedures

To calculate a travel time index for one specific section:

$$\text{Travel Time Index} = \frac{\text{Average Travel Time}}{\text{Free-Flow Travel Time}} \quad (6\text{-}1)$$

To calculate the average travel time index for multiple sections:

$$\text{Average Travel Time Index} = \frac{\sum_{\text{All Sections}} \left(\text{Travel Time Index}_{\text{Section } i} \cdot \text{VMT}_{\text{Section } i}\right)}{\sum_{\text{All Sections}} \left(\text{VMT}_{\text{Section } i}\right)} \quad (6\text{-}2)$$

Free-Flow Travel Time

Free-flow or ideal travel time can be obtained by dividing freeway section length by free-flow speed. The analyst must estimate free-flow speed in order to determine free-flow travel time. It is suggested that two possible alternatives be considered for the estimation.

First, in the absence of historical data, NCHRP Report 387 (*38*) recommends the following regression equation for estimating free-flow speed based solely on speed limit:

$$V_f = (0.88) V_{Limit} + 14 \quad (6\text{-}3)$$

Second, with sufficient historical data, the free-flow speed should be set at the lower of:

- the 85th percentile speed that occurs under low-volume conditions or
- the speed limit.

6.3.1.3. Delay per Vehicle

Delay per vehicle is defined as travel time in excess of what a traveler would need to traverse a freeway section under free-flow conditions. Delay per vehicle is a performance metric that most commuters can relate to since it can be related to their personal experience. The analyst can derive measurement-based delay from archived traffic data. There is no delay if traffic is currently in a free-flow condition or better.

Delay per vehicle alternatively can be viewed as average vehicular delay for a specific section. Delay per vehicle can be used when traffic volume data are not available. Houston's TranStar, for example, does not collect traffic volume in many freeway sections. Since the delay per vehicle does not account for traffic volume, any comparison of delay values should be made in comparable traffic conditions, e.g., weekday morning peak periods.

Data Requirement

Required data elements for calculating measurement-based total delay are:

- average link or section travel times and
- link or section travel times during free-flow or light traffic.

Calculation Procedures

Delay for a specific road section is:

$$\underset{\text{(minutes)}}{\text{Delay per Vehicle}} = \underset{\text{(minutes)}}{\text{Average Travel Time}} - \underset{\text{(minutes)}}{\text{Free-Flow Travel Time}} \tag{6-4}$$

6.3.1.4. <u>Total Delay</u>

Delay is defined as additional vehicle-hours in excess of what travelers would experience under free-flow conditions. Total delay is a sum of delay from multiple sections. Delay can be calculated when traffic volume data are available. Total delay can be used to represent delay for the entire trip (across multiple sections). Total delay over specific time periods can be used to measure the effect of freeway management strategies on particular segments. For example, the difference in total delay can be used to quantify the impacts of ramp metering on freeway traffic in before-after studies.

Data Requirement

The data elements required for calculating total delay are:

- delay per vehicle (see Section 6.3.1.3) and
- traffic volume by link or by section.

Calculation Procedures

Delay for a specific road section is:

$$\text{Delay (vehicle-hours)} = \frac{\underset{\text{(minutes)}}{\text{Delay per Vehicle}}}{60}\left(\underset{\text{(vph)}}{\text{Volume}}\right) \tag{6-5}$$

Total delay is a sum of delays from multiple sections:

$$\underset{\text{(vehicle-hours)}}{\text{Total Delay}} = \sum_{i=1}^{n} \text{Delay}_{\text{Section } i} \tag{6-6}$$

6.3.2. Reliability

Two performance metrics commonly used to measure the reliability of travel times are the buffer index and planning time index. Reliability measures can potentially be related to customer satisfaction because they indicate the degree to which extreme travel times differ from travelers' anticipation.

6.3.2.1. Buffer Index

The buffer index represents the extra time (buffer) most travelers add to their average travel time when planning trips. Buffer indices can be calculated for specific time periods such as peak and off-peak periods or for a larger time scale such as a daily or weekly basis. The 95th percentile travel time must be estimated from the travel time data when calculating the buffer index. It should be noted that travel times obtained at smaller aggregation intervals will provide a better estimate of the 95th percentile travel time (e.g., 5-minute versus 15-minute intervals).

Data Requirement

The following data elements are required for calculating the buffer index:

- section travel times for the analysis period and
- VMT by section (or other weighting index) for combining buffer indices.

Calculation Procedures

The buffer index for a specific section and analysis period is:

$$\text{Buffer Index (\%)} = \frac{\text{95th Percentile Travel Time} - \text{Average Travel Time}}{\text{Average Travel Time}} \tag{6-7}$$

The VMT-weighted average buffer index for multiple sections and time periods is:

$$\text{Average Buffer Index} = \frac{\sum_{\forall i,j}\left(\text{VMT}_{ij} \cdot \text{Buffer Index}_{ij}\right)}{\sum_{\forall i,j}\text{VMT}_{ij}} \tag{6-8}$$

where i = section number and j = time period.

6.3.2.2. Planning Time Index

Data Requirement

The planning time index requires travel time index values to be calculated as described in Section 6.3.1.2 at regular intervals on a continuous basis for the entire analysis period, preferably one year.

Calculation Procedures

The planning time index is the 95th percentile travel time index of all the travel time indices calculated during the analysis period (typically one year). The planning time index represents the total time travelers would need to plan at most for on-time arrival.

6.3.3. Throughput

Throughput measures indicate the amount of traffic carried by the freeway system. Throughput measures represent the productivity of the freeway system and are easily understood by a nontechnical audience. The analyst can quickly determine the extent of various impacts such as ITS deployment and freeway management strategies using this type of measure. Throughput is also often used in high-level decision-making processes and planning applications.

6.3.3.1. Vehicle/Person Throughput

Vehicle throughput could be used for most general-purpose lanes. Person throughput is a more appropriate measure for managed lanes such as HOV lanes.

Data Requirement

The following data element is required for calculating the vehicle throughput:

- traffic volume counts for the facilities of interest.

The following data elements are required for calculating person throughput:

- traffic volume counts for the facilities of interest and
- estimated vehicle occupancy.

Calculation Procedures

Continuous traffic volume counts are vehicle throughput. The product between traffic volume counts and average vehicle occupancy gives person throughput. The analyst can present throughput volumes on various spatial and time scales depending on the purpose of the analysis.

6.3.3.2. Vehicle/Person Miles of Travel (VMT/PMT)

VMT and PMT take into account not only the volume but also the extent of the facilities. VMT/PMT indicates the volume and the mileage handled by the facilities. It is also commonly used as an indicator of traffic exposure for the purpose of safety analysis. From a safety perspective, higher VMT implies more opportunities for traffic conflicts, thus increasing the likelihood of traffic collisions.

Data Requirement

Since volume data are typically observed through sensors deployed on the freeway network, links must be defined in a manner corresponding to the location of the sensors. The required data elements are:

- links – defined by sensor locations,
- link lengths,
- traffic volume counts for the links, and

- estimated vehicle occupancy (for PMT).

Calculation Procedures

VMT is computed by multiplying traffic volume counts by the corresponding link length. PMT is obtained by multiplying VMT with average vehicle occupancy.

6.3.4. Safety

Collision-related data are commonly used and widely accepted as an objective measurement of safety. However, incident data collected at most Texas TMCs contain information adequate just for determining its occurrence time, location, and whether the incident is a collision type. Detailed crash characteristics such as crash types, severities, and other causative factors are typically not recorded in the incident database where the data are meant for evaluating incident management operations rather than safety. A crash database is required to determine detailed crash characteristics, but it is often impractical to use due to its problem with timeliness and availability.

For safety-related performance metrics, the analyst should focus on deriving simple but reliable measures from the incident database. The two measures of interest are collision frequency and collision rates. Collision frequency is a measure for determining the absolute level of safety, and it is easy to obtain since it requires only collision records. The analyst can quickly compare collision frequencies over time, provided that traffic conditions have not changed significantly, to determine if there are any changes in safety conditions. Collision rates are relatively more difficult to calculate since they require the corresponding exposure data. Collision rates can be viewed as a measure of risk and are generally a better safety measure for comparing and evaluating multiple locations. Collision rates should be considered if traffic exposure data are available.

6.3.4.1. Collision Frequency

Data Requirement

Collision records with time and location are required to determine collision frequency. However, a crash database may not always be timely or available for the analysis. Alternatively, the analyst can examine the incident database for collision records provided that incident type (i.e., collision) is one of the attributes recorded in the database.

Calculation Procedures

Collision counts can be aggregated by locations and time periods depending on the objectives of the analysis. If collision types are available, the analyst can also examine if the frequency is unusually high for specific segments/time periods. Appropriate safety countermeasures may be considered based on the analysis.

6.3.4.2. Collision Rates

Data Requirement

Required data elements are:

- collision frequency and
- corresponding exposure data – traffic volumes or VMT are commonly used for the corresponding segments and time periods.

Calculation Procedures

Collision rates are obtained by dividing collision frequency by exposure. One commonly used collision rate for freeway segments is the number of collisions per vehicle-miles of travel. The analyst can further classify the rates of collision by types if the type attribute is available in the database.

6.3.5. Incident Characteristics

Data attributes recorded in the incident database determine the scope of incident characteristics available at Texas TMCs. In general, the incident notification times are always recorded. The incident clearance times, types, and extent of blockage are also recorded but to a lesser degree of consistency. The analyst can examine the incident characteristics for the changes in frequency, extent of blockage, and duration of lane closure. These characteristics are also important inputs for benefit/cost analysis of the incident management program as well as incident management resource planning and allocation.

6.3.5.1. Number of Incidents by Type and Extent of Blockage

Data Requirement

The required incident database contains the following attributes:

- incident type and
- blockage characteristics – number of lanes blocked, types of lanes blocked, and blockage duration.

Calculation Procedures

Aggregate the incidents by type over the analysis period (e.g., one year). Then, aggregate the incidents by type and lane blockage: for example, the number of collision incidents with zero to all lanes blocked. It is more informative to present the results in the form of pie charts or histograms.

6.3.5.2. Incident Duration

Data Requirement

The required incident database contains the following data attributes:

- the time at which the incident is notified and
- the time at which the last responder has left the incident scene.

Calculation Procedures

Incident duration is the time elapsed from the notification of an incident to when the last responder has left the incident scene. Use median statistics to represent average durations rather than the arithmetic mean whenever possible. The average durations can be classified by other data attributes such as incident types and time of day.

6.3.5.3. Blockage Duration

Data Requirement

The required incident database contains the following data attributes:

- information about lane blockage – whether travel lanes are blocked or the number of lanes blocked,
- the time at which the incident is notified, and
- the time at which the incident has been removed from the travel lanes.

Calculation Procedures

Blockage duration is the time elapsed from the notification of an incident to when the incident has been removed from the travel lanes. Similarly to incident durations, use median statistics to represent average values whenever possible. This is because empirical evidence indicates that the distribution of duration values tends to be heavily asymmetric.

