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16. Abstract

The companion guidebook (0-5485-P2) developed as part of this study provides the procedures and methodologies for effective use of historical incident data at Texas Transportation Management Centers (TMCs). This research report documents the results from the case studies conducted using the procedures outlined in the guidebook. Researchers examined the data collected from three Texas TMCs, which are Houston's TranStar, Austin's Combined Transportation and Emergency Communications Center (CTECC), and Fort Worth's TransVISION. Researchers conducted six categories of analyses in this study – (a) analysis of incident characteristics, (b) hot spot analysis, (c) incident impact estimation, (d) analysis of incident management performance measures, (e) incident duration prediction, and (f) incident-induced congestion clearance time prediction.

Researchers found that historical incident data can be effectively used to support incident management and performance evaluation processes both reactively and proactively. Some procedures need to be automated to be used efficiently in day-to-day operations. As such, various prototype tools, such as the incident duration and incident-induced congestion clearance prediction tools, were developed during this study to facilitate and automate the proposed methodologies. These prototype tools provided a platform for TxDOT to deploy the research results in the future.

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EVALUATING AND IMPROVING INCIDENT MANAGEMENT USING HISTORICAL INCIDENT DATA: CASE STUDIES AT TEXAS TRANSPORTATION MANAGEMENT CENTERS

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DISCLAIMER

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1. INTRODUCTION

This report is a result of TxDOT Project 0-5485. The objective of the project was to develop methodologies and procedures for effective use of historical incident data collected at Texas Transportation Management Centers (TMCs). This project produced two major deliverables. The first deliverable was a guidebook for effective use of historical incident data (0-5485-P2). The guidebook provides the procedures and methodologies for effective use of historical incident data at the TMCs in multiple modules. This research report (0-5485-1), which documents the research efforts conducted for this project, is the second deliverable. In this report, the researchers conducted case studies using the procedures outlined in the guidebook and the data collected from selected Texas TMCs to evaluate and improve incident management at TMCs.

1.1. Guidebook Overview

The guidebook 0-5485-P2 primarily addresses the use of incident data for various analyses and applications. The methodologies and procedures described in the guidebook are one of the following types:

- evaluation/planning analysis, or
- predictive analysis.

Table 1-1 summarizes the corresponding modules for each type of analysis. Again, the guidebook primarily addresses the use of incident data for various applications; however, some types of analyses still require the use of traffic data. Table 1-2 summarizes the data sources required for specific types of analyses.

Table 1-1: Module Structure in the Guidebook 0-5485-P2.

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

Researchers conducted phone interviews and a literature review in the first year of this project to gather feedback from the project monitoring committee, as well as from TMC operators and managers, regarding TxDOT's current practices and desires for incorporating historical data into TMC operations, with a specific emphasis on incident data archives and incident management. Module 2 of the guidebook summarizes the current practices at Texas TMCs and Appendix A in this research report documents the questionnaires and results from the interviews.

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

1.2. Report Overview

This report demonstrated and evaluated the methodologies and procedures described in the companion guidebook. This report primarily focuses on applying the methodologies and procedures described in the guidebook through the 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. These three TMCs currently collect and archive incident data on a regular basis. As for traffic data, TranStar employs an automated vehicle identification (AVI) system and radar sensors for traffic data collection while CTECC uses inductive loop detectors. TransVISION has the capability to collect the traffic data as well, but they are not archived on a routine basis. CTECC currently uses TxDOT's Advanced Transportation Management System (ATMS) for its central management software and database while TranStar and TransVISION have developed and maintain their own proprietary systems. Researchers selected these three TMCs for this case study because they provide different incident data structure and instructive comparison of data elements being collected at the TMCs. Also, the freeway traffic data currently collected at the same time allows researchers to explore the potential use of combined traffic and incident data for both evaluation and predictive analyses.

All the modules that require only incident data were evaluated and demonstrated in the case studies for all three cities. For the analysis modules that require both traffic and incident data, the researchers selected Houston's TranStar to demonstrate the performance and applicability of the methods since it possesses both point-based and probe-based traffic data collection systems. The case studies conducted for specific TMCs are summarized in Table 1-3.

All three TMCs have their own specifications for collecting incident management data. TransVISION has a unique and extensive incident database containing the information about the arrival and departure times of all incident responders. TranStar and CTECC routinely collect and archive traffic data from AVI/radar and loop detectors, respectively. The researchers believe that the case studies conducted at these three TMCs represent the majority of the types of analyses and applications that could be performed at other Texas TMCs. The detailed results from all the case studies are documented in the appendices. Specific examples were selected and are discussed in each chapter where appropriate.

Table 1-3: Summary of Case Studies.

Analysis Type	Houston	Austin	Fort Worth
Evaluation Analysis			
• Reporting incident characteristics	x	x	x
• Analyzing hot spots	x	x	x
• Estimating incident impacts	x		
• Analyzing incident management performance measures			x
Predictive Analysis			
• Predicting incident duration	x	x	x
• Predicting incident-induced congestion clearance time	x		

1.3. Report Organization

The organization of the chapters in this report bases primarily on the types of analyses conducted. The following paragraphs briefly describe the contents of each chapter.

Chapter 2 provides incident characteristics reports containing what the analyst can typically produce from the incident database. This analysis is intended to serve as a guideline on what can be reported from the incident database. The analyst can customize a list of reports to the analysis' purposes/needs at the TMC (e.g., annual performance report).

Chapter 3 describes the hot spot analysis, which is the technique for spatially analyzing the patterns of incident occurrences. This analysis utilizes the incident data to map out the locations with a high risk of incident occurrence. The analysis was conducted at all three TMCs using historical incident data. The researchers used ArcGIS as a platform for graphically displaying the hot spot results on the maps for both frequency-based and attribute-based hot spot analysis methods.

Chapter 4 demonstrates the use of incident and traffic data to estimate the impacts of an incident. Incident impact estimation provides a comprehensive set of incident-related impacts for each individual incident using the methodology developed in this study. This analysis requires both traffic and incident data and requires extensive data processing. Since the procedures would be similar for both Austin and Houston, the researchers chose to evaluate the procedures on a selected freeway segment in Houston for this study.

Chapter 5 describes the analysis of incident management (IM) performance measures, which demonstrates how the analysis can identify the factors affecting specific IM performance measures from the incident database. In this case study, researchers first calculated various IM performance measures from TransVISION data as described in the guidebook (e.g., first responder response times, total response times, on-scene times, etc.). Then the researchers conducted a statistical analysis to analyze the factors affecting the first responder response time using historical incident data.

Chapter 6 provides the detailed incident duration models calibrated for each TMC examined in this study. Researchers developed three separate sets of models for each TMC using the procedures described in the guidebook. These models were also prototyped using Visual Basic for Applications in Microsoft Excel to demonstrate researchers' vision on how these models could be implemented. The model selection is based upon the user-specified incident type and lane blockage characteristics.

Chapter 7 describes a prototype that the researchers developed for predicting the incident-induced congestion clearance time based on the methodology described in the guidebook. In order to evaluate this method, researchers used historical traffic data from radar sensors in Houston to generate pseudo-real-time and historical traffic data for a given incident. In this way, the prediction results could be compared with the congestion clearance time (traffic recovery time) measured as part of the incident estimation impact on a selected freeway segment in Houston. The testing indicated a good agreement between the predicted and the actual congestion clearance time. Researchers also conducted sensitivity analysis of the model parameters and discussed the limitations of the method in this chapter.

Chapter 8 documents the development of the prototype tools developed in this study to facilitate and/or automate methodologies and calculation procedures described in the guidebook. Researchers developed two categories of the tools in this project: (a) data processing/reduction tools, and (b) analytical tools. The first category of the tools was designed to facilitate the manipulation of traffic and incident data currently collected and archived at the TMCs. The data outputs from these tools were further used in various analyses conducted in the case studies. The second category of the tools was developed based on the methodologies and procedures described in the draft guidebook. The objectives of these tools were to expedite the analytical process by automating specific calculation routines and to demonstrate the potential applications of the procedures described in the guidebook. Researchers developed all the prototype tools in this study based on Houston's traffic and incident data structure to provide a complete picture of how various analyses and results are interconnected.

Chapter 9 provides a summary of research efforts conducted, as well as findings and recommendations from this project.

2. SUMMARY OF INCIDENT CHARACTERISTICS

This chapter provides a summary of incident characteristics collected at Houston's TranStar, Austin's CTECC, and Fort Worth's TransVISION. The researchers examined the distributions of various incident data attributes from these three TMCs. The analysis of incident characteristics and discussions is summarized for each TMC. The researchers also developed a prototype tool using Visual Basic for Applications (VBA) in MS Excel to produce standard distribution reports from Houston's incident data. The purpose of this tool was to illustrate how the analyst can facilitate the process of manipulating incident data to produce routine summary reports. Users can customize the desired time scales and data attributes. Section 8.3 describes this prototype tool in more details.

2.1. Incident Data Attributes

Table 2-1 compares the incident data attributes collected at the selected TMCs. Some data attributes are mutually exclusive, meaning that only one data element was recorded per incident. For example, each incident record at Austin's TMC is associated with only one incident type. Similar types of data were collected at these three TMCs. The researchers analyzed the distributions of these incident characteristics to determine if there were any discrepancies and to ensure that they were valid and sufficient for any subsequent uses.

The results in this chapter provide examples of standard reports produced from the incident database. The researchers selected an annual time scale to conduct the analysis on various incident data attributes. Module 3 of the guidebook provides more information on the selection of time scale and data attributes for reporting standard incident characteristics.

2.2. Houston's TranStar

This section provides a summary of incident characteristics derived from TranStar's incident data archive from 2004 to 2007. The incident data were imported into MS Excel for data processing and analysis. MS Excel 2007 is preferred to the older versions since the limit on the maximum number of data rows has been increased in the new version.

2.2.1. Temporal Analysis of Incident Frequencies

The researchers examined the trends of incident frequencies on the following time scales:

- incident frequencies by month over the analysis period (2004–2007),
- incident frequencies by year,
- incident frequencies by month,
- incident frequencies by day of week, and
- incident frequencies by time of day.

2.2.1.1. Incident Frequencies by Month over the Analysis Period

This analysis focused on the incident frequencies by month over a period of four years. Figure 2-1 shows the number of incidents per month for major incident types from January 1, 2004, to December 31, 2007. Table 2-2 shows monthly values represented in incident counts.

Table 2-1: Comparison of Incident Data Attributes.

Attributes	Houston	Austin	Fort Worth
Incident Types	Multiple types allowed.	Mutually exclusive. Congestion type is also recorded, mainly from incident detection algorithm.	Multiple types allowed. Accident/Collision type is classified into two subtypes – minor and major.
Detection Method	Mutually exclusive.	Only courtesy patrol and law enforcement are recorded.	Mutually exclusive.
Verification Method	Multiple methods allowed.	Multiple methods allowed.	Multiple methods allowed.
Responders	Responder types are recorded.	Not recorded. Some responder information is available from the comment field.	Responder types and their arrival and departure times are recorded.
Severity	Classified as minor, major, and fatal incidents.	Classified as none, possible injuries, and fatalities.	Classified as none, property damage only (PDO), injuries, and fatalities.
Environmental Conditions	Weather conditions.	Weather, surface, and lighting conditions.	Weather, surface, and lighting conditions.
Vehicles Involved	Number of vehicles involved is recorded. Vehicle types are recoded as incident types (only heavy truck and bus).	Types and number of vehicles involved are recorded.	Number of vehicles involved recorded.
Lane Blockage	Number and types of lanes blocked.	Number and types of lanes blocked.	Number and types of lanes blocked.
Incident Location	Identified by roadway, cross street, direction, location qualifier, and coordinates of cross streets.	Identified by roadway, cross street, direction, location qualifier, and coordinates of cross streets.	Identified by roadway, cross street, direction, location qualifier, and coordinates of cross streets.

The analysis essentially looked at the trends of how incidents evolved over months, seasons, or years, and identified how some major events affected incident occurrences. The scope of the analysis could vary based on the objective of the analysis. For example, instead of a monthly evaluation, the analysis could focus on a smaller timeframe such as a daily evaluation, or target a smaller area of evaluation (e.g., freeway corridor).

A preliminary analysis of the Houston incident data based on monthly incident frequencies yielded the following observations:

- The number of incidents per month, regardless of types, increased from a minimum of 935 in January 2004 to 1,202 in December 2007, with monthly variations that included a maximum of 1,450 incidents in May 2007. While the record shows that the number of incidents has increased, without incorporating the general increase of traffic volume, the analysis is not enough to determine whether the increasing trend is truly reflecting the exacerbating incident problems or is just due to more motorists on the road.
- On average, some 14,212 incidents occur per year (or about 1,184 incidents every month) in TranStar's coverage area. Accident type of incidents consists of 73 percent of all these incidents, followed by stall type at 20 percent on average. The trend varies from one incident type to another. For instance, the number of accidents grew significantly in late 2007, yet occurrence of stalls remained approximately the same. From a monthly trend, a sudden drop in the number of incidents occurred in September 2005, which was attributed to the evacuation that resulted from Hurricane Rita during that month; the peak of the frequency distribution of construction type was observed in March 2005, resulting from massive construction activities during that time.

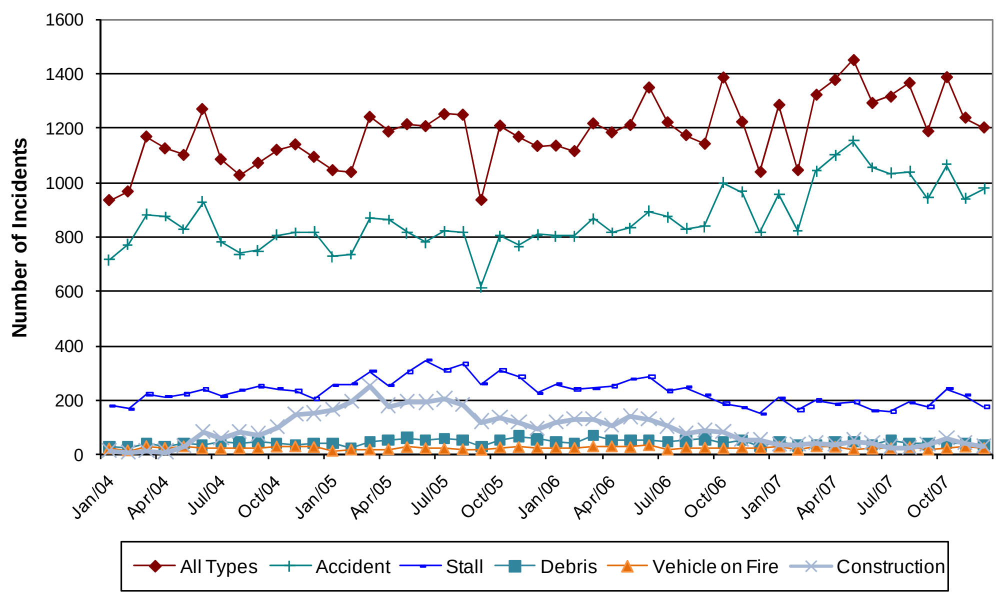


Figure 2-1: Profiles of Monthly Incident Counts from 2004 to 2007 (Houston).

Table 2-2: **Monthly Incident Counts from 2004 to 2007 (Houston).**

Month	All Types	Accident	Stall	Debris	Vehicle on Fire	Construction
Jan-2004	935	716	179	25	21	13
Feb-2004	967	772	168	23	14	7
Mar-2004	1169	883	223	40	30	11
Apr-2004	1125	874	212	25	23	9
May-2004	1101	828	222	38	29	31
Jun-2004	1270	928	239	31	21	83
Jul-2004	1085	782	214	47	20	59
Aug-2004	1027	738	236	42	22	82
Sep-2004	1072	750	251	45	23	73
Oct-2004	1120	807	241	39	28	99
Nov-2004	1140	817	234	32	29	145
Dec-2004	1094	818	206	41	26	150
Jan-2005	1045	728	255	39	12	163
Feb-2005	1038	736	259	22	17	192
Mar-2005	1241	870	305	45	17	251
Apr-2005	1187	863	253	52	18	178
May-2005	1214	815	303	60	26	194
Jun-2005	1207	781	346	53	22	191
Jul-2005	1251	821	309	56	20	202
Aug-2005	1249	818	333	52	18	182
Sep-2005	936	616	259	29	16	120
Oct-2005	1209	804	310	51	25	134
Nov-2005	1168	766	286	66	26	119
Dec-2005	1134	808	226	55	24	94
Jan-2006	1135	802	259	45	24	116
Feb-2006	1115	802	240	41	23	131
Mar-2006	1217	866	243	69	29	128
Apr-2006	1184	816	252	51	29	105
May-2006	1211	832	276	50	26	138
Jun-2006	1349	895	286	52	33	130
Jul-2006	1221	873	235	46	17	103
Aug-2006	1174	830	248	49	25	76
Sep-2006	1142	839	218	55	24	87
Oct-2006	1386	999	188	42	21	83
Nov-2006	1223	965	172	53	25	53
Dec-2006	1039	816	151	27	23	53
Jan-2007	1285	956	208	47	28	36
Feb-2007	1045	824	164	31	16	35
Mar-2007	1322	1041	200	32	29	40
Apr-2007	1377	1099	185	43	27	35
May-2007	1450	1151	194	44	18	50
Jun-2007	1292	1055	160	34	20	42
Jul-2007	1315	1034	158	52	22	26
Aug-2007	1366	1039	190	40	26	25
Sep-2007	1188	942	176	37	17	35
Oct-2007	1387	1065	241	41	22	59
Nov-2007	1238	940	218	37	28	41
Dec-2007	1202	977	176	33	22	28

2.2.1.2. Incident Frequencies by Year

This analysis focused on the incident frequencies by year. Figure 2-2 shows the total number of incidents per year for major incident types from 2004 to 2007. Table 2-3 shows frequency values for all types of incidents, as well as the percentage of each type. Note that some incidents were recorded as multiple types while some were not; the percentage sum, therefore, may not be equal to 100 percent.

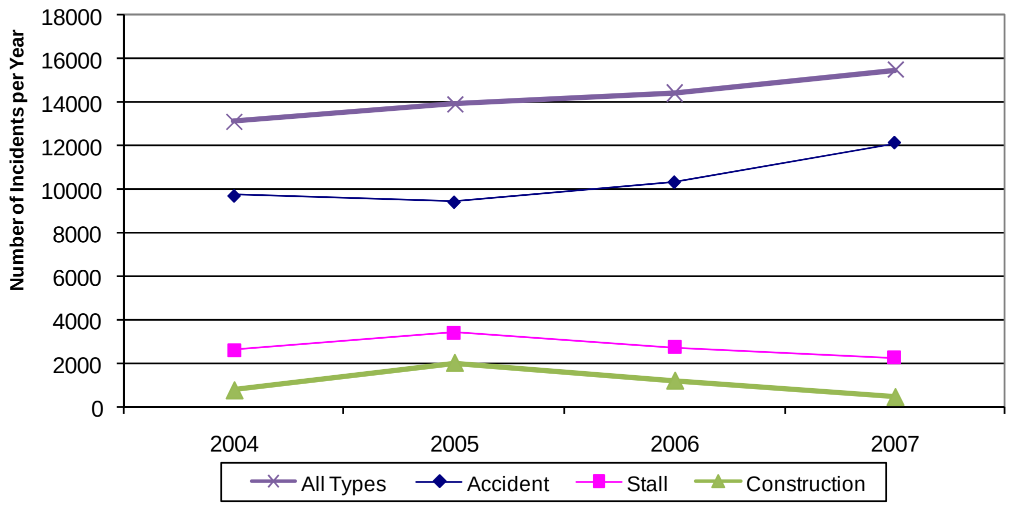


Figure 2-2: Total Number of Incidents per Year (Houston).

Table 2-3: Total Number of Incidents by Year (Houston).

Incident Type	2004	2005	2006	2007	Total	% of Total
Accident	9713	9426	10,335	12,123	41,597	73%
Stall	2625	3444	2768	2270	11,107	20%
Heavy Truck	1293	1560	1590	1534	5977	11%
Construction	762	2020	1203	452	4437	8%
Debris	428	580	580	471	2059	4%
Vehicle on Fire	286	241	299	275	1101	2%
Other	239	261	268	240	1008	2%
High Water	126	97	309	149	681	1%
Bus	150	200	140	78	568	1%
Hazmat	71	71	103	90	335	1%
Lost Load	38	49	59	54	200	0%
Ice	0	0	0	27	27	0%
All Types	13,105	13,879	14,396	15,467	56,847	

A preliminary analysis of the Houston incident data based on yearly incident frequencies yielded the following observations:

- The number of accidents increased over the four-year period.

- The number of stall and construction-related incidents decreased from the 2005 levels.

2.2.1.3. Incident Frequencies by Month

This analysis focused on incident frequencies by month. Instead of examining incident frequencies month by month over the analysis period, researchers averaged the incident counts from the same month each year over the four-year period to determine the impact of different months on incident occurrences. Figure 2-3 shows the average number of incidents per month for major incident types. Table 2-4 shows monthly average values for all types of incidents.

A preliminary analysis of the Houston incident data based on monthly incident frequencies yielded the following observations:

- The monthly average incident counts for the four major types of incidents are plotted in Figure 2-3. The monthly trends were somewhat stable throughout the year except for the first two months regardless of incident types. The drop in September was a result of Hurricane Rita's evacuation that took place in 2005.
- Among the less common incident types, on average, 41 high water incidents were recorded in June, in contrast to 12 such incidents on average from all other months. Also, ice-related incidents were reported only in the month of January. Nevertheless, trends established by a small sample size are not necessarily accurate. As a rule of thumb, a sample size with at least 30 observations for each category is desirable in order to provide a good estimate of the actual trends.

2.2.1.4. Incident Frequencies by Day of Week

This analysis focused on incident frequencies by day of week. It included incidents that occurred on both weekdays and weekends. The incident counts from the same day of the week were averaged over the analysis period. The incident rates per 1,000 hours were calculated so that the results could be compared to the analysis with different time scales. Figure 2-4 shows the average number of incidents by day of week for selected types. Table 2-5 shows the corresponding values by day of week for all types of incidents.

The following observations were made from examining the incident frequencies by day of week:

- On average, the number of incidents per 1,000 hours regardless of incident types (or all types) started to increase slightly from Monday, with 1,843 incidents, and reached a maximum of 2,034 incidents on Friday. The rates were significantly lower during the weekends, when about 815 incidents were observed per 1,000 hours. In other words, on average there were 2 and 0.8 incidents per hour during weekdays and weekends, respectively. Incident occurrence was 2.5 times more likely on the weekdays than the weekends.

- Incident frequencies by day of week share similar trends regardless of incident types. This could be attributed to the lower traffic volume during the weekends, thus reducing the incident occurrence rates.

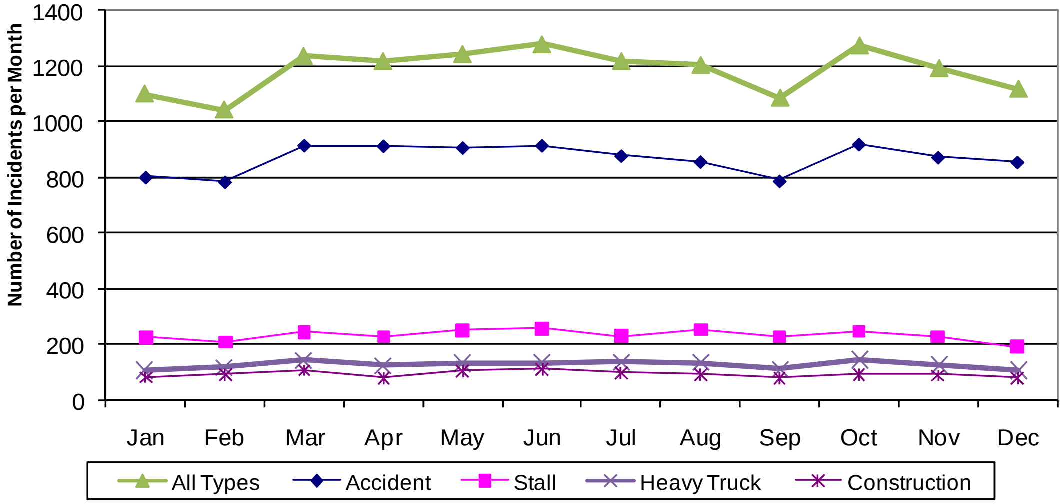


Figure 2-3: Average Number of Incidents per Month (Houston).

Table 2-4: Average Number of Incidents per Month by Types (Houston).

Incident Type	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Accident	801	784	915	913	907	915	878	856	787	919	872	855
Stall	225	208	243	226	249	258	229	252	226	245	228	190
Heavy Truck	105	115	142	122	130	133	135	133	108	145	123	104
Construction	82	91	108	82	103	112	98	91	79	94	90	81
Debris	39	29	47	43	48	43	50	46	42	43	47	39
Vehicle on Fire	21	18	26	24	25	24	20	23	20	24	27	24
Other	16	14	19	26	21	21	27	24	22	22	22	20
Bus	10	12	13	17	11	13	8	11	13	11	13	11
Ice	7	0	0	0	0	0	0	0	0	0	0	0
Hazmat	6	6	7	9	7	6	8	9	5	9	8	4
Lost Load	5	5	2	5	4	5	6	7	4	4	3	3
High Water	4	4	4	7	12	41	27	16	5	36	10	7
All Types	**1100**	**1041**	**1237**	**1218**	**1244**	**1280**	**1218**	**1204**	**1085**	**1276**	**1192**	**1117**

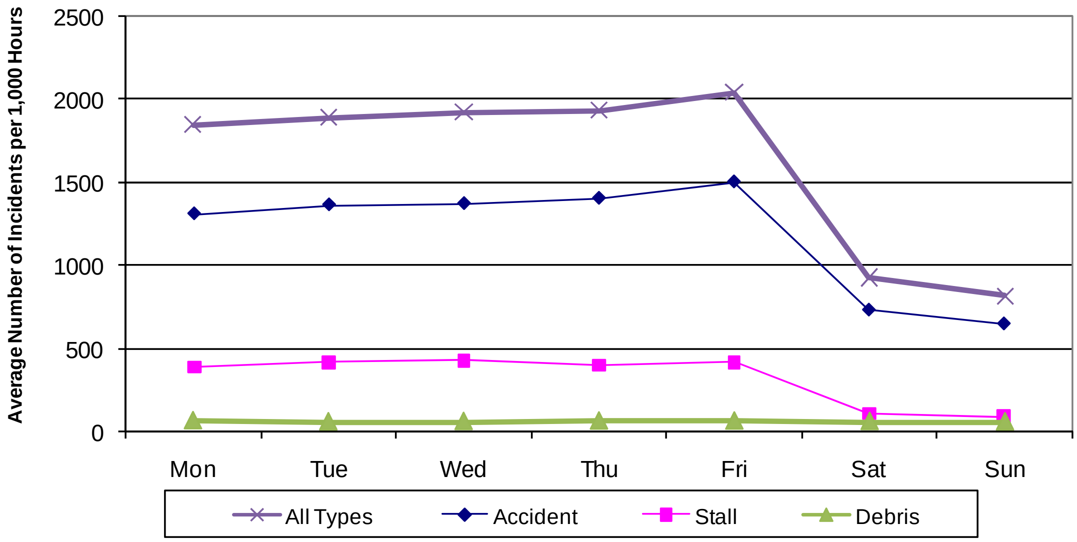


Figure 2-4: Average Number of Incidents by Day of Week (Houston).

Table 2-5: Number of Incidents per 1,000 Hours by Day of Week (Houston).

Incident Type	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Accident	1307	1361	1368	1400	1498	728	645
Stall	386	412	425	394	410	105	86
Heavy Truck	209	225	227	216	237	52	29
Debris	63	56	58	61	60	58	56
High Water	42	13	22	23	17	12	7
Vehicle on Fire	35	36	33	38	37	21	20
Other	32	32	29	38	34	17	20
Bus	23	20	23	25	16	3	3
Hazmat	11	11	10	12	13	7	3
Lost Load	7	5	8	7	9	3	1
Ice	0	1	4	0	0	0	0
Construction	157	169	163	162	158	45	32
All Types	1843	1887	1917	1930	2034	925	815

Note: From Jan 1, 2004, to Dec 31, 2007, there were 209 days for Monday, Thursday, Friday, Saturday, and Sunday and 208 days for Tuesday and Wednesday.

2.2.1.5. Incident Frequencies by Time of Day

This analysis focused on the incident frequencies by time of day. The researchers divided weekdays into four periods: AM peak (6 AM to 9 AM), midday (9 AM to 4 PM), PM peak (4 PM to 7 PM), and night hours (7 PM to 6 AM). The weekend analysis combined all 24 hours per day into one period. Figure 2-5 shows the average number of incidents per 1,000 hours for each of these time periods. Table 2-6 shows the corresponding average incident rates per 1,000 hours.

An analysis of the Houston incident frequencies by time of day yielded the following observations:

- PM peak on average experienced the highest rate of incident occurrence. There were 4,254 incidents that occurred every 1,000 hours of PM peak, which is equivalent to approximately 4.2 incidents per hour. Of these incidents, 3,026 incidents every 1,000 hours were accidents (3 accidents per hour), and 1,038 incidents were stalls (1 stall per hour).
- Nighttime period on average had the lowest incident occurrence rate at 0.6 incidents per hour.
- When examining specific types of incident by time of day, 37 percent of accidents occurred during PM peak, 28 percent during AM peak, and 21 percent during midday hours. Higher percentages of stall incidents (41.9 percent) occurred during PM peak, which could be attributed to the increase in likelihood of vehicle breakdowns in hot weather conditions. Incidents that involved vehicles on fire were found to be more frequent during PM peak period as well.

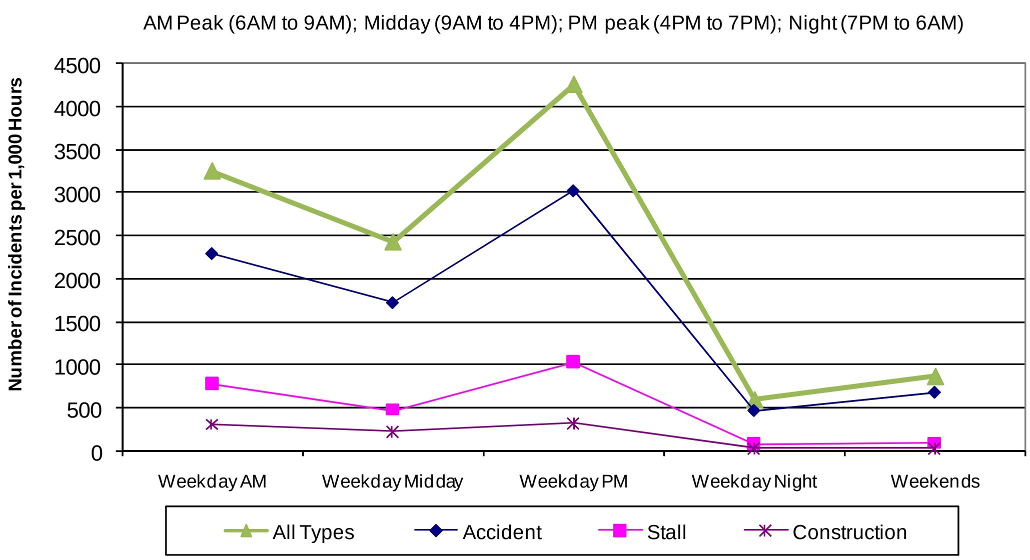


Figure 2-5: Incident Rates by Time of Day (Houston).

2.2.2. Characterizing Incident Data Attributes

Using TranStar's incident database, the researchers produced frequency distributions for the following data attributes:

- incident types,
- detection methods,
- verification methods,
- incident responders,
- incident severity,

- weather conditions,
- number of mainlanes blocked, and
- number of vehicles involved.

Appendix B documents all the distribution results (see Figure B-1 to Figure B-13). Bar charts represent the distribution trends graphically. Single bar charts as shown in Figure 2-6 were used when the attributes are mutually exclusive (i.e., only one category per incident record).

Table 2-6: Number of Incidents per 1,000 Hours by Time of Day (Houston).

Incident Type	Weekday AM Peak	Weekday Midday	Weekday PM Peak	Weekday Night	Weekends
Accident	2296	1727	3026	475	686
Stall	777	481	1038	84	95
Heavy Truck	303	377	429	46	40
Construction	312	226	324	36	38
Debris	65	109	106	14	57
Other	41	53	50	14	18
Vehicle on Fire	43	48	67	18	21
High Water	45	32	27	11	9
Hazmat	15	18	14	5	5
Bus	56	15	62	5	3
Lost Load	9	14	7	2	2
Ice	3	0	0	1	0
All Types	**3251**	**2429**	**4254**	**601**	**870**

Note: From January 1, 2004, to December 31, 2007, there were 1,043 weekdays and 418 weekends.

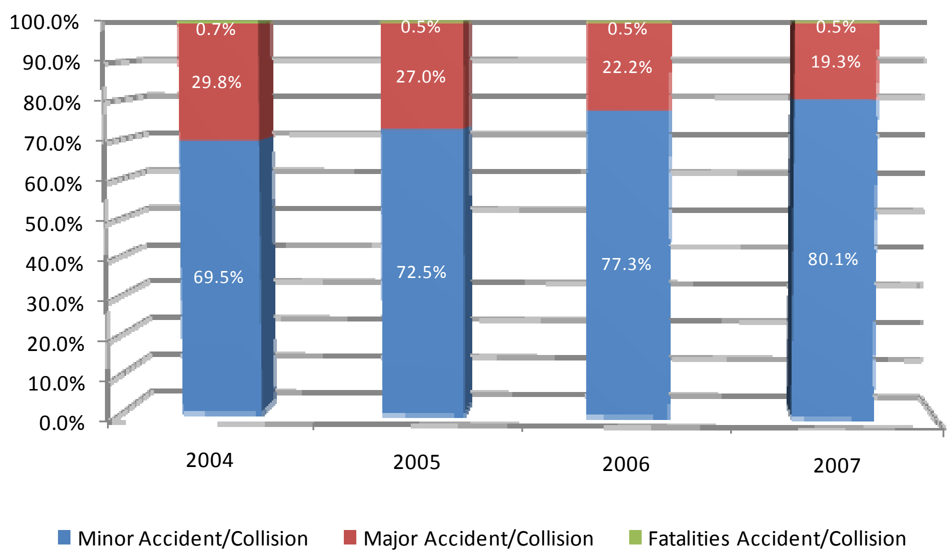


Figure 2-6: Distribution of Incident Severity (Houston).

The examination of frequency distributions of incident data attributes yielded the following observations:

- Based on four-year incident data, the most common type of incident recorded was accident (73 percent). Stall incident was the second most common type, with 20 percent of all incidents recorded.
- At TranStar, the majority of incidents were detected (>80 percent) and verified (>90 percent) by closed-circuit television (CCTV) surveillance. The percentage of CCTV detection decreased year after year with a consistent increase of incidents detected by police.
- TranStar classified incident severity into three levels – minor, major, or fatal incidents. The percents of minor incidents increased from 70 percent in 2004 to 80 percent in 2007. On the other hand, the major incidents decreased from 30 percent to 19 percent during the same timeframe. This may indicate successful TMC operations in reducing the frequency of major incidents. The rates of fatalities (0.5 percent) stayed roughly the same during the analysis period.
- The top four major responders in descending order were wrecker, city police, emergency medical service (EMS), and fire department. The corresponding percentages based on 2007 data were 73 percent, 64 percent, 26 percent, and 16 percent, respectively. Note that multiple responders could respond to a single incident, so the percent sum of all responders in a year could exceed 100 percent.
- Approximately 80 percent of all incidents were equally split between out-of-mainlane or one mainlane blocked. Incidents blocking all mainlanes represent roughly 3 percent of all incidents. Lane blockage characteristics were basically unchanged when compared on a yearly basis.
- Approximately 10 percent of all incidents had weather conditions recorded, and almost all of those conditions were rain-related. This gives some indication on what types of weather events were frequently associated with incidents observed at TranStar. Fog, high wind, and snow/ice conditions were also recorded but represented a very minor proportion of all weather conditions associated with incidents.
- The majority of incidents (75 percent) recorded at TranStar involved either one or two vehicles. Two-vehicle incidents were the most common type, representing 49 percent of the incident data in 2007. Approximately 3 percent had four or more vehicles involved in an incident. The trend in the number of vehicles involved in an incident did not change significantly from one year to the next. Non-vehicle-related incidents were usually related to events such as high water and road debris.

Table 2-7 presents the incident type distributions broken down by year at TranStar. The percentages of each incident type were basically unchanged year after year, except for the noticeable increase in construction-related incidents in 2005. This could be due to significant construction activities during that year.

Table 2-7: Distribution of Incidents by Type (Houston).

Incident Type	2004		2005		2006		2007		Total	% of Total
Accident	9713	(74.1%)	9426	(67.9%)	10335	(71.8%)	12123	(78.4%)	41597	73.2%
Stall	2625	(20.0%)	3444	(24.8%)	2768	(19.2%)	2270	(14.7%)	11107	19.5%
Heavy Truck	1293	(9.9%)	1560	(11.2%)	1590	(11.0%)	1534	(9.9%)	5977	10.5%
Construction	762	(5.8%)	2020	(14.6%)	1203	(8.4%)	452	(2.9%)	4437	7.8%
Debris	428	(3.3%)	580	(4.2%)	580	(4.0%)	471	(3.0%)	2059	3.6%
Vehicle on Fire	286	(2.2%)	241	(1.7%)	299	(2.1%)	275	(1.8%)	1101	1.9%
Other	239	(1.8%)	261	(1.9%)	268	(1.9%)	240	(1.6%)	1008	1.8%
High Water	126	(1.0%)	97	(0.7%)	309	(2.1%)	149	(1.0%)	681	1.2%
Bus	150	(1.1%)	200	(1.4%)	140	(1.0%)	78	(0.5%)	568	1.0%
HAZMAT	71	(0.5%)	71	(0.5%)	103	(0.7%)	90	(0.6%)	335	0.6%
Lost Load	38	(0.3%)	49	(0.4%)	59	(0.4%)	54	(0.3%)	200	0.4%
Ice	0	(0.0%)	0	(0.0%)	0	(0.0%)	27	(0.2%)	27	0.0%
All Types	*13105*		*13879*		*14396*		*15467*		*56847*	

* Note: Percent sum in a year exceeds 100% because multiple types can be recorded per incident.

Overall, all the incident data attributes collected at TranStar appear to be sufficient and valid for subsequent analysis. There are no unusual patterns of erroneous or missing data or any causes for concern that would prevent researchers from using specific data attributes in this study.

2.2.3. Incident Duration Statistics

This section focuses on researchers' examination of incident durations computed from archived incident data. Statistics on incident durations can be used for various purposes, such as operations planning and long-term monitoring. Incident durations are derived from incident event time logs by computing the difference between incident detection and clearance times.

An empirical observation of incident duration data indicates that extreme duration values tend to result in heavily skewed empirical distributions. The calculation of average duration from these data must be handled by the use of appropriate statistics to avoid the impacts from these extreme duration values. Upper extremes (very long duration) are occasionally attributed to unmonitored or neglected situations where operators close 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 guidebook recommends the use of percentile statistics, such as median, 85^{th}, and 95^{th} percentile of incident duration, to represent the average and the range of duration data instead of the arithmetic mean and minimum/maximum values.

The researchers examined the following duration statistics from the database:

- overall duration statistics (median, 85^{th}, and 95^{th} percentiles);
- duration statistics by incident severity (median, 85^{th}, and 95^{th} percentiles); and
- duration by incident types (median, 85^{th}, and 95^{th} percentiles).

Figure 2-7 shows the empirical distributions of incident duration data from 2004 to 2007 at TranStar. The data were classified by incident severity recorded in the database. In addition, the bottom right figure shows the distribution of duration when all duration data are combined. Incident durations larger than 300 minutes are not shown graphically to improve the visual of these graphs. Less than 1 percent of all duration data were longer than 300 minutes.

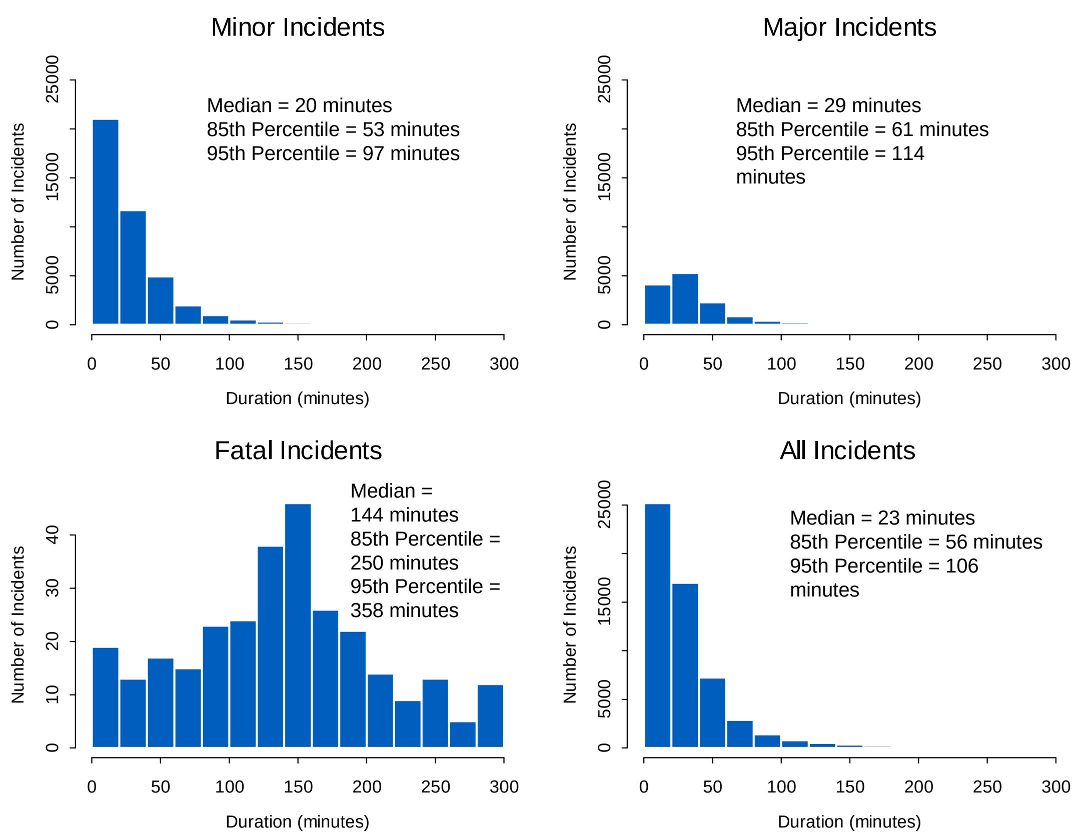


Figure 2-7: Distributions of Incident Durations by Severity (Houston).

Note that 95 percent of all incident durations at TranStar fell between 2 and 161 minutes. From these figures, it is obvious that incident durations do not follow the normal distribution and their distribution shapes are heavily asymmetric.

The median incident durations indicate that a minor incident typically lasted approximately 20 minutes on average, while a major incident lasted 9 minutes more on average. There was a significant increase in average duration for fatal incidents, where the median duration was about 144 minutes. Fatal incidents usually lasted much longer than the others because they often involved a lengthy police investigation process.

The differences between 95th percentile and median durations indicate the degree to which the incident durations vary in each category. Table 2-8 summarizes the variation in the duration data calculated from Houston's incident database. The table shows that more severe incidents were likely to have more variation in the observed durations. This implies that using average statistics alone to estimate incident durations may not give satisfactory results, given such a large variation observed from the duration data. Also, it is important to note that the differences observed between minor and major incidents were minimal. This may also indicate that the decision factors used by the operators to distinguish between minor and major incidents were not as clear as the ones used to flag fatal incidents.

Table 2-8: Differences between 95th Percentile and Median Durations.

Category	Deviation from Median (minutes)
All Incidents	83
Minor Incidents	77
Major Incidents	85
Fatal Incidents	214

Another piece of useful information that researchers can derive from the incident database is the statistics on incident duration by types. It is suggested that three values be calculated for each type of incident 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 could be viewed as an extreme case of an incident. This implies that the chance of incident duration exceeding this threshold is only 5 percent, at most.

Figure 2-8 shows median, 85th percentile, and 95th percentile incident durations by types at TranStar using four-year data, from 2004 to 2007. High water and hazardous material spill were the top two types of incidents with the longest incident durations. Stall, or disablement, on the other hand, was the type with the shortest incident durations.

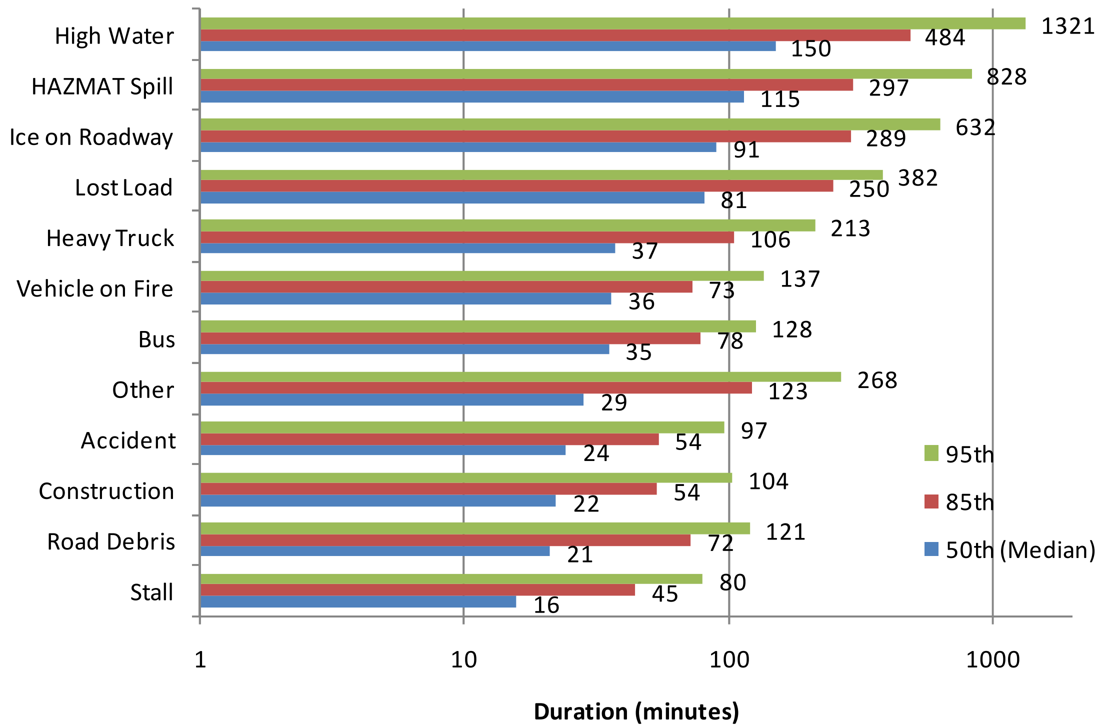


Figure 2-8: Incident Duration Percentile Statistics (Houston 2004–2007).

Table 2-9 summarizes the percentile statistics of incident durations by incident types based on Houston incident data from 2004 to 2007. Regardless of incident frequencies, the high water and hazardous material incidents were the top two types, with the highest median incident durations at 150 and 115 minutes, respectively. Stall incidents had the shortest median duration on average.

Among those incident types that accounted for at least 2 percent of all incidents, truck-related incidents were the ones with the highest median duration at 37 minutes and the 95th percentile duration at 213 minutes.

When broken down annually, as shown in Table 2-10, the median and 85th percentile durations were basically unchanged for all types except the high water, hazardous materials, and ice-related incidents, in which the year-to-year variability was significant. This is likely attributed to the randomness and rarity of the incident types themselves. Note that the variability in these statistics is negatively correlated with the number of incidents observed for each incident type (i.e., larger sample size is equal to lower variability).

Table 2-9: Incident Duration Statistics by Incident Types (Houston).

Type	Total Counts	%	Duration Percentile (minutes)				
			5%	15%	50%	85%	95%
Accident	41597	73.2%	3	7	24	54	97
Stall	11107	19.5%	2	4	16	45	80
Heavy Truck	5977	10.5%	4	12	37	106	213
Construction	4437	7.8%	3	7	22	54	104
Road Debris	2059	3.6%	2	5	21	72	121
Vehicle on Fire	1101	1.9%	7	16	36	73	137
Other	1008	1.8%	3	7	29	123	268
High Water	681	1.2%	16	38	150	484	1321
Bus	568	1.0%	5	12	35	78	128
HAZMAT Spill	335	0.6%	10	37	115	297	828
Lost Load	200	0.4%	4	15	81	250	382
Ice on Roadway	27	0.0%	30	35	91	289	632
All Types	*56847*		*2*	*7*	*23*	*56*	*106*

Table 2-10: Annual Comparison of Incident Durations by Types (Houston).

(a) Median Duration (minutes)

Incident Types	2004	2005	2006	2007	2004 - 2007
High water	72	94	239	148	150
HAZMAT	124	102	137	114	115
Ice	NA	NA	NA	90	90
Lost load	111	57	83	77	81
Heavy truck	39	36	37	38	37
Vehicle on fire	34	34	38	38	36
Bus	34	34	37	33	35
Other	25	27	28	35	28
Accident	25	24	25	24	24
Construction	23	21	23	25	22
Debris	17	20	24	23	21
Stall	16	16	16	15	16

(b) 85th Percentile Duration (minutes)

Incident Types	2004	2005	2006	2007	2004 - 2007
High water	270	203	834	350	484
HAZMAT	424	260	344	238	297
Ice	NA	NA	NA	289	289
Lost load	233	247	340	212	250
Other	110	119	120	134	123
Heavy truck	110	98	112	104	106
Bus	75	89	77	70	78
Vehicle on fire	69	73	72	73	73
Debris	65	67	78	70	72
Accident	56	53	55	54	54
Construction	59	50	57	53	54
Stall	47	45	44	42	45

2.3. Austin's CTECC

This section provides a summary of incident characteristics derived from Austin CTECC's incident database. Researchers used the incident data records from 2004 to 2007 in this analysis.

2.3.1. Temporal Analysis of Incident Frequencies

As seen in Table 2-11, congestion incidents represented 87 percent of all incidents archived in the database from 2004 to 2007. In 2007 alone, they represented 91 percent of all incidents. Most congestion incidents are automatically recorded by an incident detection algorithm at CTECC. The incident detection algorithm continuously monitors the detector occupancy and registers incident alarms once certain criteria are met. Each congestion record is therefore associated with specific detectors in the database. To avoid the overrepresentation of the congestion type in the analysis, the researchers separated congestion incidents from the database and re-classified all the remaining types of incidents as non-congestion incidents for the analysis purpose.

Table 2-11: Yearly Distribution of Incident Counts by Types (Austin).

Incident Type	2004	2005	2006	2007	Total	% of Total
Abandonment	86	274	186	367	913	2%
Collision	275	564	569	739	2147	4%
Congestion	4422	9265	10115	24777	48579	87%
HAZMAT Spill	4	7	17	61	89	0%
Overturned	10	23	38	42	113	0%
Public Emergency	4	14	19	18	55	0%
Road Debris	18	78	44	110	250	0%
Stall	289	1241	1052	1307	3889	7%
Vehicle on Fire	7	17	23	28	75	0%
Total	5115	11483	12063	27449		

Researchers took a closer look at the distribution of incident types among non-congestion incidents from 2007 (most recent year with complete data). Figure 2-9 shows that stall, collision, and abandonment represented 92 percent of all non-congestion incidents recorded in the database in 2007. Apart from congestion, stall incidents were the most frequent type of incidents reported at CTECC, followed by collision and abandonment.

The researchers then analyzed the frequencies of non-congestion incidents over the following time scales:

- incident frequencies by month over the analysis period (2004–2007),
- incident frequencies by year,
- incident frequencies by month,
- incident frequencies by day of week, and
- incident frequencies by time of day.

Subsequent sections summarize the results and findings from the analysis.

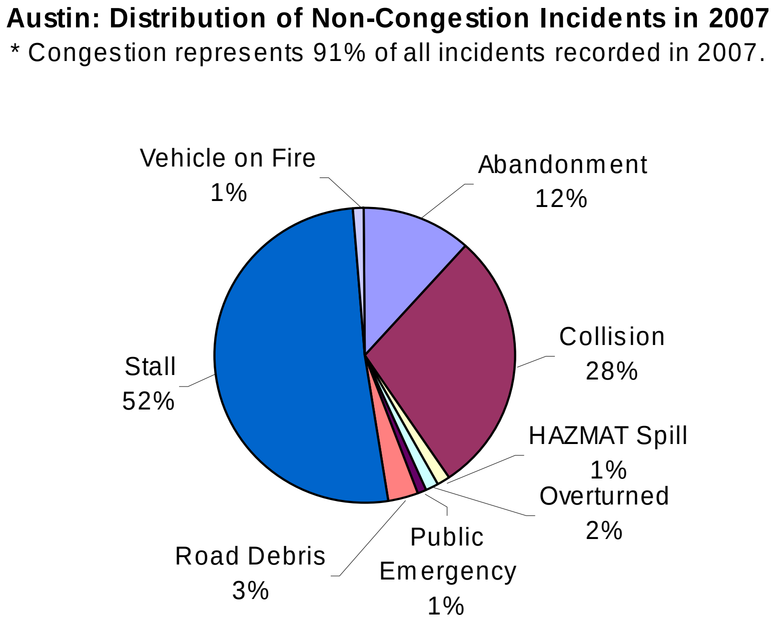


Figure 2-9: Distribution of Reported Non-Congestion Incidents in 2007.

2.3.1.1. Incident Frequencies by Month over the Analysis Period

CTECC's operating hours were from 6 AM to 10 PM prior to May 2006. Since then, the operation has changed to 24 hours a day and 7 days a week. Table 2-12 shows the total number of incidents recorded in the database month by month, which are normalized by the corresponding number of operating hours in a particular month. In this case, researchers calculated incident rates using 1,000 operating hours as a basis. The incident frequencies shown in Figure 2-10 were also normalized in a similar manner. This figure displays the rates of incident occurrence over time for all non-congestion types as well as selected major types of incidents recorded at Austin's CTECC.

Stall and abandonment were the two types of incidents that occurred more frequently during the summer months. This was likely due to the increase of likelihood of vehicle breakdowns during hot weather conditions. Collision type was basically unchanged over the analysis period. Since stall and abandonment represented a significant percentage of all non-congestion incident types, the overall trend of incident rates of all non-congestion incidents, therefore, tended to follow the patterns of stall and abandonment.

From the data, the incident rate peaked at 0.7 incidents per hour in June 2005 when combining all non-congestion incidents. The collision occurrence rates ranged from 0.01 to 0.14 incidents per hour over the analysis period.

Table 2-12: Monthly Incidents per 1,000 Hours over the Analysis Period (Austin).

Month–Year	All Non-Congestion	Collision	Stall	Abandonment	Road Debris
Jan-2004	50	26	16	2	2
Feb-2004	45	15	19	6	2
Mar-2004	65	40	16	4	2
Apr-2004	102	38	38	19	2
May-2004	65	24	30	6	4
Jun-2004	115	38	58	19	0
Jul-2004	161	30	79	44	0
Aug-2004	119	38	56	24	0
Sep-2004	110	50	40	10	4
Oct-2004	206	83	105	10	6
Nov-2004	171	79	79	8	2
Dec-2004	14	8	6	0	0
Jan-2005	117	38	65	10	0
Feb-2005	167	65	89	7	2
Mar-2005	306	85	171	38	4
Apr-2005	271	106	140	15	4
May-2005	669	139	401	81	42
Jun-2005	688	131	381	133	35
Jul-2005	585	77	379	97	14
Aug-2005	448	85	290	48	12
Sep-2005	269	63	173	19	2
Oct-2005	298	111	153	14	10
Nov-2005	225	96	100	13	4
Dec-2005	214	105	77	22	4
Jan-2006	151	63	79	2	6
Feb-2006	150	58	71	0	9
Mar-2006	216	83	107	10	4
Apr-2006	298	94	171	17	4
May-2006	285	59	198	19	4
Jun-2006	293	71	167	35	8
Jul-2006	202	42	122	20	3
Aug-2006	198	47	117	22	1
Sep-2006	235	85	113	31	1
Oct-2006	234	69	118	34	5
Nov-2006	211	67	108	26	0
Dec-2006	231	75	106	26	12
Jan-2007	204	94	82	19	4
Feb-2007	164	67	74	18	1
Mar-2007	203	73	95	24	4
Apr-2007	218	60	118	26	6
May-2007	219	74	108	24	9
Jun-2007	314	74	181	44	10
Jul-2007	250	70	129	35	11
Aug-2007	277	69	144	48	15
Sep-2007	149	33	82	13	13
Oct-2007	181	48	103	22	4
Nov-2007	206	58	103	29	7
Dec-2007	214	46	126	35	1

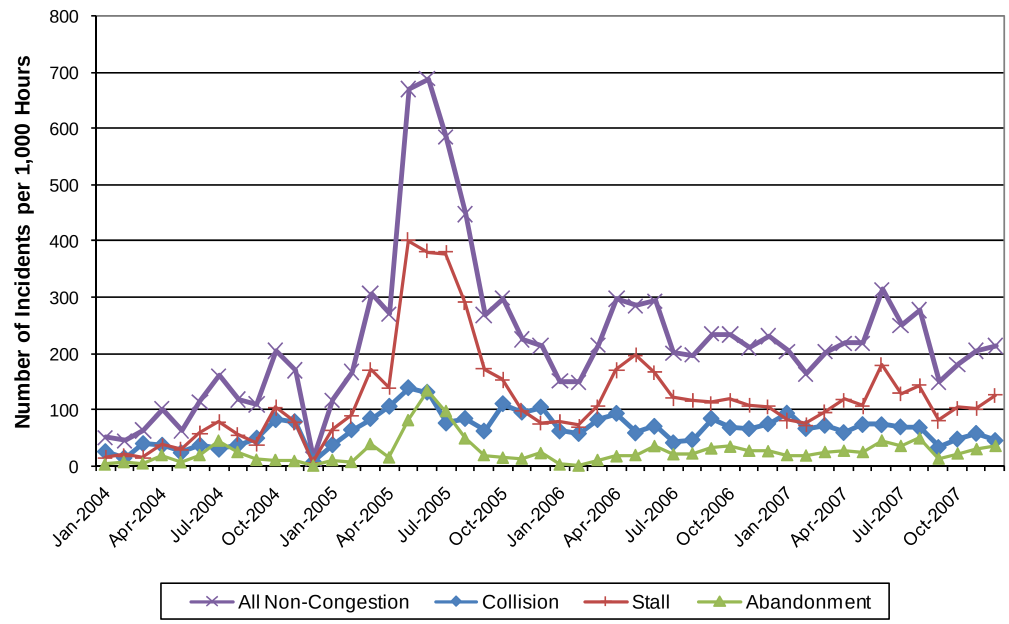


Figure 2-10: Monthly Incident Rates over the Analysis Period (Austin).

2.3.1.2. Incident Frequencies by Year

Figure 2-11 displays the trend of total number of incidents per year from 2004 to 2007. Table 2-13 shows the corresponding incident frequencies by year for all non-congestion incident types.

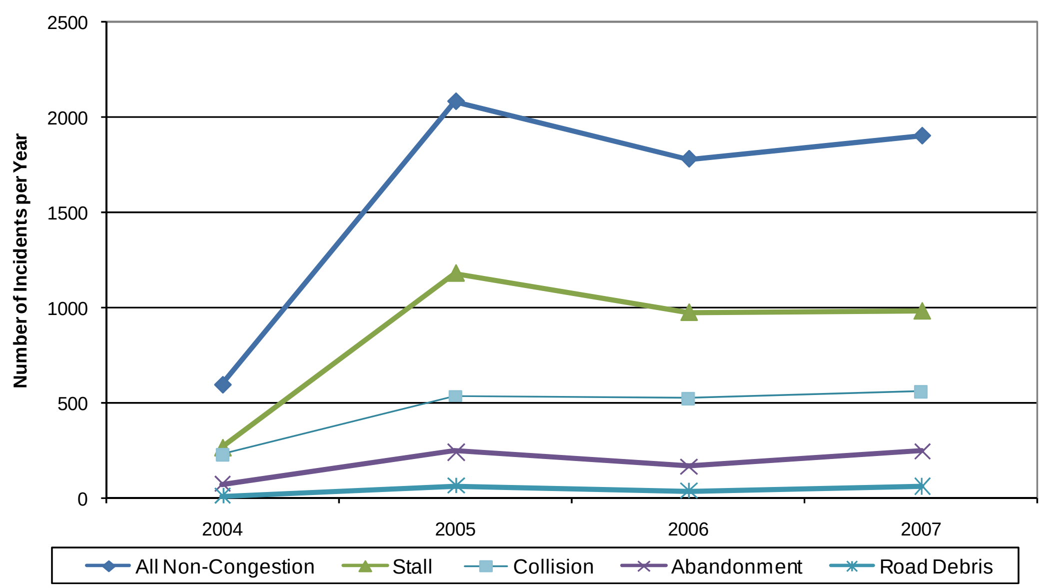


Figure 2-11: Profiles of Total Number of Incidents per Year (Austin).

Table 2-13: Total Number of Incidents per Year (Austin).

Incident Type	2004	2005	2006	2007	Total per Type	% of Total
Stall	265	1183	977	984	3409	54%
Collision	229	536	520	559	1844	29%
Abandonment	75	243	169	247	734	12%
Road Debris	12	66	37	62	177	3%
Overturned	4	21	35	33	93	1%
Public Emergency	3	12	17	8	40	1%
Vehicle on Fire	7	14	15	2	38	1%
Hazmat	2	5	9	5	21	0%
All Non-Congestion	**597**	**2080**	**1779**	**1900**	**6356**	**100%**

The significant increase in incident rates since 2005 was likely attributed to the increase in surveillance coverage. Stall incidents were still the most common type of incidents recorded in the database when broken down on an annual basis. With the exception of 2004, the annual incident rates were somewhat stable year after year for all types of non-congestion incidents.

2.3.1.3. Incident Frequencies by Month

To examine the effect of seasonality on incident occurrences, the researchers examined the monthly distributions of incidents broken down by types over the four-year period (2004–2007), as shown in Table 2-14. The trend from month to month in terms of percent of total incidents recorded was more or less the same throughout the year when the congestion incidents were included. The trend became more pronounced when congestion incidents were removed because it was previously masked by the excessive number of congestion incidents recorded by the incident detection algorithm.

To further analyze the trends on specific types, Figure 2-12 shows the monthly distributions of the three most common types of non-congestion incidents, which are collision, abandonment, and stall. Abandonment and stall incidents were found to rise during summer months, and their percentages are higher than the benchmark averages from all non-congestion incidents. Collision incidents, on the other hand, were more or less the same throughout the year, which is partly attributed to the randomness of crash occurrences.

Table 2-14: Monthly Distribution of Incidents in Austin (2004–2007).

Incident Type	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Abandonment	25	25	49	54	104	154	136	106	69	66	57	68
Collision	169	122	174	184	220	205	157	179	162	206	188	181
Congestion	3333	3251	3943	4228	4019	3922	3916	4048	3803	5058	4899	4159
HAZMAT Spill	1	6	7	5	7	8	5	7	3	23	11	6
Overturned	6	8	3	7	6	10	18	11	16	5	13	10
Public Emergency	6	3	8	3	3	4	4	5	5	4	5	5
Road Debris	11	9	9	13	38	36	22	36	16	22	17	21
Stall	163	148	241	286	497	503	476	424	278	335	277	261
Vehicle on Fire	4	4	8	6	4	2	11	5	7	9	10	5
Total	3718	3576	4442	4786	4898	4844	4745	4821	4359	5728	5477	4716
All Incidents	7%	6%	8%	9%	9%	9%	8%	9%	8%	10%	10%	8%
All Non-Congestion	5%	4%	7%	7%	12%	12%	11%	10%	7%	9%	8%	7%

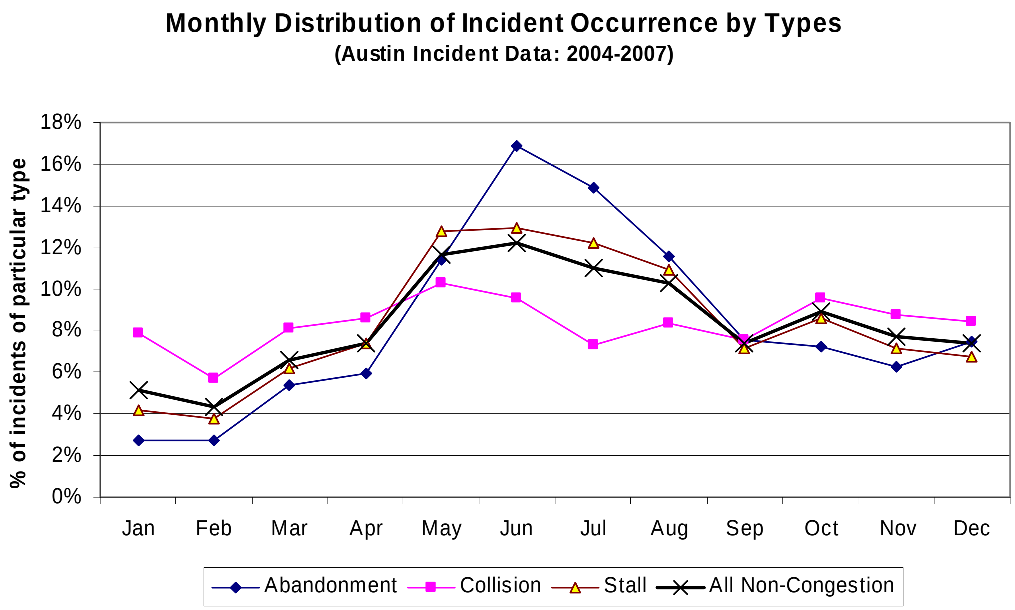


Figure 2-12: Monthly Distribution of Incidents for Selected Types (Austin).

2.3.1.4. Incident Frequencies by Day of Week

Figure 2-13 shows the average number of incidents observed per 1,000 hours by day of week. Researchers plotted the graphs for major types of incidents reported in the database. Table 2-15 shows the corresponding values of the plots in Figure 2-13, as well as the values for other non-congestion incident types. Incident rates were much higher during the weekdays than the weekends. Among the weekdays, Thursdays were the days with the highest rate of non-congestion incidents, at 249 incidents per 1,000 hours or approximately 1 in every 4 hours. For comparison, the same incident rates on the weekends were approximately 1 in every 18 hours.

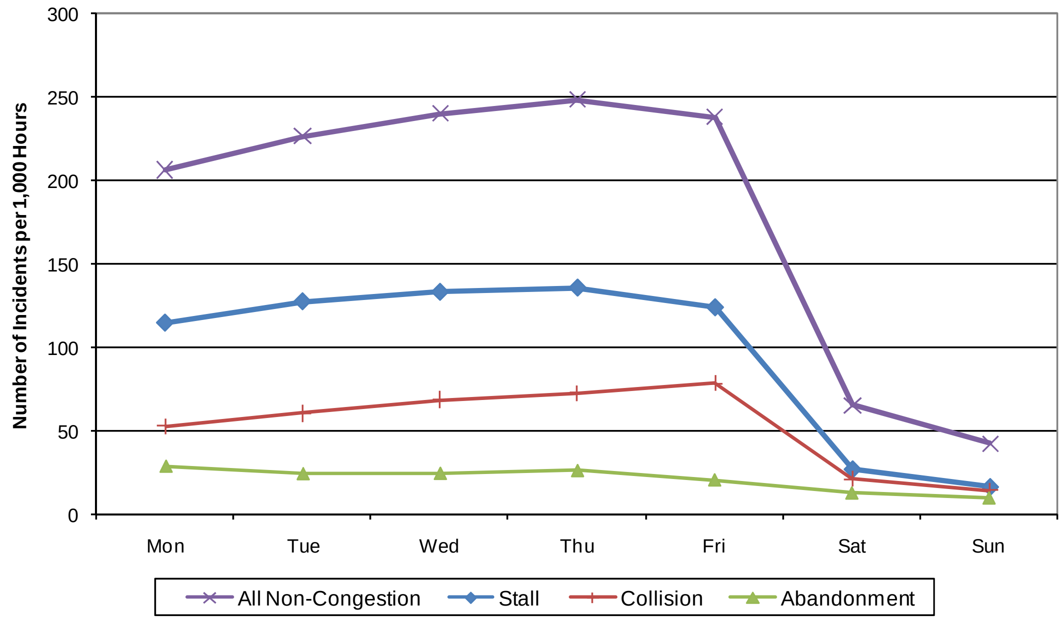


Figure 2-13: Profiles of Average Number of Incidents by Day of Week (Austin).

Table 2-15: Average Number of Incidents by Day of Week (Austin).

Incident Type	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Stall	115	128	133	136	124	28	17
Collision	53	60	69	73	78	21	14
Abandonment	29	24	24	26	21	13	10
Road Debris	6	7	7	7	6	2	0
Vehicle on Fire	2	1	2	1	1	0	0
Hazmat	1	1	0	1	1	0	0
Overturned	1	3	3	3	5	1	2
Public Emergency	1	2	1	1	2	1	0
All Non-Congestion	**207**	**227**	**240**	**249**	**238**	**66**	**43**

Note: From January 1, 2004, to December 31, 2007, there were 209 days for Mondays, Thursdays, Fridays, Saturdays, and Sundays and 208 days for Tuesdays and Wednesdays.

2.3.1.5. Incident Frequencies by Time of Day

Figure 2-14 shows the average number of incidents observed per 1,000 hours by time of day for selected types of incidents. Researchers categorized weekdays into four time periods, AM peak (6 AM to 9 AM), midday (9 AM to 4 PM), PM peak (4 PM to 7 PM), and night (7 PM to 6 AM). Weekend refers to the entire 48-hour period (Saturday and Sunday). Then, researchers used the corresponding number of hours for each time period to normalize the incidents observed in each period. Table 2-16 shows the average number of incidents by time of day for all non-congestion incident types.

Weekday PM peak was the time period with the highest rates of stall and collision occurrence. The higher stall incidents could be due to a combination of high traffic volume and warmer weather conditions during the PM peak period. Weekend was the time period with the lowest incident occurrence rates. Furthermore, the non-congestion incident rate during the weekday PM peak was roughly 10 times higher than during the weekend period.

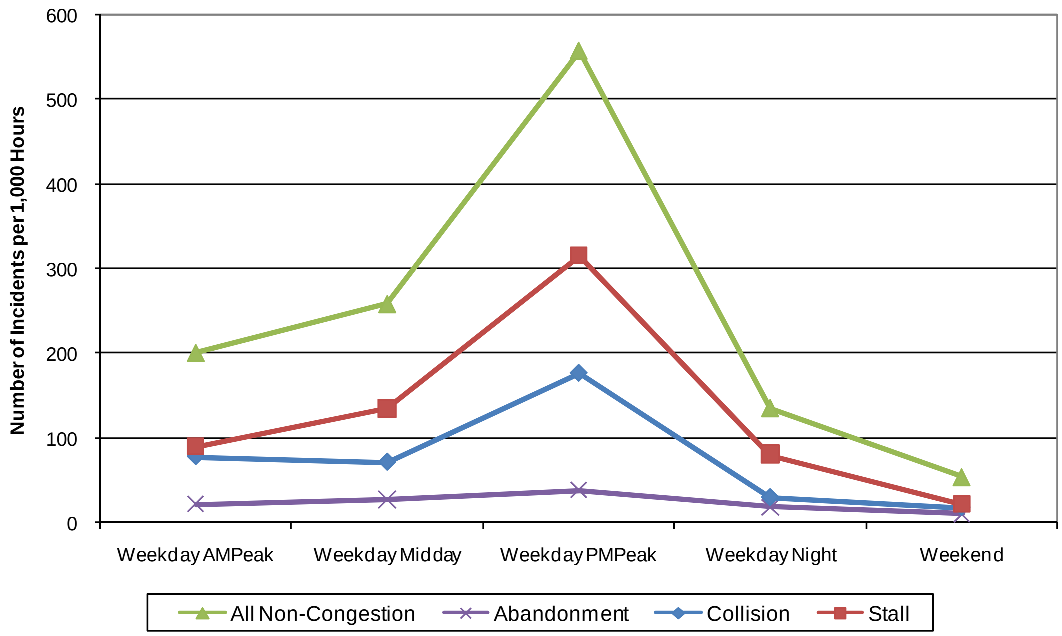


Figure 2-14: Profiles of Incident Rates by Time of Day (Austin).

Table 2-16: Incident Rates by Time of Day (Austin).

Incident Type	Weekday AM Peak	Weekday Midday	Weekday PM Peak	Weekday Night	Weekend
Abandonment	23	28	39	19	11
Collision	78	72	177	30	18
Hazmat Spill	1	2	1	0	0
Overturned	2	4	4	2	1
Public Emergency	2	2	2	1	0
Road Debris	3	12	15	2	1
Stall	90	135	316	81	22
Vehicle on Fire	2	3	3	0	0
All Non-Congestion	**201**	**258**	**557**	**136**	**54**

Note: From January 1, 2004, to December 31, 2007, there were 1,043 weekdays and 418 weekends.

2.3.2. Characterizing Incident Data Attributes

The researchers examined the distributions of various incident characteristics currently recorded in CTECC's incident database in order to determine the common characteristics of incidents in Austin and to identify whether any discrepancies existed in the database. The analysis focused only on non-congestion incidents. The incident characteristics analyzed and presented in this section are:

- detection methods,
- verification methods,
- number and types of vehicles involved,
- weather conditions,
- responders,
- lane blockage characteristics, and
- incident severity.

Figure 2-15 represents the characteristics of incident detection methods as reported in the database. Only two types of detection methods were recorded in this data field. Among those with detection methods recorded, courtesy patrol appears to be the major source of detection. Also, from the data, this data field was not used regularly until 2005.

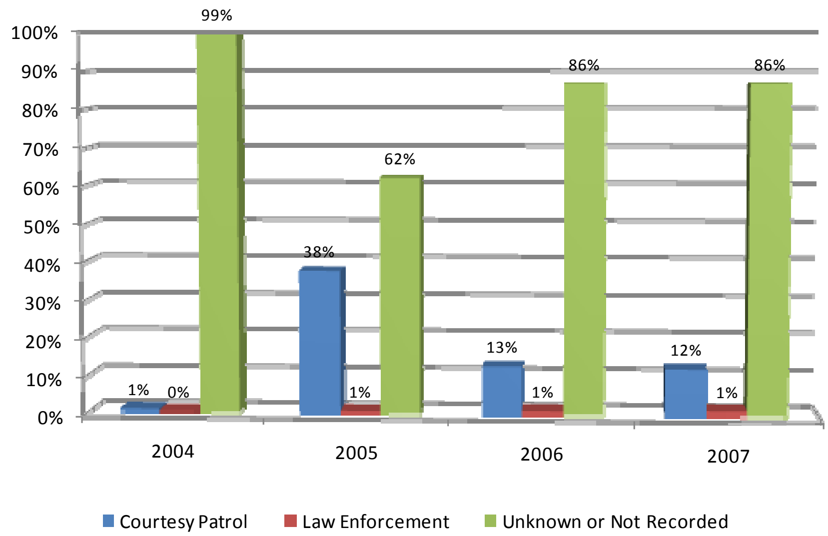


Figure 2-15: Distribution of Detection Methods (Austin).

Incident verification methods were recorded on a routine basis in the database. Figure 2-16 shows the distributions of selected verification methods in Austin year by year. The trends became more stable starting in 2006 when the majority of incidents (70 percent or more) were verified by CCTV coverage. A smaller proportion (7 percent) of incidents was verified by courtesy patrol.

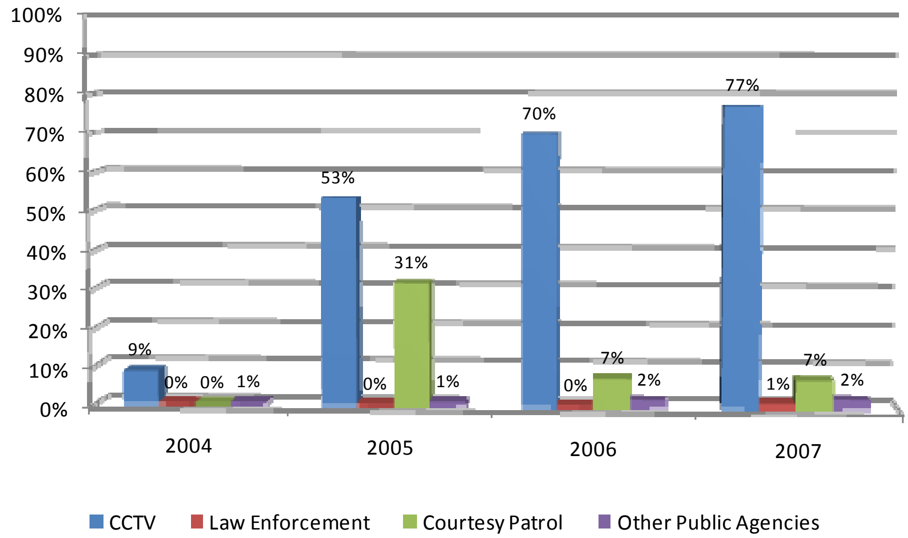


Figure 2-16: Distribution of Major Verification Methods (Austin).

CTECC currently classifies incident severity into none, possible injuries, and fatality. Figure 2-17 shows the distributions of reported incident severity year by year. The majority of severity data were not recorded in 2004. From 2005 to 2007, there appears to have been an increasing trend in possible injuries, while the percentages of non-injury (none) incidents decreased. At the end of 2007, incidents with possible injuries comprised 12 percent of all non-congestion incidents. The percentages of fatal incidents stayed roughly the same year after year, at approximately 1 percent of all non-congestion incidents.

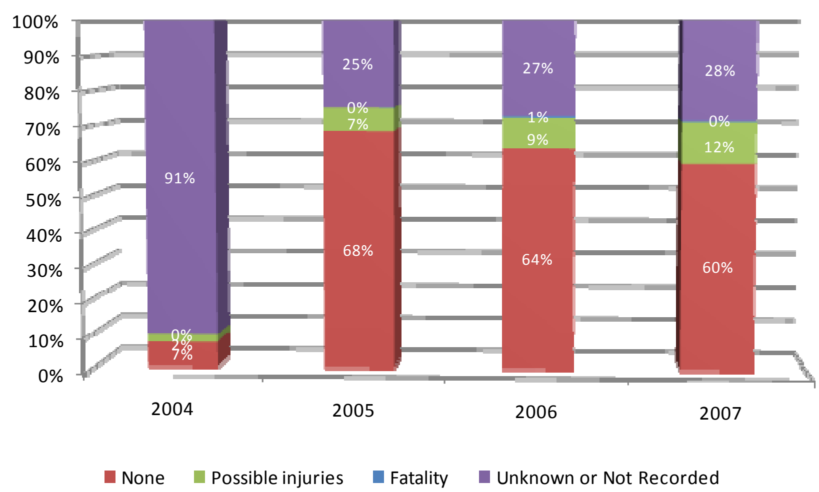


Figure 2-17: Distribution of Incident Severity (Austin).

Table 2-17 shows the distributions of incident severity classified by incident types, and Figure 2-18 shows the severity distributions graphically for selected types of incidents. Among frequent incident types, overturned incidents were the most severe incident type with 42 percent possible injuries and 3 percent fatality. In contrast, none of the abandonment and stall incidents reported were injury-related. As for the severity of collision incidents, 72 percent were either no injury or not reported, 27 percent resulted in possible injuries, and 1 percent resulted in a fatality.

Table 2-17: Distribution of Incident Severity by Types of Incidents (Austin).

Incident Types	Severity of Injuries			
	Unknown	None	Possible Injuries	Fatality
Abandonment	31%	69%	0%	0%
Collision	38%	34%	27%	1%
HAZMAT Spill	85%	12%	2%	0%
Overturned	38%	18%	42%	3%
Public Emergency	56%	24%	15%	5%
Road Debris	54%	46%	0%	0%
Stall	28%	72%	0%	0%
Vehicle on Fire	61%	31%	7%	1%
All Non-Congestion	33%	58%	9%	0%

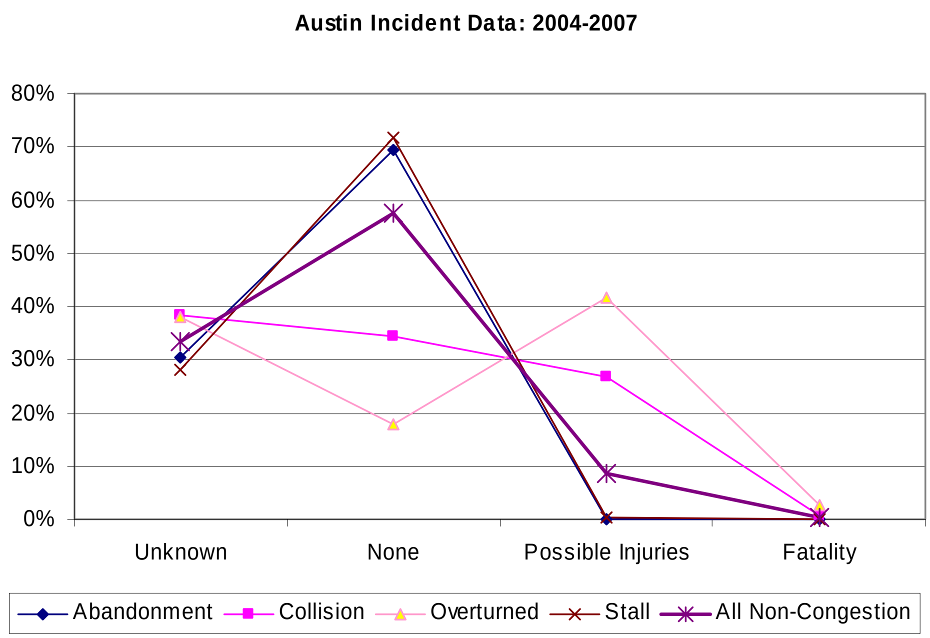


Figure 2-18: Distribution of Incident Severity for Selected Types (Austin).

Figure 2-19 shows the distributions of weather conditions recorded in the database. This data field was not always recorded, but the trend improved year after year. In 2007, the proportion of the data without weather conditions recorded was 18 percent. Among incident records with weather conditions, approximately 75 percent were normal conditions (clear/cloudy). The most common type of weather event in Austin was raining conditions, representing roughly 6 percent of all non-congestion incidents reported in 2007.

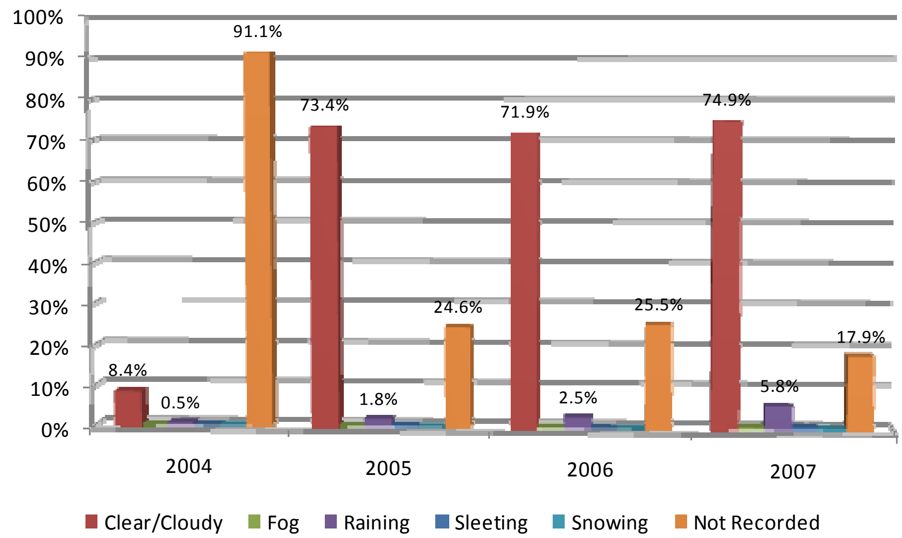


Figure 2-19: Distribution of Major Weather Conditions (Austin).

Figure 2-20 shows the distribution of the number of mainlanes blocked as a result of an incident. The lane blockage distributions were similar year after year. Approximately 70 percent of incidents were either non-lane-blocking or not recorded. Single lane blockage incidents represented approximately 25 percent of all non-congestion incidents. Only 1 percent of all non-congestion incidents involved three or more lanes blocked.

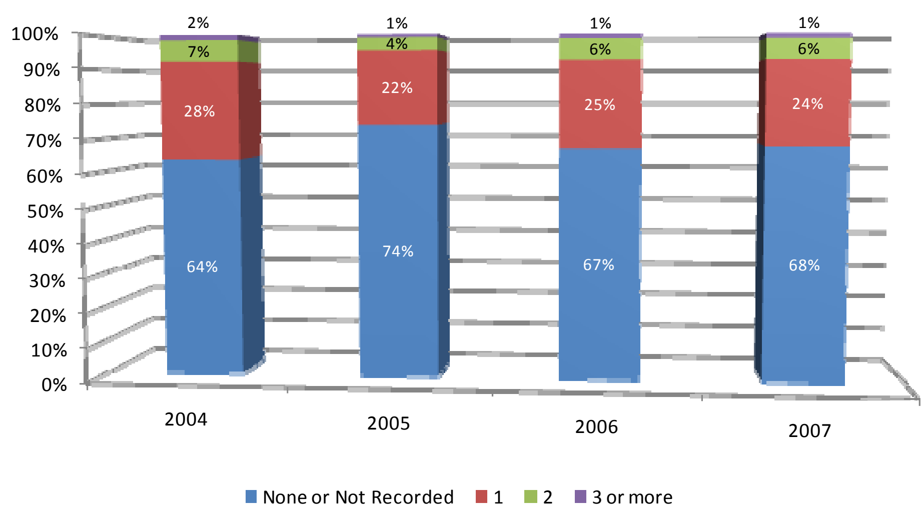


Figure 2-20: Distribution of Number of Mainlanes Blocked (Austin).

Table 2-18 shows the distributions of lanes blocked by incident types using four-year incident data. Mainlanes and shoulder lanes were considered separately in this table. As seen in Table 2-18, abandonment and stall incidents typically blocked only the shoulder lane. Figure 2-21 shows the distributions of mainlane blockage for selected types of incidents. From Figure 2-21, mainlane-blocking incidents were primarily collision and overturned incidents. Table 2-18 shows that 65 percent and 86 percent of collision and overturned incidents, respectively, blocked at least one mainlane. The overturned incidents were more likely to block multiple lanes than the collision incidents. In contrast, only 8 percent and 16 percent of abandonment and stall incidents were lane blocking, respectively.

Table 2-18: Lane Blockage Characteristics of Non-Congestion Incidents (Austin).

Incident Type	Number of Lanes Blocked					Number of Shoulders Blocked		
	None	1	2	3	4	None	1	2
Abandonment	92%	8%	0%	0%	0%	8%	92%	0%
Collision	35%	47%	15%	2%	1%	37%	62%	1%
HAZMAT Spill	9%	87%	2%	2%	0%	92%	8%	0%
Overturned	14%	43%	31%	9%	3%	61%	38%	1%
Public Emergency	25%	44%	22%	7%	2%	56%	44%	0%
Road Debris	26%	58%	15%	1%	0%	71%	28%	0%
Stall	84%	15%	0%	0%	0%	13%	87%	0%
Vehicle on Fire	27%	64%	5%	1%	3%	61%	39%	0%

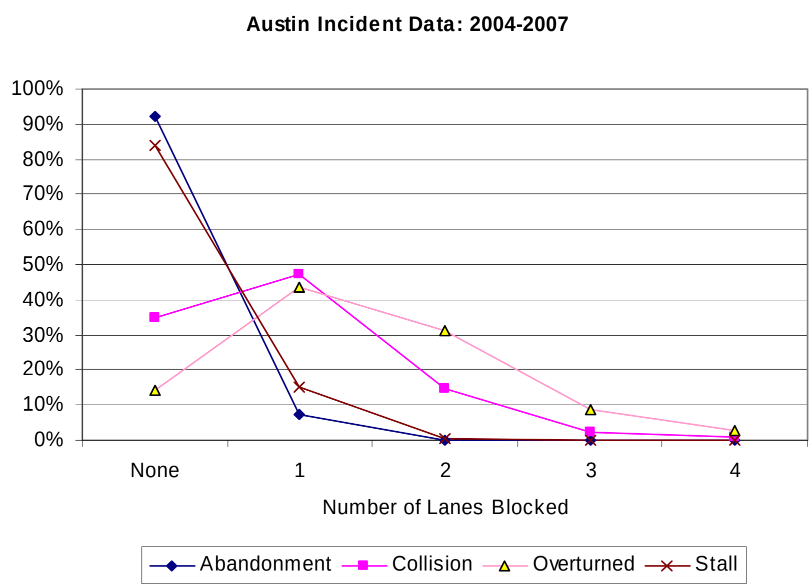


Figure 2-21: Mainlane Blockage by Incident Types (Austin).

Figure 2-22 displays the distributions of the number of vehicles involved in an incident year by year. In 2004, 91 percent of the data did not include this information. The trends became more consistent from 2005 through 2007. Approximately 55 percent of all non-congestion incidents were a single-vehicle incident. Two-vehicle and three-vehicle incidents comprised 16 percent to 19 percent of all non-congestion incidents.

Figure 2-23 shows the distributions of the number of vehicles for selected types of incidents. This figure represents the combined data from 2004 to 2007. Two-vehicle incidents were the most common for the collision incidents (35 percent), whereas single-vehicle incidents were more common for abandonment (69 percent), stall (49 percent), and overturned (35 percent) incidents. The percentage of data records without this information was approximately 30 percent of all non-congestion incident types.

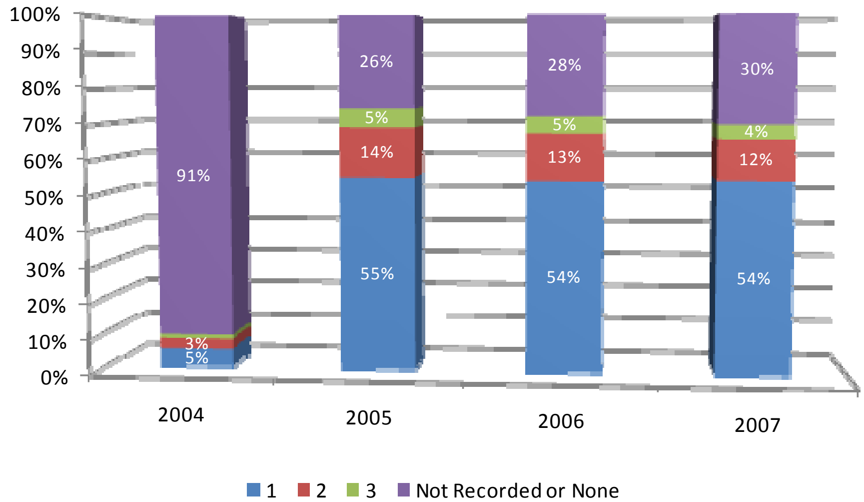


Figure 2-22: Distribution of Number of Vehicles Involved (Austin).

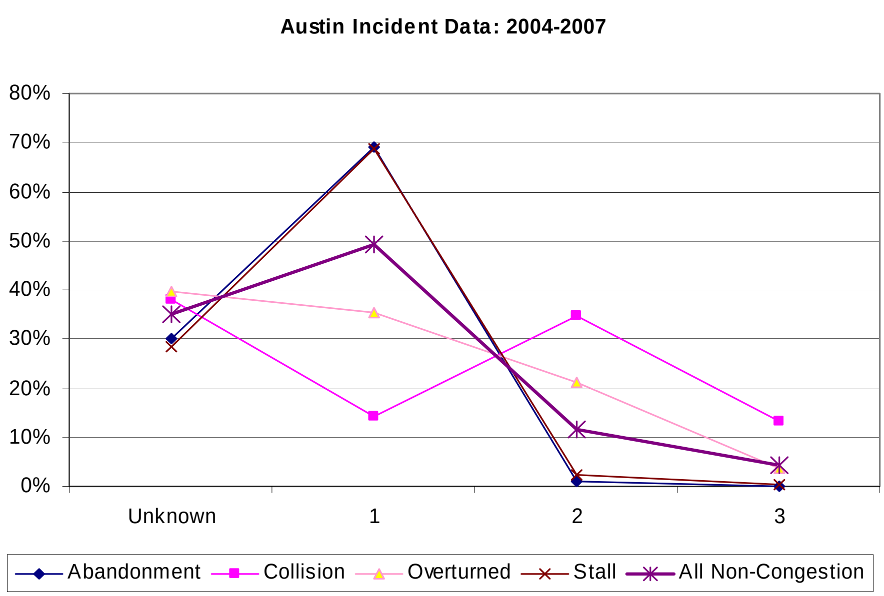


Figure 2-23: Number of Vehicles Involved by Incident Types (Austin).

CTECC also recorded the information about the types of vehicles involved. As seen in Figure 2-24, the top three major types of vehicles recorded in the database were passenger car (62 percent), truck (28 percent), and trailer (8 percent).

Overall, the analysis indicated that the Austin incident characteristics were more consistent and reliable from 2005 onwards. Certain incident data attributes before 2005 could still be valid for subsequent analyses if there were no discrepancies in the distribution trends from year to year.

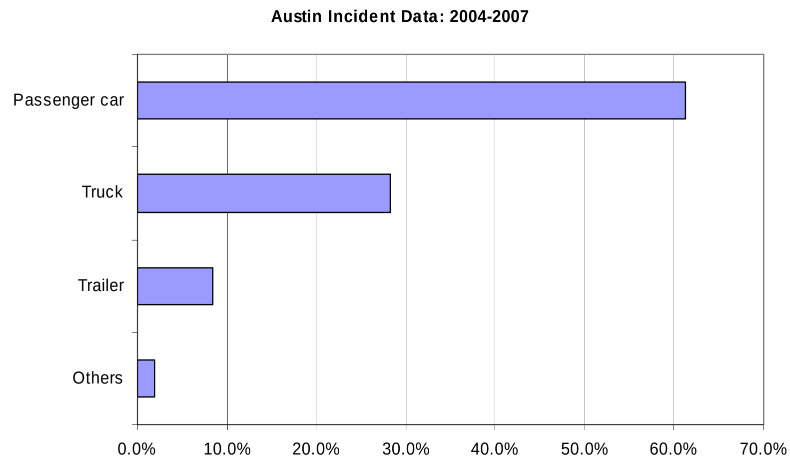


Figure 2-24: Distribution of Vehicle Types Involved (Austin).

2.3.3. Incident Duration Statistics

Incident durations can provide insight into the impacts of incidents. Lane-blocking incidents with long durations tend to be more severe than those with short durations. Lane blockage information, if available, can be used to distinguish shoulder blocking incidents from mainlane blocking incidents. Therefore, researchers examined incident duration statistics from CTECC's incident archive from 2004 to 2007. Incident durations were computed from the differences between incident logged time and cleared time in the database. The data records were flagged as invalid and removed from subsequent analysis if the computed durations were negative.

Similar to the case of Houston's incident durations, the duration data were heavily asymmetric. Figure 2-25 shows the distribution of all non-congestion incident durations using Austin data from 2004 to 2007. The left figure shows the distribution of incident duration on a normal scale. The duration data were heavily concentrated on a normal scale. To address this problem, researchers applied the natural logarithmic transformation to the data, and then re-plotted the distribution as shown in the right figure. In this way, the distribution became more spread out on a log scale and significantly improved graphically. Researchers did not separately analyze Austin data by severity as in the case of Houston because incident severity was not logged for every incident record.

Researchers used the percentile statistics to characterize incident durations due to asymmetric characteristics of duration data. Figure 2-26 shows the 50th (median), 85th, and 95th percentiles of incident duration by incident types using the data from 2004 to 2007. Abandonment incidents were the type with the longest median duration (593 minutes). This is likely because most abandonment incidents were on the shoulders and thus did not require immediate attention. Among those incidents blocking the mainlanes, incidents involving hazardous material spills, overturned vehicles, and vehicles on fire were the top three longest median durations.

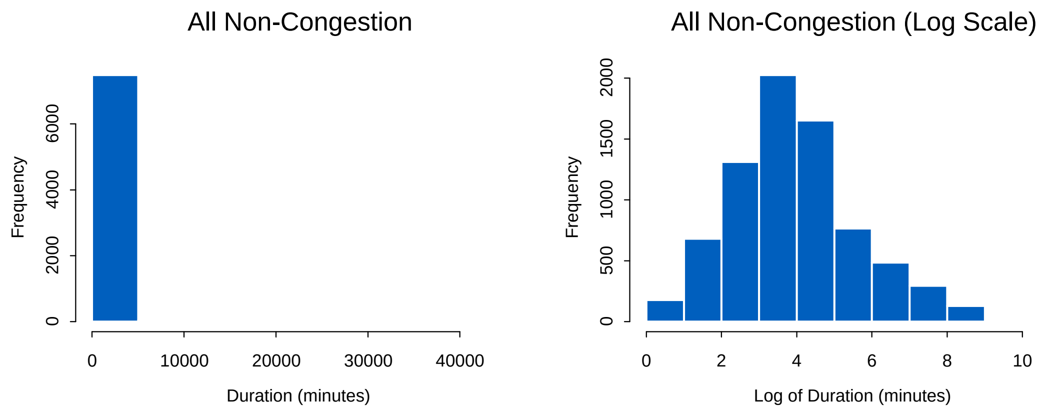


Figure 2-25: Distributions of Non-Congestion Incident Durations (Austin).

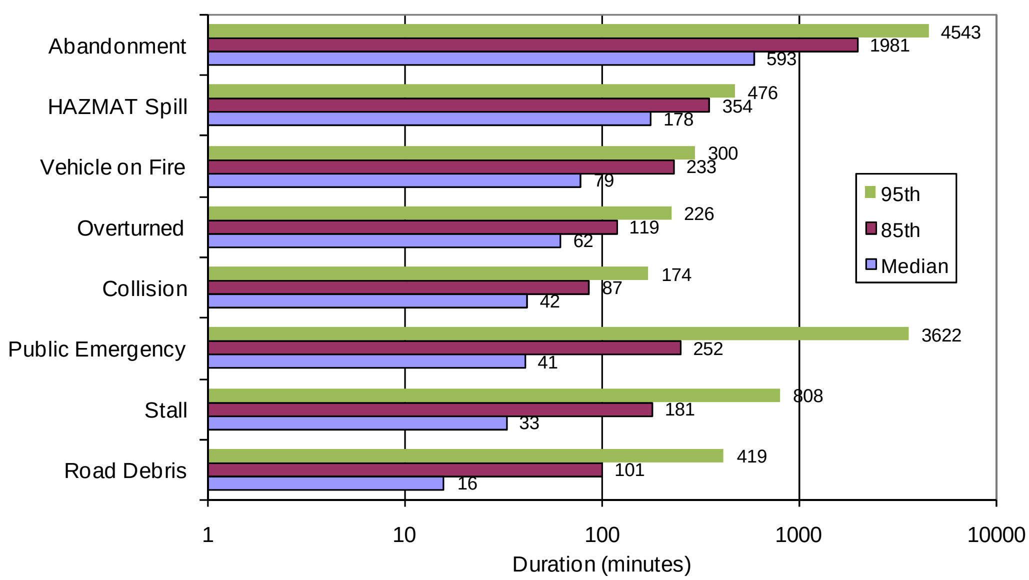


Figure 2-26: Incident Duration Percentile Statistics (Austin 2004–2007).

Table 2-19 shows a comparison of incident duration statistics year to year from 2004 to 2007. Median collision durations were basically unchanged year after year. However, median stall durations decreased from 40 minutes in 2004 to 27 minutes in 2007. This improvement could be partly due to improved incident management operations and increased surveillance coverage. The trends of median durations for other incident types were fairly mixed. This could be due to limited sample size of the duration data for other incident types. Note that collision, stall, and abandonment incidents comprised more than 92 percent of all non-congestion incidents reported in Austin.

Table 2-19: Annual Comparison of Incident Duration by Types (Austin).

Incident Type	2004 Median	2004 85th	2004 95th	2005 Median	2005 85th	2005 95th	2006 Median	2006 85th	2006 95th	2007 Median	2007 85th	2007 95th
Abandonment	381	4186	7600	783	2957	5640	566	1938	4911	578	1451	2455
HAZMAT Spill	148	160	164	82	283	477	178	407	539	199	352	426
Vehicle on Fire	53	144	255	52	78	165	73	196	258	145	255	290
Overturned	58	392	717	63	140	226	61	116	200	63	110	175
Collision	45	97	180	42	82	203	41	81	135	41	90	180
Public Emergency	49	98	109	49	3640	11956	32	84	278	66	229	252
Stall	40	198	1195	40	315	1357	36	149	396	27	128	392
Road Debris	30	291	613	9	54	127	19	346	1014	19	86	340

Incident Duration (minutes)

2.4. Fort Worth's TransVISION

This section provides a summary of incident characteristics derived from TransVISION's incident data archive. The analysis focused on three years of incident data, from 2004 to 2006. In addition to general incident characteristics, TransVISION also collects incident management data, such as arrival and departure times of each responder and observed queue length. These data can help provide additional insight into existing incident management operations at the TMC.

2.4.1. Temporal Analysis of Incident Frequencies

Using all incident data, the researchers examined the trends of incident frequencies on the following time scales:

- incident frequencies by month over the analysis period (2004–2006),
- incident frequencies by year,
- incident frequencies by month,
- incident frequencies by day of week, and
- incident frequencies by time of day.

2.4.1.1. Incident Frequencies by Month over the Analysis Period

The objective of this analysis was to ensure that there were no discrepancies in incident reporting that would require some incident data to be filtered out. Figure 2-27 shows the monthly incident counts reported over the three-year analysis period. Note that two months of data were missing in June and July 2005 (the graphs show zero counts in those two months). The overall counts ranged from approximately 40 to 120 incidents per month. There was a sharp increase towards in the end of 2006. The incident counts by type indicated that the increase was due in large part to the increase in disablement in that period. With exception to the disablement, the trends for all other major incident types, which included collision, truck-related, and vehicle on fire, were somewhat stable over the analysis period. Table 2-20 shows the corresponding incident counts classified by incident types over the analysis period.

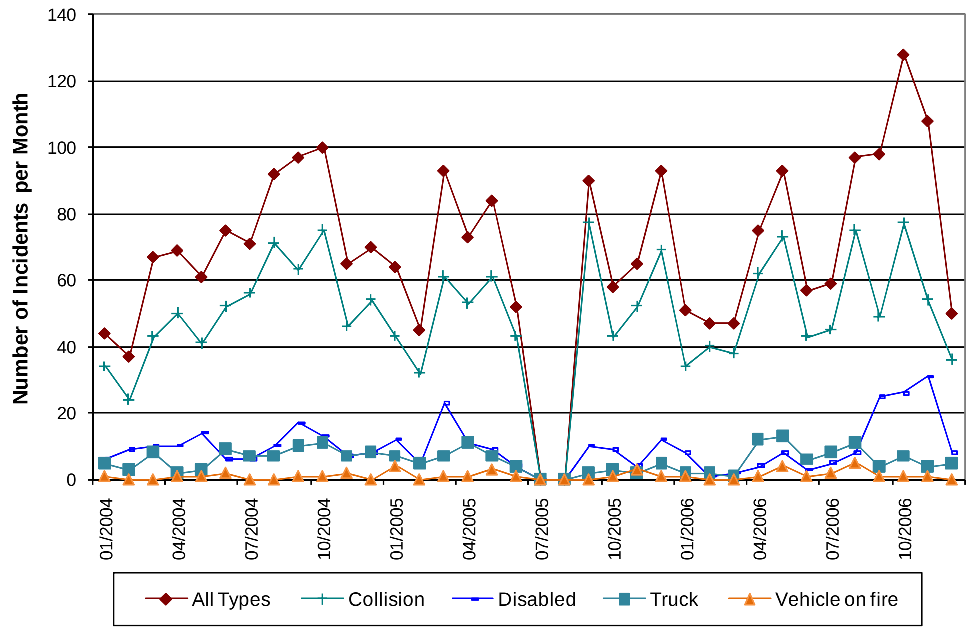


Figure 2-27: Profiles of Monthly Incident Counts from 2004 to 2006 (Fort Worth).

2.4.1.2. Incident Frequencies by Year

The researchers examined the distribution of incident types reported in the database. Table 2-21 summarizes the distribution of reported incident types from the incident database. TransVISION recorded truck-related incidents as a separate incident type. Vehicle types were not directly recorded in a separate data field as in the case of Austin's database. Collision incidents (71 percent) were the most common incident type reported, followed by disablement (13.9 percent) and truck-related (8.4 percent) incidents. TransVISION's operating hours are from 6 AM to 6 PM. Therefore, the total number of incidents reported cannot be directly compared with the number of incidents reported at 24/7 TMCs. Researchers computed incident rates using the number of monitored hours for proper comparison among TMCs. A comparison of incident counts year by year, as seen in Table 2-21, indicated a drop in incident counts in 2005. However, this drop was actually attributed to missing incident data for two months in this year, as discussed in the previous section.

2.4.1.3. Incident Frequencies by Month

This analysis examines monthly incident frequencies to determine the impacts of different months on incident occurrences. Figure 2-28 shows the average number of incidents per month using three-year incident data for selected incident types. Table 2-22 shows the corresponding values of average monthly incidents. Fall season (September to November) had the highest incident rate, at 90 incidents per month, compared to the 73 and 68 incidents per month for the entire year with and without fall data, respectively.

Researchers also adjusted the average incident rates for the month of June and July to account for missing data in 2005.

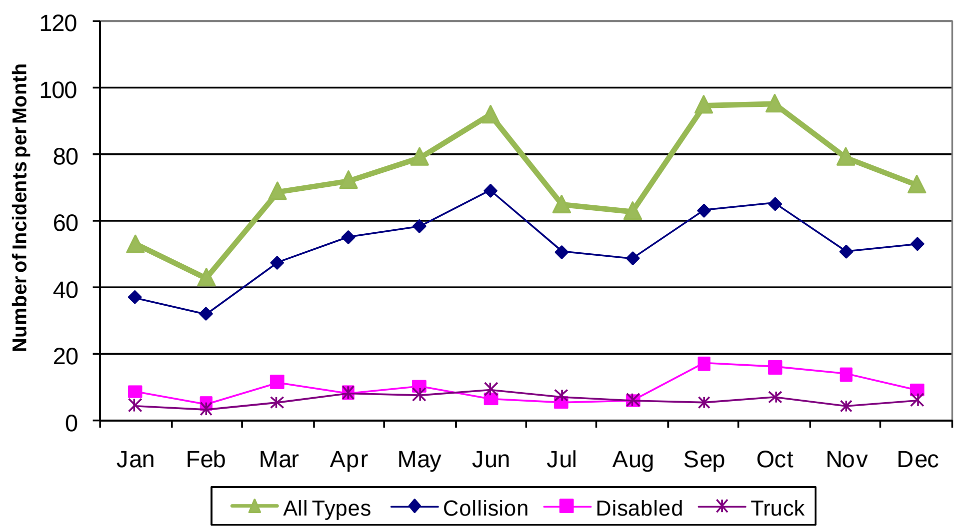
Table 2-20: Monthly Incident Counts from 2004 to 2006 (Fort Worth).

Month-Year	All Types	Collision	Disabled	Truck	Vehicle on fire	Debris
Jan-2004	44	34	6	5	1	0
Feb-2004	37	24	9	3	0	1
Mar-2004	67	43	10	8	0	2
Apr-2004	69	50	10	2	1	2
May-2004	61	41	14	3	1	1
Jun-2004	75	52	6	9	2	5
Jul-2004	71	56	6	7	0	4
Aug-2004	92	71	10	7	0	5
Sep-2004	97	63	17	10	1	3
Oct-2004	100	75	13	11	1	1
Nov-2004	65	46	7	7	2	0
Dec-2004	70	54	8	8	0	1
Jan-2005	64	43	12	7	4	0
Feb-2005	45	32	5	5	0	3
Mar-2005	93	61	23	7	1	2
Apr-2005	73	53	11	11	1	3
May-2005	84	61	9	7	3	3
Jun-2005	52	43	4	4	1	0
Jul-2005	0	0	0	0	0	0
Aug-2005	0	0	0	0	0	0
Sep-2005	90	77	10	2	0	1
Oct-2005	58	43	9	3	1	3
Nov-2005	65	52	4	2	3	1
Dec-2005	93	69	12	5	1	1
Jan-2006	51	34	8	2	1	1
Feb-2006	47	40	1	2	0	1
Mar-2006	47	38	2	1	0	2
Apr-2006	75	62	4	12	1	3
May-2006	93	73	8	13	4	1
Jun-2006	57	43	3	6	1	0
Jul-2006	59	45	5	8	2	1
Aug-2006	97	75	8	11	5	0
Sep-2006	98	49	25	4	1	0
Oct-2006	128	77	26	7	1	3
Nov-2006	108	54	31	4	1	3
Dec-2006	50	36	8	5	0	0

Examination of specific incident types indicated that on average collision incidents were slightly lower during winter (December to February). There were no significant changes in monthly incident rates for disablement and truck-related incidents over the analysis period. On average, there were 10 and 6 disablement and truck-related incidents reported per month, respectively.

Table 2-21: Total Number of Incidents per Year (Fort Worth).

Incident Type	2004	2005	2006	Total	% of Total
Collision	609	534	626	1769	71.5%
Disabled	116	99	129	344	13.9%
Truck	80	53	75	208	8.4%
Debris	25	17	15	57	2.3%
Others	19	14	16	49	2.0%
Vehicle on fire	9	15	17	41	1.7%
HAZMAT	5	4	10	19	0.8%
Emergency	2	2	1	5	0.2%
All Types	*848*	*717*	*910*	*2475*	



Note: June and July average counts were adjusted to account for missing data in 2005.

Figure 2-28: Profiles of Average Number of Incidents per Month (Forth Worth).

2.4.1.4. Incident Frequencies by Day of Week

The objective of this analysis was to analyze the pattern of incident occurrences by day of week. There were no weekend data in this analysis since TransVISION operates only on weekdays. Researchers averaged incident counts from the same of day of week over the analysis period and used 1,000 monitored hours to obtain normalized incident rates. The number of monitored hours was based on the TMC's operating hours, from 6 AM to 6 PM Monday through Friday, which is equal to 12 hours for each weekday. Figure 2-29 shows the average number of incidents by day of week, and Table 2-23 shows the corresponding values by day of week for each type of incident reported.

On average, the incident rates on Wednesdays and Fridays were slightly lower than overall incident rates. Upon further examination by specific incident types, the drops in collision incidents were a major factor of the decrease in overall incident rates. There were no unusual patterns in incident rates by day of week for disablement or truck-related incidents.

Table 2-22: Average Number of Incidents per Month (Fort Worth).

Incident Type	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Collision	37	32	47	55	58	69	51	49	63	65	51	53
Disabled	9	5	12	8	10	7	6	6	17	16	14	9
Truck	5	3	5	8	8	10	8	6	5	7	4	6
Vehicle on fire	2	0	0	1	3	2	1	2	1	1	2	0
Others	1	2	2	3	2	1	2	1	1	1	0	1
Debris	0	2	2	3	2	3	3	2	1	2	1	1
Hazmat	0	0	0	1	1	2	1	0	1	0	0	0
Emergency	0	0	0	0	0	1	0	0	1	0	0	0
All Types	**53**	**43**	**69**	**72**	**79**	**92**	**65**	**63**	**95**	**95**	**79**	**71**
% of All Types	**6%**	**5%**	**8%**	**9%**	**10%**	**10%**	**7%**	**8%**	**12%**	**12%**	**10%**	**9%**

Note: June and July average counts were adjusted to account for missing data in 2005.

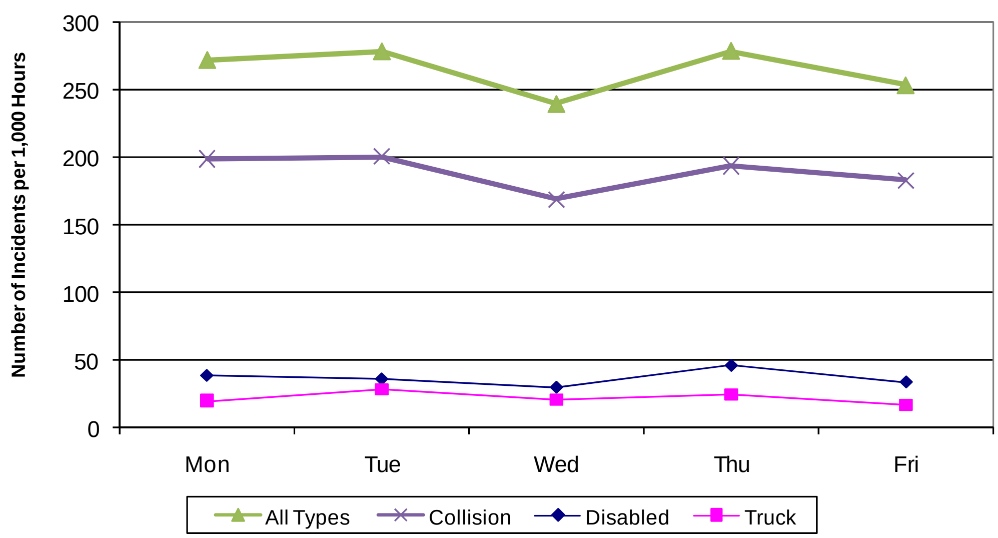


Figure 2-29: Profiles of Incident Rates by Day of Week (Fort Worth).

Table 2-23: Number of Incidents per 1,000 Hours by Day of Week (Fort Worth).

Incident Type	Mon	Tue	Wed	Thu	Fri
Collision	198.2	199.8	168.8	193.2	182.6
Disabled	38.5	35.8	29.4	46.2	33.4
Truck	19.8	28.3	20.8	24.9	17.0
Vehicle on Fire	5.3	5.3	3.2	4.2	3.7
Debris	5.3	5.3	5.9	6.4	7.4
Others	4.3	9.1	4.3	3.2	5.3
Hazmat	1.6	2.7	1.6	1.6	2.7
Emergency	0.5	0.0	0.5	0.0	1.6
All Types	271.4	277.8	238.8	278.1	252.7

Note: From January 1, 2004, to December 31, 2006, there were a total of 156 days of Mondays, Tuesdays, and Wednesdays and 157 days of Thursdays and Fridays.

2.4.1.5. Incident Frequencies by Time of Day

The objective of this analysis was to examine the patterns of incident occurrences by specific times of day. Researchers divided weekdays into three time periods: AM peak (7 AM to 9 AM), midday (9 AM to 4 PM), and PM peak (4 PM to 6 PM). The nighttime period was not considered here since it is outside the operating hours of the TMC. Figure 2-30 shows the average number of incidents per 1,000 monitored hours by time of day, and Table 2-24 shows the corresponding values for specific types of incidents. An examination of the results yielded the following observations:

- The highest incident occurrence rate occurred during the AM peak period for Fort Worth. Regardless of incident types, there was one incident reported on average for every 2.7 hours of observation during AM peak. In contrast, the incident occurrence rate during midday was the lowest, at one incident per 4.4 hours of observation on average.
- The collision incident rates by time of day followed the same trend as the overall incident rates. This is because collision type represented the largest proportion of all incidents.
- The incident rates were higher during the AM and PM peak periods because the traffic volumes were generally higher during those times. When the traffic volumes increased, the probability of incident occurrence increased as well. From the traffic safety viewpoint, this is known as an increase in traffic exposure.
- Truck-related and disablement incident rates changed only slightly by different times of day. This implies that the occurrence of these two incident types was more random than the collision types and less dependent on the traffic volume, which varied by time of day.
- When comparing the incident rates by time of day with those observed from Houston's and Austin's incident data archives, the rates for Fort Worth were comparable to those observed at Austin, but they were much lower than Houston's. Houston's incident rates ranged from one incident every 1.7 hours at night to one incident every 14 minutes during PM peak.

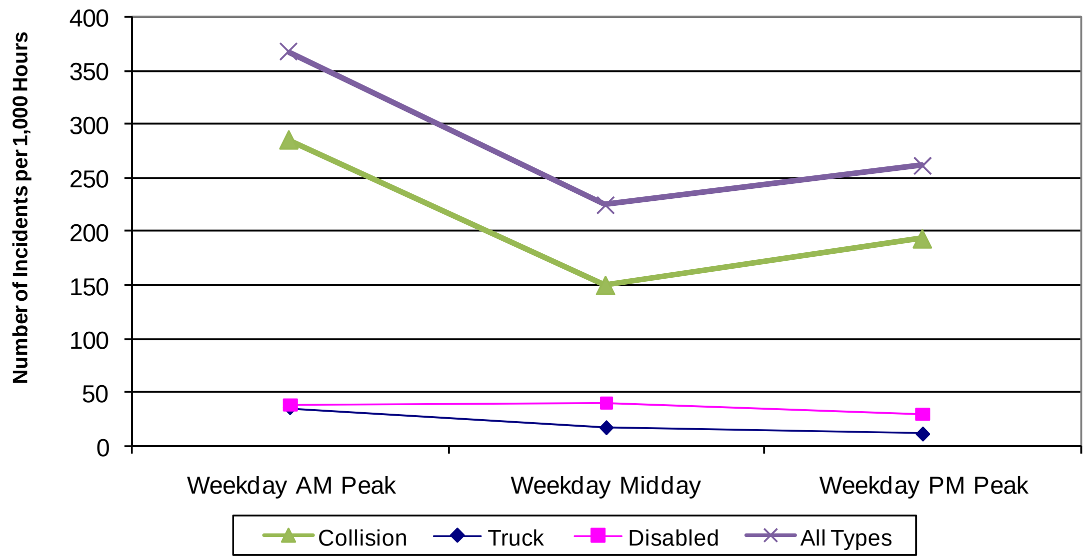


Figure 2-30: Profile of Incident Rates by Time of Day (Fort Worth).

Table 2-24: Number of Incidents per 1,000 Hours by Time of Day (Fort Worth).

Incident Type	Weekday AM Peak	Weekday Midday	Weekday PM Peak
Collision	285	149	192
Truck	35	17	12
Disabled	38	40	29
Others	12	3	2
Vehicle on Fire	5	3	8
Debris	4	7	3
Hazmat	1	2	1
Emergency	0	1	0
All Types	366	225	261

Note: From January 1, 2004, to December 31, 2006, there were a total of 782 weekdays.

2.4.2. Characterizing Incident Data Attributes

The researchers examined the distribution of various data attributes recorded in TransVISION's incident database. The objectives of this analysis were to characterize incident data attributes and determine if any discrepancies existed in the recorded incident data. Incident data attributes examined in this section are:

- incident detection methods,
- incident verification methods,
- weather conditions,
- lane blockage characteristics,

- number of vehicles involved,
- incident responders, and
- incident severity.

Figure 2-31 shows the characteristics of incident detection methods recorded in the incident data archive. The majority of incidents were detected by either CCTV (68 percent) or commercial traffic services (18 percent) at TransVISION. Nearly 90 percent of all incidents were verified via CCTV (see Figure 2-32). The distributions of both incident detection and verification methods changed only slightly over the analysis period.

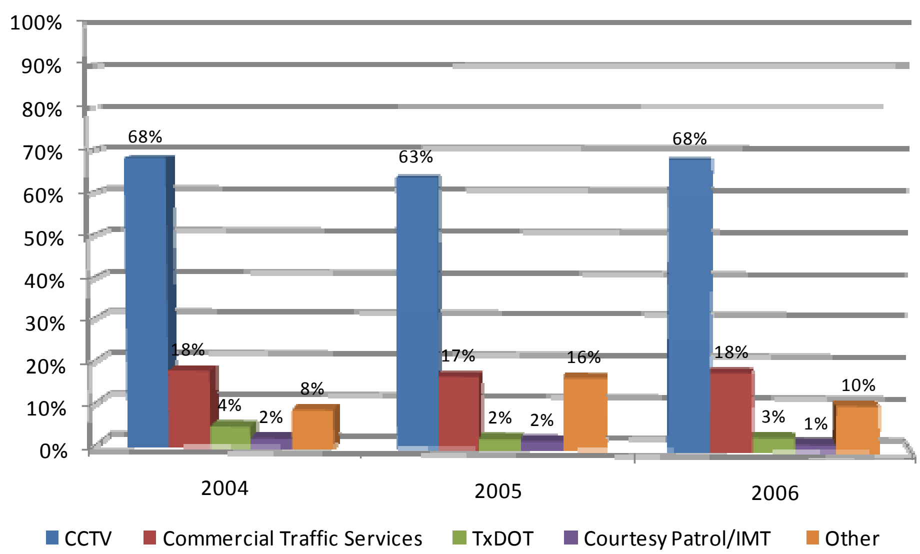


Figure 2-31: Distribution of Detection Methods (Fort Worth).

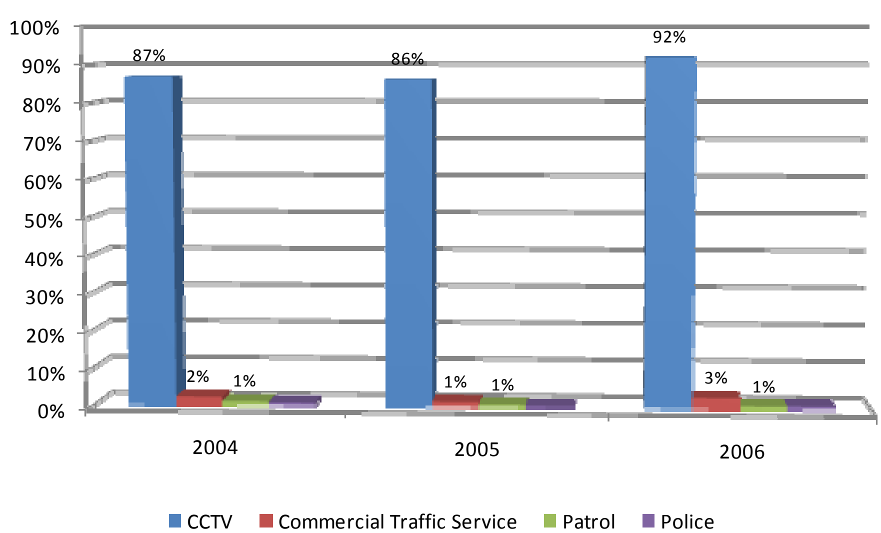


Figure 2-32: Distribution of Major Verification Methods (Fort Worth).

Weather conditions were also recorded in the incident database. As illustrated in Figure 2-33, frequent weather conditions recorded include sunny, cloudy, rainy, and nighttime, with and without lighting. Each incident record may have more than one type of weather condition; therefore, the sum of percentage could exceed 100 percent. Weather events that were typically recorded in the database were raining and thunderstorm conditions.

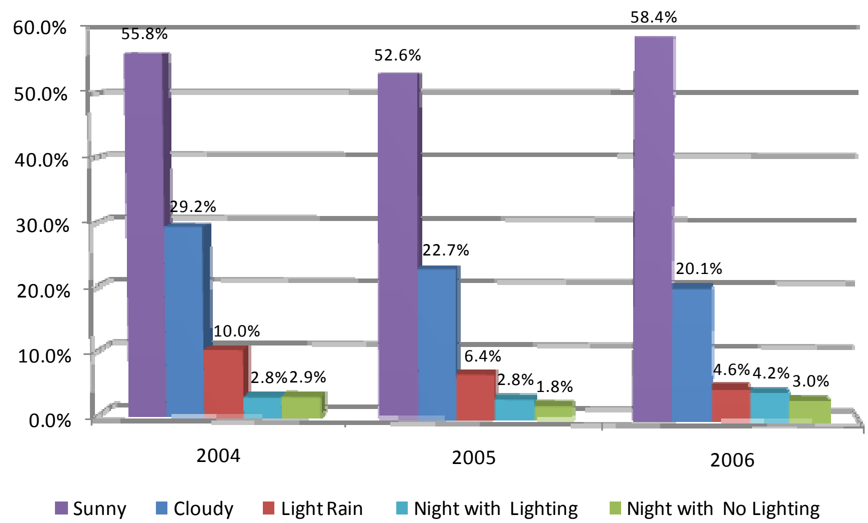


Figure 2-33: Distribution of Major Weather Conditions Recorded (Fort Worth).

Figure 2-34 shows the distribution of the number of mainlanes blocked for all types of incidents. More than 50 percent of all incidents blocked either one or two mainlanes. About 5 percent blocked at least three or more mainlanes. Approximately 30 percent to 40 percent of all incidents were non-mainlane blocking.

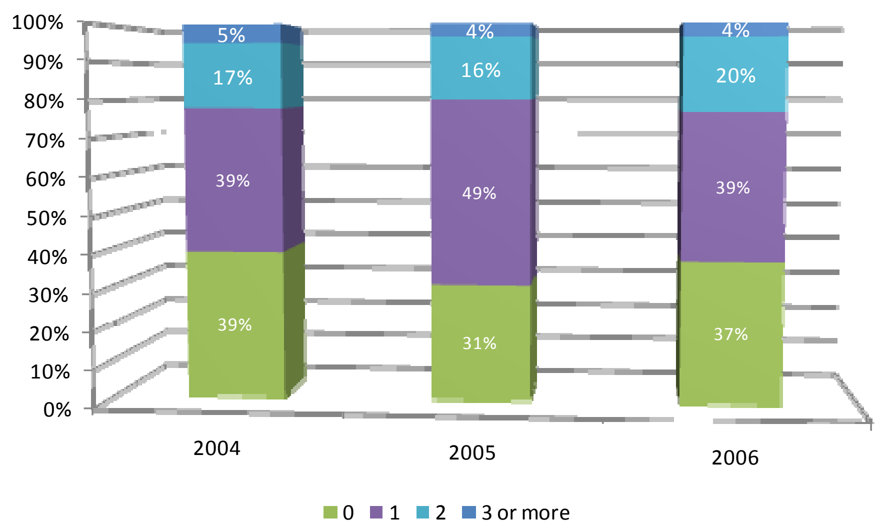


Figure 2-34: Distribution of Number of Mainlanes Blocked (Fort Worth).

Figure 2-35 examines the distribution of the number of mainlanes blocked by incident types. Collision and truck-related incidents typically blocked one or two mainlanes. On the other hand, the majority of disablement incidents (65 percent) were non-mainlane blocking. This also implies that a large proportion of disablement was restricted to the shoulder lanes. Truck-related incidents had the highest percentage of incidents blocking at least three mainlanes (7 percent).

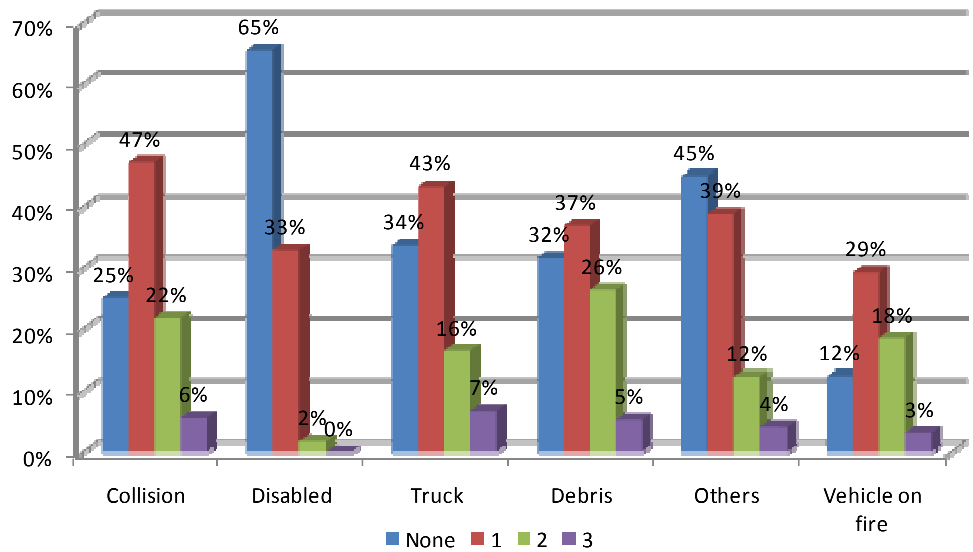


Figure 2-35: Distribution of Mainlane Blockage by Incident Type (Fort Worth).

Figure 2-36 shows the distributions of the number of vehicles involved in an incident year by year. The distributions changed only slightly from year to year. The majority of incidents involved one or two vehicles (approximately 70 percent). Three-vehicle incidents represented approximately 22 percent of all incidents. Figure 2-37 examines the distribution of the number of vehicles by incident types. Disablement and vehicle on fire were frequently one-vehicle incidents, whereas collision and truck-related incidents were generally multi-vehicle incidents. Unidentified (others) incident types were mostly either one-vehicle (45 percent) or two-vehicle (29 percent) incidents.

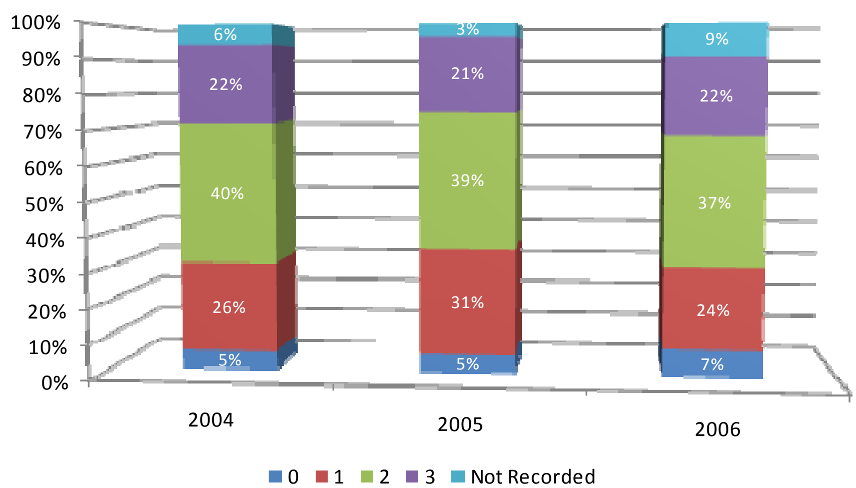


Figure 2-36: Distribution of Number of Vehicles Involved (Fort Worth).

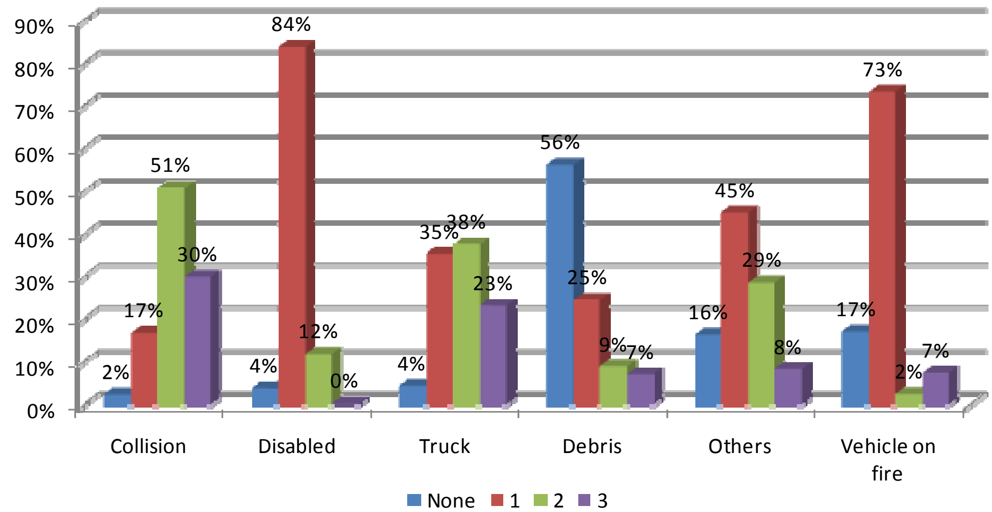


Figure 2-37: Number of Vehicles Involved by Incident Types (Fort Worth).

TransVISION also recorded incident responder data. Figure 2-38 shows that police, fire department, EMS, and wreckers, in descending order, were the top four major responders for Fort Worth. Since there could be multiple responders for a single incident, the percentage sum of the distribution in each year might not be equal to 100 percent. Figure 2-39 examines the distributions of major responders for incident types commonly recorded in the database. Police, fire department, and EMS were the most common responders for collision and truck-related incidents. These two types of incidents tended to be more severe and were also more likely to result in injuries. For incidents involving debris on the roadway, the courtesy patrol/incident management team (CP/IMT), police, and TxDOT personnel were the most common responders.

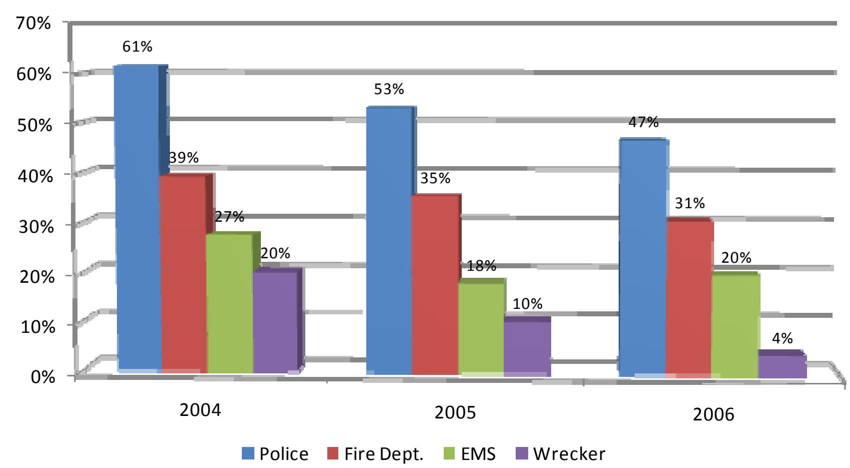


Figure 2-38: Distribution of Major Incident Responders (Fort Worth).

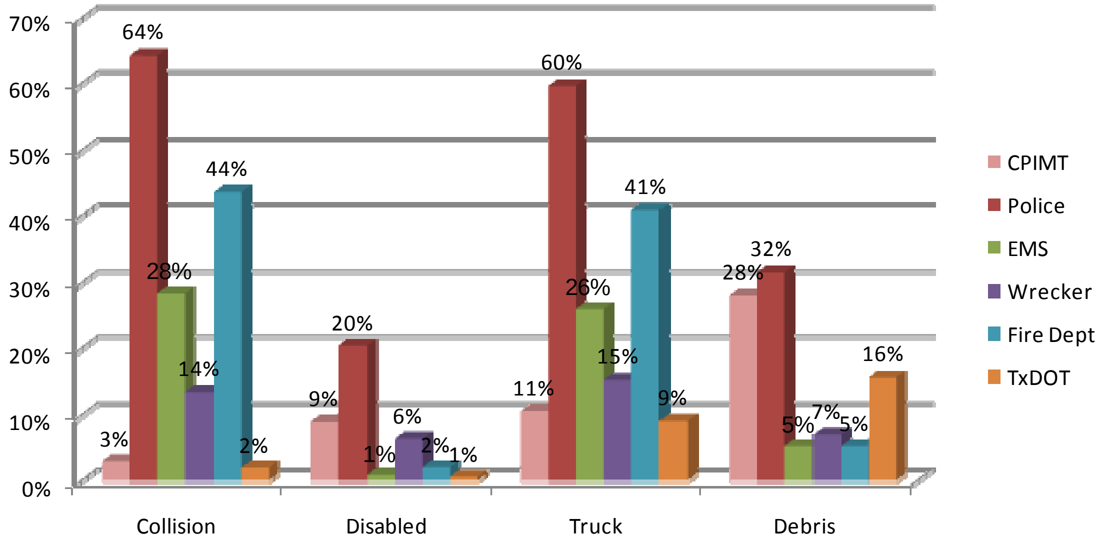


Figure 2-39: Distributions of Major Responders by Incident Types (Fort Worth).

TransVISION classifies incident severity into four levels, which are none, property damage only (PDO), injuries, and fatalities. From an annual comparison, as illustrated in Figure 2-40, fatalities remained at approximately 1 percent of all incidents, while the percentage of injuries and PDO reduced from 35 percent and 32 percent, respectively, in 2004 to 31 percent and 23 percent, respectively, in 2006. This indicates that while the incident occurrence rates were roughly the same, the severity of incidents declined from year to year.

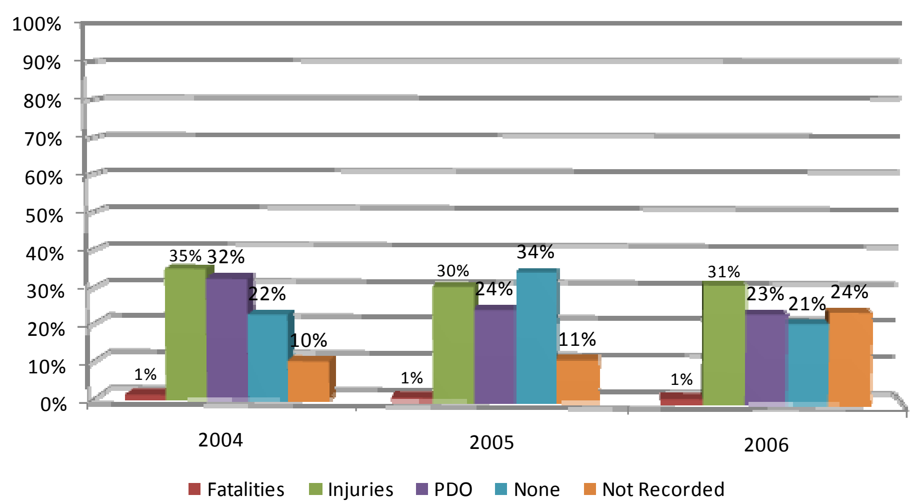


Figure 2-40: Distribution of Incident Severity (Fort Worth).

Figure 2-41 further examines the distributions of incident severity by major incident types. Collision and truck-related incidents were the two major types with high percentages of injuries, at 44 percent and 36 percent, respectively. As for disablement incidents, the severity was the lowest, with 98 percent none or not recorded and 2 percent

PDO. Debris incidents on average resulted in 18 percent PDO and only 5 percent for injuries.

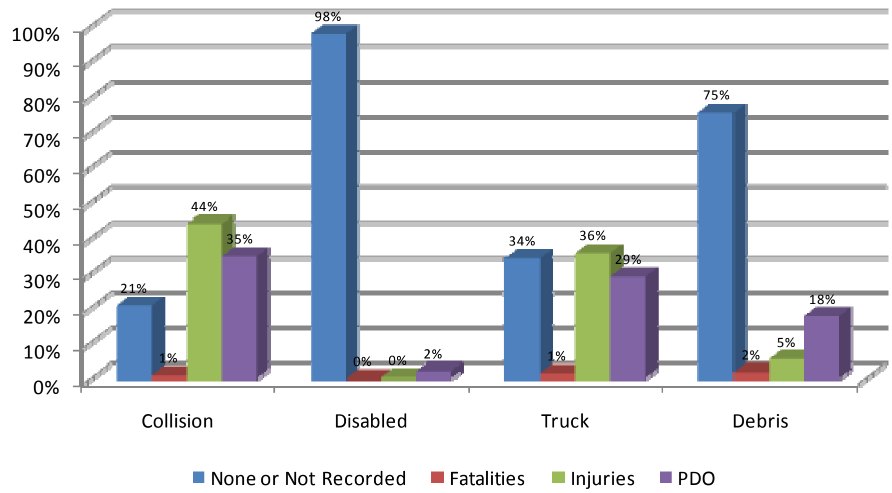


Figure 2-41: Distribution of Incident Severity by Incident Type (Fort Worth).

2.4.3. Incident Duration Statistics

The researchers examined incident duration statistics using TransVISION's incident archive from 2004 to 2006. The earliest of the following three time logs – occurrence time, detection time, and verification time – signifies the beginning of an incident. The latest of the two clearance time logs in the database defines the end of an incident. If both the beginning and the end time logs of an incident existed and were valid for an incident record, researchers then computed incident durations by calculating the difference between those two times. Incident records with either invalid time logs or negative incident durations were removed from further analysis.

Researchers used the percentile statistics to characterize the incident durations due to the asymmetric nature of the duration data. Figure 2-42 shows the 50th (median), 85th, and 95th percentile of incident duration by incident types recorded in the data archive. As illustrated in the figure, public emergency and hazardous materials were the two incident types with the longest median incident durations. However, these two types of incidents represented less than 1 percent of all incidents reported in the database. Table 2-25 shows the full range of the duration percentile statistics and the sample size for each incident type. As can be seen, the median statistics could be easily affected by a few extreme incidents in this case. For instance, if researchers take a threshold of 1 percent representation in the database for the incident duration statistics to be valid, the top two longest types would be truck-related and debris incidents. In this case, the chance that the duration data would be affected by certain abnormal events is much less likely.

TransVISION also reported collision incidents by severity, either as minor collisions or major collisions. When combined, the median and 85th percentile durations were 57 and 129 minutes, respectively. The minor collisions represented 88 percent of all collisions reported at Fort Worth. Separately, the median and 85th percentile durations for minor collisions were 55 and 119 minutes, respectively. The corresponding figures for major collisions were 74 and 208 minutes, respectively. Based on median statistics, the durations of major collisions lasted 35 percent longer, on average, than those of minor collisions.

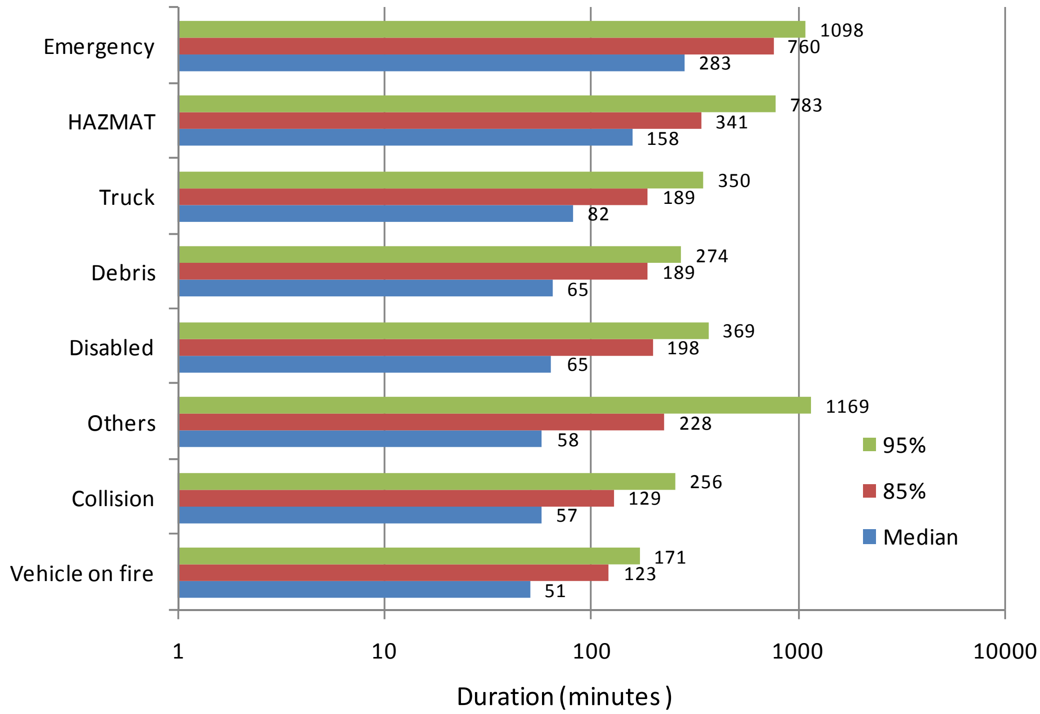


Figure 2-42: Incident Duration Percentile Statistics (Fort Worth 2004–2006).

Table 2-25: Incident Duration Statistics by Incident Types (Fort Worth).

Type	Total Counts	% of Total	Duration Percentile (minutes)				
			5%	15%	50%	85%	95%
Collision	1769	71.5%	8	21	57	129	256
Disabled	344	13.9%	5	14	65	198	369
Truck	208	8.4%	11	30	82	189	350
Debris	57	2.3%	7	20	65	189	274
Others	49	2.0%	8	16	58	228	1169
Vehicle on fire	41	1.7%	8	23	51	123	171
HAZMAT	19	0.8%	16	21	158	341	783
Emergency	5	0.2%	7	12	283	760	1098
All Types	2475		7	20	58	140	273

* Multiple types can be recorded for a single incident at TransVISION.

2.5. Summary

In this chapter, the researchers examined historical incident databases from Houston's TranStar, Austin's CTECC, and Fort Worth's TransVISION and provided the descriptive summary statistics from the database. Three types of analyses were conducted at each TMC:

- temporal analysis of incident frequencies,
- characterization of incident data attributes, and
- analysis of incident duration statistics.

Table 2-26 compares summary statistics derived from the three incident databases evaluated in this chapter.

Table 2-26: Comparison of Incident Data Statistics.

Statistics	Houston	Austin*	Fort Worth
Analysis Period	2004–2007	2004–2007	2004–2006
Incident Frequencies			
• AM Peak (Per Hour)	3.251	0.201	0.366
• Midday (Per Hour)	2.429	0.258	0.225
• PM Peak (Per Hour)	4.254	0.557	0.261
Collision/Accident Frequencies			
• AM Peak (Per Hour)	2.296	0.078	0.285
• Midday (Per Hour)	1.727	0.072	0.149
• PM Peak (Per Hour)	3.026	0.177	0.192
Stall/Disablement Frequencies			
• AM Peak (Per Hour)	0.777	0.090	0.038
• Midday (Per Hour)	0.481	0.135	0.040
• PM Peak (Per Hour)	1.038	0.316	0.029
Incident Type Distribution			
• Collision/Accident	73.2%	28.4%	71.5%
• Stall/Disablement	19.5%	51.4%	13.9%
• Heavy Truck	10.5%	-	8.4%
• Hazmat Spill	0.6%	1.4%	0.8%
Median Duration (minutes)			
• Collision/Accident	24	42	57
• Stall/Disablement	16	33	65
• Heavy Truck	37	-	82
• Hazmat Spill	115	178	158
85^{th} Percentile Duration (minutes)			
• Collision/Accident	54	87	129
• Stall/Disablement	45	181	198
• Heavy Truck	106	-	189
• Hazmat Spill	297	354	341

*Note: Only non-congestion incidents were included in the analysis.

As seen in Table 2-26, the incident rates from Austin and Fort Worth were comparable, whereas Houston's was approximately 10 times higher. This could have been due to the fact that Houston had more traffic volume and more freeway miles under surveillance coverage. The incident type distributions for Houston and Fort Worth were similar. Austin, on the other hand, had a significantly higher proportion of stall incidents. Among the three cities examined, Houston had the shortest incident durations on average. Several factors could have contributed to the shorter incident durations, such as courtesy patrol coverage, CCTV surveillance coverage, and availability of incident management resources. As for the incident durations by specific types, the hazmat spill and truck-related incidents experienced longer incident durations than collision and stall incidents, and this trend was consistently observed from the data of all three cities.

3. ANALYSIS OF HOT SPOTS

Historical incident data with incident location information can be used to spatially and temporally identify the incident-prone locations or hot spots. This chapter documents the procedures and the results from applying the hot spot analysis techniques described in Module 4 of the guidebook (0-5485-P2). In contrast to the previous chapter, the analyses in this chapter specifically focus on detecting the spatial patterns of incident occurrences in addition to other incident data attributes.

3.1. Hot Spot Identification Methods

Depending on data availability, two methods for identifying hot spots are: (1) the frequency-based method, and (2) 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 analysis also does not incorporate the impacts of the incidents.

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.

Researchers conducted the hot spot analyses described below using the incident data from three TMCs – Houston's TranStar, Austin's CTECC, and Fort Worth's TransVISION. The incident locations were referenced to the nearest cross streets in all the three cities analyzed. The analysis used the coordinates of the nearest cross streets to map the analysis results visually on the map using the ArcGIS platform.

3.2. Houston's TranStar

This section summarizes the hot spot analyses conducted using TranStar's incident data archives from 2004 to 2007.

3.2.1. Data Preparation

The incident data from 2004 to 2007 were imported into Microsoft Access, and specific queries were developed to perform data validation prior to the hot spot analyses:

- Temporal attributes – Default unused time logs recorded as 12/31/9999 11:59:59 PM in the fields of DETECTION_DATE_TIME and CLEARED_DATE_TIME were marked, and the corresponding incident records were then removed. Particularly, since DETECTION_DATE_TIME carries information about incident occurrence time, this data field was validated to ensure its accuracy.
- Spatial attributes – The geographical coordinates of cross streets in the database were used to reference incident locations. There are four data fields in the incident database containing coordinate information: LONGITUDE_IB_CW, LATITUDE_IB_CW, LONGITUDE_OB_CW, and LATITUDE_OB_CW. Researchers selected the first two for all hot spot analyses and checked their according validities. The city of Houston is approximately bounded by the longitude within the range of -94.58967 and -96.31836 and the latitude within the range of 28.94175 and 30.61119. These coordinates are measured in decimal degree. Any coordinates outside these ranges were excluded from the analyses.
- Supplemental attributes – Incident duration was used as a proxy measure of incident impact. Incident durations were obtained by calculating the differences between the start time as recorded in DETECTION_DATE_TIME and the end time as recorded in CLEARED_DATE_TIME of each incident record. The incident records with negative incident durations were designated as invalid and then removed from further analysis.
- Other checks – Duplicate incident records were identified and then removed. The IDs of duplicate incident records are 15590 and 15591 for 2004 data; 23509, 23574, 35243, and 35319 for 2005 data; 40672, 44107, 49573, and 51587 for 2006 data; and 57190, 57249, 66280, and 66841 for 2007 data.

In summary, through the validation process, 45 records were removed from a total of 56,847 records in the database. In addition to the validation of incident data, certain data attributes from incident database were recoded into a format convenient for the analyses:

- To assess the temporal effects on the hot spot analyses, incident detection time based on DETECTION_DATE_TIME was classified into one of the following groups: AM peak (6 AM to 9 AM), midday (9 AM to 4 PM), PM peak (4 PM to 7 PM), night (7 PM to 6 AM), or weekend if incidents occurred on Saturdays or Sundays.
- An indicator variable for signifying a lane-blocking situation was created using combined data from both the TXDOT_LANES_AFFECTED and MAINLANES_BLOCKED fields.
- To maintain consistency in spatially referencing to specific incident locations, a table of unique locations was constructed as shown in Table 3-1. The unique locations were defined by the unique sets of ROADWAY_NAME, CROSS_STREET_NAME, and TXDOT_ROADWAY_DIRECTION. Each unique location has its own coordinate values. Researchers constructed the unique location table to handle the non-unique coordinates (same location, multiple coordinates) found in the incident data archive. Although TranStar's incident database did not have such a problem based on these analyses, a table was constructed in order to be consistent with other cities', which resulted in a total of 1,984 unique locations.

Table 3-1: Example of Unique Incident Locations (Houston).

ID	Roadway	Cross Street	Direction	Latitude	Longitude
1	US-59 SOUTHWEST	IH-610 WEST LOOP	Northbound	29.7288	-95.4606
2	IH-610 WEST LOOP	US-59 SOUTHWEST	Northbound	29.7288	-95.4604
3	IH-45 NORTH	IH-610 NORTH LOOP	Southbound	29.81483	-95.37582
4	IH-45 NORTH	IH-610 NORTH LOOP	Northbound	29.81483	-95.37582
5	IH-610 WEST LOOP	WOODWAY DR	Northbound	29.766	-95.4559
6	IH-45 GULF	W DALLAS ST	Southbound	29.75771	-95.37486
7	IH-610 WEST LOOP	POST OAK RD	Northbound	29.754	-95.4555
8	IH-10 KATY	IH-610 WEST LOOP	Westbound	29.7805	-95.4539

3.2.2. Frequency-Based Hot Spot Analysis

The frequency-based hot spot identification method defines hot spots as the locations that experience above-normal incident rates. The incident rates here are the number of incidents divided by the time period over which the incidents occurred.

In this part, researchers illustrated how to produce more visually distinctive maps for frequency-based hot spot analysis using combined temporal and spatial attributes from the incident database. Specifically, researchers produced five maps by time of day (AM peak, midday, PM peak, nighttime, and weekend), and one map by combining all data. Appendix B documents all the maps plotted in this analysis.

Figure 3-1 shows the top 20 locations with the highest incident rates regardless of time of day, and Table 3-2 shows a listing of corresponding locations. The junction between IH-610 West Loop and US-59 experienced the highest incident rate of all locations evaluated in the database. The junction between IH-610 North Loop and IH-45 North experienced the second highest incident rates. Note that the incident locations that experience very high incident rates are generally at freeway junctions or major cross streets. This is partly because the traffic volume, which is widely accepted as a significant crash-contributing factor, is generally very high at these locations.

Depending on available incident management resources at the TMC and analysis objectives, the number of hot spots identified can be adjusted by defining a proper threshold for incident rates. As an alternative to the pre-specified number of hot spots, a specific percentage of all locations analyzed can be specified. For example, a threshold can be set such that the top 5 percent – based on incident rates – of all locations considered are treated as hot spots.

The maps created were aimed at illustrating how the temporal and spatial attributes can be used to construct queries to identity frequency-based hot spots and then display the map-based results. A variety of queries can be created based on these two attributes to answer specific questions. For example, the analyst can determine the distributions of incidents over the freeway network with respect to seasonality, holiday, and special event effects. This information can also be useful for determining proper staffing requirements during certain periods at the TMC.

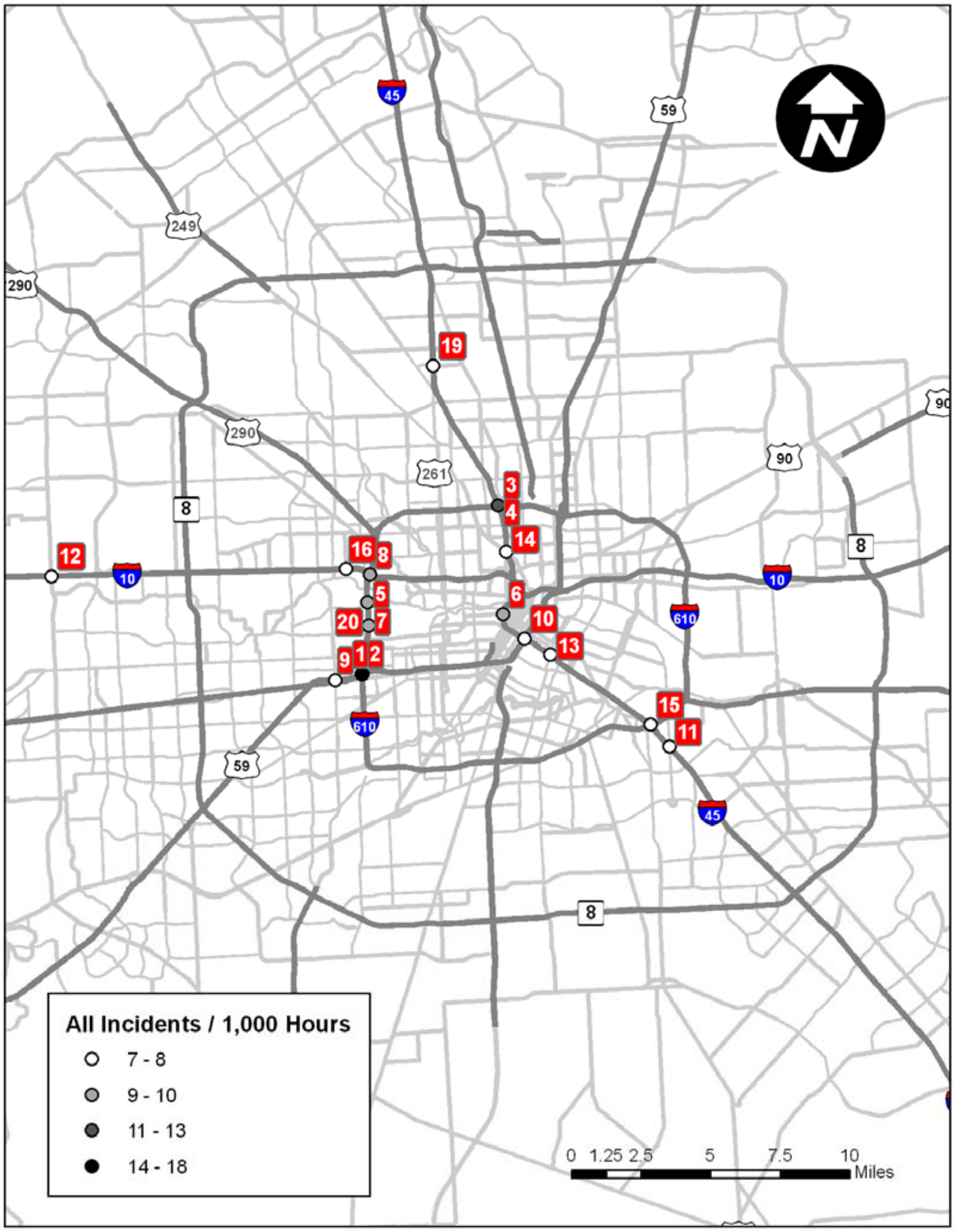


Figure 3-1: Hot Spots Ranked by Average Number of Incidents (Houston).

Table 3-2: Locations with Highest Number of Incidents (Houston).

Rank	Roadway	Cross Street	Direction	Total	Avg*
1	US-59 SOUTHWEST	IH-610 WEST LOOP	Northbound	643	18
2	IH-610 WEST LOOP	US-59 SOUTHWEST	Northbound	464	13
3	IH-45 NORTH	IH-610 NORTH LOOP	Southbound	406	12
4	IH-45 NORTH	IH-610 NORTH LOOP	Northbound	386	11
5	IH-610 WEST LOOP	WOODWAY DR	Northbound	347	10
6	IH-45 GULF	W DALLAS ST	Southbound	329	9
7	IH-610 WEST LOOP	POST OAK RD	Northbound	311	9
8	IH-10 KATY	IH-610 WEST LOOP	Westbound	308	9
9	US-59 SOUTHWEST	CHIMNEY ROCK RD	Northbound	296	8
10	IH-45 GULF	US-59 EASTEX	Northbound	291	8
11	IH-45 GULF	BROADWAY ST/PARK PLACE	Northbound	290	8
12	IH-10 KATY	SH-6	Eastbound	286	8
13	IH-45 GULF	SCOTT ST	Northbound	277	8
14	IH-45 NORTH	N MAIN ST	Northbound	275	8
15	IH-45 GULF	IH-610 SOUTH LOOP	Northbound	263	8
16	IH-10 KATY	SILBER RD	Westbound	263	8
17	IH-10 KATY	IH-610 WEST LOOP	Eastbound	256	7
18	US-59 SOUTHWEST	IH-610 WEST LOOP	Southbound	253	7
19	IH-45 NORTH	GULF BANK RD	Southbound	249	7
20	IH-610 WEST LOOP	POST OAK RD	Southbound	245	7

Note: * Incident rates are per 1,000 hours of observation.

3.2.3. Attribute-Based Hot Spot Analysis

The frequency-based identification method primarily uses only location and time of incident occurrences to identify hot spots. The attribute-based identification method incorporates specific incident data attributes that are not captured through the frequency-based method. The analysis can incorporate any qualified incident attributes as long as they have logical causations with the distribution patterns of incident occurrence. Typical examples of incident attributes include incident duration, incident type, incident delay, lane blockage characteristics, and incident severity.

In this part, the researchers considered the incident duration as the data attribute for measuring the impacts of an incident type. Researchers developed specific queries to identify clusters of incidents that experienced long duration values from TranStar's incident database. Researchers conducted two types of attribute-based analyses in this study:

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

The advanced attribute-based identification method requires the use of the *Spatial Analyst* toolbox in ArcGIS software to conduct the analysis.

3.2.3.1. Duration-Based Hot Spot Analysis

Incident duration is one important attribute that can be incorporated into the hot spot analysis due to its logical correlation with incident impact. Incident duration is also measurable on a continuous scale and easily calculable from the incident database provided that incident occurrence and clearance time logs are available.

The magnitude of incident durations generally differs among various incident types. Further, the underlying causal factors that may contribute to the duration values can also be different. This can be illustrated by considering the two most common incident types in Houston – accident versus stall. Accidents generally require more immediate response and more incident management resources for the same level of severity. The impacts of stall incidents, on the other hand, can vary depending on the lane blockage. Lane-blocking stalls are typically cleared faster than non-lane-blocking stalls, but that does not necessarily mean that their impacts are less. In this case, faster clearance of lane-blocking stalls implies the urgency of the situation rather than the severity. Thus, the consideration of incident duration as a measure of incident impact must also take into account specific types of incidents and their lane blockage characteristics. In Houston's case, researchers found that the durations of non-lane-blocking stalls had relatively large means and variances indicating the high degree of randomness of the situations. Hence, researchers evaluated duration-based hot spot analyses for specific types of incidents rather than combining all data. Without doing so, the results from the analyses can be somewhat misleading.

The researchers performed the duration-based hot spot analysis using the following steps:

- Researchers calculated incident durations for all incident records in the database. Then, using incident type, number of lanes blocked, and all mainlanes blocked attributes, accidents and lane-blocking stalls were flagged for subsequent analysis.
- Sample size for each data category was checked. Both types were found to have sufficient number of records for the analysis.
- For each unique location (refer to the unique location table), the incident counts were queried and joined to the unique location table.
- A minimum number of data points must be checked before median calculation in order to avoid the biased medians from a small sample size. A minimum of three duration values was considered as the absolute minimum for median calculation. Incident counts were sorted, and multiple trials were tested to determine appropriate minimum thresholds. Researchers retained the top 25 percent of all locations in terms of incident counts for the median duration analysis, which is equivalent to the minimum of 30 accidents and 13 lane-blocking stalls per unique location in Houston over the four-year period, 2004 to 2007. As a result, there were a total of 441 and 169 valid unique locations for hot spot analysis of accidents and lane-blocking stalls, respectively.
- Researchers calculated median duration values for each location retained from the previous step. The top 20 locations in terms of median durations were considered as hot spots for both types of incidents.

- Researchers plotted the identified hot spots on the map using the GIS-based tool. Similar to the frequency-based analysis, displaying the results require only coordinate data of the hot spot locations.

Figure 3-2 and Figure 3-3 show accident hot spots and lane-blocking-stall hot spots, respectively, using median duration values. Appendix B contains detailed tables illustrating more information about these locations. The analysis results yielded the following observations:

- Locations with high accident durations are spread out more around the city of Houston, as compared to frequency-based maps. This is because the factors affecting incident duration are less dependent on the prevailing traffic volumes at those locations. Incident duration is more likely influenced by the severity of an incident and the efficiency of incident management responses.
- About one-third of the hot spots were clustered along SH-288 in the southern area of Houston. This could be due to lack of courtesy patrol coverage at those locations.
- The site with the longest accident duration was on SH-288 northbound at Bellfort Boulevard, with a median value of 56.2 minutes, which indicates that approximately 50 percent of all accidents at that location lasted at least 56.2 minutes.
- Four accident hot spots (No. 3, 8, 10, and 15) were located in the northern and southeastern areas of Houston with median durations ranging from 37 to 42 minutes.
- Locations with high median duration resulting from lane-blocking stalls were mostly outside or on Loop 610. The spatial pattern of occurrences was more random. Lane-blocking stalls could take longer to clear if they were outside courtesy patrol coverage area.
- Comparing the median durations between accident and lane-blocking stalls, the latter type lasted shorter on average. The longest lane-blocking stall, located on IH-610 East Loop northbound at Manchester Street, had a median duration of 37 minutes, which was almost 20 minutes shorter than the longest median accident duration.

3.2.3.2. Getis-Ord (Gi*) Spatial Statistics

The analysis of Gi* spatial statistics is a hot spot analysis tool implemented in ArcGIS software. Gi* spatial statistics is a statistical index for determining the locations of spatial clusters of either high or low attribute values. The high index values indicate that the clusters of high attribute values are not random at specific locations and vice versa for low index values. In particular, the researchers incorporated the incident duration as an attribute of interest. This tool can locate and statistically confirm the sites that have both high frequency of incident occurrences and long incident durations. Statistical significance can be specified to screen for only the sites that meet the criteria. Figure 3-4 and Figure 3-5 show examples of results from a Gi* hot spot analysis.

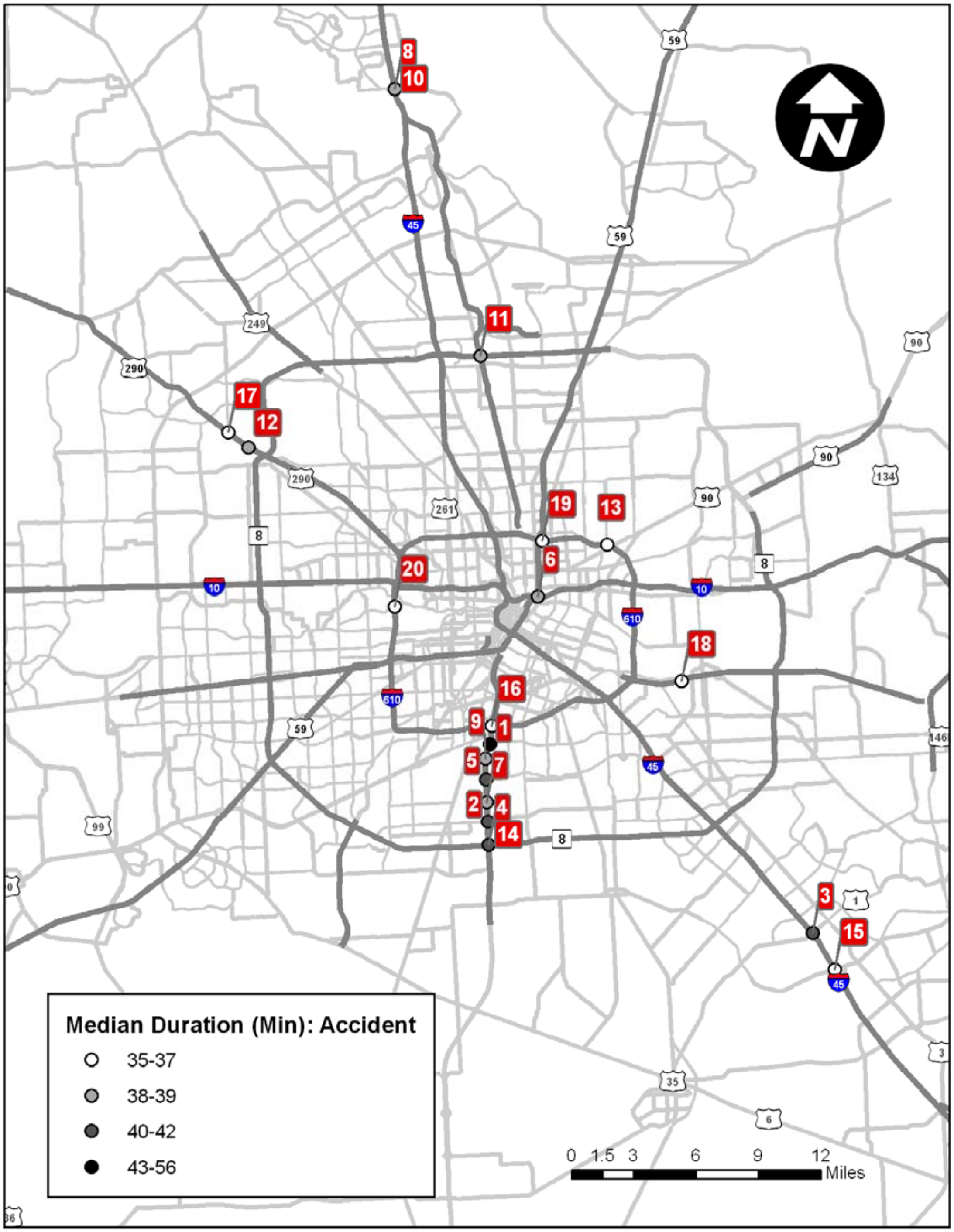


Figure 3-2: Accident Hot Spots with High Median Durations (Houston).

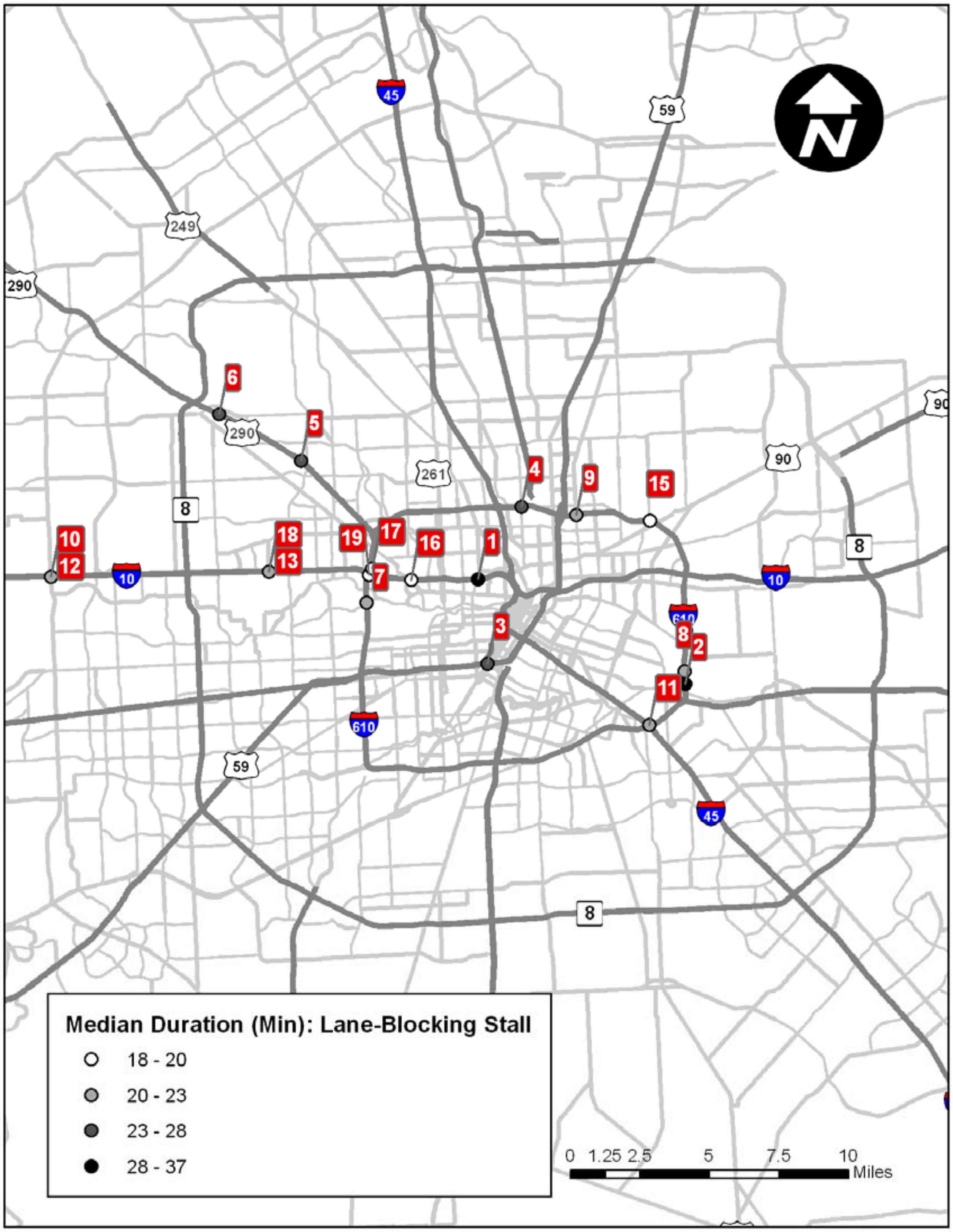


Figure 3-3: Lane-Blocking Stall Hot Spots with High Median Durations.

Analytical Procedures

Researchers conducted the Gi* hot spot analysis using duration attribute as follows:

- Incident types of accident and lane-blocking stalls were selected for this analysis. These two types represent the majority of incident types recorded at TranStar; thus, their sample sizes are sufficiently large.
- Gi* statistics considers both the frequency and the attribute value (i.e., incident duration) in the identification of hot spots. Extremely large incident durations resulting from unmonitored incidents can significantly influence the accuracy of hot spot analysis (increasing the chance of false positive hot spots). Researchers specified the upper duration threshold to filter out incident records with unrealistically large duration values. This analysis removed incidents with a duration greater than one day (1,440 minutes).
- Since the Gi* analysis examines the cluster of incidents, the number of incident counts at each site must be sufficiently large. Researchers queried and retained the top 50 percent of all locations by incident counts for the analysis utilizing the counts by unique locations from the previous basic duration-based analysis. This was equivalent to a minimum of 30 accidents and five lane-blocking stalls per unique location over the four-year period. As a result, there were 888 and 498 candidate locations for the Gi* analysis for accident and lane-blocking stalls, respectively.
- To account for the scaling effect of duration values, researchers used natural logarithms of duration values as input attribute values for the Gi* analysis. This step involved only incidents retained from the previous step.
- Researchers specified the following parameters for the Gi* hot spot analysis: "Spatial Relationships" = *Zone of Indifference*, "Distance Method" = *Euclidean Distance*, and "Distance Band" = *30 feet*.
- The calculated Gi* spatial statistics are essentially z scores from a standard normal distribution. Confidence level can be used to statistically determine the lower threshold of Gi* spatial statistics. This analysis specified a 99 percent confidence level for accidents and a 95 percent confidence level for lane-blocking stalls. As a result, the procedure resulted in 81 accident hot spots and 21 lane-blocking hot spots.
- Researchers plotted these hot spots on the GIS maps using geographic coordinates of the nearest cross streets. In the next step, researchers used the hot spots to construct hazardous or incident-prone segments, which are the freeway segments within the specified proximity of the hot spots.

Incident-prone or hazardous segments are the freeway segments adjacent to the hot spots derived from the Gi* analysis. The hot spots tend to cluster in the same area but not exactly in the same spot. First, each hot spot has a distance-based influential boundary. Then, the union sets of freeway segments within the influential boundary define hazardous segments. From an incident management perspective, control center operators can frequently monitor these segments to improve incident detection and response times.

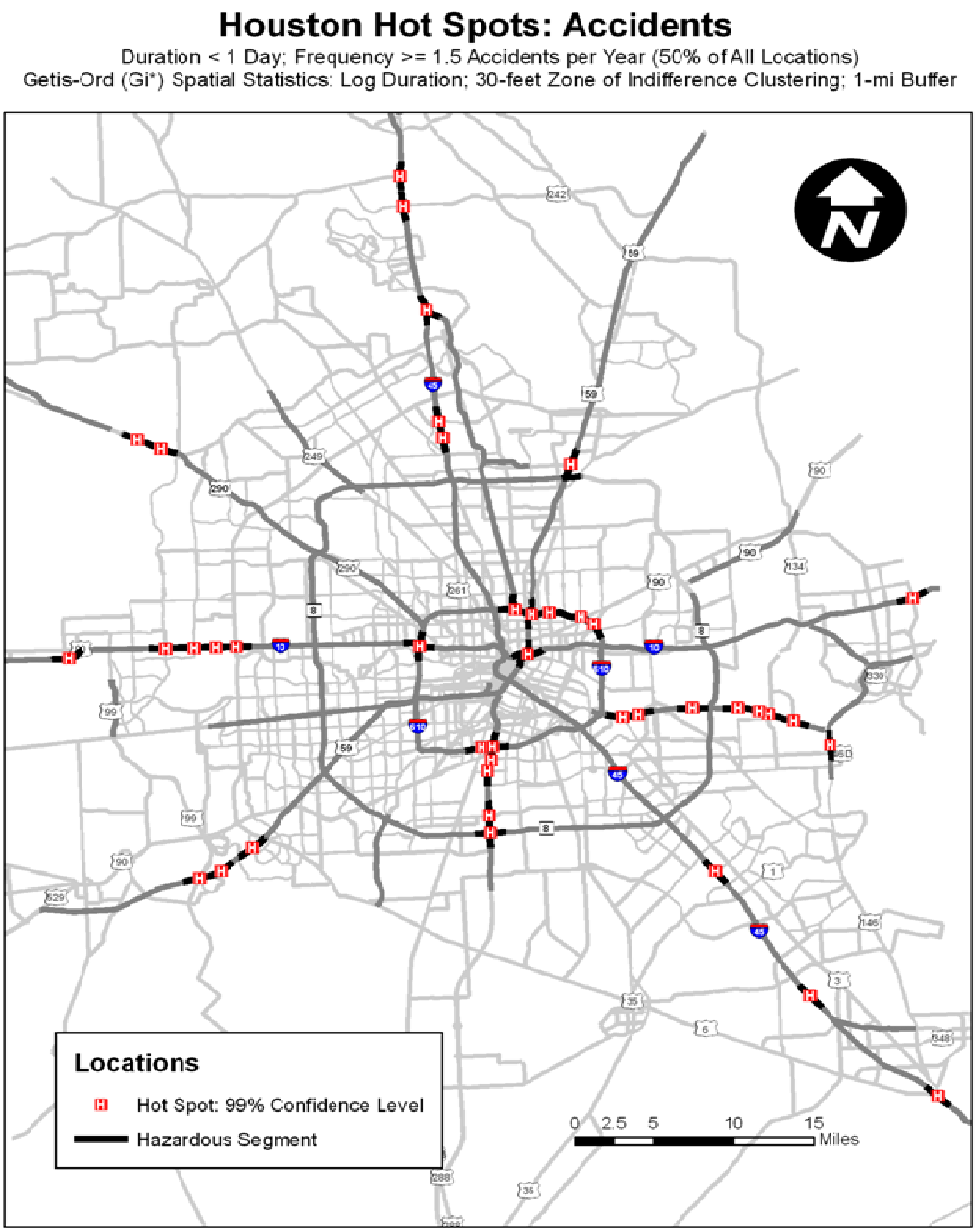


Figure 3-4: Accident Hot Spots Using Gi* Spatial Statistics (Houston).

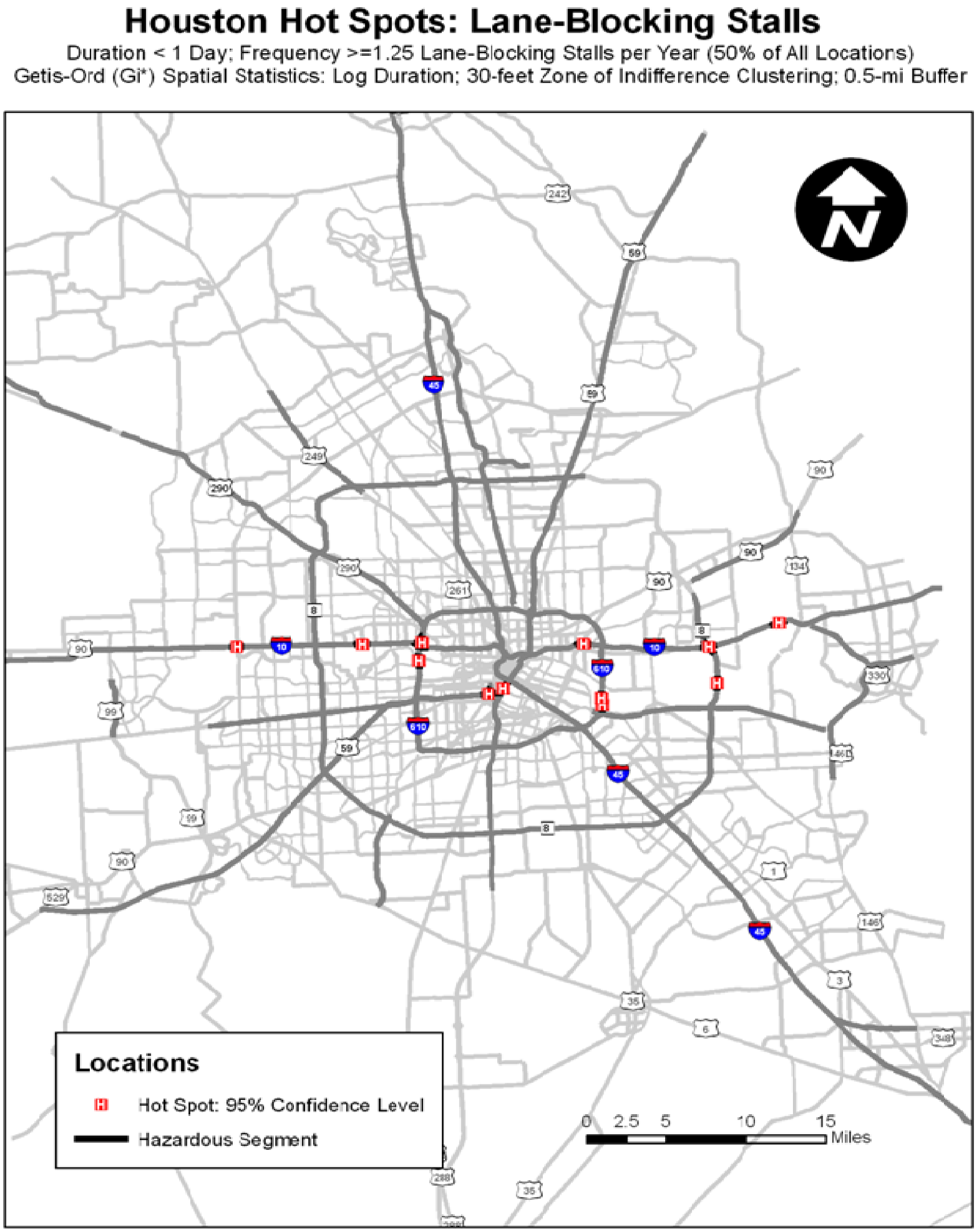


Figure 3-5: Lane-Blocking Stall Hot Spots Using Gi* Spatial Statistics (Houston).

Researchers used the following step-by-step procedure for constructing hazardous segments using ArcGIS:

- Using the buffer analysis module in ArcGIS, researchers specified two different radii – 1-mile radius buffer for accident hot spots and 0.5-mile radius buffer for lane-blocking stall hot spots. These buffers are the influential boundaries of the hot spots. Freeway segments within the overlapped buffers form continuous hazardous segments.

- Using the clip analysis module in ArcGIS, the layer of hazardous segments was created by intersecting the layer of union-set influential buffers with the layer of Houston freeway networks.

Results and Findings

Figure 3-4 and Figure 3-5 display Gi* hot spots along with hazardous segments for accidents and lane-blocking stalls, respectively. Some interesting observations from both maps are as follows:

- Compared to frequency-based and duration-based analyses, accident hot spots identified by Gi* spatial statistics clustered at locations both inside and outside of Beltway-8. Some hot spot locations were the same as those from the previous frequency-based or duration-based analyses, such as locations along the IH-45 segment north of Beltway-8, the IH-10 segment west of Beltway-8, and the SH-288 segment. Additionally, some hot spots were identified exclusively from this analysis, such as sites along SH-225.
- Gi* analysis results consider the joint effects of high frequency and high duration in detecting hot spots. Extremely large incident durations can strongly influence the hot spot results even though the incident frequencies are very low at those locations. For example, several hot spot locations from both median duration and Gi* spatial statistics analyses were the same, such as US-59 EASTEX southbound at IH-10 EAST. On the contrary, none of the hot spots from frequency-based and Gi* analyses were identical.
- Gi* analysis for lane-blocking could identify some locations with very few incidents as hot spots if their incident durations were extremely large. Careful examination of hot spot results should be conducted in this case.
- The Gi* analysis identified several locations along SH-225 as accident hot spots. This freeway segment experienced moderate traffic volume and significant heavy truck activities. Heavy truck incidents are generally more severe and take longer to clear. When analyzed using frequencies alone, these locations may not be justified as hot spots. However, in this case, when researchers incorporated the severity of incidents into the analysis through the duration attribute, these locations became potential hot spots on the basis of combined frequency and duration. In this way, the impacts of incidents were taken into account as another hot spot criterion in addition to incident frequencies.

3.3. Austin's CTECC

This section summarizes the hot spot analyses conducted using CTECC's incident data archives from 2004 to 2007.