6.3.5.4. Lane-Hours Loss Due to Incidents

Data Requirement

The required incident database contains the following data attributes:

- number of lanes blocked and
- corresponding blockage durations.

Calculation Procedures

The lane-hours loss is calculated by multiplying the number of lanes blocked by the number of hours the lanes are blocked. If the changes in lane blockage status are logged in the incident database, the analyst can calculate the lane-hours loss based on the duration of each lane blockage status (e.g., the lane blockage sequence for one particular incident could be 1 lane for 15 minutes, 3 lanes for 10 minutes, and 1 lane for 10 minutes).

6.3.6. Incident Management

As part of the NCHRP report (*17*), five performance metrics are recommended for monitoring and evaluating incident management operations. These metrics can be used to evaluate the operational efficiency across different components required for incident management functions. However, not all the measures discussed in this section can be derived from the existing incident databases in Texas. Additional time logs may be considered as part of incident reporting such that these metrics can be quantified at Texas TMCs.

Table 6-2 summarizes the recommended metrics, definitions, and their required time logs. If the agency collects the arrival and departure time logs separately for each individual responder, these metrics can be calculated specifically for each responder as well.

Table 6-2: Incident Management Performance Metrics.

Performance Metrics	Definition	Required Time Logs					
		Incident First Detected	All Responders Notified	First Responder Arrived	Last Responder Arrived	Travel Lanes Cleared	All Responders Left
First Responder Response Time	Time difference between when the incident was first detected by an agency and the on-scene arrival of the first responder.	•		•			
Notification Time	Time difference between when the incident was first detected to when the last agency needed to respond to the incident was notified.	•	•				
Total Response Time	Time difference between when the incident was first detected by an agency and the on-scene arrival of the last responder.	•			•		
Clearance Time	Time difference between when the first responder arrived on the scene and blockage of a travel lane is removed.			•		•	
On-Scene Time	Time difference between when the first responder arrived and the last responder left a scene; also may be computed for individual responders.			•			•

6.4. Summary of Data Requirements

This section summarizes data requirements for calculating performance metrics described in this module. Table 6-3 provides a summary of traffic-related data required for calculating performance measures. Table 6-4 summarizes data elements required for computing incident characteristics and incident management performance from historical incident data.

Table 6-3: Data Requirement Matrix for Traffic-Related Data.

Category	Performance Metrics	Average Travel Time (1)	Free-Flow Travel Time (2)	Section Length (3)	Vehicle Count per Unit Time (4)	Incident Count per Year
Congestion Condition	Travel Time	•				
	Travel Time Index	•	•			
	Average Travel Time Index	•	•	•	•	
	Delay Per Vehicle	•	•			
	Total Delay	•	•		•	
Reliability	Buffer Index	•				
	Average Buffer Index	•		•	•	
	Planning Time Index	•	•			
Throughput	Vehicle Throughput				•	
	Vehicle Miles of Travel			•	•	
Safety	Collision Frequency					•
	Collision Rates			•	•	•

Note: (1) Average travel time can be obtained either (a) by the actual time needed for vehicles to traverse a section or (b) by converted travel time from speed and section length data. (2) Free flow travel time can be (a) observed during low-volume conditions or (b) calculated from roadway speed limit by applying appropriate coefficients. (3) Section length is typically defined with reference to the locations of traffic sensors. (4) Vehicle count per unit time varies according to the length of time predefined.

Table 6-4: Data Requirement Matrix for Incident Data.

Category	Performance Metrics	Incident Type	Types of Lanes Blocked	Incident Detection Time	All Responder Notification Time	First Responder Arrival Time	Last Responder Arrival Time	Blocked Travel Lane Clearace Time	All Responder Departure Time	Number of Lanes Blocked
Incident Characteristics	Number of Incident by Type and Extent of Blockage	•	•		•			•		•
	Incident Duration			•	•				•	
	Blockage Duration			•				•		•
	Lane-Hours Loss due to Incidents				•			•		•
Incident Management	First Responder Response Time			•		•				
	Notification Time			•	•					
	Total Response Time			•			•			
	Clearance Time					•		•		
	On-Scene Time					•			•	

6.5. Using Performance Measures

A recent NCHRP report *(17)* describes various examples of using performance measures in Chapter 9. The key considerations for applying for performance measures are:

- What are the objectives of the uses?
- Who are the target audiences?
- What performance measures should be reported?

Some examples of using performance measures are presented in Table 6-5. The timeframe for analysis can be classified in an ascending order as follows:

- real-time applications,
- operations planning,
- short-range planning, and
- long-range planning.

Table 6-5: Examples of Using Performance Measures.

Analysis Timeframe	Examples
Real Time	• Travel time dissemination website • Real-time traveler information website (includes incidents, work zones, and other relevant information)
Operations	• Evaluation of congestion frequency • Evaluation of incident impacts on traffic conditions • Evaluation of HOV lane performance • Summary of incident management operations performance
Short Range	• Missouri dashboard measurements of performance *(39)* • Volume trend comparison • Speed and time contour diagram • Peer city comparison of travel time indices
Long Range	• Map display of congestion delay • Survey of customer satisfaction responses and trend • Urban mobility report *(40)*

Also, reporting needs to change over time as the audience becomes more familiar with the reports. When the objectives for reporting are accomplished, the need for reporting may also become less frequent over time while the new issues may become more important. The whole reporting process is somewhat dynamic and should be adaptive enough to respond to invariably changing needs.

7. PREDICTING INCIDENT DURATION

This module describes a set of guidelines and procedures for developing and applying models for predicting incident duration using historical incident data. Numerous data attributes (incident characteristics) are being collected in the incident database at several Texas TMCs. Predicting incident duration involves selecting the right set of statistically significant incident characteristics and using the right tools and techniques to develop equations for predicting incident durations. Available methods range from simple descriptive statistics to more advanced statistical modeling approaches.

In general, at the start of a freeway incident, traffic managers may be able to provide some ballpark estimates on how long the incident will last or how much time the responders will take to clear the incident. The current practice to estimate incident durations is mainly based on incident characteristics, current traffic conditions, and past experiences of traffic managers. This module provides quantitative methods and tools to objectively estimate incident durations based on prevailing incident characteristics. The methods discussed in this section mathematically capture incident characteristics that are typically statistically correlated with incident durations. Once these incident characteristics are observed, the analyst can determine the approximate duration of an incident to a certain degree of accuracy. The suggested methods and the results that follow are neither aimed at replacing common sense nor overriding engineering judgment but rather supplementing the traffic control and advisory decisions of traffic managers during the incident management process.

7.1. Defining Incident Durations

According to the NCHRP guidebook (*17*), incident durations are defined as the time elapsed from the notification of an incident to when the last responder leaves the scene. To perform the analysis, the analyst must identify if incident notification time and clearance time are recorded in the incident database. It should be noted that the definition of the time at which the incident has been cleared may not be consistent across Texas TMCs. For instance, this could be the time when the incident has been removed from the travel lanes or the time when all the response units have left the incident scene. Techniques outlined in this document can be used regardless of how this time point is defined. However, the end users of the results should be aware that these estimations must be interpreted in a manner consistent with how incident durations were determined from the database. Figure 7-1 illustrates the common definition of incident duration.

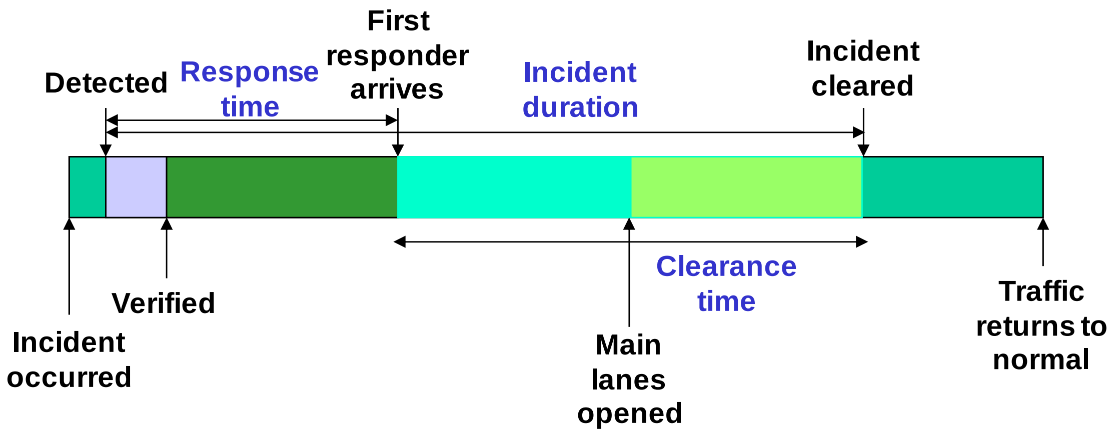


Figure 7-1: Incident Timeline and Incident Duration.

7.2. Data Requirements

Incident duration prediction is a two-stage process. The first stage – model building – is a one-time task using historical incident data to build the models for predicting incident durations. The second stage is using the models developed to predict the duration of a new incident. The second stage also includes the process of fine-tuning and recalibrating the models to reflect the most recent observations and thus improving the performance of the prediction. This process is also known as "model maintenance."

The data elements required for the model development are incident duration and incident characteristics. The incident duration can be computed from the difference between incident detection and incident clearance times. The incident characteristics are all the attributes recorded by the operator as part of the incident management process. To use the models, only specific incident characteristics are required in a format specified as part of the model-building process.

It is recommended that at least one year of incident data be used to calibrate the models. The rule of thumb is to use more data whenever possible. The most recent data should be preferred to the older data in order for the established models to reflect prevailing traffic and incident conditions.

Incident durations can be influenced by many characteristics collected in the incident database. It is difficult to generalize the characteristics that will be statistically significant predictors of incident durations for all agencies because each agency has its own database specifications and incident data collection procedure. There are also no standardized definitions for data elements being collected. For example, while most agencies record the severity of an incident, each agency has its own procedures on how to distinguish between minor and major incidents. Many agencies record the incident types, but what constitutes a collision incident for one TMC may be classified as another type for another TMC. For these reasons, it is not possible at the moment to develop a generic set of prediction models for statewide deployment.

Incident databases generally share common data attributes that can be classified into the following major categories:

- general incident characteristics – general characteristics of an incident such as location, type, and severity;
- detection and verification methods – descriptions of the methods used to detect and verify an incident;
- environmental characteristics – weather, surface, and lighting conditions at the time of an incident occurrence;
- incident timeline – various time points for key actions and milestones for the incident management process such as incident notification time, first responder arrival time, incident removal time, and incident clearance time;
- blockage characteristics – the impact of the incident on travel lanes in terms of the types and number of lanes blocked and the types and number of vehicles involved; and
- incident response characteristics – descriptions of incident responders such as type of response units and equipment used.

7.3. Methodology

Hazard-based duration models are recommended for predicting incident durations based on incident characteristics. Duration data are often encountered in the field of transportation research. In this case, the duration of an incident is of interest. While duration data are typically continuous and can be modeled with traditional linear regression, hazard-based duration models provide several advantages over linear regression models, which are:

- ability to provide additional insights into the underlying duration problem based on hazard functions;
- ability to handle non-negative constraints on the predicted incident duration;
- ability to model various types of duration data (in addition to incident durations) such as incident response time, incident clearance time, etc.;
- ability to account for censored data, i.e., when the actual starting or ending point of the duration data is not observed; and
- ability to properly incorporate various incident characteristics that influence the incident duration.

Nam and Mannering (*41*) were among the first researchers to apply hazard-based duration models to statistically evaluate the time it takes to detect/report, respond to, and clear incidents. Weibull models with gamma heterogeneity (i.e., inhomogeneous survival distribution across all observations) were used to estimate incident detection and response times. A log-logistic survival model was used to estimate incident clearance times. The temporal stability of the coefficients of model estimates over time was also investigated using likelihood ratio test statistics.

To provide some background on the hazard-based models, let us define the cumulative distribution function as:

$$F(t) = P(T < t) \tag{7-1}$$

where P denotes probability, T is a random time variable, and t is some specified time. $F(t)$ can be considered the probability that an incident will last no longer than time t. The corresponding density function is:

$$f(t) = \frac{dF(t)}{dt}, \tag{7-2}$$

and the hazard function is:

$$h(t) = \frac{f(t)}{1 - F(t)} \tag{7-3}$$

where $h(t)$ is the conditional probability that an incident will end at time t given that the incident has lasted until time t. In other words, $h(t)$ gives the rate at which an incident is ending at time t. The cumulative hazard $H(t)$ is the integrated hazard function that provides the cumulative rate at which an incident is ending up to or before time t.

The survivor function, which can be alternatively viewed as a complement of the distribution function, provides a probability that an incident will be equal to or greater than some specified time t. The survivor function is:

$$S(t) = P(T \geq t). \tag{7-4}$$

The relationships between the density, cumulative distribution, survivor, and hazard functions can be summarized as shown in the following equations:

$$S(t) = 1 - F(t) = 1 - \int_0^t f(t)\,dt = e^{-H(t)} \tag{7-5}$$

$$H(t) = \int_0^t h(t)\,dt = -\ln S(t) \tag{7-6}$$

$$h(t) = \frac{f(t)}{S(t)} = \frac{f(t)}{1 - F(t)} = \frac{dH(t)}{dt} \tag{7-7}$$

Incident characteristics as well as other data attributes available from the incident database can be incorporated into the hazard models. These variables are typically referred to as “covariates” in the modeling term. These covariates can be incorporated into the hazard-based models, which in turn affect the probability of either increasing or decreasing incident durations.

Fully parametric models are tested in this task to determine the appropriate distributional form for characterizing incident durations. The distributions typically used in this type of analysis include lognormal, logistic, log-logistic, and Weibull models. We conducted a test to determine the suitable distribution for hazard models and found that the Weibull distribution is the preferred alternative for two reasons. First, using TranStar data, the

Weibull distribution was found to give the best goodness-of-fit (GOF) statistics using log-likelihood ratio tests. Second, the Weibull distribution allows positive duration dependence, which gives intuitive interpretation of incident duration data. In other words, the Weibull distribution with positive duration dependence implies that the likelihood that the incident duration is ending (i.e., incident is cleared) increases over time.

The Weibull is a more generalized form of the exponential distribution. The Weibull density function is defined as:

$$f(t) = \lambda P(\lambda t)^{P-1} e^{-(\lambda t)^P}, \lambda > 0, P > 0 \tag{7-8}$$

and the corresponding hazard function is:

$$h(t) = (\lambda P)(\lambda t)^{P-1}. \tag{7-9}$$

For Weibull, the parameter P specifies the shape of the hazard function. If $P > 1$, the hazard is monotone increasing in duration. If $P < 1$, it is monotone decreasing in duration. If $P = 1$, the hazard is constant in duration and the Weibull distribution becomes the exponential.

The natural way to relate a covariate vector $\boldsymbol{x}$ to a parameter λ while satisfying the positivity constraint is to take:

$$\log \lambda_i = \beta^T \mathbf{x}_i,\ \lambda_i = e^{\beta^T \mathbf{x}_i}. \tag{7-10}$$

For the Weibull distribution, the hazard function becomes:

$$h(t) = Pt^{P-1} e^{P\beta^T \mathbf{x}}. \tag{7-11}$$

Once the model for predicting incident duration is calibrated, we can calculate the following quantities of interest, given a covariate vector of incident characteristics, from the model:

- expected incident duration – use the median value instead of the arithmetic mean whenever possible to avoid bias caused by the skewness of the distribution,
- confidence interval of the predicted incident duration, and
- probability that an incident will last longer than some specified time t.

The expected incident duration using the median value of the Weibull distribution is:

$$\tilde{T}_i = \lambda_i \ln(2)^{1/P}. \tag{7-12}$$

The (1-α) percent confidence interval of the predicted incident duration is:

$$\left[\lambda_i \left(-\ln\left(1 - \frac{\alpha}{2}\right)\right)^{1/P}, \lambda_i \left(-\ln\left(\frac{\alpha}{2}\right)\right)^{1/P} \right]. \tag{7-13}$$

The probability that an incident will last longer than some specified time t is equivalent to the value obtained from the survivor function, that is:

$$S(t) = 1 - F(t) = 1 - e^{-(t/\lambda)^P}. \qquad (7\text{-}14)$$

7.4. Model Development

This section describes the model development process starting from selecting the tools to calibrating and selecting the models.

7.4.1. Analytical Tools

The analytical tools are used for two primary purposes: data manipulation and model calibration. Data manipulation involves the procedures required to clean up and prepare the data in a format compatible for the analysis with the tool of choice. Model development is the procedure of calibrating the models, selecting the inputs, and fine-tuning the results. Data manipulation can be carried out using any common office software such as Microsoft Excel and Microsoft Access. Model development requires a more specialized statistical package such as SAS, R, LIMDEP, and S-PLUS. The researchers have tested a combination of Microsoft Excel and S-PLUS for both data manipulation and model development in this project.

It should be noted that the model development is a one-time task that requires some expertise in statistical modeling and experience with transportation data. This skill set may not be common within small- to medium-sized Texas TMCs. In such cases, the agencies may consider outsourcing this task to a qualified entity.

7.4.2. Procedures

Figure 7-2 summarizes the procedures to develop models for predicting incident durations using a historical incident database. The procedures consist of the following major steps:

- Data preparation – Clean the data set and prepare the data in a format that is convenient for subsequent analysis.
- Preliminary analysis – Analyze data attributes available in the incident database to determine if the data are valid and the sample size and its variability are sufficient.
- Model calibration – Estimate the models using the selected statistical software package and then examine the results.
- Model selection – Select the models based on the overall goodness of fit and the meaningful interpretation of the model covariates.
- Model implementation (deployment) – Recode the developed models into a user-friendly platform with a simplified graphical user interface (GUI) for inputs and outputs. This step is intended to facilitate the application by the end users.

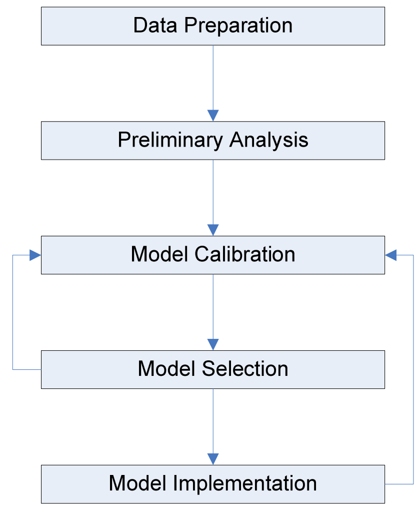


Figure 7-2: Procedures for Developing Incident Duration Models.

7.4.2.1. Data Preparation

Data preparation is the process of cleaning and manipulating the data to convert into a format compatible for the analysis. Two critical tasks in the data preparation are data validation and data recoding.

Data Validation

Data validation is a process of checking the data to make sure that they are accurate for subsequent analysis. When checking the data, a valid response variable (i.e., incident duration) is required for the entire incident record to be valid. Some invalid explanatory variables (i.e., incident characteristics), on the other hand, are allowed as long as they are not selected as part of model calibration. There are three major types of data validation:

- Missing data checks – Common types of missing data are incomplete data records such as incident clearance time and incident type information.
- Error checks – This indicates that the data elements exist but should be excluded from the analysis. The erroneous data are flagged differently depending on the agencies. This may include obvious errors such as duplicate records, invalid time logs, false entries, and test records. For example, the incident clearance times can be logged as 01/01/1900 00:00, or the number of vehicles involved can be logged as 99.
- Logical checks – This is the most difficult type of data validation as it requires experience with the data records. Logical errors are the scenarios in which the data exist and appear normal but in fact are logically incorrect. For example, the recorded clearance times earlier than the detection times should be checked by removing negative incident durations. As another example, TranStar's incident database contains two fields that can be used to determine the characteristics of lane blockage, i.e., TXDOT_LANES_AFFECTED and

MAINLANES_BLOCKED. However, the latter field will not be entered if the former one is used. Therefore, the zero entered in the first field does not always imply a non-lane-blocking incident in this case.

All these types of validation must be addressed prior to subsequent analysis based on thorough examination of the incident database.

Data Recoding

Data recoding is the process of converting the data attributes in the incident database into a format convenient for analysis and modeling. For example, the incident severity may be recoded into integer variables 0, 1, and 2 representing personal damage only (PDO), injuries, and fatality incident respectively. The data recoding also has an implication on how the data will be treated in the modeling and analysis. There are three major types of data treatment in the recoding process:

- Categorical – A categorical variable (sometimes called a nominal variable) is one that has two or more categories, but there is no intrinsic ordering to the categories. For example, the type of responders or the day of week is a categorical variable that has multiple categories and no intrinsic ordering to the categories. If the variable has a clear ordering, then that variable is an ordinal variable.
- Ordinal – An ordinal variable is similar to a categorical variable. The difference between the two is that there is a clear ordering of the variables. For example, the number of lanes blocked or the number of vehicles involved can be ordered with the size between categories equally spaced. Some variables can be treated as ordinal also, but the differences between categories are difficult to assign consistently (e.g., incident severity).
- Interval – An interval variable is similar to an ordinal variable, except that the intervals between the values of the interval variable are equally spaced. For example, the number of vehicles can be grouped by 0, 1-2, 3-4, 5-6, and 7 or more. Time of day is another type of variable that can be grouped into multiple intervals such as AM peak, PM peak, and the non-peak periods.

7.4.2.2. Preliminary Analysis

In this step, the data attributes and the recoded variables from the incident database must be examined if:

- there is sufficient variability in particular attributes being considered as potential variables in incident duration modeling and
- there is a sufficient sample size for the analysis of particular variables.