3.3.1. Data Preparation

Austin's incident data contain both operator-based records and detector-based alarms. Detector-based alarms are automatically recorded as congestion incidents. These incidents typically record only time logs and detector locations, which are of limited use for detailed analysis. Therefore, the hot spot analysis did not consider any congestion incidents. The remaining non-congestion incident data were then imported into Microsoft Access, and specific queries were developed to perform data validation and prepare the dataset for the hot spot analysis. Researchers checked specific data attributes as follows:

- Temporal attributes – The incident log time and clearance time define the beginning and the end of an incident. Researchers removed incident records with required time logs missing.
- Spatial attributes – The geographical coordinates of the nearest cross streets were used to reference incident locations. The city of Austin is approximately bounded by the longitude between 3059110 and 3164942 and the latitude between 10013863 and 10176523. Any coordinates outside the defined boundary were considered invalid and excluded from the hot spot considerations.
- Supplemental attributes – Incident duration was used as a supplemental attribute for quantifying the incident impacts in the hot spot analysis. Researchers computed duration values by calculating the difference between incident log and clearance times. The analysis considered only the incident records with positive duration values.
- Other checks – The incident data archive also contains "test" records. These records are not valid for the analysis. In order to identify these records, researchers conducted a pattern search of the keyword "TEST" in the following data fields: roadway name, location description, and cross street name. Researchers removed these "test" records from the analysis.

In summary, through the validation process, researchers removed 50,009 records from a total of 56,365 records in the database. In addition to the validation of incident data, researchers recoded certain data attributes from the database into the format suitable for the quantitative analysis:

- To assess the time of day effects on the spatial distribution of incident occurrences, researchers classified the incident time logs into the following categories: AM peak (6 AM to 9 AM), midday (9 AM to 4 PM), PM peak (4 PM to 7 PM), night (7 PM to 6 AM), and weekend if incidents occurred on Saturdays or Sundays.
- To identify a lane-blocking incident, researchers searched the keyword "lane" in the `single_lane_str` data field. If the keyword was found, it implied that at least one lane was blocked. Then an indicator variable was assigned to each incident record to identify the lane blocking situation.

Table 3-3 shows a table of unique locations for Austin's CTECC. The unique locations were defined by a unique combination of roadway name, cross street name, and direction.

- Researchers' analysis of CTECC incident records indicated that there were cases of non-unique coordinates for the same description of locations. This could complicate the incident counts and the visual display of the results on the GIS maps. To resolve this issue, researchers considered the frequencies of reported incidents at these non-unique coordinates. For each location with a group of non-unique coordinates, researchers selected the coordinate with the highest incident count as the only coordinate for each unique location.

- The database contained a total of 186 unique locations.

Table 3-3: Example of Unique Incident Location (Austin).

ID	Roadway	Cross Street	Direction	Latitude	Longitude
1	IH 0035	51st Street	Southbound	10086090	3124167
2	IH 0035	51st Street	Northbound	10086044	3124235
3	IH 0035	Braker Lane	Northbound	10110863	3134466
4	IH 0035	Rundberg Lane	Northbound	10103913	3130841
5	IH 0035	US 290E	Southbound	10090692	3125168
6	IH 0035	US 183/Anderson Lane	Northbound	10096873	3127189
7	IH 0035	Braker Lane	Southbound	10110879	3134400
8	IH 0035	St. Johns Ave	Southbound	10094585	3125915
9	IH 0035	Rundberg Lane	Southbound	10103941	3130787
10	IH 0035	US 183/Anderson Lane	Southbound	10096921	3127128

3.3.2. Frequency-Based Hot Spot Analysis

Frequency-based hot spot analysis considers the locations that experience above-normal incident rates as hot spots. Figure 3-6 displays the top 20 locations ordered by the incident rates regardless of time of day. Table 3-4 shows a corresponding list of location descriptions. Researchers applied similar procedures to analyze the frequency-based hot spots by specific times of day. Appendix C documents all the map results and detailed location descriptions. The following paragraphs summarize findings from the analysis results:

- Hot spots clustered mostly along IH-35 and US-183 routes. Frequency-based hot spots tended to have a strong correlation with locations that experienced high traffic volume.
- Regardless of incident type and time of day, the location with the highest incident rate was IH-35 at 51st Street. The southbound and northbound directions were ranked the first and the second, respectively, in terms of incident rates.
- Analysis of frequency-based hot spots by time of day revealed that the hot spots were shifting from mostly on IH-35 and US-183 in the AM peak to mostly on IH-35 only in the PM peak.
- Some of the sites in Figure 3-6, such as No. 7, 8, and 17, were located off the freeway segment, which may be due to the inaccuracy of cross street coordinates recorded in the database. This issue, however, only affects the visual display of the hot spot results. The rankings, location descriptions, and calculated incident rates are still accurate.

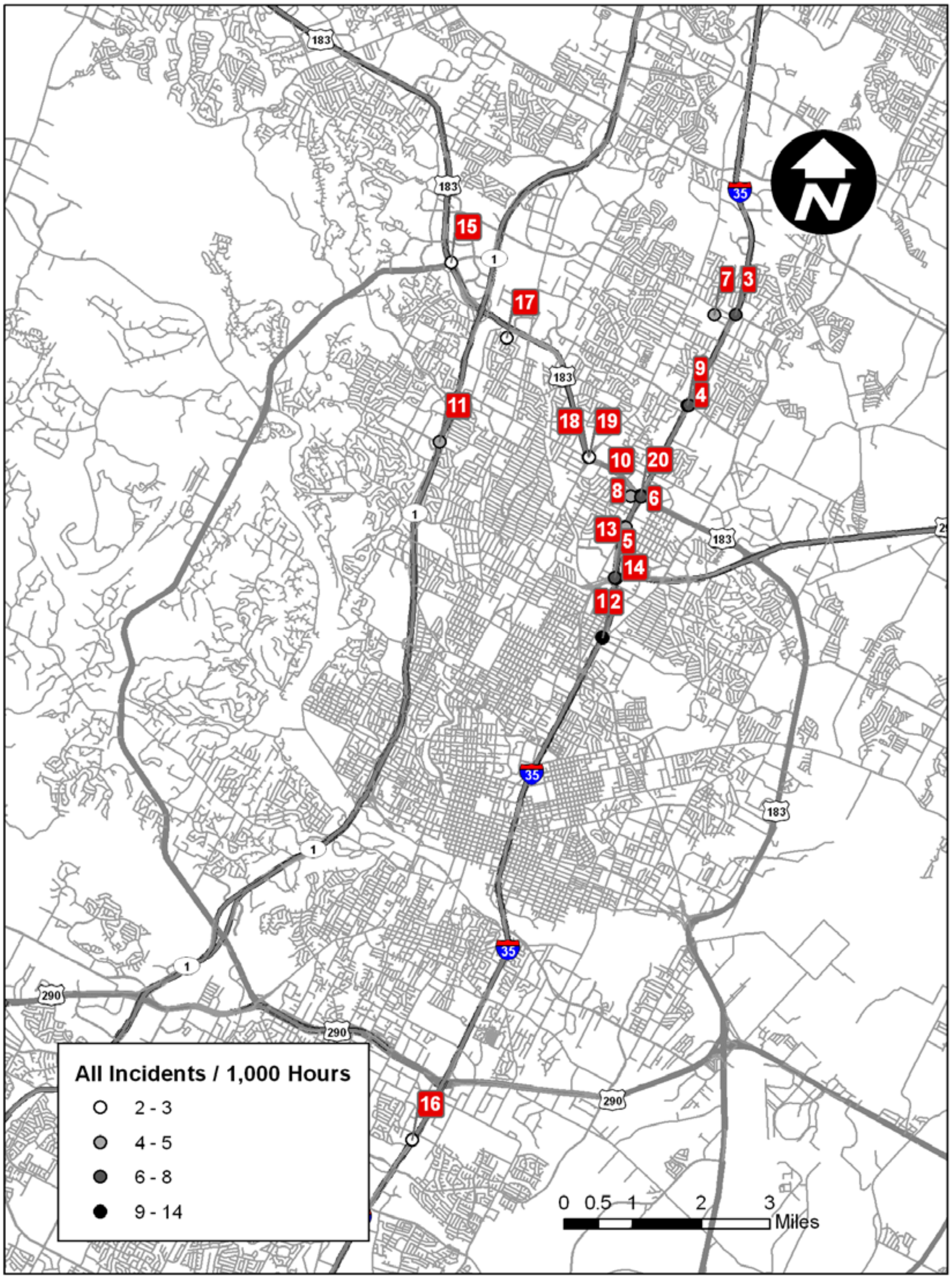


Figure 3-6: Hot Spots Ranked by Average Number of Incidents (Austin).

Table 3-4: Locations with Highest Number of Incidents (Austin).

Rank	Roadway	Cross Street	Direction	Total	Avg*
1	IH 0035	51st Street	Southbound	486	14
2	IH 0035	51st Street	Northbound	350	10
3	IH 0035	Braker Lane	Northbound	289	8
4	IH 0035	Rundberg Lane	Northbound	241	7
5	IH 0035	US 290E	Southbound	207	6
6	IH 0035	US 183/Anderson Lane	Northbound	199	6
7	IH 0035	Braker Lane	Southbound	183	5
8	IH 0035	St. Johns Ave	Southbound	179	5
9	IH 0035	Rundberg Lane	Southbound	170	5
10	IH 0035	US 183/Anderson Lane	Southbound	168	5
11	LP 0001	Far West Blvd.	Northbound	134	4
12	IH 0035	US 183 NB / Anderson Ln	Northbound	130	4
13	IH 0035	St. Johns Ave	Northbound	128	4
14	IH 0035	US 290E	Northbound	113	3
15	US 0183	Cap. Of Tx Hwy./LP 360	Northbound	110	3
16	IH 0035	End of Instrumentation	Southbound	110	3
17	US 0183	Burnet Rd./FM 1325	Northbound	90	3
18	US 0183	Lamar Blvd./LP 275	Southbound	89	3
19	US 0183	Lamar Blvd./LP 275	Northbound	74	2
20	IH 0035	US 183 NB / Anderson Ln	Southbound	70	2

Note: * Incident rates are per 1,000 hours of observation.

3.3.3. Attribute-Based Hot Spot Analysis

Specific data attributes from the incident database can be used to identify clusters of incidents with high/low attribute values that are unlikely to occur by randomness. Similar to the attribute-based analyses of Houston, researchers used the incident duration attribute to measure incident impacts, and to conduct two types of attribute-based analyses in this study:

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

As discussed in section 3.2.3.1, the same incident characteristics can have contradicting effects on incident durations for different incident types. Researchers therefore analyzed hot spot analyses for specific incident types to avoid this problem. Collision and lane-blocking stall hot spot analyses were conducted in this attribute-based analysis. These two incident types represented the majority of non-congestion incidents recorded in CTECC's database.

3.3.3.1. Duration-Based Hot Spot Analysis

The researchers performed the following steps in the duration-based hot spot analysis:

- The incident durations were calculated for all collision and lane-blocking stall incidents.
- Incident counts were queried for each unique location. Researchers then checked incident counts at these locations to ensure that they are sufficient for calculation of median duration values.
- The top 25 percent of all locations in terms of incident counts was retained for calculating median durations. In this way, minimum sample size for each location could be maintained. This criterion was equivalent to at least 12 and 5 collisions and lane-blocking stalls from 2004 to 2007, respectively.
- Median duration values were calculated for each location retained from the previous step. The top 20 locations in terms of median durations were considered as hot spots for both types of incidents.
- Researchers plotted the selected hot spots on the map using the GIS-based tool. Similar to the frequency-based analysis, only coordinate data of the hot spot locations were required for displaying the results.

Figure 3-7 and Figure 3-8 display the top 20 sites identified as collision and lane-blocking stall hot spots, respectively, based on median incident durations. Comparisons of these maps and with corresponding maps for Houston produced the following observations:

- Median-based collision hot spots were spread out more than the frequency-based counterparts. Hot spots were located primarily on IH-35, US-183, and LP-1. This is because duration-based hot spots can be influenced by a multitude of factors (e.g., vehicle types, number of lanes blocked, and injury severity) in addition to the prevailing traffic volumes.
- The location with the longest median duration (70 minutes) was southbound of US-183 at MoPac Expressway.
- The top 20 duration-based collision hot spots were in the range of 44 to 70 minutes. This range is slightly larger than Houston's, which was between 35 and 56 minutes. This is not unexpected due to denser CCTV coverage area and more frequent courtesy patrol in Houston's metropolitan area.
- Lane-blocking stall hot spots were noticeably clustered along IH-35. The location with the highest median duration was IH-35 northbound at Howard Lane. Lane-blocking stalls had a much wider range of median duration (i.e., 18 to 83 minutes for the top 20 locations).
- Comparatively, the durations of lane-blocking stalls are shorter than those of accidents in Houston. However, the differences in durations between these two types in Austin are less distinct.

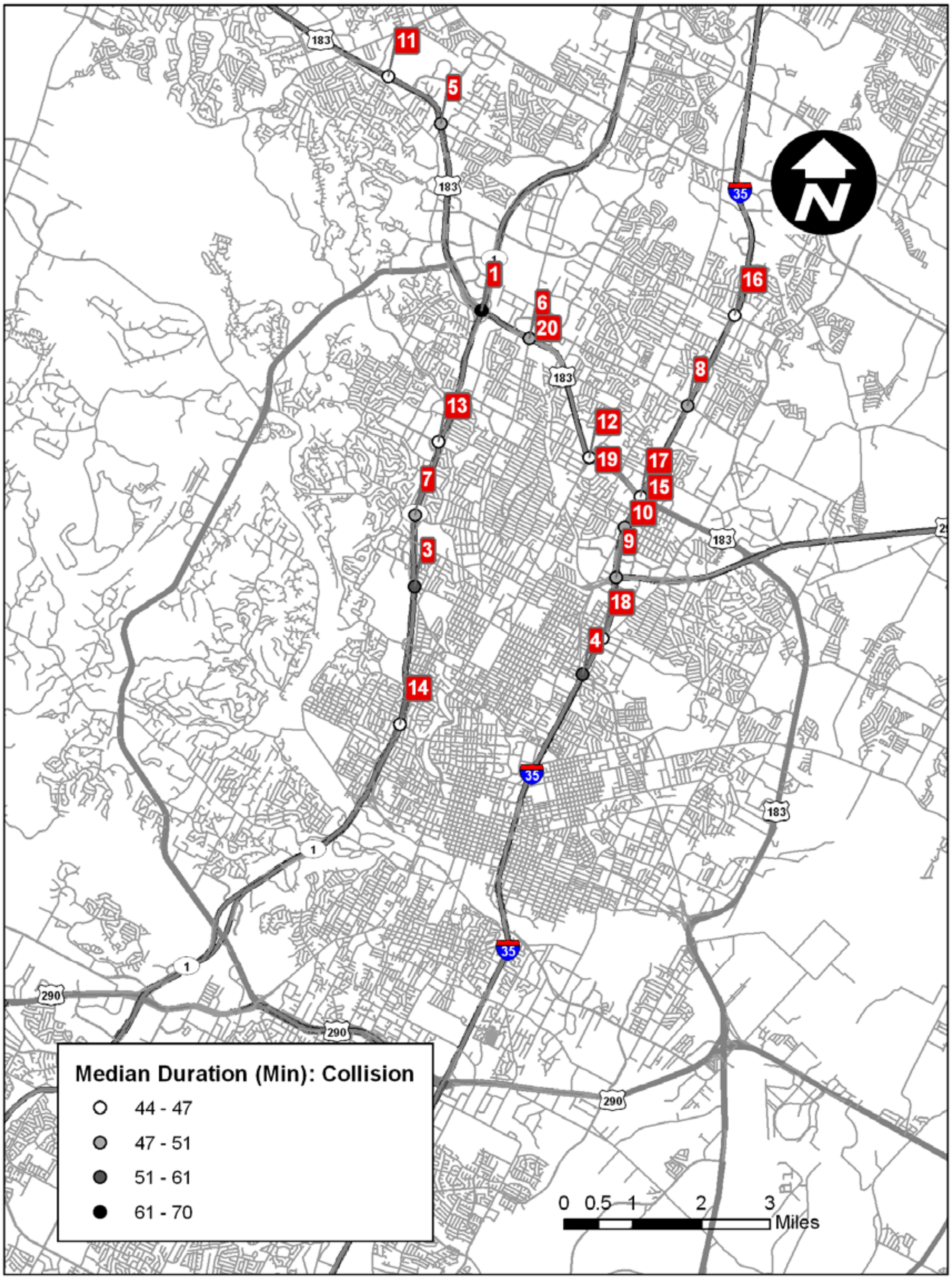


Figure 3-7: Collision Hot Spots with High Median Durations (Austin).

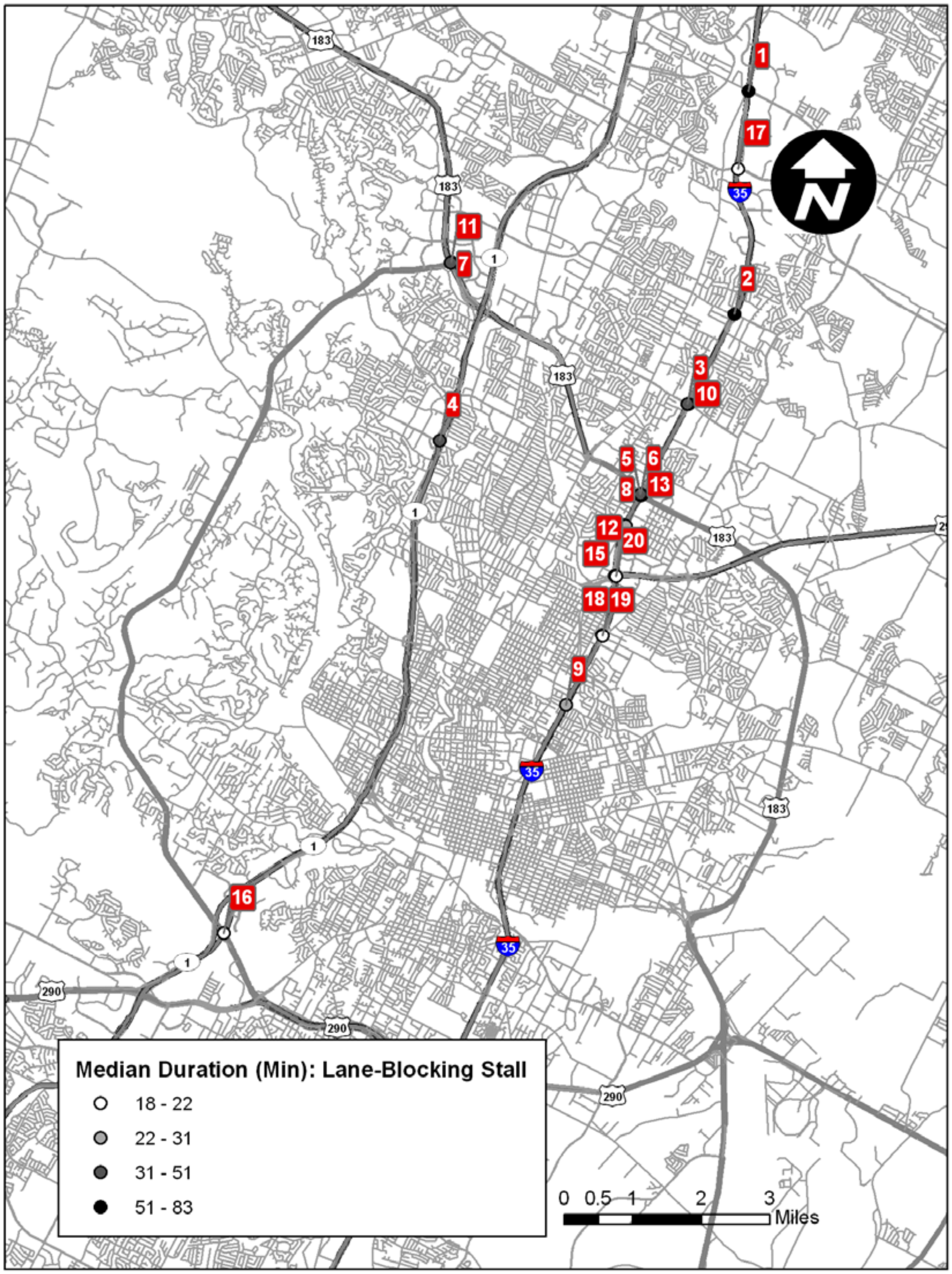


Figure 3-8: Lane-Blocking Stall Hot Spots with High Median Durations (Austin).

3.3.3.2. Getis-Ord (Gi*) Spatial Statistics

In this section, researchers used the ArcGIS Spatial Analyst Tool to calculate Gi* statistics from the incident data from Austin's CTECC. The examples of Gi* spatial statistics results are shown in Figure 3-9 and Figure 3-10, and the detailed locations are documented in Appendix C.

Analytical Procedures

The procedures were similar to the Gi* hot spot analysis for Houston. The high Gi* statistics indicate that there is a high probability that the clusters of incidents with high durations did not occur by chance. Two types of incidents considered were collision and lane-blocking stalls. Specific parameters used for this analysis are as follows:

- Upper threshold of incident durations was set at 1,440 minutes.
- The top 50 percent of all locations in terms of incident counts was retained for the analysis. Specifically, from 2004 to 2007, 86 out of 166 locations had at least five collisions, and 50 out of 106 locations had at least two lane-blocking stalls.
- Natural logarithms of incident durations were used as input attribute values for Gi* analysis to account for the scaling effect of duration values.
- The Gi* hot spot analysis was carried out using the following parameters: "Spatial Relationships" = *Zone of Indifference*, "Distance Method" = *Euclidean Distance*, and "Distance Band" = *30 feet*.
- In this case, 90 percent confidence level was specified as a hot spot threshold for both collision and lane-blocking stall incidents. As a result, four collision and five lane-blocking stall hot spots were identified, as shown in Figure 3-9 and Figure 3-10, respectively.
- Using the hot spots identified from the previous step, a distance-based buffer of 1-mile and 0.5-mile radii were used to define hazardous freeway segments for collision and lane-blocking stall hot spots, respectively.

Results and Findings

The collision and lane-blocking stall hot spots along with the hazardous segments are shown in Figure 3-9 and Figure 3-10, respectively. The comparison of these two maps with the corresponding maps in Houston yielded the following observations:

- In Austin, the collision hot spots were located closer to the city compared to the lane-blocking stall hot spots. This could be attributed to the fact that the Gi* statistics consider both frequency and duration. The effect of frequency influenced the collision hot spots more than the effect of the duration. Conversely, the opposite was true for the lane-blocking stall hot spots.
- The lane-blocking stall hot spots tended to be the areas that experienced repeated long-duration incidents compounded by limited courtesy patrol and/or surveillance coverage. Although similar analytical procedures applied in the two cities, the number of hot spots identified in Austin was much fewer than that of Houston. This is mainly because of the difference in the sample size used to conduct the hot spot analysis. Houston's incident database was much larger than

Austin's. In order to achieve the comparable number of hot spots, the statistical confidence level could be adjusted for each city.

- Due to a large sample size, the confidence level would have to be raised as high as 99.5 percent in order to reduce Houston's number of hot spots significantly, and that still would not yield a comparable number to Austin's at 90 percent confidence level.
- Similar to the Houston's analysis, large incident duration values can significantly influence the calculated Gi* spatial statistics. The longest duration collision site was US-183 at MoPac Expessway, and this location was the second-ranked hot spot on the Gi* map.

3.4. Fort Worth's TransVISION

This section summarizes the hot spot analyses conducted using TransVISION's incident data from 2004 to 2006.

3.4.1. Data Preparation

Researchers imported the incident data into Microsoft Access and developed specific queries to perform data validation and prepare the dataset for the hot spot analysis. Specific data attributes were checked as follows:

- Temporal Attributes – The earliest of three time logs – occurrence time, detection time, and verification time – was used to define the beginning of an incident.
- Spatial Attributes – The city of Fort Worth is approximately bounded by the longitude between 32.51727 and 32.00304 and the latitude between -97.57801 and -97.030701. Invalid coordinates such as missing values or coordinates outside the city boundary were identified and the associated incident records were removed from subsequent analysis.
- Supplemental Attribute – Researchers again considered incident duration as a supplemental attribute for Fort Worth hot spot analysis. The latest of the two clearance time logs in the database defines the end of an incident. If both the beginning and the end time logs of an incident existed and were valid for an incident record, the incident duration was then computed by calculating the difference between these two times. Researchers removed incident records with either invalid time logs or negative incident durations from further analysis.
- Other checks – Researchers also checked for duplicate records and did not find this problem in the database.

Duration < 1 Day; Frequency >=1.25 Collisions per year (50% of All Locations)
Getis-Ord (Gi*) Spatial Statistics: Log Duration; 30-feet Zone of Indifference Clustering; 1-mi Buffer

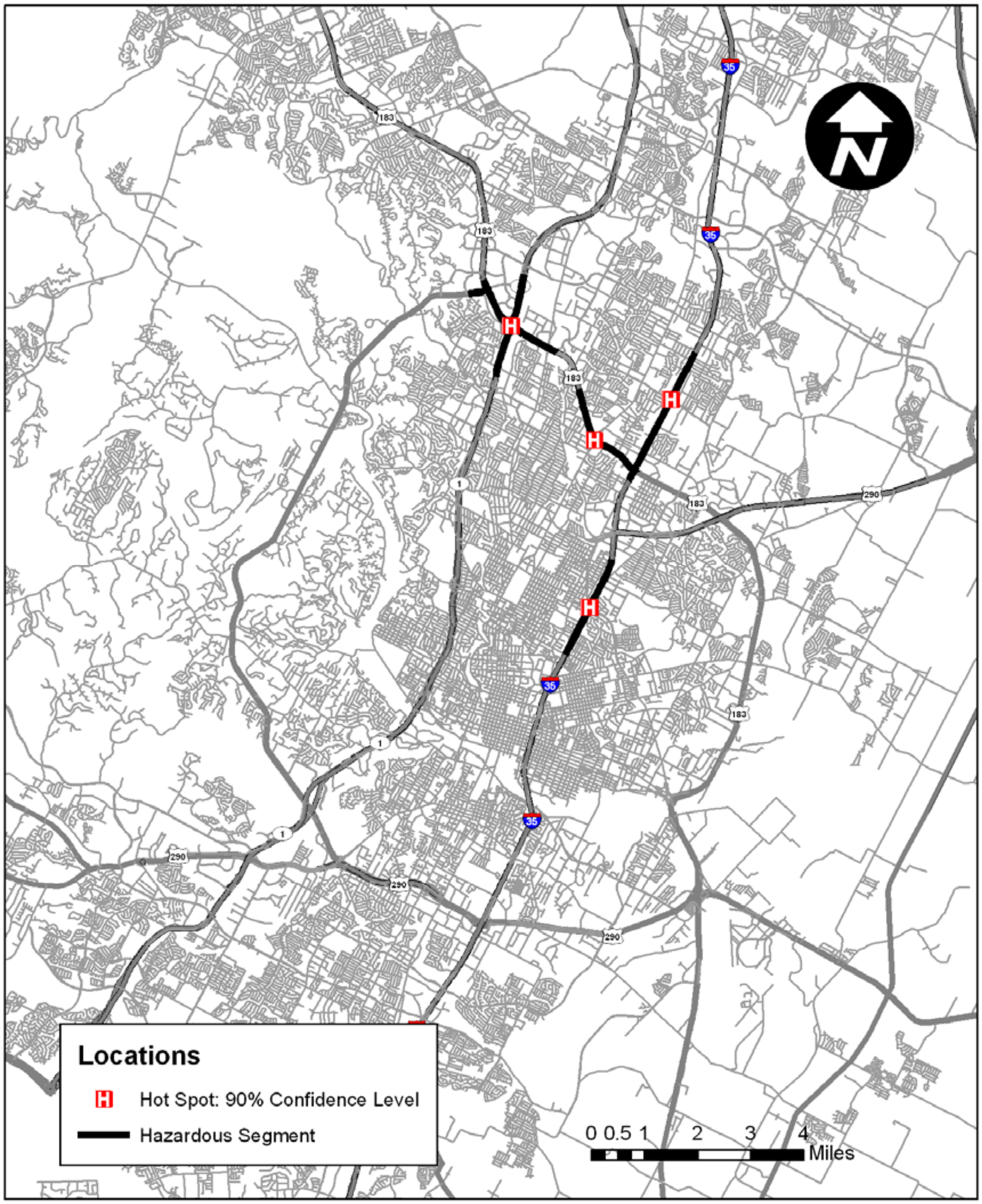


Figure 3-9: Collision Hot Spots Using Gi* Spatial Statistics (Austin).

Duration < 1 Day; Frequency >=0.5 Lane-Blocking Stalls per year (50% of All Locations)
Getis-Ord (Gi*) Spatial Statistics: Log Duration; 30-feet Zone of Indifference Clustering; 0.5-mi Buffer

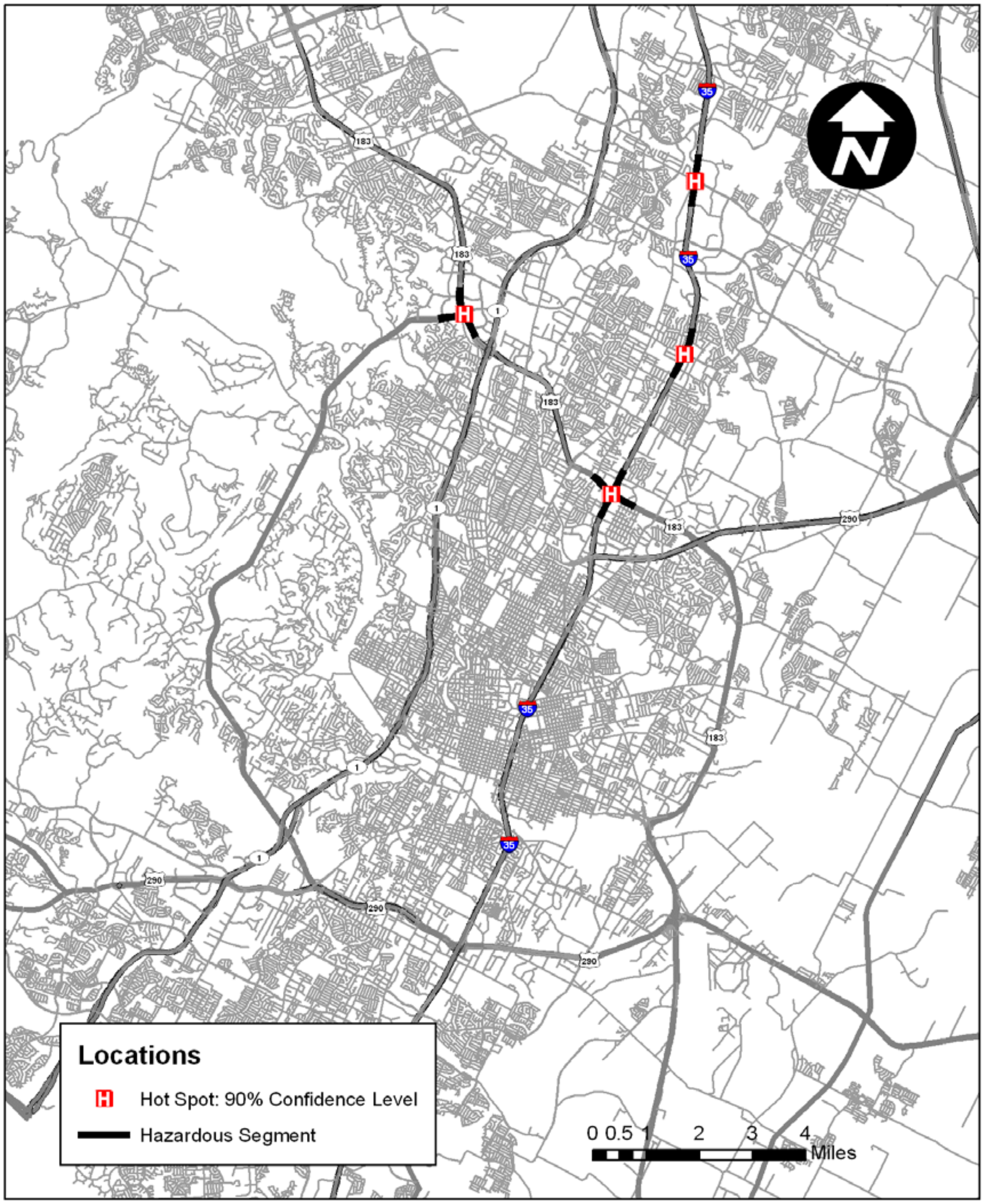


Figure 3-10: Lane-Blocking Stall Hot Spots Using Gi* Spatial Statistics (Austin).

Through the validation process, researchers removed 176 invalid entries from a total of 2,580 incident records and then conducted the following data processing and recoding on the incident records retained from the data validation process:

- To assess the temporal effects on the spatial distribution, researchers categorized the incident occurrence time into the following groups: AM peak (7 AM to 9 AM), midday (9 AM to 4 PM), and PM peak (4 PM to 6 PM). Researchers defined the time periods here based on TMC operating hours, which were daytime weekday only (i.e., 6 AM to 6 PM weekdays). TransVISION had a very few number of incidents recorded after hours for this reason.
- Researchers logically derived lane blockage characteristics from the database, and then created an indicator variable specifically for this condition. The newly created variable was used to identify lane-blocking incidents and could be combined with specific incident types, such as lane-blocking stalls.
- Researchers constructed a unique location table for Fort Worth from the database as shown in Table 3-5 by querying a unique set of roadway name, cross street name, and travel direction.
- Researchers' analysis of incident records indicated that there were cases of non-unique coordinates for the same description of locations. To resolve this issue, for each location with a group of non-unique coordinates, the coordinate with the highest incident count was retained as the only coordinate for each unique location. A total of 353 unique locations were identified at the end of this step.

Table 3-5: Example of Unique Incident Locations (Fort Worth).

ID	Roadway	Cross Street	Direction	Latitude	Longitude
1	SH183	AMON CARTER BLVD	Eastbound	32.8375	-97.0491
2	SH183	AMON CARTER BLVD	Westbound	32.8375	-97.0462
4	SH183	BEDFORD RD	Westbound	32.8391	-97.1501
5	SH183	BEDFORD/EULESS	Eastbound	32.8354	-97.1955
6	SH183	BEDFORD/EULESS	Westbound	32.8331	-97.2020
8	SH183	BROWN TRL	Westbound	32.8401	-97.1594
9	SH183	CENTRAL DR	Eastbound	32.8371	-97.1307
10	SH183	CENTRAL DR	Westbound	32.8373	-97.1307

3.4.2. Frequency-Based Hot Spot Analysis

Frequency-based hot spot identification analysis focuses on the sites that experienced above-normal rates of incident occurrence. Figure 3-11 displays the top 20 locations with the highest incident frequency regardless of incident types and time of day. Table 3-6 shows detailed descriptions of corresponding hot spot locations. Researchers performed similar analyses to examine the hot spot distributions by time of day. All the frequency-based analysis results and detailed location descriptions for Fort Worth are summarized in Appendix D.

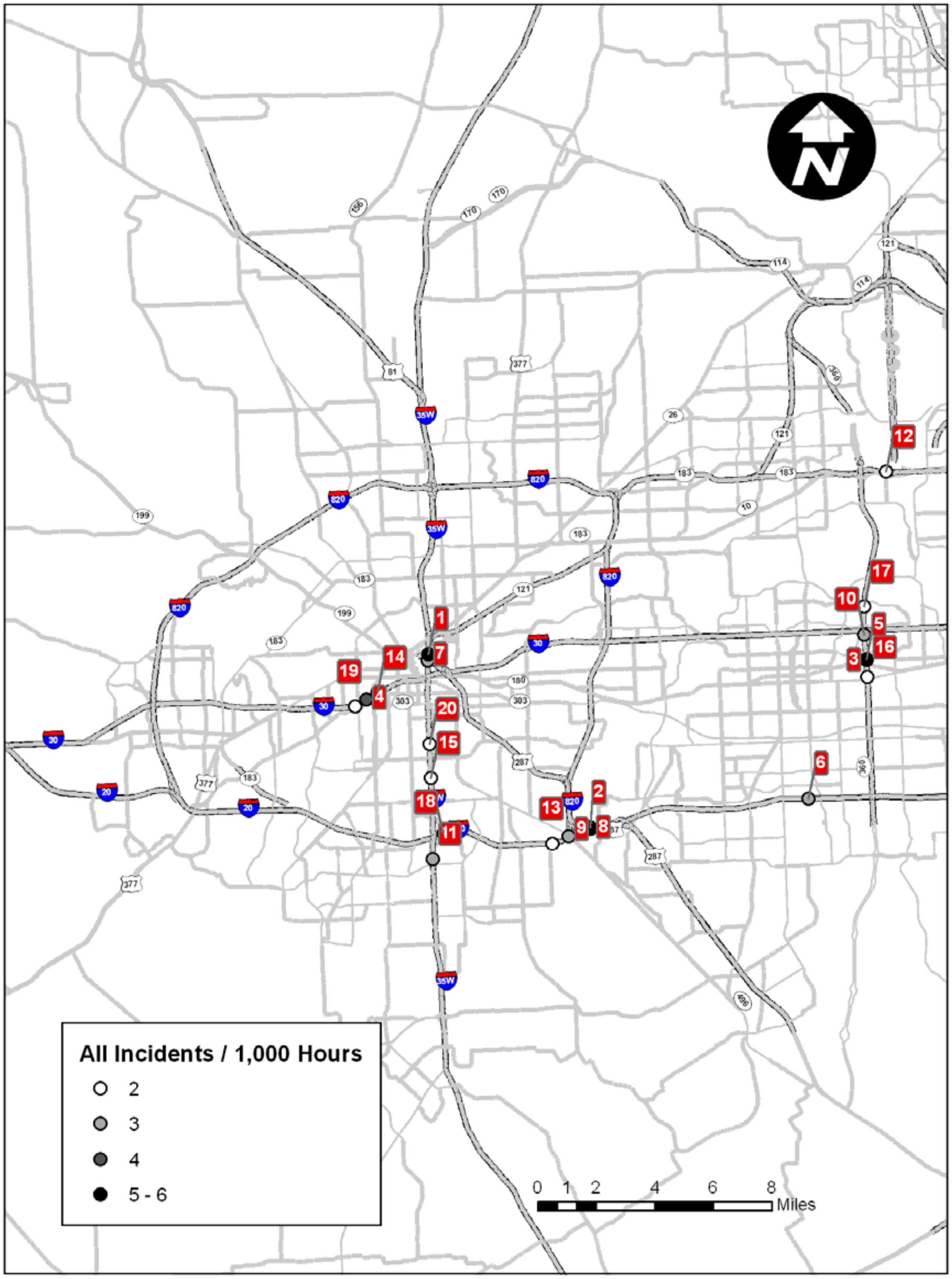


Figure 3-11: Hot Spots Ranked by Average Number of Incidents (Fort Worth).

Table 3-6: Locations with Highest Number of Incidents (Fort Worth).

Rank	Roadway	Cross Street	Direction	Total	Average
1	I35	SPUR 280	Northbound	54	6
2	I20	BOWMAN SPRINGS RD	Westbound	48	5
3	SH360S	DIVISION ST/US-180	Northbound	46	5
4	I30	FOREST PARK BLVD	Eastbound	37	4
5	SH360S	DIVISION ST/US-180	Southbound	33	4
6	I20	S COLLINS ST	Westbound	31	3
7	I35	SPUR 280	Southbound	30	3
8	I20	BOWMAN SPRINGS RD	Eastbound	29	3
9	I20	MANSFIELD HWY/US-287	Eastbound	29	3
10	SH360S	SIX FLAGS	Southbound	25	3
11	I35	ALTAMESA BLVD	Northbound	25	3
12	SH183	AMON CARTER BLVD	Westbound	22	2
13	I20	ANGLIN DR	Eastbound	22	2
14	I30	FOREST PARK BLVD	Westbound	22	2
15	I35	RIPY ST	Southbound	22	2
16	SH360S	ABRAM ST	Northbound	21	2
17	SH360S	BROWN/AVE K	Southbound	20	2
18	I20	OAK GROVE RD	Westbound	20	2
19	I30	UNIVERSITY DR	Eastbound	20	2
20	I35	MORNINGSIDE DR	Northbound	20	2

Note: * Incident rates are per 1,000 hours of observation.

Below are some findings from the frequency-based hot spot analysis using Fort Worth's incident data:

- Fort Worth had the lowest incident rates among the three cities evaluated in this study. The incident counts were normalized by the same 1,000 hours of observation. In Houston, incident rates ranged from 7 to 18 per 1,000 hours. In Austin, the range was between 2 and 14. The corresponding figures for Fort Worth were 2 and 6. Traffic volume is a major determinant of the differences in incident rates among these three cities.
- An evaluation of incident rates among the top 20 locations by time of day indicated that AM peak (7 AM to 9 AM) experienced the highest incident occurrence rate at 4 to 15 incidents per 1,000 hours.
- The incident rates during midday and PM peak were lower than the AM peak and somewhat comparable at 2 to 6 and 3 to 7 incidents per 1,000 hours, respectively.
- The analysis of frequency-based hot spots indicated that the hot spots varied by time of day. During the AM peak, the majority of hot spots were located on IH-35W. The hot spots were concentrated mostly along US-287 during midday and along US-360 during PM peak. Overall, the majority of hot spots were located on one of these three corridors.

3.4.3. Attribute-Based Hot Spot Analysis

Specific data attributes from incident databases can be used to identify clusters of incidents with high/low attribute values that are unlikely to occur by randomness. Similar to the previous analyses, researchers used the incident duration attribute to measure incident impacts and to conduct two types of attribute-based analyses in this study:

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

Section 3.2.3.1 explained the basis for analyzing attribute-based hot spots by incident types and incorporating incident duration as the attribute of interest. Collision and disablement were the two major incident types recorded in the TransVISION's incident database. Lane-blocking disablement refers to a non-collision incident blocking at least one main travel lane and thus is similar to the lane-blocking stall analyzed for Houston and Austin. As for collision, TransVISION classified each collision into either a minor or major collision. Researchers combined both types of collision and simply referred to it as a collision type in this analysis.

3.4.3.1. Duration-Based Hot Spot Analysis

Researchers conducted similar procedures for analyzing hot spots based on median durations using Fort Worth's incident data. The analysis separately evaluated collision and lane-blocking disablement:

- For collision incidents, the analysis considered the top 50 percent of all locations by incident counts. A total of 92 out of 339 locations had at least seven collisions over the three-year analysis period.
- For lane-blocking disablement, only 12 locations, or 15 percent of all locations with disablement reported, had at least three lane-blocking disablements. Researchers were unable to obtain representative median durations because of limited sample size. Hence, researchers did not conduct the median-duration hot spot analysis for lane-blocking disablement.
- For collision incidents, researchers computed median durations for each unique location. The analysis identified the top 20 locations with the highest median duration as collision hot spots, as shown in Figure 3-12.

Figure 3-12 displays the top 20 sites identified as collision hot spots based on median durations. These collision hot spots were dispersed over the major freeway segments with no distinct patterns. The majority of the hot spots were still located closer to the downtown area, partly because of higher traffic volume and thus higher incident frequencies. Note that researchers calculated the median duration only for locations that experience a sufficient number of incidents.

When compared with the median durations observed from Houston's or Austin's hot spots, the top 20 locations in Fort Worth had much larger duration values (i.e., 72 to 139 minutes). This range is nearly double the median values observed in Austin and triple those observed in Houston.

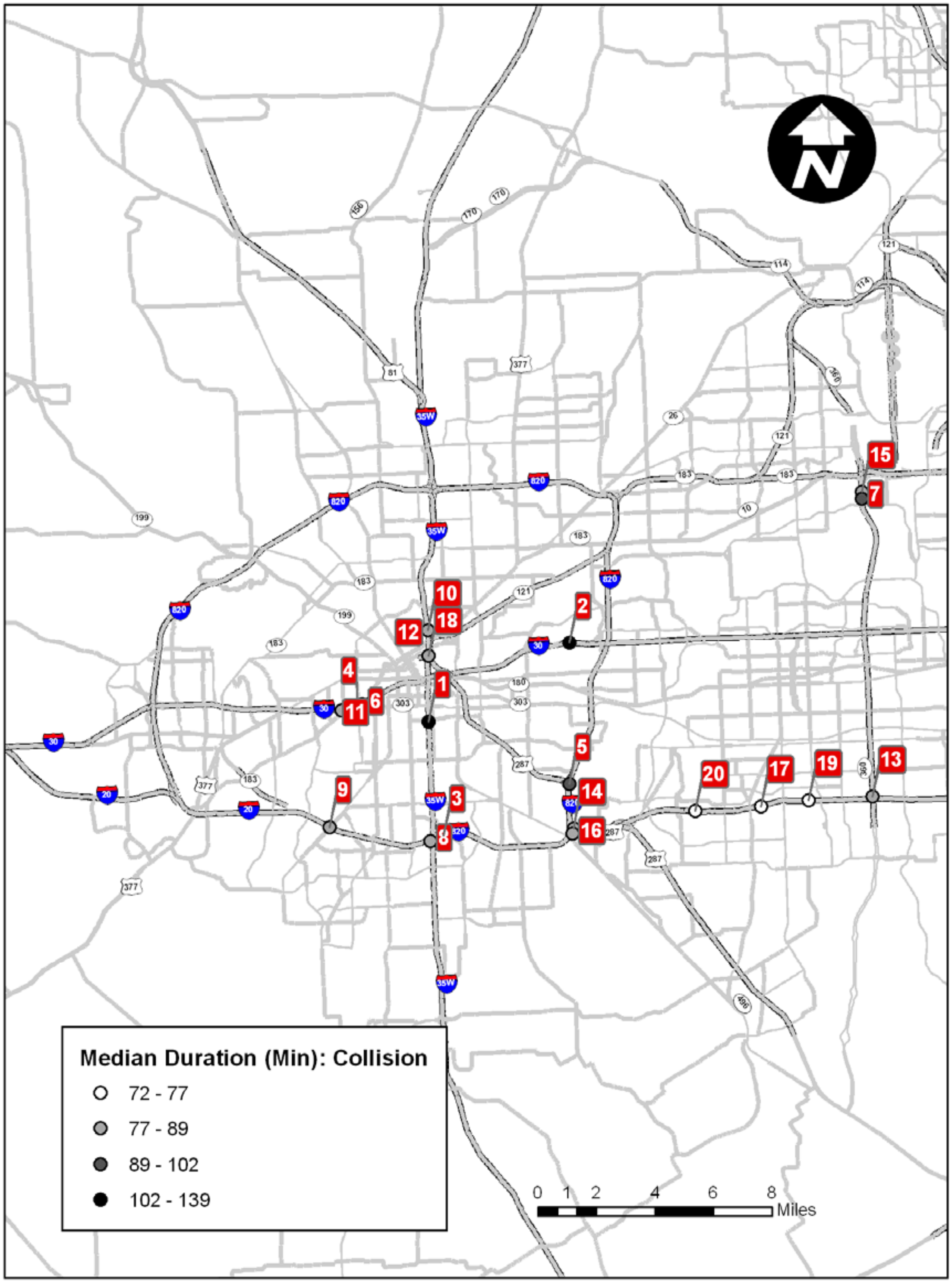


Figure 3-12: Collision Hot Spots with High Median Durations (Fort Worth).

3.4.3.2. Getis-Ord (Gi*) Spatial Statistics

In this section, researchers used the ArcGIS Spatial Analyst Tool to calculate Gi* statistics from TransVISION's incident database. Figure 3-13 and Figure 3-14 show the examples of Gi* spatial statistics results and Appendix D documents the detailed locations.

Analytical Procedures

Researchers conducted the Gi* hot spot analysis using the duration attribute as follows:

- Both collision and lane-blocking disablement were considered in this analysis. These two types represented the majority of incident types recorded at TransVISION; thus, their sample sizes were sufficiently large.
- Gi* statistics considers both the frequency and the attribute value (i.e., incident duration) in the identification of hot spots. Extremely large incident durations resulting from unmonitored incidents can significantly influence the accuracy of hot spot analysis (increasing the chance of false positive hot spots). Researchers therefore specified the upper duration threshold to filter out incident records with unrealistically large duration values. Incidents with the duration greater than one day (1,440 minutes) were removed from this analysis.
- Since the Gi* analysis examines the cluster of incidents, the number of incident counts at each site must be sufficiently large. Utilizing the incident counts by unique locations from the previous basic duration-based analysis, researchers queried and retained the top 50 percent of all locations by incident counts for the analysis. This was equivalent to a minimum of three collisions over the three-year period, and a total of 199 out of 349 locations met this requirement.
- Researchers applied the same procedure to the lane-blocking disablement. However, the sample size was very limited when the top 50 percent of all locations were used as a threshold. In this case, the number of locations considered was instead restricted by the number of lane-blocking disablement observed at the site. Only the locations with at least three lane-blocking disablements were considered in this step. As a result, a total of 40 incident records from 11 unique locations were retained for the analysis.
- To account for the scaling effect of duration values, researchers used natural logarithms of duration values as input attribute values for Gi* analysis. Note that only incidents retained from the previous step were analyzed in this step.
- Researchers carried out the Gi* hot spot analysis using the following parameters: "Spatial Relationships" = *Zone of Indifference*, "Distance Method" = *Euclidean Distance*, and "Distance Band" = *30 feet*.
- In this case, researchers specified a 95 percent confidence level for collision hot spot analysis, and an 85 percent confidence level for lane-blocking disablement hot spots.
- Using the hot spots identified from the previous step, researchers used a distance-based buffer of 1-mile and 0.5-mile radii to define hazardous freeway segments for collision and lane-blocking stall hot spots, respectively.

Duration < 1 Day; Frequency >=1 Collisions per year (50% of All Locations)
Getis-Ord (Gi*) Spatial Statistics: Log Duration; 30-feet Zone of Indifference Clustering; 1-mi Buffer

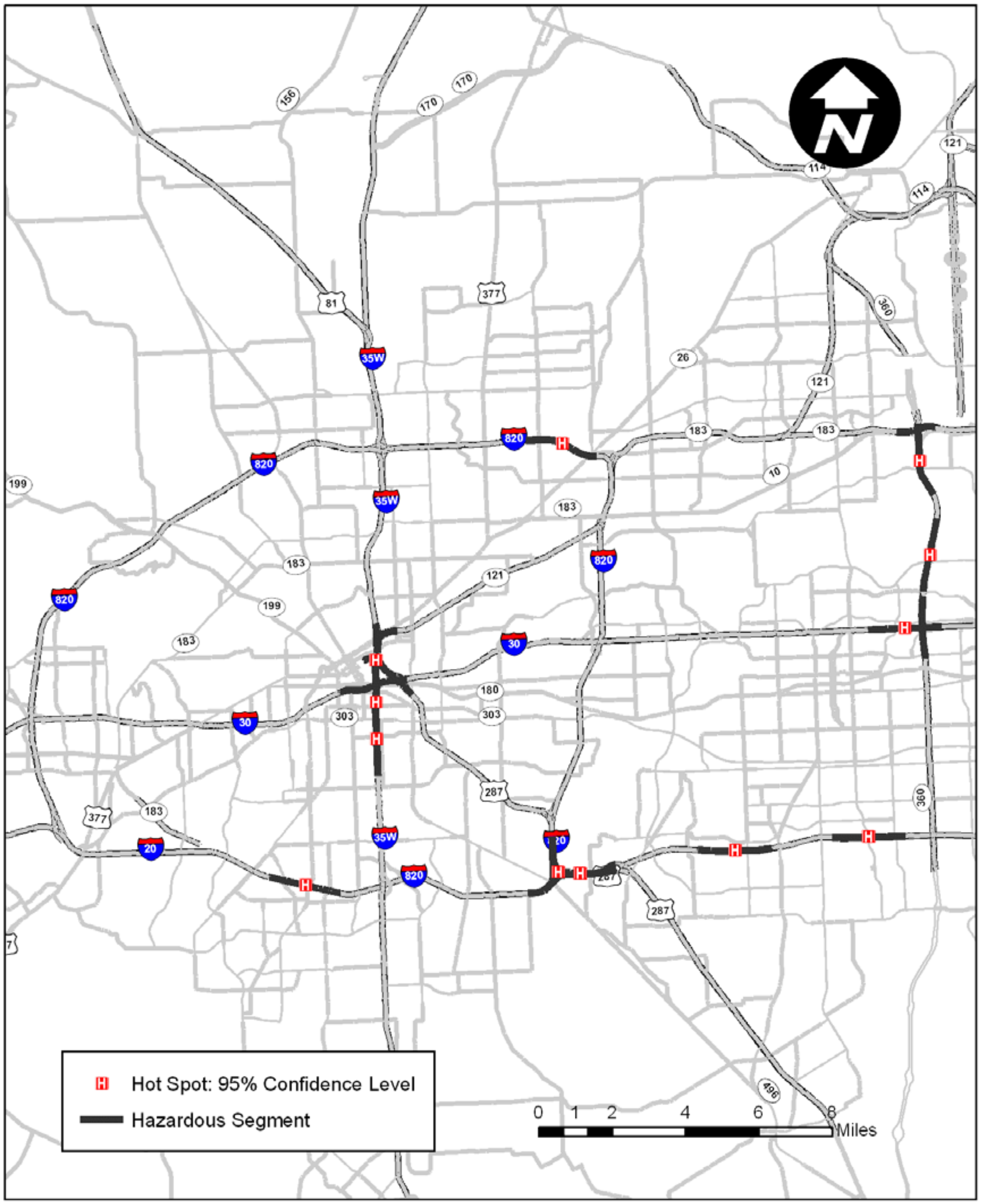


Figure 3-13: Collision Hot Spots Using Gi* Spatial Statistics (Fort Worth).

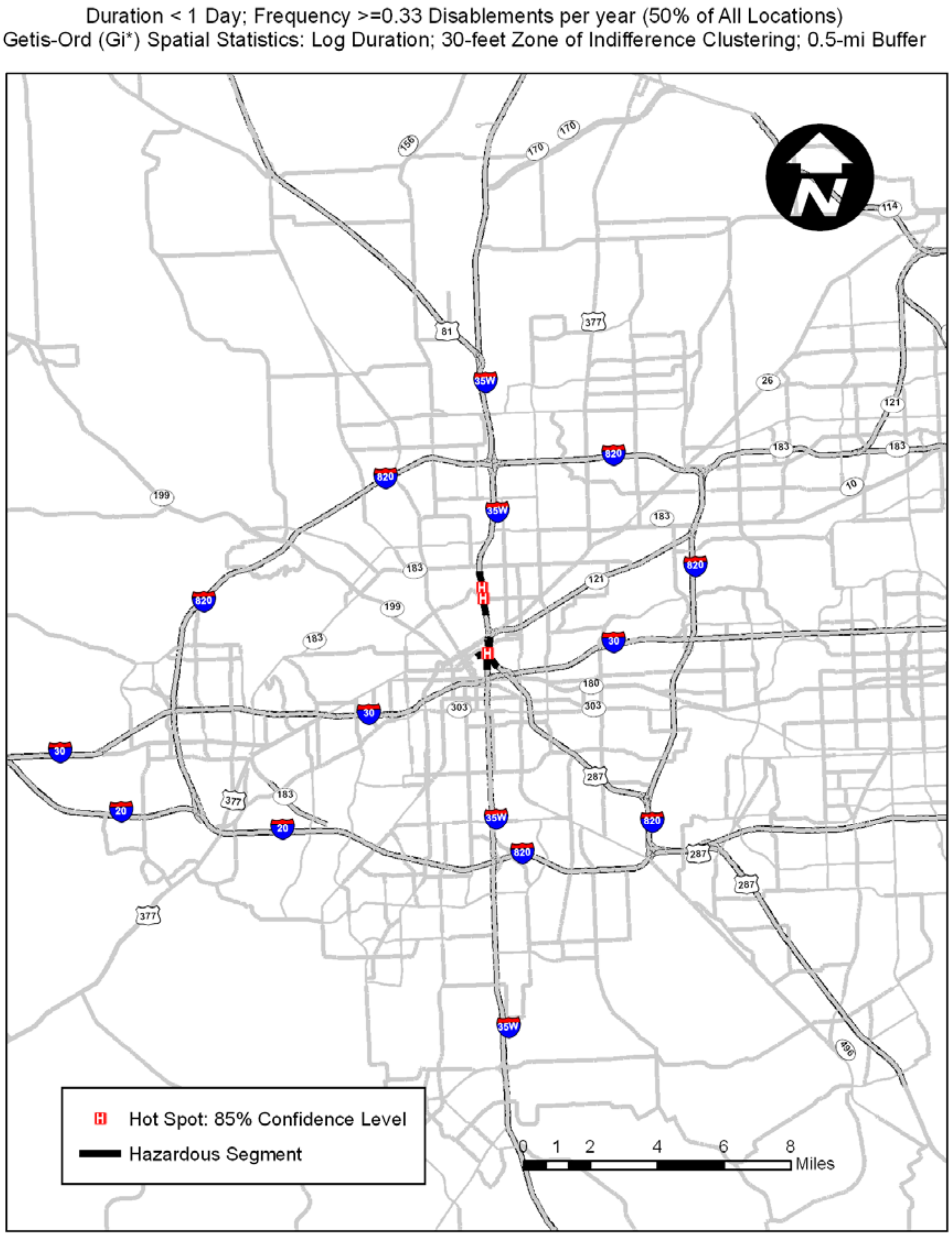


Figure 3-14: Lane-Blocking Disablement Hot Spots Using Gi* (Fort Worth).

Observations and Results

Figure 3-13 and Figure 3-14 show the hot spots for collision and lane-blocking disablement incidents for Fort Worth, respectively, using Gi* spatial statistics with the logarithm of duration values as the attribute of interest. The lane-blocking disablement results required a careful review as the sample size used in the analysis was very small. Researchers, however, successfully carried out the method. The findings from the hot spot results are as follows:

- Collision hot spots were located throughout the city, and their spatial patterns were similar to those observed in frequency-based and duration-based analyses. For instance, hot spots clustered primarily along IH-35, IH-20, and US-360.
- Traffic volume was likely a major determinant of hot spots located closer to downtown, and the collision duration was likely a determinant of hot spots located farther away from the city. In general, Gi* spatial statistics identified hot spots from repeating incidents at specific locations with sufficiently large incident durations.
- There were four hot spots for lane-blocking disablement, and all of them were located on the middle segment of IH-35W.
- The advantage of employing Gi* spatial statistics is that there are no minimum requirements of input sample size. In this case, as few as 11 locations with 41 incidents reported could still be used to perform the analysis. Nevertheless, as with all statistical analyses, the larger sample size is always desirable, and in most cases this can be done by expanding the analysis period or considering more incident types of similar characteristics.

3.5. Summary

In this part of the project, researchers conducted hot spot analyses for the three cities using the incident data archives collected at the TMCs. Spatial analysis and pattern of incident occurrences were fully examined using two major types of the analyses:

- frequency-based analysis, and
- attribute-based analysis.

Frequency-based analysis examined the incident occurrence rates at all unique incident locations and then determined hot spots from those that experienced unusually high rates of incident occurrences. Attribute-based analysis was subcategorized into basic attribute analysis and advanced attribute analysis. Basic attribute analysis, in this case study, considered the incident duration as a measurable attribute and treated those locations with unusually large median durations as hot spots. The advanced attribute analysis incorporated the Gi* spatial statistic featured in the ArcGIS software package to identify locations that experienced both high frequency and high duration incidents simultaneously. Researchers then determined the hot spot locations based on the desirable statistical significance level and the calculated z scores from the Getis-Ord spatial statistics.

The case studies conducted at these three cities have demonstrated the applicability and the utility of the methodology and procedures described in the guidebook. Specific parameters fine-tuned for the analysis in each city were discussed. Appendix B through Appendix D (hot spot sections) document the hot spot results and detailed location descriptions. Researchers prepared a total of 27 hot spot maps at the end of the analysis.

From experience with the procedures and methodologies applied in these case studies, the researchers have drawn the following conclusions on the advantages and limitations of the procedures as follows:

- All the hot spot analyses can be implemented without difficulty. At the minimum, the incident location and the attribute of interest must be available and sufficiently accurate.
- Frequency-based hot spot analysis is the simplest approach and requires the least amount of data and effort to carry out the analysis. However, the disadvantage of this method is that it does not consider any impacts from individual incidents. Incident rates and spatial distributions were found to vary by time of day and day of week. In the future study, the seasonality effect on the spatial patterns could be examined as well.
- Basic attribute-based analysis incorporates incident impacts through any user-specified attributes measurable or calculable from the incident database. In this study, the incident duration attribute served as a good proxy of incident impact, and it helped identify the locations that frequently experienced extremely long incidents. When considering specific attributes, researchers recommend the analysis for specific types of incidents rather than combining all types. The analysis should also consider the lane blockage situation when using the incident duration as a measurable attribute because it can have different implications on the severity of an incident. Consider an extremely long duration for lane-blocking versus non-lane-blocking stalls, for example.
- The Gi* spatial statistics analysis accounts for both frequency and specific attributes of an incident in the analysis. Researchers used a logarithm of duration as a measurable attribute in this case study. The method requires proper configuration of the parameters, such as thresholds for incident durations and the calculation parameters for Gi* statistics. The method addresses the shortcomings of the previous two methods by considering both frequency and severity of an incident in the identification of the hot spots. However, it is also more complicated and requires the most computational resources among the three approaches evaluated in this study.

Upon examination of hot spot results, researchers identified some commonality from all the cities analyzed as follows:

- Hot spots tend to be concentrated at the corridors that have high traffic volumes in frequency-based analysis where traffic volume is a major determinant of incident frequency.
- Comparatively, the hot spots from the basic median duration analysis were found to be more spread out. Logically, several factors can influence the duration of an incident, such as severity of injuries, number of lanes blocked, lack of courtesy patrol, lack of CCTV coverage, and types of vehicles involved. The duration-based analysis results are less dependent on the prevailing traffic volumes.
- The hot spot results from Gi* spatial statistics using incident durations tend to be a combination of both frequency-based and duration-based analyses. The hot spot results, in general, tend to be more spread out over the entire freeway network

than the frequency-based analysis due to the joint effects of two contributing factors.

The agencies can use the hot spot results in various ways. Hot spot and hazardous segment maps are very useful in provide visualized information to aid decision-making processes in designing, evaluating, and managing incident management strategies and resources. Table 3-7 summarizes some of the strategies that the agencies can use to improve incident detection and response times based on the results from the analysis in this case study.

Table 3-7: Examples of Strategies for Improving Incident Detection and Response.

Strategies	Descriptions	Pros	Cons
Roving Courtesy Patrols / Service Patrols	This strategy involves the use of specially equipped vehicles to provide emergency repairs and rapid clearance of stalled or disabled vehicles from the roadway. Vehicles can either be pre-positioned at strategic locations or can 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 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 more at 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.
Intelligent Transportation System (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 patterns 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 to indicate 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.

4. ESTIMATION OF INCIDENT IMPACTS

In this chapter, researchers demonstrate the procedures for calculating various incident-related impacts for each incident using a combination of traffic data and incident records. Module 5 of the guidebook describes this methodology. The traffic data required for calculation here are travel time and traffic volume. Researchers obtained the travel time data from TranStar's AVI system. The freeway system in Houston was segmented based on the location of AVI tag readers. The objectives of the analysis were to:

- apply the procedure in the companion guidebook for measuring and evaluating incident impacts, and
- illustrate how the analyst can interpret and use the results for freeway and incident management performance monitoring.

4.1. Study Segment

The researchers selected a freeway segment of 2.45 miles on westbound US-290 from 34th Street to Pinemont Drive for a case study (see Figure 4-1). Then, researchers queried the incidents that occurred within this segment from August to September 2007 for the analysis. The researchers selected this time period based on its traffic and incident data availability, which was the most recent at the time of the analysis. The method, however, can be applied to other freeway segments and analysis periods as well.

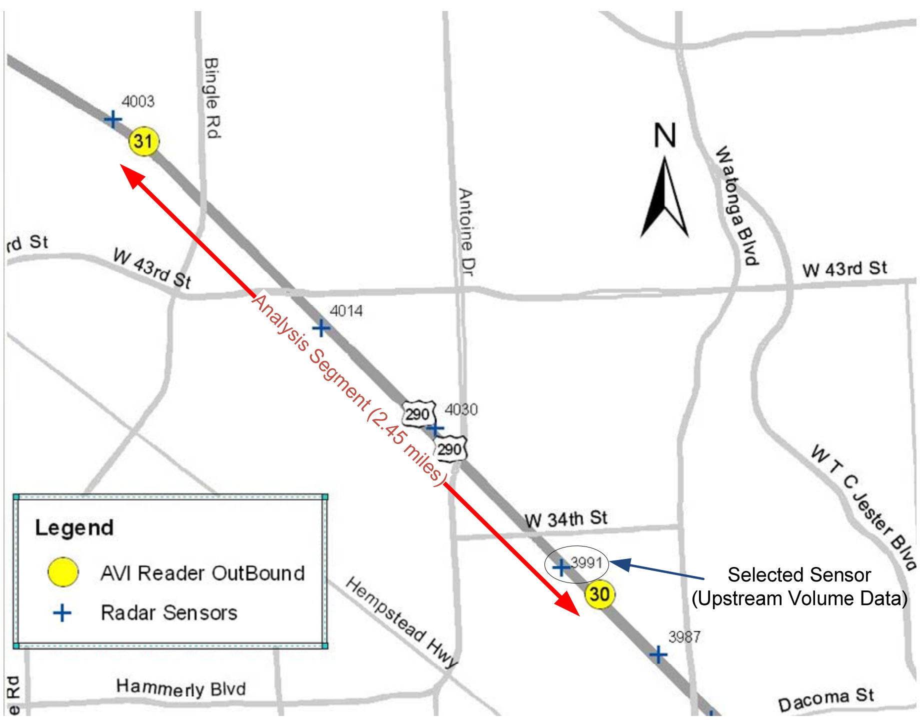


Figure 4-1: Selected Freeway Segment for Houston's Case Study.

4.2. Data Preparation

To calculate incident-related impacts, researchers prepared the following data elements, as well as background profiles, prior to the analysis:

- incident data – at a 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 data – collected for specific freeway segments and time periods during both incident and incident-free conditions.

Incident Data

Incident data must contain the incident occurrence or notification time and geographic reference for the locations for the analysis of incident impacts. Further, researchers examined only incidents that blocked at least one mainlane and occurred within the studied AVI segment during August and September 2007 in this case study. Table 4-1 lists the incidents considered in this analysis along with their selected incident characteristics.

Table 4-1: List of Incidents Evaluated.

Incident Characteristics							
ID	Incident Detection Date & Time	Incident Clearance Time	Type	Severity	Number of Lanes Blocked	Vehicles Involved	Incident Duration (Min)
61726	Mon 8/6/2007 17:24	Mon 8/6/2007 17:54	Stall	Minor Accident/Collision	1 of 4	1	29
61760	Tue 8/7/2007 13:16	Tue 8/7/2007 13:56	Accident	Major Accident/Collision	2 of 3	2	40
61912	Fri 8/10/2007 22:25	Fri 8/10/2007 22:46	Accident	Major Accident/Collision	2 of 4	2	20
61919	Sat 8/11/2007 4:05	Sat 8/11/2007 7:46	Accident	Major Accident/Collision	4 of 4	2	221
62087	Thu 8/16/2007 5:42	Thu 8/16/2007 6:10	Accident	Minor Accident/Collision	2 of 4	2	27
62088	Thu 8/16/2007 5:43	Thu 8/16/2007 5:44	Accident	Minor Accident/Collision	1 of 4	3	1
62361	Tue 8/21/2007 17:53	Tue 8/21/2007 18:20	Stall	Minor Accident/Collision	1 of 3	1	26
62489	Fri 8/24/2007 5:04	Fri 8/24/2007 5:16	Accident	Major Accident/Collision	1 of 3	2	12
62869	Fri 8/31/2007 15:33	Fri 8/31/2007 15:34	Accident	Minor Accident/Collision	1 of 4	2	1
63000	Tue 9/4/2007 7:08	Tue 9/4/2007 7:33	Accident	Minor Accident/Collision	1 of 3	3	25
63037	Tue 9/4/2007 21:41	Tue 9/4/2007 22:20	Accident	Minor Accident/Collision	2 of 4	2	38
63075	Wed 9/5/2007 15:05	Wed 9/5/2007 15:37	Accident	Minor Accident/Collision	1 of 4	2	31
63122	Thu 9/6/2007 14:45	Thu 9/6/2007 15:07	Stall	Minor Accident/Collision	1 of 3	1	22
63153	Thu 9/6/2007 21:35	Thu 9/6/2007 22:14	Accident	Major Accident/Collision	2 of 3	4	39
63236	Sun 9/9/2007 20:00	Sun 9/9/2007 20:36	Accident	Minor Accident/Collision	1 of 3	2	35
63282	Tue 9/11/2007 3:13	Tue 9/11/2007 3:44	Accident	Major Accident/Collision	2 of 3	1	30
63358	Wed 9/12/2007 15:50	Wed 9/12/2007 16:07	Accident	Minor Accident/Collision	1 of 4	2	16
63368	Wed 9/12/2007 18:50	Wed 9/12/2007 19:32	Accident	Minor Accident/Collision	1 of 4	2	42
63379	Thu 9/13/2007 7:01	Thu 9/13/2007 7:26	Accident	Major Accident/Collision	2 of 4	2	25
63470	Sat 9/15/2007 1:01	Sat 9/15/2007 5:35	Accident	Fatalities Accident/Collision	3 of 3	1	274
63632	Wed 9/19/2007 16:46	Wed 9/19/2007 17:03	Stall	Minor Accident/Collision	1 of 4	1	17
63863	Mon 9/24/2007 22:20	Mon 9/24/2007 22:32	Accident	Major Accident/Collision	2 of 3	2	12
63943	Wed 9/26/2007 9:19	Wed 9/26/2007 9:29	Accident	Minor Accident/Collision	1 of 3	2	10

Travel Time Data

Travel time data are a critical input for incident delay calculation using the difference-in-travel-time method. Researchers obtained travel time data in the case study from Houston’s AVI system, which is essentially a probe-vehicle-based system. An AVI segment was defined based on the AVI tag reader locations, which stretched 2.45 miles in length from 34th Street (origin checkpoint #30) to Pinemont Drive (destination checkpoint #31).

Using the travel time extraction tool (see section 8.1), researchers retrieved and computed travel times from the AVI database on those days with incidents reported. The following were the parameters specified for each incident-affected day examined:

- A 5-minute aggregation interval was used to aggregate travel time data. The use of smaller time resolutions such as a 5-minute interval for the analysis reasonably reflects the changes in traffic conditions in response to freeway incidents.
- Researchers configured 75 miles per hour and 5 miles per hour as the upper and the lower thresholds for initial validation of individual travel times.
- The error tolerance method was used to screen out travel time outliers (those with unusually high or low travel time values) – see section 8.1.1.3 for detailed descriptions of the method.

Note that there were some incomplete travel time data during the analysis period. Parts of data on August 11, 2007, and September 15, 2007, were not available because severe accidents blocked all mainlanes, and thus no vehicles were able to complete the travel time segment for an extended period of time.

Traffic Volume Data

The calculation of segment total delay requires traffic volume data. In the study, researchers obtained volume data from the radar sensor ID 3991 for a 24-hour period on those incident-affected days.

Traffic volume data were originally recorded every 30-second interval. Researchers aggregated these data into 5-minute intervals to simplify the analysis using the traffic data processing tool (see section 8.2).

Researchers observed that the change in daylight savings start and end times was also an issue, causing the time stamps to overlap in some cases. Correcting these affected time stamps was not straightforward and could not always be done accurately. Hence, researchers excluded historical traffic data during those affected periods from the analysis.

4.3. Impact Estimation Procedure

The researchers conducted the analysis of incident-related impacts for each incident during the study period.

In this case study, researchers selected incident ID 63379, which occurred within the study segment at 7 AM on Monday, September 13, 2007, to illustrate the procedure for constructing the background and current travel time profiles, as well as to calculate the incident-related impacts.

Researchers used macro-enabled Excel spreadsheets as the primary data manipulation tool to generate and analyze the profiles. Appendix B documents all the profiles derived from the traffic and incident data in this case study. Table 4-2 through Table 4-5 in subsequent sections summarize all the measured impacts in this case study.

4.3.1. Constructing Background Profile

Background profiles are the travel time profiles expected under normal incident-free traffic conditions. Background profiles should reflect the impacts of varying traffic demand and recurrent traffic congestion on segment travel times. In this case, the researchers constructed the 24-hour background profiles for every day of the week using the median-based profile approach (see details in Section 5.2.2.2 of the guidebook). For instance, the Monday background profile was constructed using the travel time data from several Mondays regardless of incident conditions. Once the sample size is large enough (4–6 days), the median-based profile approach can be used to construct the background profile even if parts of the traffic data are affected by incidents.

Figure 4-2 displays an example of Monday background travel time and speed profiles derived from eight Mondays during June and August 2007. The Monday background profile reveals the pattern of a conspicuous recurrent congestion in the PM peak and a barely noticeable one during the AM peak as the segment is in outbound direction. Six to eight days of data were used to establish other background profiles for other days of week. Typical weekday profiles share a similar pattern in both travel time and speed profile as the Monday profile above. The weekend profiles are relatively stable throughout the day. All the background profiles as well as specific days used to derive the profiles are documented in Appendix B.

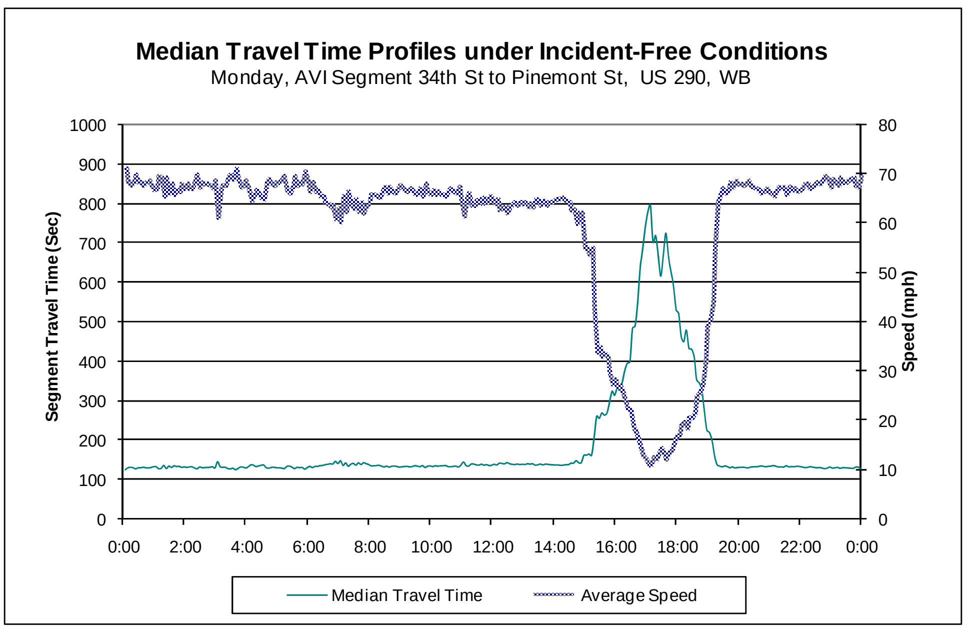


Figure 4-2: Monday Background Travel Time and Speed Profiles.

4.3.2. Constructing Current Profiles

Current profiles are the travel time profiles under incident conditions. Current profiles reflect the impacts of both recurrent traffic congestion and incident-induced traffic congestion on segment travel times. The researchers developed current travel time profiles for each incident examined during this study period.

Figure 4-3 shows an example of travel time and speed profiles obtained on an incident day. The vertical dashed lines indicate the time from which the incident was detected until it was cleared. In addition to the AM incident of interest, the second incident (i.e., ID 63403) occurred at 5:18 PM in another segment downstream of this one. The second incident noted in this figure illustrated how the travel time profile can capture the impact of an incident-related lane closure downstream of the segment of interest.

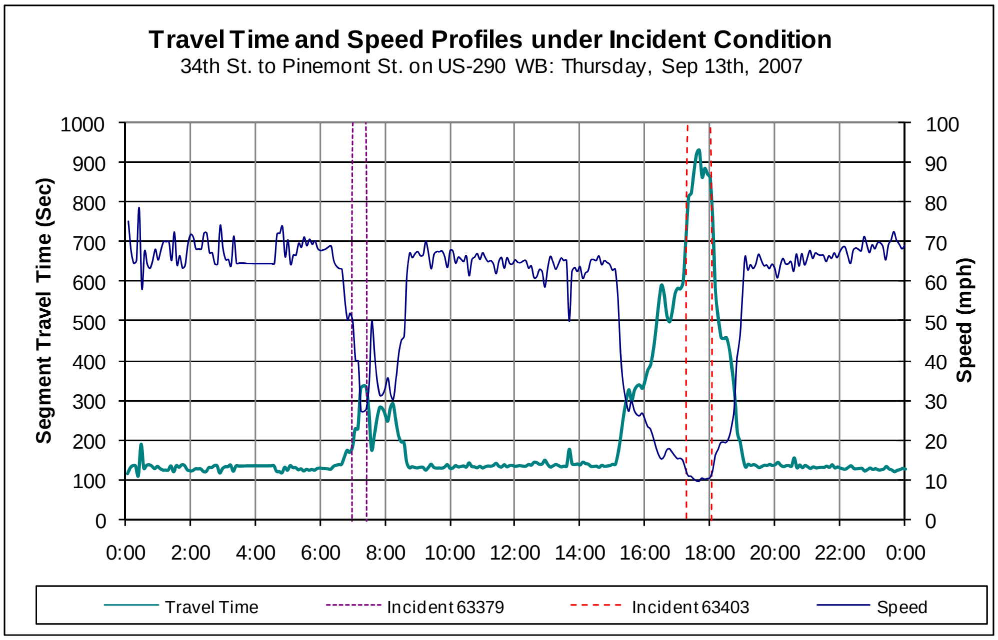


Figure 4-3: Travel Time and Speed Profiles under Incident Condition.

4.3.3. Deriving Incident Impact Profiles

Researchers constructed three key profiles to measure the impacts for each incident:

- average delay profile,
- delay index profile, and
- total delay profile.

Appendix B documents all the incident impact profiles.

Average Delay Profile

An examination of current travel time profile alone makes it difficult to determine whether the increase in travel time was caused by either traffic congestion or an incident or both. A profile representing an average delay per vehicle over time addresses this issue. Researchers constructed the average delay profile by computing the difference between incident-affected and background travel times from the analysis segment. This profile serves as an indicator of how much travelers are being delayed on average over the course of an incident event.

In this example, Figure 4-4 shows the resulting profiles of average delay per vehicle and the corresponding traffic volume on the incident day. From the figure, it can be seen that the travelers within the analysis segment experienced on average approximately the same amount of maximum delays for both incidents. Additionally, by incorporating the clearance time log from incident database, researchers can show that the congestion induced by the AM incident did not dissipate until about one hour after the end of the incident. As for the second incident, the impact did not extend beyond the incident clearance time. Since the PM incident originated in the downstream segment, the queue extended from the downstream segment may have incurred less delay on this analysis segment.

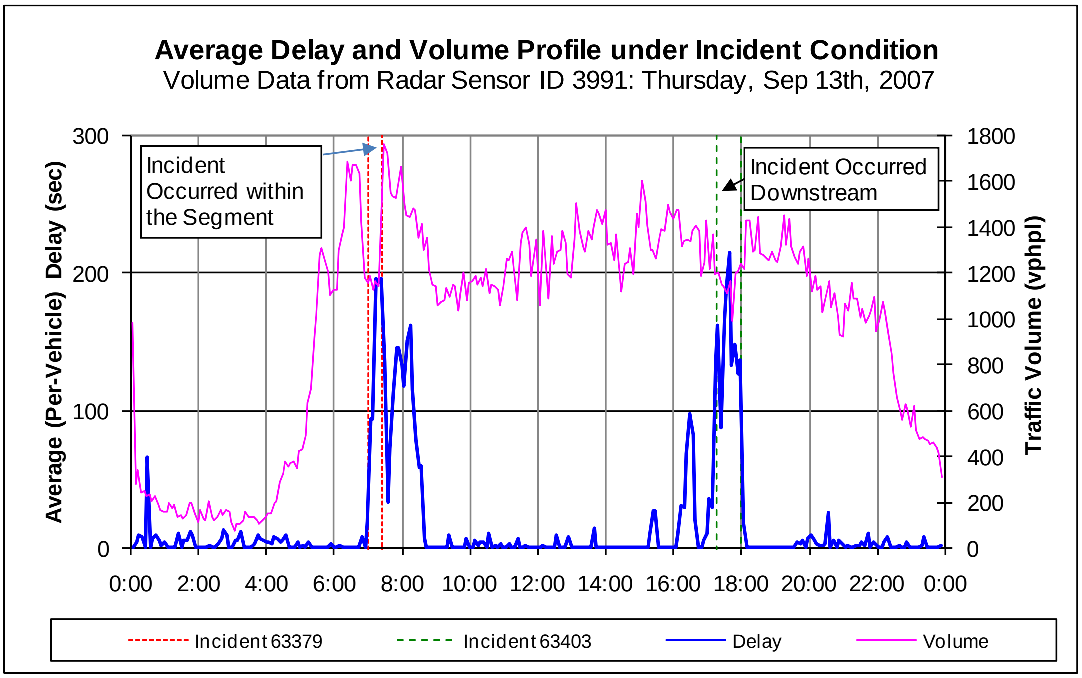


Figure 4-4: Average Delay and Traffic Volume Profiles.

Delay Index Profile

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 additional time the travelers would require to traverse the analysis segment with respect to their anticipation. A delay index is defined by:

$$\text{Delay Index} = \frac{\text{Average Delay per Vehicle}}{\text{Background Travel Time}} \times 100 . \qquad (4\text{-}1)$$

Researchers used this measure as a proxy for quantifying the degree of customer satisfaction over the course of an incident event and comparing travelers' attitudes toward multiple incidents at different times of day and locations. For example, an index of 100 percent would imply that travelers would need to spend twice their expected travel time to travel through this segment.

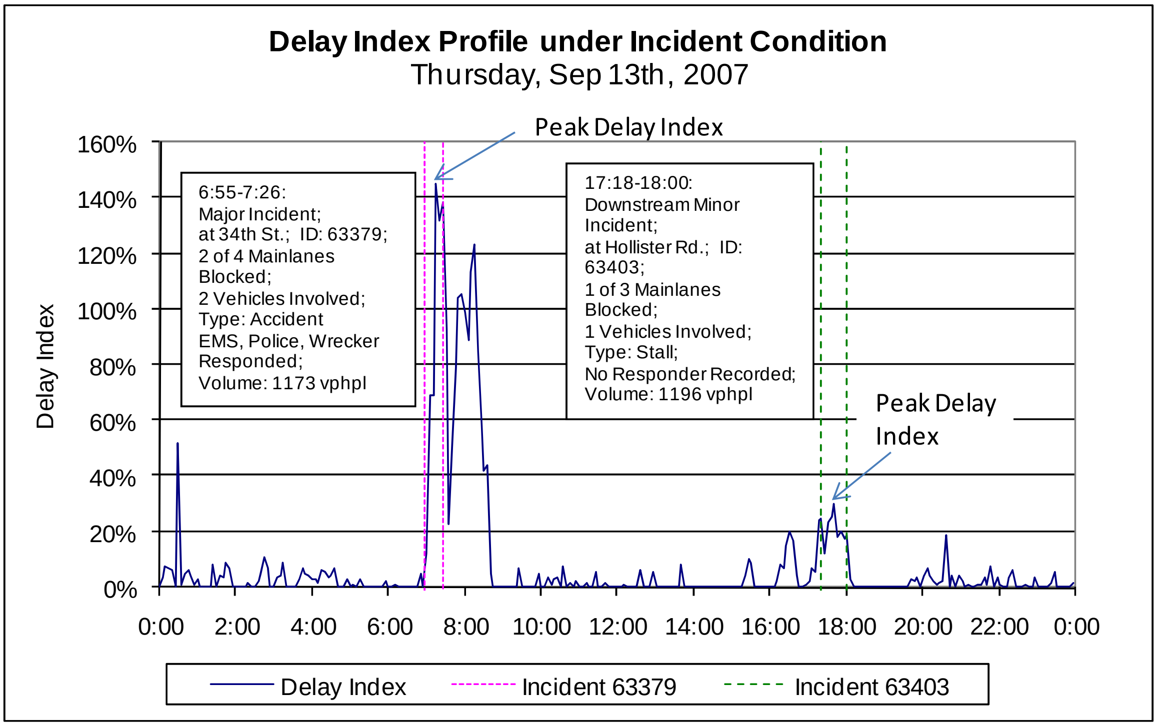


Figure 4-5: Delay Index Profile.

Figure 4-5 illustrates the delay index profile for the two example incidents. Researchers computed the profile by applying Equation (4-1) to every aggregation interval (i.e., five minutes). The delay index peaks during the morning rush hours as a result of an accident blocking two main lanes, as compared to the index 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 4-4). 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.

Total Delay Profile

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.

Researchers constructed total delay profiles using the products of the average delays and corresponding traffic volumes measured at the upstream of the analysis segment, which in this case is radar sensor ID 3991. Figure 4-6 shows the total delay profile for incident ID 63379 during morning peak hours on the day of analysis. Total segment delay per incident is a measure widely used to represent the impacts caused by a single incident and can be obtained by summing total delays for all intervals affected by the incident of interest, as illustrated by the shaded area in Figure 4-6.

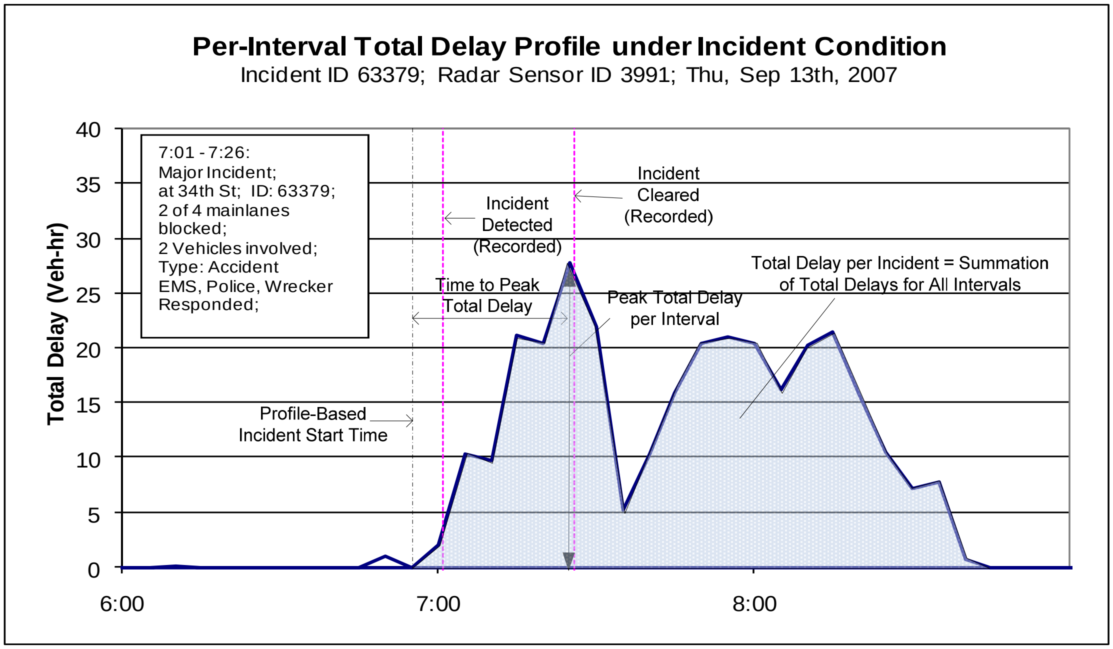


Figure 4-6: Total Delay Profile.

4.3.4. Calculating Incident Impact Measures

There are a number of incident impacts measurable from either one or more of the above profiles. For all the incidents with measurable incident impacts (i.e., discernible delay profiles), researchers extracted or computed the following measures:

- Incident duration – The time difference between the recorded incident detection and clearance time.
- Traffic volume – Researchers obtained traffic volume before and after the incident to provide a snapshot of traffic conditions at the time of incident occurrence. To account for the capacity of the segment being analyzed, researchers calculated flow rates in vehicles per hour per lane.
- Profile-based incident start time – The time at which the impact of incident on traffic conditions was first observed from the delay profile. The profile-based start time may not necessarily always coincide with the recorded detection time. In such cases, researchers used the profile-based incident start time since it is directly based on the traffic data.

- Profile-based impact end time – The time at which the impact of incident on traffic conditions was last observed from the delay profile. This time point frequently extends beyond the incident clearance time log since it also includes the time it takes for the queue built up from the incident-induced congestion to dissipate.
- Lane blockage duration – Researchers calculated this by computing the time difference between profile-based incident start time and recorded incident clearance time. However, when the recorded incident clearance time was not available, the lane blockage duration could be approximated by the time to peak delay per vehicle. Based on the observation of all the incidents in the study, lane blockage durations were always longer than incident durations since the profile-based incident start times were detected earlier than the recorded incident detection times.
- Traffic recovery time – The time elapsed from the moment at which the incident has been removed to the traffic-return-to-normal time. Researchers calculated this by computing the time difference between the incident clearance time and profile-based impact end time.
- Total incident-induced congestion duration – The time period lasted from the beginning to the end of the incident impact. Researchers computed this by calculating the difference between the profile-based incident start and end times. Alternatively, this is equivalent to the sum of lane blockage duration and traffic recovery time.
- Maximum delay per vehicle – The peak of the average delay profile.
- 85^{th} percentile of delay per vehicle – The 85^{th} percentile of delay values from all intervals of the average delay profile.
- Time to peak delay per vehicle – The time it took from the beginning of an incident impact to the peak of the average delay profile (peak delay time). In this case study, researchers used the profile-based start time as a reference for calculating the time to peak delay per vehicle rather than the incident detection time.
- Total segment delay per incident – The summation of total delay per interval over the course of an incident event.

Similarly for the delay index and total delay profiles, researchers also calculated the maximum values, the 85^{th} percentile values, and the time to peak values. Table 4-2 summarizes all measurable impacts and relevant incident information for the examples used in this case study.

4.4. Results

Table 4-3 summarizes the incident and traffic characteristics for all measurable incidents during the analysis period. Researchers used the pre-incident 10-minute flow rates to provide the information about the traffic conditions at the time of the incident occurrence. Table 4-4 lists all the incident impact measures derived from average delay profiles, and Table 4-5 tabulates those measures calculated from the delay index and total delay profiles.

Table 4-2: 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.

Table 4-3: Incident and Traffic Characteristics.

Incident Characteristics								Traffic Charateristics	
ID	Incident Detection Time	Incident Clearance Time	Type	Severity	Number of Lanes Blocked	Vehicles Involved	Incident Duration (min)	Pre-Incident 10-minute Flow Rate (vphpl)	Average Flow Rate during Incident-Affected Duration (vphpl)
61726	Mon 8/6/2007 17:24	Mon 8/6/2007 17:54	Stall	Minor Accident/Collision	1 of 4	1	29	1298	1119
61760	Tue 8/7/2007 13:16	Tue 8/7/2007 13:56	Accident	Major Accident/Collision	2 of 3	2	40	1304	1111
61912	Fri 8/10/2007 22:25	Fri 8/10/2007 22:46	Accident	Major Accident/Collision	2 of 4	2	20	930	858
62087	Thu 8/16/2007 5:42	Thu 8/16/2007 6:10	Accident	Minor Accident/Collision	2 of 4	2	27	540	1161
62361	Tue 8/21/2007 17:53	Tue 8/21/2007 18:20	Stall	Minor Accident/Collision	1 of 3	1	26	1250	1182
62489	Fri 8/24/2007 5:04	Fri 8/24/2007 5:16	Accident	Major Accident/Collision	1 of 3	2	12	354	653
63000	Tue 9/4/2007 7:08	Tue 9/4/2007 7:33	Accident	Minor Accident/Collision	1 of 3	3	25	1671	1501
63037	Tue 9/4/2007 21:41	Tue 9/4/2007 22:20	Accident	Minor Accident/Collision	2 of 4	2	38	815	654
63122	Thu 9/6/2007 14:45	Thu 9/6/2007 15:07	Stall	Minor Accident/Collision	1 of 3	1	22	1260	1284
63153	Thu 9/6/2007 21:35	Thu 9/6/2007 22:14	Accident	Major Accident/Collision	2 of 3	4	39	944	780
63236	Sun 9/9/2007 20:00	Sun 9/9/2007 20:36	Accident	Minor Accident/Collision	1 of 3	2	35	1004	953
63368	Wed 9/12/2007 18:50	Wed 9/12/2007 19:32	Accident	Minor Accident/Collision	1 of 4	2	42	1235	1117
63379	Thu 9/13/2007 7:01	Thu 9/13/2007 7:26	Accident	Major Accident/Collision	2 of 4	2	25	1299	1431
63863	Mon 9/24/2007 22:20	Mon 9/24/2007 22:32	Accident	Major Accident/Collision	2 of 3	2	12	678	516
63934	Wed 9/26/2007 9:19	Wed 9/26/2007 9:29	Accident	Minor Accident/Collision	1 of 3	2	10	1286	1200

Table 4-4: Measured Impacts from Average Delay Profile.