First, basic statistics should be computed for each data attribute to determine if the sample is sufficient and its variability is acceptable. Many of these statistics can be taken directly as part of routine incident characteristics reports described in Module 3. Examples of these statistics, depending on the data attributes available in the database, include:

- distributions of incidents by types and severities,

- distributions of weather-related incidents,
- distributions of incident responders,
- lane blockage characteristics, and
- distributions of number of vehicles involved.

Second, statistics on incident durations should be derived to give some idea as to whether particular attributes will strongly influence incident durations. The use of median duration as the average incident duration is strongly recommended rather than the arithmetic mean. This is due to the heavily asymmetric distribution of duration data where the mean value can be significantly influenced by a small portion of outliers.

An empirical observation of incident duration data indicates that extreme duration values do not represent well the actual duration and thus should be excluded. Upper extremes (very long duration) are occasionally attributed to unmonitored or neglected situations where operators closed the record long after the event was over. Lower extremes, or very short durations, on the contrary, are typically caused by false entries. To mitigate the impacts from extreme duration data, the analyst may apply lower and upper thresholds to screen out invalid duration data. For example, if 5 percent of the duration data are to be excluded from the analysis, trim the duration data at the 2.5th and 97.5th percentiles from the lower and upper ends, respectively.

Statistics on incident durations by types and severities are a useful piece of information since they provide TMC managers as well as operators a quick look-up table on how long an incident may last, particularly at the beginning of an incident where very little is known about the incident. Three recommended statistics for incident durations by type are as follows:

- Median incident duration – This is equal to the 50th percentile, which indicates that 50 percent of the time an incident may last longer or shorter than these values.
- 85th percentile incident duration – This value may be used for planning purposes if no better information is available for a particular type of incident.
- 95th percentile incident duration – This value can be considered as an extreme case of an incident. This implies that the chance of incident duration exceeding this threshold is only 5 percent at most.

7.4.2.3. Model Calibration and Selection

Model calibration and selection are the two critical steps in the model development process. All major statistical software packages (e.g., SAS, S-PLUS, R) can be used to calibrate hazard-based duration models. Characteristics of data attributes and incident durations from the preliminary analysis will provide a basis for variable selection and testing. For the parametric model choices, the analyst should consider the following three distributions for testing in this step: Weibull, logistic, and log-logistic distribution. The best set of model inputs should be selected based upon three criteria:

- overall GOF statistics of the model,
- statistical significance of each variable, and

- interpretation of the variables.

The log-likelihood ratio test is typically used to determine overall GOF of the model estimated using the maximum likelihood ratio technique. In this case, the model is considered favorable if the p-value obtained for the corresponding GOF statistics is less than 0.05 (i.e., $\alpha = 5\%$).

Each variable included in the model should be statistically significant at $\alpha = 5\%$. While this is a desirable criterion, it may not be easily achieved since more variables being considered for the model will likely lead to confounding effects on its significance. When this becomes an issue, this criterion may be relaxed such that certain variables can meet this test at α = 10-20%.

The interpretation of the variables, and in turn of the duration model, must be logical. The usefulness of the model can become questionable if it does not give intuitive results. One important rule of thumb for this check is to evaluate if the signs of estimated model coefficients are sensible. In general, positive model coefficients are supposed to increase incident duration and vice versa for negative coefficients. An analyst can perform this basic logical check by reviewing the signs of all the variables in the model with respect to its impact on incident durations.

There are several ways to set up the models. The first consideration is whether to use a single model for the entire dataset or to split the dataset into multiple categories and then calibrate the submodel for each category. It is recommended that the multiple submodels be used if the variability in the dataset is sufficient for multiple data categories. In this way, the same factors are allowed to have different impacts on incident durations in different submodels. For example, the increase in number of lanes blocked in general is likely to give rise to the duration of a lane-blocking incident. However, for specific types of incidents (e.g., stall) with significant representation of non-lane-blocking scenarios, the increase in the number of lanes blocked can have a reverse effect. In such cases, the presence of lane-blocking situations is more likely to receive immediate attention by the operators, thus leading to a decrease in incident durations instead. For these reasons, multiple submodels should be favored whenever there is strong evidence that the same factors can potentially have contradicting effects on incident durations if included in the same model.

The general guidelines for developing categories for incident duration submodels are summarized in Figure 7-3. The recommended classifications are based on the characteristics of incident types and availability of lane blockage information. When classifying the data by incident types, the analyst will need to construct separate submodels for major incident types only. The analyst can refer to the distribution of incident types to identify the major incident types. All other non-major incident types can be incorporated into one submodel with separate model coefficients to account for effects on different types in the same model. The lane blockage refers to main lane blocking. Some agencies also collect information on the types of lanes blocked (e.g., ramp, frontage, and main lane). In such cases, the lane-blocking category can be further categorized into more sublevels provided that the types of lanes blocked are consistently recorded.

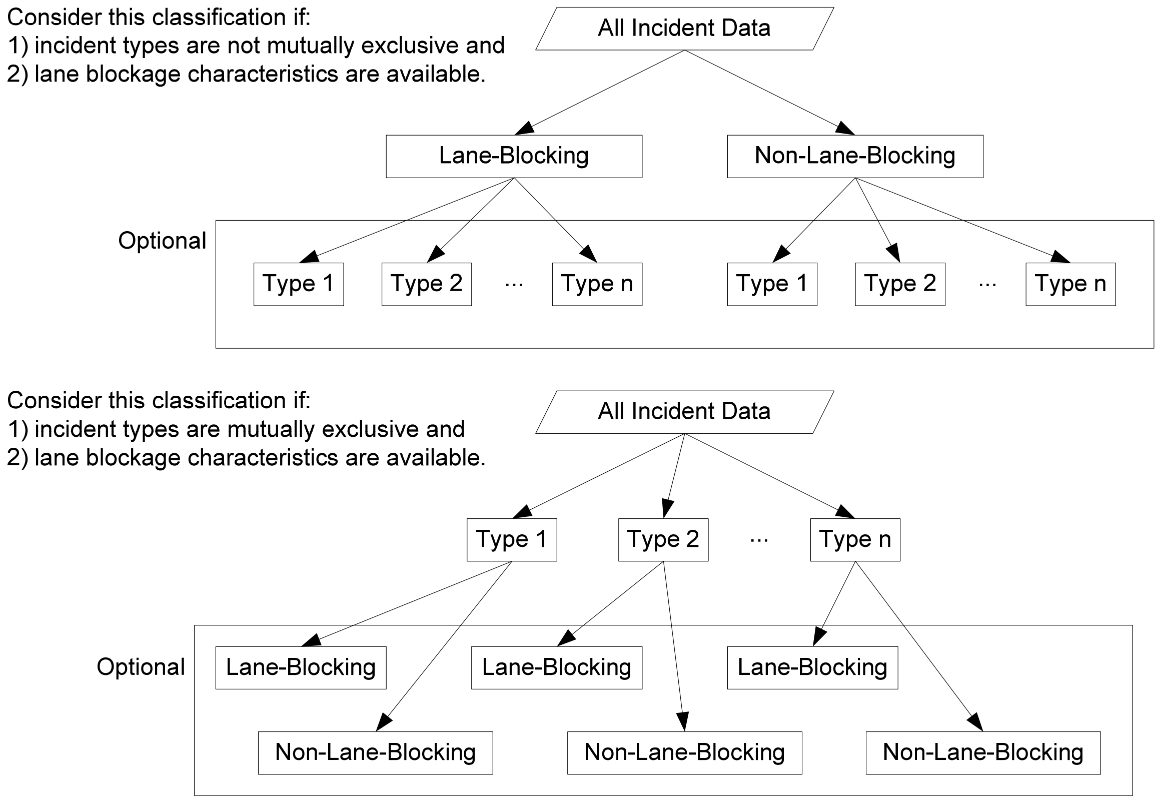


Figure 7-3: Recommended Categories for Incident Duration Submodels.

The entire model development process typically requires continual updating as more recent data become available. Therefore, the following model implementation should be conducted in a fashion that treats the core models themselves as a separate module. Agencies should allow capable users to have access to this module for fine-tuning and adjustment.

7.5. Model Deployment

Model deployment (also known as model implementation) is the process of transforming and repackaging the model developed from the previous step into a functional and user-friendly format. Several implementation options can be considered at this point depending on the following factors:

- degree of automation desired and
- availability of computing and manpower resources.

The level of automation refers to the degree at which manual intervention is required to either run or modify the tool. In the case of low-level automation and limited availability of resources, Excel-based implementation could be a viable option since it can serve as a proof-of-concept prototype. An Excel-based tool is easy to use since it requires merely appropriate entries of model inputs. Toward the high-end implementation, the full-scale programming of the distributable module in a developer environment such as Visual

Basic would be a more suitable option. The module can be designed such that it features automated entry of inputs and error checking. This also typically requires database connectivity to be set up with an existing incident database.

7.6. Example: Houston's Incident Duration Models

The four-year incident data (2004-2007) from Houston's TranStar were used to establish incident duration models in this example. Four submodels were developed based on incident types and lane blockage characteristics as follows:

- lane-blocking accident,
- lane-blocking stall,
- lane-blocking other types (neither accident nor stall), and
- all non-lane-blocking incidents.

Table 7-1 summarizes the four incident duration submodels calibrated for Houston. The model coefficients shown in the table are statistically significant at a 95% confidence interval (p-value < 0.05) unless they are noted otherwise. The positive coefficients indicate that a presence of such factors would likely increase the duration of an incident and vice versa for negative coefficients. The larger coefficient values also signify a greater impact on incident durations. The Weibull hazard models were estimated for each incident type. Then, if the scale parameter is not statistically significant at $\alpha = 0.05$, the model would be re-estimated using an exponential hazard model where the scale parameter was fixed at 1.0. Note that the exponential distribution is a special case of Weibull distribution. For each model calibrated, a summary of model statistics is provided that are:

- selected distribution for the hazard model;
- scale parameter – determines if the Weibull distribution can be reduced to exponential in this case;
- chi-square statistics and the corresponding degrees of freedom – determines the overall goodness of fit of the respective model;
- overall model p-value – indicates the overall statistical significance of the model. For example, the model p-value < 0.01 indicates that the explanatory variables included in the model can help explain the duration of incidents better than just an intercept alone at a 99% confidence level; and
- number of observations used to calibrate each submodel.

The models developed can be prototyped using Visual Basic for Applications (VBA) in Excel. Figure 7-4 and Figure 7-5 show the input and output of graphical user interfaces of an Excel-based prediction tool.

Users can enter appropriate inputs through the input GUI. Basic input validation can be internally performed here to ensure that the input entries are conformed to the model specifications. For instance, the number of lanes blocked and the all main lanes blocked data fields are mutually exclusive in Houston's incident database. Thus, the input GUI can be designed such that these two entries cannot exist concurrently.

Table 7-1: Houston's Incident Duration Models.

Incident Characteristics	Lane-Blocking Accident		Lane-Blocking Stall		Lane-Blocking Others		All Non-Lane-Blocking Incidents	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Intercept	3.2737	0.0000	2.8294	0.0000	3.4378	0.0000	3.7553	0.0000
Incident Type								
1 if accident; 0 if otherwise							-0.1609	0.0000
1 if construction; 0 if otherwise	0.0882	0.0000	0.1834	0.0000	0.1872	0.0306		
1 if HAZMAT spill; 0 if otherwise	0.7465	0.0000	0.5690	0.0974	0.8182	0.0000	0.6328	0.0000
1 if high water; 0 if otherwise	1.2592	0.0006			1.6316	0.0000	1.8007	0.0000
1 if ice on roadway; 0 if otherwise							1.2826	0.0000
1 if lost load; 0 if otherwise	0.7949	0.0000			0.5253	0.0020	0.3034	0.0040
1 if other type; 0 if otherwise	0.2776	0.0021			0.4205	0.0000	0.5060	0.0000
1 if stall; 0 if otherwise							-0.2882	0.0000
1 if vehicle on fire; 0 if otherwise	0.4229	0.0000			0.3051	0.0005		
Detection Method								
1 if automated detection; 0 if otherwise	-0.1910	0.0917					-0.4005	0.1052
1 if CCTV; 0 if otherwise	-0.1214	0.0046	-0.2090	0.0018	-0.2697	0.0000	-0.1087	0.0224
1 if citizen; 0 if otherwise	-0.1217	0.0571						
1 if commercial traffic service; 0 if otherwise	-0.1682	0.0020	-0.1620	0.1394			-0.1818	0.0058
1 if MAP; 0 if otherwise			-0.2638	0.0587	-0.5512	0.0353		
1 if METRO; 0 if otherwise							-0.0982	0.1457
1 if other public agencies; 0 if otherwise	-0.2611	0.0000					-0.3283	0.0000
1 if police; 0 if otherwise	-0.0731	0.1131	-0.1544	0.1274			-0.0860	0.1042
Verification Method								
1 if CCTV; 0 if otherwise	-0.1456	0.0000			-0.2253	0.0331	-0.1059	0.0004
1 if commercial traffic service; 0 if otherwise	0.0976	0.1195						
1 if MAP; 0 if otherwise							-0.1910	0.1322
1 if other; 0 if otherwise	0.2399	0.0005	0.2939	0.1235	0.2928	0.0635	0.6591	0.0000
1 if city police; 0 if otherwise	-0.1463	0.0353					0.1354	0.1127
1 if county police; 0 if otherwise	-0.0912	0.0217			-0.2486	0.0427	-0.6006	0.0000
1 if METRO police; 0 if otherwise					-1.3134	0.0658		
Severity Level								
1 if fatal incident; 0 if otherwise	1.1398	0.0000					1.4249	0.0000
1 if major incident; 0 if otherwise	0.1650	0.0000					0.2082	0.0000
Weather Condition								
1 if limited visibility; 0 if otherwise	0.0492	0.0102						
Vehicles Involved								
1 if bus involved; 0 if otherwise	0.1804	0.0266	0.8681	0.0000	0.4717	0.0945	0.2685	0.0000
1 if heavy truck involved; 0 if otherwise	0.5104	0.0000	0.8280	0.0000	0.5829	0.0000	0.6145	0.0000
Number of vehicles involved	0.0681	0.0000						
Time of Day								
1 if weekday 6AM-9AM; 0 if otherwise			0.1396	0.0000	0.1208	0.0757		
1 if weekday 4PM-7PM; 0 if otherwise					0.1676	0.0046		
1 if weekday 7PM-6AM; 0 if otherwise					0.4272	0.0000	0.0722	0.0013
1 if weekend; 0 if otherwise			0.1559	0.0001	0.3598	0.0000	0.0401	0.0631
Responders								
1 if city responded; 0 if otherwise							0.5213	0.0007
1 if coroner responded; 0 if otherwise	0.2791	0.0267						
1 if county responded; 0 if otherwise	0.1128	0.1633					0.3814	0.0024
1 if EMS responded; 0 if otherwise	0.0392	0.0125	0.3138	0.0349	-0.2658	0.0111		
1 if fire dept responded; 0 if otherwise	0.1177	0.0000	0.5133	0.0013	0.3954	0.0000	0.1970	0.0000
1 if HAZMAT team responded; 0 if otherwise	0.1955	0.1269					0.3811	0.0055
1 if HCFCD responded; 0 if otherwise			1.1290	0.2282			0.1667	0.0523
1 if MAP responded; 0 if otherwise	-0.0948	0.0024	-0.1968	0.0000	-0.4188	0.0009		
1 if METRO responded; 0 if otherwise	0.1567	0.1100					0.3200	0.0000
1 if city police responded; 0 if otherwise	-0.0285	0.0601	0.1040	0.0006	-0.1767	0.0018	-0.0435	0.0323
1 if county police responded; 0 if otherwise	0.0916	0.0012	0.3374	0.0008				
1 if METRO police responded; 0 if otherwise					-0.6434	0.0179	0.2530	0.0000
1 if state police responded; 0 if otherwise	0.1110	0.1153					0.2199	0.0210
1 if TxDOT responded; 0 if otherwise	0.5450	0.0000	0.3240	0.0212	0.3035	0.0000	0.5616	0.0000
1 if wrecker responded; 0 if otherwise			-0.1082	0.0009	-0.1126	0.0649	-0.0295	0.1520
Lane Blockage								
1 if all mainlanes blocked; 0 if otherwise	0.6761	0.0000	0.3680	0.1286	0.5026	0.0000		
Number of mainlanes blocked	0.0732	0.0000	0.1470	0.0090	0.1174	0.0002		
Distribution	Weibull		Weibull		Exponential		Exponential	
Scale	0.813		0.915		1		1	
Chi-Square Statistics	6275.37		1213.62		1457.79		7598.41	
Degree of Freedom	37		21		27		35	
Model p-value	<0.0001		<0.0001		<0.0001		<0.0001	
Number of Observations	23851		7120		2676		23140	

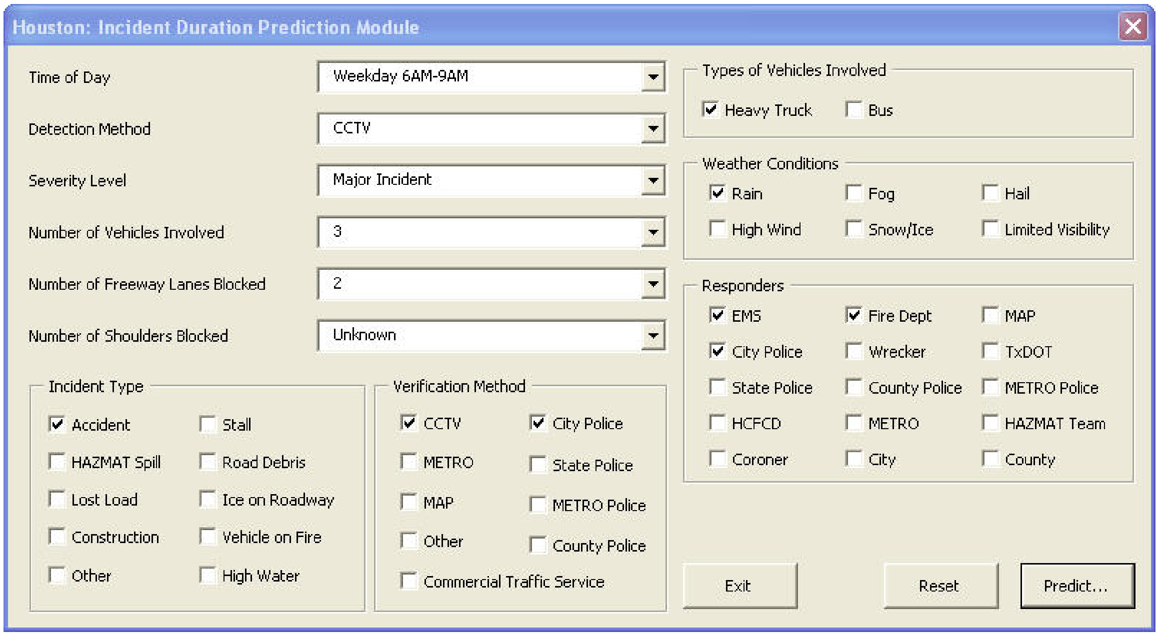


Figure 7-4: Input GUI of Incident Duration Prediction Tool (Houston).

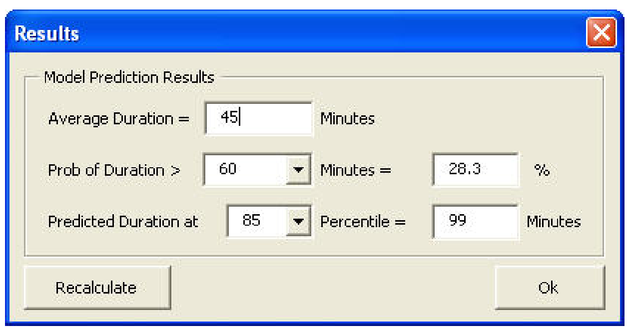


Figure 7-5: Output GUI of Incident Duration Prediction Tool (Houston).

The module outputs provide the following information:

- average incident duration (expected value),
- predicted incident duration in minutes for any given percentile values (50th percentile corresponds to a median value), and
- probability that an incident will last longer than a specified time period (user-specified values can be either selected from a group of default values or manually entered).

To illustrate the use of module outputs, assume that the module is predicting the average and 85th percentile durations at 16 and 51 minutes, respectively, based on the incident characteristics entered by the users. This would imply the range of predicted incident durations between 16 and 51 minutes. Alternatively, users can also look at the probability that an incident will last longer than some specified thresholds. For example, users can specify the time periods and recalculate the corresponding probabilities of exceedance for 30-minute, 1-hour, and 2-hour thresholds.

Users can compare the actual incident durations once the incidents are over with the predicted values from the module. The module performance is considered acceptable if the actual incident durations are consistently well within the range of the predicted values. If the performance of the models is not satisfactory, the analyst may consider the following strategies to enhance the predictability of the module:

- Evaluate if the submodel classifications need revisions.
- Revisit the model recoding process to determine if certain variables should be treated otherwise – The effects of categorical, ordinal, and interval treatment on the modeling results can vary.
- If data supported, consider modeling various phases of incident management instead of the entire incident duration. This is based on the fact that the factors affecting specific phases of incident management can be different; for example, consider the factors that can potentially affect incident response time versus incident clearance time.
- Consider the second-order model that includes the interactions between explanatory variables. Interaction effects on incident duration can be very complex and difficult to interpret logically. This strategy should be considered as a last resort to improve the model performance.

It should be emphasized that the model development is a continual process that requires regular updating and fine-tuning. The fine-tuning process should also reflect any changes implemented by the agencies to the incident data structure. Any predictions resulting from the models should be treated as a decision-supported tool for the users to make an informed decision. The prediction results under no circumstances should override engineering judgment and common sense.