Incident Data		Average Delay Profile								
ID	Incident Detection Time	Profile-based Incident Start Time	Lane Blockage Duration (min)	Incident Recovery Time (min)	Total Incident-Induced Time (min)	Time to Peak Average Delay (min)	Max Average Delay (sec)	85th Percentile of Average Delay (sec)	Max Average Delay during Lane Blockage (sec)	Max Average Delay during Recovery Period (sec)
61726	Mon 8/6/2007 17:24	Mon 8/6/2007 16:50	63	NA*	63	20	297	259	297	0
61760	Tue 8/7/2007 13:16	Tue 8/7/2007 12:40	76	14	90	75	809	687	809	344
61912	Fri 8/10/2007 22:25	Fri 8/10/2007 22:00	46	14	60	45	348	317	348	55
62087	Thu 8/16/2007 5:42	Thu 8/16/2007 5:10	60	30	90	60	292	150	292	140
62361	Tue 8/21/2007 17:53	Tue 8/21/2007 17:40	40	15	55	40	321	314	321	316
62489	Fri 8/24/2007 5:04	Fri 8/24/2007 5:04	12	0	12	12	7	5	7	0
63000	Tue 9/4/2007 7:08	Tue 9/4/2007 6:45	48	27	75	45	164	154	164	89
63037	Tue 9/4/2007 21:41	Tue 9/4/2007 21:25	54	0	54	40	795	765	795	0
63122	Thu 9/6/2007 14:45	Thu 9/6/2007 14:45	22	25	47	15	182	163	182	157
63153	Thu 9/6/2007 21:35	Thu 9/6/2007 21:35	39	5	44	30	708	634	708	127
63236	Sun 9/9/2007 20:00	Sun 9/9/2007 19:05	91	0	91	90	378	308	379	3
63368	Wed 9/12/2007 18:50	Wed 9/12/2007 18:15	77	23	100	80	725	583	725	556
63379	Thu 9/13/2007 7:01	Thu 9/13/2007 6:55	31	69	100	30	196	162	196	162
63863	Mon 9/24/2007 22:20	Mon 9/24/2007 22:10	22	8	30	25	552	473	552	254
63934	Wed 9/26/2007 9:19	Wed 9/26/2007 8:50	39	11	50	25	149	114	149	117

Note: * Incident clearance time recorded in the database was after the profile-based incident impact end time

Table 4-5: Measured Impacts from Delay Index and Total Delay Profiles.

Incident Data		Delay Index Profile					Total Delay Profile					
ID	Incident Detection Time	Time to Peak Delay Index (min)	Max Delay Index	85th Percentile of Delay Index	Max Delay Index during Lane Blockage	Max Delay Index during Recovery Time	Time to Peak Total Delay (min)	Max Total Delay (veh-hr)	85th Percentile of Total Delay (veh-hr)	Max Total Delay during Lane Blockage (veh-hr)	Max Total Delay during Recovery (veh-hr)	Total Delay Per Incident (veh-hr)
61726	Mon 8/6/2007 17:24	20	37%	36%	37%	0%	20	31	29	31	0	113
61760	Tue 8/7/2007 13:16	75	554%	491%	554%	226%	80	79	62	79	35	496
61912	Fri 8/10/2007 22:25	45	263%	240%	263%	42%	45	35	25	35	4	207
62087	Thu 8/16/2007 5:42	60	227%	115%	227%	105%	60	31	150	292	140	173
62361	Tue 8/21/2007 17:53	45	72%	63%	70%	72%	40	35	33	35	31	274
62489	Fri 8/24/2007 5:04	12	6%	4%	6%	0%	12	1	0	1	0	1
63000	Tue 9/4/2007 7:08	35	97%	87%	97%	57%	50	26	19	26	13	193
63037	Tue 9/4/2007 21:41	45	612%	587%	612%	0%	45	69	50	69	0	340
63122	Thu 9/6/2007 14:45	15	70%	67%	70%	69%	15	24	18	24	18	128
63153	Thu 9/6/2007 21:35	30	542%	484%	542%	98%	30	49	43	49	8	223
63236	Sun 9/9/2007 20:00	90	284%	236%	284%	0%	90	30	27	30	0	291
63368	Wed 9/12/2007 18:50	80	530%	426%	530%	413%	45	76	58	76	61	697
63379	Thu 9/13/2007 7:01	20	145%	123%	145%	123%	30	28	21	28	22	307
63863	Mon 9/24/2007 22:20	25	428%	365%	428%	195%	25	24	20	24	11	82
63934	Wed 9/26/2007 9:19	25	111%	86%	111%	88%	25	17	13	17	13	88

4.5. Discussions

This section discusses the performance and limitations of the methodology observed from the case study. Specific findings and general applications of some impact measures are provided as well.

4.5.1. Performance and Limitations

Researchers queried all the incidents that occurred on the selected freeway segment and blocked at least one mainlane during the analysis period from the incident database. Table 4-6 provides a list of incidents evaluated during the two-month period as well as the status of the analysis for each incident. There were a total of 21 valid incidents reported within this segment during this period. The researchers were able to complete the evaluation of incident-related impacts on 15 of these (71 percent). There were two invalid incidents recorded during the same period. Researchers were unable to evaluate four incidents (19 percent) because the data were either unavailable or inaccurate. There were two incidents (10 percent) with barely discernible impacts on traffic conditions; therefore, researchers excluded them from the analysis as well. In summary, the profile-based incident impact estimation proposed in the guidebook generally works well for typical lane-blocking incidents.

The proposed profile-based approach can also be used to measure the full impact of an incident by summing the total segment delays for all affected segments. In this case, all the delays incurred by an incident must be calculated for all upstream segments in addition to the segment where the incident was located.

Table 4-6: List of Incidents Evaluated in the Houston Case Study.

Incident Characteristics								
ID	Incident Detection Time	Incident Clearance Time	Type	Severity	No. of Lanes Blocked	Vehicles Involved	Incident Duration (min)	Analysis Notes
61726	Mon 8/6/2007 17:24	Mon 8/6/2007 17:54	Stall	Minor Accident/Collision	1 of 4	1	29	Completed
61760	Tue 8/7/2007 13:16	Tue 8/7/2007 13:56	Accident	Major Accident/Collision	2 of 3	2	40	Completed
61912	Fri 8/10/2007 22:25	Fri 8/10/2007 22:46	Accident	Major Accident/Collision	2 of 4	2	20	Completed
61919	Sat 8/11/2007 4:05	Sat 8/11/2007 7:46	Accident	Major Accident/Collision	4 of 4	2	221	Missing Data
62087	Thu 8/16/2007 5:42	Thu 8/16/2007 6:10	Accident	Minor Accident/Collision	2 of 4	2	27	Completed
62088	Thu 8/16/2007 5:43	Thu 8/16/2007 5:44	Accident	Minor Accident/Collision	1 of 4	3	1	False Record
62361	Tue 8/21/2007 17:53	Tue 8/21/2007 18:20	Stall	Minor Accident/Collision	1 of 3	1	26	Completed
62489	Fri 8/24/2007 5:04	Fri 8/24/2007 5:16	Accident	Major Accident/Collision	1 of 3	2	12	Completed
62869	Fri 8/31/2007 15:33	Fri 8/31/2007 15:34	Accident	Minor Accident/Collision	1 of 4	2	1	False Record
63000	Tue 9/4/2007 7:08	Tue 9/4/2007 7:33	Accident	Minor Accident/Collision	1 of 3	3	25	Completed
63037	Tue 9/4/2007 21:41	Tue 9/4/2007 22:20	Accident	Minor Accident/Collision	2 of 4	2	38	Completed
63075	Wed 9/5/2007 15:05	Wed 9/5/2007 15:37	Accident	Minor Accident/Collision	1 of 4	2	31	Off-Boundary
63122	Thu 9/6/2007 14:45	Thu 9/6/2007 15:07	Stall	Minor Accident/Collision	1 of 3	1	22	Completed
63153	Thu 9/6/2007 21:35	Thu 9/6/2007 22:14	Accident	Major Accident/Collision	2 of 3	4	39	Completed
63236	Sun 9/9/2007 20:00	Sun 9/9/2007 20:36	Accident	Minor Accident/Collision	1 of 3	2	35	Completed
63282	Tue 9/11/2007 3:13	Tue 9/11/2007 3:44	Accident	Major Accident/Collision	2 of 3	1	30	No Impact
63358	Wed 9/12/2007 15:50	Wed 9/12/2007 16:07	Accident	Minor Accident/Collision	1 of 4	2	16	Off-Boundary
63368	Wed 9/12/2007 18:50	Wed 9/12/2007 19:32	Accident	Minor Accident/Collision	1 of 4	2	42	Completed
63379	Thu 9/13/2007 7:01	Thu 9/13/2007 7:26	Accident	Major Accident/Collision	2 of 4	2	25	Completed
63470	Sat 9/15/2007 1:01	Sat 9/15/2007 5:35	Accident	Fatalities Accident/Collision	3 of 3	1	274	Missing Data
63632	Wed 9/19/2007 16:46	Wed 9/19/2007 17:03	Stall	Minor Accident/Collision	1 of 4	1	17	No Impact
63863	Mon 9/24/2007 22:20	Mon 9/24/2007 22:32	Accident	Major Accident/Collision	2 of 3	2	12	Completed
63943	Wed 9/26/2007 9:19	Wed 9/26/2007 9:29	Accident	Minor Accident/Collision	1 of 3	2	10	Completed

Note:
1. The analysis included all the incidents with at least one mainlane closure that occurred within AVI segment from 34th St to Pinemont Dr from Aug to Sep 2007.
2. Four cross streets within this analysis segment are 34th, Antoine, 43rd, and Pinemont.
3. "No Impact" indicates that the impact of incident was not detected from the average delay profile.
4. "Completed" indicates that the analysis of incident impact was completed for this incident.
5. "Off-Boundary" indicates that the delay profile derived from this incident does not coincide with the recorded incident detection and clearance times.

The following are some limitations of the incident impact estimation methodology observed from the case study:

- The accuracy of the impact measures calculated using this methodology greatly depends on the accuracy and availability of incident time logs in the database, which in turn depend on the accuracy and consistency of the incident logging procedure at the agency. For example, a significant time lag may occur between the actual incident clearance time and the clearance time log for a minor incident.
- The proposed method assumes that the impact of an incident must be significant enough to cause the traffic conditions to deviate from the background conditions. As such, this approach may not work well for measuring the impacts from minor incidents, non-lane-blocking incidents, and incidents that occur under light traffic conditions.
- Defining the profile-based start and end times can be subjective, as was visually verified in this case study. In many cases, researchers observed a series of small bumps in the vicinity of the actual profile-based start and end times. All these small bumps were ignored in this study, and the start and end times were defined from an uninterrupted delay profile. This issue must be carefully examined when considering automating these procedures. For example, at the end of the delay profile, the delay values can drop to a very low level, which can make it difficult to determine exactly when the impact from an incident should be terminated.
- The selection of the sensor for obtaining traffic data is central to the accuracy of total delay calculation. The location of the traffic sensor must be upstream of the incident location in order to properly capture the incoming traffic volume.

- The distance between the incident location and the upstream sensor can influence the results of delay calculation. In general, the upstream sensor nearest to the incident location would be able to detect the most impacts from an incident in terms of changes in traffic conditions.
- In addition to the distance to the incident location, the sensors upstream of the incident location may observe different changes in traffic patterns if the segment geometry is not homogeneous. For example, the difference in the number of lanes at the cross section where the sensors are located can result in different traffic volume profiles and thus cause the difference in the calculated total segment delays.
- When using the AVI system to retrieve the travel time, an incident blocking all mainlanes for an extended period can result in missing travel time data because none of the vehicles were able to traverse the analysis segment. In this scenario, this methodology may not use the AVI travel time data for the analysis.

4.5.2. Findings

The following are some of the findings that researchers observed from the case study results:

- Delay index varies significantly from one incident to another. From the pool of incidents evaluated in this case study, the maximum delay index ranges from 6 to 612 percent, which implies that road users experienced varying amounts of delay, ranging from 6 percent to six times their anticipated travel time.
- Time to peak average delay, time to peak total delay, and time to peak delay index are generally in proximity to each other. The time to peak total delay can be significantly different from the others if the traffic volume changes significantly during incident-affected duration, as in the case of the incident ID 63368.
- The time to peak average delay usually coincides with the recorded incident clearance time, which also indicates that the maximum average delay is usually encountered at the last interval of lane blockage duration. As observed from the average delay profile, 12 out of 15 successfully evaluated incidents have time to peak average delays that coincide with incident clearance time. Therefore, the time to peak delay derived from the average delay profile is a valid and practical estimate of the lane blockage duration, particularly when the incident clearance time is unavailable or invalid.
- Incident durations have a positive correlation with total segment delays per incident. Figure 4-7 shows the relationship between incident duration and total segment delay. The longer incident duration generally leads to higher total delay.
- Traffic recovery time can be very large if the traffic volume is increasing. Normally, given traffic demands stay unchanged before and during an incident, traffic flow rate measured by the point-based detectors will decrease because of the lane blockage. Table 4-3 shows increasing traffic demands for incident IDs 62087, 63122, and 63379 where traffic volumes measured over the entire incident durations were higher than the 10-minute pre-incident flow rates. The impact

results in Table 4-4 show that the traffic recovery times for these incidents were among the highest. Therefore, increasing traffic volume tends to generate backlog conditions, which result in a longer traffic recovery time.

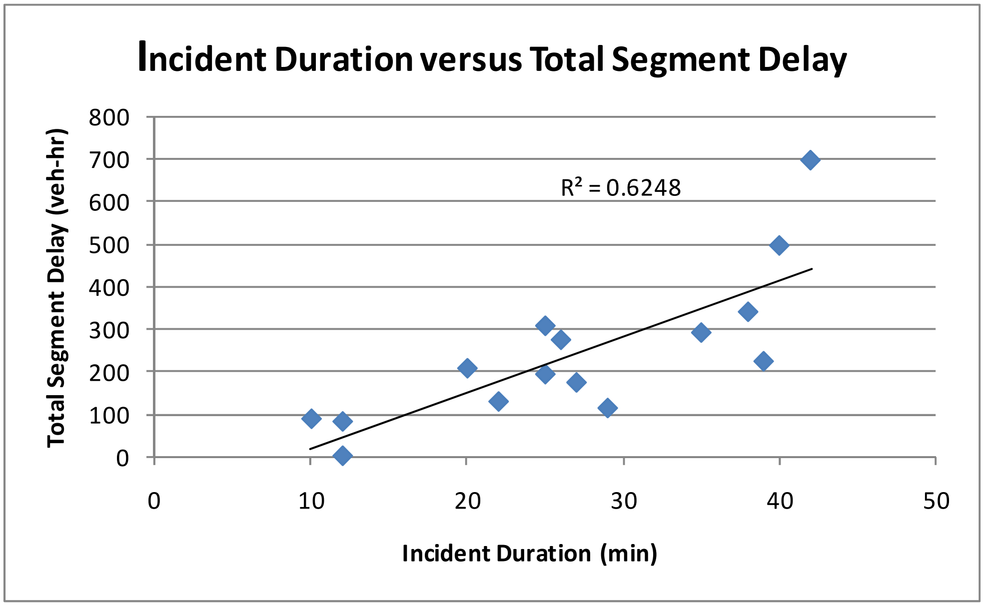


Figure 4-7: Relationship between Incident Duration and Total Segment Delay.

4.5.3. Using Impact Measures

The proposed methodology utilized 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 the methodology demonstrated in the case study can serve as supplemental measures for characterizing and evaluating specific incident impacts in addition to the incident delay. In particular, 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?

From an incident management 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. From a traveler's perspective, the impact of incidents can be related to individual travel experience through the derivation of average delay and delay index profiles. In this manner, the analyst can examine measures such as peak delay per vehicle, time to peak delay, and peak delay index to evaluate the magnitude of delay as perceived by travelers, as well as the time at which the worst condition took place.

To summarize, these measures can be utilized as part of incident management performance monitoring and evaluation efforts through the following aspects:

- evaluate the impacts of a specific incident from both the system and travelers' perspectives;
- evaluate the degree of travelers' satisfaction, such as estimated average delay, delay with respect to anticipation, worst delay experience, and so forth;
- 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.

4.6. Summary

In this chapter, researchers applied the profile-based methodology to calculate the incident-related impacts. Researchers obtained the travel time and traffic volume data at Houston's TranStar from the AVI system and radar sensors, respectively. Researchers selected a freeway segment along US-290 westbound and examined a total of 21 archived incidents with at least one mainlane blocked during August and September 2007 in the case study. Researchers first constructed background travel time profiles and current travel time profiles and then derived average delay profile, delay index profile, and total delay profile for all incidents evaluated. Consequently, researchers either computed or approximated a total of 19 impact measures from the three key profiles derived for each incident.

The following are the researchers' recommendations based on the experience with the procedures and methodologies applied in this case study:

- The proposed profile-based approach can provide extensive measurements of impacts resulting from an individual delay provided that the changes in traffic conditions are significant enough to deviate from background conditions.
- The current methodology still requires visual verification of certain elements derived from the profile. An agency should consider automating this procedure in order to use it on a routine basis.

- The proposed approach offers insight into two elements that are typically difficult to quantify – travelers' experience and traffic recovery time. The former one is addressed through the concept of delay index while the latter is achieved by superimposing the incident time logs onto the average delay profile.
- Accuracy of total delay calculation also depends on the proper selection of the traffic sensor for retrieving traffic data. The analyst must be aware of the effects of the sensor location and the geometric conditions in this analysis.

5. INCIDENT MANAGEMENT PERFORMANCE MEASURES

This chapter describes the analysis of IM performance measures, which was conducted to demonstrate how the analysis can identify the factors affecting specific IM performance measures from the incident database. In this case study, researchers first examined the responder characteristics from Fort Worth's TransVISION incident database. Then researchers calculated various IM performance measures (e.g., first responder response times, total response times, on-scene times, etc.) as described in Module 6 of the guidebook. Finally, the researchers conducted a statistical analysis to analyze the factors affecting the first responder response time using historical incident data.

5.1. Characterizing Incident Responders

Section 2.4 of this report analyzed and discussed the Fort Worth incident data characteristics. This section focuses on the analysis of specific attributes related to incident responders, such as their arrival and departure times. These data provide useful information about the incident management process. They can help determine the sequence, the responsiveness, and the time spent on the scene by the responders. The researchers used Fort Worth's incident data from 2004 to 2006 to conduct this analysis.

First, researchers examined the distribution of all incidents that responders recorded in the incident database, as shown in Table 5-1. The top four major responders were police, fire department, emergency medical service, and wrecker. Other responders, such as TxDOT or hazmat team, were not frequently reported because their roles in incident management are specific to the types of incidents that are less common (e.g., hazmat team for hazmat spill incidents).

Table 5-1: Distribution of All Incident Responders (Fort Worth).

Responders	% of Reported Incidents
Police	52.6%
Fire Department	34.4%
EMS	21.6%
Wrecker	10.9%
Courtesy Patrol/Incident Management Team (CP/IMT)	4.4%
TxDOT	2.0%
City	0.3%
Hazmat Team	0.3%
Coroner/Medical Examiner (CME)	0.1%
Federal Emergency Management Agency (FEMA)	0.1%
County	0.1%

Using the arrival time of all responders in the database, researchers can logically identify the first responder for each incident record by sorting their arrival times. Table 5-2 summarizes the distribution of incident responders from all the incident records. Note that the agencies can tailor all the analysis by other incident data attributes to suit the need for the analysis (e.g., the distribution of first responders for specific incident types).

From the data, except for the "unknown," which is the designation for cases in which the incident responders were not recorded, the most common responder to arrive at the scene first was police, followed by emergency medical service and fire department. Wreckers, while among the common responders, are less likely to be the first on the scene.

Table 5-2: Distribution of First Responders (Fort Worth).

Distribution of First Responders		
Responder	Freq	Percent
Unknown	1062	41.2%
Police	525	20.3%
EMS	425	16.5%
Fire Dept	417	16.2%
CPIMT	96	3.7%
TxDOT	30	1.2%
Wrecker	19	0.7%
City	5	0.2%
CME	1	0.0%

* Based on 2,580 incidents from 2004-2006

5.2. Incident Management Performance Measures

This section presents the examination of two performance metrics that researchers recommended in the guidebook for monitoring and evaluating incident management operations:

- 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.
- Total response time – Time difference between when the incident was first detected to when the last agency needed to respond to the incident was notified.
- On-scene time – Time difference between when the first responder arrived and the last responder left the scene. The on-scene time is also useful when computed for individual responders.

The first responder response time was derived from the database for selected responders, as shown in Table 5-3. The median response times for the two most common first responders were 18 and 13.5 minutes for police and fire department, respectively. The median first responder response time for specific responders should be carefully interpreted. For example, while TxDOT as the first responder appears to have a short median response time, it is most likely because those specific incidents were not responded to by any other responders. Therefore, when TxDOT was the only responder, the response time could be reported and logged into the database as soon as TxDOT arrived at the scene.

The first responder response time also reflects the overall responsiveness of the incident management program. The next section presents further evaluation of the relationships between the first responder response time and other incident characteristics to identify ways to improve the first responder response time.

Table 5-3: First Responder Response Time (Fort Worth).

First Responder Response Time (min)			
First Responder	Percentile		
	5%	50%	95%
TxDOT	4.0	6.0	445.4
EMS	4.0	8.0	57.8
Fire Department	4.0	13.5	301.9
Police	4.0	18.0	188.3
CPIMT	6.8	28.0	139.4

Total response times were calculated from the database as well. Researchers did not classify the total response times by the responders because total response time does not have any specific implications on incident management performance. Rather, the agency can use this measure to compare itself with another agency, provided that the data are available, or to compare the total response times internally by different time scales (e.g., quarterly or annually) to measure the responsiveness of the incident management program. Overall, the median total response time was 24 minutes for Fort Worth's TransVISION. A lower median total response time would indicate an improved responsiveness and better coordination of required incident responders for an agency.

Researchers calculated the summary statistics of on-scene times for each responder, and summarized the results in Table 5-4. The median on-scene time of the police was the longest among all major responders considered. This is not unexpected because police usually arrive at the scene first and stay on until the incident has been cleared and all the responders have left the scene. Wreckers were found to have the shortest median on-scene time. This is because the role of wreckers is clearly defined in the incident management activities, and they can leave the scene as soon as the lane blockage is removed.

Table 5-4: On-Scene Time of Major Responders (Fort Worth).

On-Scene Time by Major Responders			
Responder	Percentile		
	5%	50%	95%
Wrecker	3.0	16.0	59.9
CPIMT	1.0	19.0	86.0
EMS	3.0	20.0	68.9
Fire Department	4.0	25.0	73.0
TxDOT	6.3	35.0	80.9
Police	5.0	37.0	90.0

5.3. Analysis of First Responder Response Time

This section presents researchers' use of a statistical analysis methodology known as the hazard duration model to explore the factors affecting the first responder response time. The methodology described herein is similar to the one used to model incident duration (see Module 7 in the guidebook).

Researchers calculated first responder response times for each incident record. Then researchers performed the data validation on incident data characteristics such as invalid time logs, duplicate entries, and missing data to ensure that only valid data remained for the analysis in the next step.

From this process, researchers retained only first responder response times equal to or greater than four minutes for the analysis. This was because there were a significant number of incident records where the incident beginning time and first responder arrival time log were unrealistically close. This situation was likely due to the way the incident logs were entered into the database. The incidents in many cases were not detected immediately (significant time lag), and thus by the time the records were entered into the database, the first responder had almost or already arrived at the scene. This scenario often resulted in unrealistically short response times recorded into the database.

The analysis included a total of 355 incident records. Researchers then recoded specific incident characteristics into indicator variables where they could be incorporated into the model for the analysis. The variables evaluated in this analysis include:

- incident types,
- type and number of vehicles involved,
- number of mainlanes blocked,
- injury severity,
- weather conditions,
- responder type, and
- time of day – AM peak (6 AM to 9 AM), midday (9 AM to 4 PM), and PM peak (4 PM to 7 PM).

Researchers treated the first responder response time as a response variable. The exponential distribution gave the best overall goodness-of-fit statistics. Table 5-5 summarizes final model specifications, which include selected variables and their corresponding statistical significance.

From the model estimation results, researchers found that the first responder response time tended to be slow under the following conditions:

- Low-severity incidents – This is most likely due to the fact that low-severity incidents will receive lower priority when there are multiple incidents.
- Good weather condition – The operators may not expect an unusually high number of incidents or severe incidents under normal weather conditions. Therefore, when incidents do occur, they may not get reported to the responders as fast as in the case of bad weather conditions, thus increasing the first responder response time.

- Night time – Because TransVISION operates only during the day, a delay in incident response is more likely during nighttime.

From the model estimation results, the first responder tended to arrive faster under the following conditions:

- First responder is emergency medical service.
- Time period is PM peak.
- More vehicles are involved – This is because the impact on traffic conditions is increased with the increase in the number of vehicles involved; thus, they are more likely to respond faster.
- Heavy rain conditions exist – This is the opposite to the case of good weather conditions discussed previously.

Table 5-5: Analyzing First Responder Response Times (Fort Worth).

Variable	Value	Standard Error	p-value
Intercept	3.832	0.187	1.11E-93
Disabled Incident	-0.916	0.189	1.31E-06
Number of Vehicles Involved	-0.074	0.070	2.91E-01
Severity: None	0.765	0.141	6.22E-08
Severity: PDO	-0.455	0.135	7.26E-04
Heavy Rain	-1.109	0.520	3.28E-02
Sunny Day	0.330	0.119	5.48E-03
Nighttime with no lighting	1.063	0.399	7.74E-03
Nighttime with lighting	1.227	0.371	9.47E-04
EMS responded	-0.697	0.126	2.99E-08
PM peak (4 PM-7 PM)	-0.776	0.140	3.19E-08

Exponential distribution
Log-likelihood (model) = -1621.4
Log-likelihood (intercept only) = -1715.6
Chisq= 188.41 on 10 degrees of freedom, p-value = 0
n = 355 (17 observations deleted due to missing values)

5.4. Summary

Researchers found that the incident responder information, such as arrival and departure time logs, can provide additional insight into incident management characteristics of an agency. However, the degree to which an agency can use this information depends on several factors, including:

- accuracy, consistency, and standardized definitions of incident time logs, and
- accuracy and details of other incident characteristics recorded in the database.

The analysis conducted in this chapter demonstrated the potential of using specific performance measures from the database to identify and assess the influence of various incident characteristics on such measures. A similar approach can be applied to evaluate other measures, such as notification time, total response time, and clearance time. This could be very helpful because various factors can have different implications on the time spent in each phase of incident management. When separately analyzed, an agency can use the historical incident data to examine and help improve the overall responsiveness and effectiveness of an incident management program.

6. PREDICTING INCIDENT DURATION

This chapter applies the methodology described in Module 7 of the guidebook to develop models for predicting incident durations based upon incident characteristics recorded in historical incident data archives. Researchers used incident data from three cities – Houston, Austin, and Fort Worth – to calibrate equations for predicting incident durations. This chapter summarizes model development procedures, model estimation results, and findings from the analysis.

6.1. Methodology

Statistical regression techniques were commonly used in developing a model for predicting incident duration. Past studies indicated that incident duration can be predicted by accident type, severity, number of lanes affected, number of vehicles involved, truck involvement, time of day, police response time, and weather condition (*1-3*). Jones et al. (*4*) made further improvements by estimating a conditional probability that the incident will end in the Y^{th} minute given that the incident has lasted X minutes. Nam and Mannering (*5*) further developed the hazard duration model in an analysis of incident duration. This study provided evidence that hazard-based approaches are suited to incident analysis for the individual stage of the incident, including detection time, response time, and clearance time. More recently, non-parametric regression approaches such as a decision tree (*6*) and nearest neighbor's technique (*7*) have been used for estimating incident duration as well. However, these techniques have not been proved to significantly outperform traditional parametric regression models.

The guidebook recommends hazard-based duration models for predicting incident durations based on incident characteristics. To provide some background on the hazard-based models, the cumulative distribution function is defined as:

$$F(t) = P(T < t) \tag{6-1}$$

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

$$f(t) = \frac{dF(t)}{dt}, \tag{6-2}$$

and the hazard function is:

$$h(t) = \frac{f(t)}{1 - F(t)} \tag{6-3}$$

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:

$$S(t) = P(T \geq t). \tag{6-4}$$

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

$$S(t) = 1 - F(t) = 1 - \int_0^t f(t)\,dt = e^{-H(t)}, \tag{6-5}$$

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

$$h(t) = \frac{f(t)}{S(t)} = \frac{f(t)}{1 - F(t)} = \frac{dH(t)}{dt}. \tag{6-7}$$

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, and doing so affects the probability of either increasing or decreasing incident durations.

The distributions typically used in this type of model include lognormal, logistic, log-logistic, and Weibull models. For example, when using a Weibull distribution, which is a more generalized form of the exponential distribution, the density function is defined as:

$$f(t) = \lambda P(\lambda t)^{P-1} e^{-(\lambda t)^P}, \lambda > 0, P > 0, \tag{6-8}$$

and the corresponding hazard function is:

$$h(t) = (\lambda P)(\lambda t)^{P-1}. \tag{6-9}$$

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:

$$\log \lambda_i = \beta^T \mathbf{x}_i, \; \lambda_i = e^{\beta^T \mathbf{x}_i}. \tag{6-10}$$

For the Weibull distribution, the hazard function becomes:

$$h(t) = Pt^{P-1}e^{P\beta^T \mathbf{x}}. \quad (6\text{-}11)$$

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

- average incident duration – use the median value instead of the arithmetic mean whenever possible to avoid bias caused by the skewness of the distribution;
- predicted incident duration at specific percentile values; 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:

$$\tilde{T}_i = \lambda_i \ln(2)^{1/P}. \quad (6\text{-}12)$$

The $(1-\alpha)$ percent confidence interval of the predicted incident duration is:

$$\left[\lambda_i\left(-\ln\left(1-\frac{\alpha}{2}\right)\right)^{1/P}, \lambda_i\left(-\ln\left(\frac{\alpha}{2}\right)\right)^{1/P}\right]. \quad (6\text{-}13)$$

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:

$$S(t) = 1 - F(t) = 1 - e^{-(t/\lambda)^P}. \quad (6\text{-}14)$$

6.2. Houston

Researchers imported the incident data from 2004 to 2007 into Microsoft Excel for preparing the data into the format convenient for the analysis and model development.

6.2.1. Data Preparation

Data preparation consists of two important tasks – data validation and data recoding. In the data validation, the researchers examined the data for any discrepancies and either fixed or removed them prior to the analysis. The data recoding involved transforming the data values into a numerical format compatible with model calibration.

Data validation is a process of checking the data to make sure that they are accurate for the subsequent analysis. Researchers performed the following data validation checks:

- Invalid duration data – Researchers filtered out the incident records with invalid time logs, missing time logs, and negative incident durations. TranStar recorded unused time logs as `12/31/9999 11:59:59 PM` by default. Researchers marked these default time logs as `NA` as part of data preparation to ensure that these default time logs were excluded from the calculation of incident durations.

- Missing data – Researchers flagged missing data elements in the database using the standard notation for the selected statistical software package (S-Plus).
- Logical checks – Researchers checked the values recorded in the data fields against pre-specified thresholds to ensure that they were logical. This included specifying the minimum and maximum thresholds for data fields such as incident duration, number of vehicles involved, and number of lanes blocked.
- Duplicate incident records – Researchers queried and removed any duplicate records.

Data recoding is the process of converting the data attributes in the incident database into a format suitable for model calibration. Researchers recoded the following data elements into indicator variables (0/1 indicator) suitable for analysis and model development:

- Time periods – Researchers classified incident logged times into the following time periods: AM peak (weekday 6 AM to 9 AM), midday (weekday 9 AM to 4 PM), PM peak (weekday 4 PM to 7 PM), nighttime (weekday 7 PM to 6 AM), and weekend (all non-weekday periods). Researchers used these indicator variables to assess the temporal effects on incident durations.
- Incident severity.
- Incident types.
- Weather conditions.
- Incident detection methods.
- Incident verification methods.
- Incident responders.
- An indicator variable for all mainlanes blocked.

Recoding was not required for some data elements since they were already in ordinal numerical format and their values had logical relationships with incident durations. These data elements included:

- number of lanes blocked, and
- number of vehicles involved.

Researchers previously derived and examined descriptive statistics of potential data attributes as part of the analysis in Chapter 2. The sample sizes of data attributes evaluated were adequate. The variability of incident characteristics observed from the database was also sufficient for potential inclusion into the models. The researchers did not find any abnormalities in the dataset that would prevent them from excluding specific data attributes from the model development process. Section 2.2.2 provided more information about the characteristics of Houston's incident data attributes.

The next section discusses the testing process that the researchers conducted to determine appropriate model structure and select incident data attributes that are statistically significant for predicting incident durations using hazard-based duration models. The calibration process involves a series of adding and removing a number of potential variables in the models and then evaluating their statistical significance. This procedure will eventually converge to the selection of appropriate model structure and the best set of variables for each submodel. The final models should yield satisfactory goodness-of-fit statistics while offering intuitive model interpretation.

6.2.2. Model Development

To determine appropriate model structure, researchers first fitted the hazard models using all the variables. Then researchers used the stepwise variable selection process and Akaike information criterion (AIC) to select and retain the statistically significant model variables. Researchers found Weibull distribution to consistently give the best overall goodness-of-fit statistics among all the distributions tested, which also included exponential, logistic, and log-logistic.

Researchers considered two modeling approaches in the model development process – single model versus multiple submodels. Researchers found that the model estimation results from using multiple submodels are more logical and yield better prediction performance. The selection of the submodels was based on lane blockage characteristics and incident types. The examination of modeling results when using a single model revealed that some factors, such as the number of vehicles involved and incident types, can have contradicting effects on incident durations. For example, lane-blocking stall tends to be much shorter in average duration than non-lane-blocking stall because its impacts on the freeway are much higher. The one-vehicle vehicle on fire incident is typically more severe and takes longer to clear than two-vehicle PDO crashes. Hence, the effects of the number of vehicles on incident duration can be easily confounded without looking into the specific types of an incident. Researchers ultimately developed four submodels for Houston 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.

Researchers separately modeled accident and stall because these two types represented a majority of incidents archived in the database. To select an appropriate submodel, researchers first used the number of mainlanes blocked to distinguish between lane-blocking and non-lane-blocking incidents. Then incident types were used to further classify submodels among lane-blocking incident types. Researchers calibrated the models using the S-Plus statistical software package.

6.2.3. Model Estimation Results

Table 6-1 summarizes the duration models calibrated for four submodels using Houston's incident data from 2004 to 2007.

Table 6-1: 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	

Notes: * MAP = Motorist Assistance Program; ** METRO = Metropolitan Transit Authority of Harris County;
*** HCFCD = Harris County Flood Control District.

The model coefficients shown in the table are statistically significant at 95 percent confidence interval (p-value < 0.05) unless 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 was not statistically significant at $\alpha = 0.05$, the model was re-estimated using the exponential hazard model where the scale parameter was fixed at 1.0. Note that the exponential distribution is a special case of Weibull distribution.

Individual examination of the signs of model coefficients was found to be intuitive. The models produced a better predictive capability when separately calibrated for each submodel. For each submodel calibrated, a summary of model statistics is provided which are:

- selected parametric distribution;
- scale parameter;
- chi-square statistics and the corresponding degrees of freedom;
- overall model p-value indicating 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 99 percent confidence level; and
- number of observations or sample size.

The interpretation for most of the model coefficients in Table 6-1 is intuitive and straightforward. Since the incident duration is linked to model covariates using a logarithmic link function, a one-unit change in the value of model variables would have a multiplicative impact on incident durations by the amount equal to the exponent of the coefficient value. Consider the lane-blocking accident submodel as an example. A presence of major incident would increase the duration by $e^{0.1650}$, which is equivalent to an additional 18 percent of base incident duration. Vice versa, a negative coefficient value would decrease the duration of an incident. In the same example, if the incident was detected by CCTV, the duration would decrease by $e^{-0.1214}$, which is equivalent to a reduction of 11 percent from the base incident duration.

6.2.4. Model Implications

Based on the model estimation results shown in Table 6-1, Table 6-2 summarizes incident characteristics that strongly correlated with incident durations.

Table 6-2: Statistically Significant Incident Characteristics (Houston).

Incident Characteristics	Lane-Blocking Accident	Lane-Blocking Stall	Lane-Blocking Others	All Non-Lane-Blocking
Incident Type	x	x	x	x
Detection Method	x	x	x	x
Verification Method	x	x	x	x
Incident Severity	x			x
Weather Conditions	x			
Vehicle Types	x	x	x	x
Number of Vehicles Involved	x			
Number of Lanes Blocked	x	x	x	
Time of Day		x	x	x
Responders	x	x	x	x

Note that incident types are still significant factors even if the submodels are already predetermined by either accident or stall. This is because multiple incident types can be registered for a single incident. For example, if an incident is recorded as an accident and vehicle on fire, then a lane-blocking accident submodel would be used to predict the duration with a vehicle on fire type as one of the model inputs. Weather conditions were statistically significant only for lane-blocking incidents. This was because the weather conditions were not always recorded. In fact, weather conditions were available for only approximately 10 percent of all incident data. The number of vehicles involved has the influence on the durations of the lane-blocking accident type because it is the only type where multi-vehicle incidents are common and frequent. Also, researchers found the time of day to be statistically significant for all submodels except the lane-blocking accident type. Since the time of day has a strong correlation with incident severity (particularly for accidents during peak periods with high volume and thus considered high impacts), its statistical significance was reduced by the multicollinearity effect when both factors were included in the model.

In addition, using the estimated coefficients from the duration models, the researchers can prioritize the incident characteristics that strongly influence the incident durations either positively or negatively. Impact of incident characteristics on incident durations can be quantified as a percentage change on incident duration from one-unit change in the values of incident characteristics. Table 6-3 provides a list of high-impact incident characteristics identified by their influences on incident durations for each submodel.

Table 6-3: High-Impact Incident Characteristics (Houston).

Submodel	Selected Incident Characteristics	% Change
Lane-Blocking Accident	Positive Effect on Duration	
	• High water	252%
	• Fatality incident	213%
	• Hazmat spill	111%
	Negative Effect on Duration	
	• Detected by other public agencies	-23%
	• Detected by automated detection	-17%
	• Detected by commercial traffic services	-15%
Lane-Blocking Stall	Positive Effect on Duration	
	• Involved bus	138%
	• Involved heavy truck	129%
	• Hazmat spill	77%
	Negative Effect on Duration	
	• Detected by MAP	-23%
	• Detected by CCTV	-19%
	• MAP responded	-18%
Lane-Blocking Others	Positive Effect on Duration	
	• High water	411%
	• Hazmat spill	127%
	• Heavy truck involved	79%
	Negative Effect on Duration	
	• Verified by METRO police	-73%
	• METRO police responded	-47%
	• MAP responded	-34%
All Non-Lane-Blocking	Positive Effect on Duration	
	• High water	505%
	• Fatality incident	316%
	• Hazmat spill	88%
	Negative Effect on Duration	
	• Verified by county police	-45%
	• Verified by other public agencies	-28%
	• Stall incident	-25%

In Table 6-3, the percentage change implies either an increase or a decrease in incident durations given all else being equal. For instance, a hazmat spill lane-blocking accident is likely to increase the duration by 111 percent given all other factors being the same. Similarly, a lane-blocking stall incident that is detected by motorist assistance program (MAP) is likely to last on average 23 percent shorter in incident duration given all else being equal. The model structure mathematically assumes the effects of multiple factors are multiplicative. For example, the incident duration of a lane-blocking stall incident that is detected and responded by MAP would be reduced by a factor of $(1 - 0.23)(1 - 0.18) = 0.63$, which is equivalent to 37 percent. In this manner, the agency can use the model estimation results to assess, identify, and prioritize the impacts of incident characteristics on incident durations. The agency can use the same information as a decision support tool for incident management planning as well.

6.3. Austin

The researchers used CTECC's incident data archive from 2004 to 2007 to calibrate equations for predicting incident durations. Section 2.3 described the analysis and the characteristics of the incident data attributes from CTECC in details.

6.3.1. Data Preparation

Data preparation consists of two major tasks – data validation and data recoding. Researchers performed the data validation to detect and remove duplicate, missing, and erroneous data from the analysis. Congestion incidents automatically recorded by an automated incident algorithm represented 87 percent of all incidents recorded in the database. These congestion incidents had only time logs and locations of detectors recorded; therefore, they did not provide other incident characteristics useful for incident duration analysis and modeling. Researchers retained and used only non-congestion incidents to develop incident duration models.

Researchers recoded the following data attributes into a numerical format convenient for analysis and modeling:

- Time periods – Researchers used incident detection time logs to define the beginning of an incident. Researchers categorized the time logs into the following periods: AM peak (weekday 6 AM to 9 AM), midday (weekday 9 AM to 4 PM), PM peak (weekday 4 PM to 7 PM), nighttime (weekday 7 PM to 6 AM), and weekend (all non-weekday periods).
- Incident types – Incident types recorded in Austin's database were mutually exclusive. Each incident can associate with only one incident type.
- Affected lanes – Researchers converted mainlanes and shoulder lanes affected by an incident into indicator variables representing each specific lane.
- Number of lanes blocked – Researchers computed the number of mainlanes blocked by summing the indicator variables for each mainlane blocked.
- Detection methods.
- Verification methods.
- Surface conditions.
- Lighting conditions.
- Weather conditions.
- Severity of injuries.
- Types of vehicles involved.

Section 2.3.2 provided the analysis of the distributions of incident data attributes from CTECC. The incident data from 2004 have more incomplete records compared to the data from the other years. The model development process excluded the records with incomplete data attributes if such attributes were selected in the final model specifications. Therefore, the data from 2004 was still retained in the subsequent analysis but a significant proportion of the incident records were not used in the analysis when specific data attributes were chosen for the models.

6.3.2. Model Development

The researchers examined various incident characteristics, such as incident type, duration, lane blockage, and severity, to explore each characteristic's potential for estimating the duration of an ongoing incident. Researchers attempted several approaches to appropriately model incident durations given incident characteristics available in the Austin database. Ultimately, the most promising approach was to calibrate the submodel for each incident type recorded and then determine the characteristics that would statistically correlate with the incident duration. Since the number of lanes blocked was not directly recorded in the database, researchers could not use the lane blockage information to determine the submodel structure as in the case of Houston.

The researchers used Weibull hazard duration models to estimate the incident durations based on various incident characteristics. Researchers calibrated eight separate models for the following types of incidents in Austin's database:

- collision,
- stall,
- abandonment,
- hazmat spill,
- overturned,
- public emergency,
- road debris, and
- vehicle on fire.

6.3.3. Model Estimation Results

Table 6-4 summarizes the duration models calibrated for different types of incidents in Austin using the data from 2004 to 2007. The model coefficients shown in the table are statistically significant at 95 percent 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. First, researchers estimated the Weibull hazard models for each incident type. Then, if the estimated scale parameter was not statistically significant at $\alpha = 0.05$, the model was re-estimated using the exponential hazard model. Note that the exponential distribution is a special case of Weibull distribution where the scale parameter is constant at 1.0.

Table 6-4: Austin's Incident Duration Models.

Incident Characteristics	Incident Types							
	Abandonment	Collision	HAZMAT Spill	Overturned	Public Emergency	Road Debris	Stall	Vehicle on Fire
Intercept	7.1045	4.0578	5.4048	4.7810	6.1076	3.9863	4.9069	5.204
Detection/Verification								
1 if verified by courtesy patrol; 0 if otherwise	0.2933*	0.1285*						
1 if verified by maintenance; 0 if otherwise		1.9285						
1 if verified by CCTV; 0 if otherwise	-0.4298		-1.6249	-0.6878			-0.7356	-1.5750
1 if verified by law enforcement; 0 if otherwise							0.4685	
Incident Notification								
1 if media is notified; 0 if otherwise		-0.1205*			-2.5960		-0.5304	-0.7180
1 if county constable is notified; 0 if otherwise		0.2844**					1.8736	
Injury Severity								
1 if possible injuries; 0 if otherwise		0.2719		0.4227				
1 if fatal; 0 if otherwise		0.9872		1.2575				
Surface Condition								
1 if surface is not dry; 0 if otherwise		0.2153			1.2176		0.2225	
Lighting Condition								
1 if during daylight; 0 if otherwise	-0.5072	-0.5247	0.6567	-0.2030[#]		-0.4692		
Affected Locations								
1 if connector is affected; 0 if otherwise		0.3246**					-1.2350	
1 if frontage is affected; 0 if otherwise				0.2819***		-0.8984*	0.3637	0.5095**
1 if entrance ramp is affected; 0 if otherwise						-1.3059		
1 if exit ramp is affected; 0 if otherwise				-0.6748		0.8410*	-0.2525*	
Vehicle Types Involved								
1 if passenger car is involved; 0 if otherwise	0.3783	-0.1845						1.3903
1 if truck is involved; 0 if otherwise		0.0972***	0.9433*					
1 if trailer is involved; 0 if otherwise	-0.7593**	0.2329*						0.9744
1 if bus is involved; 0 if otherwise		0.7378**						
Number of Vehicles Involved								
1 if 1 vehicle is involved; 0 if otherwise		0.2390						
1 if 2 vehicles are involved; 0 if otherwise		0.3474						
1 if 3 vehicles are involved; 0 if otherwise		0.4435						
1 if 1 or more vehicles involved; 0 if otherwise							0.4685	
Lane Blockage								
1 if 3 or more lanes are blocked; 0 if otherwise		0.2783						
1 if 1 or more lanes are blocked; 0 if otherwise							-0.6424	
Shoulder Blockage								
Number of Shoulders Blocked						0.7665		
Distribution	Weibull	Exponential	Weibull	Weibull	Weibull	Weibull	Weibull	Weibull
Scale	1.260	1.000	0.676	0.815	1.500	1.650	1.650	0.762
Chi-Square Statistics	69.1	239.4	10.7	22.4	29.1	34.7	333.2	24.2
Degree of Freedom	5	17	3	6	2	6	10	5
Model p-value	< 0.0001	< 0.0001	0.014	0.001	<0.0001	<0.0001	<0.0001	0.0002
Number of Observations	913	2146	89	113	55	250	3889	75

Notes: All the variables have p-value < 0.05 except where noted; * p-value < 0.10; ** p-value <0.15; *** p-value <0.20; # p-value <0.30

Each calibrated model contained the following summary statistics:

- distribution;
- scale parameter;
- chi-square statistics and the corresponding degrees of freedom;
- 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 99 percent confidence level; and
- number of observations.

Individual examination of the signs of model coefficients was found to be intuitive. The models produced a better predictive capability when separately calibrated because different types of incidents can have different causative factors. Injury severity, for example, can be an important factor for the duration collision or overturned incidents but not for the stall or abandonment incidents. Below are interesting observations from the estimation results with respect to each model.

For the collision incident, researchers found that the effect of the number of vehicles on the duration was not linear, and, therefore, the model coefficients were separately calibrated for the different number of vehicles involved. The effect of vehicle types was also more pronounced in that heavy vehicle involvement (e.g., truck, trailer, bus) would likely lead to longer duration than those with passenger cars alone. Researchers found that only the collision type followed the exponential distribution, whereas all other types were better fitted to the Weibull distribution.

Several types of incidents were likely to have shorter durations if they could be verified by CCTV. Incidents located within surveillance coverage may be more efficiently cleared because the operators can effectively coordinate the assistance required from various incident responders and determine appropriate actions from visual assessment of the events on the screen.

Severity of injury influenced only the durations of collision and overturned incidents. Other types of incidents were less likely to involve injuries and/or did not occur frequently enough to have sufficient sample size in order to account for the effect of injury severity on the duration.

For the abandonment, incidents with trailer involvement were more likely to have a shorter duration than passenger car incidents because they are more disruptive to traffic flow and generate more immediacy to be removed.

6.3.4. Model Implications

Table 6-5 summarizes the incident characteristics that researchers included into the duration submodels calibrated for each incident type. These characteristics are those that are found to statistically correlate with the duration of particular incident types. For example, several incident characteristics could influence the collision duration: detection/verification, incident notification, injury severity, surface condition, lighting condition, vehicle types involved, number of vehicles involved, and number of lanes blocked.

As illustrated in Table 6-5, researchers found that most of the incident characteristics currently collected at CTECC carry significant explanatory power for the duration of collision incidents. However, the utility of the same characteristics decreases when used to explain the duration of other incident types. This is partly attributed to the rarity and randomness of other incident types as well as the accuracy of the records manually entered by control center operators. Therefore, only a few characteristics were found to be useful for estimating the durations of certain types of incidents, such as public emergency or road debris.

Table 6-5: Statistically Significant Incident Characteristics (Austin).

Incident Characteristics	Incident Types							
	Abandonment	Collision	HAZMAT Spill	Overturned	Public Emergency	Road Debris	Stall	Vehicle on Fire
Detection/Verification	x	x	x	x		x	x	x
Incident Notification		x			x		x	x
Injury Severity		x		x				
Surface Condition		x			x		x	
Lighting Condition	x	x	x	x		x		
Affected Locations		x		x		x	x	x
Vehicle Types Involved	x	x	x					x
Number of Vehicles Involved		x					x	
Lane Blockage		x					x	
Shoulder Blockage						x		

Table 6-6 provides a list of selected high-impact incident characteristics identified by their influences on incident durations for collision and stall incidents. These two incident types represent the majority of all incident types recorded in the database. In this table, the percentage change implies either an increase or a decrease in incident durations given all else being equal.

Some of the factors that were likely to significantly increase the duration of collision incidents included fatalities and the number of vehicles involved. From the table, a fatality or the involvement of three or more vehicles would likely increase the duration of an incident by 168 percent and 56 percent, respectively. Also, collisions that occurred during the daytime or involved only passenger cars would likely reduce the duration by 41 percent and 17 percent, respectively. The effects of these factors on the incident duration are multiplicative. For example, the net effect on the duration for a fatal collision that occurred during the daytime would be $(1 + 1.68)(1 – 0.41) = 1.58$, which is a 58 percent increase on the incident duration given all other factors being constant.

Researchers found the lane blockage to have a negative effect on stall duration. This is because the lane-blocking stall is more likely to get immediate attention from the operators and thus reduce the incident duration. Similarly, if the stall incident is verified by CCTV or notified to the media, this implies that the location of the stall is under surveillance coverage. Appropriate responders can be promptly notified, thus reducing response times and overall durations.

Table 6-6: High-Impact Incident Characteristics (Austin).

Submodel	Selected Incident Characteristics	% Change
Collision	Positive Effect on Duration	
	• Verified by maintenance	588%
	• Fatality incident	168%
	• Involved bus	109%
	• 3 or more vehicles involved	56%
	Negative Effect on Duration	
	• Occurred during daytime	-41%
	• Involved passenger car	-17%
	• Media is notified	-11%
Stall	Positive Effect on Duration	
	• Verified by law enforcement	60%
	• Frontage road is affected	44%
	• Surface condition is not dry	25%
	Negative Effect on Duration	
	• Verified by CCTV	-52%
	• 1 or more lanes are blocked	-47%
	• Media is notified	-41%

6.4. Fort Worth

The researchers used TransVISION's incident data from 2004 to 2006 to calibrate incident duration models. Section 2.4.2 previously discussed the analysis of the incident data attributes from Fort Worth's database. In addition to common data attributes, TransVISION also collects queue length and arrival and departure time of each responder. These data are not currently collected by other TMCs examined in this study. The researchers previously examined these additional data and analyzed the factors affecting first responder response time in Chapter 5.

6.4.1. Data Preparation

Data preparation consists of two major tasks – data validation and data recoding. Researchers performed the data validation to detect and remove duplicate, missing, and erroneous data from the analysis. To compute incident durations, researchers used the earliest of three time logs – occurrence time, detection time, and verification time – to define the beginning of an incident. The latest of the two clearance time logs in the database was used to define the end of an incident. If both the beginning and the end time logs of an incident existed and were valid for an incident record, researchers then computed the incident duration by calculating the difference between those two times. Incident records with either invalid time logs or negative incident durations were removed from further analysis.

Several data attributes in TransVISION's database were recorded using a series of numerical digit format. For example, the incident type can be recorded as "03001100," where each digit represents one type of incident. The digit can be 0/1 or another numerical number depending on how it was defined. In this example, the second digit indicates a major collision, the fifth digit indicates truck involvement, and the sixth digit indicates that the incident also involved hazardous material spills. Researchers recoded this type of record into a series of indicator variables for modeling purposes. Each variable represented a specific type of incident. With this format, multiple incident types could be recorded for each incident (i.e., not mutually exclusive). In summary, incident data attributes that required this type of recoding process included:

- incident types;
- weather conditions;
- specific lanes blocked – researchers calculated the number of lanes blocked by summing up all the indicator variables for each lane. A similar procedure was also applied for shoulder blockage;
- all mainlanes blocked;
- verification methods;
- road conditions; and
- incident responders.

Researchers categorized the time periods for weekdays as follows: AM peak (6 AM to 9 AM), midday (9 AM to 4 PM), and PM peak (4 PM to 7 PM). This analysis did not consider the nighttime and weekend periods because they were outside the operating hours of the TMC, and thus very limited incident data were available.

In the next step, the researchers conducted a model development process, which involved identifying appropriate model structure and selecting the incident data attributes that correlated with incident durations with satisfactory statistical significance. The researchers used Microsoft Excel to prepare the data and then imported them into S-Plus for statistical analysis and modeling.

6.4.2. Model Development

To develop appropriate model structure, the researchers examined the distribution of incident types recorded in the database. The top four incident types recorded were collision, disablement, truck, and debris. Since the incident types were not mutually exclusive, researchers reclassified the truck-related incident as a vehicle type and treated as a potential variable in all submodels. Researchers also considered the lane blockage characteristics as a potential variable in all submodels. The lane blockage can have either positive or negative influence on incident duration depending on the type of an incident. Because of limited sample size, researchers combined the remaining incident types and then referred to it as “others.” The final model structure for Fort Worth included four submodels as follows:

- collision,
- disabled,
- debris, and
- others.

With this structure, the potential variables affecting the incident durations could differ by the type of an incident reported. Also, researchers checked the sample sizes for each submodel to make sure that they were sufficient for model calibration. Researchers then calibrated hazard-based duration models with stepwise selection of model variables. The next section describes the estimation results for the best-fitted models.

6.4.3. Model Estimation Results

Table 6-7 summarizes the incident duration models calibrated for Fort Worth. Exponential distribution gave the best fit for all submodels except for the debris incident type.

For each model calibrated, a summary of the following model statistics is provided:

- distribution;
- scale parameter;
- chi-square statistics and the corresponding degrees of freedom;
- 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 99 percent confidence level; and
- number of observations.

Note that incident types were not mutually exclusive. Therefore, researchers also considered incident types as potential variables even if the submodels were selected based on the incident type. For example, in a collision submodel, major collision, public emergency, and others were statistically significant variables for predicting incident durations as well. TransVISION classifies a collision incident into either a minor or major collision. Because of this classification, the effect of injury severity could have already been captured and thus was not found to have significant impact on incident duration.

Researchers included two mutually exclusive alternatives for lane blockage characteristics in the collision submodel. The number of mainlanes blocked is generally recorded for a typical lane-blocking incident; however, this field is not be used if an incident is blocking all mainlanes. Instead, an "all mainlanes blocked" data field is used in that scenario. Both variables were found to correlate with the collision duration, but they should not be used simultaneously in the prediction. The model parameter inputs should reflect the way the incidents were logged at the TMC in order for the model to provide realistic estimates.

Researchers found that a collision that occurred at night tended to last longer on average. Also, a heavy truck incident was also found to increase the duration of both collision and debris. Impacts of weather conditions on incident durations were mixed and depended on incident types. Weather conditions during an incident were not always recorded. Hence, there is a lack of statistical evidence to conclude if some weather events, such as heavy rain and fog conditions, can affect the duration of specific incident types.

Table 6-7: Fort Worth's Incident Duration Models.

Incident Characteristics	Incident Types			
	Collision	**Disabled**	**Debris**	**Others**
Intercept	4.2634	5.1870	3.0530	5.9920
Incident Type (Not Mutually Exclusive)				
1 if minor collision; 0 if otherwise			1.3860	
1 if major collision; 0 if otherwise	0.2385			
1 if public emergency; 0 if otherwise	-2.5208			1.5150
1 if others; 0 if otherwise	0.4122*	1.7130	1.7570	
Verification Method				
1 if verified by public agency; 0 if otherwise	0.9324***			
1 if verified by CCTV; 0 if otherwise	-0.2430	0.4570		-0.7930
1 if verified by commercial traffic service; 0 if otherwise	-0.2590*			
1 if verified by police; 0 if otherwise			-3.4320	
Injury Severity				
1 if none; 0 if otherwise	0.4616	-0.8040	0.4660*	
1 if PDO; 0 if otherwise		-1.8070	1.3750	
1 if injuries; 0 if otherwise			-0.9200**	
1 if fatalities; 0 if otherwise				-2.9260
Weather Condition				
1 if sunny; 0 if otherwise	0.2100	-0.1790*	0.7780	-0.3770
1 if fog is present; 0 if otherwise				-3.4620
1 if hail is present; 0 if otherwise	-4.7890			
1 if light rain is present; 0 if otherwise			1.1510**	
1 if heavy rain is present; 0 if otherwise		2.4510		
1 if thunderstorm is present; 0 if otherwise		-3.6190		
Lighting Condition				
1 if night with no lighting; 0 if otherwise	0.7990	-0.6180*	7.3490	
1 if night with lighting; 0 if otherwise	0.4120		3.6600	-1.2600*
Time of Day				
1 if during AM peak (6AM-9AM); 0 if otherwise	0.1990	0.2200*	-1.4320	
1 if during PM peak (4PM-7PM); 0 if otherwise		-0.5410		-0.5200
Responders				
1 if CPIMT responded; 0 if otherwise	-0.2160***	-0.4640	0.6000	0.7570
1 if fire department responded; 0 if otherwise			1.5170	-0.3270*
1 if police responded; 0 if otherwise			-1.6620	
1 if EMS responded; 0 if otherwise	0.1170		-2.3200	
1 if wrecker responded; 0 if otherwise		-0.6450	1.0350*	
1 if city responded; 0 if otherwise	2.2300		-5.1280	-2.2120
1 if HAZMAT team responded; 0 if otherwise	0.9570		-2.4450	
1 if CME responded; 0 if otherwise			3.5770*	
Vehicles Involved				
Number of Vehicles Involved		0.2280*	-1.1140	-0.1910
1 if heavy truck is involved; 0 if otherwise	0.2456		0.7860	
Lane Blockage				
1 if all mainlanes are blocked; 0 if otherwise	0.3098			
Number of mainlanes blocked	0.0957	-0.5160	0.5090	-0.2010*
Shoulder Blockage				
Number of Shoulders Blocked			1.0360	
Distribution	Exponential	Exponential	Weibull	Exponential
Scale	1.000	1.000	0.484	1.000
Chi-Square Statistics	248.55	140.75	81.5	146.02
Degree of Freedom	19	14	23	12
Model p-value	< 0.0001	< 0.0001	< 0.0001	< 0.0001
Number of Observations	1769	343	55	166

Notes: All the variables have p-value < 0.05 except where noted; * p-value < 0.10; ** p-value <0.15; *** p-value <0.20; # p-value <0.30

Researchers found shoulder blockage to be a statistically significant predictor only for debris incidents. A shoulder blockage implies that debris may not block the travel lanes and not require immediate clearance, which may result in an increase in incident duration on average. On the other hand, the higher number of lanes blocked by the debris tended to increase the duration, but this was more likely attributed to the complexity of the clearance process itself.

Researchers also found different responders to have statistically significant impacts on incident durations. Specific types of responders can be used to infer the characteristics and severity of an incident. Incidents that require a hazmat team to respond likely involve hazardous material spills. Also, incidents would likely involve a fatality if a coroner/medical examiner (CME) responded.

6.4.4. Model Implications

Using the model estimation results in Table 6-7, Table 6-8 summarizes statistically significant predictors for incident durations for Fort Worth. Since the sample size of debris incidents is relatively small ($n = 55$), when both debris and collision types are recorded in the same incident, the collision model should always take precedence in this case. Researchers found the majority of incident characteristics to have certain degrees of influence on the resulting incident durations. Closer examination of model coefficients reveals the magnitude of the influence of specific incident characteristics on incident durations. Table 6-9 provides a list of common incident characteristics that have a strong influence either positively or negatively on the collision and disablement durations. These two types represent a majority of incidents recorded at TransVISION.

Table 6-8: Statistically Significant Incident Characteristics (Fort Worth).

Incident Characteristics	Collision Incident	Disabled Incident	Debris Incident	Others Incident
Incident Type	x	x	x	x
Verification Method	x	x	x	x
Injury Severity		x	x	x
Weather Conditions	x	x	x	x
Lighting Conditions	x	x	x	x
Vehicle Types	x		x	
Number of Vehicles Involved		x	x	x
Number of Lanes Blocked	x	x	x	x
Time of Day	x	x	x	x
Responders	x	x	x	x

As seen in Table 6-9, the percentage change indicates the effect of particular incident characteristics on the incident duration for each submodel. Several factors can increase the collision duration, and all the effects are multiplicative of the base incident duration. For example, a major collision with all mainlanes blocked would increase the duration of an incident by (1.27)(1.36) = 1.73, or 73 percent, given all else being the same. Similar interpretation also applies to the duration of disabled incidents as well. In this manner, the agency can use the results from the duration models to assess and identify specific incident characteristics for evaluating and improving incident management responses.

Table 6-9: High-Impact Incident Characteristics (Fort Worth).

Submodel	Selected Incident Characteristics	% Change
Collision Incident	Positive Effect on Duration	
	• Major collision	27%
	• AM peak period	22%
	• Heavy truck involved	28%
	• All mainlanes blocked	36%
	• Hazmat team responded	160%
	Negative Effect on Duration	
	• Verified by CCTV	-22%
	• Verified by commercial traffic services	-23%
	• CP/IMT responded	-19%
Disabled Incident	Positive Effect on Duration	
	• AM peak	25%
	• Heavy rain condition	1060%
	• Number of vehicles involved	26% each
	Negative Effect on Duration	
	• PM peak	-42%
	• Sunny weather condition	-16%
	• PDO only	-84%

6.5. Summary

The researchers examined the incident databases from TranStar, CTECC, and TransVISION and then developed incident duration models for each TMC. Researchers discussed the data preparation, model development, estimation results, and model implications separately for each TMC. Researchers found that incident data characteristics and the manner in which they are logged significantly differ among studied TMCs. A generalized incident duration model that would embrace all the differences and effectively estimate the incident duration is not possible unless the incident data archives are standardized.

6.5.1. Application of Incident Duration Models

There are several ways to implement the incident duration models depending on the resources available and the preferred level of automation. The researchers developed a prototype tool in this case study to simplify the use of the incident duration models calibrated from incident databases. Researchers implemented this tool using VBA in Microsoft Excel. VBA is an implementation of Microsoft's Visual Basic, an event-driven programming language and associated integrated development environment (IDE) that is built into most Microsoft Office applications. By embedding the VBA IDE into their applications, developers can build custom solutions using Microsoft Visual Basic. Researchers chose Microsoft Excel as a platform for this development due to its spreadsheet calculation capability and availability in most workplaces.

This tool aims at facilitating three tasks: (a) the process of entering the appropriate set of data required for predicting incident duration, (b) the display of the prediction results, and (c) the modification of data inputs and outputs to evaluate the impacts of the estimation results. Using Houston's incident duration models as an example, the graphical user interface for data inputs shown in Figure 6-1 was designed based on the incident characteristics collected at Houston's TranStar, such as the types of incidents, the classification of incident severity, and the types of vehicles involved. Researchers coded each submodel described in Table 6-1 into Excel worksheets. In this manner, the tool developer can review and adjust specific model parameters as needed without affecting changes to other working models.

To use the tool, the users first enter all the information known about an incident. The module will concurrently perform a data validation check for any inconsistent entries. Then the users must click the "Predict…" button to calculate the predicted incident duration. At the same time, the module will select an appropriate submodel for prediction based upon the lane blockage characteristics and incident types entered by the users. Figure 6-2 shows an example of the display of prediction results according to the user inputs as provided in Figure 6-1. Once the module specified the correct submodel, the module will transfer the user inputs into the appropriate model to perform the calculation. The module outputs provide three types of interrelated predictions:

- Average incident duration – This is the mean estimate of the incident duration for a given set of incident characteristics. This value may not be a good estimate if the distribution of duration is heavily skewed. In such cases, the users might want to check the median estimate as well. A user can obtain median estimate from the third type of the predictions by setting the percentile value at 50 percent.
- Probability of incident duration longer than specified value – If the agency has a target value of incident duration (e.g., 120 minutes or longer for major incidents), the users can specify the duration value and then obtain the probability that the specified duration would be exceeded. As shown in Figure 6-2, the probability that the incident will last longer than 60 minutes is 28.3 percent.
- Incident duration at specific percentile value – The user can specify percentile values and then determine the corresponding upper or lower extremes of the predicted incident duration. As shown in the same figure, the 85th percentile of the predicted duration is 99 minutes. In other words, the chance that an incident will last longer than 99 minutes is 15 percent.

By default, the module will provide three predictions, which are (a) average duration, (b) probability of duration exceeding 60 minutes, and (c) 85th percentile of the predicted duration. The users can specify different parameters (duration and percentile values) other than the default values to see the impacts on the predictions. After any changes, the users must click "Recalculate" in order to update the predicted values.

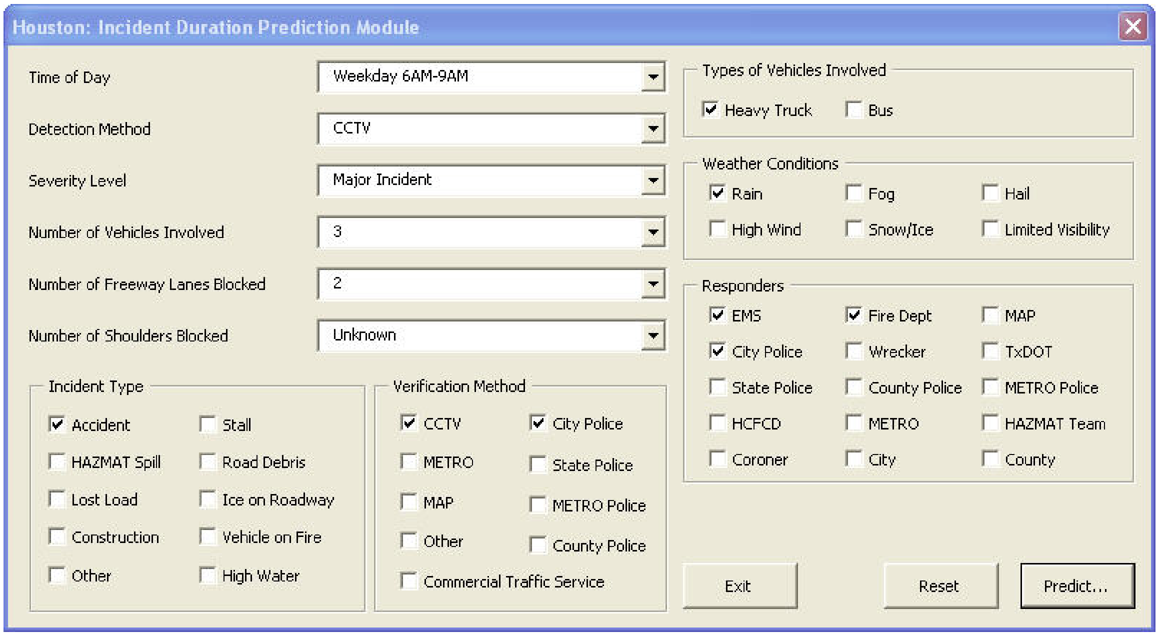


Figure 6-1: Input GUI for Houston Incident Duration Prediction Tool.

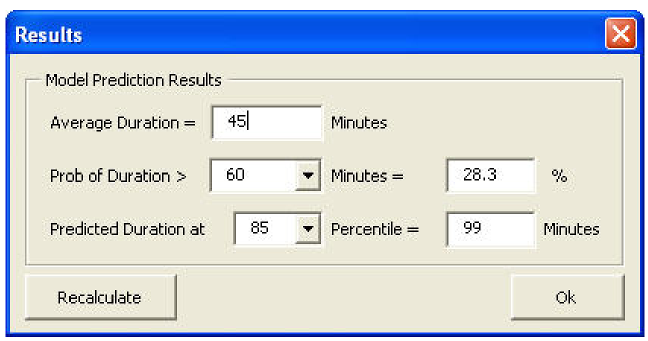


Figure 6-2: Output GUI for Houston Incident Duration Prediction Tool.

6.5.2. Selected Examples

To illustrate the use of the tool, this section describes selected examples of duration prediction using the prototype module developed for Houston's TranStar. Figure 6-3 provides incident duration statistics by incident types reported. The analysts can use the incident duration statistics provided as a performance benchmark for the prediction results. The following examples discuss three specific incident types: accident, truck-related, and hazmat spills. The median durations for accident, heavy truck, and hazmat spill incidents are 24, 37, and 115 minutes, respectively.

The first example (see Figure 6-4) considers a scenario of a minor two-vehicle, passenger-car-only accident verified by CCTV and responded to by city police. The accident occurs during the weekday PM peak period and closes two travel lanes. The prediction module first uses the lane blockage information and incident type to determine the appropriate submodel, which in this case is the lane-blocking accident. The expected incident duration for this scenario is 21 minutes. The probability that this incident will last longer than one hour is 10 percent. The 85th percentile duration for this type of scenario is 47 minutes. This value can be viewed as the upper threshold of predicted incident duration. Comparing the prediction results with duration statistics, the median and 85th percentile values for all accidents were 24 and 54 minutes, respectively. The prediction results are fairly close to historical duration statistics because this is one of the most common scenarios for lane-blocking accidents.

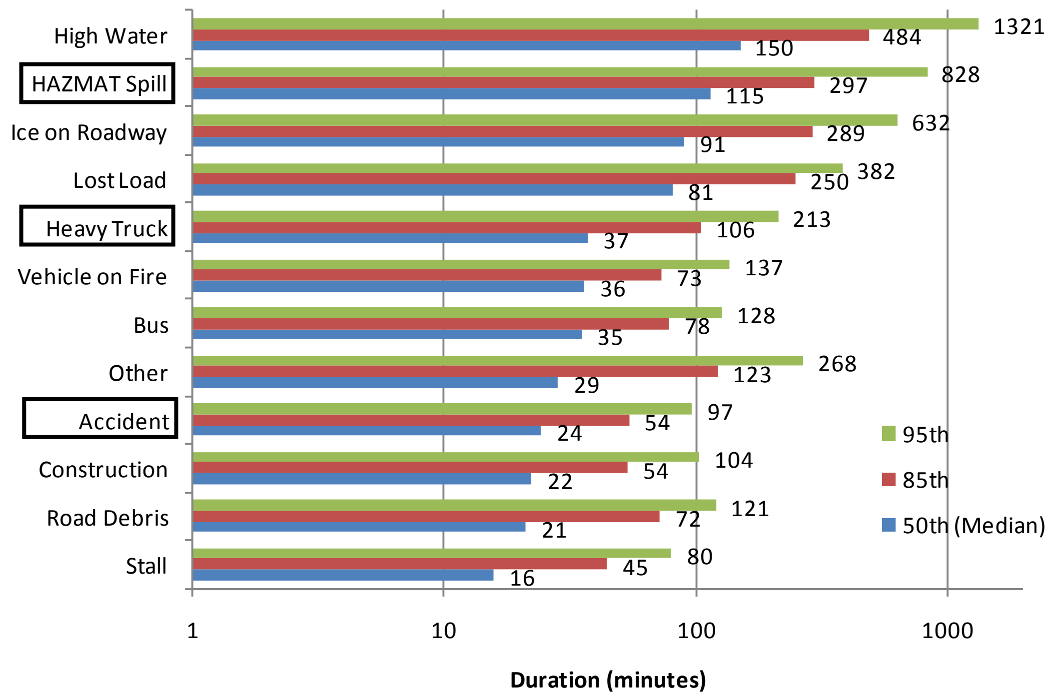


Figure 6-3: Percentile Statistics of Incident Duration (Houston).

The second example (see Figure 6-5) considers a major three-vehicle accident involving a heavy truck blocking two travel lanes. The incident is detected and verified by CCTV. A user can update the predicted results in stages as more information about the incident becomes available. In this case, a user can retrieve the first prediction results prior to entering responder information. Once all the responders arrive, a user can update the prediction results again. In this case, EMS, fire department, city police, and wrecker respond to the scene. The predicted mean duration is 52 minutes, and the 85th percentile duration is 115 minutes. The probability that this accident will last longer than 60 minutes is 32.6 percent. The median and 85th percentile durations of all heavy truck incidents were 37 and 106 minutes, respectively. The predicted durations account for factors beyond incident types, such as the number of vehicles involved, number of lanes blocked, and time of day, thus resulting in a relatively higher range of predicted values compared to the historical statistics.

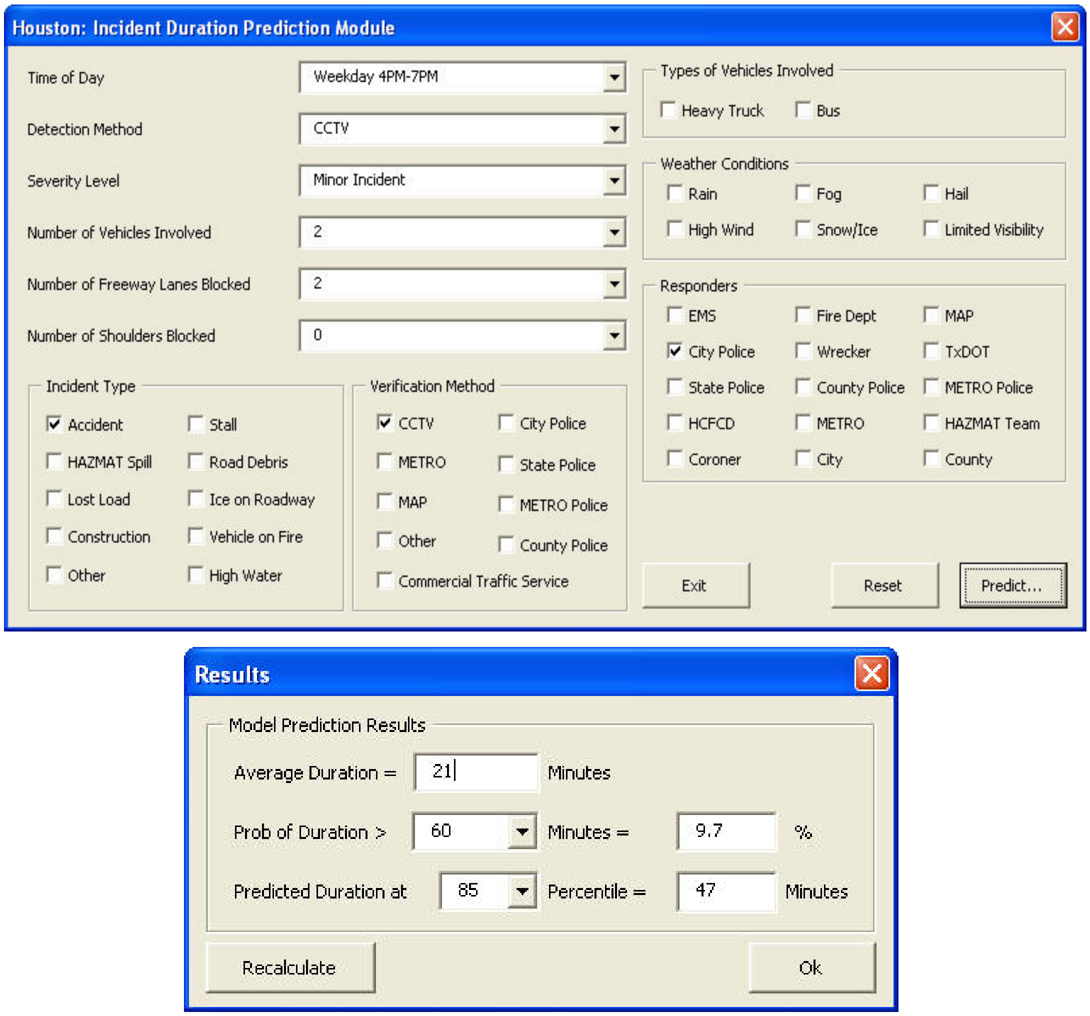


Figure 6-4: Prediction Example – Minor Two-Vehicle Accident.

The final example, shown in Figure 6-6, considers the case of a major heavy truck accident involving hazardous material spills. The accident occurs during the daytime off-peak period blocking all travel lanes. EMS, fire department, city police, wrecker, and hazmat team respond to the scene. In this case, even though the accident involves only one vehicle and occurs during the non-peak period, the severity of the accident as indicated by the type of responders and lane blockage would strongly influence the incident duration. The module predicted the mean duration of 198 minutes and 85th percentile duration of 436 minutes. The range of the predicted values has become noticeably large, reflecting the duration characteristics of severe incidents – high variance, infrequent occurrence, small sample size, and relatively lower predictability. The median and 85th percentile statistics from all incidents related to hazmat spills were 115 and 297 minutes, respectively. The lane closure and vehicle type characteristics likely account for the higher range of predicted values.

From these examples, the predicted values appear to be well within the historical range of duration data classified by specific incident types. The actual as well as predicted durations would deviate from these ranges by varying degree depending on the characteristics of an ongoing incident. These application examples also show the potential of this module as a decision support tool in the incident management process.

It should be emphasized that the module described herein must be further fine-tuned and evaluated for its accuracy once fully implemented. The fine-tuning process may involve development of different submodels for specific incident severity, as well as different sets of model inputs based on various phases of incident management. In addition, provided that the data are available, the analyst can separately analyze and model each time component throughout the incident event to increase the predictability of the models; for example, the analyst can model response time and clearance time as two interrelated components of total incident duration.

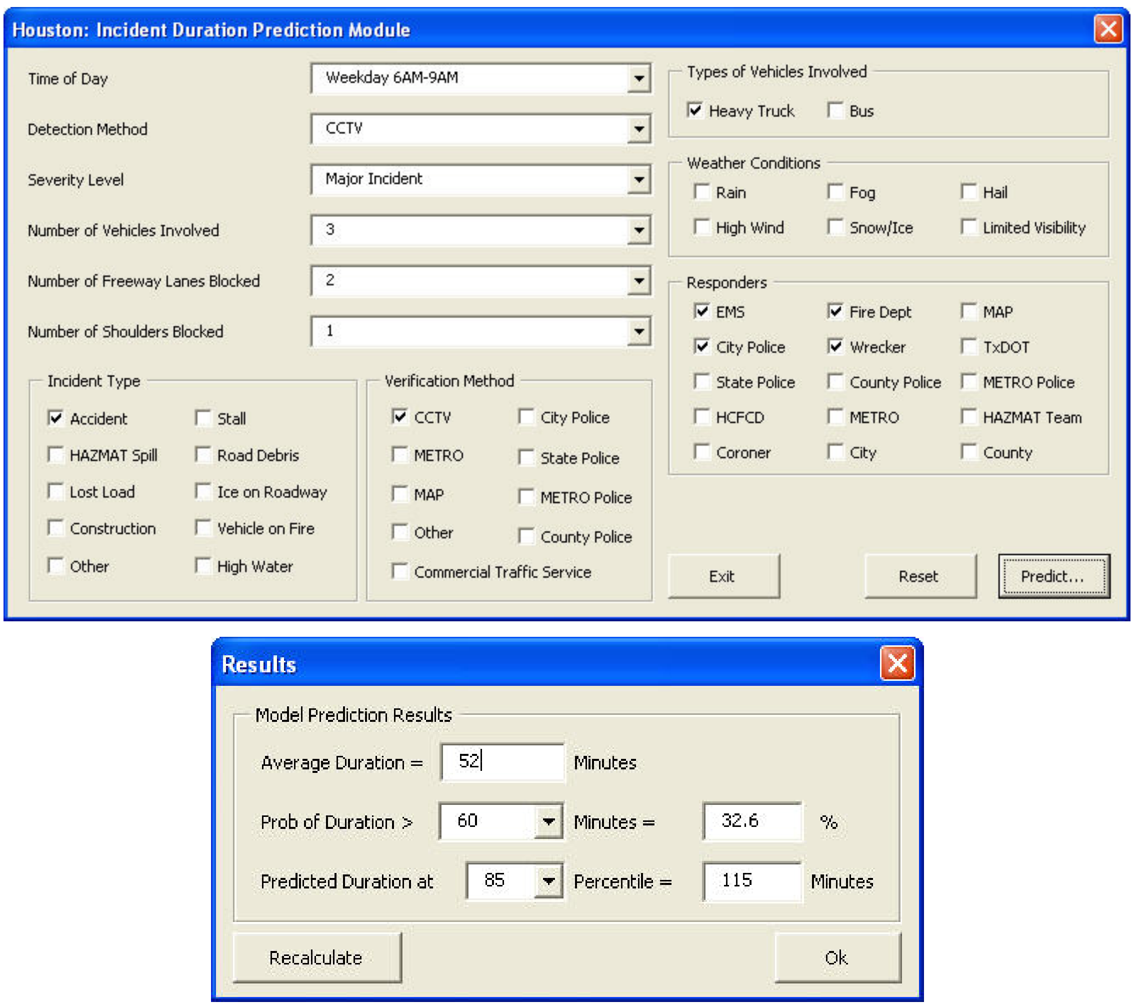


Figure 6-5: Prediction Example – Major Three-Vehicle Truck-Related Accident.

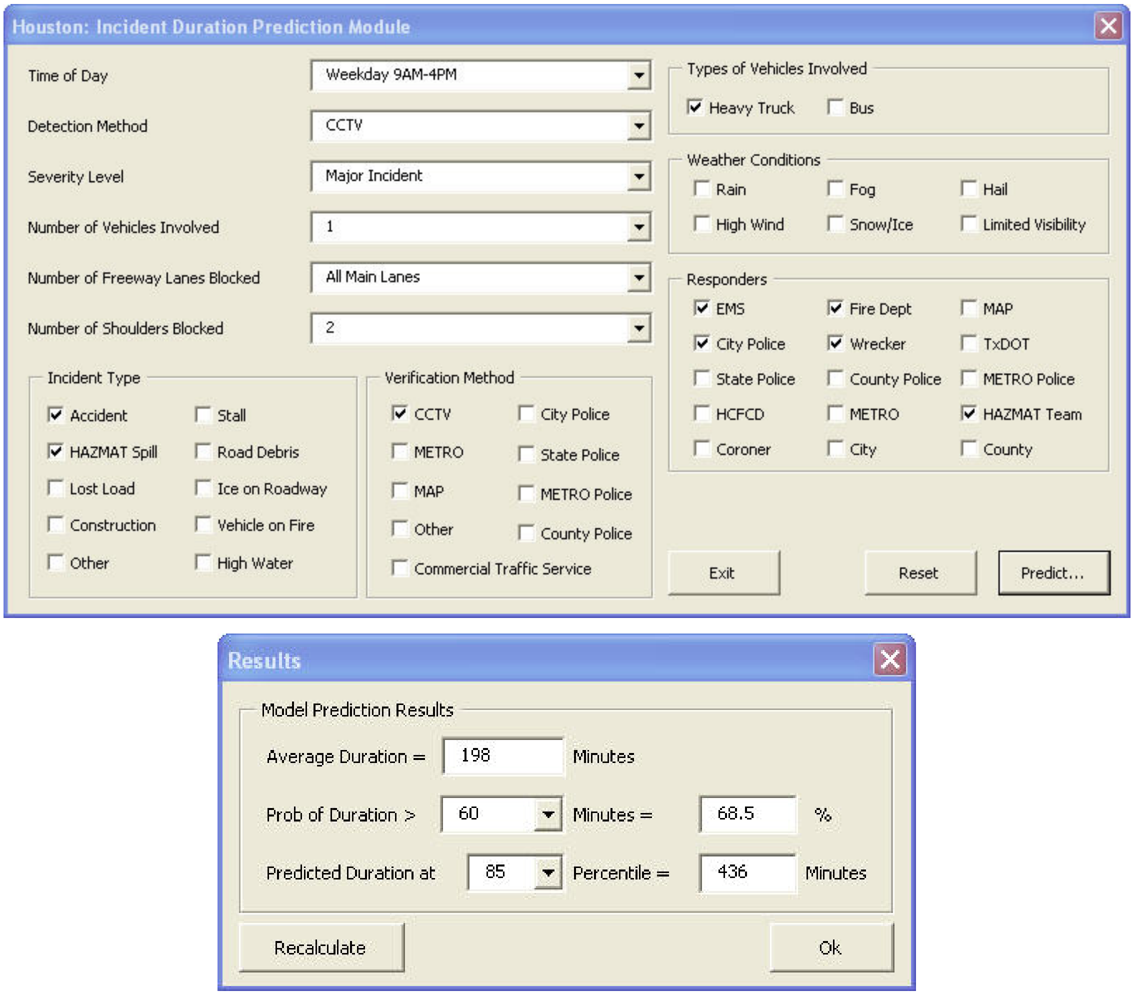


Figure 6-6: Prediction Example – Hazmat Truck Spills Blocking All Lanes.

6.5.3. Findings and Recommendations

From the modeling analysis and calibration, the researchers observed the following findings and recommendations for improving the model performance:

- The model parameter inputs should reflect the way the operators logged the incidents at the TMC in order for the model to provide the best estimate possible. For the same reason, the performance of the prediction is also strictly limited by how the operators log the incident data. Inconsistent entries of similar incident types will significantly degrade the model's performance because the calibrated models are based on historical trends. When incidents of similar characteristics and durations are inconsistently recorded, the model calibration procedure will not be able to identify key incident characteristics that would otherwise be useful for the prediction. Therefore, standardized and consistent incident data entries are critical to the performance of incident duration prediction.

- For incident durations to be comparable between TMCs, TxDOT should establish and use standardized definitions for incident event time logs statewide.
- Researchers summarized incident characteristics that are statistically significant predictors of the incident duration for TranStar, CTECC, and TransVISION in Table 6-2, Table 6-5, and Table 6-8, respectively.
- Researchers found the Weibull and exponential distributions to give the best overall model goodness-of-fit statistics for duration models analyzed at all the three TMCs evaluated in this study. Exponential distribution is a special case of Weibull distribution where the scale parameter is fixed at 1.0.
- Researchers used two key incident characteristics to categorize and determine the appropriate model for predicting incident duration, which are lane blockage and incident types. All the models calibrated in this study were classified by either one or both of these criteria.

If the performance of the models is not satisfactory, the following strategies could be considered to fine-tune and/or improve the predictability of the models:

- 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, interval treatment on the modeling results can vary.
- If data support doing so, 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, which includes the interactions between explanatory variables. Interaction effects on incident duration can be very complex and difficult to interpret logically. The analyst should consider this strategy as a last resort to improve the model performance.

An agency should be aware 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, such as the incident data logging process or the incident data structure. The users should treat any predictions resulting from the models as a decision-supported tool for making an informed decision. The prediction results under no circumstances should override engineering judgment and common sense.

7. PREDICTING INCIDENT-INDUCED CONGESTION CLEARANCE TIME

This chapter discusses the evaluation and application of the incident-induced congestion clearance time prediction methodology described in Module 8 of the guidebook. First, this chapter provides a brief review of the methodology. Then, using the traffic data collected from Houston TranStar in 2007, researchers illustrate the real-time application of the model. Researchers also examined and discussed the sensitivity of this prediction model, followed by a remark on using this model.

7.1. Data Preparation

The procedure for estimating the incident-induced congestion clearance time requires the following data elements:

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

To mimic the real-time application, researchers divided the traffic data into two sub-databases: one serves as the historical database and the other serves the role of "real-time" data. These two databases share the same data format as illustrated in Table 7-1.

Table 7-1: Example of TranStar Traffic Data.

ID	tstamp	lane	vol	spd	occ	pctSmall	pctMed	pctLarge
3991	9/13/07 0:00:00	1	3	65	0.98	100	0	0
3991	9/13/07 0:00:00	2	1	65	0.68	100	0	0
3991	9/13/07 0:00:00	3	3	74	0.78	100	0	0
3991	9/13/07 0:00:00	4	0	64	0	0	0	0
3991	9/13/07 0:00:00	5	1	78	0.29	100	0	0
3991	9/13/07 0:00:00	6	3	77	1.07	66.6	33.3	0
3991	9/13/07 0:00:00	7	1	73	0.39	100	0	0
3991	9/13/07 0:00:00	8	2	67	0.98	100	0	0
3987	9/13/07 0:00:00	1	4	59	0.88	100	0	0
3987	9/13/07 0:00:00	2	1	68	0.29	100	0	0
3987	9/13/07 0:00:00	3	4	72	1.27	100	0	0
3987	9/13/07 0:00:00	4	0	74	0	0	0	0
3987	9/13/07 0:00:00	5	0	62	0	0	0	0
3987	9/13/07 0:00:00	6	0	63	0	0	0	0
3987	9/13/07 0:00:00	7	0	57	0	0	0	0
3987	9/13/07 0:00:00	8	4	70	2.83	75	25	0

As shown in Table 7-1, TranStar archived lane-based traffic data at each radar location (identified by "ID"). Since the radar sensors could be set up to monitor the traffic data from both freeway directions, it was necessary to separate the traffic data according to travel direction. To this end, an inventory file that provided lane information was used to obtain the approach volume from the traffic database. Table 7-2 illustrates an example of the radar inventory data file format.

Table 7-2: Radar Sensor Inventory Data.

Name	MultiDropID	Lane1	Lane2	Lane3	Lane4	Lane5	Lane6	Lane7	Lane8
US-290 Northwest@Mangum OB	3987	WB Lane 4	WB Lane 3	WB Lane 2	WB Lane 1	Bidirectional HOV	EB Lane 1	EB Lane 2	EB Lane 3
US-290 Northwest@W 34th IB	3991	EB Lane 4	EB Lane 3	EB Lane 2	EB Lane 1	WB Lane 1	WB Lane 2	WB Lane 3	WB Lane 4
US-290 Northwest@Antoine OB	4030	WB Lane 4	WB Lane 3	WB Lane 2	WB Lane 1	Bidirectional HOV	EB Lane 1	EB Lane 2	EB Lane 3
US-290 Northwest@W 43rd IB	4014	EB Lane 3	EB Lane 2	EB Lane 1	WB Lane 1	WB Lane 2	WB Lane 3		
US-290 Northwest@Pinemont OB	4003	WB Lane 3	WB Lane 2	WB Lane 1	Bidirectional HOV	EB Lane 1	EB Lane 2	EB Lane 3	
US-290 Northwest@Tidwell OB	4026	WB Lane 3	WB Lane 2	WB Lane 1	EB Lane 1	EB Lane 2	EB Lane 3		
US-290 Northwest@Hollister IB	4010	EB Lane 3	EB Lane 2	EB Lane 1	WB Lane 1	WB Lane 2	WB Lane 3		

TranStar originally archived traffic volume data in 30-second intervals for each lane at each radar location. Using the radar inventory data, researchers aggregated traffic volumes according to the direction at each location. Then researchers further aggregated the measured traffic data into five-minute intervals to mitigate short-term, minute-to-minute fluctuations.