8. PREDICTING INCIDENT-INDUCED CONGESTION CLEARANCE TIME

This module describes a proactive use of historical and real-time traffic data for estimating incident-induced congestion clearance times. The analyst can proactively predict the impact of traffic incidents based on the time that it will take for the traffic to return to normal conditions after incident occurrence. Historical traffic data collected from sensors deployed at the TMCs can be used to establish "expected" normal traffic conditions for particular freeway segments and time periods. It is envisioned that TxDOT can use this information to proactively manage the incidents.

One delay-related component that TMC managers can use to make an informed operational decision on incident management activities is the total incident-induced congestion period, which is the time it takes from the incident occurrence until the traffic returns to normal traffic conditions. This time is the summation of the incident duration (from incident notified to incident removed) and the traffic recovery time (from incident removed to congestion cleared). The time point at which the traffic returns to normal conditions is referred to as the incident-induced congestion clearance time. This information, in combination with real-time travel time information, could potentially be used by operators to decide on which DMSs and what messages should be disseminated. For example, TMC managers may choose to post incident-related messages onto the DMSs with travel times estimated to be 20 minutes or less upstream of the incident because the traffic is expected to return to normal conditions within the next 20 minutes. In this way, only the travelers that could potentially be impacted by the incident are informed instead of all the travelers upstream of the incident, thus improving the credibility of the traveler information system.

Predicting the incident-induced congestion period requires two components to be estimated:

- incident duration and
- traffic recovery time.

The first component can be predicted using the incident duration model described in Module 7. This section describes the methodology to estimate the second component using the deterministic queuing diagram.

The prediction methodology described in this module can be used at any stage of incident management activities provided that incident duration is properly updated. The accuracy of the approach increases as the uncertainty of incident duration decreases. The result is the most accurate at the stage of incident where the incident duration is known with certainty and capacity flow rates can be reasonably estimated, i.e., when the incident is already removed from the roadway (thus predicted incident duration is no longer required) and traffic flow rates gradually resume to pre-incident levels. At this point, the only remaining component to be estimated is incident-induced congestion clearance time.

8.1. Data Requirement

The following data elements are required for estimating the incident-induced congestion clearance time:

- historical traffic volume data,
- real-time traffic volume data,
- incident duration and lane blockage characteristics, and
- assumption for traffic diversion rate during incidents.

Traffic volume data must be continuously collected at regular intervals from the sensors upstream of the incident location. This methodology estimates reduced freeway capacity from real-time traffic conditions. Therefore, if available, lane blockage characteristics (number of lanes blocked and durations) could alternatively be considered instead of real-time traffic volume data.

One limitation of this approach is that the impact of incidents on traffic conditions must be significant enough for roadway traffic sensors to detect the changes in traffic flow patterns. In other words, the analyst may find the incident-induced congestion clearance time for minor and/or non-main-lane blockage incidents to be negligible. The methodology is also sensitive to traffic diversion rate and incident duration. The former requires a realistic assumption since the diversion rate is typically unavailable, while the latter is difficult to estimate with a high degree of accuracy.

8.2. Prediction Procedures

Figure 5-1 illustrates cumulative flow profiles during incident-induced congestion. The parameters in the diagram are defined as follows:

q: traffic flow rate (vph),
r: incident duration (minutes),
s: freeway capacity (vphpl),
s_1: reduced freeway capacity during the incident (vphpl), and
t_c: incident-induced congestion clearance period.

The incident-induced congestion clearance period (t_c) is the time from when the incident is detected until the incident-induced congestion is cleared. t_c also includes incident duration, and its value could be much longer than the incident duration since it also accounts for the time it takes to clear the queue built up during incident-induced lane blockage.

If all the parameters in the deterministic queuing diagram are known, t_c can be calculated from the geometric relationship as follows:

$$t_c = r \cdot \frac{(s - s_1)}{(s - q)} \tag{8-1}$$

Though the parameters of Equation (8-1) are not known for certain, they can be estimated and Equation (8-1) can be updated over time as the parameter estimates change. Let i be the time elapsed from the beginning of the incident. The estimates of t_c at time i can be expressed as:

$$\hat{t}_{c,i} = \hat{r}_i \cdot \frac{\left(\hat{s}_i - \hat{s}_{1,i}\right)}{\left(\hat{s}_i - \hat{q}_i\right)}. \tag{8-2}$$

The techniques and important considerations for estimating each parameter in Equation (8-2) are described in subsequent sections. Note that the time i mentioned subsequently is referenced to the incident occurrence. We denote t_r as actual incident duration and t_c as actual incident-induced congestion clearance duration.

8.2.1. Estimate Incident Duration

Incident duration (r_i) can be estimated using an incident duration model calibrated from the incident database. If the model is not available, the analyst can derive summary statistics from incident records to obtain a set of default values for average incident durations, which can be categorized by various incident characteristics, such as incident types, severities, and lane blockage characteristics.

At the beginning of the incident ($i = 0$), the analyst will have to rely on the predicted incident duration or default values. As the event progresses, the analyst should update the incident duration manually to reflect the actual situation on the scene. The value is known with certainty when the incident is removed from the scene. At this stage, the analyst should use the actual incident duration ($\hat{r}_i = t_r$) and discard the predicted or default values.

8.2.2. Estimate Expected Incoming Traffic Demand

The expected incoming traffic demand (q_i) is the expected flow rate under the incident-free condition adjusted for traffic diversion. This represents the backlog traffic demand that accumulates during incident blockage. In reality, incoming traffic demand during the incident period will be lower than what we would expect under incident-free conditions because some of the traffic will start diverting to alternate routes. Therefore, incident-free traffic demand estimated from historical data must be reduced by the amount of diverted traffic in order to realistically estimate the demand flow rate.

Traffic diversion rate (δ) is difficult to estimate with accuracy. The percentage of diversion depends on the presence of alternate routes, the incident severity, and the ability to disseminate incident-related information to both pre-trip and en-route travelers. The general guideline is to use a higher diversion rate for more severe incidents at the locations with alternate routes. The analyst will need to examine prediction outputs from the method and fine-tune this rate to reflect actual traffic conditions.

The procedures to estimate q_i can be summarized into the following steps:

1. First, obtain incident-free historical traffic flow data recorded earlier on the same days of the week during the same time period in which the incident occurs. Use

the average or median from multiple weeks if available to reduce the possibility of anomalies within a one-day dataset. For example, if a major incident occurs at 9:00AM on May 28, 2007, use the traffic data from 9:00AM on May 21, 2007, (and May 14, 2007, or more if available) to calculate historical flow rates.

2. Specify the time window for calculating the historical flow rate. The time window should be approximately the same as the expected incident-induced duration. Increase the time window size for major incidents and vice versa for minor incidents. Use the default value of two hours if no other information is available. For the previous example, we will use a three-hour window for a major incident. Thus, from historical flow data on May 21, 2007, the time period for calculating historical flow rates would be from 9:00AM to 12:00PM.
3. Calculate the average flow rate (in vph or vphpl) from the historical data during the specified time window. This average flow rate (q^*) is the expected incoming demand under incident-free conditions.
4. Apply the diversion rate δ to q^* to obtain the estimate for incoming traffic demand, i.e., $\hat{q}_i = \left(1-\hat{\delta}\right)\cdot q^*$ where $\hat{\delta}$ is the estimated proportion of the diverted traffic.

The estimated values of $\hat{q}_i$ are generally constants throughout the analysis period, i.e., $\hat{q}_i$ is fixed for all i. However, the analyst may find a need to update $\hat{q}_i$ if the incident-induced duration is extended well beyond the time window specified in Step 2. In this case, the time window in Step 2 must be increased and $\hat{q}_i$ must be re-estimated as described in the subsequent steps.

8.2.3. Estimate Capacity Flow Rate

The capacity flow rate (s_i) is the expected flow rate after the incident has been removed. This rate determines how long it will take to clear the backlog traffic demand during the blockage.

Before the incident is removed, i.e., at $0 < i < t_r$, the capacity flow rate can be estimated using the maximum historical flow rate. However, a particular freeway section may never operate at or close to full capacity, or it may temporarily service the traffic at an unsustainable flow rate before the operation breaks down. In either case, the maximum historical flow rate will not be an appropriate estimate for the true capacity. As such, a lower and upper threshold should be imposed in addition to the use of maximum historical flow rate as an estimate. We recommend that the lower threshold be in the range of 1600 to 1,800 vphpl and the upper threshold be in the neighbor of 2,000 to 2,200 vphpl. In summary, the estimated capacity flow rate can be determined using the maximum historical flow rate observed at the sensor station with appropriate adjustment when the estimate is not within the recommended range.

At $i > t_r$, the incident has been removed. In this case, use the average of maximum historical flow rate and the actual flow rate observed from the real-time data. This average rate is to account for the fact that it will take some time for the traffic flow to resume to the maximum flow rate once the incident has been removed.

8.2.4. Estimate Reduced Flow Rate

The reduced freeway capacity flow rate ($s_{1,i}$) can be estimated using real-time traffic flow data. However, at the beginning of the incident, these data are not yet available; thus lane blockage characteristics could be used to estimate this flow rate. In summary, the reduced flow rate can be estimated as follows:

- At $i = 0$, estimate the reduced flow rate from the lane blockage characteristics. For example, if all main lanes are blocked, $\hat{s}_{1,i=0} = 0$. Methods provided in the *Highway Capacity Manual* (*34*) can be used to estimate freeway capacity reduction under different scenarios.
- At $0 < i < t_r$, use the average flow rates observed at the upstream detector station after the incident occurrence. This value should be updated at regular intervals as more real-time flow data become available.

8.2.5. Calculate Incident-Induced Congestion Clearance Time

The analyst can calculate the incident-induced congestion clearance times (measured from when the incident is detected) and then update the estimates at regular intervals using Equation (8-2). It is convenient to specify the updating frequency that corresponds to the size of time interval used to aggregate real-time traffic flow data. For example, if the real-time data are being aggregated every 5 minutes, the analyst can choose to update the estimates every 5 or 10 minutes; that is:

$$\hat{t}_{c,i} = \hat{r}_i \cdot \frac{\left(\hat{s}_i - \hat{s}_{1,i}\right)}{\left(\hat{s}_i - \hat{q}_i\right)}; i = 5,10,15,... \qquad (8\text{-}3)$$

8.3. Application Example

This section provides an example of incident-induced congestion clearance time prediction using the procedures described in the previous section. To demonstrate the calculation process, we use the same example as shown in Section 5.3, in which actual data from TranStar's incident and traffic data archives are employed.

8.3.1. Scenario

In this example, a major incident occurred on US-290 at 34th Street blocking two main lanes of traffic going westbound on Thursday, September 13, 2007, at 7:01AM. The incident was removed at 7:32AM. Figure 8-1 shows the traffic flow and speed profiles observed from the upstream detectors. The data were aggregated for every five-minute interval. Table 8-1 shows the example of actual traffic data from both days aggregated for every five-minute interval. These data will be used to calculate the inputs for the congestion clearance time prediction procedure.