7.2. Prediction Methodology

This section provides a brief review of the incident-induced congestion clearance prediction model. Researchers developed this model based on the cumulative flow profile. As illustrated in Figure 7-1, it is easy to verify that the incident-induced clearance time t_c can be calculated as follows:

$$t_c = r \cdot \frac{(s - s_1)}{(s - q)} \tag{7-1}$$

where:
- r: incident duration (min),
- s: freeway capacity (vphpl),
- s_1: reduced freeway capacity during the incident (vphpl), and
- q: traffic flow rate (vph).

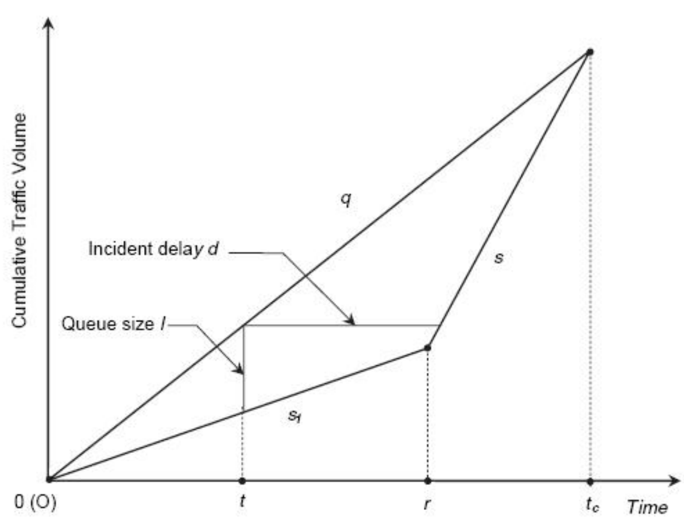


Figure 7-1: Typical Deterministic Queuing Diagram.

Though the parameters of Equation (7-1) are not known for certain, the analyst can estimate and update the prediction over time. For example, the analyst can estimate the incident duration (r) using the incident duration prediction model or default average values for specific types of incidents. As for the freeway capacity flow rate (s), the analyst can use maximum historical flow rates observed at the detector stations as a proxy. Since a particular freeway section may never operate at full capacity, the analyst should consider imposing a minimum freeway capacity flow rate at around 1,600 to 1,800 vphpl. On the other hand, a freeway may temporarily sustain traffic flow at more than 2,200 or even 2,400 vphpl before the traffic flow breaks down. As such, researchers recommend a maximum freeway capacity rate of 2,200 vphpl for this method.

Once the incident has been removed, the analyst can update both s and r values with real-time data. The analyst can estimate reduced flow rates (s_1) from incident characteristics at the beginning of an incident. Once the real-time reduced flow rates become available (e.g., 5 or 10 minutes after the occurrence), the analyst can update this value using real-time data instead. The demand flow rate (q) is the expected incoming flow rates during the incident-induced period. In other words, it is the expected incident-free traffic flow adjusted for the effects of traffic diversion. The analyst can estimate incident-free flow rates using historical traffic data.

Let i be the time elapsed from the beginning of the incident. The estimates of t_c at time i can be expressed as:

$$\hat{t}_{c,i} = \hat{r}_i \cdot \frac{\left(\hat{s}_i - \hat{s}_{1,i}\right)}{\left(\hat{s}_i - \hat{q}_i\right)}; i = 5,10,15,... \tag{7-2}$$

7.3. Model Implementation

This section demonstrates the model using the record of a major incident that occurred on Thursday, September 13, 2007, at 7:01 AM on US-290 at 34th Street and was blocking two mainlanes of traffic going westbound. The incident was removed at 7:32 AM, and the incident-induced congestion clearance time measured from the average delay profile was 8:35 AM, or 94 minutes after the beginning of the incident (Figure 7-2). This time point was considered as the true incident-induced congestion clearance time, which was used as a benchmark for the prediction performance of this method in this example.

Researchers simulated the real-time application of the model in this example where the prediction was updated every five minutes. At the beginning of the incident (i = 0), researchers estimated the input parameters as follows.

Incident Duration

To estimate the incident duration, researchers used the incident prediction module described in section 6.2 for Houston. The module predicted that the incident duration would have an average of 26 minutes and an 85th percentile at 57 minutes (Figure 7-3). To be conservative, researchers used 55 minutes as the predicted incident duration. Therefore, $\hat{r}_{i=0}$ = 55 minutes. The incident duration estimate should be updated when more information is available. In this example, this value was reduced to 40 minutes at 7:25 AM, 6 minutes before the incident was removed. Once the incident was cleared, $\hat{r}_{i \geq 31} = 31$ minutes since the incident duration was now known with certainty.

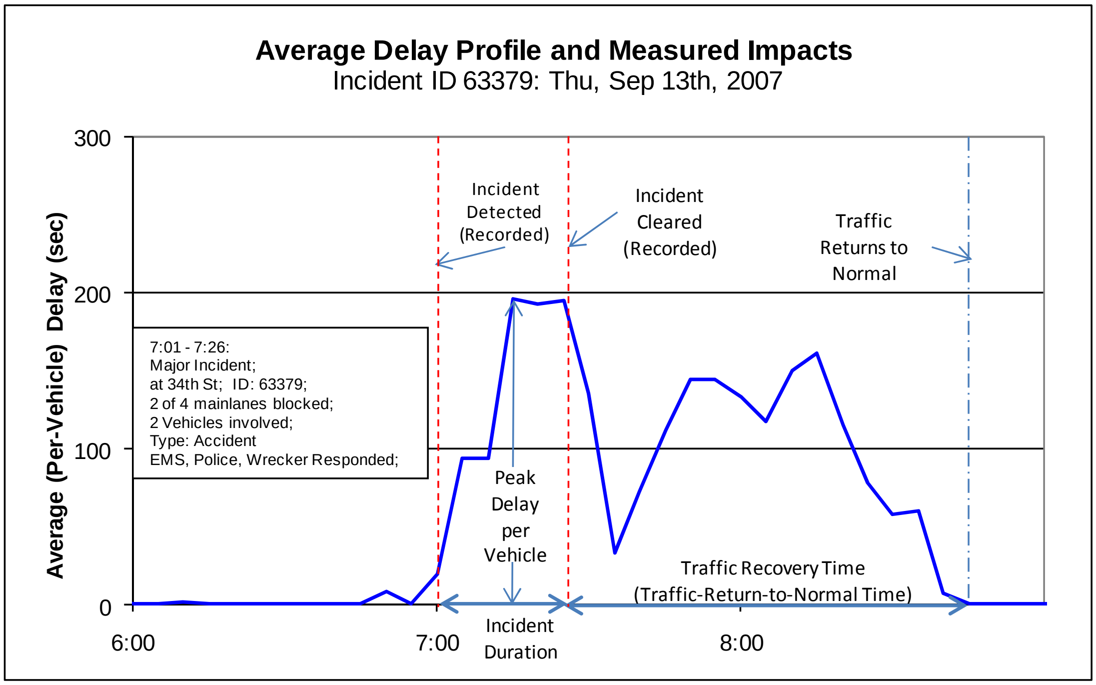


Figure 7-2: Measuring Traffic-Return-to-Normal Time from Average Delay Profile.

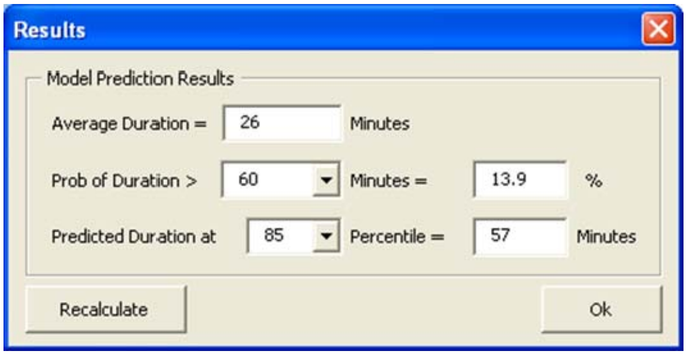


Figure 7-3: Incident Duration Prediction.

Expected Incoming Traffic Demand

For this incident, researchers chose a one-hour window to calculate average incident-free flow rates using the historical data from the previous five Thursdays. The average historical flow rate from 7:00 AM to 8:00 AM (q^*) was 1,570 vphpl. Then researchers applied a diversion rate of 5 percent, or $\hat{\delta} = 0.05$, to q^* to account for the diverted traffic during the incident period. Thus, the expected incoming traffic demand throughout the analysis period was estimated to be $\hat{q} = (1 - 0.05)(1570) = 1{,}492$ vphpl.

Capacity Flow Rate

From the five-minute historical volume data, the maximum volume was 564 vehicles, which is equivalent to 1,692 vphpl. At time $i = 0$, there was no real-time traffic data available yet, and this value was used as a proxy for the capacity flow rate. This value was updated again after the incident was removed, and "real-time" capacity flow rates were observed from the detectors.

Reduced Flow Rate

At the beginning of the incident, researchers used the average real-time flow rate as the input for this value. In this case, at 7:05 AM, four minutes into the incident, the average five-minute flow rate observed was $\hat{s}_{1,i=5} = 396$ vehicles, or 1,188 vphpl.

Prediction

Once all the parameters required for the prediction were available, at 7:05 AM, researchers calculated the first estimate for t_c using Equation (7-2) as follows:

$$\hat{t}_c = \hat{r} \cdot \frac{(\hat{s} - \hat{s}_1)}{(\hat{s} - \hat{q})} = 55 \cdot \frac{(1692 - 1188)}{(1692 - 1491)} = 138 \text{ minutes.} \qquad (7\text{-}3)$$

Similarly, at 7:10 AM, we have:

$$\hat{t}_c = 55 \cdot \frac{(1692 - 1157)}{(1692 - 1491)} = 147 \text{ minutes.} \qquad (7\text{-}4)$$

Researchers repeated the procedure every five minutes to obtain new estimates for t_c. Table 7-3 shows the prediction results using real-time traffic data to update the estimates every five minutes.

Table 7-3: Prediction for Incident 63379, September 13, 2007.

Incident location	US-290 at 34th 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 historcial incident-free flow rate (vphpl)	1570	1570	1570	1570	1570	1570	1570
Expected incoming demand after diversion (vphpl)	1492	1492	1492	1492	1492	1492	1492
Predicted incident-induced congestion clearance period (min)	**138**	**147**	**146**	**147**	**92**	**74**	**113**

As illustrated in Table 7-3, the model overestimated the clearance period until 7:25 AM. This is the result of the conservative estimate of the incident duration (55 minutes). At 7:25 AM, the estimated incident duration was updated, and the prediction became more accurate. When the incident was cleared at 7:31 AM, the incident duration was known for certain. Furthermore, the real-time traffic data, together with the historical capacity flow rate, served as a better proxy for the estimated capacity flow rate once the incident was removed. As a result, the model provided better predictions after the incident was cleared.

7.4. Sensitivity Analysis

In practical applications of this model, prediction duration and diversion rate are difficult to estimate with a high degree of accuracy. It is important for practitioners to understand the effects of these estimates on the prediction results when using this model. To this end, researchers performed simple sensitivity analyses of predicted incident-induced congestion period with respect to the changes of these parameters and this section describes the results and findings.

Researchers used two incidents to perform this task, namely incident 63379 and incident 72591. The previous section described the details of incident 63379. Incident 72591 was a major incident that occurred on westbound US-290 at Pinemont Drive on Friday, March 14, 2008. The incident blocked two mainlanes and lasted for 36 minutes. The incident duration prediction module predicted that the 85th percentile of the incident duration would be 67 minutes with an average of 31 minutes. The results of the incident-induced congestion clearance time prediction, with 60 minutes used as the initial incident duration estimate, are presented in Table 7-4.

Table 7-4: Prediction for Incident 72591, March 14, 2008.

Incident location	US-290 at Pinemont Drive							
Incident characteristics	11:23AM-11:59AM 2 main lanes blocked on a 3-lane section							
Traffic diversion rate	5%							
Time	**11:25AM**	**11:30AM**	**11:35AM**	**11:40AM**	**11:45AM**	**11:50AM**	**11:55AM**	**12:00PM**
Incident Duration (min)	60	60	60	60	60	60	40	36
Capacity flow rate (vphpl)	2200	2200	2200	2200	2200	2200	2200	1684
Reduced flow rate (vphpl)	400	468	495	488	502	493	554	631
Average historcial incident-free flow rate (vphpl)	1188	1188	1188	1188	1188	1188	1188	1188
Expected incoming demand after diversion (vphpl)	1129	1129	1129	1129	1129	1129	1129	1129
Predicted incident-induced congestion clearance period (min)	**101**	**97**	**96**	**96**	**95**	**96**	**61**	**68**

7.4.1. Incident Duration

This section presents the researchers' evaluation of the prediction sensitivity with respect to the incident duration estimate. In practice, the analyst would have updated the incident duration estimate before the incident was cleared as more information regarding the incident became available. However, in this analysis, to understand the robustness of the prediction, the incident duration estimate was assumed to be constant before the incident was cleared.

7.4.1.1. Incident 63379

The actual duration of this incident was 31 minutes. To observe the effect of the incident duration estimate on the incident-induced congestion clearance period predictions, researchers tested five incident duration estimates, namely 20, 31, 40, 50, and 60 minutes. Figure 7-4 presents the results of the corresponding predicted incident-induced congestion clearance periods.

Predicted incident-induced congestion clearance period (min)

		Time					
		7:05AM	7:10AM	7:15AM	7:20AM	7:25AM	7:30AM
Incident Duration	20 min	50	53	53	54	46	37
	31 min	78	83	82	83	71	58
	40 min	101	107	106	107	92	74
	50 min	126	134	133	134	115	93
	60 min	151	160	160	161	138	111

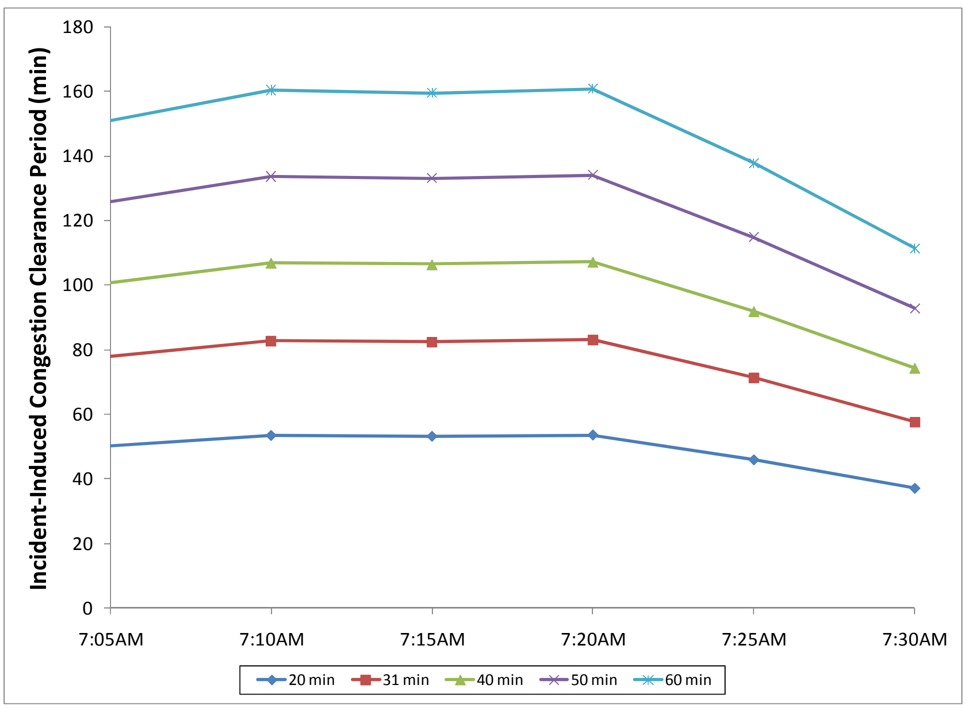


Figure 7-4: Sensitivity of Incident Duration on Prediction for Incident 63379.

In this analysis, the incident-induced congestion clearance period prediction ranged from 37 to 161 minutes. As shown in Figure 7-4, it is obvious that changes in the incident duration estimates had significant effects on the congestion clearance period prediction. At any particular time, the congestion clearance period prediction increased roughly by 20 minutes for every 10-minute increase in the indent duration estimate. Also, researchers found that the predictions were stable for particular incident durations before 7:25 AM, at which time there were sudden declines in the clearance period predictions. These sudden drops signaled that something happened between 7:20 AM and 7:25 AM, which required re-evaluation of the incident duration estimate. Also observed was that the percentage changes in the congestion clearance time prediction increased as the incident duration estimates increased from 20 minutes to 60 minutes. This result was expected because the marginal incident-induced congestion clearance time prediction was a multiple of the incident duration estimate.

7.4.1.2. Incident 72591

For this incident, researchers calculated the predicted incident-induced congestion clearance period for six incident duration estimates. These estimates are 20, 30, 36, 40, 50, and 60 minutes, and 36 minutes was the actual incident duration. Figure 7-5 shows the corresponding prediction results.

		Time						
		11:25AM	11:30AM	11:35AM	11:40AM	11:45AM	11:50AM	11:55AM
Incident Duration	20 min	34	32	32	32	32	32	31
	30 min	50	48	48	48	48	48	46
	36 min	60	58	57	58	57	57	55
	40 min	67	65	64	64	63	64	61
	50 min	84	81	80	80	79	80	77
	60 min	101	97	96	96	95	96	92

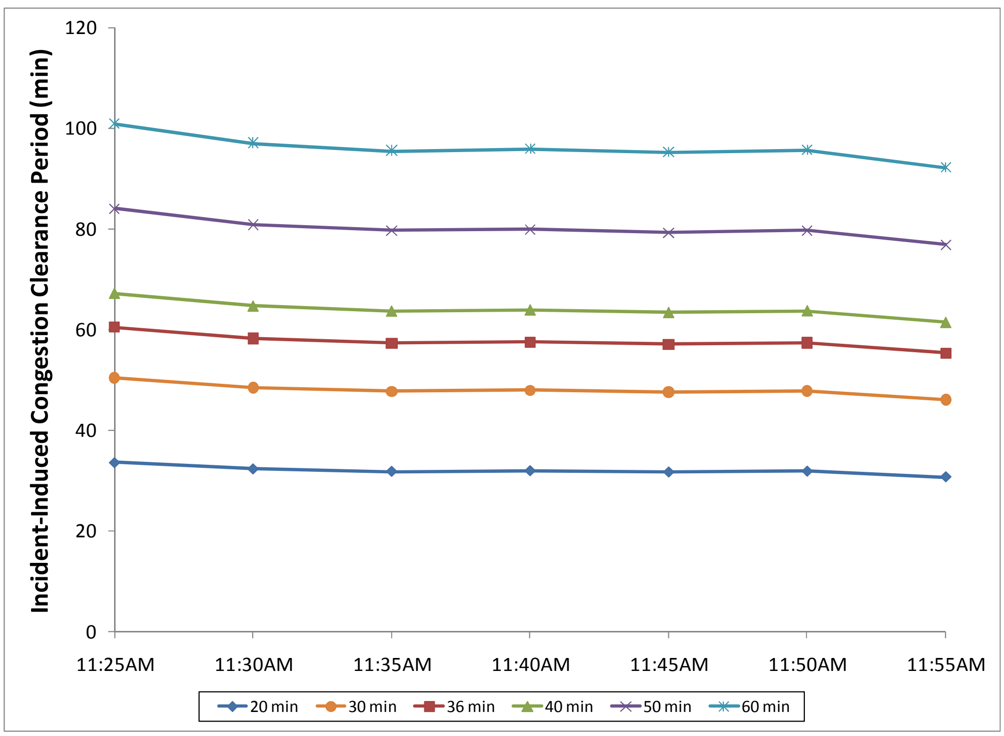


Figure 7-5: Sensitivity of Incident Duration on Prediction for Incident 72591.

Similar to the results researchers observed in the analysis for incident 63379, it is obvious that changes in the incident duration estimates had significant effects on the congestion clearance period prediction, which ranged from 31 minutes to 101 minutes in this analysis. At any given time, the model predicted the congestion clearance time would roughly increase 15 minutes for every 10-minute increase in incident duration estimate. On the other hand, the prediction remained fairly stable for a given incident duration estimate in which the variation over time was well below 10 minutes for each incident duration estimate.

7.4.2. Diversion Rate

This section presents researchers' examination of the prediction sensitivity with respect to diversion rate. To this end, researchers used constant incident duration estimates during the prediction period. In particular, researchers used the actual incident durations for the two incidents under investigation. Researchers varied diversion rates to calculate the incident-induced congestion clearance period over time, namely 0 percent, 5 percent, 10 percent, and 15 percent.

Figure 7-6 presents the results regarding the incident-induced congestion clearance period prediction of incident 63379 with respect to the diversion rate.

Predicted incident-induced congestion clearance period (min)

		Time					
		7:05AM	7:10AM	7:15AM	7:20AM	7:25AM	7:30AM
Traffic Diversion Rate	0.0%	128	136	135	136	117	95
	5.0%	78	83	82	83	71	58
	10.0%	56	60	59	60	51	41
	15.0%	44	46	46	47	40	32

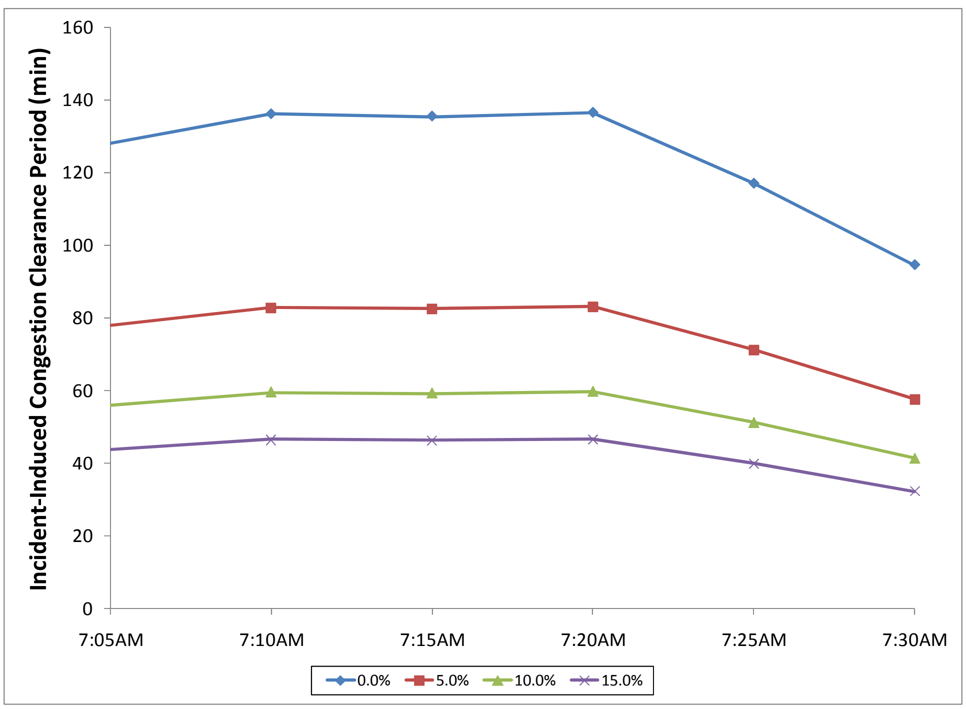


Figure 7-6: Prediction Sensitivity with Respect to Diversion Rate for Incident 63379.

In this scenario, researchers found that the changes in diversion rate had a significant effect on the model prediction capability. The incident-induced congestion clearance period prediction ranged from 44 minutes with a 15 percent diversion rate to 136 minutes with no diversion at the beginning of the incident, and from 32 minutes (15 percent) to 95 minutes (0 percent) at 7:30 AM when the incident was about to clear. Since the prediction seems to be very sensitive to the changes in the diversion rate, the accuracy of estimating the diversion rate becomes very critical in this case. On the other hand, the analysis on incident 72591 reveals a different picture regarding the effect of diversion rate, as is seen in the results summarized in Figure 7-7.

Predicted incident-induced congestion clearance period (min)

		Time						
		11:25AM	11:30AM	11:35AM	11:40AM	11:45AM	11:50AM	11:55AM
Traffic Diversion Rate	0.0%	64	62	61	61	60	61	59
	5.0%	60	58	57	58	57	57	55
	10.0%	57	55	54	55	54	54	52
	15.0%	54	52	52	52	51	52	50

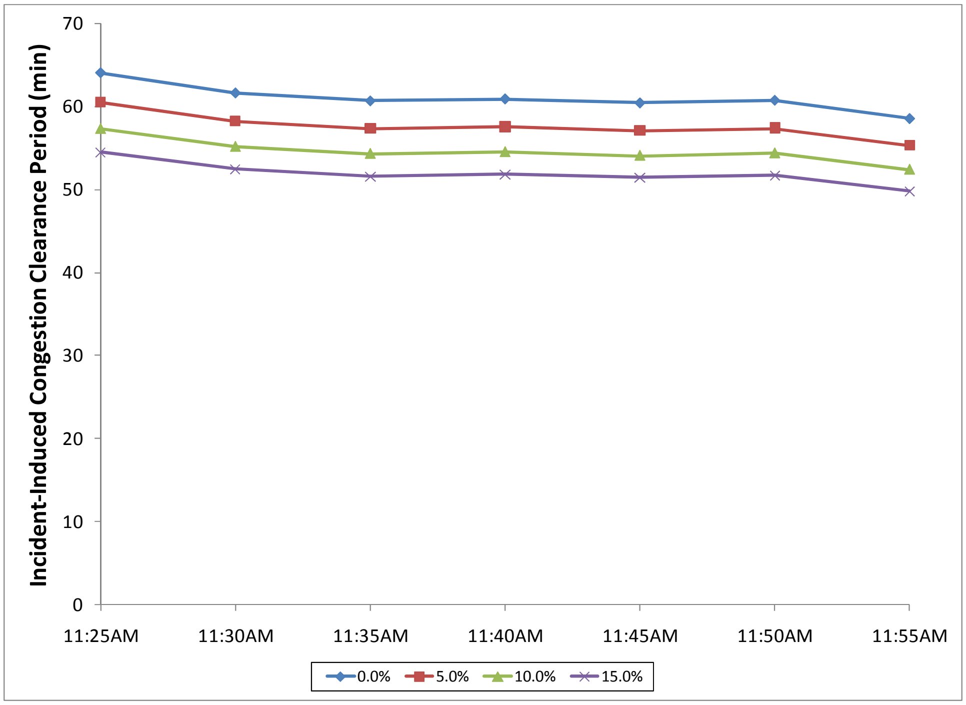


Figure 7-7: Prediction Sensitivity with Respect to Diversion Rate for Incident 72591.

As illustrated in Figure 7-7, the incident-induced congestion clearance period prediction was within a 15-minute window, ranging from 50 minutes to 64 minutes. In other words, the prediction was very robust to the changes in diversion rate. The different behavior with respect to the diversion rate of these two incidents was mainly due to the ratio of expected incoming traffic demand to capacity (i.e., degree of saturation), as explained below.

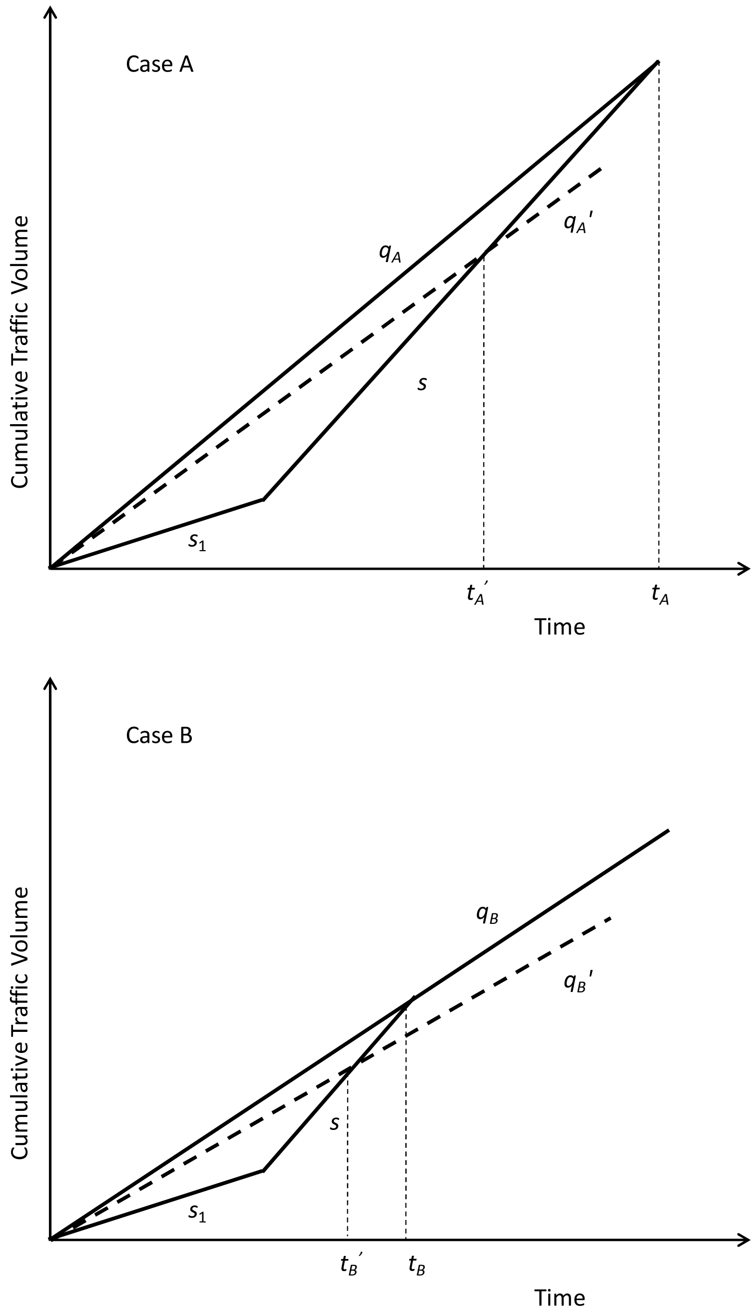


Figure 7-8: Sensitivity of Expected Incoming Demand.

As previously illustrated in Figure 7-1 and Equation (7-1), the incident-induced congestion clearance time depends on the difference between capacity, s, and the expected incoming demand rate, q. As shown in Case A of Figure 7-8, if the expected incoming demand rate is close to capacity, a small change in diversion rate will decrease q_A to q_A' and shorten the congestion clearance time significantly from t_A to t_A'. On the other hand, if the expected incoming demand rate is much smaller than the capacity, as in

Case B of Figure 7-8, then a small change in diversion rate will change the expected incoming demand rate from q_B to q_B', and the congestion clearance time prediction will change to a lesser extent from t_B to t_B'.

As seen by examining Table 7-3, the average historical incident-free flow rate was 1,570 vphpl while the capacity flow rate was 1,692 vphpl at the location where incident 63379 occurred. In other words, the degree of saturation was in the neighborhood of 0.92 under the normal incident-free situation. In this case, the prediction of the model was very sensitive to the changes in diversion rate, as shown in Case A of Figure 7-8. As for incident 72591, the average historical incident-free flow rate was 1,188 vphpl while the capacity flow rate was 2,200 vphpl, and the degree of saturation was barely 54 percent. As exemplified by Case B of Figure 7-8, the congestion clearance period prediction was fairly robust in this case.

7.5. Remarks

In the previous section, researchers tested the robustness of the incident-induced clearance period prediction with respect to incident duration and diversion rate. Based on the analyses, researchers have the following observations.

- It seems that it is critical to have an accurate incident duration estimate, as it has significant impact on the prediction. However, as the incident duration is updated as more information is available, the analyst can correct the initial error in the estimate during the prediction period. As such, the accuracy of the initial estimation of the incident duration should not be overly focused.
- The impact of diversion rate on the prediction varies with degree of saturation, as shown in Figure 7-8. Since diversion rate is difficult to estimate to a high degree of accuracy and the prediction is very sensitive to diversion rate when degree of saturation is high, researchers recommend that practitioners use this model with caution during congested periods.

Furthermore, a limitation of the incident-induced clearance period prediction model 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-mainlane blockage incidents to be negligible. Besides, there are occasions when the reduced flow rate is higher than the expected incoming demand, which will render this model unusable. Incident 61898 that occurred on US-290 at FM 529 exemplified this situation.

Incident 61898 lasted from 5:01 PM to 5:45 PM. As shown in Table 7-5, the initial reduced flow rate was 1,656 vphpl, and the average historical incident-free flow rate was 1,607 vphpl. In this case, the reduced flow rate was more than the expected incoming demand rate even with an assumption of no traffic diversion at the beginning of the incident. As such, the predicted incident-induced congestion clearance period was shorter than the incident duration, which is illogical. Researchers observed the same behavior for 5:20 PM to 5:35 PM predictions. In this case, this model is inadequate for predicting the incident-induced clearance time and some other more complex model may be needed.

Table 7-5: Prediction for Incident 61898, October 10, 2007.

Incident location	US-290 at FM 529						
Incident characteristics	17:01- 17:45AM 1 main lanes blocked on a 3-lane section						
Traffic diversion rate	0						
Time	**5:05PM**	**5:10PM**	**5:15PM**	**5:20PM**	**5:25PM**	**5:30PM**	**5:35PM**
Incident Duration (min)	44	44	44	44	44	44	44
Capacity flow rate (vphpl)	1824	1824	1824	1824	1824	1824	1824
Reduced flow rate (vphpl)	1656	1596	1589	1628	1629	1630	1626
Average historcial incident-free flow rate (vphpl)	1607	1607	1607	1607	1607	1607	1607
Expected incoming demand after diversion (vphpl)	1607	1607	1607	1607	1607	1607	1607
Predicted incident-induced congestion clearance period (min)	**34**	**46**	**48**	**40**	**40**	**39**	**40**

8. TOOLS

This chapter summarizes the tools developed in this project to facilitate and/or automate methodologies and calculation procedures in the guidebook. Researchers developed two categories of tools in this study: (a) data processing/reduction tools, and (b) analytical tools.

The first category of tools aimed at facilitating the manipulation of traffic and incident data currently collected and archived at the TMCs. Researchers used the data outputs from these tools in various analyses conducted in the case studies. This category consists of the following tools:

- Travel Time Extraction Module – This tool extracts Houston's AVI tag data and performs the tag ID matching and data aggregation to produce average travel time for a given AVI segment.
- Traffic Data Processing Module – This tool extracts the traffic data from point-based sensors, such as loop and radar sensors, archived at a fixed interval and then performs the aggregation at a specified interval size. The data outputs from this tool are aggregated volume, average occupancy, average speed, vehicle classification, and variation in speed.

Researchers developed the second category of tools based on the methodologies and procedures described in the draft guidebook. The objectives of these tools are to expedite the analytical process by automating specific calculation routines and to demonstrate the potential applications of the procedures described in the guidebook. Researchers used VBA in Microsoft Excel to develop all the tools in this category. This project developed the following analytical prototype tools:

- Incident Characteristics Reporting Tool – This prototype tool demonstrates the automation of basic incident characteristics reports. The tool features the analysis of frequency distributions of various incident characteristics for both single attribute and two-level, cross-attribute analyses from an existing incident database.
- Incident Duration Prediction Tool – This tool allows the analyst to estimate the duration for an ongoing incident based on its characteristics. The tool provides a graphical user interface (GUI) for users to enter typical incident characteristics collected at TMCs. The tool incorporates the pre-calibrated incident duration models to perform the incident duration prediction once the users enter specific incident characteristics.
- Incident-Induced Congestion Clearance Prediction Tool – This tool allows the analyst to predict the extent of the impact from incident-induced congestion. Using a combination of real-time, historical traffic data and user-specified incident duration, this module utilizes the equations developed based on queue diagram to predict the time at which the traffic will return to normal condition.

Researchers developed all the prototype tools based on Houston's traffic and incident data structure to provide a complete picture of how various analyses and results are interconnected. In addition, researchers also developed an incident duration prediction tool for Austin. The following sections provide the descriptions of the tools developed throughout the course of this project to facilitate data extraction, manipulation, analysis, and evaluation procedures.

8.1. Travel Time Extraction Tool

This section describes the tool developed for extracting travel time data from Houston's AVI database. The AVI system consists of a series of tag readers (checkpoints) collecting tag identifications and time stamps for each vehicle passing through the checkpoints along the Houston freeway system. Analysts can calculate travel times for each vehicle by matching the vehicles by their tag IDs. Averaging travel time data extracted from multiple vehicles gives average travel times for traveling through the segment of interest.

The critical features of the algorithm to extract travel times from the AVI data are:

- Data aggregation – The size of the interval generally correlates with the sample size of matched tag IDs. The algorithm traces the tag IDs from the destination to the origin checkpoints. The travel times are extracted and averaged based on the tag IDs of vehicles that arrived at the destination checkpoints during the specified interval. For example, to calculate the travel time from origin A to destination B between 14:00 to 14:05, the algorithm will identify all the vehicles that arrived at destination B during that interval, then trace back to search for the same vehicles at origin A. The travel times can then be calculated for all matched vehicles during that interval.
- Data validation – The algorithm also addresses the possibility of invalid travel time data, such as vehicles taking a trip detour, vehicles entering the freeway after the origin checkpoint, and vehicles exiting the freeway before the destination checkpoint. This section also describes the methodology used to validate the travel time data.

8.1.1. Algorithm

Figure 8-1 provides an overview of the travel time extraction algorithm developed in this study.

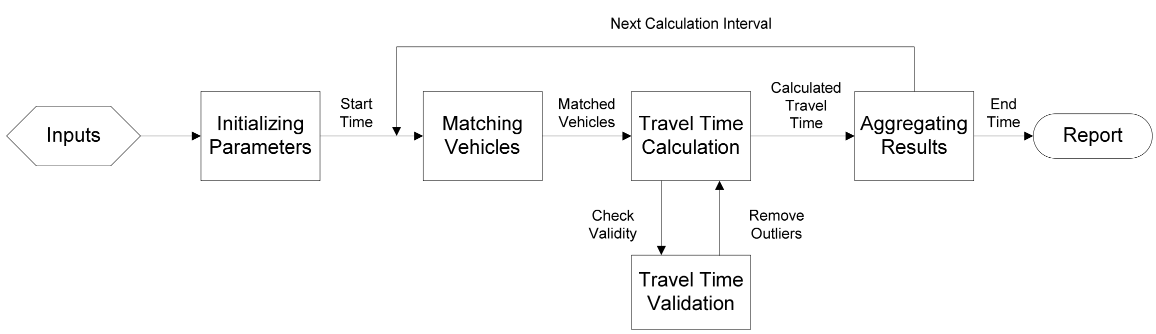


Figure 8-1: Overview of Algorithm Process.

8.1.1.1. Initializing the Algorithm

The initialization process takes the parameter inputs specified by the users to prepare the data for travel time extraction. The algorithm requires the following parameters to initialize the travel time extraction process based on the format of Houston's AVI database:

- date and time for the extraction;
- time interval for travel time aggregation – should be a divisor of 60 minutes to simplify the process;
- origin and destination checkpoints;
- segment lengths;
- free-flow and congested speeds to construct the upper and lower thresholds of segment travel times; and
- methods for removing outliers.

The algorithm uses free-flow speeds to calculate the free-flow travel time for the specified segment. The free-flow travel time establishes the lower threshold for segment travel time in the algorithm. This lower threshold signifies the lowest travel time possible for the AVI segment. Unless incident-free speed data are available, the posted speed limit could be used to establish free-flow speeds. The specification for the lower threshold is:

$$\text{Lower Travel Time Threshold} = \frac{\text{Segment Length}}{\text{Free-Flow Speed}}(1-p) \tag{8-1}$$

where p is the adjustment ratio to capture the vehicles traveling faster than the free-flow speeds.

For example, $p = 0.2$ implies an additional 20 percent reduction from the calculated free-flow travel time. A brief evaluation test conducted using actual speed data indicated that 20 percent is generally sufficient to capture most vehicles traveling faster than the specified free-flow speeds.

The algorithm uses congested speeds to calculate the travel time under congested conditions for the segment. The congested travel time defines the upper threshold of the segment travel time. This threshold is required to improve the efficiency of the tool, as it determines the amount of AVI data the algorithm will need to search for the matching tag IDs at the origin checkpoint. The upper threshold is calculated by:

$$\text{Upper Travel Time Threshold} = \frac{\text{Segment Length}}{\text{Congested Speed}}(1+p) \tag{8-2}$$

Given the date, time, origin-destination (O-D) pair, and thresholds, the algorithm will query the AVI raw data to generate an intermediate dataset containing tag IDs and time stamps of vehicles within the specified time period. The algorithm will utilize this dataset for further processing in the next step.

8.1.1.2. Matching Tag IDs

In this step, the algorithm will match the vehicle tag IDs between the specified origin and destination checkpoints. An interval size must be configured for travel time averaging in this step. The interval must be a divisor of 60, can range from 1 to 60 minutes, and has to be large enough to accommodate the longest possible travel time of the segment. Researchers recommend the intervals of 5, 10, and 15 minutes for typical evaluations.

This step generates a dataset containing matched tag IDs and their corresponding time stamps. Note that the algorithm will search the tag IDs at the origin checkpoint for possible matching only within the time window specified by the lower and upper travel time thresholds in the initialization process. The algorithm will remove vehicles that enter the freeway after the origin checkpoint or exit the freeway before the destination checkpoint at this stage.

8.1.1.3. Calculating and Validating Travel Time Data

This step will calculate the travel time of all the matched tag IDs from the previous step based on the difference of the time stamps obtained at the origin and destination checkpoints. The validation algorithm checks to see if the calculated travel times stay within the valid range and excludes those that exit and re-enter the freeway between the O-D pairs of interest. Figure 8-2 provides an overview of the validation process.

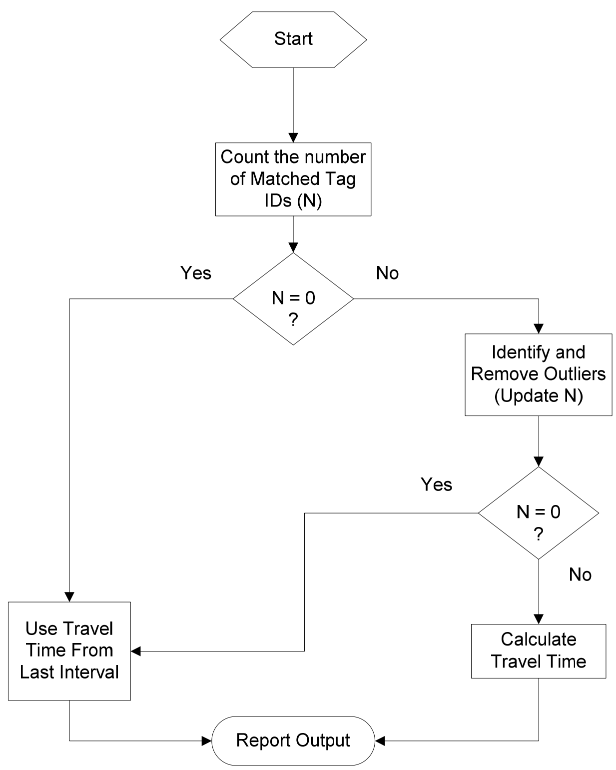


Figure 8-2: Travel Time Calculation and Validation Process.

First, the validation process will check the number of matched tag IDs (N) for the specified interval. Then the algorithm applies the following rules:

- If $N = 0$, the algorithm will retrieve the average travel time from the previous interval for the current interval.
- If $N = 1$, the algorithm will use that single value as a travel time for that interval.
- If $N > 1$, the algorithm will calculate the average travel time and perform the validation process for that interval.

The validation algorithm statistically defines a validation window based on all the observed travel times from that interval. The algorithm designates observed travel times outside this window as outliers. The algorithm then removes these outliers and re-averages the remaining travel times observed in that interval. There are two alternative approaches for constructing a validation window in this step:

- error tolerance method, and
- z-score method.

Error Tolerance Method

In this method, the validation window is established by:

$$\overline{tt_i} \pm \delta \overline{tt_i} \tag{8-3}$$

where $\overline{tt_i}$ is the mean of all the travel times observed within the interval i, and δ is the ratio of error tolerance. For example, $\delta = 0.2$ implies a validation window of ± 20 percent from the mean of travel times observed in that interval. This is also a current method used to validate travel time data displayed on Houston's TranStar website. The size of the validation window can be increased or decreased by adjusting the value of δ. Figure 8-3(a) depicts the intervals constructed by this approach.

Z-score Method

The z-score method utilizes a normal distribution to statistically identify outliers. The method assumes the observed travel time data for the interval to follow normal distribution. Then z-scores for each individual travel time are:

$$z_k = \frac{tt_k - \overline{tt}}{\sigma_{tt}} \tag{8-4}$$

where tt_k is the k^{th} observed individual travel time during the interval, $\overline{tt}$ is the mean of all the travel times observed in that interval, and σ_{tt} is the standard deviation of the travel times in the same interval.

z_k is the normalized value of individual travel time, which follows standard normal distribution or $N(0,1)$. Then users can determine whether the z_k falls within a realistic range statistically. Here are examples of the rules to define outliers based on the z-scores and the level of confidence:

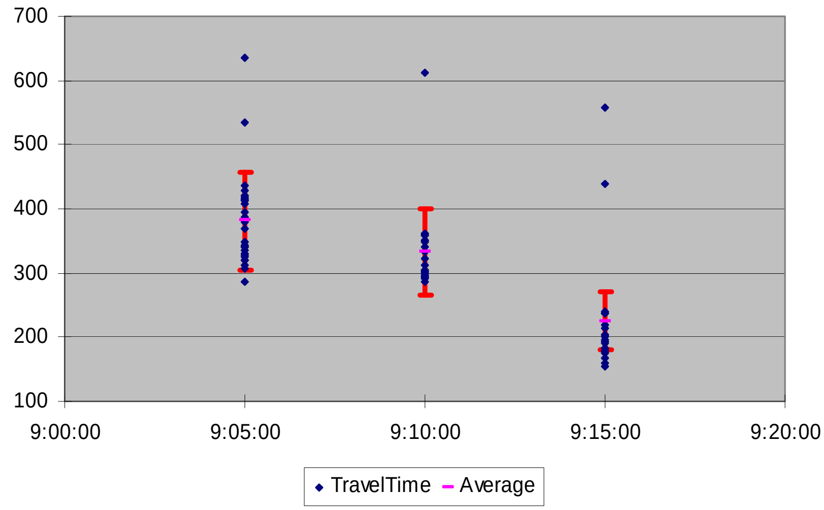
- At 99 percent confidence level, tt_k is an outlier if $|z_k| > 2.56$.
- At 95 percent confidence level, tt_k is an outlier if $|z_k| > 1.96$.
- At 90 percent confidence level, tt_k is an outlier if $|z_k| > 1.64$.
- At 80 percent confidence level, tt_k is an outlier if $|z_k| > 1.28$.

The users have an option to choose the appropriate level of confidence for identifying outliers in this method. The higher confidence level will result in a wider validation window, thus allowing more data to be kept in the interval. On the other hand, the lower confidence level will produce a more restrictive validation window, thus removing more data from the interval.

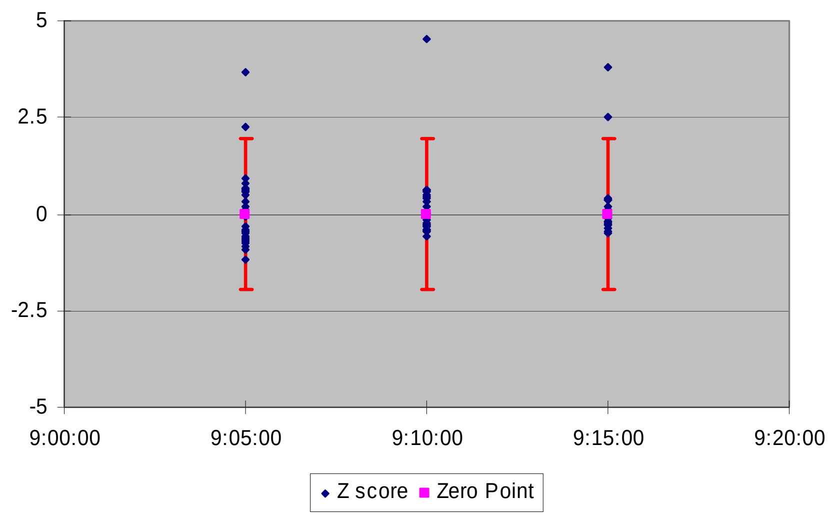
When comparing the two methods, it should be noted that the z-score method relies on a statistical basis for screening outliers, which is less arbitrary than specifying a percentage value in the error tolerance method. Figure 8-3 illustrates the validation windows generated by the two approaches. The error tolerance method fixes the validation window only to the mean of the travel time. The z-score method also accounts for the travel time variability in the dataset by incorporating the standard deviation. The validation window of the z-score method will be wider if the standard deviation is large, while that of the other method will remain the same regardless of the data dispersion. Nevertheless, the z-score method is more computationally intensive in that the algorithm must calculate both means and standard deviations for every interval.

Researchers conducted an evaluation of both methods using sample travel time data over a 24-hour period. Researchers specified the value of 20 percent for the error tolerance method, and the 95 percent confidence interval for the z-score method. The methods identified and removed the outliers, and the algorithm re-calculated travel times based on the remaining data. The travel time profiles obtained from both approaches were comparable in most cases. Therefore, researchers prefer the z-score method in general for its sound statistical basis, except for cases in which there are only a few matched tag IDs during the interval. Researchers recommend a minimum of five matched vehicles per five-minute interval for the z-score method to work properly. Analysts can adjust this threshold based on the size of the interval. The following conditions account for a low count of matched tag IDs:

- low traffic volume during free-flow traffic conditions,
- highly congested traffic conditions,
- low market penetration of tag users in certain freeway segments, and
- small aggregation interval (e.g., one or two minutes).



(a) Validation Using Error Tolerance Method at 20%



(b) Validation Using Z-score Method at 95% Confidence Level

Figure 8-3: Comparison of Methods for Identifying Outliers.

8.1.2. Reporting Travel Time Outputs

Figure 8-4 shows the example of a travel time output table, which can be viewed directly from the graphical user interface or exported into either a raw text file or MS Access database tables. The output contains the following data:

- time stamp (at the end of the interval),
- origin checkpoint,
- destination checkpoint,
- average speed,
- average travel time,

- standard deviation of travel time, and
- vehicle counts (matched tag IDs).

TimePeriod	ChkptOrigin	ChkptDestin	AverageSpeed	AverageTravelTi	StandardDeviati	SampleVehicleCour
9/15/2007 6:20:00 AM	23	24	64.79	284.4	25.61835	5
9/15/2007 6:25:00 AM	23	24	76.01	241	0	1
9/15/2007 6:30:00 AM	23	24	69.47	264.38	14.49076	8
9/15/2007 6:35:00 AM	23	24	68.64	268.63	22.8969	8
9/15/2007 6:40:00 AM	23	24	69.31	266.25	24.81215	8
9/15/2007 6:45:00 AM	23	24	70.64	261	21.72556	10
9/15/2007 6:50:00 AM	23	24	70.92	259.45	18.39219	11
9/15/2007 6:55:00 AM	23	24	72.07	255.22	17.49127	9
9/15/2007 7:00:00 AM	23	24	70.76	259.25	11.05667	4
9/15/2007 7:05:00 AM	23	24	71.59	256.71	15.91346	7
9/15/2007 7:10:00 AM	23	24	70.49	260.92	16.97837	12
9/15/2007 7:15:00 AM	23	24	72.95	251.83	14.7162	6
9/15/2007 7:20:00 AM	23	24	69.37	264.33	10.21437	3
9/15/2007 7:25:00 AM	23	24	71.9	255.4	13.20101	10
9/15/2007 7:30:00 AM	23	24	70.8	259.62	15.49483	13
9/15/2007 7:35:00 AM	23	24	71.44	257.46	17.24633	13

Figure 8-4: Example of Travel Time Output Table.

8.2. Traffic Data Processing Tool

This section describes an implementation of a tool for aggregating lane-based traffic data collected at fixed intervals, such as 30 seconds and 1 minute. Lane-based traffic data refers to traffic volume, speed, occupancy, and vehicle classification (if available) logged at a fixed interval on a lane-by-lane basis. A station is defined as a group of lanes with common characteristics, such as same traveling direction or same entry traffic. This tool allows a user to define a station as a group of lanes. Then the algorithm will aggregate the data from the designated lanes, perform data validation, calculate station-based measures, and then output station-based aggregated data into a text file format. Four station-based measures currently calculated by the tool are:

- total volume,
- average occupancy,
- weighted average speed, and
- coefficient of variation in speed.

The purpose of this tool in this project was to aggregate 30-second traffic data collected from Wavetronix SmartSensor into 5-minute station-based data. However, the analysts can use the same tool to aggregate any point-based detector data provided that they are available or prepared in the same format (e.g., Austin's loop detector data). The interval size for aggregation must be a divisor of 60 and can range from 1 to 60 minutes.

8.2.1. Input Requirement

The traffic data processing tool requires the following data inputs:

- traffic data collected at a fixed interval prepared in a format as shown in Table 8-1, and
- lane configuration table.

At a minimum, the input traffic data must contain the sensor ID, time stamp, lane number, volume, speed, and occupancy information. For the SmartSensor data archive, vehicle classification data are also available, as shown in Table 8-1. The raw SmartSensor data require a protocol to decode the data properly. Researchers decoded the raw data into a comma-delimited text file format, as shown in the example below, to facilitate subsequent data processing.

Table 8-1: Sample of Input Traffic Data from SmartSensor Radar System.

ID	tstamp	lane	vol	spd	occ	pctSmall	pctMed	pctLarge
8583	01/11/2008 15:26:30	1	14	53	16.02	71.39	21.39	7.13
8583	01/11/2008 15:26:30	2	15	61	17.29	53.32	33.3	13.28
8583	01/11/2008 15:26:30	3	17	66	17.68	41.11	46.97	11.72
8583	01/11/2008 15:26:30	4	11	71	8.5	54.49	45.41	0
8583	01/11/2008 15:26:30	5	7	71	4.79	57.13	42.77	0
3876	01/11/2008 17:30:00	1	11	61	5.76	90.82	9.08	0
3876	01/11/2008 17:30:00	2	11	67	9.86	54.49	36.33	9.08
3876	01/11/2008 17:30:00	3	7	70	3.32	100	0	0
3876	01/11/2008 17:30:00	4	13	15	21.58	100	0	0
3876	01/11/2008 17:30:00	5	14	23	17.38	100	0	0
3876	01/11/2008 17:30:00	6	10	35	12.11	89.94	9.96	0

In addition to the input traffic data, the tool requires a lane labeling scheme to aggregate the data properly. The SmartSensor radar system labels the lane in an ascending order starting with one for the lane nearest to the sensor. TxDOT typically labels the lane directionally in an ascending order starting with one from the lane nearest to the median. This tool implemented the latter numbering scheme since it is easier to relate the numbers to the lanes physically. Table 8-2 illustrates the relationship between two lane numbering schemes. The table headings are the numbering used for SmartSensor installation. Multidrop ID is an identification number for a radar sensor.

Table 8-2 Sample of Lane Configuration Table.

Name	...	MultiDropID	...	Lane1	Lane2	...	Lane8
IH-45 Gulf SB/NB@FM-1959	…	1366	…	SB Outside	SB Middle		
US-59 Eastex SB@Quitman		889		SB Exit	SB 5		
SH-288 NB@Holly Hall		1077		NB Lane 5	NB Lane 4	…	
SH-288 SB@Holly Hall	…	1099	…	SB Lane 4	SB Lane 3		
US-59 Southwest SB/NB@West Airport Exit		1039		SB Lane 4	SB Lane 3	…	NB Lane 4
US-59 Southwest NB/SB@SH-288		1083		NB Exit Ra	NB Lane 3	…	SB Lane 4
Spur-527@US-59 Southwest	…	382	…	NB Lane 2	NB Lane 1	…	
IH-610 West Loop NB/SB@Fournace		1078		NB Lane 5	NB Lane 4	…	SB Lane 3

8.2.2. Calculation Procedures

As mentioned in the previous section, Houston's radar sensor provides a stream of 30-second observations of volume, speed, occupancy, and vehicle classification. This section describes the calculation procedures and routines to derive the station-based measures from the data.

The current implementation of the tool is capable of calculating the following measures: total volume, average speed, average occupancy, and coefficient of variation in speed (CVS). Additional measures could be added as an independent subroutine if needed.

Users can change aggregation output interval size for different analysis purposes. In testing runs, researchers chose 5, 10, and 15 minutes for output interval size to calibrate these models.

The total volume per output interval is calculated as:

$$Q_k = \sum_{j=1}^{l}\sum_{i=1}^{n} q_{ij} \tag{8-5}$$

where q_{ij} is the 30-second volume count of the i^{th} input interval at lane j, Q_k is the aggregated volume count of the k^{th} output interval, n is the number of intervals within the aggregation time window, and l is the number of lanes in a station (configurable by users).

The average occupancy per lane per interval is calculated using:

$$\overline{O}_k = \frac{1}{n}\cdot\frac{1}{l}\sum_{j=1}^{l}\sum_{i=1}^{n} o_{ij} \tag{8-6}$$

where o_{ij} is the 30-second average percent occupancy of the i^{th} input interval at lane j, and $\overline{O}_k$ is the averaged occupancy rate of the k^{th} output interval. Note that the occupancy is a proportional indicator of density.

The weighted average speed per lane is calculated as:

$$\overline{V}_k = \frac{\sum_{j=1}^{l}\sum_{i=1}^{n} q_{ij} v_{ij}}{\sum_{j=1}^{l}\sum_{i=1}^{n} q_{ij}} \tag{8-7}$$

where v_{ij} is the 30-second weighted average speed of the i^{th} interval at lane j, and $\overline{V}_k$ denotes the weighted average speed of the k^{th} output interval. The weighted average speed has an advantage that better describes the true fluctuation of vehicles' speed over time, particularly during the light traffic volume condition.

The CVS is calculated as:

$$CVS_k = \frac{\sigma_{v_{ij}}}{\overline{V}} = \sqrt{\frac{\sum_{j=1}^{l}\sum_{i=1}^{n} q_{ij}\left(v_{ij} - \overline{V}\right)^2}{\sum_{j=1}^{l}\sum_{i=1}^{n} q_{ij}}}\cdot\frac{1}{\overline{V}} \tag{8-8}$$

where CVS_k represents the fluctuation of average speeds for the k^{th} output intervals. The CVS can be used as a surrogate safety measure where the higher CVS values indicate instability in the traffic stream, which leads to a higher risk of collisions (*8*).

In cases where invalid or missing volume data are present in the interval, the tool re-estimates the total volume by linear extrapolation using the following equation:

$$\hat{\theta}_k = \frac{1}{p}\cdot\theta_k \tag{8-9}$$

where θ_k is the measure (e.g., volume) calculated for the k^{th} output interval, $\hat{\theta}_k$ is the re-estimated measure extrapolated from θ_k, and p denotes the proportion of valid data.

The tool can aggregate the traffic data either on a lane-by-lane or a station-based basis. Note that when the number of lanes specified for a station is equal to one, the output becomes lane-based measures. Therefore, the tool can apply the same calculation procedures either for lane-based or station-based outputs by simply configuring the number of lanes defined for a station.

Figure 8-5 shows a procedural routine implemented in this tool. The routine starts with configuring the lanes for a station. Next, the data are retrieved and processed for every output interval. The algorithm also checks for valid data and performs the adjustment if needed for every interval. The process iterates until the end of the dataset.

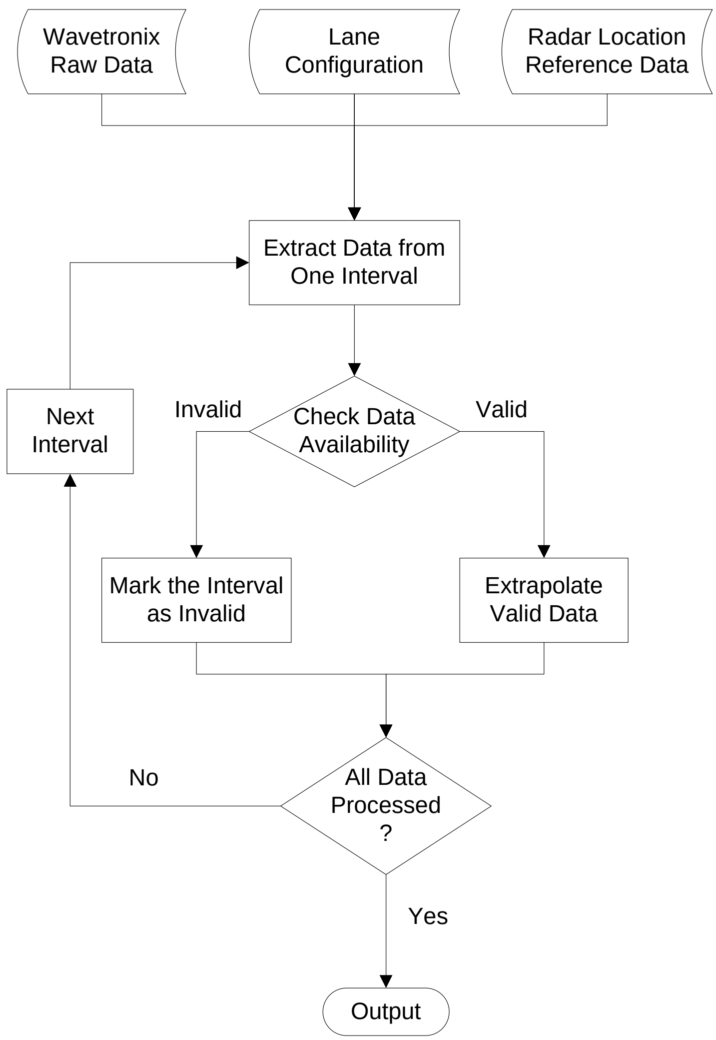


Figure 8-5: Calculation Routine for Traffic Data Processing Tool.

Table 8-3 shows an example of invalid data records. The data validation process is optional and can be turned off by the users. The validation process will first check to see if there are sufficient valid data for calculation. If the number of valid records for aggregation is more than half, the calculation process continues; otherwise, the module will flag the data for that interval as invalid. This validation module currently examines volume, speed, and occupancy. For volume data, if more than half of the data records are valid in an output interval, the module applies Equation (8-9) to re-estimate the extrapolated volume for the interval.

Table 8-3: Example of Invalid Data Records.

ID	tstamp	lane	vol	spd	occ	pctSmall	pctMed	pctLarge
3876	01/11/2008 00:31:30	-1	-1	-1	-1	-1	-1	-1
3876	01/11/2008 00:32:00	-1	-1	-1	-1	-1	-1	-1
3876	01/11/2008 00:32:30	-1	-1	-1	-1	-1	-1	-1
3876	01/11/2008 00:33:00	-1	-1	-1	-1	-1	-1	-1
3876	01/11/2008 00:33:30	1	1	64	0.29	100	0	0
3876	01/11/2008 00:33:30	2	1	64	0.49	100	0	0
3876	01/11/2008 00:33:30	3	0	76	0	0	0	0
3876	01/11/2008 00:33:30	4	1	70	0.49	100	0	0
3876	01/11/2008 00:33:30	5	2	71	0.98	100	0	0
3876	01/11/2008 00:33:30	6	1	65	0.68	100	0	0

8.2.3. Graphical User Interface

Figure 8-6 shows the graphical user interface for the tool developed in this study. The users need to supply two configuration files: (a) the lane configuration table, as exhibited in Table 8-2, and (b) the data source file. Then users should specify the sensor ID and the size of the output interval. Once the sensor ID is specified, the tool will ask for the lane configuration as shown in the figure. The users can then check the lanes to be combined as a station. If only one lane is checked, the output will be lane-based instead of station-based measures.

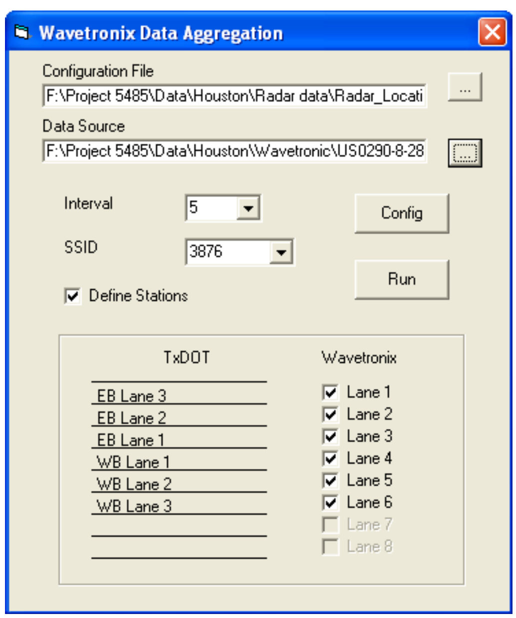


Figure 8-6: Graphical User Interface of Traffic Data Processing Tool.

8.2.4. Formatted Output

Table 8-4 shows an example of the aggregated data outputs. This example aggregated the 30-second lane-based SmartSensor radar data into the station-based measures every 15-minute interval. The data elements in the output table are:

- SSID – the SmartSensor identification number.
- StationStamp – a combination of SSID and lanes used to define a station. The first four digits are SSID, and the last eight digits refer to the lanes used to calculate the measures. For example, if lanes 1, 2, and 3 at the sensor ID 1234 are configured as a station, the station stamp would be 1234_11100000.
- TimeStamp – the time at the end of each aggregation interval.
- SumVol – the total volume per interval.
- AvgSpd – the weighted average speed for the interval.
- AvgOcc – the average occupancy for the interval.
- CVS – the coefficient of variation in speed for the interval.

Table 8-4: Example of Processed Data Outputs.

SSID	StationStamp	TimeStamp	SumVol	AvgSpd	AvgOcc	CVS
8583	8583_01000000	1/16/2008 0:15	65	64.49	2.44	0.07
8583	8583_01000000	1/16/2008 0:30	61	69.93	2.11	0.058
8583	8583_01000000	1/16/2008 0:45	48	65.83	1.95	0.078
8583	8583_01000000	1/16/2008 1:00	43	60.56	1.99	0.034
8583	8583_01000000	1/16/2008 1:15	50	63.8	1.83	0.078
8583	8583_01000000	1/16/2008 1:30	46	62.43	1.77	0.062
8583	8583_01000000	1/16/2008 1:45	31	62.9	1.36	0.04
8583	8583_01000000	1/16/2008 2:00	30	57.23	1.47	0.047
8583	8583_01000000	1/16/2008 2:15	32	55.94	1.46	0.068

8.3. Incident Characteristics Reporting Tool

This section describes a tool developed for reporting standard incident characteristics. Researchers developed this tool using Microsoft Excel using VBA because it offers a variety of chart types and chart formats that are very useful in providing a visual summary for incident characteristics.

To use this tool, the user must provide an incident dataset in Microsoft Excel format or in comma-separated format. The user can choose the desired analysis type from the GUI, as shown in Figure 8-7. Currently, this tool is capable of performing a frequency analysis and cross-attribute analysis for a selected set of attributes.

For frequency analysis, the user needs to select the data attribute, the categories of the data attribute that he/she wants to analyze, and the time scale for producing the reports. By clicking the “Run” button, the results of the analysis will show on a new sheet in Microsoft Excel. Figure 8-8 and Figure 8-9 show an example of the input settings and the output of the frequency analysis on incident type, respectively.

If the user chooses to perform a cross-attribute analysis, the input screen will change, as shown in Figure 8-10. In this case, the user must select a pair of data attributes for analysis, in which the results of the first attribute are grouped by the second attribute. In this prototype, the second attribute is limited to only “Severity” for demonstration purposes, and the time scale option is disabled. Figure 8-11 presents a sample result of a cross-attribute analysis.

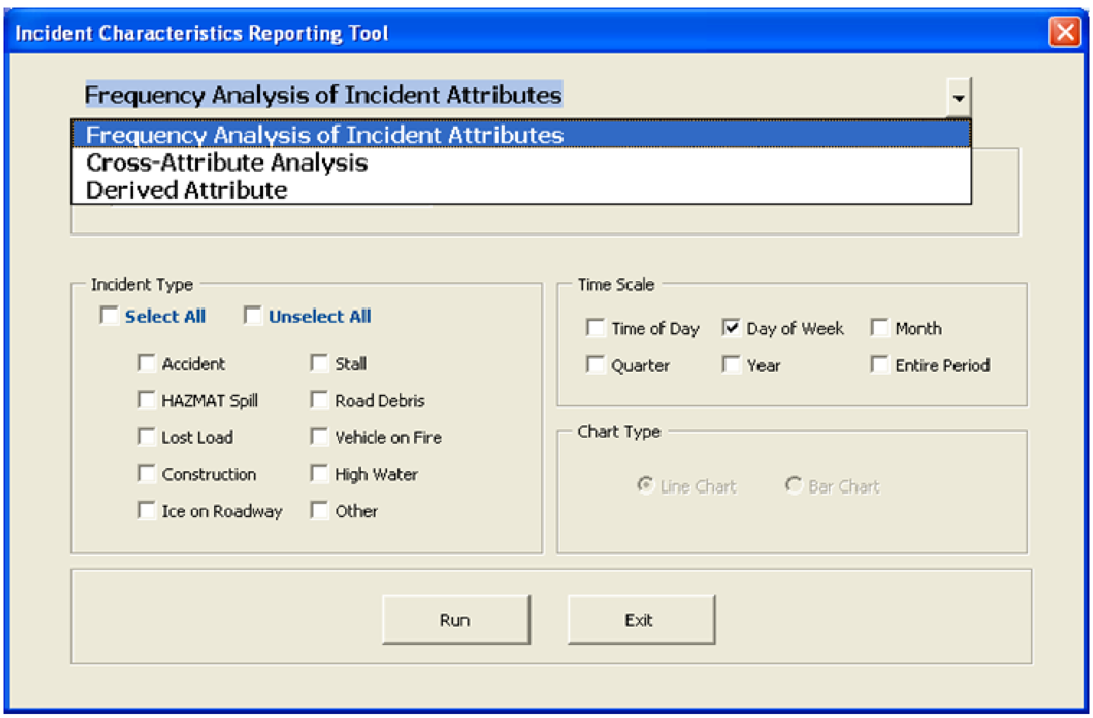


Figure 8-7: User-Interface of the Incident Summary Reporting Tool.

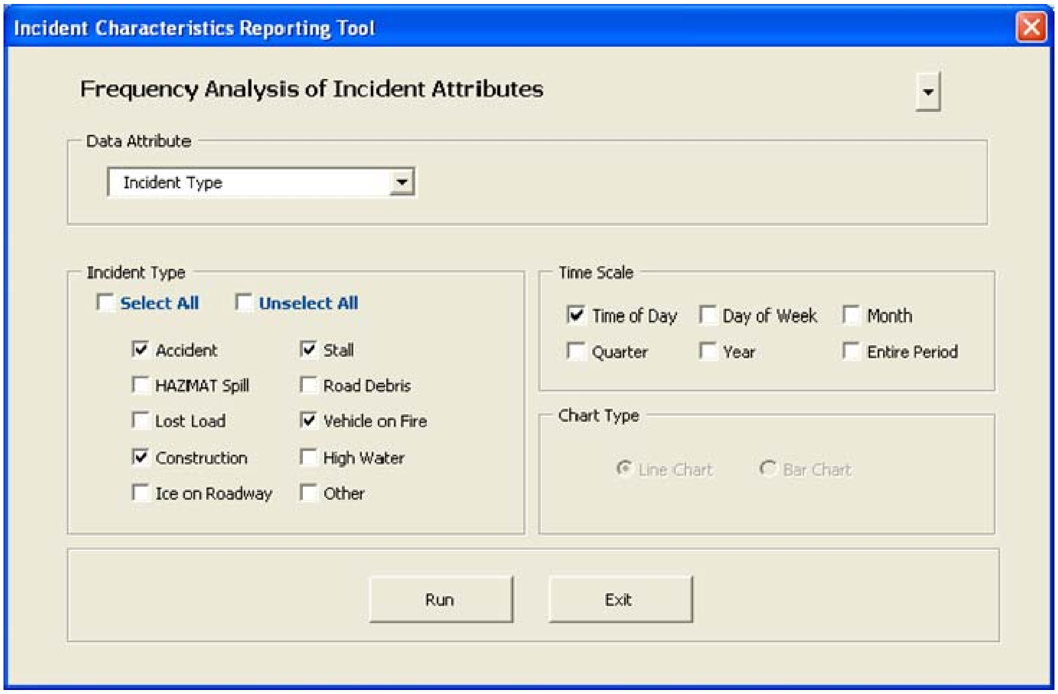


Figure 8-8: Sample Input Entry for Distribution Report by Incident Types.

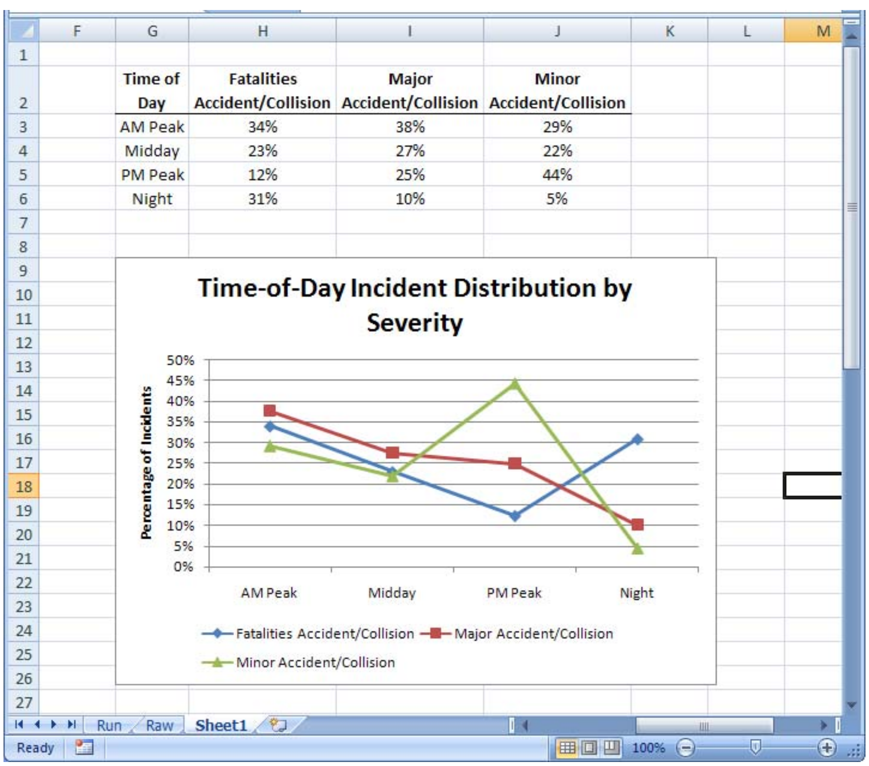


Figure 8-9: Output of Frequency Analysis by Incident Types.

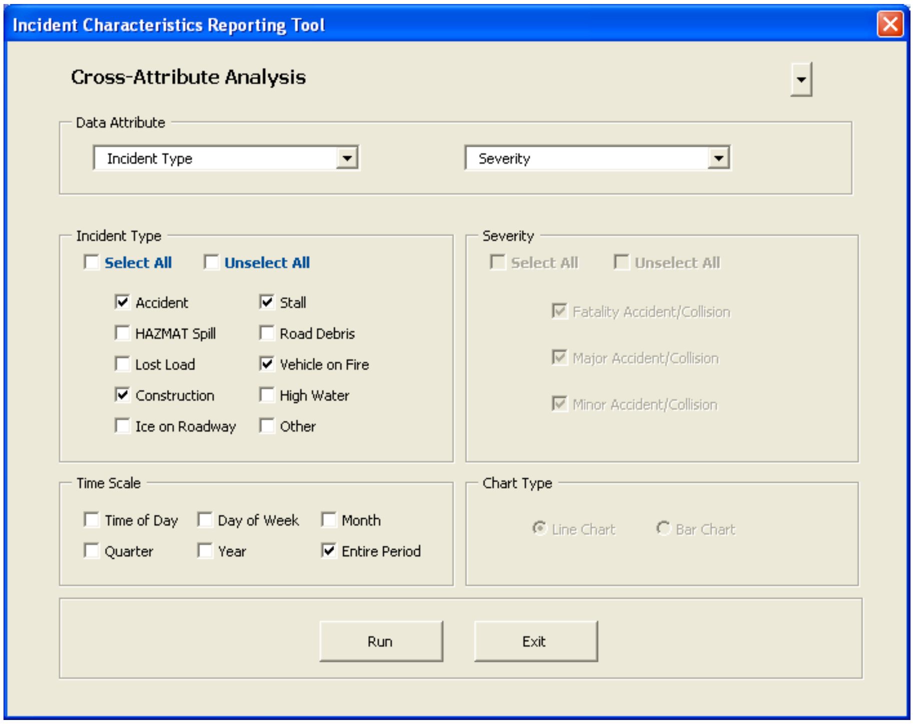


Figure 8-10: Input GUI for Cross-Attribute Analysis.

Severity	Accident	Stall	Construction	Vehicle on Fire
Fatalities Accident/Col	1%	0%	0%	1%
Major Accident/Colli	33%	1%	19%	13%
Minor Accident/Colli	66%	99%	80%	86%

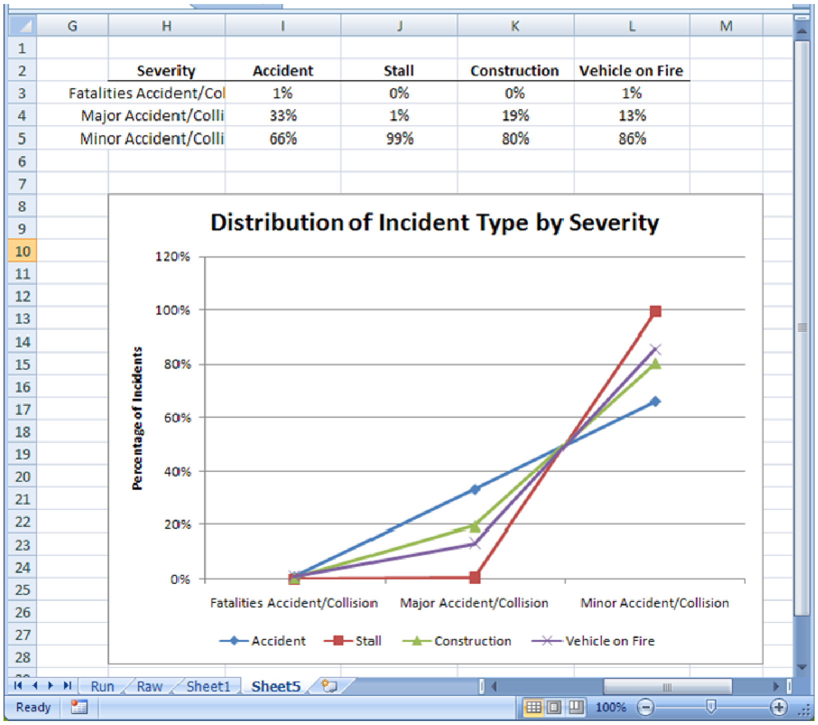


Figure 8-11: Example of Cross-Attribute Analysis Report.

8.4. Incident Duration Estimation Tool

The researchers developed a tool using VBA in Microsoft Excel in this case study to simplify the use of the incident duration models. VBA is an implementation of Microsoft's Visual Basic, an event-driven programming language and associated IDE that is built into most Microsoft Office applications. By embedding the VBA IDE into their applications, developers can build custom solutions using Microsoft Visual Basic. Researchers chose MS Excel as a platform for this development due to its spreadsheet calculation capability and availability in most workplaces.

This tool aims at facilitating three tasks: (a) the process of entering the appropriate set of data required for predicting incident duration, (b) the display of the prediction results, and (c) the modification of data inputs and outputs to evaluate the impacts of the estimation results. Researchers designed the graphical user interface for data inputs shown in Figure 8-12 based on the types of incident characteristics collected at CTECC, such as the types of incidents, the classification of injury severity, and the types of vehicles involved. Researchers coded the models shown in Table 6-4 into Excel worksheets classified by incident types. In this manner, the tool developer can review and adjust specific model parameters as needed without affecting changes to other working models.

To use the tool, the users should first enter all the information known about an incident. The module will continually perform data validation checks for any inconsistent entries. Then the users must click the "Predict…" button to see the prediction results. Figure 8-13 shows an example of the display of prediction results according to the user inputs as provided in Figure 8-12. When the users click "Predict…" the module will first determine the appropriate model based on the type of an incident. Once the correct model is selected, the module will transfer the user inputs into the appropriate model to perform the calculation. The module outputs provide three types of interrelated predictions:

- Average incident duration – This is the mean estimate of the incident duration for a given set of incident characteristics. This value may not be a good estimate if the distribution of duration is heavily skewed. In such cases, the users might want to check the median estimate as well. Median estimate can be obtained from the third type of the predictions where percentile value is set to be 50 percent.
- Probability of incident duration longer than specified value – If the agency has a target value of incident duration (e.g., 120 minutes or longer for major incidents), the users can specify the duration value and then obtain the probability that the specified duration will be exceeded. As shown in Figure 8-13, the probability that the incident will last longer than 60 minutes is 46.1 percent.
- Incident duration at specific percentile value – A user can specify percentile values and then determine the corresponding upper or lower extremes of the predicted incident duration. As shown in the same figure, the 85^{th} percentile of the predicted duration is 147 minutes. In other words, the chance that an incident will last longer than 147 minutes is 15 percent.

By default, the module will provide three predictions, which are (a) average duration, (b) probability of duration exceeding 60 minutes, and (c) 85^{th} percentile of the predicted duration. The users can specify different parameters (duration and percentile values) other than the default values to see the impacts on the predictions. After any changes, the users must click “Recalculate” in order to update the predicted values.

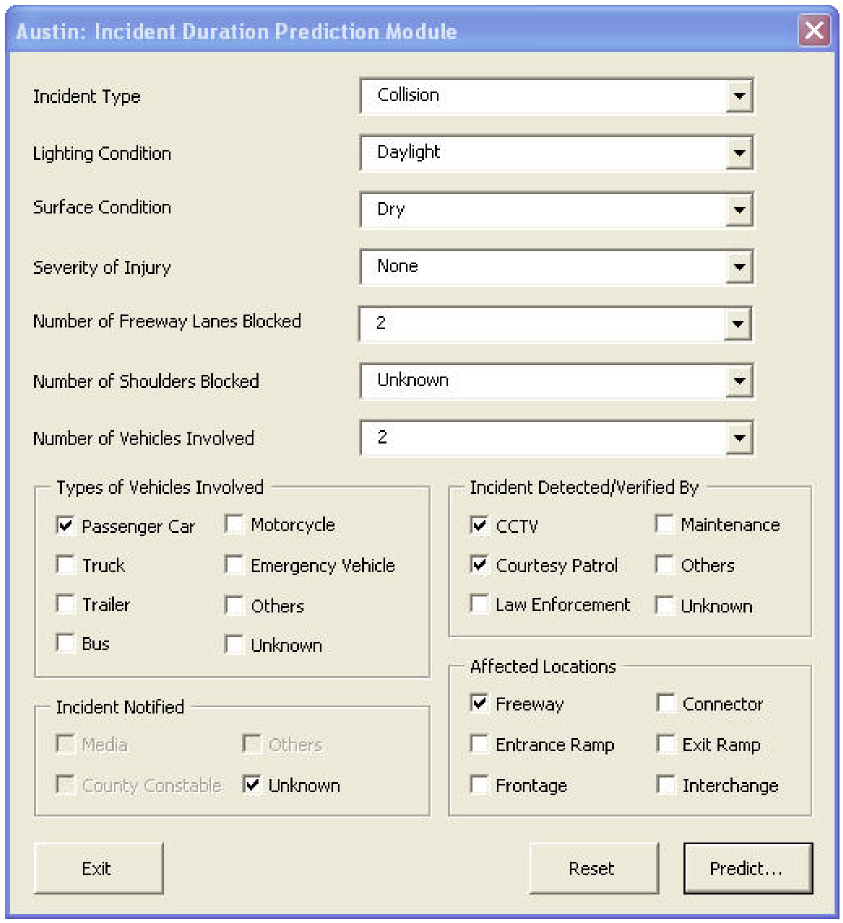


Figure 8-12: Incident Duration Prediction Module – GUI for Prediction Inputs.

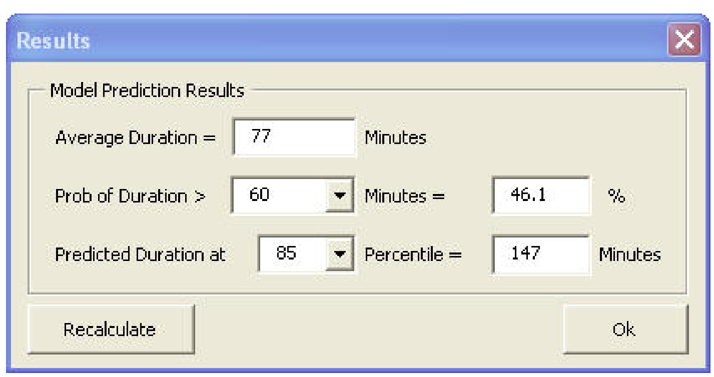


Figure 8-13: Incident Duration Prediction Module – GUI for Prediction Results.

8.5. Incident-Induced Congestion Clearance Prediction Tool

In this project, researchers developed a tool to implement the incident-induced congestion clearance time prediction model using traffic data collected from Wavetronix SmartSensor. Researchers developed this tool using VBA in Microsoft Excel as the platform due to its spreadsheet-based functionality and availability in most workplaces.

This tool is intended to be a real-time application for predicting incident-induced congestion clearance time. When invoked, this tool is responsible for the following two tasks:

- updating the cumulative flow profile when real-time data are received, and
- performing incident-induced congestion clearance prediction when an incident is verified and added by the user.

8.5.1. Input Requirement

The incident-induced congestion clearance prediction tool requires the following data inputs:

- historical traffic volume data in a format as shown in Table 8-1,
- real-time traffic volume data collected at a fixed interval and prepared in a format as shown in Table 8-1, and
- a lane configuration table as shown in Table 8-2.

In addition, when an incident occurs, the user will need to provide estimates on the incident duration and traffic diversion rate during the incident. The former estimate can be predicted using the incident duration prediction tool described in Section 8.4, while the latter estimate can be supplied based on past experience.

8.5.2. Calculation Procedures

Module 8 of the guidebook describes the incident-induced congestion clearance prediction methodology employed by this tool. In summary, provided historical traffic volume and real-time traffic volume data are available, the module estimates the incident-induced congestion clearance period at time *i* ($\hat{t}_{c,i}$) using the following equation:

$$\hat{t}_{c,i} = \hat{r}_i \cdot \frac{\left(\hat{s}_i - \hat{s}_{1,i}\right)}{\left(\hat{s}_i - \hat{q}_i\right)} \tag{8-10}$$

where: $\hat{r}_i$: estimated incident duration at time *i* (min),

$\hat{s}_i$: estimated freeway capacity at time *i* (vphpl),

$\hat{s}_{1,i}$: estimated reduced freeway capacity during the incident at time *i* (vphpl),

$\hat{q}_i$: estimated traffic flow rate at time *i* (vph).

To use Equation (8-10), the parameters should be estimated as follows. The incident duration can be estimated using the incident duration prediction model or default average values for specific types of incidents. The freeway capacity flow rate 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 freeway capacity and incident duration can be updated with real-time data. The reduced flow rates 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 is the expected incoming flow rates 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.

8.5.3. Graphical User Interface

Figure 8-14 shows the input screen of this tool. Assuming that the historical flow rate profile (as a background incident-free traffic condition) is not available or pre-loaded, this tool will search historical traffic database and calculate this flow rate when the tool is first executed. This tool provides the user an option to build the historical profile based on day-of-week or weekday/weekend. To use this tool, the user should also provide the corresponding file locations shown on the input screen.

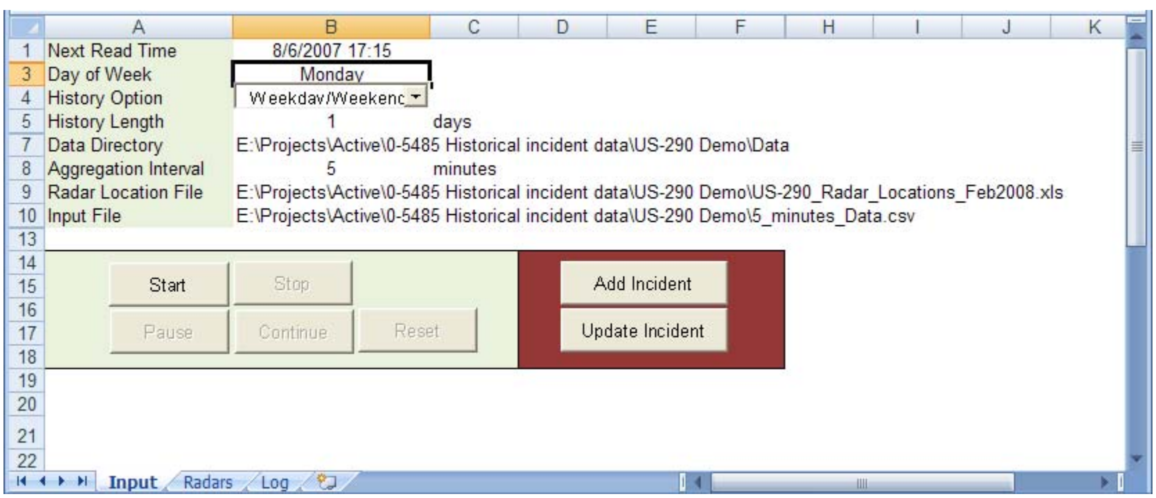


Figure 8-14: Input GUI of Incident-Induced Congestion Clearance Prediction Tool.

When the user clicks the "Start" button, the tool will first create a historical traffic flow profile and then update the profile when it receives the new real-time traffic data. When an incident occurs, the user should provide relevant incident characteristics. By clicking the "Add Incident" button, a form with a list of radar locations will pop up, as shown in Figure 8-15. Once the user identified the incident location, the user should click the "Select Location" button to invoke the "New Incident" screen, as shown in Figure 8-16.

The tool will then estimate the incident-induced clearance time after providing the necessary information of the new incident. Figure 8-17 shows the resulting estimation on the “Radar” tab of the MS Excel worksheet.

As the incident event progresses, the user can update the estimated incident duration to reflect the actual situation. The user can update this information on the “Update Predicted Incident Duration” GUI, as shown in Figure 8-18, by clicking the “Update Incident” button. This GUI also allows the user to provide the time when the incident is removed so that the tool will provide the final congestion clearance estimation for the corresponding location.

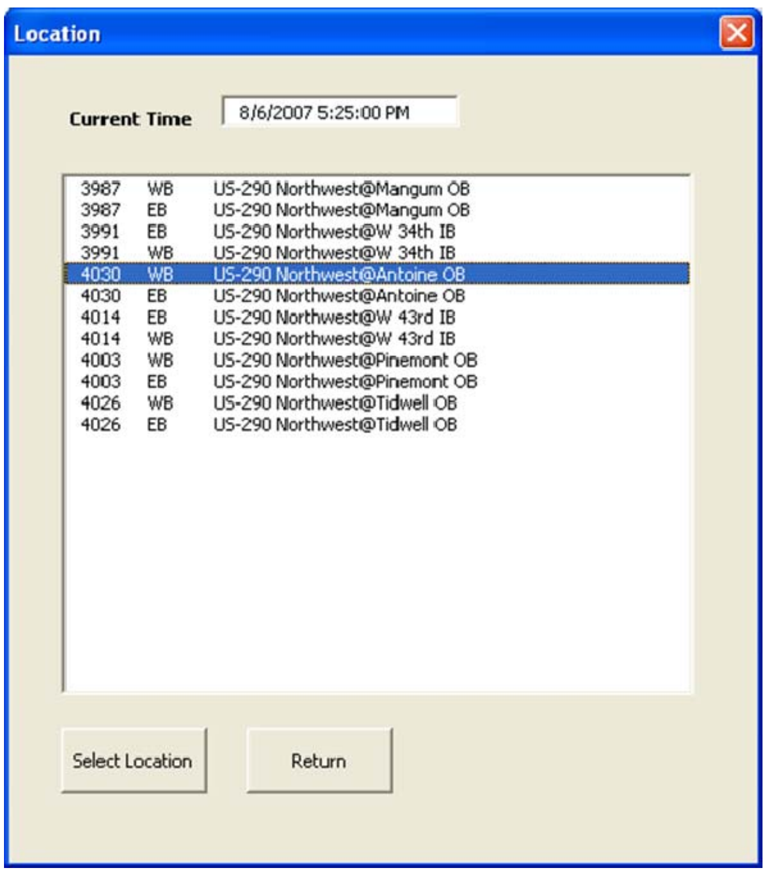


Figure 8-15: GUI of Identifying the Incident Location.