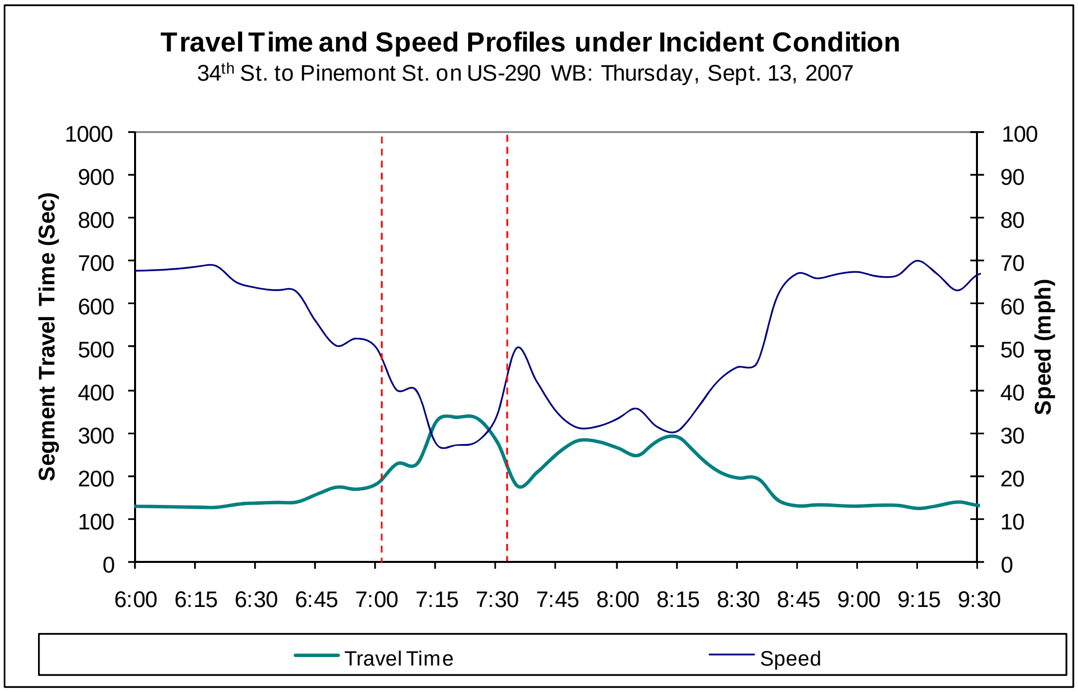


Figure 8-1: Traffic Conditions under Incident Impacts.

Table 8-1: SmartSensor Data (US-290 at 34th Street, Westbound Main Lanes).

Time	Volume	Time	Volume
9/13/2007 6:50 AM	473	9/13/2007 8:20 AM	493
9/13/2007 6:55 AM	393	9/13/2007 8:25 AM	491
9/13/2007 7:00 AM	386	9/13/2007 8:30 AM	451
9/13/2007 7:05 AM	396	9/13/2007 8:35 AM	472
9/13/2007 7:10 AM	375	9/13/2007 8:40 AM	433
9/13/2007 7:15 AM	388	9/13/2007 8:45 AM	451
9/13/2007 7:20 AM	381	9/13/2007 8:50 AM	406
9/13/2007 7:25 AM	513	9/13/2007 8:55 AM	382
9/13/2007 7:30 AM	587	9/13/2007 9:00 AM	380
9/13/2007 7:35 AM	574	9/13/2007 9:05 AM	352
9/13/2007 7:40 AM	517	9/13/2007 9:10 AM	357
9/13/2007 7:45 AM	511	9/13/2007 9:15 AM	361
9/13/2007 7:50 AM	508	9/13/2007 9:20 AM	377
9/13/2007 7:55 AM	523	9/13/2007 9:25 AM	365
9/13/2007 8:00 AM	555	9/13/2007 9:30 AM	383
9/13/2007 8:05 AM	499	9/13/2007 9:35 AM	381
9/13/2007 8:10 AM	484	9/13/2007 9:40 AM	345
9/13/2007 8:15 AM	480	9/13/2007 9:45 AM	368

For this incident, the impact estimation methodology described in Section 5.3 was used to measure the actual time that the traffic returns to normal conditions. The incident-induced congestion clearance time measured from the average delay profile as shown Figure 8-2 is 8:35AM or 94 minutes after the beginning of the incident. This time point is considered the true incident-induced congestion clearance time, which is used as a benchmark for the prediction performance of this method in this example. The predicted values calculated at each time step can be compared against this actual value.

The next section discusses how historical and real-time traffic data observed from a SmartSensor radar sensor upstream of the incident can be used to predict the incident-induced congestion clearance time in this example.

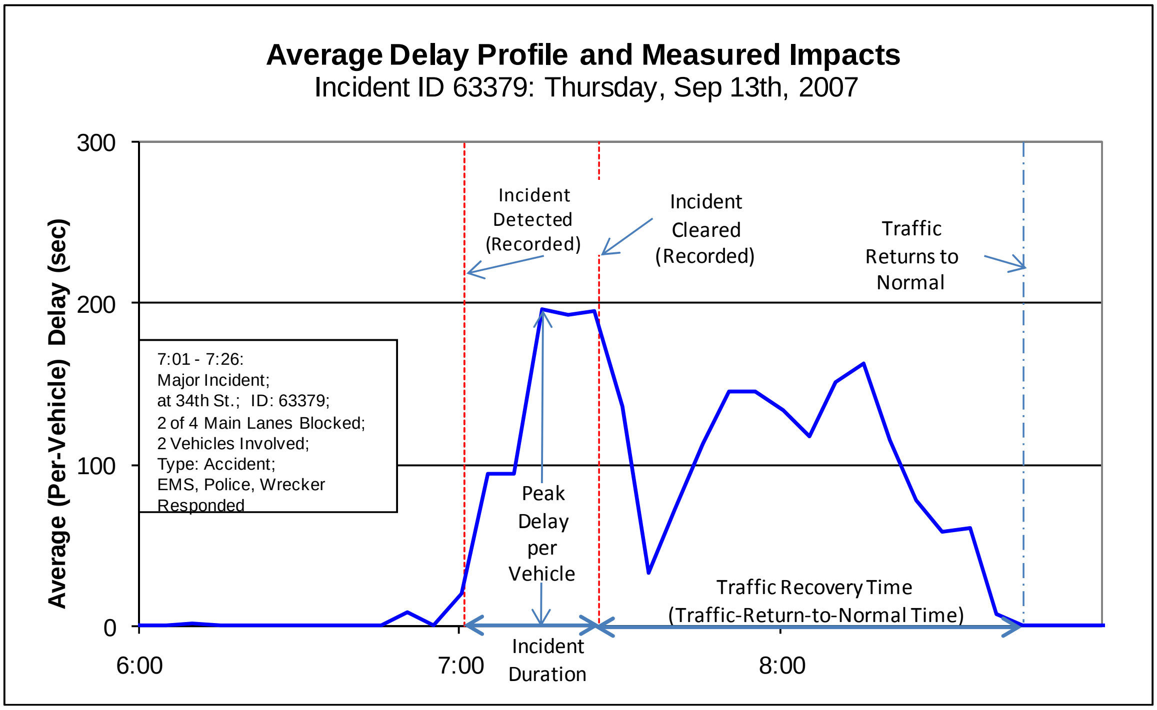


Figure 8-2: Measuring Traffic-Return-to-Normal Time from Average Delay Profile.

8.3.2. Prediction Example

The prediction is updated every five minutes in this example. The actual incident-induced congestion period was 94 minutes. At the beginning of the incident ($i = 0$), the input parameters can be estimated as follows.

8.3.2.1. <u>Incident Duration</u>

The analyst can use the incident duration prediction model to estimate incident duration. To illustrate, the incident prediction module for Houston described in the example in Module 7 was used to predict the incident duration. The module predicted that the incident duration would have an average of 26 minutes and an 85th percentile at 57 minutes as shown in Figure 8-3. To be conservative, take 55 minutes as the predicted incident duration. Therefore, at the beginning, $\hat{r}_{i=0}$ = 55 minutes. The incident duration estimate can be updated every five minutes and should be updated when more information is available. In this example, this value is reduced to 40 minutes at 7:25AM, 6 minutes before the incident is removed. Once the incident has been removed, $\hat{r}_{i\geq 31} = 31$ minutes since the incident duration is now known with certainty.

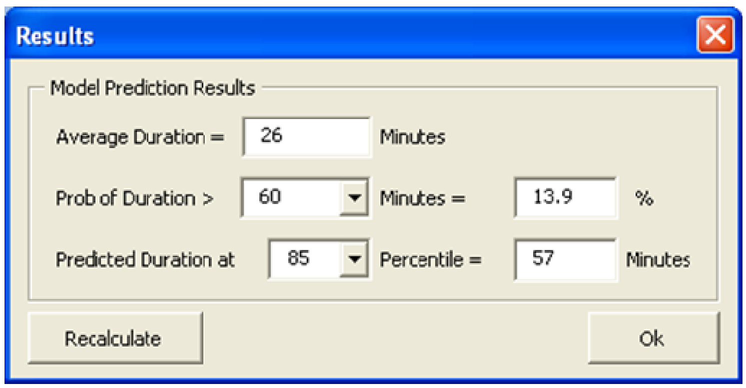


Figure 8-3: Incident Duration Prediction.

8.3.2.2. Expected Incoming Traffic Demand

For this incident, a one-hour window was chosen to calculate average incident-free flow rates using the historical data from the previous five Thursdays. The average historical flow rate, q^*, from 7:00AM to 8:00AM was 1570 vphpl.

Then, the diversion rate of 5 percent or $\hat{\delta} = 0.05$ is applied to q^* to account for the diverted traffic during the incident period. Therefore, the expected incoming traffic demand throughout the analysis period is estimated to be $\hat{q} = (1\text{-}0.05)(1570) = 1492$ vphpl.

8.3.2.3. Capacity Flow Rate

From the observation of five-minute historical flow rates, the maximum value was 564 vehicles, which is equivalent to 1692 vphpl. At time $i = 0$, there are no real-time traffic data available yet; the estimated $\hat{s}_{i=0}$ is equal to 1692 vphpl. This value will be updated again after the incident has been removed and real-time capacity flow rates can be observed from the detectors, i.e., time $i > t_r$ (incident duration).

8.3.2.4. Reduced Flow Rate

At the beginning of the incident, we used the incident characteristics to estimate the reduced flow rates. In this case, the average real-time flow rates should be used as the input for this value. For example, at 7:05AM, four minutes into the incident, the average five-minute flow rate observed is $\hat{s}_{1,i=5}$ = 396 vehicles or 1188 vphpl.