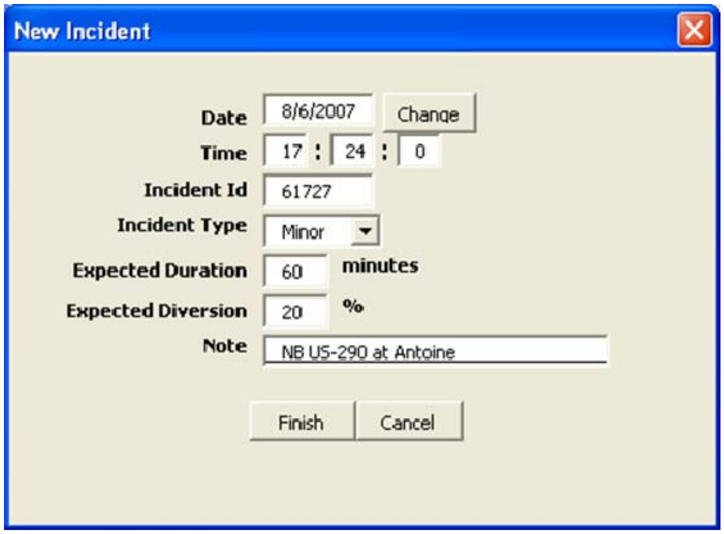


Figure 8-16: GUI for New Incident Input.

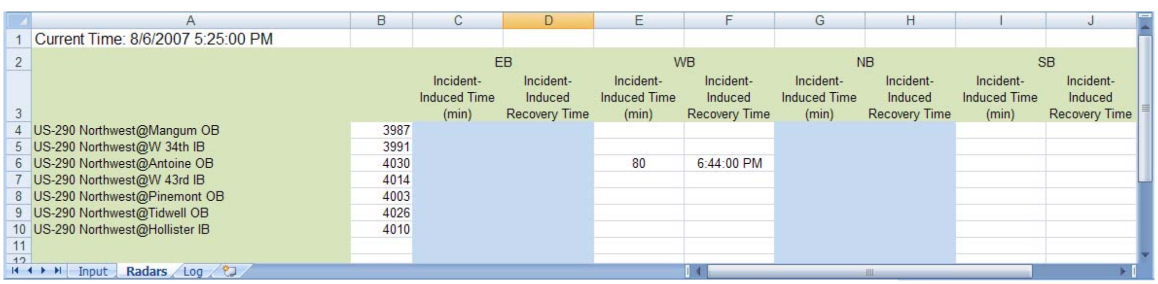


Figure 8-17: Output GUI of the Prediction Tool.

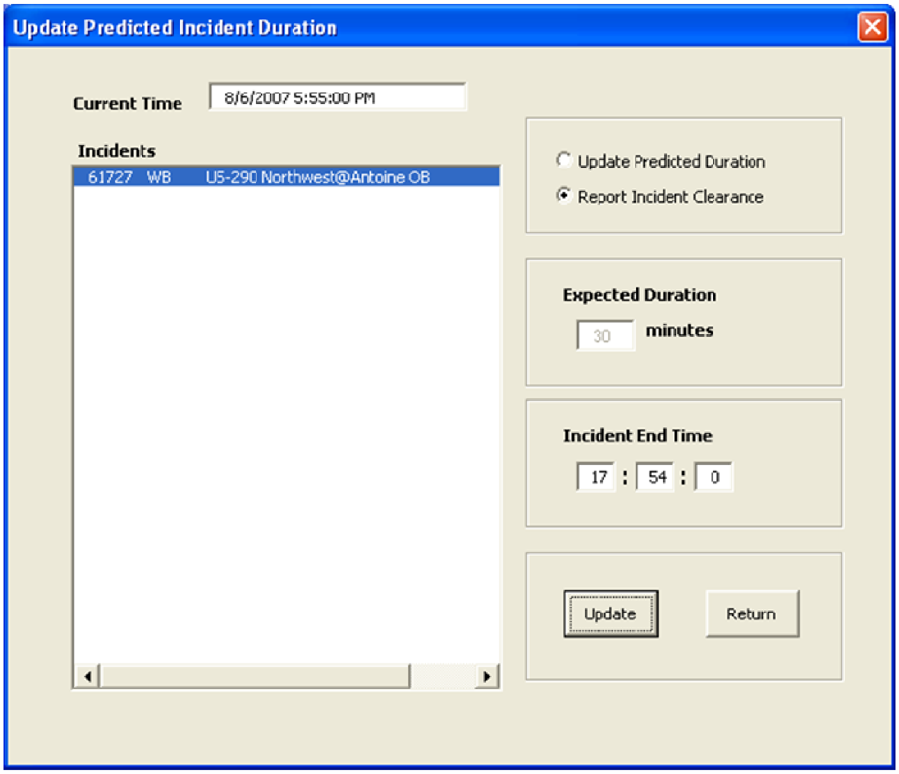


Figure 8-18: GUI of Update Predicted Incident Duration.

9. CONCLUSIONS

Incidents continue to be a major source of congestion and delay in most of the major metropolitan areas in Texas. TxDOT has made a significant investment in developing and deploying ATMS throughout Texas. These systems generate and archive a considerable amount of traffic operations data and information about the impacts of and responses to incidents. While there is a growing amount of historical data, relatively little has been done to explore the potential of these data and incorporate them into applications that can assist day-to-day operations at the center. Most of the centers use only real-time operation data (such as speed, volume, occupancy, and travel time) to drive management tools and resources, such as automated incident detection (AID), to assist in detecting and responding to incidents. Differences in configuration, deployment, and data management processes across Texas TMCs add additional complexity to this issue. To respond to a growing interest in identifying areas where TMCs can use historical data to improve their operations, TxDOT has identified a research need to assess how it could use incident data to improve incident management and performance measures at TMCs.

9.1. Summary

As part of this project, researchers developed a guidebook, 0-5485-P2, to provide the Texas Department of Transportation with methodologies and procedures for effective use of historical incident data collected at Texas TMCs. This guidebook describes the developed procedures and methodologies in separate modules. Two major types of analyses covered in the guidebook are evaluation/planning and predictive analyses. For the evaluation/planning type, this guidebook provides (a) guidelines for reporting incident characteristics, (b) methods for analyzing hot spots, (c) methodologies for estimating incident impacts, and (d) guidelines and procedures for calculating performance measures. For the predictive type, this guidebook describes (a) methodologies for predicting incident duration using incident characteristics, and (b) methodologies for predicting incident-induced congestion clearance time using combined historical and real-time traffic data.

Next, the researchers conducted case studies using the procedures outlined in the guidebook and the data collected from three Texas TMCs, which are Houston's TranStar, Austin's CTECC, and Fort Worth's TransVISION. All three TMCs have their own specifications for collecting traffic and incident data. The case studies conducted at these three TMCs represented the majority of the types of analyses and applications that could also be conducted at other Texas TMCs. This research report, 0-5485-1, documents the results and findings from the case studies.

9.2. Recommendations

Researchers recommend that TxDOT consider the following in applying the evaluation/planning analysis modules of the guidebook:

- Several incident data attributes are useful for incident characteristics reporting. Major considerations are the type of data, time scale used in the analysis, data validity, reporting objectives, and reporting frequency.
- The appropriate hot spot analysis method should be based on data availability and the objectives of the analysis. Consider the frequency-based method if the agency's priority is to reduce the frequency of incident occurrences. Consider the attribute-based method if 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 the incident response time, etc.)
- An agency can use combined incident and traffic data to evaluate incident impacts from both system and travelers' perspectives. From a system perspective, an agency can estimate the amount of traffic delay caused by an incident or the time it takes for the traffic flow to resume normal conditions. From travelers' perspectives, an agency can account for travelers' anticipation with the concept of background travel time.
- Delay index is defined as a ratio of incident delay to expected incident-free travel time. The delay index profile can account for the impact of incidents over time with respect to travelers' anticipation.
- An agency should consider multiple metrics for describing the performance of the facilities and operations of the TMCs. Potential uses of these metrics include traveler information provision, operations evaluation, resource evaluation, safety evaluation, monitoring, planning, and customer satisfaction measurement.

In addition, researchers recommend that TxDOT consider the following in applying the predictive analysis modules of the guidebook:

- An agency can predict the incident duration with reasonable degree of accuracy if the detailed incident characteristics are available.
- Several incident characteristics were very useful for predicting incident duration, but incident type and lane blockage characteristics were major determinants for selecting appropriate models.
- The incident prediction models must reflect the standard operating procedure that TMC operators use in logging incident data.
- An agency can predict incident-induced congestion clearance time using the combined historical and real-time traffic data and the characteristics of an ongoing incident.
- Researchers' analysis indicated that the method for predicting incident-induced congestion clearance time is most sensitive to the estimated incident duration and the incident-induced traffic diversion rate.

Finally, researchers recommend that TxDOT consider the following suggestions to enhance the utility of the incident database for incident management and performance monitoring efforts:

- Record the number of lanes blocked along the total number of lanes available at the incident location.

- Develop consistent definitions of all incident data attributes and standardized data entry procedures for Texas TMCs.
- Traffic and weather data are generally available in real time but from different data sources. Consider integrating these two data sources directly into the incident data archive.

9.3. Closure

Researchers found that TxDOT can use historical incident data to support incident management and performance evaluation processes both reactively and proactively. TxDOT may need to implement and automate some procedures to make them more efficient in day-to-day operations. As such, this project developed various prototype tools to facilitate and automate the proposed methodologies, including the incident duration and incident-induced congestion clearance prediction tools. Our case study results have successfully demonstrated the potential of the guidebook, and the prototype tools developed have provided a platform for TxDOT to deploy the research results in the future.

10. REFERENCES

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APPENDIX A. SURVEY RESULTS

This appendix documents the results and findings of Task 1 in this project. The objective of this task was to determine TxDOT's vision for incorporating historical data into TMC operations and performance measures. The purpose of this task was to gather feedback from the project monitoring committee as well as TMC operators and managers regarding TxDOT's current practices and desires for incorporating historical data into TMC operations, with a specific emphasis on incidents and incident management. Through a survey of TMC operating personnel and TTI researchers who are stationed at the Regional Implementation Offices and who have direct working knowledge of TMC operations in respective cities, researchers gained valuable insight into the following issues: critical performance measures at TMCs as perceived by TxDOT, desirable performance goals at various TMCs, prioritized performance measures as perceived by TxDOT, current uses of performance at TMCs, and additional needs for performance measures at TMCs.

Survey Approach

Table A-1 provides a list of Texas TMCs categorized by city population (based on 2000 census data).

Table A-1: Texas Transportation Management Centers.

City Population (2000 Census Data)	Transportation Management Center
Greater than 1 million	• HOU: Houston's TranStar • DAL: Dallas' DalTrans • SAT: San Antonio's TransGuide
Between 500,000 and 1 million	• AUS: Austin's Combined Transportation and Emergency Communications Center (CTECC) • FTW: Fort Worth's TransVISION • ELP: El Paso's TransVista
Less than 500,000	• AMA: Amarillo's Panhandle Electronic Guidance and Safety Information System (PEGASIS) • LRD: Laredo's South Texas Regional Advanced Transportation Information System (STRATIS) • WFS: Wichita Falls' Texoma Vision

Six Texas TMCs that routinely archive traffic and incident management data are Houston's TranStar, Dallas' DalTrans, San Antonio's TransGuide, Austin's CTECC, Fort Worth's TransVISION, and El Paso's TransVista. In general, TMCs in Texas cities with populations greater than 500,000 tend to have area-wide intelligent transportation systems (ITS) deployment and a more comprehensive data management program. Researchers focused their attention on these TMCs because these centers generate large archives of freeway traffic data and incident management information and responses.

In this study, researchers asked TxDOT operating personnel from each of these six locations to respond to three-page questionnaires. The objectives of the questionnaires were to determine current status and TxDOT's opinions on the applications and performance measurements at Texas TMCs using historical data. These TMCs have routinely collected and archived operations data and/or incident data from daily operations. All six TMCs responded to the survey, with the last response received on April 9, 2007.

In several questions, researchers asked the survey respondents to rank the responses, in addition to identifying the appropriate items associated with the questions. In this case, researchers determined the final rankings of each item using weighted scores calculated based on frequency and ranking of the responses. The weighted score was computed using the following expression:

$$S_i = \sum_{\forall j} w_{ij} I_{ij} \tag{A-1}$$

where S_i = weighted score of item i, w_{ij} is an assigned weight based on the ranking of item i for response j (3 if first rank, 2 if second rank, 1.5 if third rank, and 1.0 if unranked), and I_{ij} is 1 if item i is selected in a response j.

For instance, using Equation (A-1), the weighted score of the third item (i.e., estimation of incident impacts) in Table A-2 is:

$$S_3 = \underbrace{(2.0)(1)}_{DAL} + \underbrace{(1.5)(1)}_{HOU} + \underbrace{(3.0)(1)}_{FTW} = 6.5$$

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Survey Results

The following sections summarize the survey results conducted in this study.

Applications of Historical Data

Researchers asked the following question to identify the applications of historical data that respondents perceive most useful for the TMC.

Please rank the top three applications of historical data that would be the most useful for your agency. Please assign the numeric rankings from 1 to 3 with 1 being the most desirable application: _____ Automated incident detection _____ Using incident statistics to identify high incident locations _____ Estimation of incident duration _____ Estimation of incident impacts _____ Estimation of travel times _____ Please specify your application: _____ _____ Please specify your application: _____ Does your TMC currently have any of the above applications? If yes, please specify: _____

Table A-2 summarizes the responses to this question.

Table A-2: Most Useful Applications of Historical Data.

Applications	Rankings						Freq	Weighted Score	Final Rank
	DAL	ELP	HOU	AUS	SAT	FTW			
Using incident statistics to identify high incident location	1		1		1		3	9.0	1
Automated incident detection		1*	*	1*	3*	3*	4	9.0	1
Estimation of incident impacts	2		3			1	3	6.5	3
Estimation of incident duration	3	2	2				3	5.5	4
Estimation of travel times	*	3	*	2	2*	*	3	5.5	4
Others: planning, calculating MOEs and benefits				3		2	2	3.5	6

Notes:
* Already implemented at the TMC.

The top two applications of historical data at TMCs are (a) the use of historical incident data to identify high incident locations, and (b) the use of combined real-time and historical data to automate incident detection. Systems to automate incident detection and estimate travel times are implemented at most TMCs surveyed in this study. However, historical data were rarely used in these two applications. None of the TMCs uses historical data in the algorithm to estimate travel times. On a limited basis, historical data have been used to calibrate and improve the performance of the detection algorithm. For example, TranStar compares real-time speed data with historical averages to generate traffic alarms. The occupancy thresholds for TxDOT ATMS can be adjusted based on historical performance of the detection algorithm. None of the TMCs has implemented a system to identify high incident locations, estimate incident impacts, or estimate incident duration.

TMC Operations Goals

Researchers asked the following question to identify any existing operations goals/objectives at the TMCs and determine the priority of the objectives.

Does your agency currently have specific operations goal(s)?
☐ Yes, please specify: _____
☐ No. Which of the following statements best describes your agency in managing incidents?

Please check all that apply:	Please assign the numeric rankings based on the priority of the checked items (1 is the highest priority)
☐ Minimize incident response time	_____
☐ Minimize incident duration	_____
☐ Minimize the risk of secondary crashes	_____
☐ Restore freeway capacity speedily (open all lanes)	_____
☐ Others – specify: _____	_____
☐ Others – specify: _____	_____

Per TMC responses, only CTECC and TransGuide have established specific operations goals/objectives. Also, incident duration receives the highest priority in managing incidents.

Table A-3 lists CTECC's suggested objectives and performance measures of the operations as outlined in Exhibit F of the Operations and Maintenance Interlocal Agreement (*1*).

Table A-3: CTECC's Suggested Objectives and Performance Measures.

Improve efficiencies • Reduce response time • Reduce clearance time	National recognition • Tours given • Presentation made
Integrate systems • Number of systems integrated	Reduce costs • Reduction of expenditures • Dollars saved
Real-time sharing of information • Type of information exchanged during incident • Minutes of video available	Economy of scale benefits • Reduction of expenditures • Benefit cost ratio (B/C) greater than 1.05
Seamless exchange of information • Type of data exchanged automatically	Improve safety • Reduction in deaths • Reduction in injuries • Reduction in incidents
Integrate data analysis • Number of data sources in report	Provide public information • Minutes of information broadcast
Improve coordination and cooperation • Number of agencies involved in response	Dynamic assignment performance • Type of information viewed during incident • Video available during incident
Real time status and monitoring • Type of information exchanged during incident	Replace obsolete and inadequate systems • Number of systems replaced
	Manage increasing demand • Mile of service area increased

TransGuide's operations goals are to detect an incident within two minutes of its occurrence and to formulate and implement a pre-planned/dynamic scenario response within one minute after the detection.

TransVista's operations and performance evaluation activities are similar to many other smaller TMCs across the nation. Performance measurement, reporting, and decision-making do not seem to be a major focus of the higher management at this time. The agency is, however, interested in finding out more about best practices in this field and the particular actions taken/considered by other TMCs.

Table A-4 summarizes the results of this question. The top two priorities in managing freeway incidents are both operations-related objectives, specifically to minimize incident duration and to speedily restore freeway capacity (i.e., clear an incident and open travel lanes to the traffic).

Table A-4: Priority Rankings of Operations Goals.

Priority of TMC operations goals	Rankings						Freq	Weighted Score	Final Rank
	DAL	ELP	HOU	AUS	SAT	FTW			
Minimize incident duration	2		1	2		1	4	10	1
Restore freeway capacity	1		3	3		2	4	8	2
Minimize the risk of secondary crashes	3		2			1	3	6.5	3
Minimize incident response time			4	1		2	3	6	4
Others: maximize diversion and incident area avoidance						1	1	3	5
Others: minimize queue development and congestion						1	1	3	5

Notes:
1. AUS: refers to CTECC operations and maintenance agreement for specific operations goal(s).
2. ELP: provided no response for this question.
3. SAT: To detect an incident within two minutes of its occurrence and to formulate and implement a pre-planned/dynamic scenario response within one minute after the detection.

Two additional goals identified from the responses are to maximize the diversion from the incident area and minimize queue/congestion. Achieving the former goal would require a significant level of advanced traveler information systems (ATIS) deployment in the area, as well as properly managed and coordinated strategies to provide traffic information to travelers.

From the overall rankings, current goals and objectives of TMC operations emphasize mobility followed by safety and operational efficiency.

Usage of Performance Measures

The second part of the questionnaire was intended to gauge the opinions on if and how the performance measures can be used to support TMC operations. None of the TMCs is currently using performance measures to either support or evaluate TMC operations on a regular basis. The responses obtained from this part were used in conjunction with National Transportation Operations Coalition (NTOC) performance measurement initiative *(2)* and a recently published National Cooperative Highway Research Program (NCHRP) guidebook *(3)* to select and produce appropriate performance measures using historical data. NCHRP research project 3-68 developed a comprehensive guidebook on freeway performance measurement and monitoring.

Classification of Performance Measures

Researchers asked the following question to determine how performance measures should be categorized for the TMCs. Table A-5 summarizes the responses. Approximately 85 percent of the respondents indicated that function-based classification of performance measures would be the most beneficial. This classification would help measure if and how the TMCs are achieving specific operations goals.

2.2.1. Which of the following classifications of performance measures would be the most beneficial to your agency?

☐ Mobility-based performance measures

Example of Categories	Example of measures
Quantity of travel	Person-miles traveled Vehicle-miles traveled
Quality of travel	Average speed Average travel time Travel time reliability
System utilization	Percent freeway congested Congested duration

☐ Component-based performance measures

Example of Categories	Example of measures
Emergency response units	Incident response time Incident clearance time Freeway blockage time
Control center operators	Incident verification time Incident notification time Average number of incidents per operator
Freeway system	Sensor coverage in lane-miles Percent freeway congested Average speed
Customer satisfaction	Incident response times Satisfaction with HOV lanes Satisfaction with traveler information Satisfaction with service patrols

☐ Function-based performance measures

Example of Categories	Example of measures
Incident management	Incident duration Incident detection, response, and clearance times
Traveler information dissemination	Average travel time Travel time reliability Traveler information website usage statistics
Congestion management	Percent freeway congested Average recurring delay Average non-recurring delay
Safety management	High incident location Emergency vehicle response time Incident detection, response, and clearance times

☐ Others – Please specify: _____

Table A-5: Preferred Classification of Performance Measures.

Preferred classification of performance measures	Responses						Freq	Final Rank
	DAL	ELP	HOU	AUS	SAT	FTW		
Function-based performance measures	x	x	x		x	x	5	1
Mobility-based performance measures				x			1	2
Component-based performance measures						x	1	2

Anticipated Use of Performance Measures

Researchers asked the following question to identify anticipated use of performance measures at the TMCs. Since there is a large catalogue of performance measures that can be obtained and computed from both real-time and historical data, researchers will use the responses from this question to assist the process of screening and choosing appropriate performance measures for reporting. Operational objectives of the TMCs and the characteristics of the performance measures (discussed in the next section) were considered as well.

2.2.2. How do you envision using performance measures in your agency?

Please check all that apply:

(a) ☐ Responding to legislative mandates
(b) ☐ Improving and evaluating incident management program
(c) ☐ Improving planning process including budget allocations
(d) ☐ Congestion management and evaluation
(e) ☐ Safety management and evaluation
(f) ☐ Improving and evaluating traveler information systems
(g) ☐ Assessing environmental impacts
(h) ☐ Better maintenance of ITS equipment and facilities
(i) ☐ Improving customer satisfaction
(j) ☐ Others – specify: _____
(k) ☐ Others – specify: _____

From the above list, please specify the top three priorities: _____

Table A-6 presents the responses to this question. The top three anticipated uses of performance measures at the TMCs were:

- improving and evaluating incident management program,
- safety management and evaluation, and
- improving and evaluating traveler information systems.

It is interesting to note that respondents ranked congestion management and customer satisfaction highly. One respondent suggested using tangible monetary benefits as a performance measure.

Table A-6: Anticipated Use of Performance Measures at TMCs.

Anticipated use of performance measures at TMCs	Responses with Rankings						Freq	Weighted Score	Final Rank
	DAL	ELP	HOU	AUS	SAT	FTW			
Improving and evaluating incident management program		1	x	1	1	1	5	13.0	1
Safety management and evaluation	1	2	x		x		4	7.0	2
Improving and evaluating traveler information systems	2	x	x		2		4	6.0	3
Congestion management and evaluation	3	x	x		3		4	5.0	4
Improving customer satisfaction		3	x			2	3	4.5	5
Improving planning process including budget allocations	x	x	x			x	4	4.0	6
Assessing environmental impacts		x	x		x	x	4	4.0	6
Better maintenance of ITS equipment and facilities		x	x		x		3	3.0	8
Others: reporting tangible monetary benefits						3	1	1.5	9
Responding to legislative mandates		x					1	1.0	10

Criteria for Selecting Performance Measures

Researchers asked the following question to identify important criteria for selecting performance measures. Table A-7 summarizes the responses.

2.2.3. What do you perceive as important criteria for good performance measures?

Please assign appropriate ratings from 1 (most important) to 5 (least important):

Criteria	Please assign importance ratings: 1	2	3	4	5
The measure is simple to understand for technical and non-technical audiences.	☐	☐	☐	☐	☐
The measure describes existing conditions.	☐	☐	☐	☐	☐
The measure can be used to predict change and forecast conditions.	☐	☐	☐	☐	☐
The measure can be calculated or estimated easily.	☐	☐	☐	☐	☐
The measure achieves consistent results.	☐	☐	☐	☐	☐
The accuracy level of the measure is acceptable.	☐	☐	☐	☐	☐
Others – specify: _____	☐	☐	☐	☐	☐
Others – specify: _____	☐	☐	☐	☐	☐

In selecting the performance measures, the two most important criteria identified from the responses are the ease of understanding and accuracy. Of less importance are the calculation complexity, ability to describe existing conditions and predict changes, and consistency.

Table A-7: Criteria for Selecting Performance Measures.

Criteria for selecting performance measures	Responded Ratings -- 1 (least important) to 5 (most important)						Avg Ratings	Final Rank
	DAL	ELP	HOU	AUS	SAT	FTW		
Simple to understand for technical and non-technical audiences.	4	5	5	5	5	4	4.67	1
The accuracy level of the measure is acceptable.	5	5	4	4	5	5	4.67	1
The measure describes existing conditions.	4	5	5	1	5	5	4.17	3
The measure can be calculated or estimated easily.	4	5	5	4	3	4	4.17	3
The measure achieves consistent results.	4	4	5	5	2	5	4.17	3
The measure can be used to predict change and forecast conditions.	3	4	5	2	3	2	3.17	6

General Comments

Researchers also asked the respondents to provide specific performance measures that they would like to use in the future. The list below summarizes the responses to this question:

- incident detection related performance measures,
- incident duration based on different types of incidents,
- cost-to-benefit ratio,
- explicit comparison of managed versus unmanaged incident impacts, and
- improved resolution of incident detection with respect to physical location.

The respondents also pointed out specific concerns that may stem from or are related to the use of performance measures as listed below:

- Emphasis should be made on prediction since the greatest impact on travel quality and congestion is from non-recurring incidents. Recurrent congestion is more predictable and easily observable with good operations data archive.
- Ambiguity.
- Reliability.
- Exposure to public scrutiny.
- Tying personnel performance evaluations to system measurements.
- Participation of partners is needed for successful performance measurement.

References

1. Interlocal Agreement for Operations and Maintenance of the Combined Emergency Communications Facility and Supported Systems. Texas Department of Transportation, Austin, Texas.
2. National Transportation Operations Coalition (NTOC) Performance Measurement Initiative. *Final Report*, http://www.ntoctalks.com/action_teams/ntoc_final_report.pdf, 2005.
3. Margiotta, R., T. Lomax, M. Hallenbeck, S. Turner, A. Skabardonis, C. Ferrell and B. Eisele. Guide to Effective Freeway Performance Measurement: Final Report and Guidebook. *NCHRP Web-Only Document 97*, National Cooperative Highway Research Program, TRB, http://onlinepubs.trb.org/onlinepubs/nchrp/nchrp_w97.pdf, August 2006.

APPENDIX B. HOUSTON: DATA ANALYSIS AND RESULTS

Standard Reports of Incident Characteristics

Table B-1: Distribution of Incident Responders (Houston).

Distribution of Responders	
Wrecker	73.9%
City Police	65.7%
EMS	26.7%
Fire Department	15.3%
County Police	7.7%
TxDOT	4.9%
MAP	3.4%
METRO Police	2.5%
METRO	2.1%
HCFCD	0.8%
State Police	0.5%
County	0.3%
HAZMAT	0.2%
City	0.1%
Coroner	0.1%

Table B-2: Incident Frequency and Duration by Types (Houston).

Incident Type and Duration (Houston 2004-2007)							
Type	Counts	%	Duration Percentile (minutes)				
			5%	15%	50%	85%	95%
Accident	41597	73.2%	3	7	24	54	97
Stall	11107	19.5%	2	4	16	45	80
Heavy Truck	5977	10.5%	4	12	37	106	213
Construction	4437	7.8%	3	7	22	54	104
Debris	2059	3.6%	2	5	21	72	121
Vehicle on Fire	1101	1.9%	7	16	36	73	137
Other	1008	1.8%	3	7	29	123	268
High Water	681	1.2%	16	38	150	484	1321
Bus	568	1.0%	5	12	35	78	128
HAZMAT	335	0.6%	10	37	115	297	828
Lost Load	200	0.4%	4	15	81	250	382
Ice	27	0.0%	30	35	91	289	632
All Types	56847		7	20	58	140	273

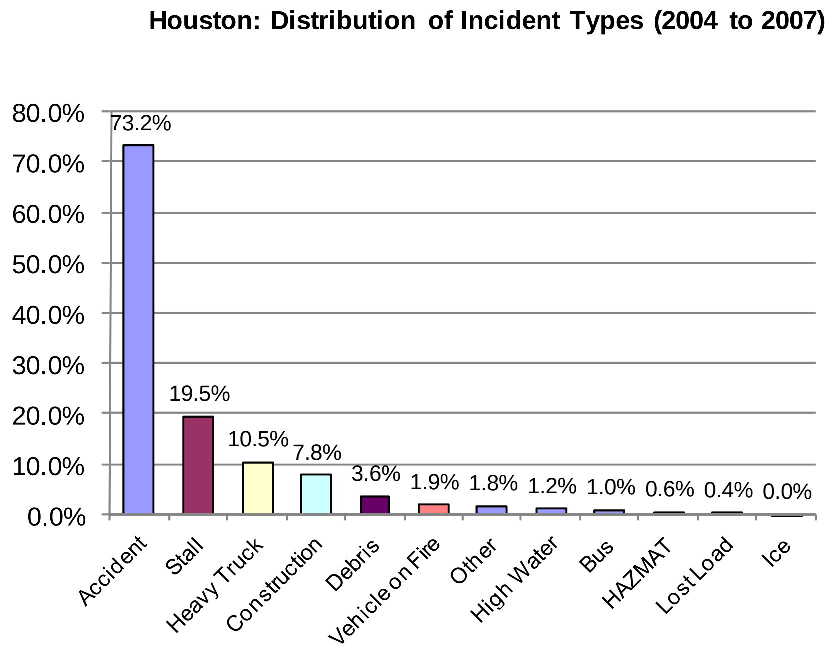


Figure B-1: Distribution of Incident Types (Houston: 2004–2007).

Table B-3: Incident Distribution by Types (Houston).

Incident Type	2004	2005	2006	2007	Total	% of Total
Accident	9713	9426	10335	12123	41597	73%
Stall	2625	3444	2768	2270	11107	20%
Heavy Truck	1293	1560	1590	1534	5977	11%
Construction	762	2020	1203	452	4437	8%
Debris	428	580	580	471	2059	4%
Vehicle on Fire	286	241	299	275	1101	2%
Other	239	261	268	240	1008	2%
High Water	126	97	309	149	681	1%
Bus	150	200	140	78	568	1%
HAZMAT	71	71	103	90	335	1%
Lost Load	38	49	59	54	200	0%
Ice	0	0	0	27	27	0%
All Types	13105	13879	14396	15467	56847	

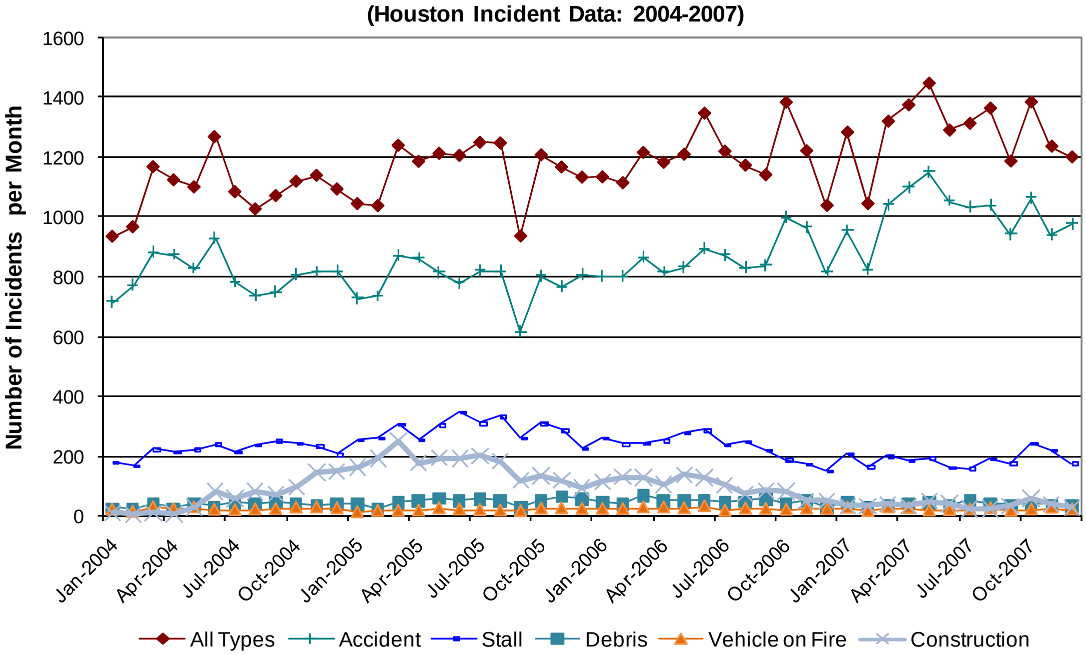


Figure B-2: Monthly Incident Rates over the Analysis Period (Houston).

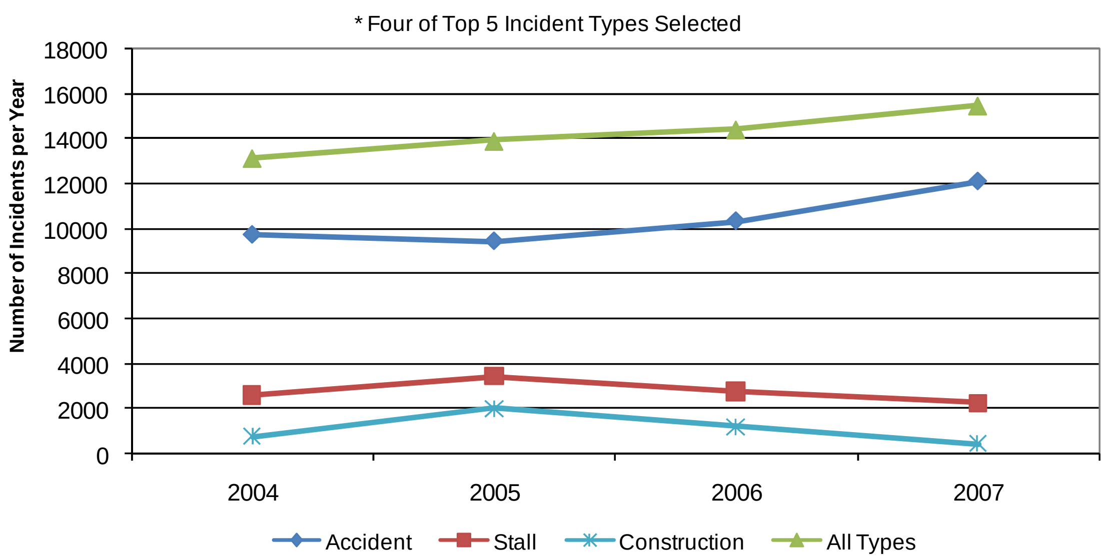


Figure B-3: Yearly Incident Rates by Incident Type (Houston).

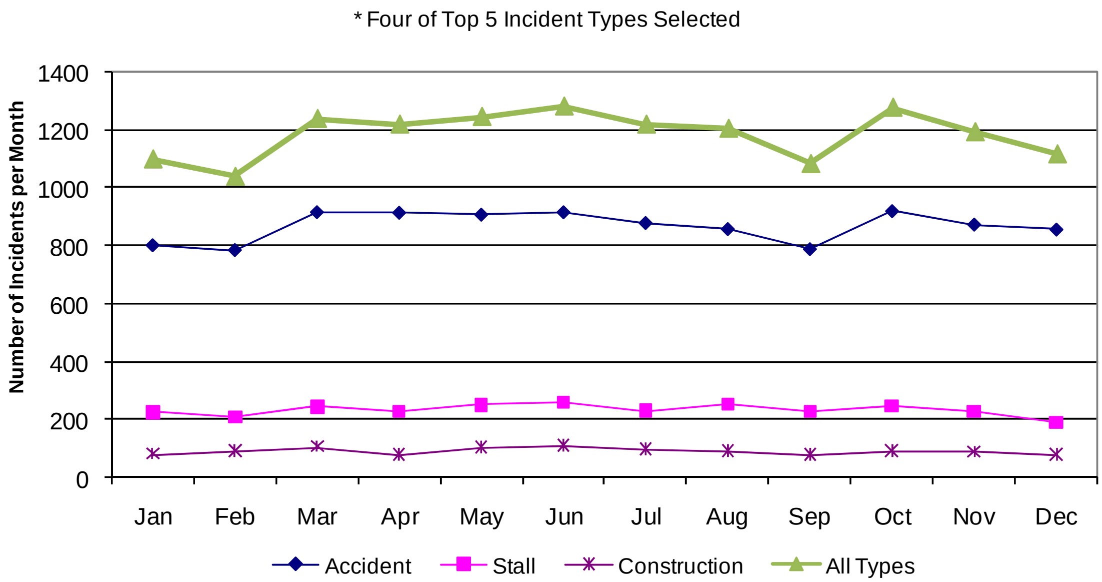


Figure B-4: Monthly Incident Rates by Incident Types (Houston).

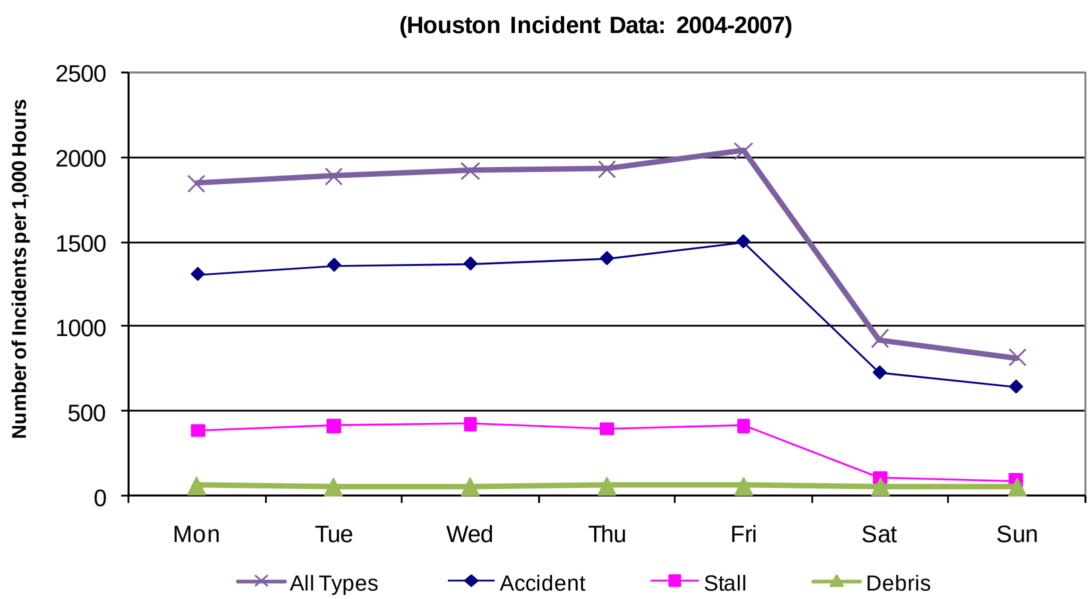


Figure B-5: Daily Incident Rates by Incident Types (Houston).

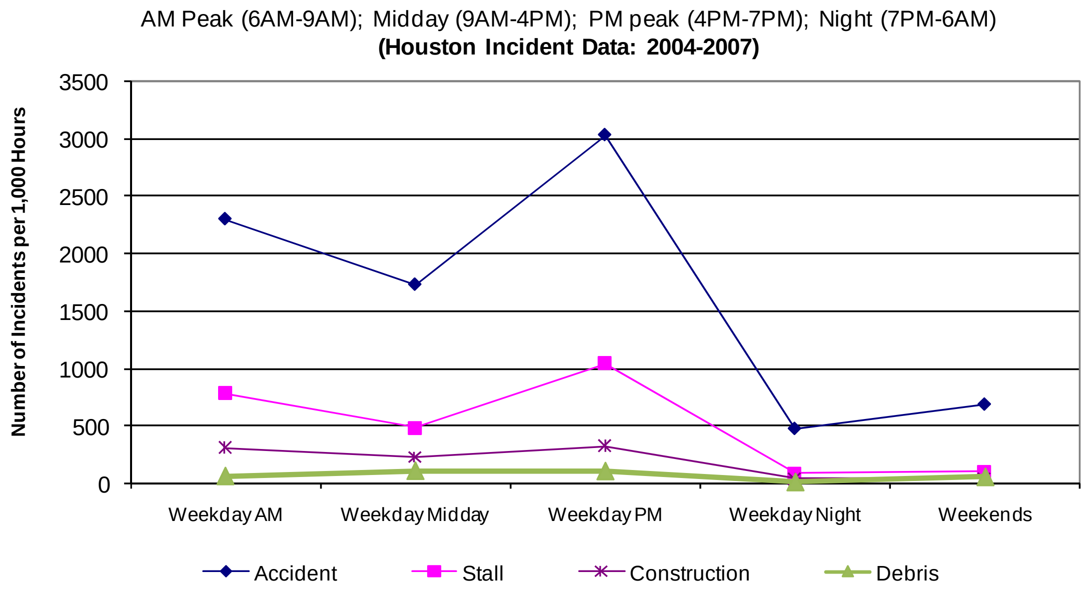


Figure B-6: Incident Rates at Different Times of Day by Incident Types (Houston).

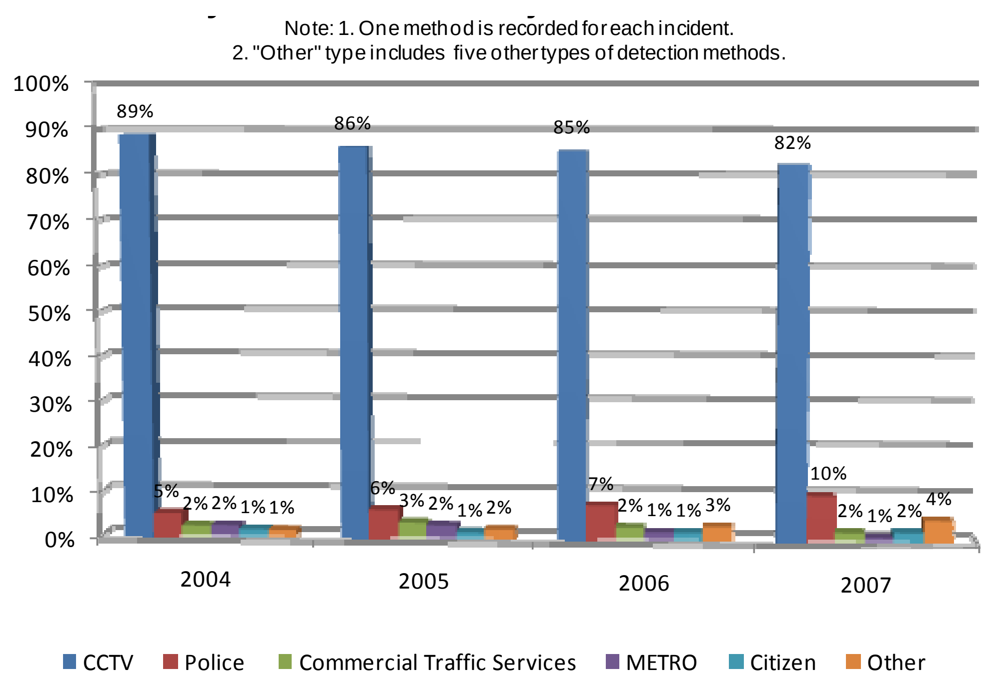


Figure B-7: Distribution of Incident Detection Methods (Houston).

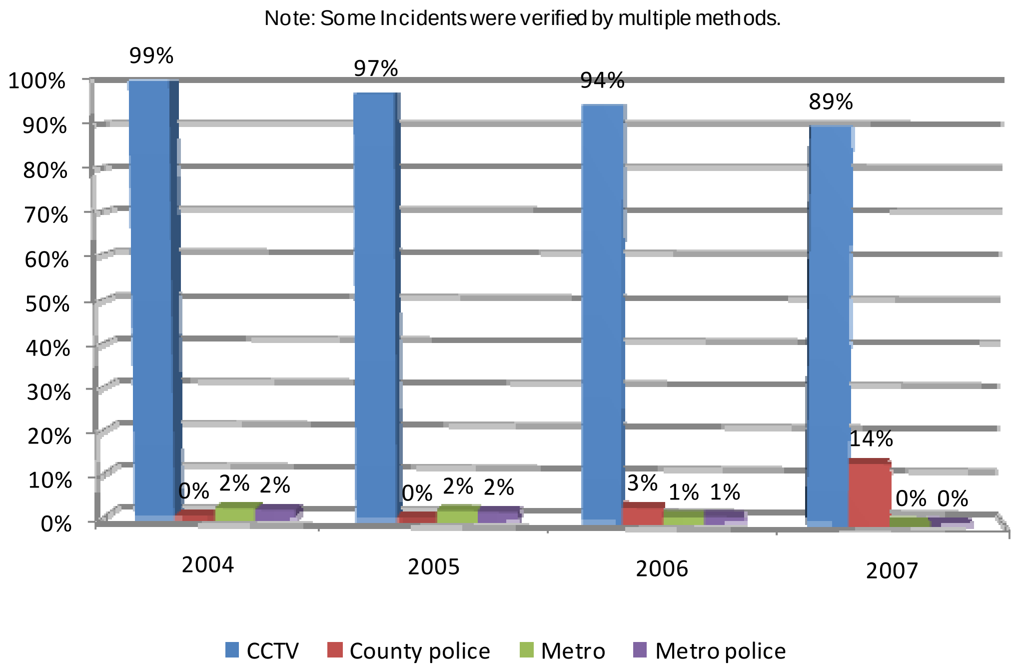


Figure B-8: Distribution of Verification Methods (Houston).

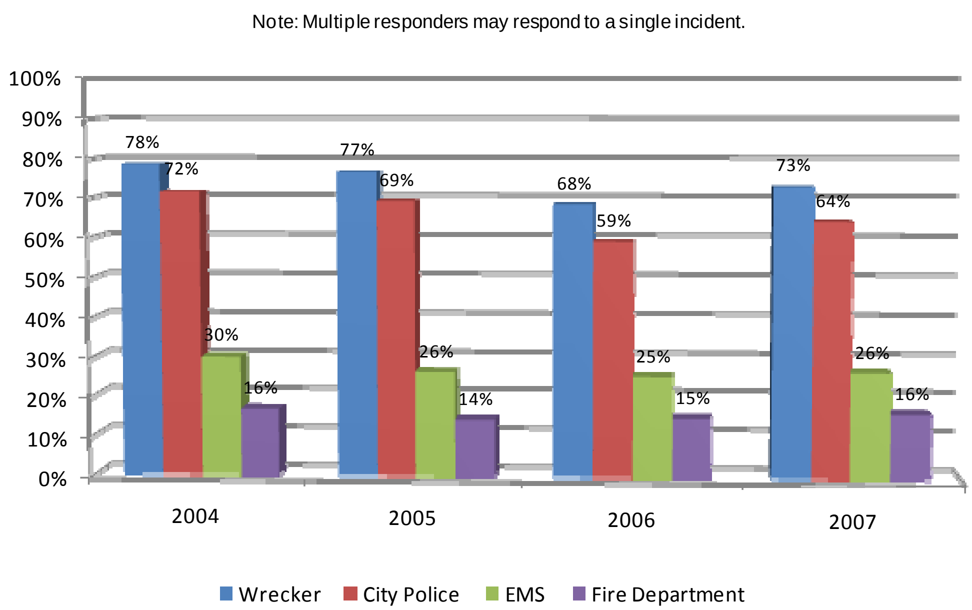


Figure B-9: Distribution of Incident Responders (Houston).

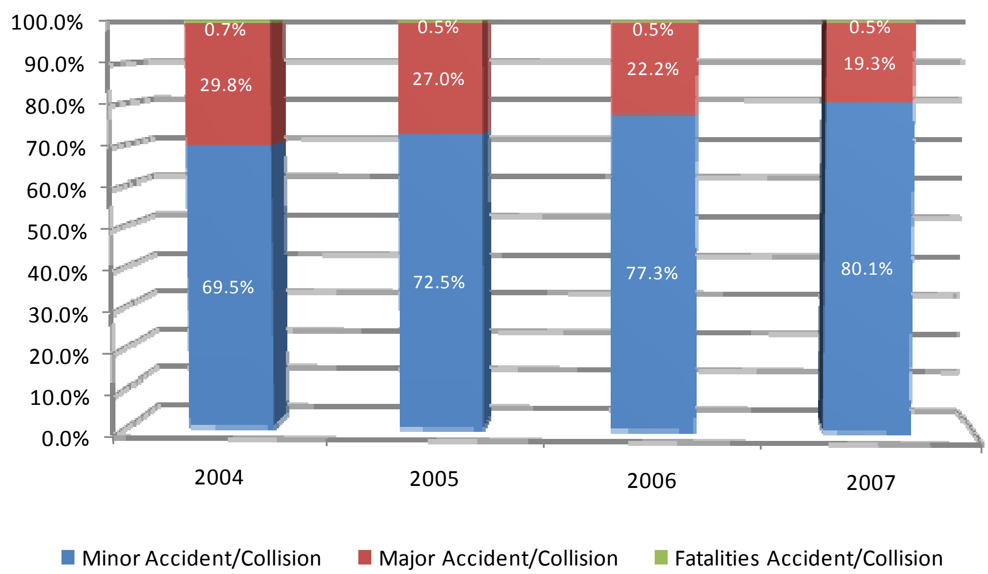


Figure B-10: Distribution of Incident Severity (Houston).

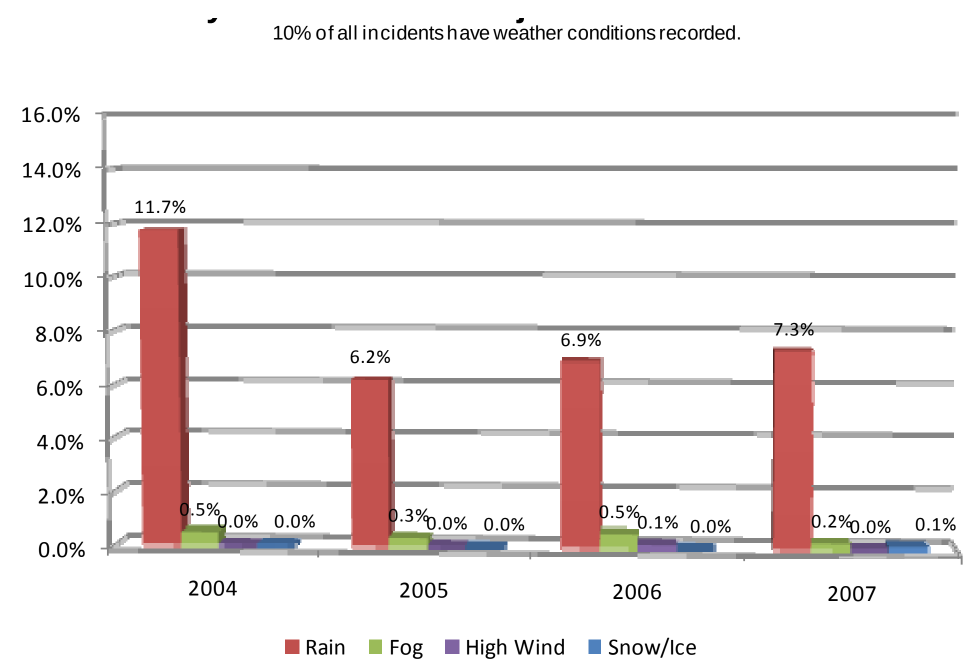


Figure B-11: Distribution of Recorded Weather Conditions (Houston).

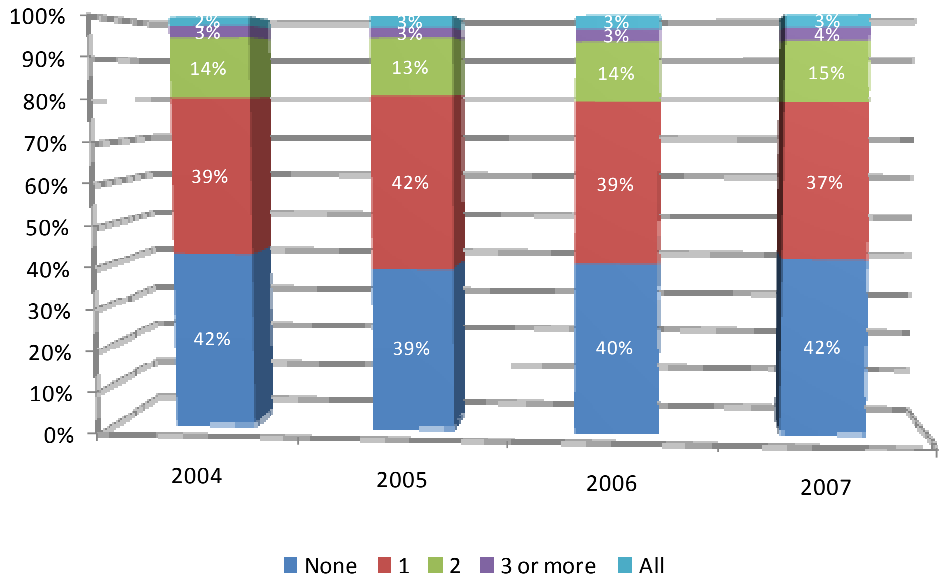


Figure B-12: Distribution of Number of Mainlanes Blocked (Houston).

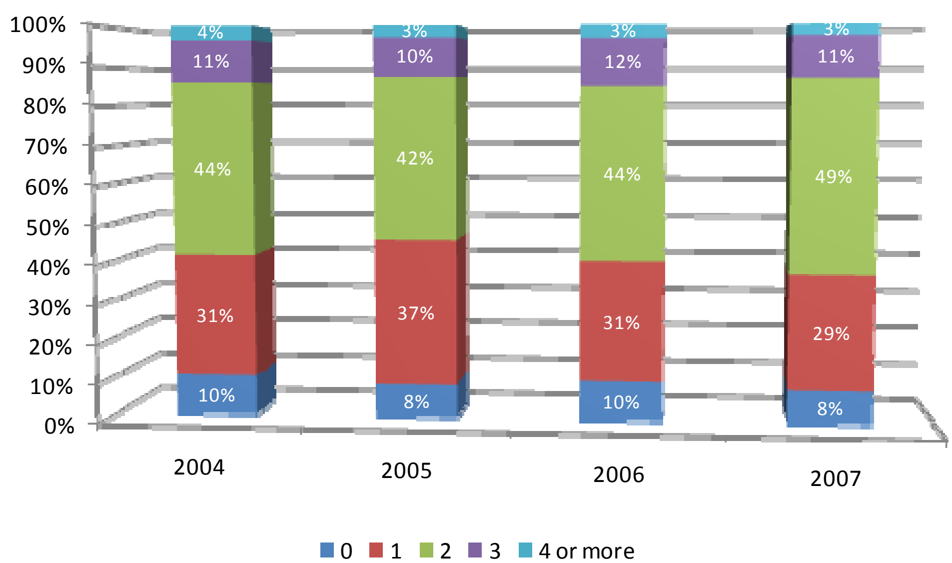


Figure B-13: Distribution of Number of Vehicles Involved (Houston).

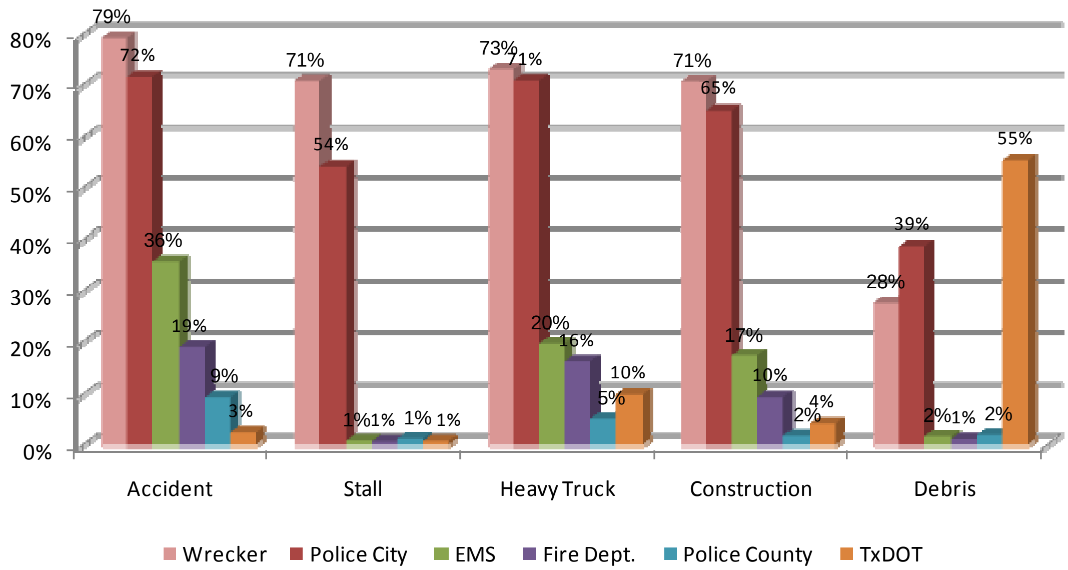


Figure B-14: Distribution of Major Responders by Incident Type (Houston).

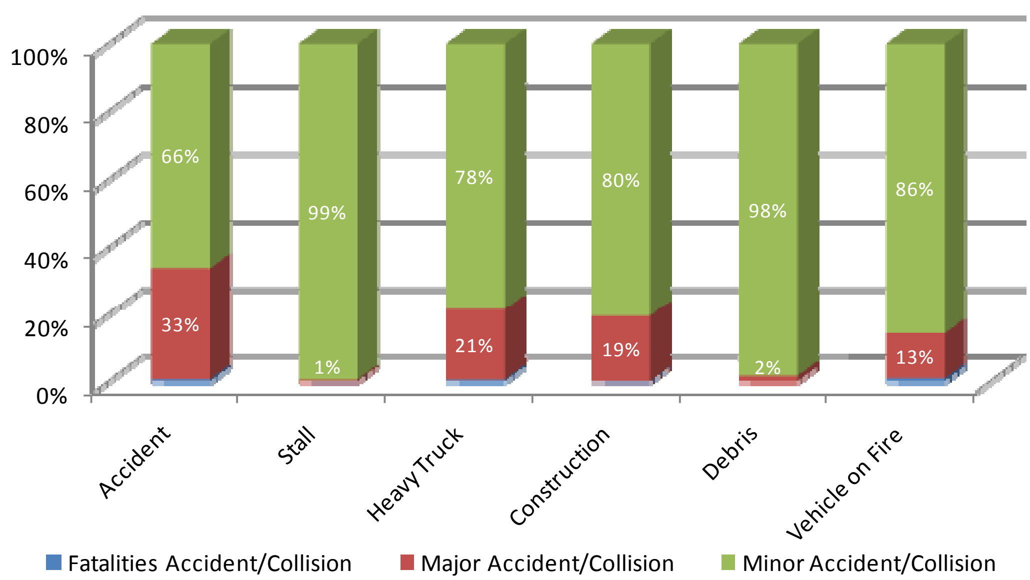


Figure B-15: Distribution of Severity by Incident Type (Houston).

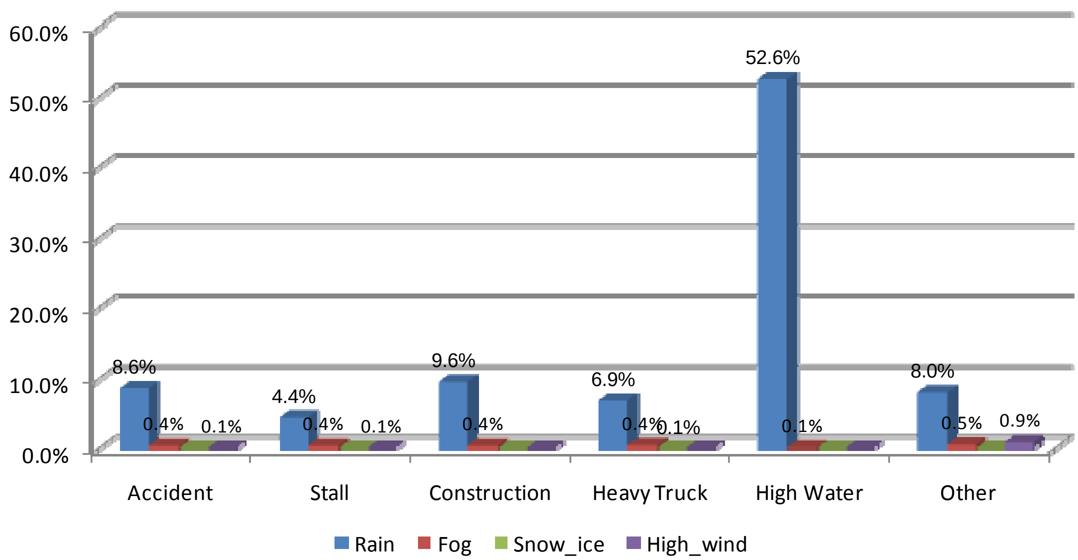


Figure B-16: Distribution of Weather Conditions by Incident Type (Houston).

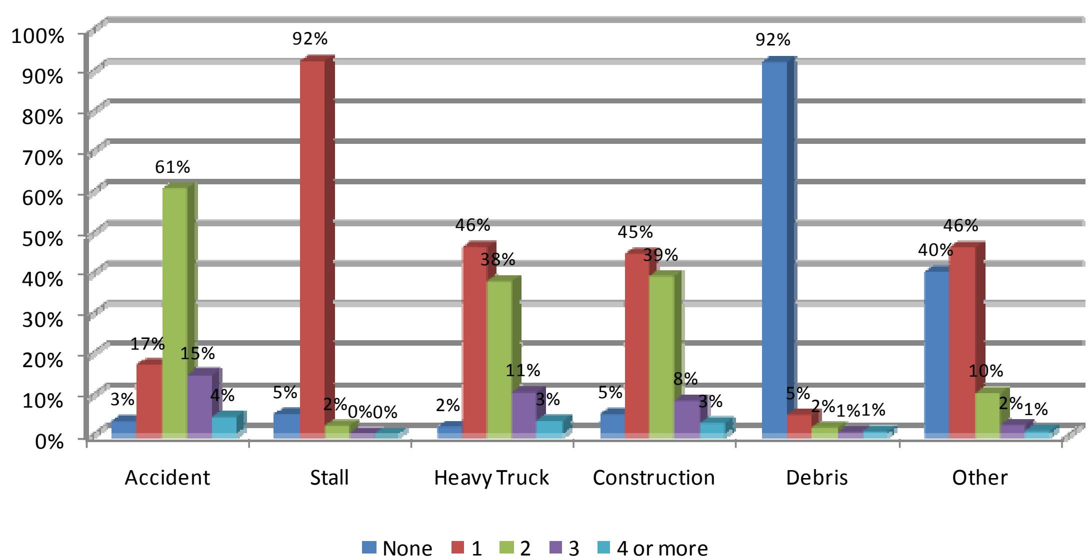


Figure B-17: Distribution of Vehicles Involved by Incident Type (Houston).

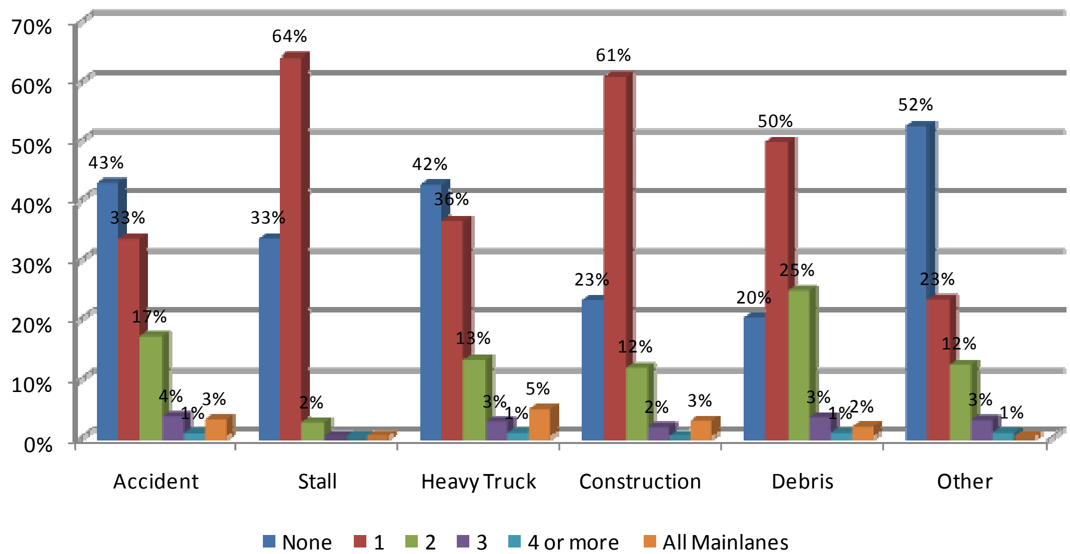


Figure B-18: Distribution of Lane Blockage by Incident Type (Houston).

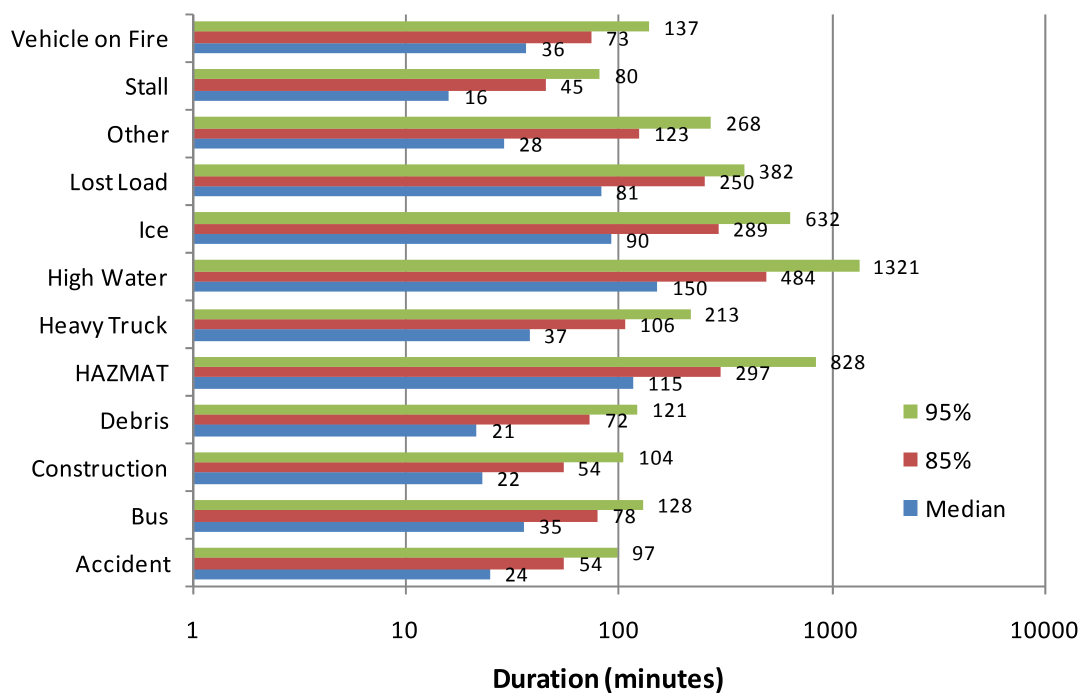


Figure B-19: Incident Duration Percentile Statistics (Houston: 2004–2007).

Hot Spot Analysis

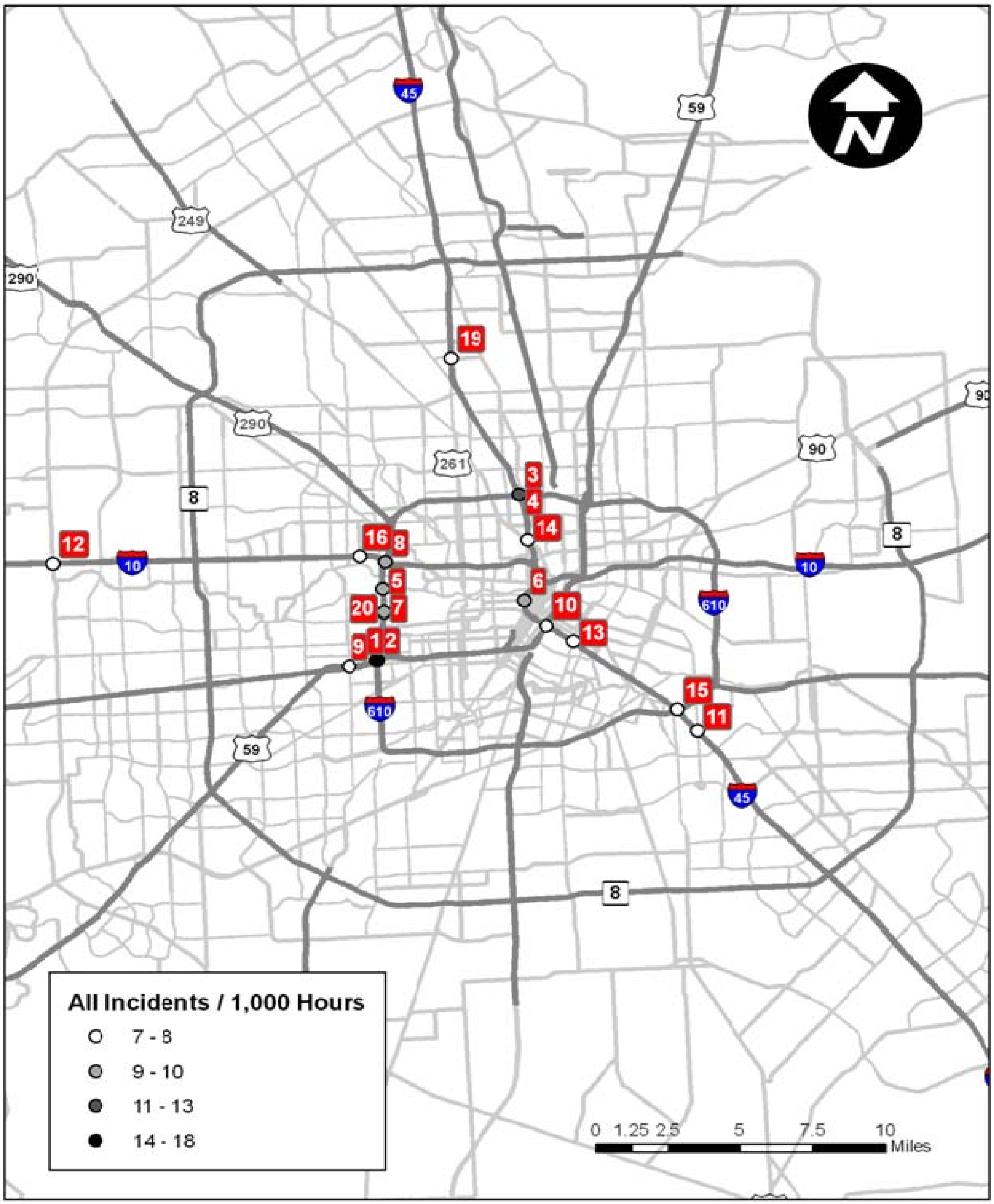


Figure B-20: Frequency-Based Hot Spots during All Times of Day.

Table B-4: Locations with Highest Incident Frequencies during All Times of Day.

Rank	Roadway	Cross Street	Direction	Total	Avg*
1	US-59 SOUTHWEST	IH-610 WEST LOOP	Northbound	643	18
2	IH-610 WEST LOOP	US-59 SOUTHWEST	Northbound	464	13
3	IH-45 NORTH	IH-610 NORTH LOOP	Southbound	406	12
4	IH-45 NORTH	IH-610 NORTH LOOP	Northbound	386	11
5	IH-610 WEST LOOP	WOODWAY DR	Northbound	347	10
6	IH-45 GULF	W DALLAS ST	Southbound	329	9
7	IH-610 WEST LOOP	POST OAK RD	Northbound	311	9
8	IH-10 KATY	IH-610 WEST LOOP	Westbound	308	9
9	US-59 SOUTHWEST	CHIMNEY ROCK RD	Northbound	296	8
10	IH-45 GULF	US-59 EASTEX	Northbound	291	8
11	IH-45 GULF	BROADWAY ST/PARK PLACE	Northbound	290	8
12	IH-10 KATY	SH-6	Eastbound	286	8
13	IH-45 GULF	SCOTT ST	Northbound	277	8
14	IH-45 NORTH	N MAIN ST	Northbound	275	8
15	IH-45 GULF	IH-610 SOUTH LOOP	Northbound	263	8
16	IH-10 KATY	SILBER RD	Westbound	263	8
17	IH-10 KATY	IH-610 WEST LOOP	Eastbound	256	7
18	US-59 SOUTHWEST	IH-610 WEST LOOP	Southbound	253	7
19	IH-45 NORTH	GULF BANK RD	Southbound	249	7
20	IH-610 WEST LOOP	POST OAK RD	Southbound	245	7

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

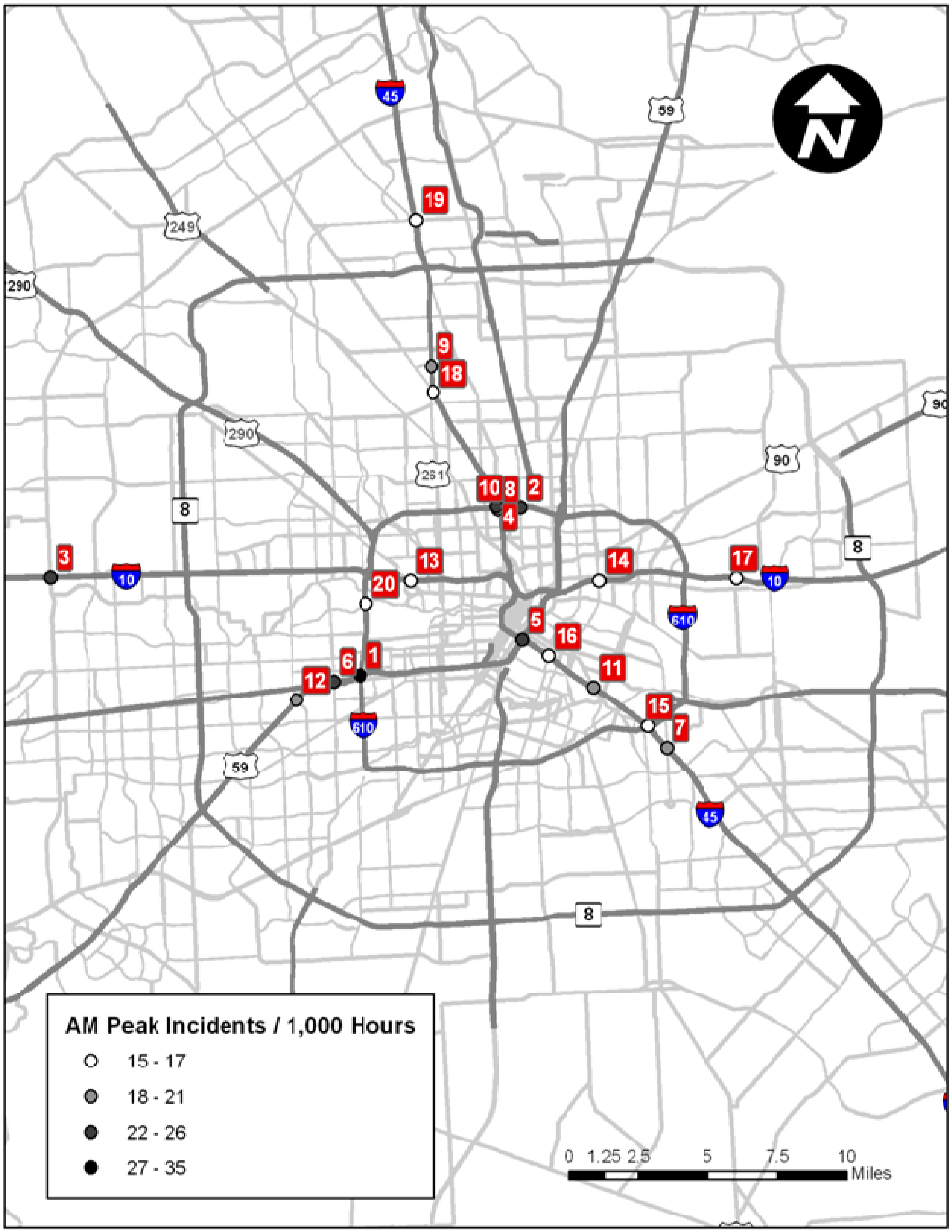


Figure B-21: Weekday AM Peak Frequency-Based Hot Spots.

Table B-5: Locations with Highest Incident Frequencies during AM Peak.

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).

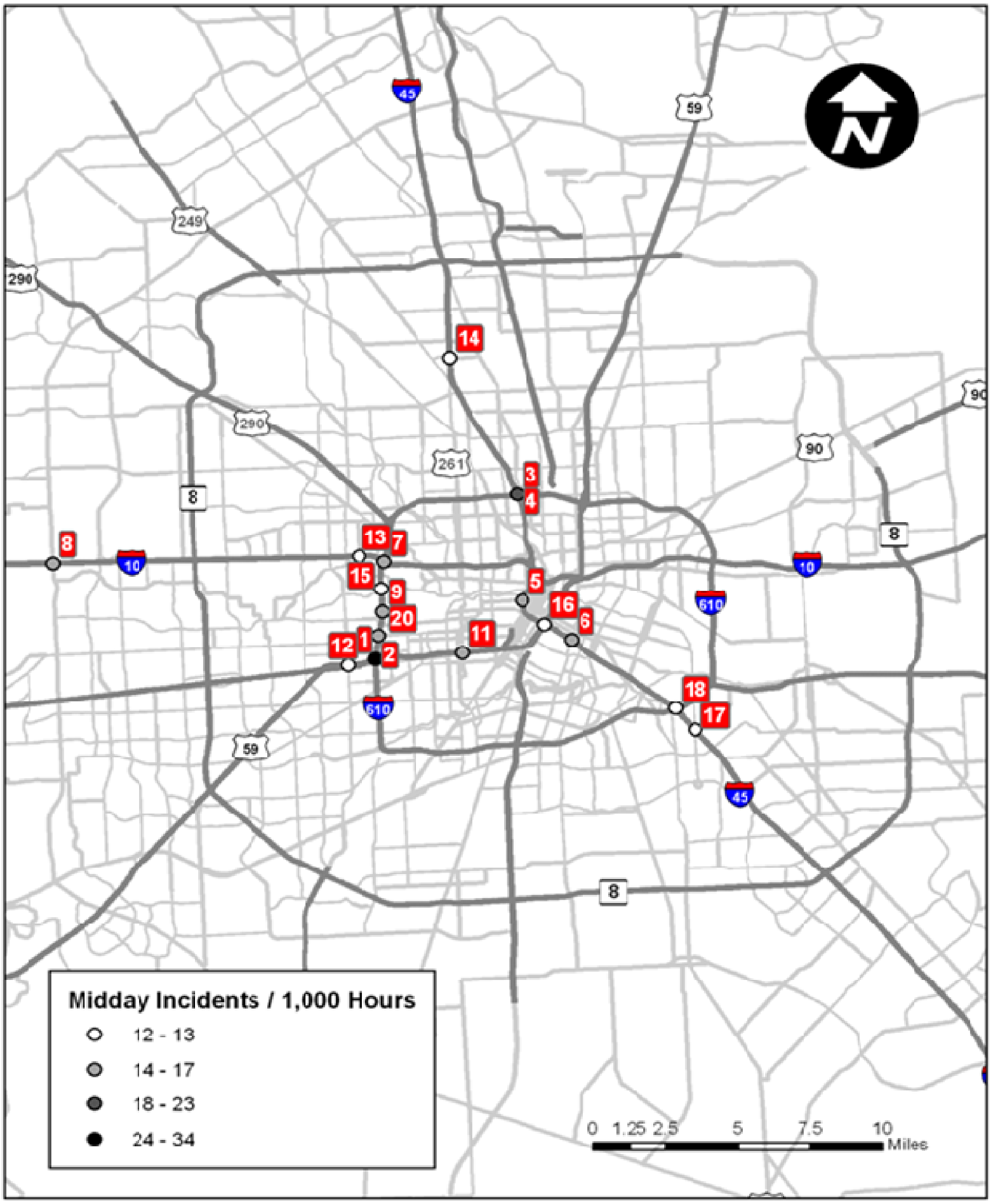


Figure B-22: Weekday Midday Frequency-Based Hot Spots.

Table B-6: Locations with Highest Incident Frequencies during Midday.

Rank	Roadway	Cross Street	Direction	Total	Avg*
1	US-59 SOUTHWEST	IH-610 WEST LOOP	Northbound	249	34
2	IH-610 WEST LOOP	US-59 SOUTHWEST	Northbound	166	23
3	IH-45 NORTH	IH-610 NORTH LOOP	Southbound	154	21
4	IH-45 NORTH	IH-610 NORTH LOOP	Northbound	150	21
5	IH-45 GULF	W DALLAS ST	Southbound	125	17
6	IH-45 GULF	SCOTT ST	Northbound	113	15
7	IH-10 KATY	IH-610 WEST LOOP	Westbound	110	15
8	IH-10 KATY	SH-6	Eastbound	108	15
9	IH-610 WEST LOOP	POST OAK RD	Northbound	108	15
10	IH-610 WEST LOOP	FM-1093/WESTHEIMER RD	Southbound	100	14
11	US-59 SOUTHWEST	SHEPHERD DR	Northbound	100	14
12	US-59 SOUTHWEST	CHIMNEY ROCK RD	Northbound	96	13
13	IH-10 KATY	SILBER RD	Westbound	95	13
14	IH-45 NORTH	GULF BANK RD	Southbound	95	13
15	IH-610 WEST LOOP	WOODWAY DR	Northbound	95	13
16	IH-45 GULF	US-59 EASTEX	Northbound	92	13
17	IH-45 GULF	BROADWAY ST/PARK PLACE	Northbound	90	12
18	IH-45 GULF	IH-610 SOUTH LOOP	Northbound	89	12
19	IH-10 KATY	IH-610 WEST LOOP	Eastbound	87	12
20	IH-610 WEST LOOP	POST OAK RD	Southbound	87	12

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

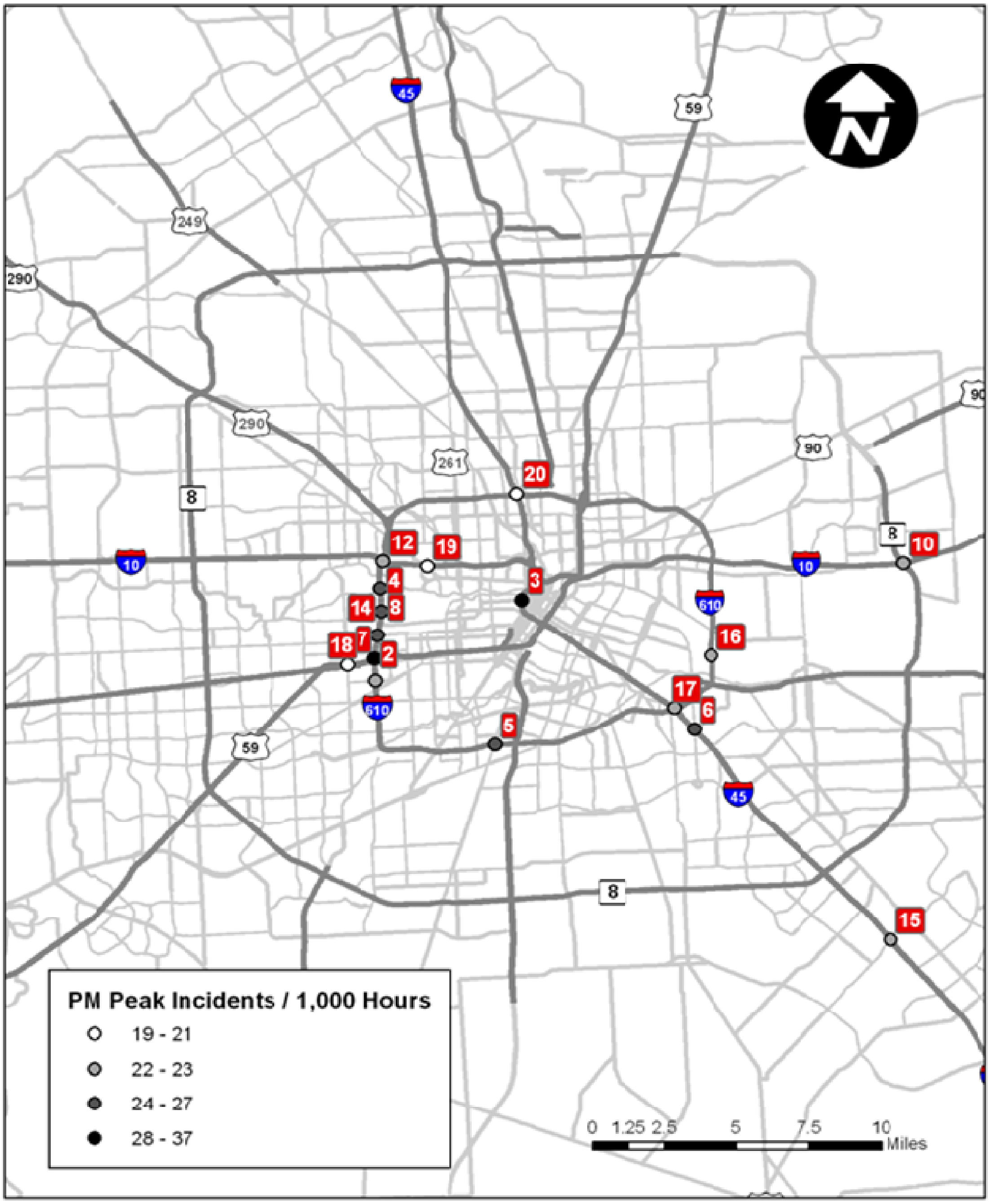


Figure B-23: Weekday PM Peak Frequency-Based Hot Spots.

Table B-7: Locations with Highest Incident Frequencies during PM Peak.

Rank	Roadway	Cross Street	Direction	Total	Avg*
1	US-59 SOUTHWEST	IH-610 WEST LOOP	Northbound	117	37
2	IH-610 WEST LOOP	US-59 SOUTHWEST	Northbound	110	35
3	IH-45 GULF	W DALLAS ST	Southbound	104	33
4	IH-610 WEST LOOP	WOODWAY DR	Northbound	84	27
5	IH-610 SOUTH LOOP	FM-521 ALMEDA RD	Eastbound	82	26
6	IH-45 GULF	BROADWAY ST/PARK PLACE	Southbound	79	25
7	US-59 SOUTHWEST	IH-610 WEST LOOP	Southbound	79	25
8	IH-610 WEST LOOP	POST OAK RD	Northbound	78	25
9	IH-610 WEST LOOP	FM-1093/WESTHEIMER RD	Southbound	77	25
10	IH-10 EAST	BELTWAY 8-EAST	Eastbound	73	23
11	IH-610 WEST LOOP	FM-1093/WESTHEIMER RD	Northbound	72	23
12	IH-10 KATY	IH-610 WEST LOOP	Westbound	71	23
13	IH-610 WEST LOOP	FOURNACE PL	Northbound	69	22
14	IH-610 WEST LOOP	POST OAK RD	Southbound	69	22
15	IH-45 GULF	FM-2351/CLEAR LAKE CITY BLVD	Southbound	68	22
16	IH-610 EAST LOOP	SHIP CHANNEL	Northbound	68	22
17	IH-610 SOUTH LOOP	IH-45 GULF	Eastbound	68	22
18	US-59 SOUTHWEST	CHIMNEY ROCK RD	Northbound	66	21
19	IH-10 KATY	WASHINGTON AVE/WESTCOTT ST	Westbound	64	20
20	IH-45 NORTH	IH-610 NORTH LOOP	Northbound	59	19

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

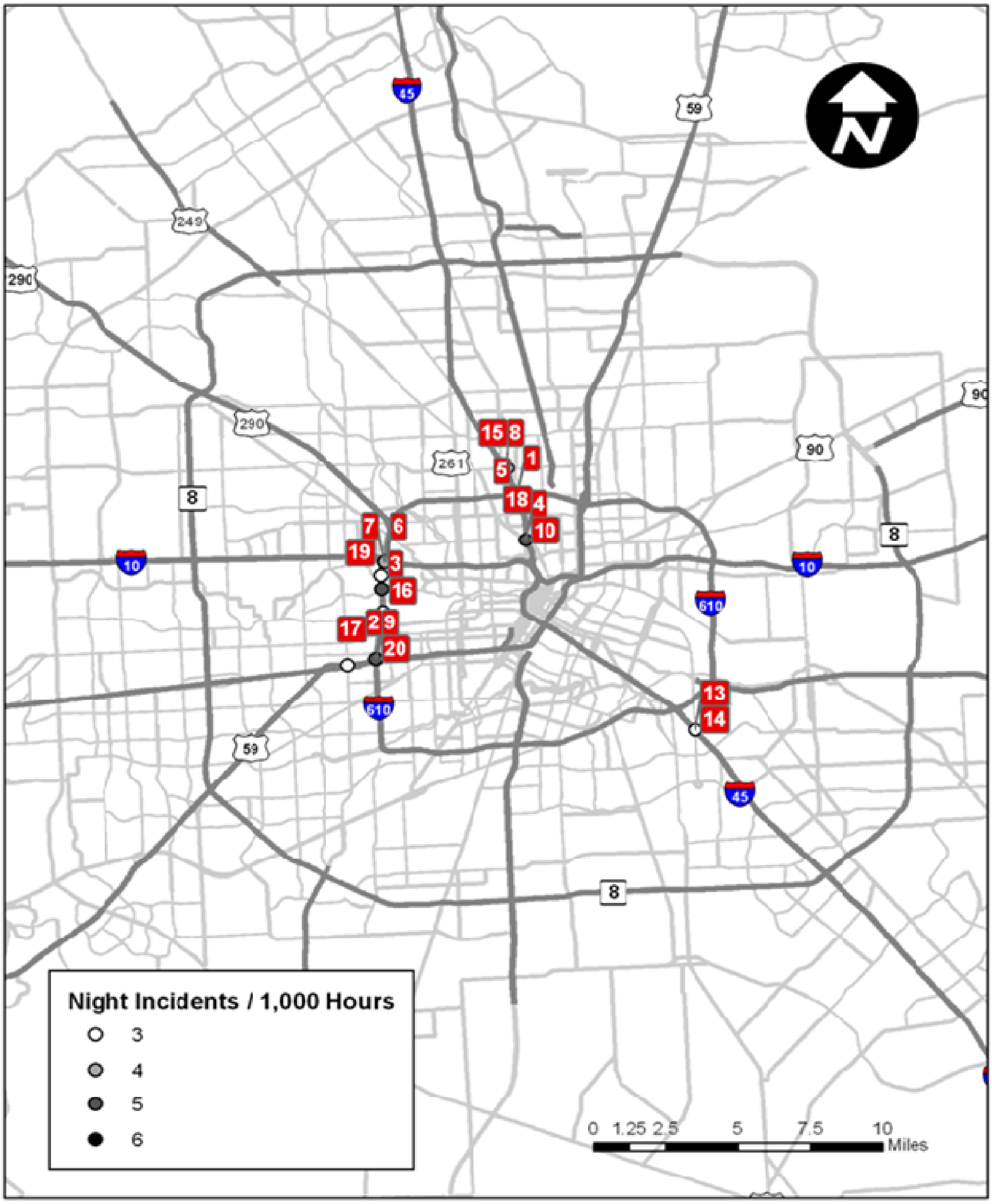


Figure B-24: Weekday Night Frequency-Based Hot Spots.

Table B-8: Locations with Highest Incident Frequencies during Nighttime.