8.3.2.5. Incident-Induced Congestion Clearance Time

Now that all the parameters required for the prediction are estimated, at 7:05AM, the first estimate for t_c can be calculated using Equation (8-3) as follows:

$$\hat{t}_c = \hat{r} \cdot \frac{(\hat{s} - \hat{s}_1)}{(\hat{s} - \hat{q})} = 55 \cdot \frac{(1692 - 1188)}{(1692 - 1491)} = 138 \text{ minutes.} \tag{8-4}$$

Similarly, at 7:10AM, we have

$$\hat{t}_c = 55 \cdot \frac{(1692 - 1157)}{(1692 - 1491)} = 147 \text{ minutes.} \tag{8-5}$$

The procedure can be repeated every 10 minutes to obtain new estimates for t_c.

8.3.2.6. Summary of Predicted Values

Table 8-2 shows the prediction results using real-time traffic data to update the estimates every five minutes.

Table 8-2: Predicted Incident-Induced Congestion Clearance Times.

Incident location	US-290 at 35th Street						
Incident characteristics	7:01AM-7:32AM 2 main lanes blocked on a 4-lane section						
Traffic diversion rate	5%						
Incident-induced congestion clearance period	94 minutes						
Time	**7:05AM**	**7:10AM**	**7:15AM**	**7:20AM**	**7:25AM**	**7:30AM**	**7:35AM**
Incident Duration (min)	55	55	55	55	40	40	31
Capacity flow rate (vphpl)	1692	1692	1692	1692	1692	1692	1535
Reduced flow rate (vphpl)	1188	1157	1159	1155	1232	1320	1377
Average historical incident-free flow rate (vphpl)	1570	1570	1570	1570	1570	1570	1570
Expected incoming demand after diversion (vphpl)	1491	1491	1491	1491	1491	1491	1491
Predicted incident-induced congestion clearance period (min)	**138**	**147**	**146**	**147**	**92**	**74**	**112**

8.3.3. Cumulative Flow Profiles

The estimates obtained in this example can be represented through cumulative flow profiles showing:

- expected incoming traffic demand and
- predicted flow profile under incident condition.

Figure 8-4 shows cumulative flow profiles of the expected incoming demand and the predicted flow profile under incident condition at the beginning of the incident. The point at which these two profiles intersect corresponds to the time the congestion cleared, which in this case is 9:19AM (138 minutes after incident occurrence).

Figure 8-5 shows the predicted cumulated flow profile at 7:25AM when the predicted incident duration is updated to 40 minutes, and Figure 8-6 presents the predicted cumulative flow profile after the incident is removed.

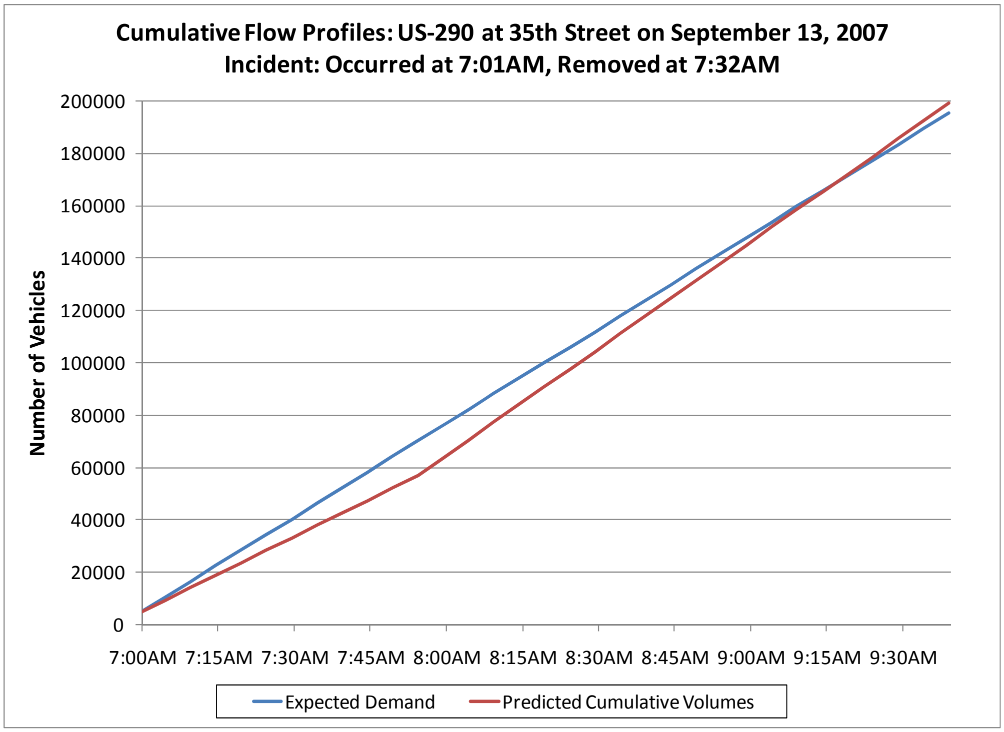


Figure 8-4: Predicted Cumulative Flow Profile at 7:05AM.

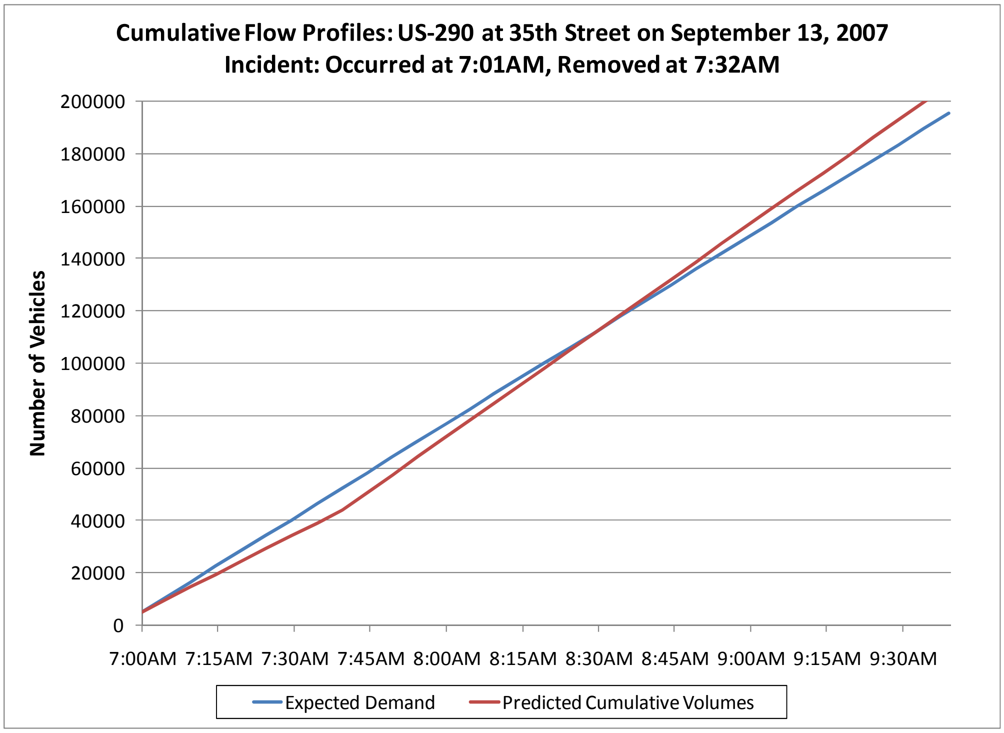


Figure 8-5: Predicted Cumulative Flow Profile at 7:25AM.

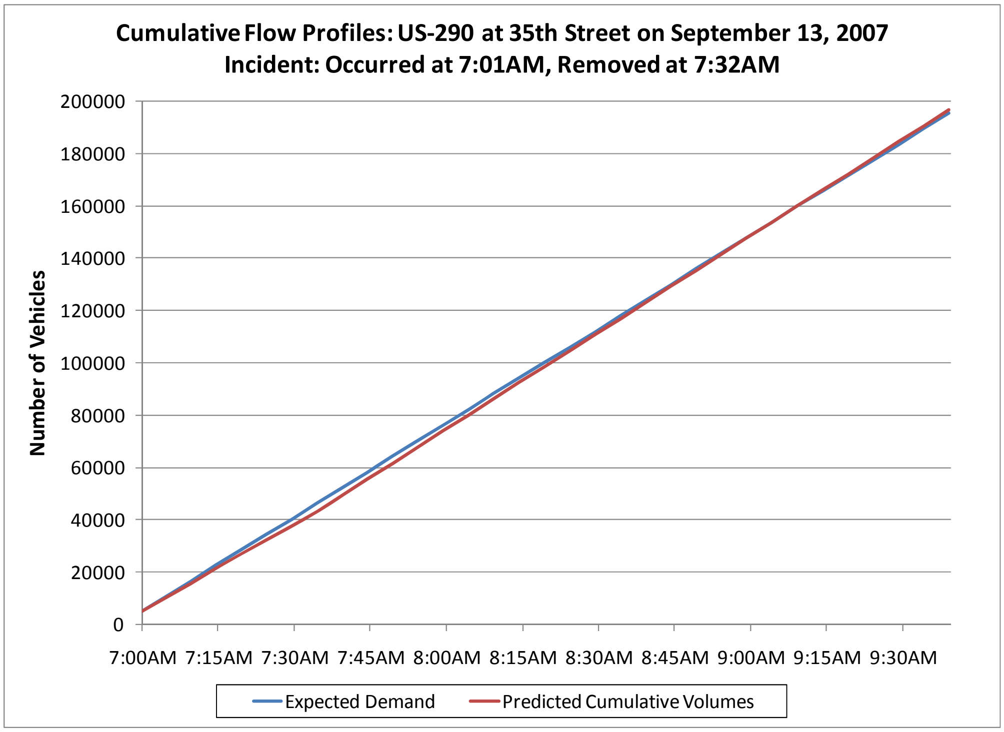


Figure 8-6: Predicted Cumulative Flow Profile at 7:35AM.

8.4. Summary

Provided historical traffic volume and real-time traffic volume data are available, the incident-induced congestion clearance period can be estimated using the following equation:

$$\hat{t}_{c,i} = \hat{r}_i \cdot \frac{\left(\hat{s}_i - \hat{s}_{1,i}\right)}{\left(\hat{s}_i - \hat{q}_i\right)}. \tag{8-6}$$

The incident duration (r) can be estimated using the incident duration prediction model or default average values for specific types of incidents. The freeway capacity flow rate (s) can be estimated using maximum historical flow rates observed at the detector stations and adjusted for the threshold capacity. Once the incident has been removed, both s and r values can be updated with real-time data. The reduced flow rates (s_1) can be estimated from incident characteristics at the beginning of the incident. Once the real-time reduced flow rates become available (e.g., 5 or 10 minutes after the occurrence), this value can be updated using real-time data instead. The demand flow rate (q) is the expected incoming flow rate during the incident-induced period. The demand flow rate is the expected incident-free traffic flow adjusted for the effects of traffic diversion, which can be estimated using historical traffic data.

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