Rank	Roadway	Cross Street	Direction	Total	Avg*
1	IH-45 NORTH	IH-610 NORTH LOOP	Southbound	68	6
2	US-59 SOUTHWEST	IH-610 WEST LOOP	Northbound	59	5
3	IH-610 WEST LOOP	WOODWAY DR	Northbound	58	5
4	IH-45 NORTH	N MAIN ST	Northbound	55	5
5	IH-45 NORTH	IH-610 NORTH LOOP	Northbound	49	4
6	IH-610 WEST LOOP	IH-10 KATY	Northbound	48	4
7	IH-10 KATY	IH-610 WEST LOOP	Westbound	47	4
8	IH-45 NORTH	CROSSTIMBERS ST	Northbound	47	4
9	US-59 SOUTHWEST	IH-610 WEST LOOP	Southbound	46	4
10	IH-45 NORTH	N MAIN ST	Southbound	45	4
11	IH-610 WEST LOOP	US-59 SOUTHWEST	Northbound	45	4
12	IH-10 KATY	IH-610 WEST LOOP	Eastbound	42	4
13	IH-45 GULF	BROADWAY ST/PARK PLACE	Southbound	40	3
14	IH-45 GULF	BROADWAY ST/PARK PLACE	Northbound	38	3
15	IH-45 NORTH	CROSSTIMBERS ST	Southbound	38	3
16	IH-610 WEST LOOP	POST OAK RD	Northbound	38	3
17	US-59 SOUTHWEST	CHIMNEY ROCK RD	Northbound	37	3
18	IH-610 NORTH LOOP	IH-45 NORTH	Westbound	35	3
19	IH-610 WEST LOOP	MEMORIAL DR	Northbound	35	3
20	IH-610 WEST LOOP	US-59 SOUTHWEST	Southbound	35	3

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

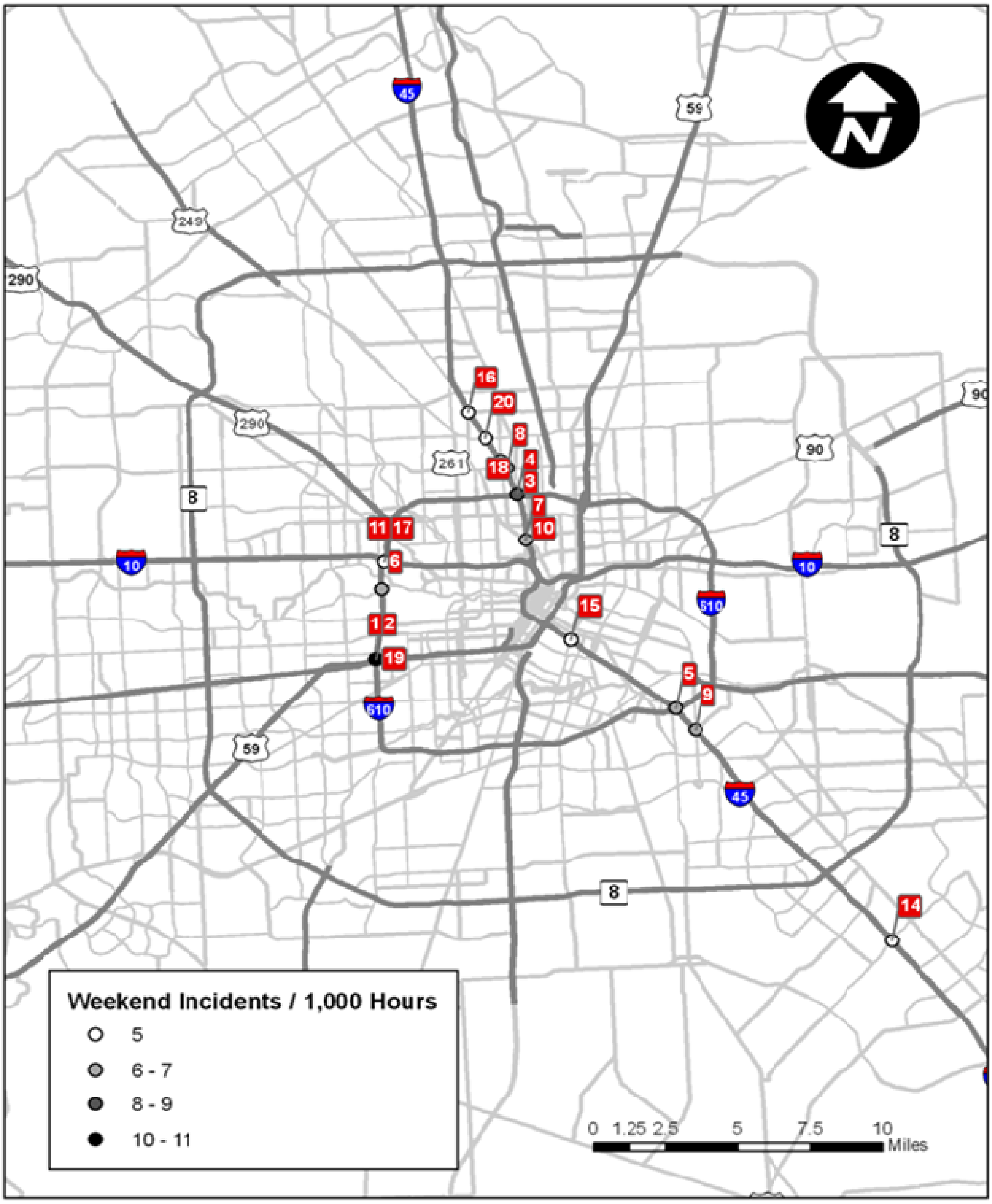


Figure B-25: Weekend Frequency-Based Hot Spots.

Table B-9: Locations with Highest Incident Frequencies during Weekend.

Rank	Roadway	Cross Street	Direction	Total	Avg*
1	US-59 SOUTHWEST	IH-610 WEST LOOP	Northbound	107	11
2	IH-610 WEST LOOP	US-59 SOUTHWEST	Northbound	98	10
3	IH-45 NORTH	IH-610 NORTH LOOP	Northbound	91	9
4	IH-45 NORTH	IH-610 NORTH LOOP	Southbound	76	8
5	IH-45 GULF	IH-610 SOUTH LOOP	Northbound	68	7
6	IH-610 WEST LOOP	WOODWAY DR	Northbound	64	6
7	IH-45 NORTH	N MAIN ST	Northbound	60	6
8	IH-45 NORTH	CROSSTIMBERS ST	Southbound	60	6
9	IH-45 GULF	BROADWAY ST/PARK PLACE	Northbound	58	6
10	IH-45 NORTH	N MAIN ST	Southbound	58	6
11	IH-10 KATY	IH-610 WEST LOOP	Eastbound	55	5
12	IH-45 NORTH	AIRLINE DR	Northbound	55	5
13	IH-45 NORTH	AIRLINE DR	Southbound	53	5
14	IH-45 GULF	FM-2351/CLEAR LAKE CITY BLVD	Southbound	51	5
15	IH-45 GULF	SCOTT ST	Northbound	51	5
16	IH-45 NORTH	PARKER RD	Northbound	51	5
17	IH-10 KATY	IH-610 WEST LOOP	Westbound	49	5
18	IH-45 NORTH	CROSSTIMBERS ST	Northbound	49	5
19	US-59 SOUTHWEST	IH-610 WEST LOOP	Southbound	48	5
20	IH-45 NORTH	TIDWELL RD	Southbound	47	5

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

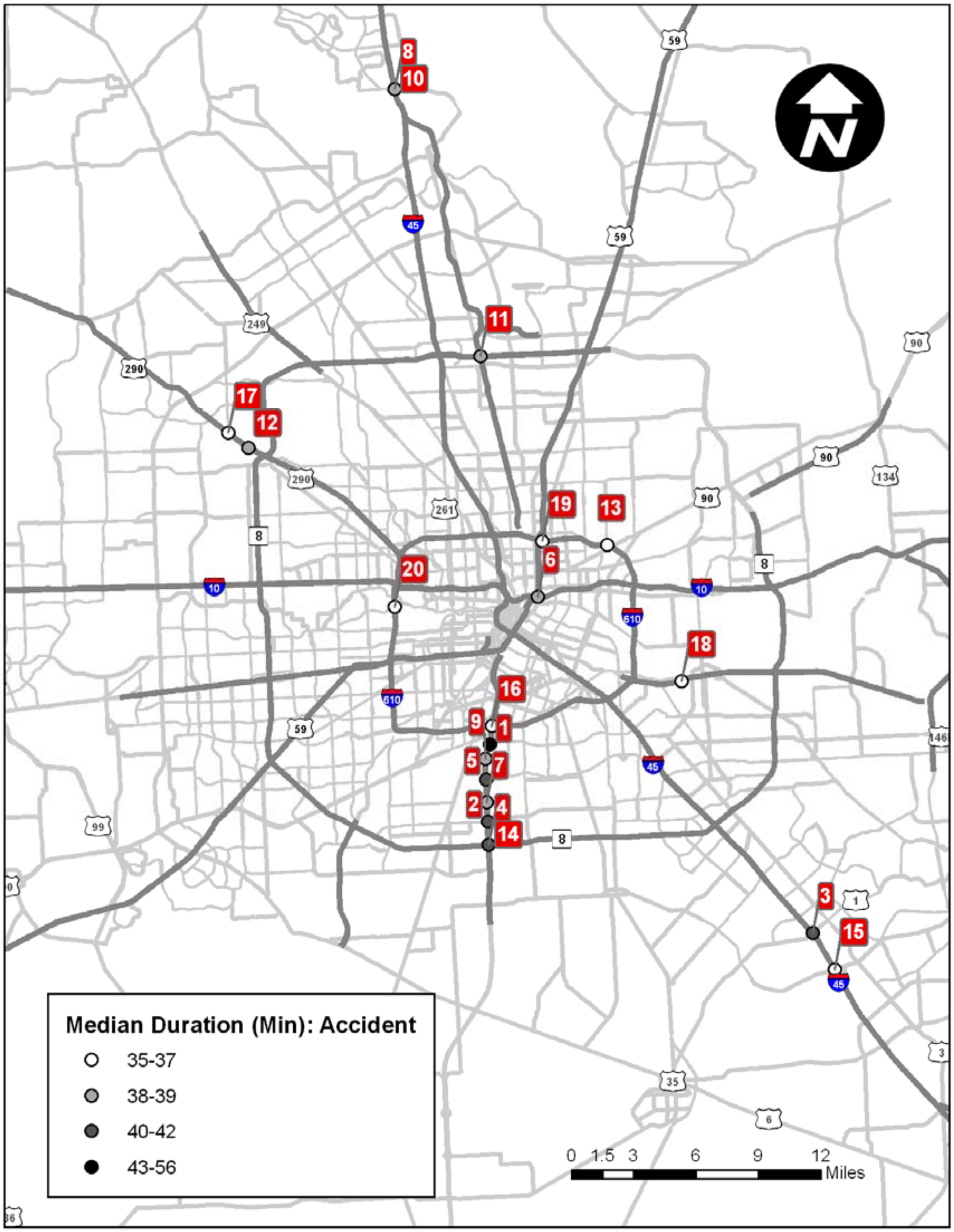


Figure B-26: Median-Durations Based Accident Hot Spots.

Table B-10: Accident Locations with Highest Median Duration.

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

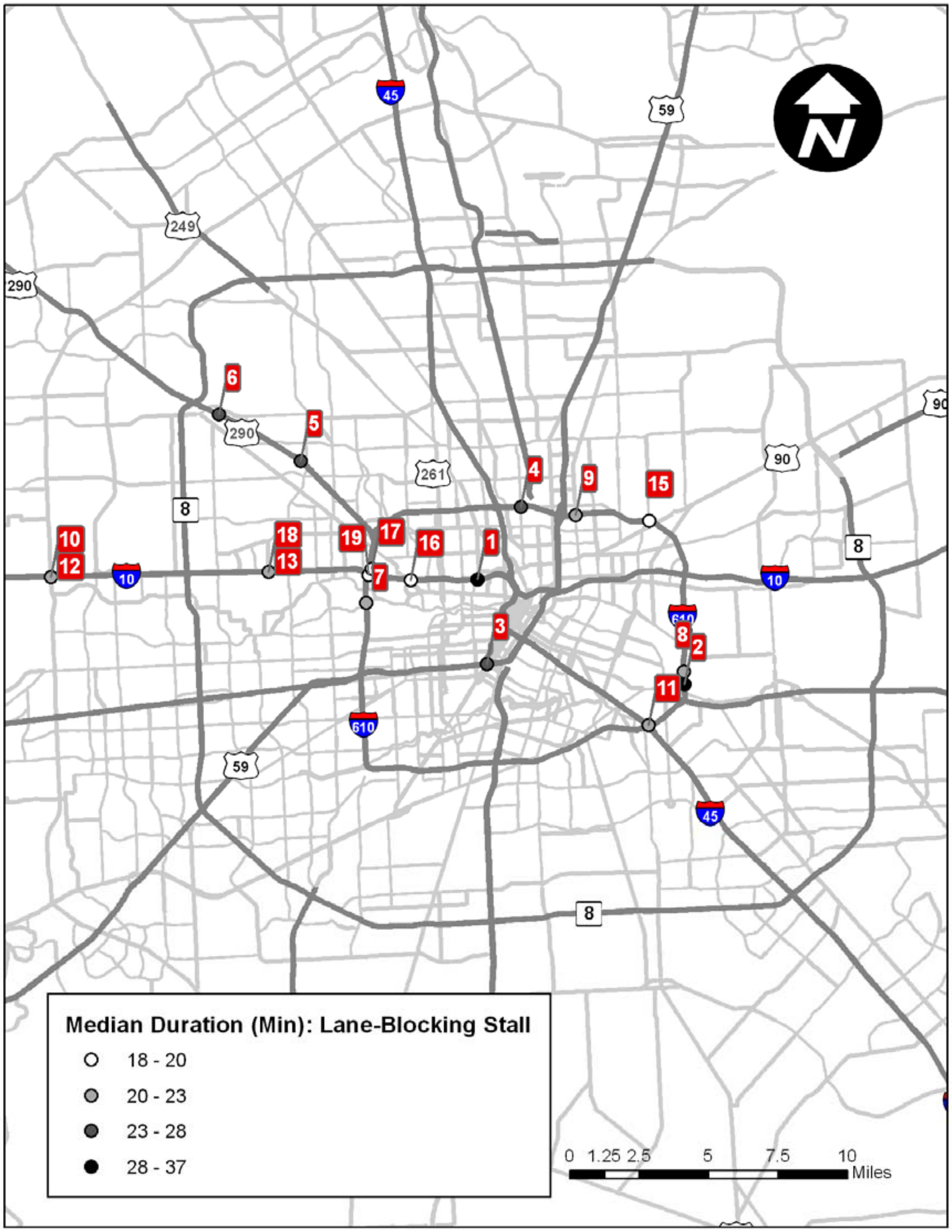


Figure B-27: Median-Durations Based Lane-Blocking Stall Hot Spots.

Table B-11: Lane-Blocking Stall Locations with Highest Median Duration.

Rank	Roadway	Cross Street	Direction	Median Duration (min)	# of Incidents
1	IH-610 EAST LOOP	MANCHESTER ST	Northbound	36.7	51
2	IH-10 KATY	STUDEMONT ST	Eastbound	35.2	16
3	IH-610 NORTH LOOP	IRVINGTON BLVD	Eastbound	35.2	14
4	IH-610 NORTH LOOP	WAYSIDE DR	Westbound	34.8	13
5	IH-10 KATY	CAMPBELL RD	Eastbound	34.2	17
6	IH-610 SOUTH LOOP	IH-45 GULF	Eastbound	32.2	35
7	IH-10 KATY	SH-6	Eastbound	31.5	55
8	IH-610 WEST LOOP	OLD KATY RD	Northbound	29.6	15
9	IH-610 EAST LOOP	SHIP CHANNEL	Northbound	28.4	96
10	IH-10 KATY	CAMPBELL RD	Westbound	27.5	13
11	US-59 SOUTHWEST	MAIN	Northbound	26.3	36
12	US-290 NORTHWEST	PINEMONT DR	Westbound	25.7	16
13	IH-45	GALVESTON CAUSEWAY BRIDGE	Southbound	25.7	20
14	IH-610 WEST LOOP	WOODWAY DR	Southbound	24.8	48
15	IH-610 EAST LOOP	TURNING BASIN DR	Northbound	24.4	54
16	US-290 NORTHWEST	GESSNER RD	Eastbound	24.1	19
17	IH-10 KATY	WASHINGTON AVE/WESTCOTT ST	Westbound	23.4	41
18	IH-10 KATY	SH-6	Westbound	23.0	27
19	IH-610 NORTH LOOP	HIRSCH RD	Westbound	22.7	13
20	IH-10 KATY	IH-610 WEST LOOP	Westbound	22.4	54

Duration < 1 Day; Frequency >= 1.5 Accidents per Year (50% of All Locations)
Getis-Ord (Gi*) Spatial Statistics: Log Duration; 30-feet Zone of Indifference Clustering; 1-mi Buffer

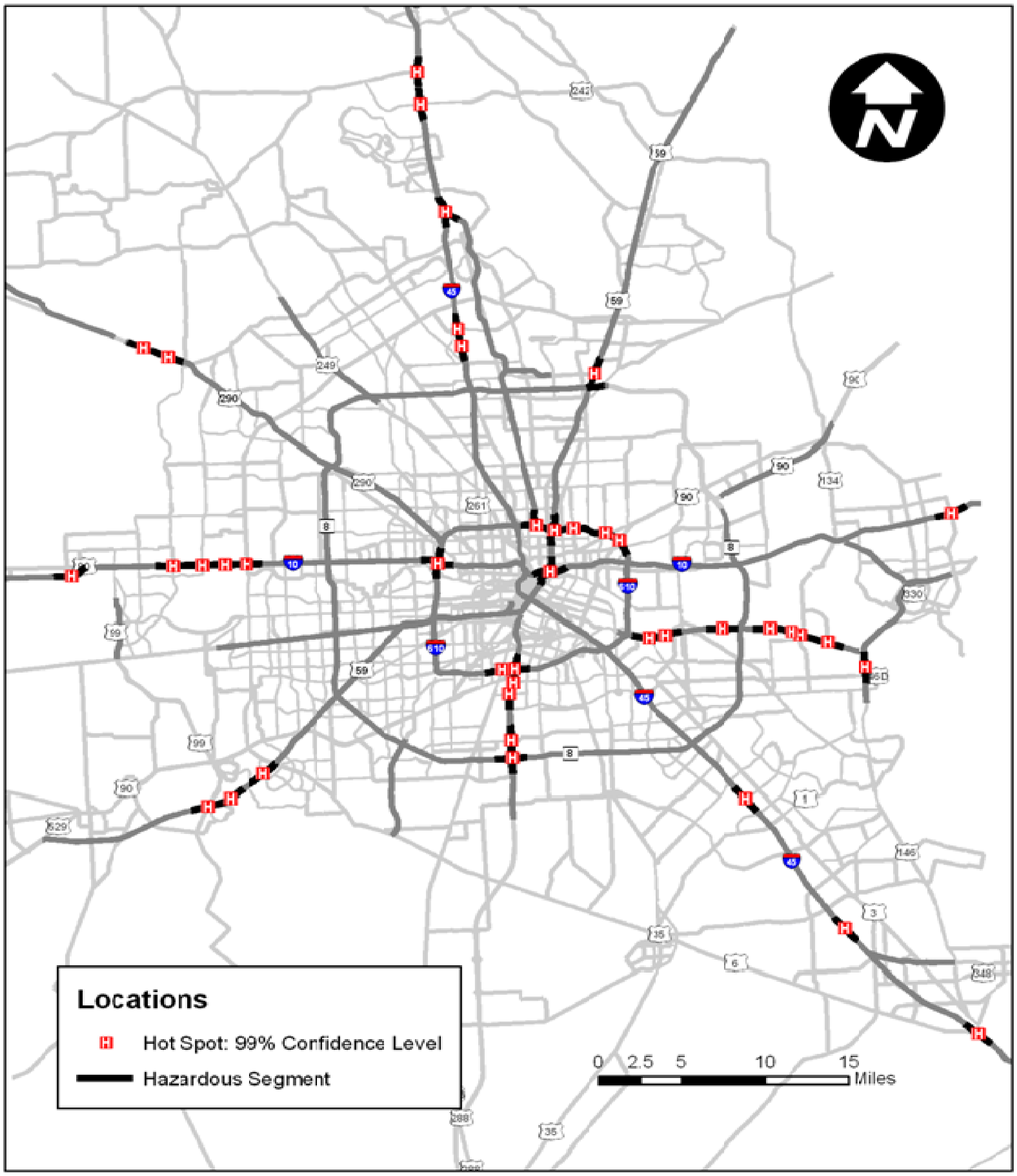


Figure B-28: Accident Hot Spots Using Gi* Spatial Statistics.

Table B-12: Partial List of Unique Accident Locations Using Gi* Spatial Statistics.

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

Duration < 1 Day; Frequency >=1.25 Lane-Blocking Stalls per Year (50% of All Locations)
Getis-Ord (Gi*) Spatial Statistics: Log Duration; 30-feet Zone of Indifference Clustering; 0.5-mi Buffer

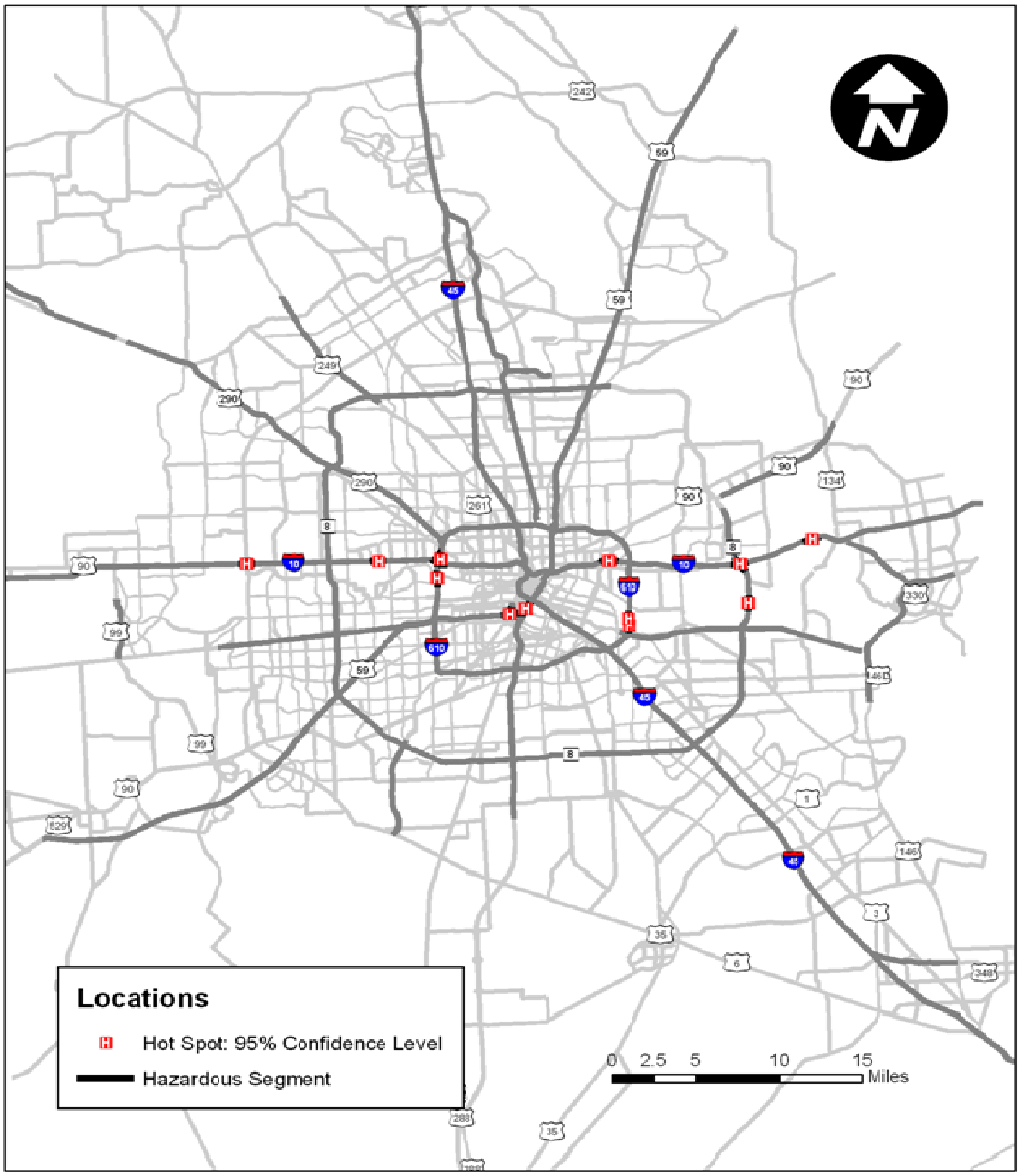
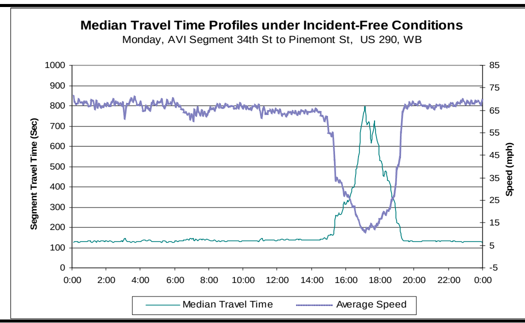
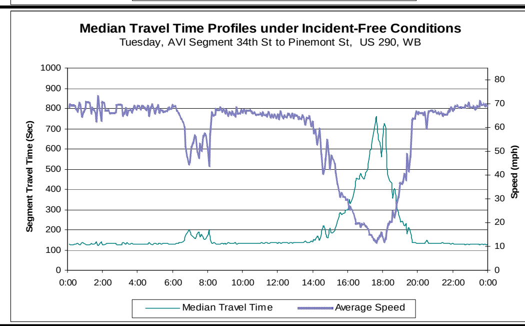
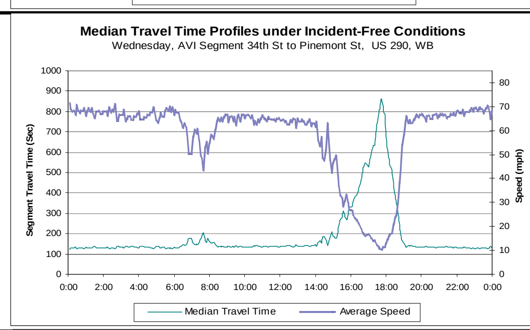
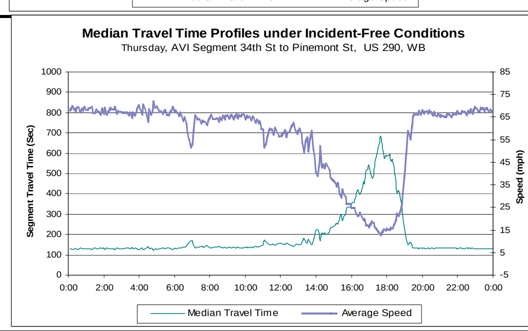


Figure B-29: Lane-Blocking Stall Hot Spots Using Gi* Spatial Statistics.

Table B-13: Lane-Blocking Stall Locations Using Gi* Spatial Statistics.

Rank	Roadway	Cross Street	Direction	Gi* Score
1	IH-610 EAST LOOP	SHIP CHANNEL	Southbound	4.17
2	IH-610 EAST LOOP	SHIP CHANNEL	Northbound	4.17
3	IH-610 EAST LOOP	MANCHESTER ST	Northbound	3.60
4	IH-610 EAST LOOP	MANCHESTER ST	Southbound	3.60
5	IH-10 KATY	SH-6	Eastbound	3.21
6	IH-10 KATY	SH-6	Westbound	3.21
7	IH-10 EAST	MC CARTY ST/US-90 ALTERNATE	Westbound	2.57
8	IH-10 EAST	MC CARTY ST/US-90 ALTERNATE	Eastbound	2.57
9	IH-610 WEST LOOP	WOODWAY DR	Northbound	2.56
10	IH-610 WEST LOOP	WOODWAY DR	Southbound	2.56
11	IH-610 WEST LOOP	OLD KATY RD	Southbound	2.38
12	IH-610 WEST LOOP	OLD KATY RD	Northbound	2.38
13	IH-10 KATY	CAMPBELL RD	Eastbound	2.37
14	IH-10 KATY	CAMPBELL RD	Westbound	2.37
15	US-59 SOUTHWEST	MAIN	Northbound	2.37
16	US-59 SOUTHWEST	MAIN	Southbound	2.37
17	IH-10 EAST	BELTWAY 8-EAST	Eastbound	2.32
18	IH-10 EAST	BELTWAY 8-EAST	Westbound	2.32
19	IH-10 EAST	MONMOUTH DR	Eastbound	2.32
20	SH-288	IH-45 GULF	Northbound	2.23
21	EAST SAM HOUSTON TOLLWAY	SHIP CHANNEL/TOLL BRIDGE	Northbound	2.15

Incident Impact Analysis

Day of Week	Date	Presence of Incidents*	Median Travel Time Profiles
Monday	06/18/2007	No	
	06/25/2007	Yes	
	07/09/2007	No	
	07/16/2007	No	
	07/23/2007	Yes	
	08/06/2007	Yes	
	08/13/2007	No	
	08/20/2007	No	
Tuesday	02/06/2007	Yes	
	02/13/2007	Yes	
	02/20/2007	No	
	04/03/2007	No	
	04/10/2007	Yes	
	04/24/2007	No	
Wednesday	02/07/2007	Yes	
	02/14/2007	No	
	02/21/2007	Yes	
	04/04/2007	Yes	
	04/11/2007	No	
	04/25/2007	No	
Thursday	06/21/2007	No	
	06/28/2007	No	
	07/12/2007	No	
	07/19/2007	No	
	07/26/2007	No	
	08/09/2007	No	
	08/16/2007	Yes	
	08/23/2007	No	

Note: * As recorded at the following cross streets: 34th, 43rd, Antoine

Figure B-30: Background Profiles (Mondays–Thursdays).

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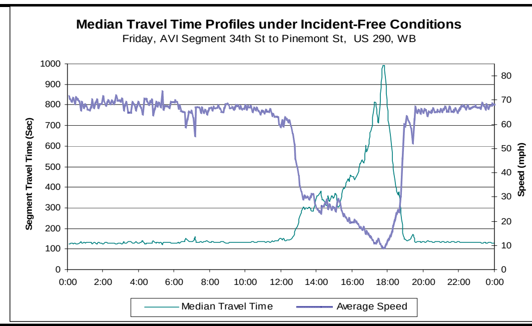
<tr><th>Day of Week</th><th>Date</th><th>Presence of Incidents*</th><th>Median Travel Time Profiles</th></tr>
<tr><td rowspan="6">Friday</td><td>02/09/2007</td><td>No</td><td rowspan="6">
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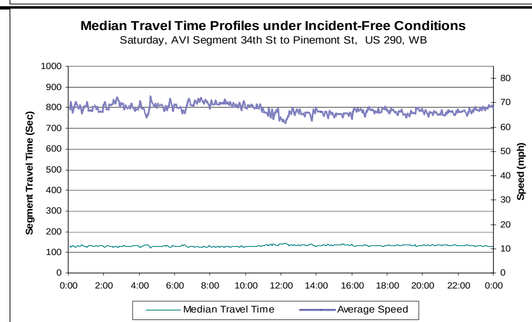
<tr><td rowspan="6">Saturday</td><td>02/10/2007</td><td>No</td><td rowspan="6">
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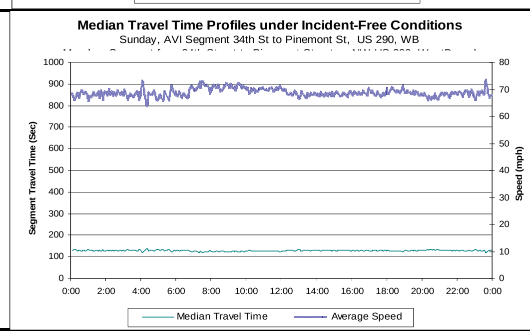
<tr><td rowspan="6">Sunday</td><td>08/05/2007</td><td>No</td><td rowspan="6">
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Note: * As recorded at the following cross streets: 34th, 43rd, Antoine

Figure B-31: Background Profiles (Fridays–Sundays).

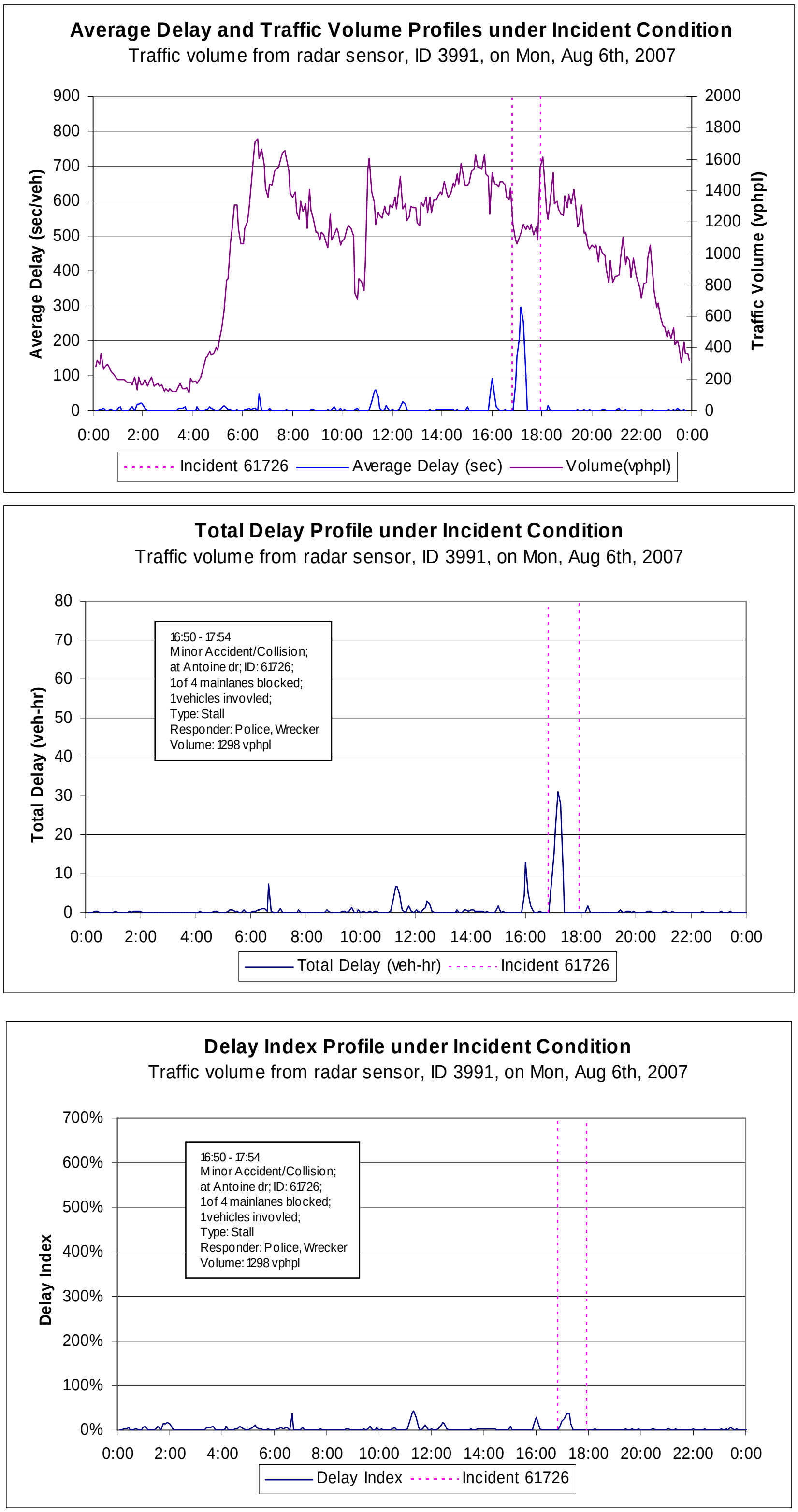


Figure B-32: Incident Impact Analysis for Incident ID 61726.

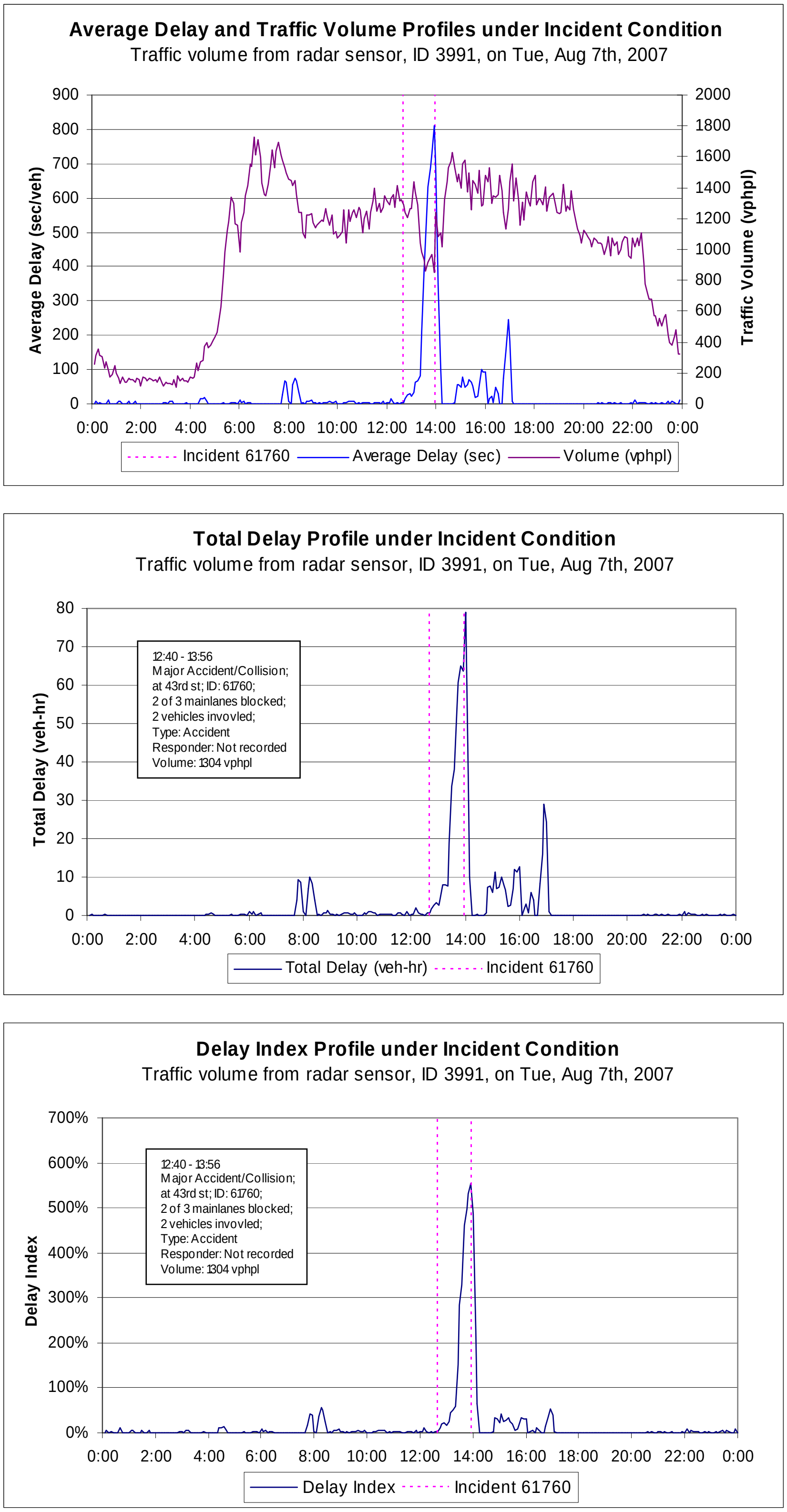
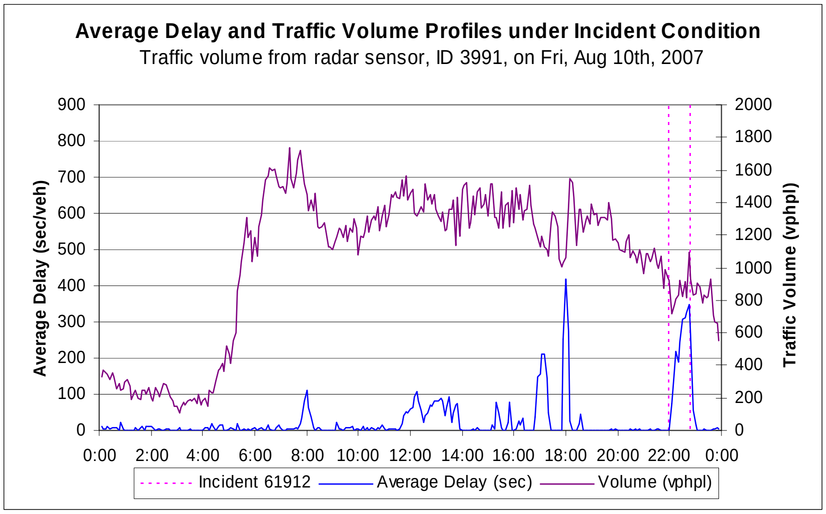
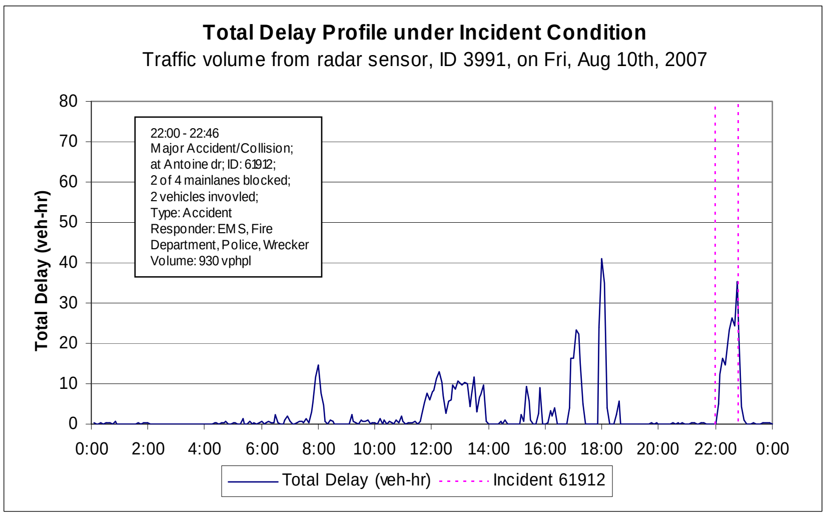


Figure B-33: Incident Impact Analysis for Incident ID 61760.





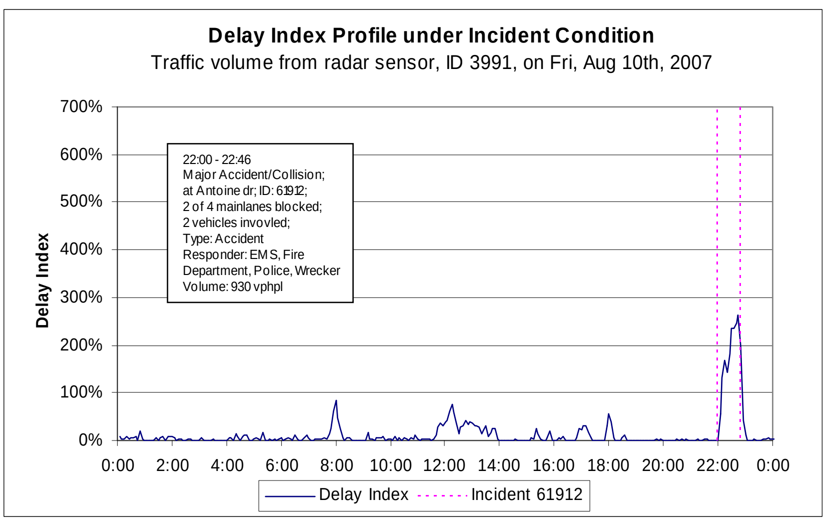
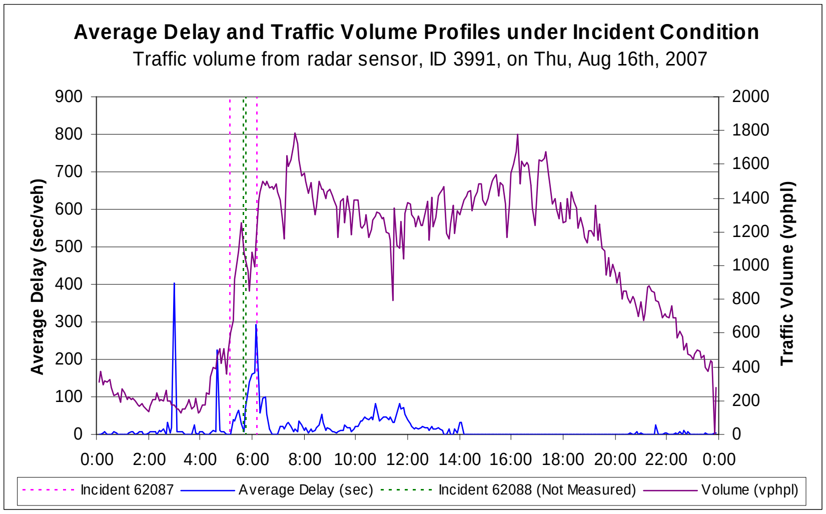
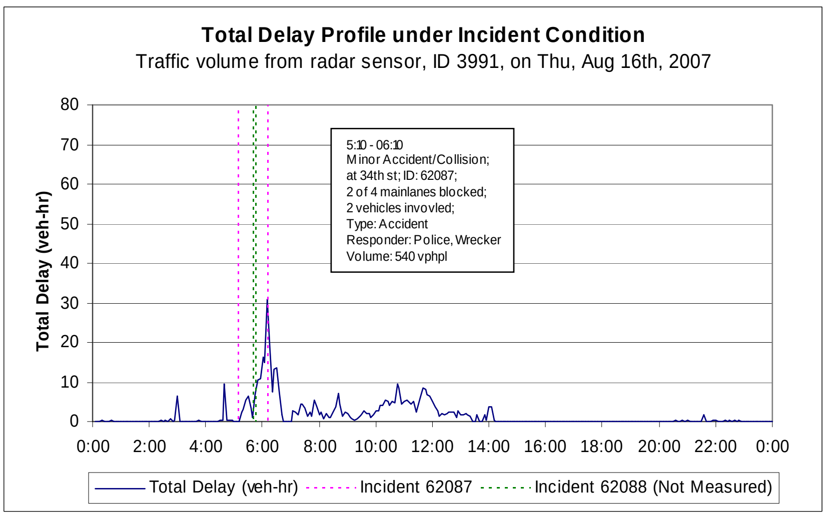


Figure B-34: Incident Impact Analysis for Incident ID 61912.





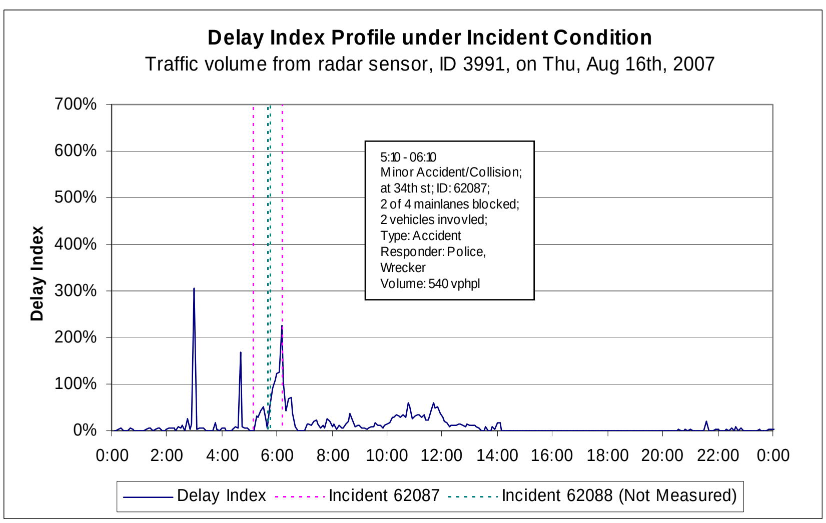


Figure B-35: Incident Impact Analysis for Incident ID 62087.

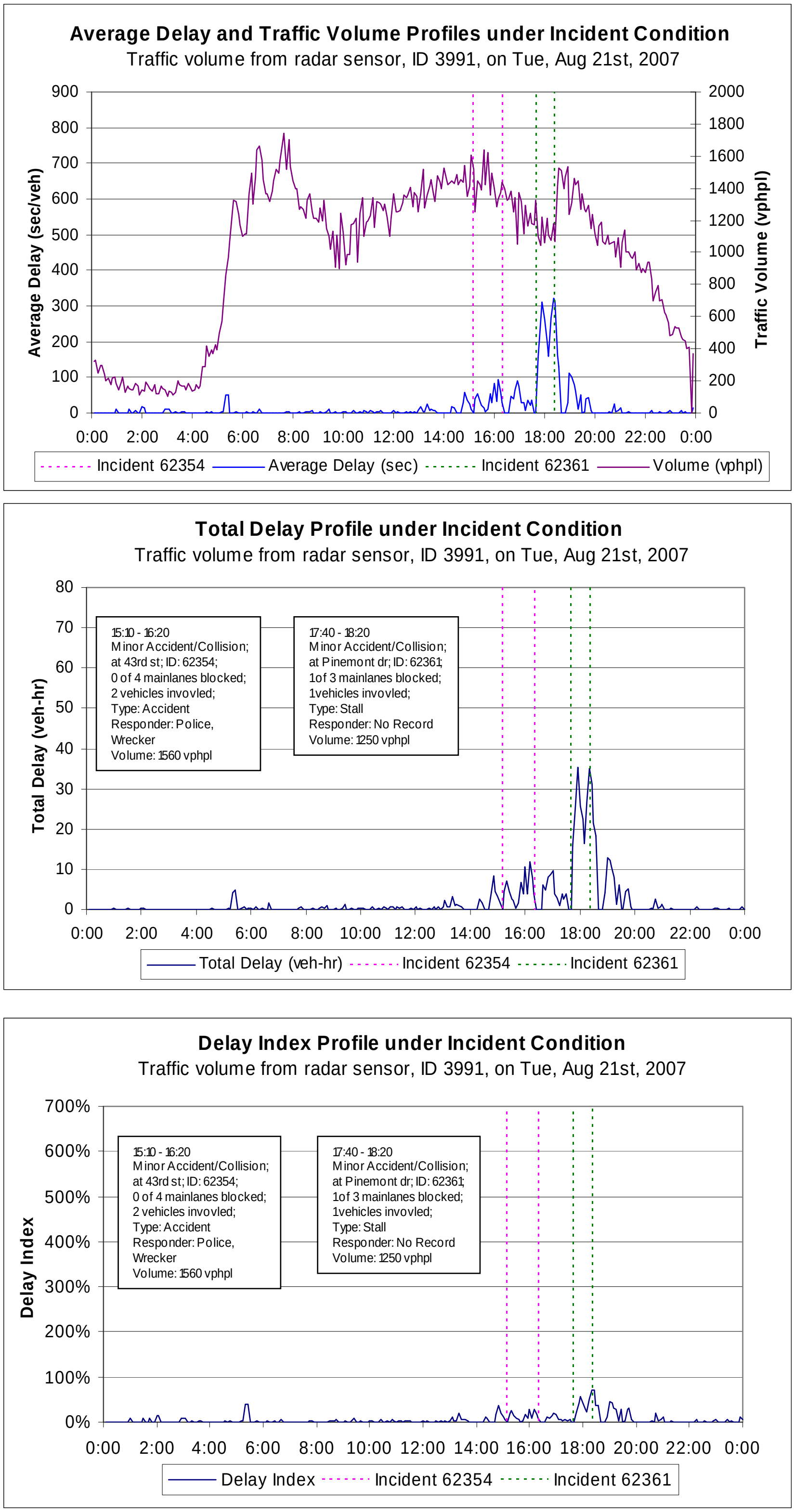


Figure B-36: Incident Impact Analysis for Incident ID 62354 & 62361.

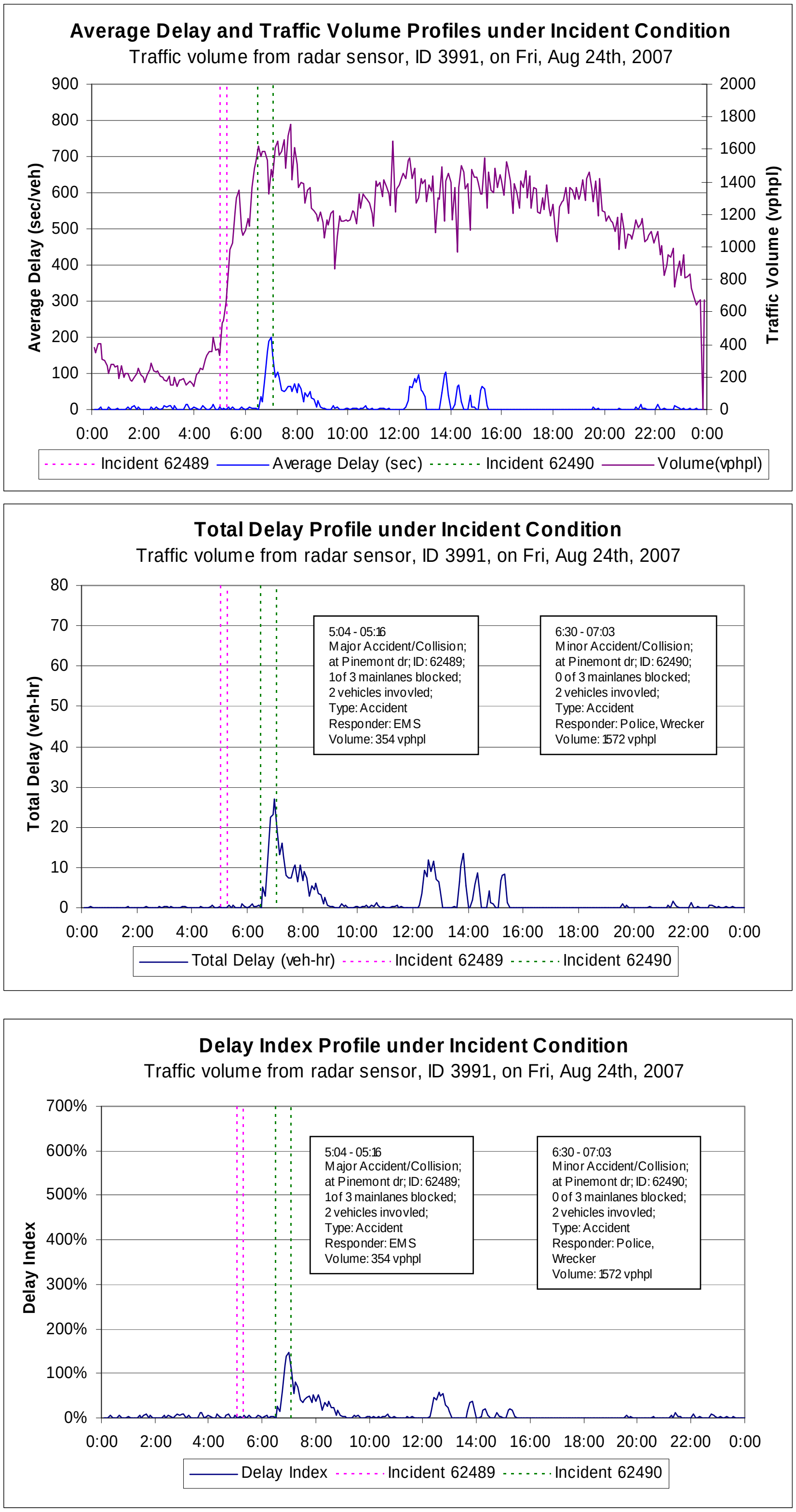


Figure B-37: Incident Impact Analysis for Incident ID 62489 & 62490.

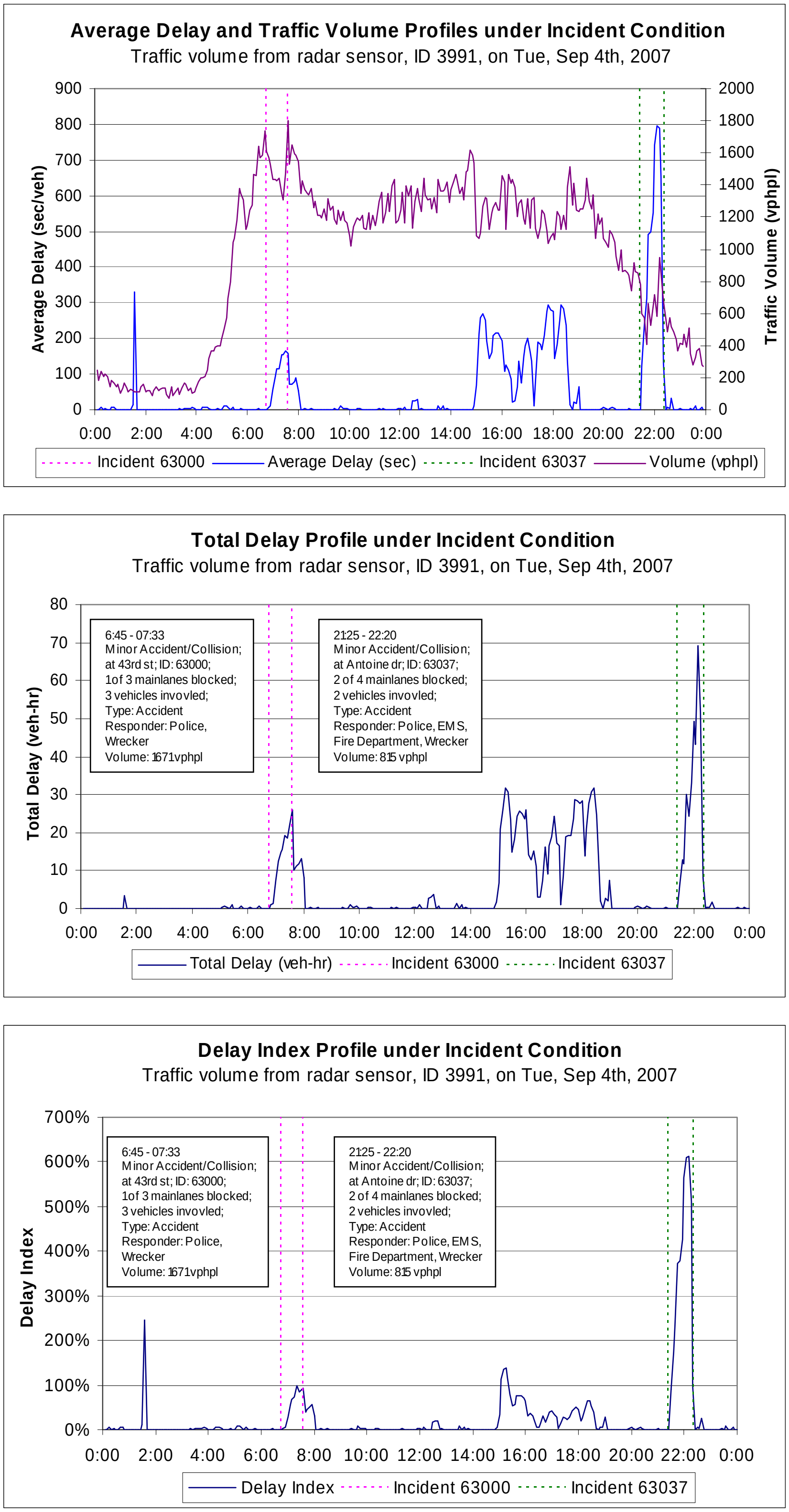


Figure B-38: Incident Impact Analysis for Incident ID 63000 & 63037.

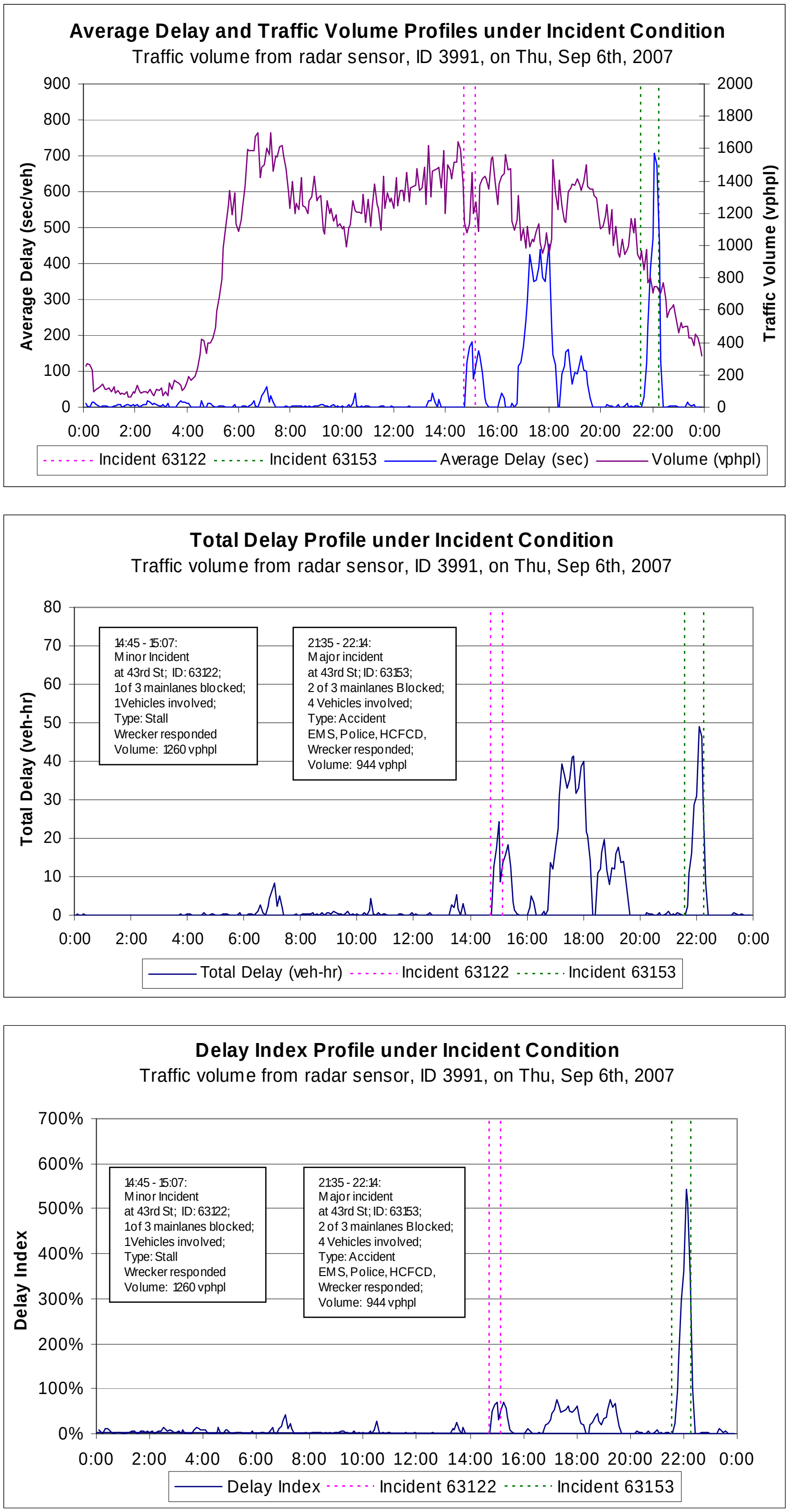
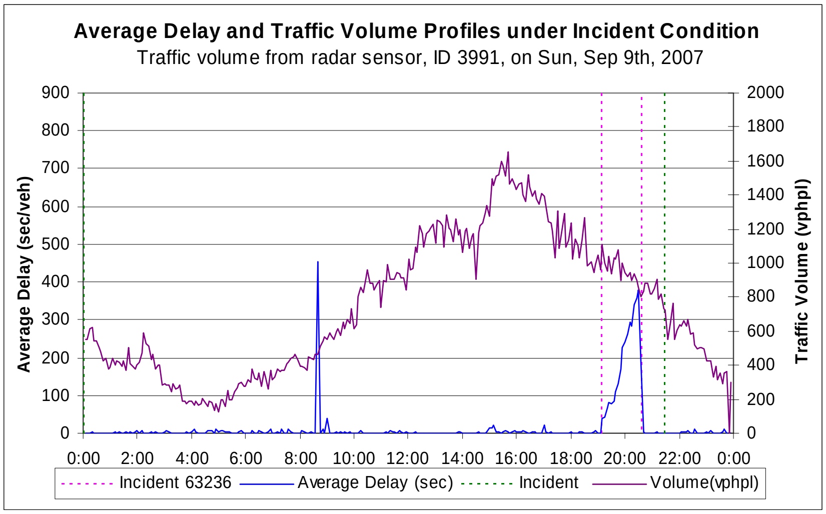
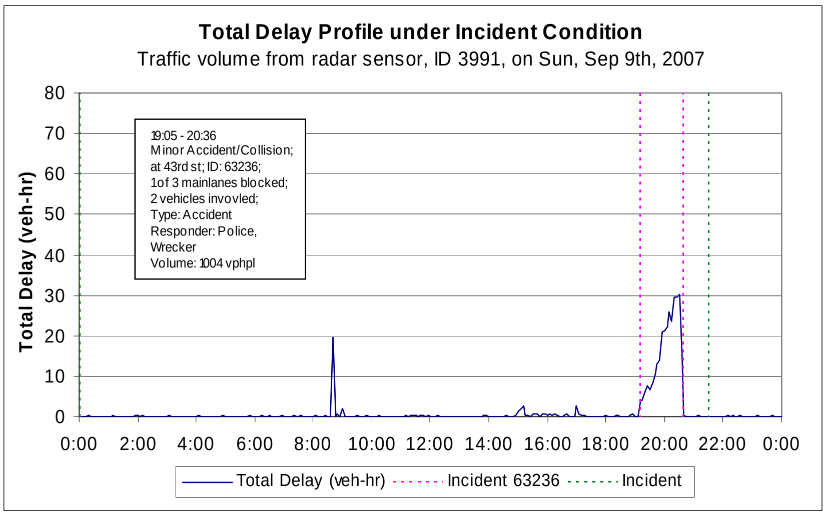


Figure B-39: Incident Impact Analysis for Incident ID 63122 & 63153.





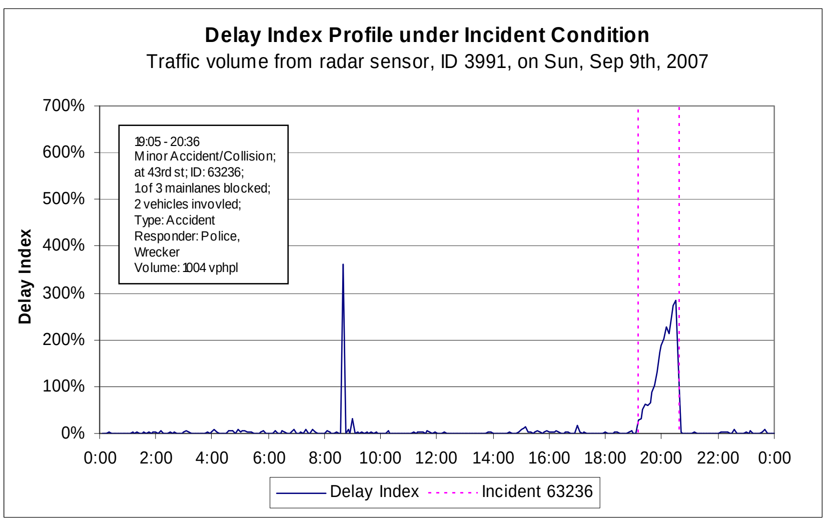
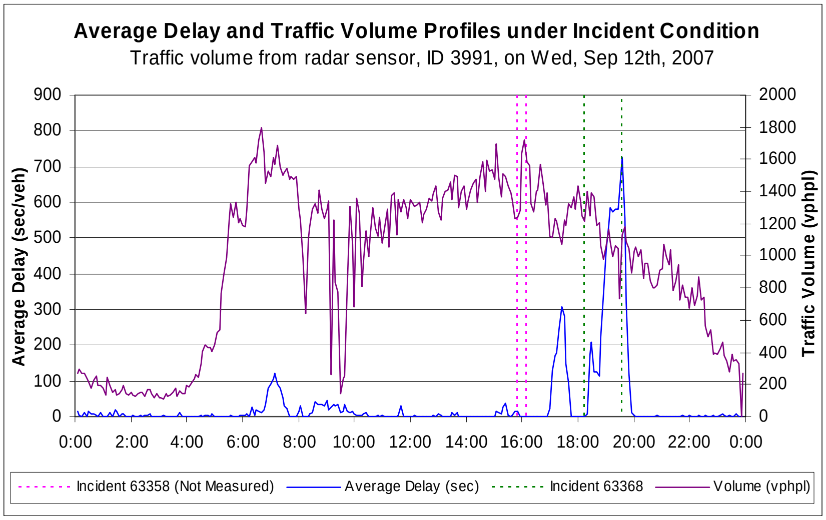
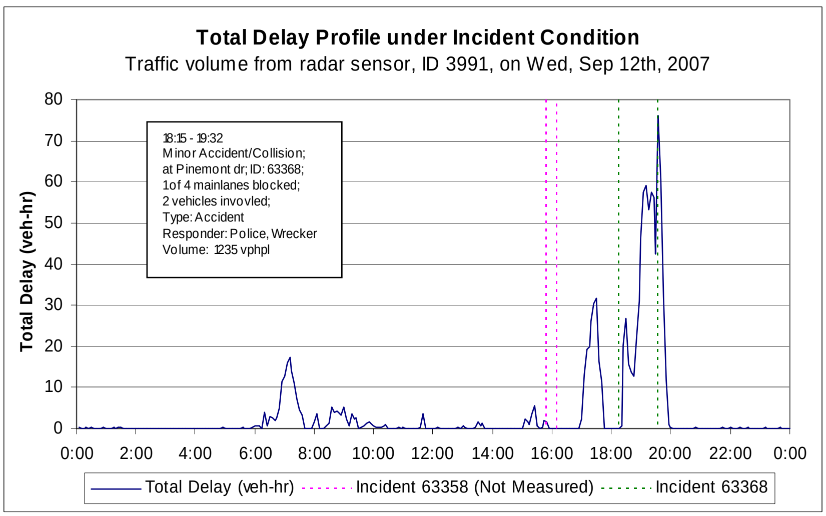


Figure B-40: Incident Impact Analysis for Incident ID 63236.





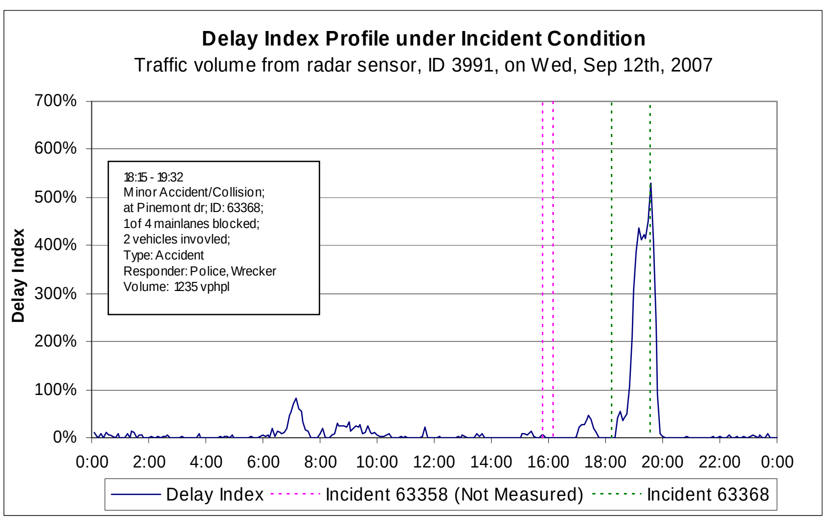
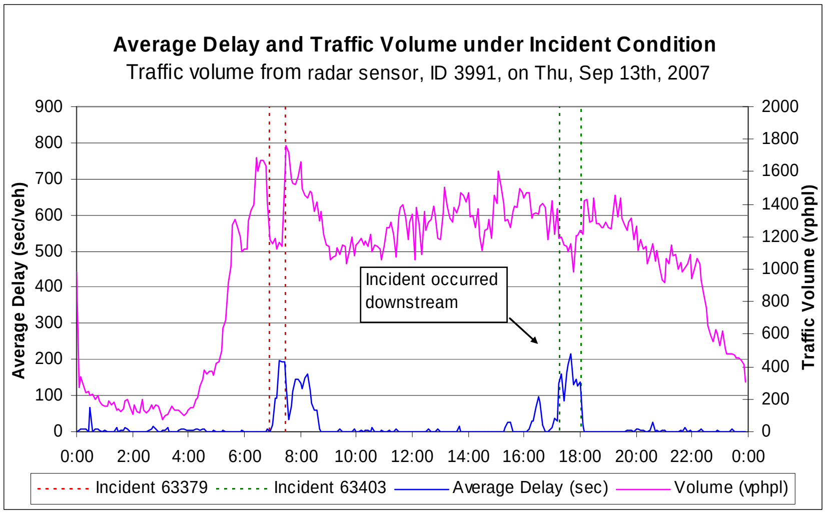
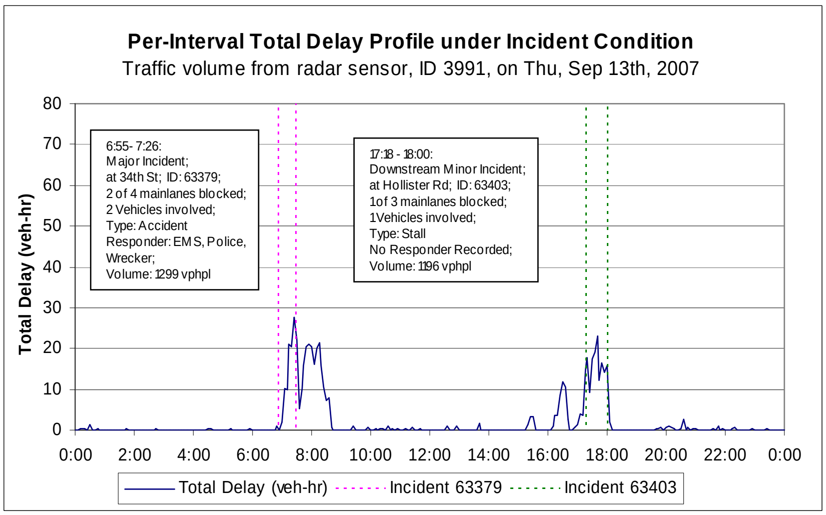


Figure B-41: Incident Impact Analysis for Incident ID 63368.





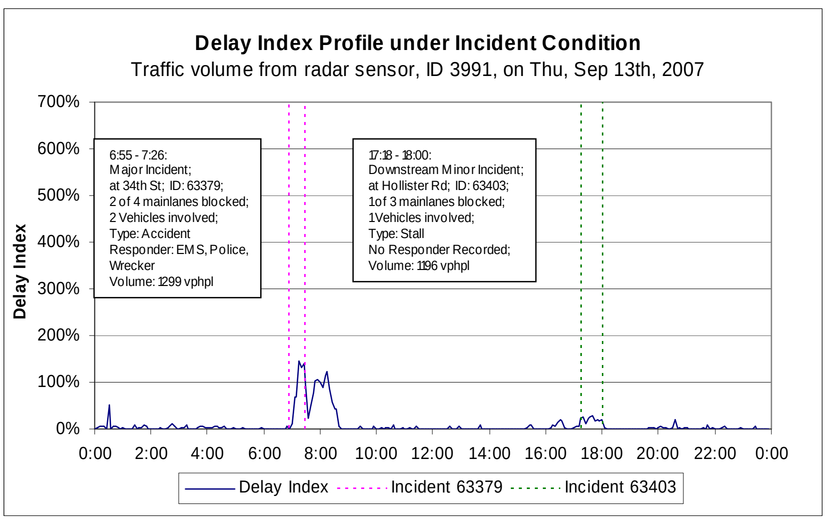
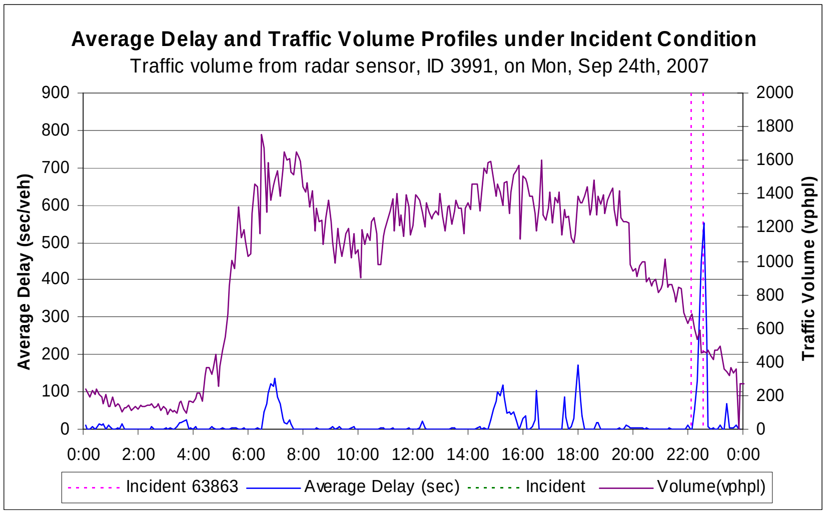
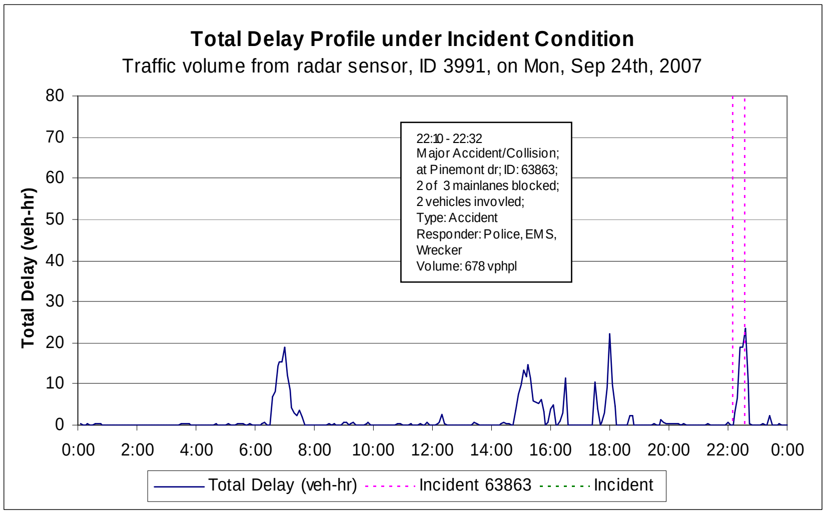


Figure B-42: Incident Impact Analysis for Incident ID 63379 & 63403.





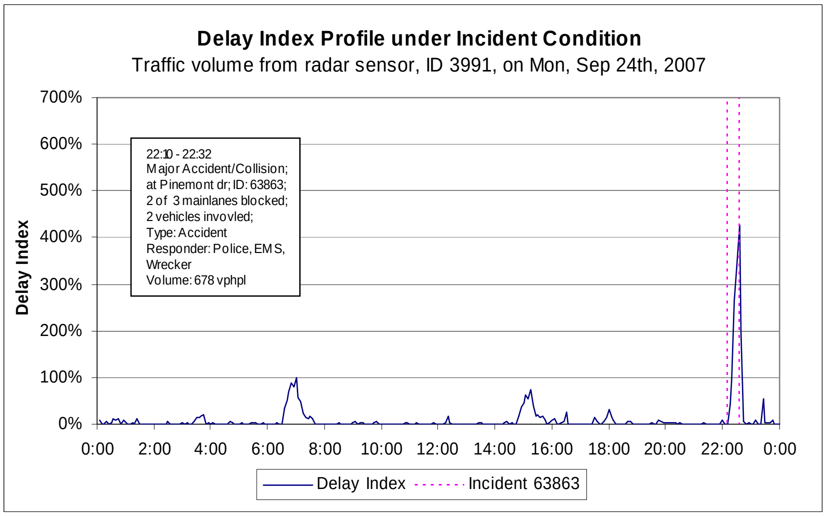
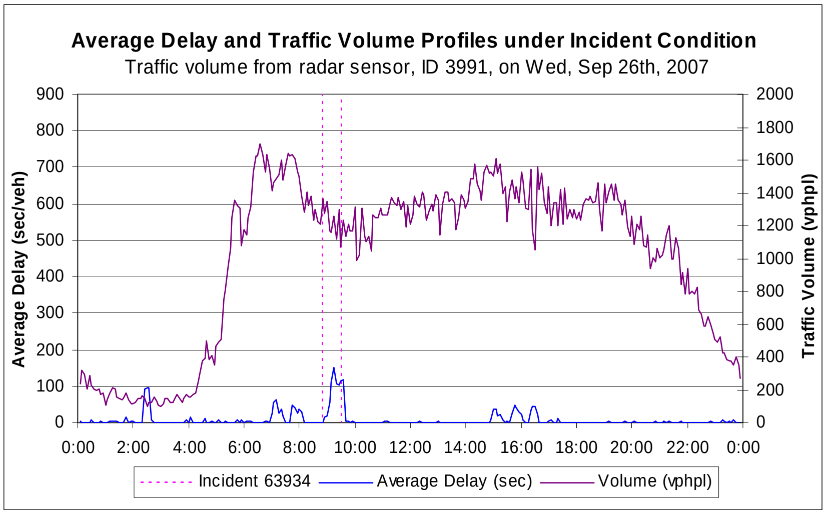
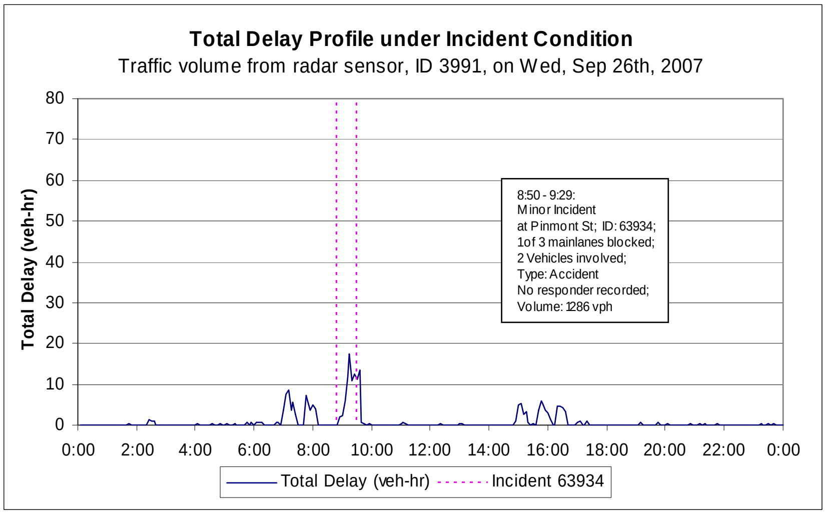


Figure B-43: Incident Impact Analysis for Incident ID 63863.





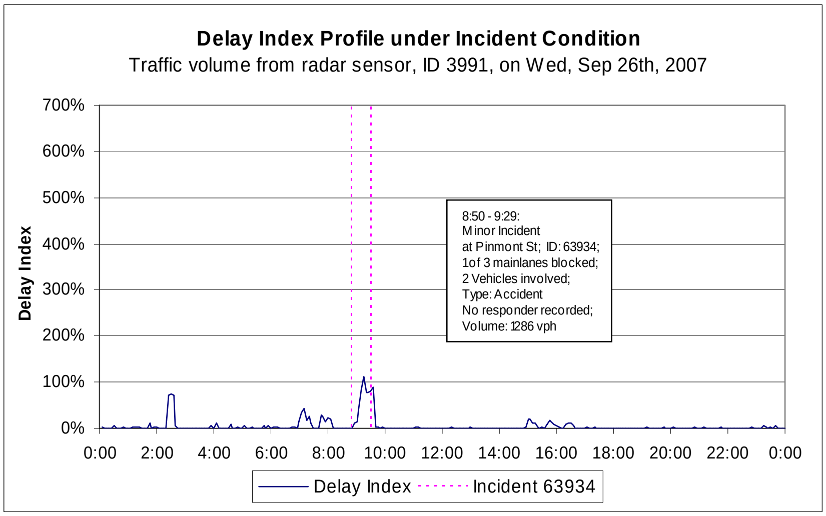
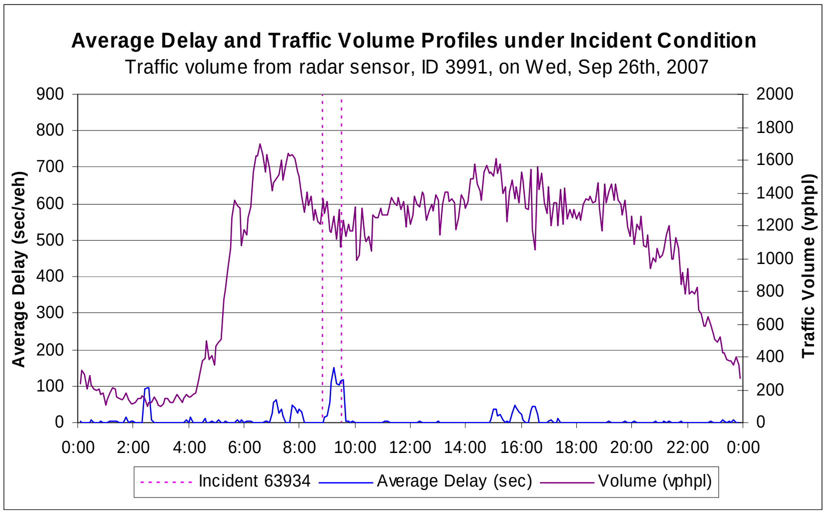
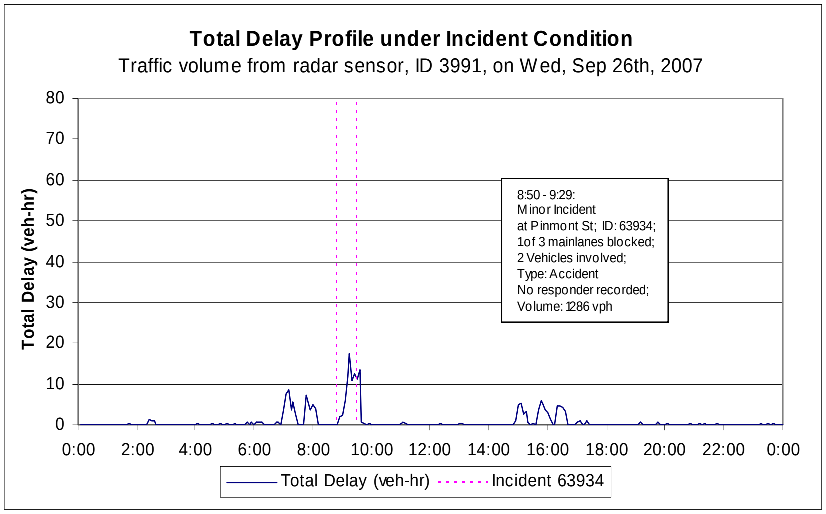


Figure B-44: Incident Impact Analysis for Incident ID 63934.





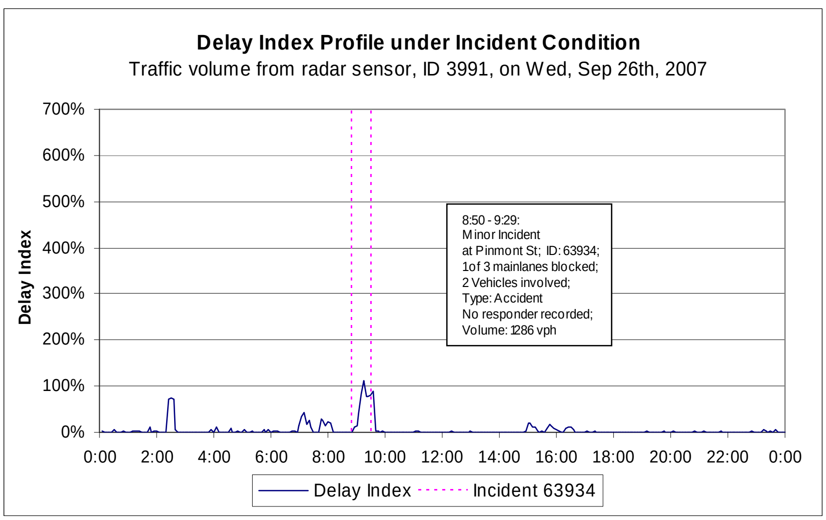
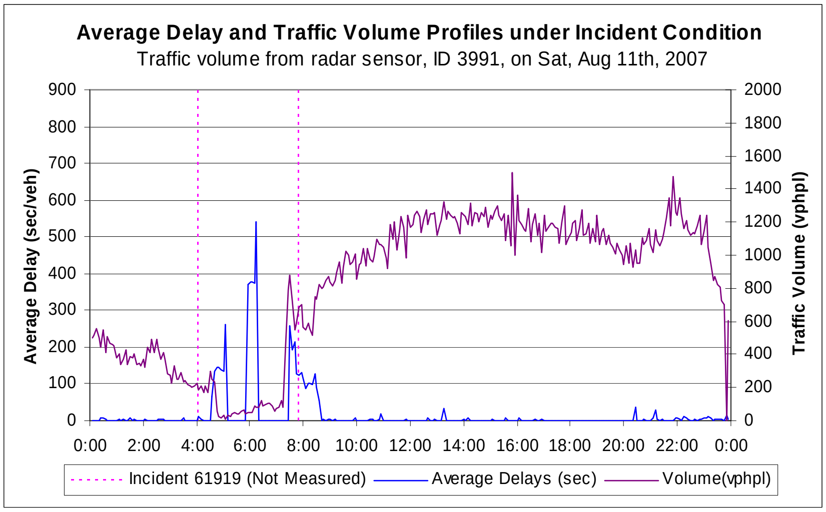


Figure B-45: Incident Impact Analysis for Incident ID 63934.

The below are incidents that had incomplete data, were recorded falsely, or had little impact, sorted by date.



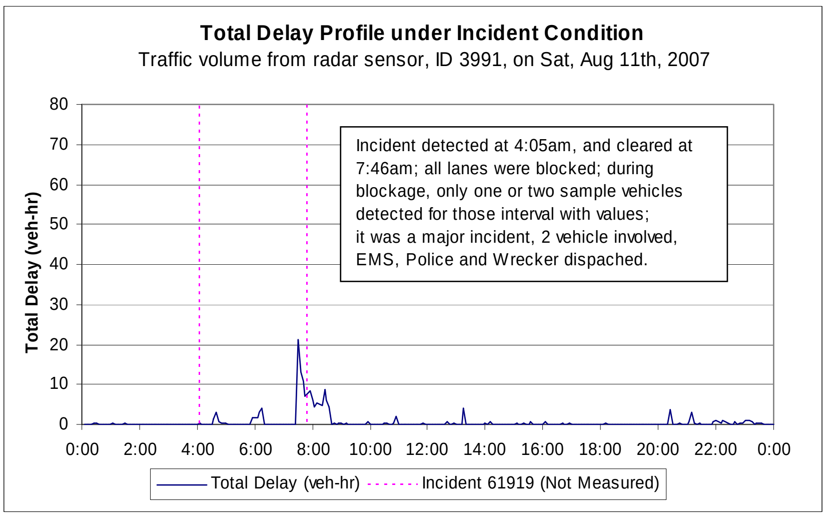


Figure B-46: Incident Impact Analysis for Incident ID 61919.

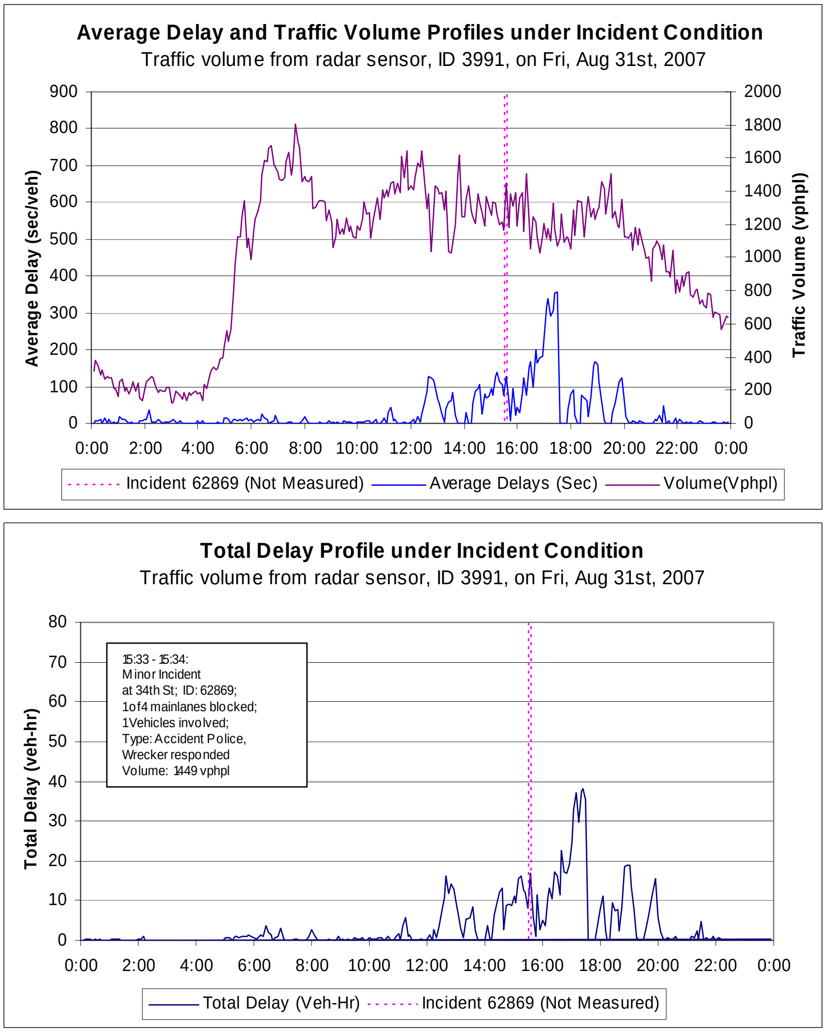
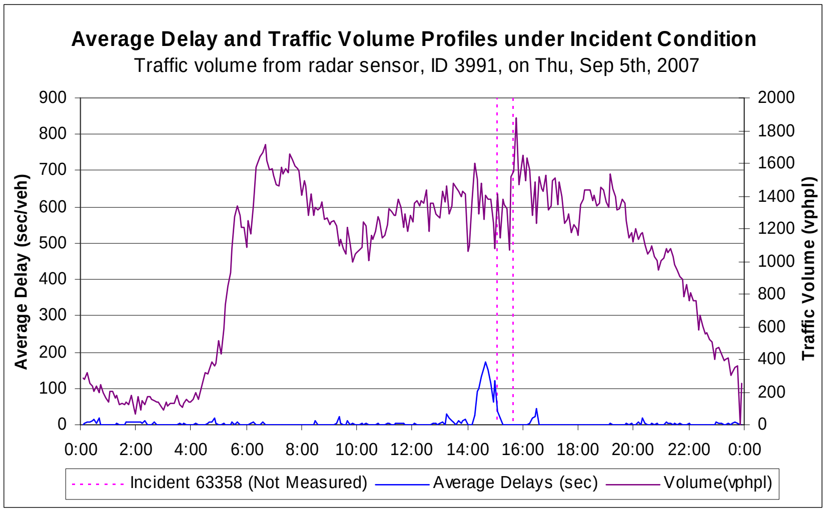


Figure B-47: Incident Impact Analysis for Incident ID 62869.



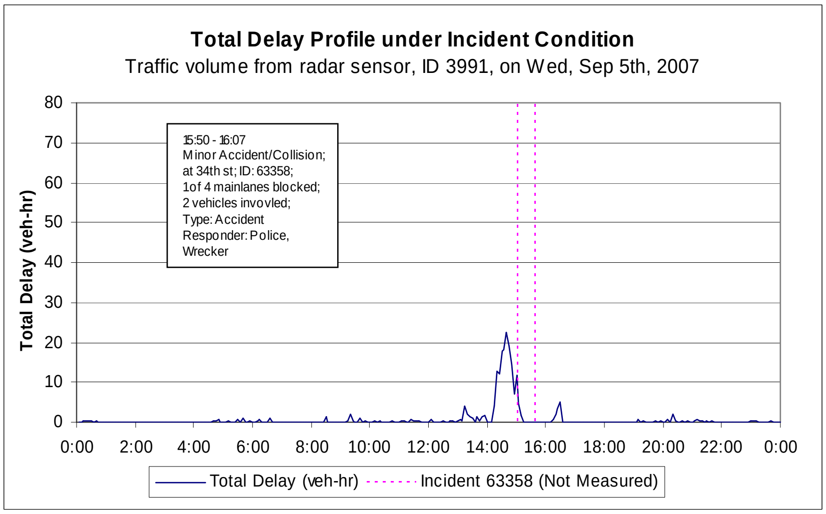
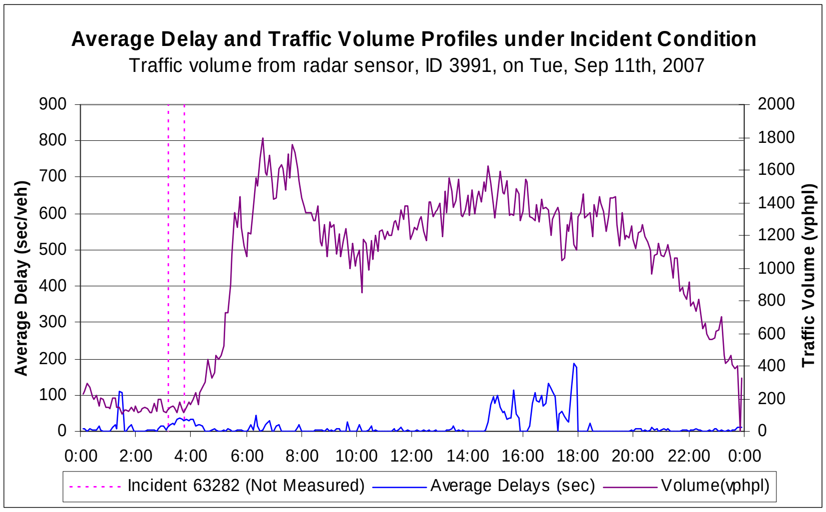


Figure B-48: Incident Impact Analysis for Incident ID 63358.



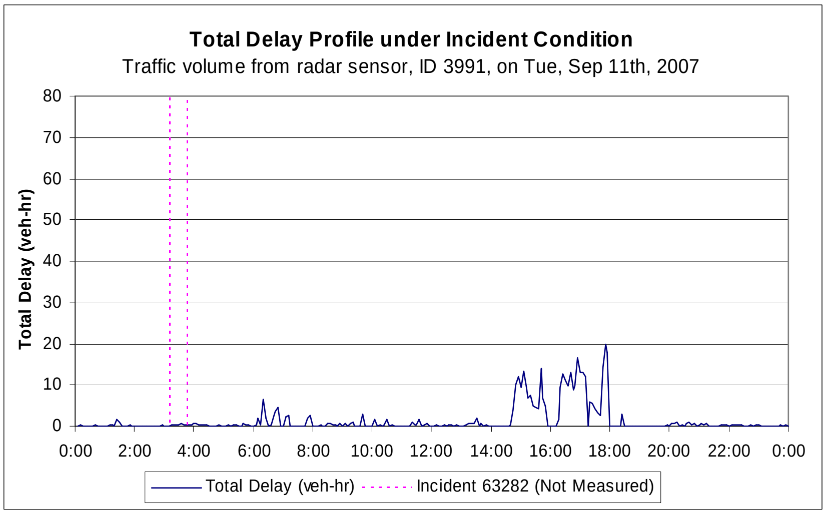


Figure B-49: Incident Impact Analysis for Incident ID 63282.

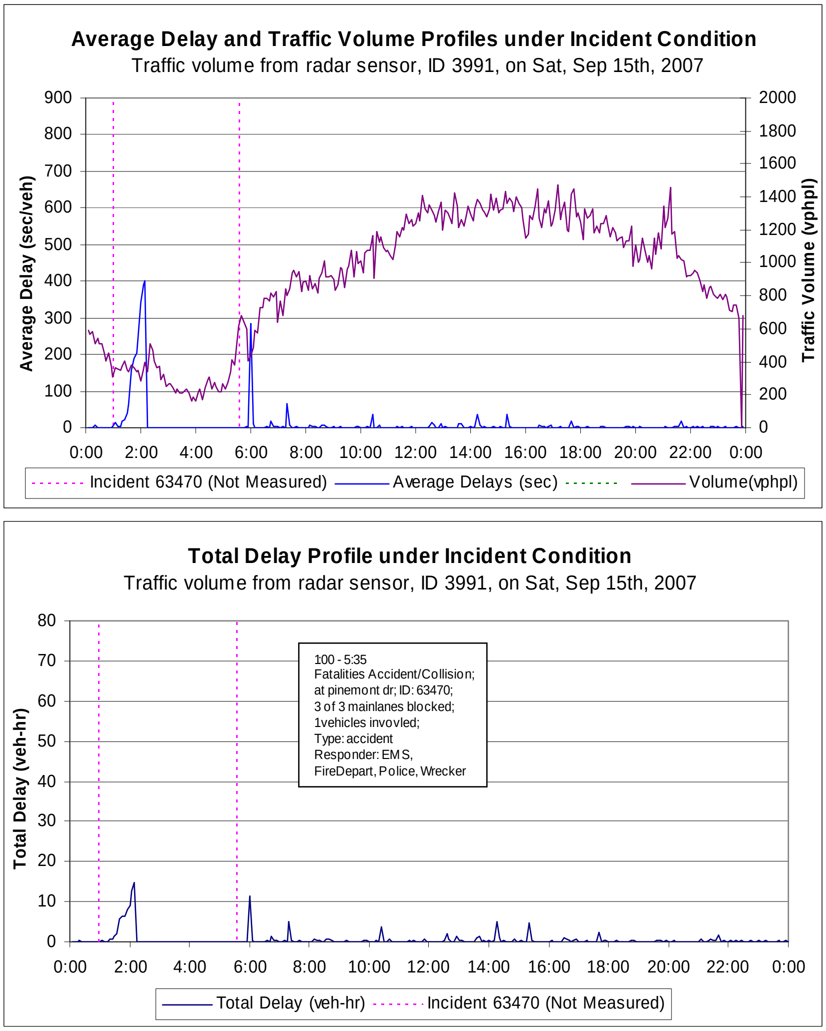
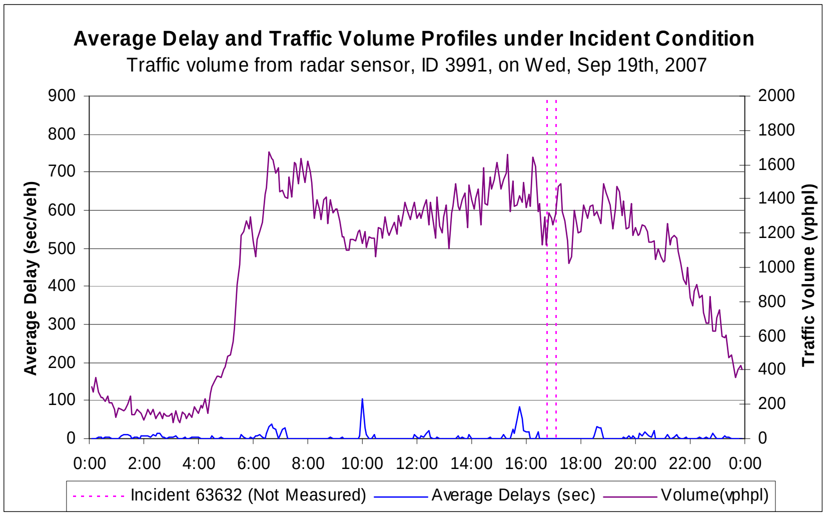


Figure B-50: Incident Impact Analysis for Incident ID 63470.



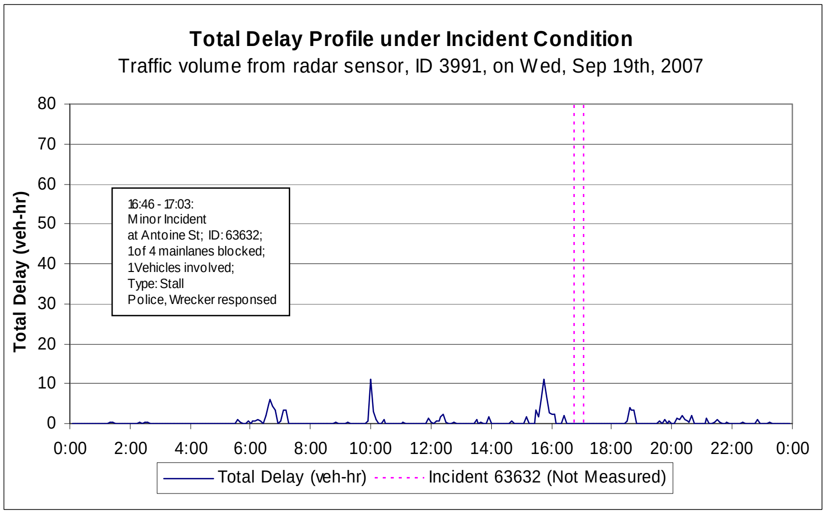


Figure B-51: Incident Impact Analysis for Incident ID 63632.

APPENDIX C. AUSTIN: DATA ANALYSIS AND RESULTS

Standard Reports of Incident Characteristics

Table C-1: Incident Frequency and Duration by Types (Austin).

Incident Type and Duration (Austin 2004-2007)							
Type	**Counts**	**%**	**Duration Percentile (minutes)**				
			5%	15%	50%	85%	95%
Stall	3409	53.6%	3	7	32	175	838
Collision	1844	29.0%	5	14	42	82	158
Abandonment	734	11.5%	31	100	656	1941	4319
Road Debris	177	2.8%	1	3	16	103	419
Overturned	93	1.5%	23	30	62	129	226
Public Emergency	40	0.6%	5	9	33	204	614
Vehicle on Fire	38	0.6%	13	24	53	96	267
HAZMAT Spill	21	0.3%	8	9	109	235	565
All Types	6356	100%	4	10	44	257	1210

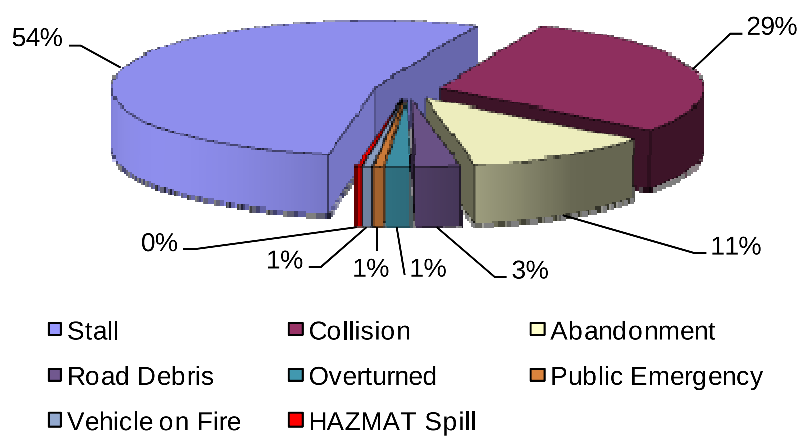


Figure C-1: Distribution of Non-Congestion Incident Types (Austin 2004–2007).

Table C-2: Yearly Distribution of Incident Counts by Types (Austin).

Incident Type	2004	2005	2006	2007	Total	% of Total
Abandonment	86	274	186	367	913	2%
Collision	275	564	569	739	2147	4%
Congestion	4422	9265	10115	24777	48579	87%
HAZMAT Spill	4	7	17	61	89	0%
Overturned	10	23	38	42	113	0%
Public Emergency	4	14	19	18	55	0%
Road Debris	18	78	44	110	250	0%
Stall	289	1241	1052	1307	3889	7%
Vehicle on Fire	7	17	23	28	75	0%
Total	5115	11483	12063	27449		

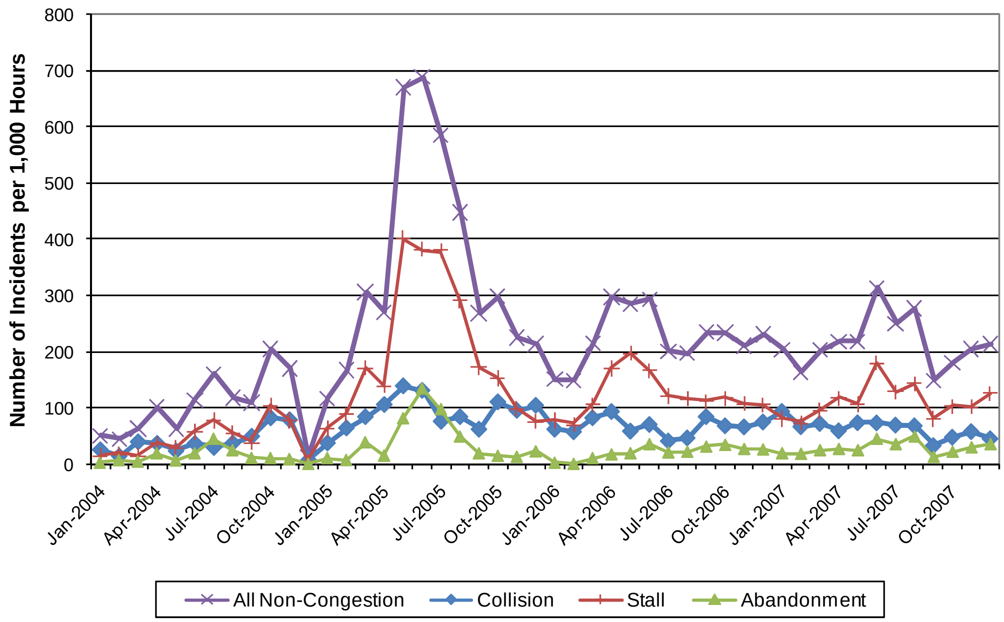


Figure C-2: Monthly Incident Rates over the Analysis Period (Austin).

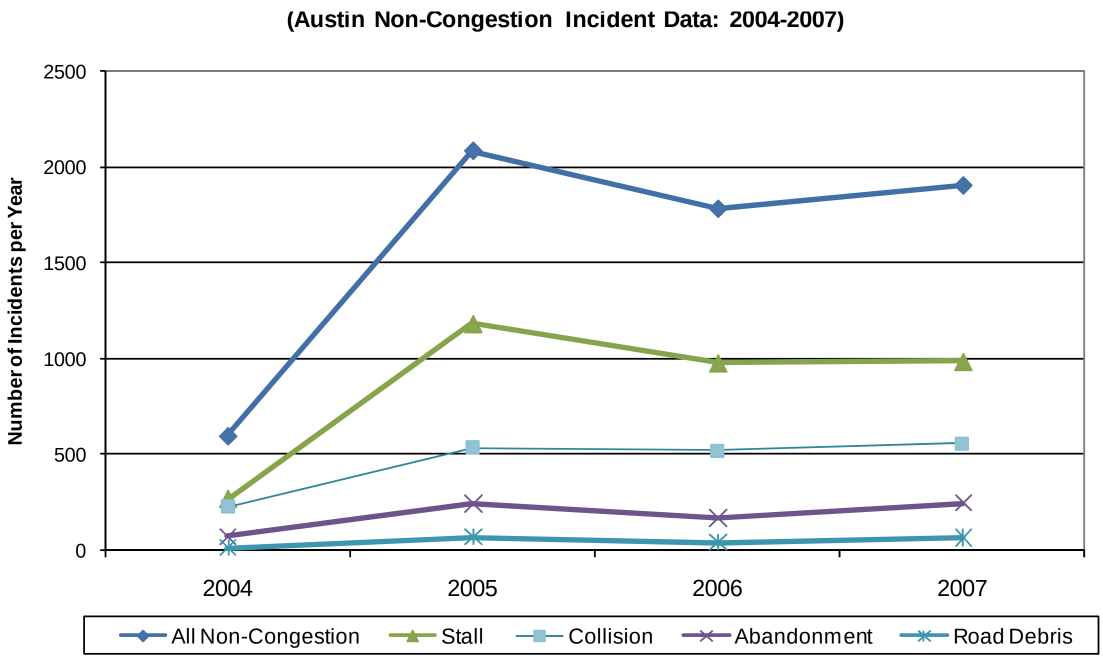


Figure C-3: Yearly Incident Rates by Incident Types (Austin).

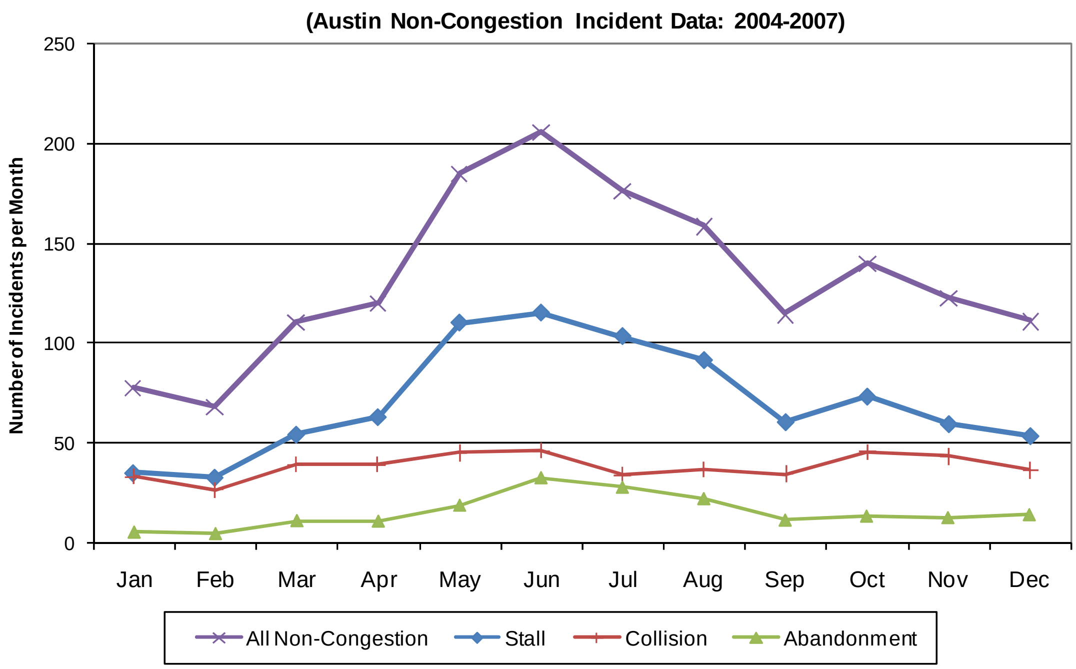


Figure C-4: Monthly Incident Rates by Incident Types (Austin).

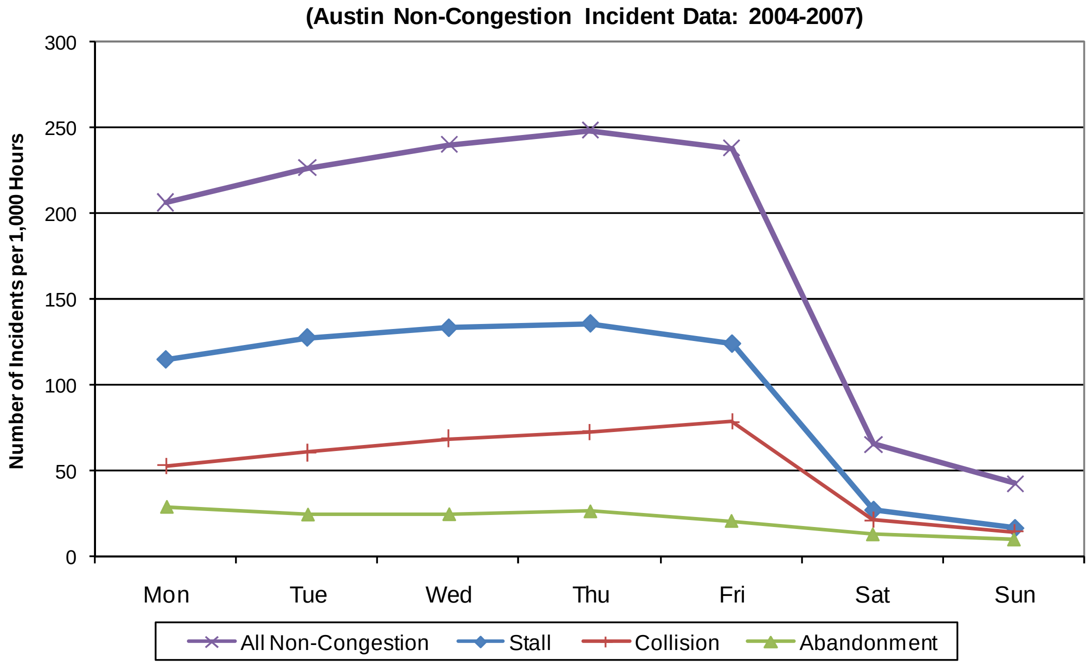


Figure C-5: Daily Incident Rates by Incident Type (Austin).

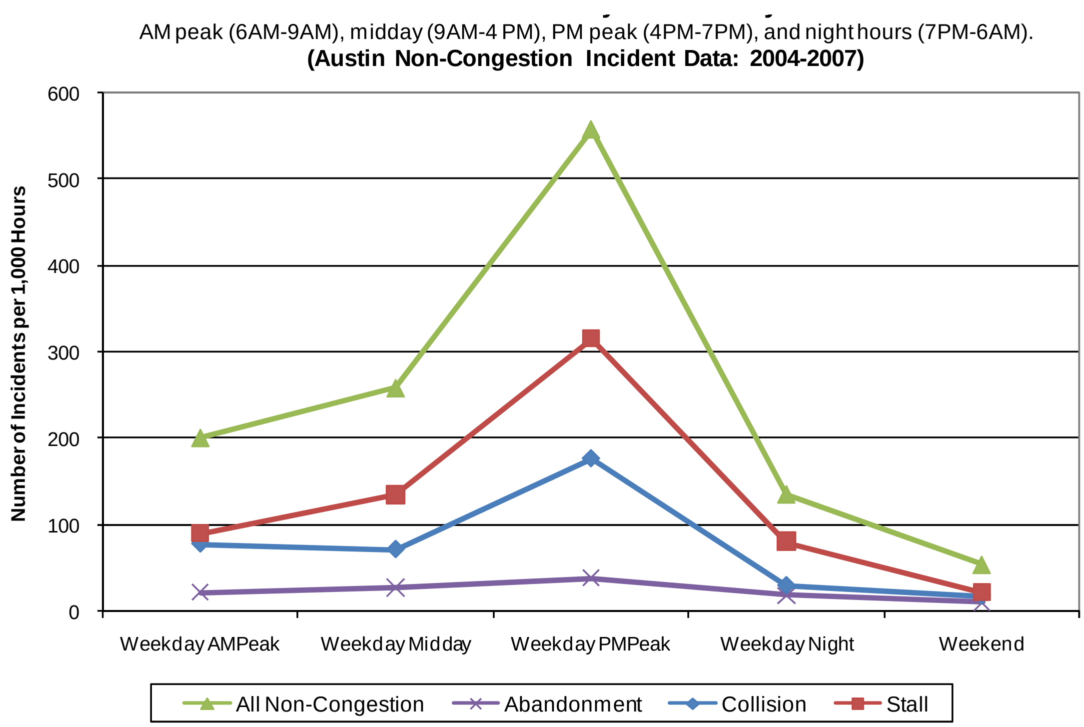


Figure C-6: Incident Rates at Different Times of Day by Incident Type (Austin).

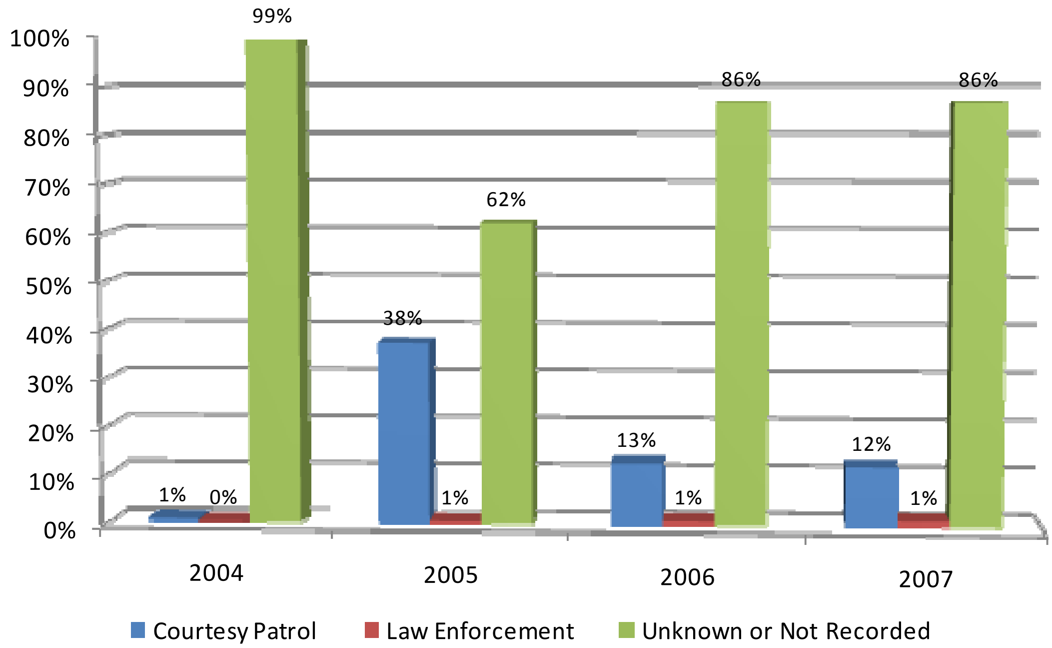


Figure C-7: Distribution of Incident Detection Methods (Austin).

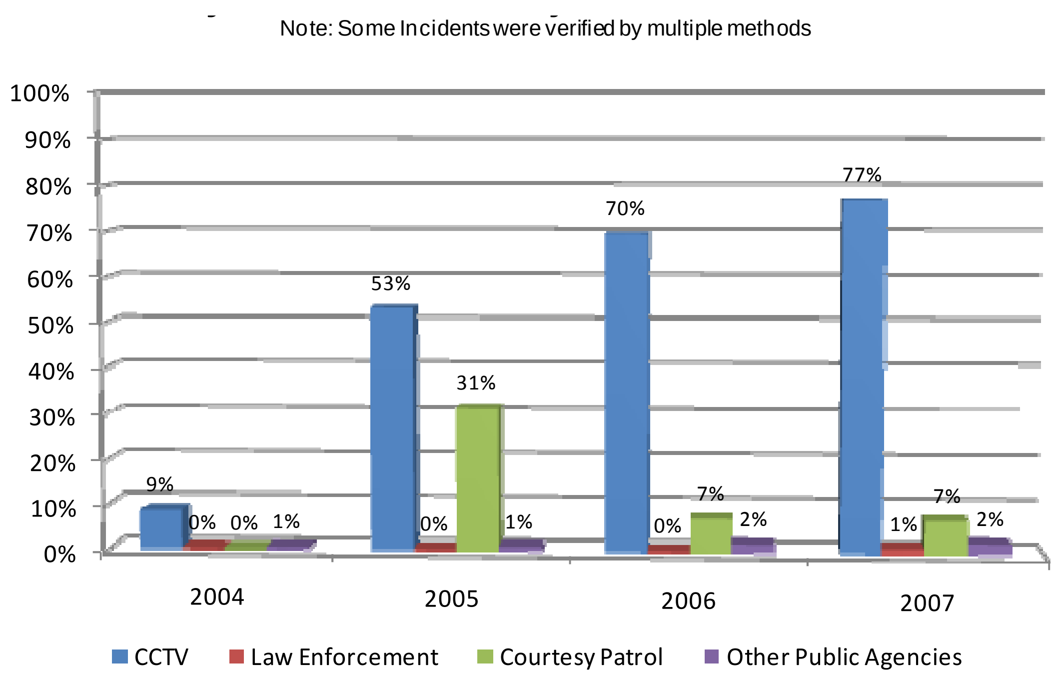


Figure C-8: Distribution of Verification Methods (Austin).

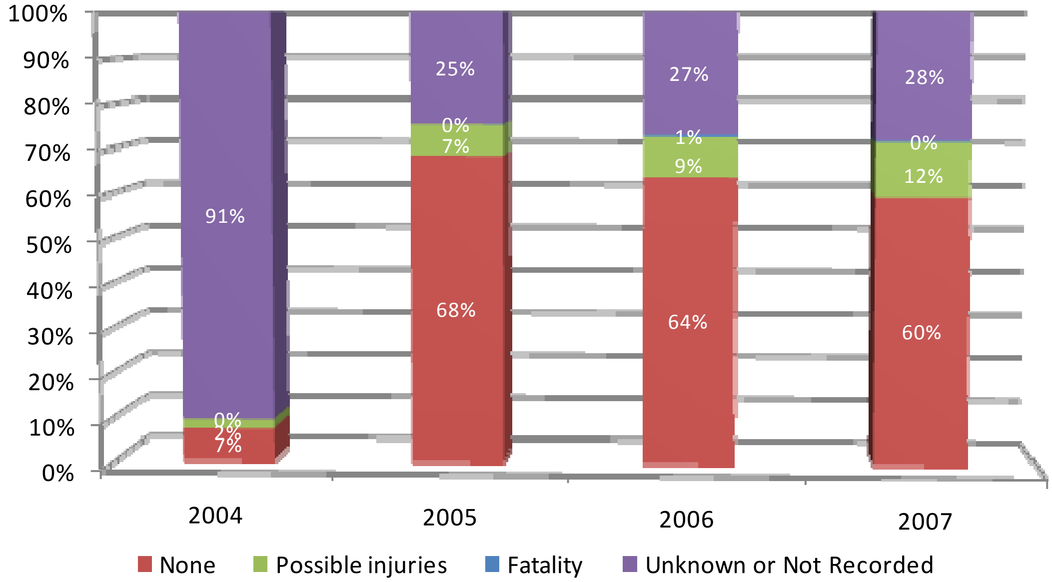


Figure C-9: Distribution of Incident Severity (Austin).

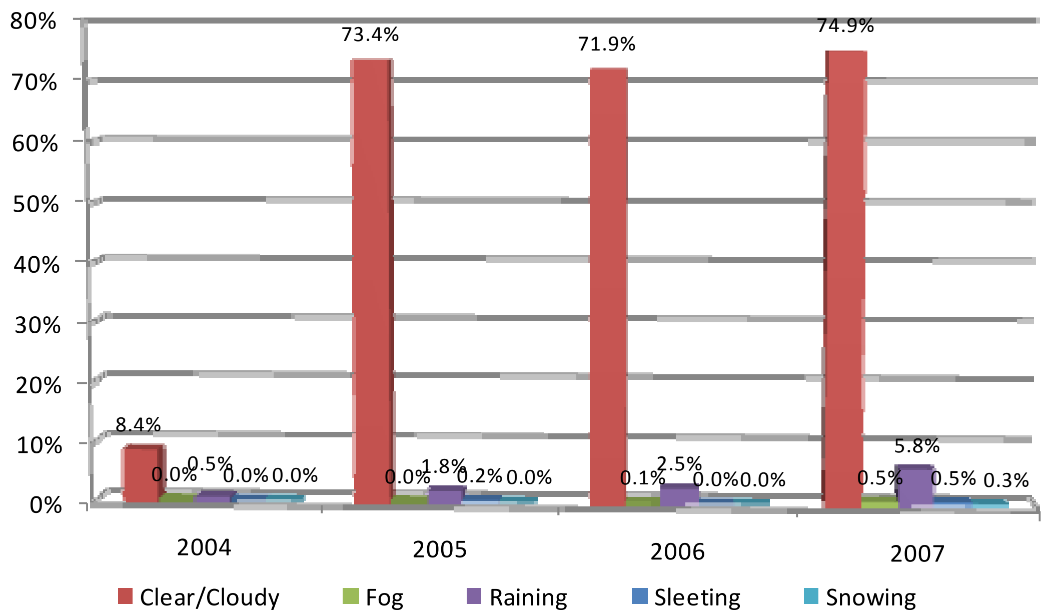


Figure C-10: Distribution of Recorded Weather Conditions (Austin).

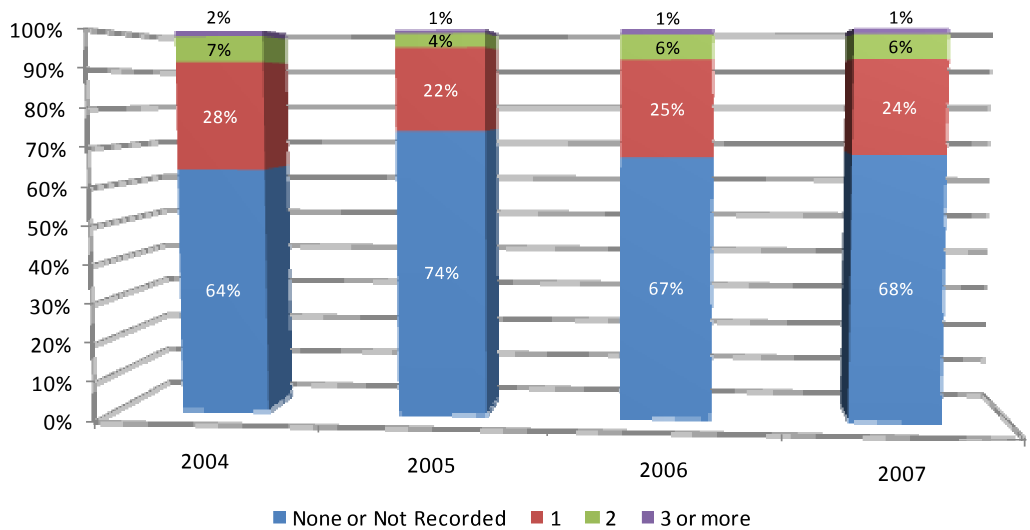


Figure C-11: Distribution of Number of Mainlanes Blocked (Austin).

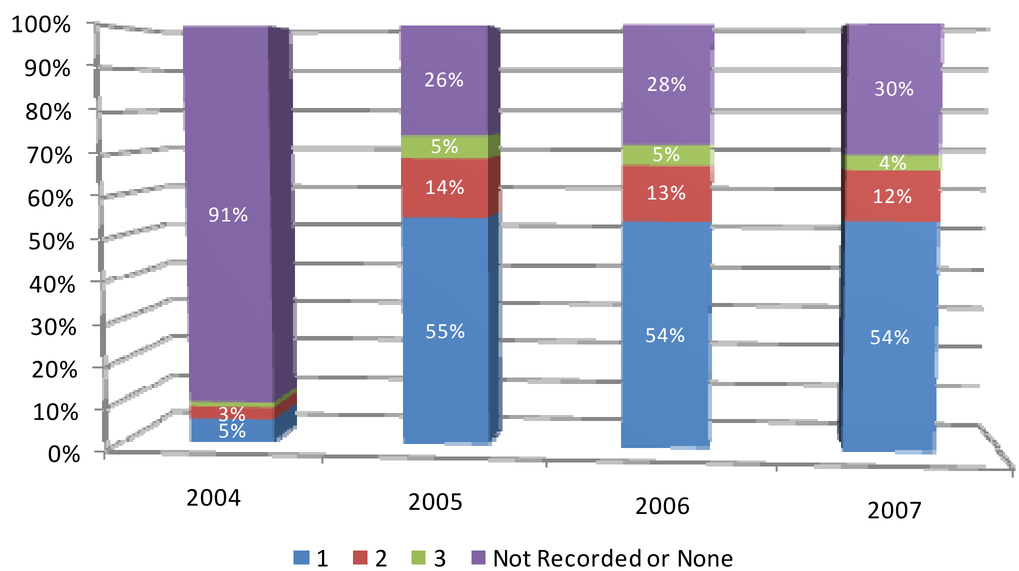


Figure C-12: Distribution of Number of Vehicles Involved (Austin).

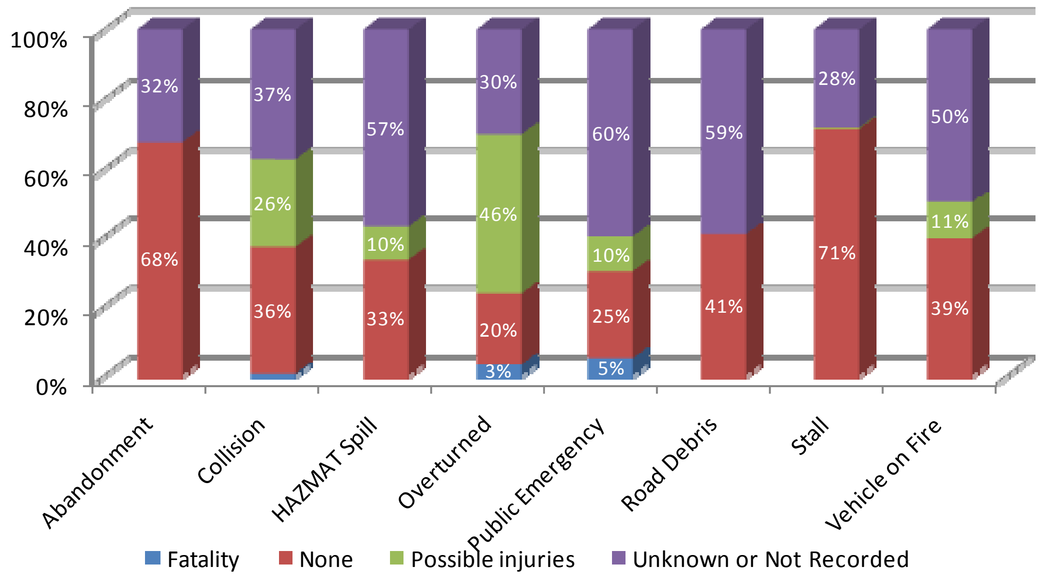


Figure C-13: Distribution of Severity by Incident Type (Austin).

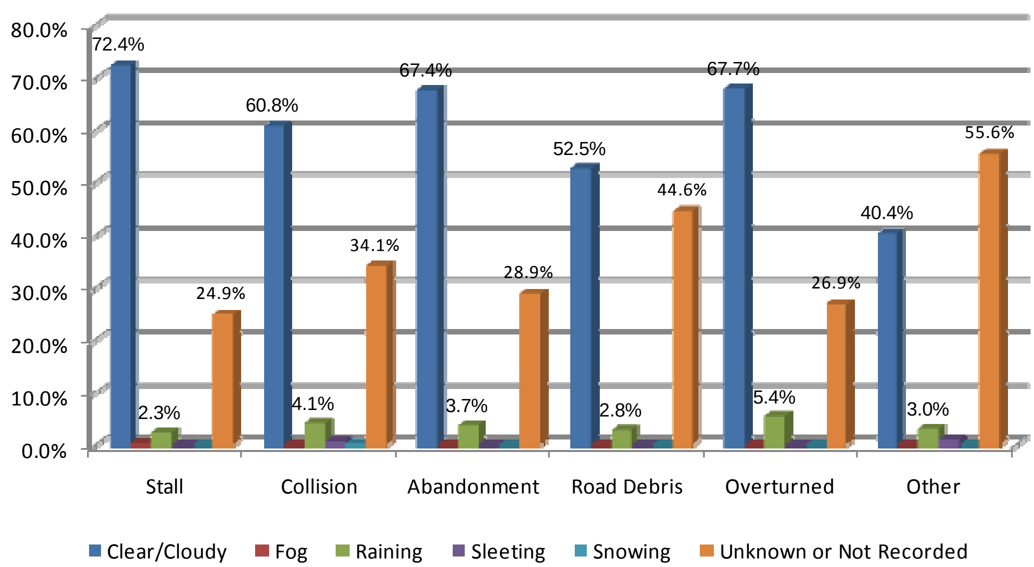


Figure C-14: Distribution of Weather Condition by Incident Type (Austin).

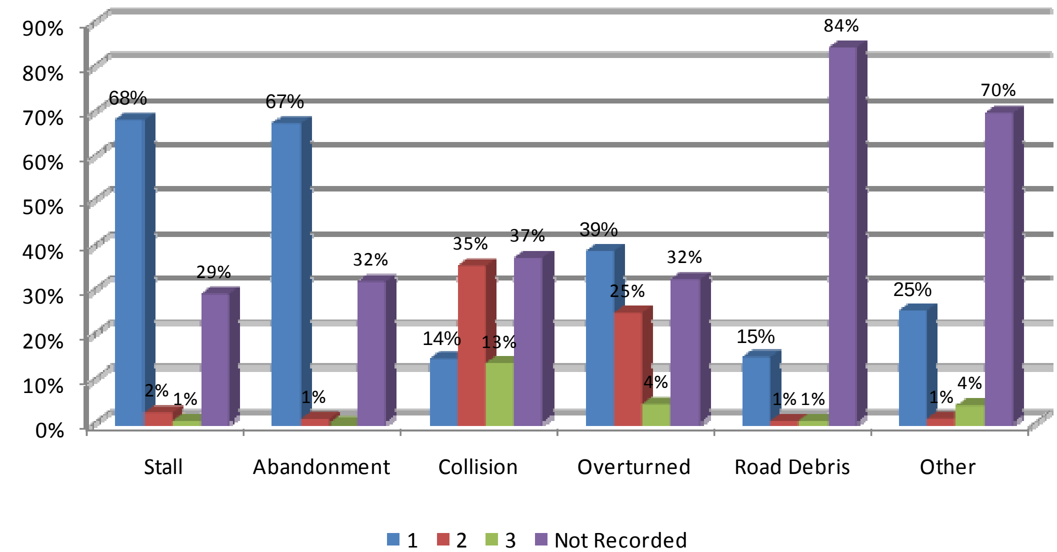


Figure C-15: Distribution of Number of Vehicles Involved by Incident Type (Austin).

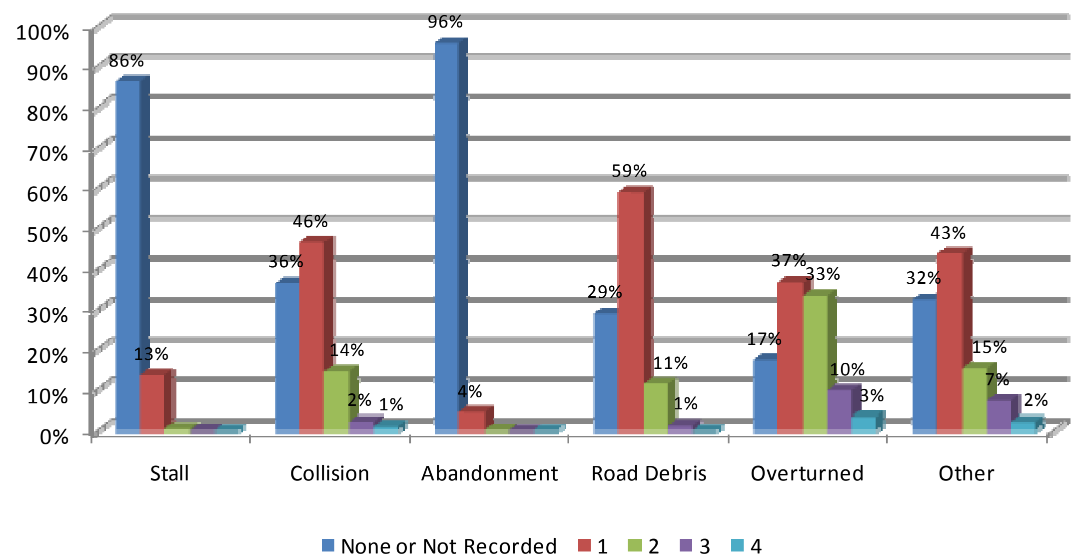


Figure C-16: Distribution of Lane Blockage by Incident Type (Austin).

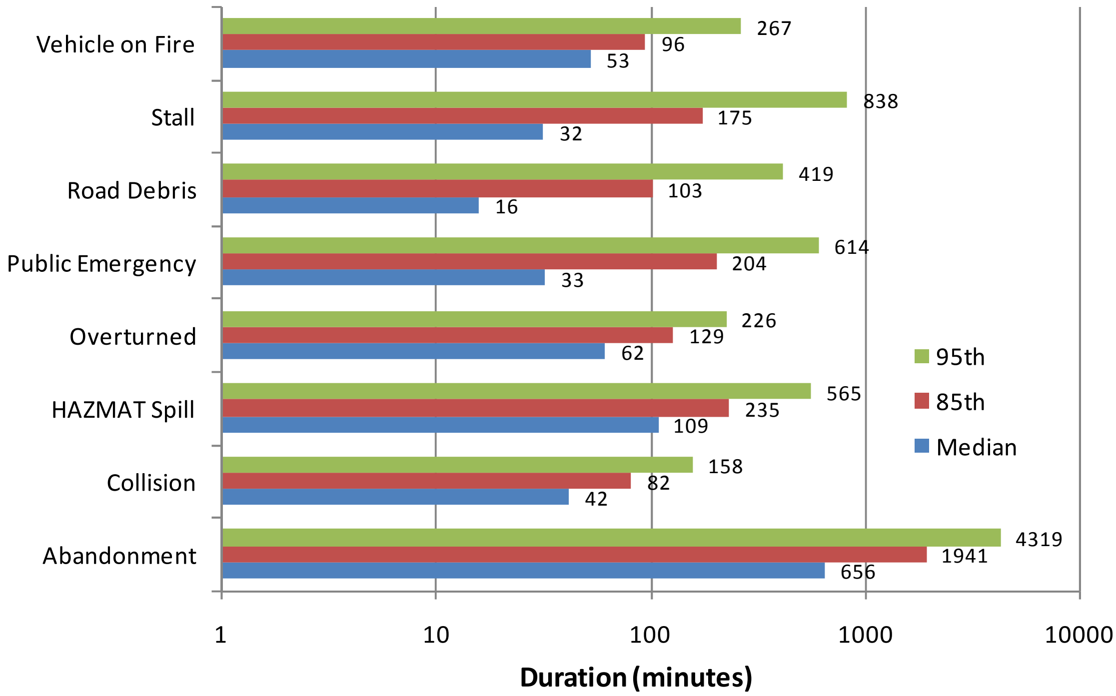


Figure C-17: Incident Duration Percentile Statistics (Austin 2004–2007).

Hot Spot Analysis

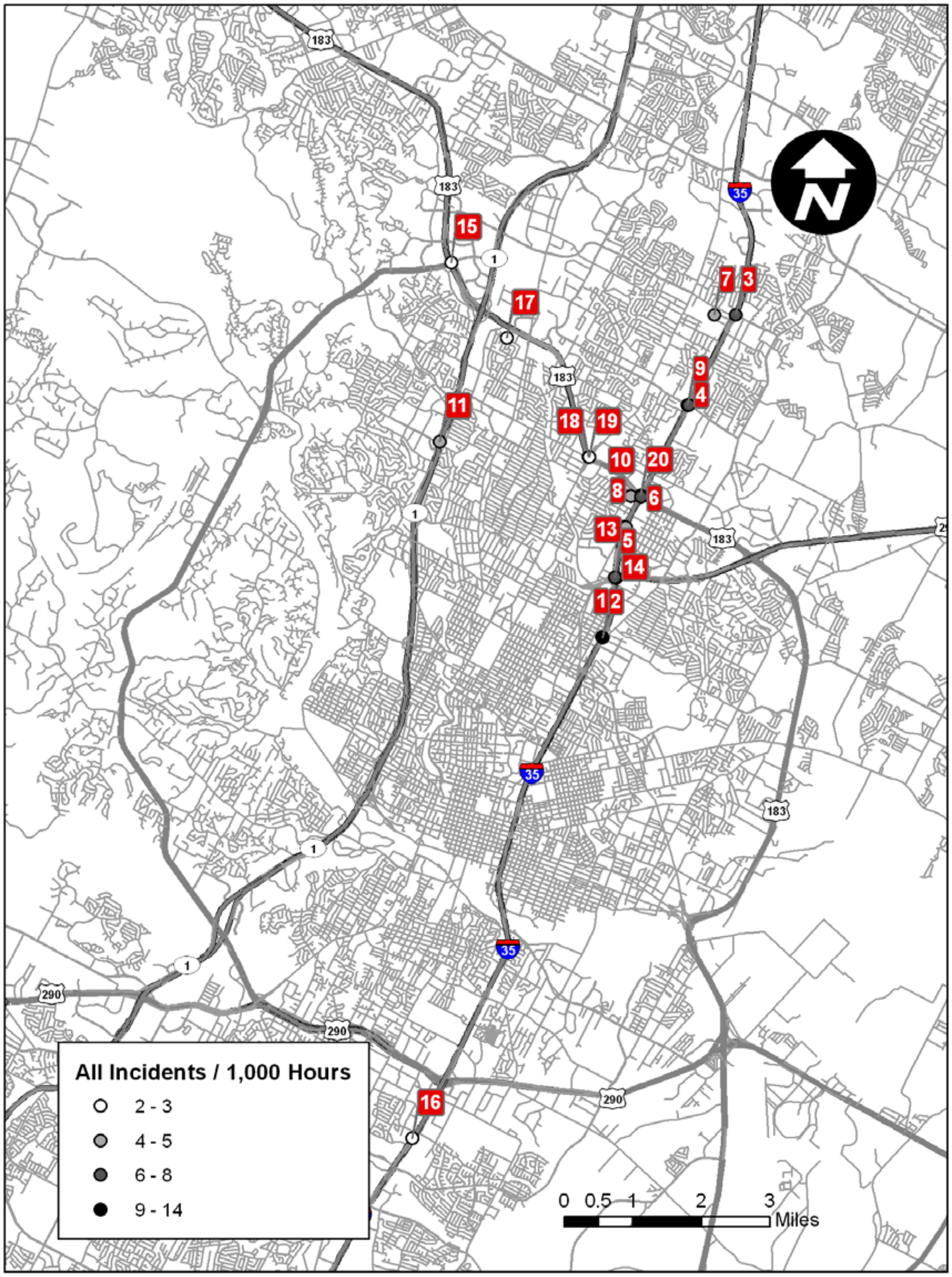


Figure C-18: Frequency-Based Hot Spots during All Times of Day.

Table C-3: Locations with Highest Incident Frequencies during All Times of Day.

Rank	Roadway	Cross Street	Direction	Total	Avg*
1	IH 0035	51st Street	Southbound	486	14
2	IH 0035	51st Street	Northbound	350	10
3	IH 0035	Braker Lane	Northbound	289	8
4	IH 0035	Rundberg Lane	Northbound	241	7
5	IH 0035	US 290E	Southbound	207	6
6	IH 0035	US 183/Anderson Lane	Northbound	199	6
7	IH 0035	Braker Lane	Southbound	183	5
8	IH 0035	St. Johns Ave	Southbound	179	5
9	IH 0035	Rundberg Lane	Southbound	170	5
10	IH 0035	US 183/Anderson Lane	Southbound	168	5
11	LP 0001	Far West Blvd.	Northbound	134	4
12	IH 0035	US 183 NB/Anderson Ln	Northbound	130	4
13	IH 0035	St. Johns Ave	Northbound	128	4
14	IH 0035	US 290E	Northbound	113	3
15	US 0183	Cap. of Tx Hwy./LP 360	Northbound	110	3
16	IH 0035	End of Instrumentation	Southbound	110	3
17	US 0183	Burnet Rd./FM 1325	Northbound	90	3
18	US 0183	Lamar Blvd./LP 275	Southbound	89	3
19	US 0183	Lamar Blvd./LP 275	Northbound	74	2
20	IH 0035	US 183 NB/Anderson Ln	Southbound	70	2

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

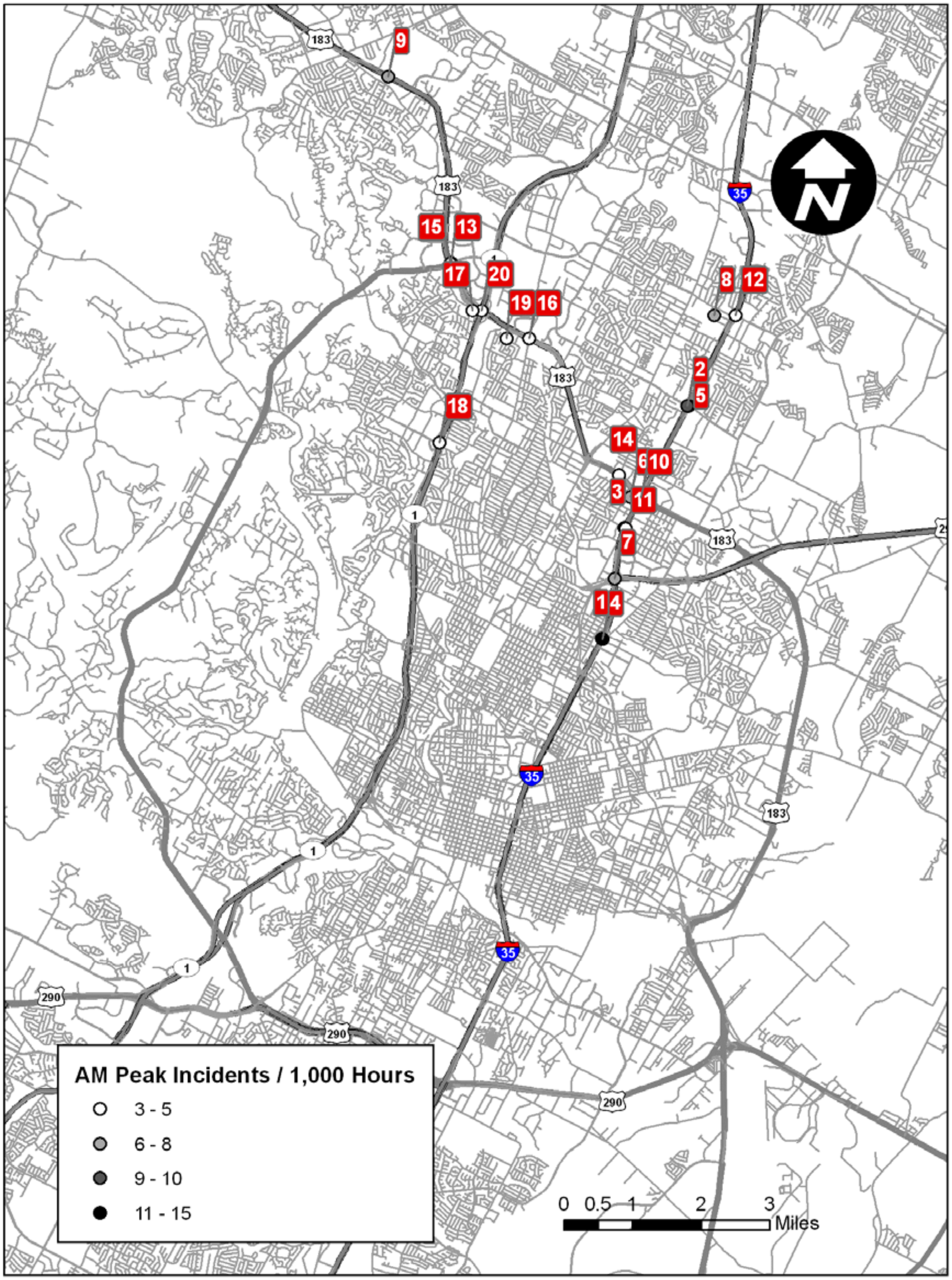


Figure C-19: Weekday AM Peak Frequency-Based Hot Spots.

Table C-4: Locations with Highest Incident Frequencies during AM Peak.

Rank	Roadway	Cross Street	Direction	Total	Avg*
1	IH 0035	51st Street	Southbound	48	15
2	IH 0035	Rundberg Lane	Southbound	32	10
3	IH 0035	St. Johns Ave	Southbound	28	9
4	IH 0035	51st Street	Northbound	25	8
5	IH 0035	Rundberg Lane	Northbound	24	8
6	IH 0035	US 183/Anderson Lane	Southbound	22	7
7	IH 0035	US 290E	Southbound	21	7
8	IH 0035	Braker Lane	Southbound	21	7
9	US 0183	Oak Knoll Drive	Southbound	20	6
10	IH 0035	US 183/Anderson Lane	Northbound	15	5
11	IH 0035	St. Johns Ave	Northbound	15	5
12	IH 0035	Braker Lane	Northbound	13	4
13	US 0183	Cap. Of Tx Hwy./LP 360	Northbound	13	4
14	US 0183	Georgian Dr.	Northbound	12	4
15	US 0183	Cap. Of Tx Hwy./LP 360	Southbound	11	4
16	US 0183	Burnet Rd./FM 1325	Southbound	11	4
17	US 0183	LP 0001 SB / MoPac	Southbound	11	4
18	LP 0001	Far West Blvd.	Northbound	10	3
19	US 0183	Burnet Rd./FM 1325	Northbound	10	3
20	US 0183	MoPac/Loop 1	Southbound	10	3

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

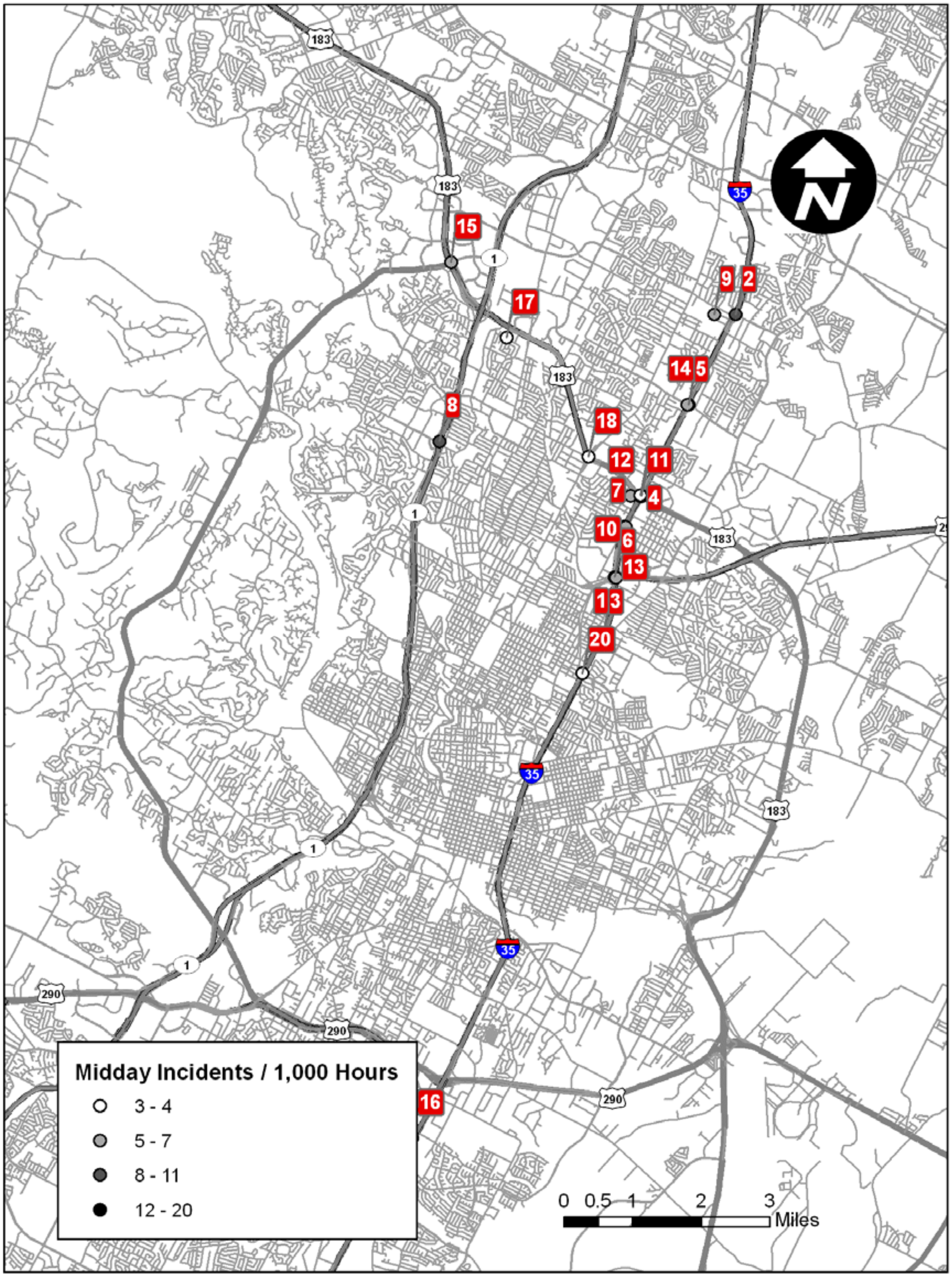


Figure C-20: Weekday Midday Frequency-Based Hot Spots.

Table C-5: Locations with Highest Incident Frequencies during Midday.

Rank	Roadway	Cross Street	Direction	Total	Avg*
1	IH 0035	51st Street	Southbound	143	20
2	IH 0035	Braker Lane	Northbound	79	11
3	IH 0035	51st Street	Northbound	76	10
4	IH 0035	US 183/Anderson Lane	Northbound	68	9
5	IH 0035	Rundberg Lane	Northbound	63	9
6	IH 0035	US 290E	Southbound	63	9
7	IH 0035	St. Johns Ave	Southbound	60	8
8	LP 0001	Far West Blvd.	Northbound	56	8
9	IH 0035	Braker Lane	Southbound	54	7
10	IH 0035	St. Johns Ave	Northbound	49	7
11	IH 0035	US 183 NB / Anderson Ln	Northbound	47	6
12	IH 0035	US 183/Anderson Lane	Southbound	42	6
13	IH 0035	US 290E	Northbound	41	6
14	IH 0035	Rundberg Lane	Southbound	39	5
15	US 0183	Cap. Of Tx Hwy./LP 360	Northbound	33	5
16	IH 0035	End of Instrumentation	Southbound	28	4
17	US 0183	Burnet Rd./FM 1325	Northbound	28	4
18	US 0183	Lamar Blvd./LP 275	Southbound	27	4
19	IH 0035	US 183 NB / Anderson Ln	Southbound	22	3
20	IH 0035	Airport Blvd.	Southbound	21	3

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

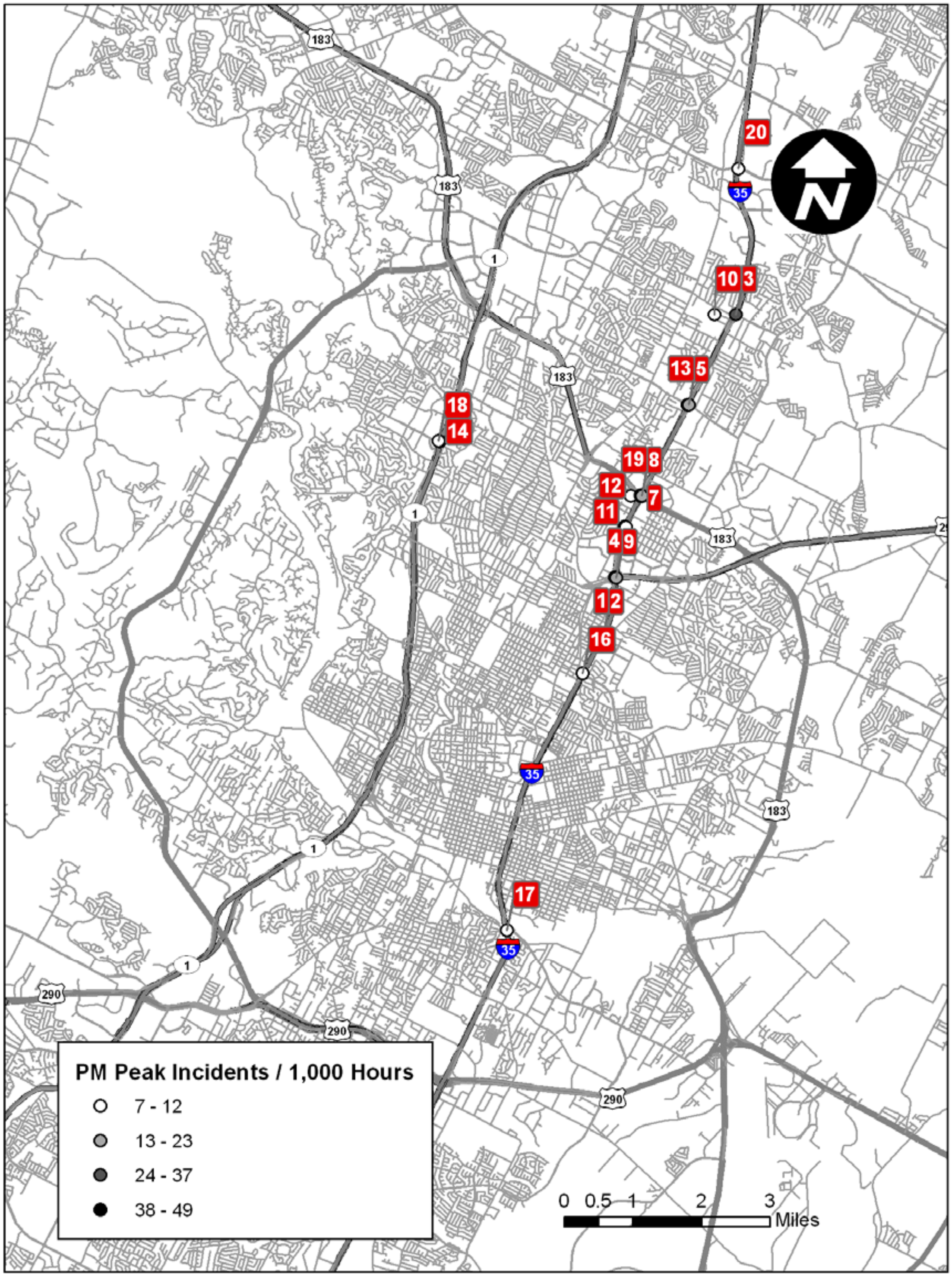


Figure C-21: Weekday PM Peak Frequency-Based Hot Spots.

Table C-6: Locations with Highest Incident Frequencies during PM Peak.

Rank	Roadway	Cross Street	Direction	Total	Avg*
1	IH 0035	51st Street	Southbound	152	49
2	IH 0035	51st Street	Northbound	115	37
3	IH 0035	Braker Lane	Northbound	98	31
4	IH 0035	US 290E	Southbound	72	23
5	IH 0035	Rundberg Lane	Northbound	68	22
6	IH 0035	End of Instrumentation	Southbound	62	20
7	IH 0035	US 183/Anderson Lane	Northbound	56	18
8	IH 0035	US 183 NB / Anderson Ln	Northbound	51	16
9	IH 0035	US 290E	Northbound	51	16
10	IH 0035	Braker Lane	Southbound	39	12
11	IH 0035	St. Johns Ave	Southbound	38	12
12	IH 0035	US 183/Anderson Lane	Southbound	34	11
13	IH 0035	Rundberg Lane	Southbound	32	10
14	LP 0001	Far West Blvd.	Northbound	30	10
15	IH 0035	St. Johns Ave	Northbound	30	10
16	IH 0035	Airport Blvd.	Southbound	29	9
17	IH 0035	Riverside Dr	Northbound	25	8
18	LP 0001	Far West Blvd.	Southbound	24	8
19	IH 0035	US 183 NB / Anderson Ln	Southbound	23	7
20	IH 0035	Parmer Lane	Northbound	23	7

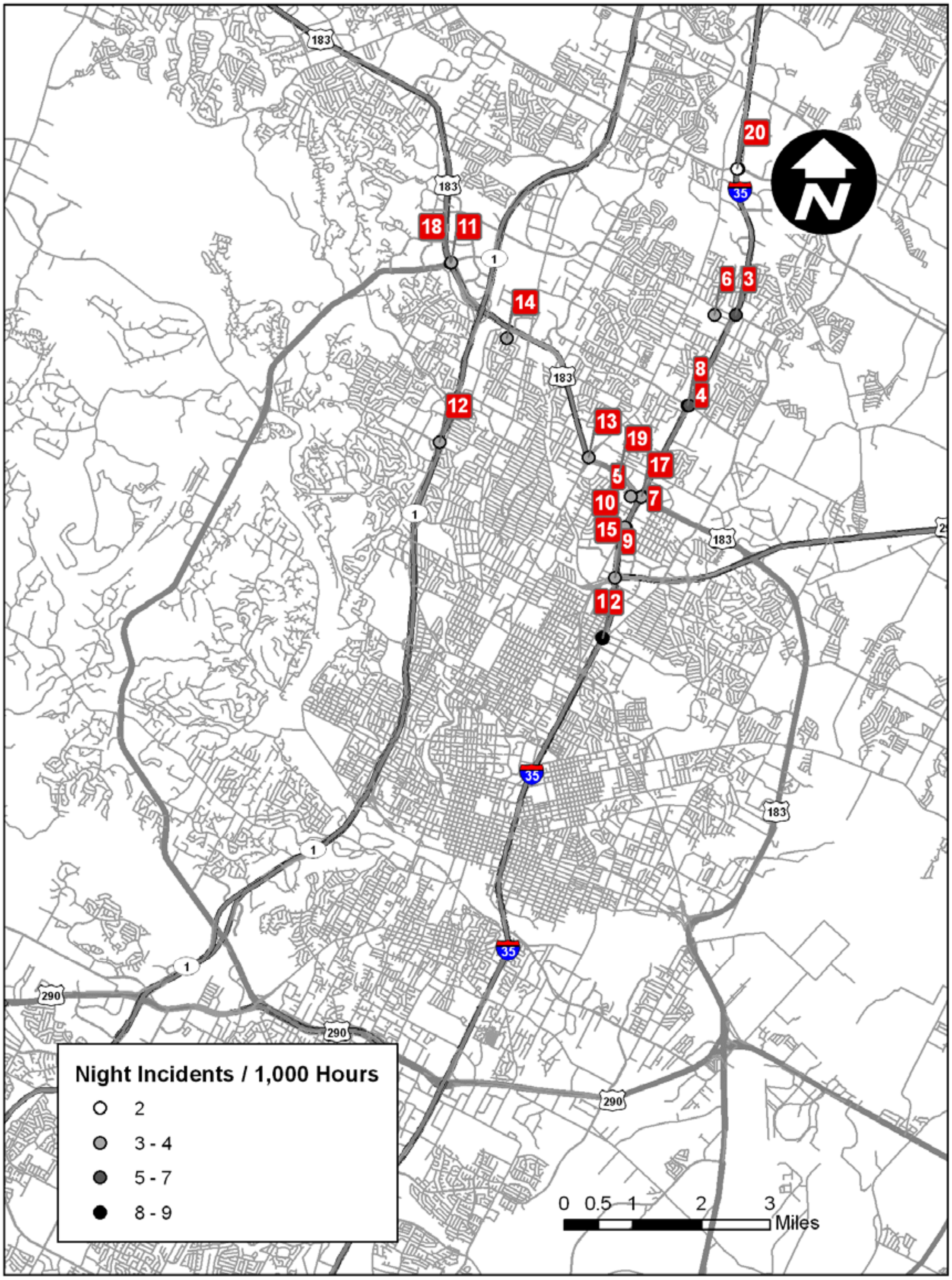


Figure C-22: Weekday Night Frequency-Based Hot Spots.

Table C-7: Locations with Highest Incident Frequencies during Night.

Rank	Roadway	Cross Street	Direction	Total	Avg*
1	IH 0035	51st Street	Southbound	101	9
2	IH 0035	51st Street	Northbound	101	9
3	IH 0035	Braker Lane	Northbound	78	7
4	IH 0035	Rundberg Lane	Northbound	70	6
5	IH 0035	US 183/Anderson Lane	Southbound	50	4
6	IH 0035	Braker Lane	Southbound	49	4
7	IH 0035	US 183/Anderson Lane	Northbound	48	4
8	IH 0035	Rundberg Lane	Southbound	48	4
9	IH 0035	US 290E	Southbound	40	3
10	IH 0035	St. Johns Ave	Southbound	39	3
11	US 0183	Cap. Of Tx Hwy./LP 360	Northbound	35	3
12	LP 0001	Far West Blvd.	Northbound	31	3
13	US 0183	Lamar Blvd./LP 275	Southbound	30	3
14	US 0183	Burnet Rd./FM 1325	Northbound	29	3
15	IH 0035	St. Johns Ave	Northbound	24	2
16	IH 0035	Parmer Lane	Northbound	24	2
17	IH 0035	US 183 NB / Anderson Ln	Northbound	22	2
18	US 0183	Cap. Of Tx Hwy./LP 360	Southbound	22	2
19	US 0183	Georgian Dr.	Northbound	21	2
20	IH 0035	Parmer Lane	Southbound	20	2

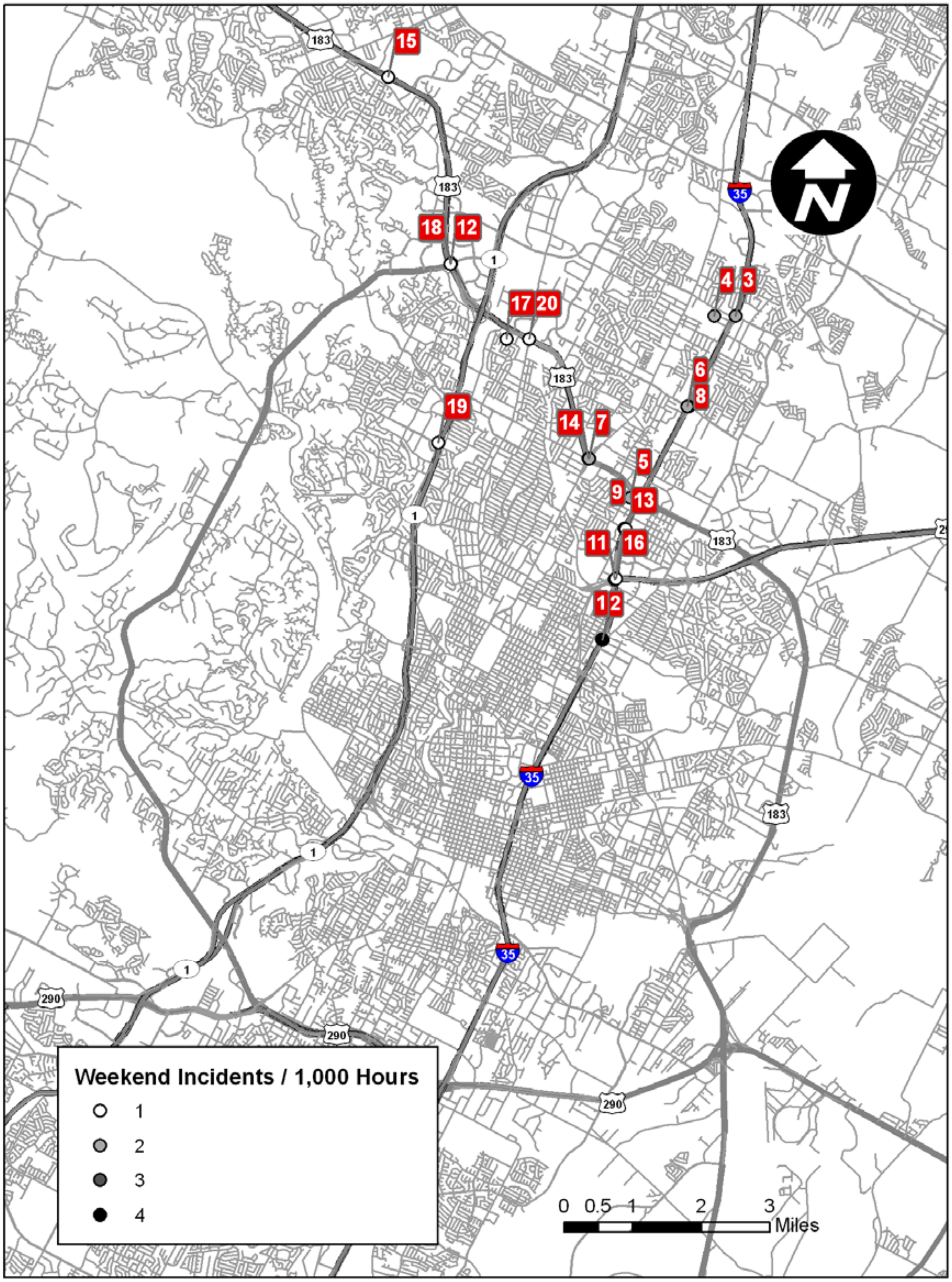


Figure C-23: Weekend Frequency-Based Hot Spots.

Table C-8: Locations with Highest Incident Frequencies during Weekend.

Rank	Roadway	Cross Street	Direction	Total	Avg*
1	IH 0035	51st Street	Southbound	42	4
2	IH 0035	51st Street	Northbound	33	3
3	IH 0035	Braker Lane	Northbound	21	2
4	IH 0035	Braker Lane	Southbound	20	2
5	IH 0035	US 183/Anderson Lane	Southbound	20	2
6	IH 0035	Rundberg Lane	Southbound	19	2
7	US 0183	Lamar Blvd./LP 275	Northbound	17	2
8	IH 0035	Rundberg Lane	Northbound	16	2
9	IH 0035	St. Johns Ave	Southbound	14	1
10	IH 0035	US 183/Anderson Lane	Northbound	12	1
11	IH 0035	US 290E	Southbound	11	1
12	US 0183	Cap. Of Tx Hwy./LP 360	Northbound	11	1
13	IH 0035	St. Johns Ave	Northbound	10	1
14	US 0183	Lamar Blvd./LP 275	Southbound	9	1
15	US 0183	Oak Knoll Drive	Southbound	9	1
16	IH 0035	US 290 WB east of IH35	Northbound	9	1
17	US 0183	Burnet Rd./FM 1325	Northbound	8	1
18	US 0183	Cap. Of Tx Hwy./LP 360	Southbound	8	1
19	LP 0001	Far West Blvd.	Southbound	8	1
20	US 0183	Burnet Rd./FM 1325	Southbound	8	1

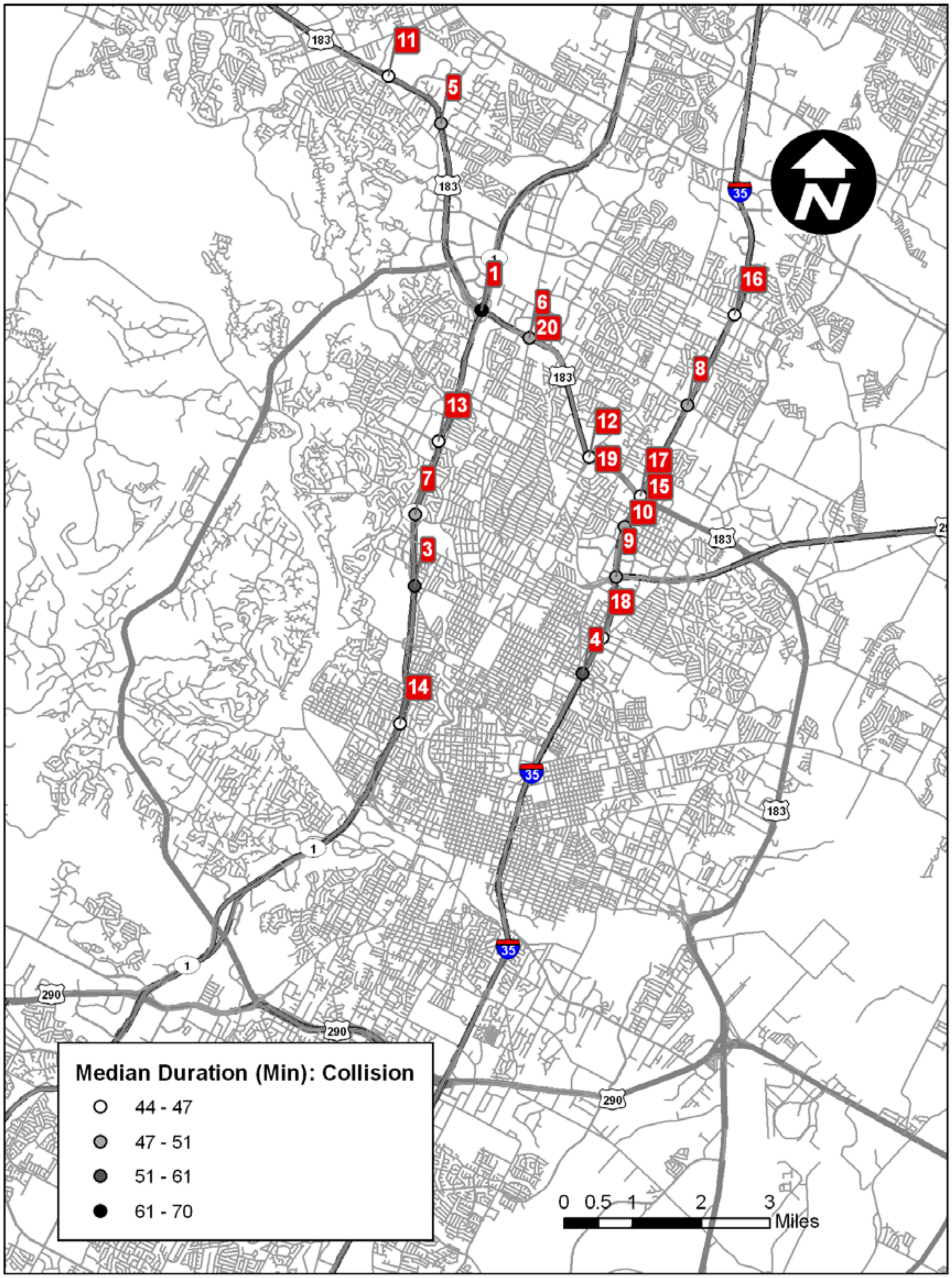


Figure C-24: Median-Duration Based Collision Hot Spots.

Table C-9: Collision Locations with Highest Median Duration.

Rank	Roadway	Cross Street	Direction	Median Duration (min)	# of Incidents
1	US 0183	LP 0001 SB / MoPac	Southbound	70	19
2	US 0183	MoPac/Loop 1	Southbound	61	17
3	LP 0001	45th Street	Northbound	55	14
4	IH 0035	Airport Blvd.	Southbound	54	32
5	US 0183	Duval Rd.	Northbound	51	14
6	US 0183	Burnet Rd./FM 1325	Northbound	49	27
7	LP 0001	RM 2222	Northbound	49	12
8	IH 0035	Rundberg Lane	Southbound	49	46
9	IH 0035	US 290 WB east of IH35	Northbound	49	12
10	IH 0035	St. Johns Ave	Southbound	48	42
11	US 0183	Oak Knoll Drive	Northbound	47	12
12	US 0183	Lamar Blvd./LP 275	Northbound	46	23
13	LP 0001	Far West Blvd.	Southbound	46	19
14	LP 0001	Windsor Rd.	Southbound	46	18
15	IH 0035	US 183/Anderson Lane	Northbound	46	56
16	IH 0035	Braker Lane	Southbound	45	27
17	US 0183	IH 35 Southbound	Southbound	45	33
18	IH 0035	51st Street	Northbound	45	58
19	US 0183	Lamar Blvd./LP 275	Southbound	44	37
20	US 0183	Burnet Rd./FM 1325	Southbound	44	18

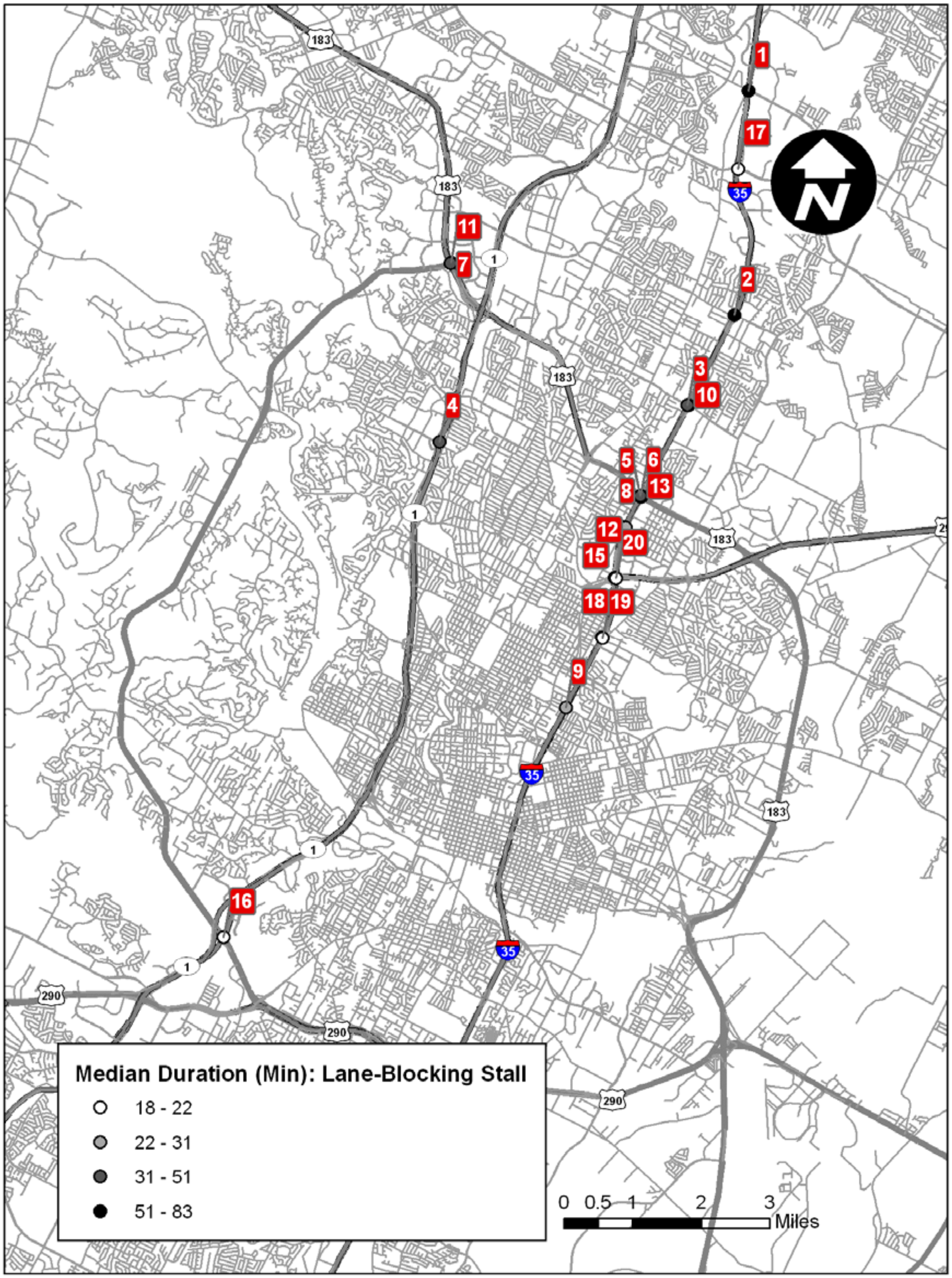


Figure C-25: Median-Durations Based Lane-Blocking Stall Hot Spots.

Table C-10: Lane-Blocking Stall Locations with Highest Median Duration.

Rank	Roadway	Cross Street	Direction	Median Duration (min)	# of Incidents
1	IH 0035	Howard Lane	Northbound	83	6
2	IH 0035	Braker Lane	Southbound	73	8
3	IH 0035	Rundberg Lane	Southbound	51	10
4	LP 0001	Far West Blvd.	Northbound	46	5
5	IH 0035	US 183/Anderson Lane	Southbound	43	10
6	IH 0035	US 183 NB / Anderson Ln	Southbound	38	5
7	US 0183	Cap. Of Tx Hwy./LP 360	Southbound	37	5
8	IH 0035	St. Johns Ave	Southbound	31	15
9	IH 0035	38 1/2 Street	Southbound	31	5
10	IH 0035	Rundberg Lane	Northbound	31	22
11	US 0183	Cap. Of Tx Hwy./LP 360	Northbound	29	5
12	IH 0035	St. Johns Ave	Northbound	27	6
13	IH 0035	US 183 NB / Anderson Ln	Northbound	26	9
14	IH 0035	US 183/Anderson Lane	Northbound	22	14
15	IH 0035	US 290E	Southbound	21	14
16	LP 0001	LP 360/Capital of Tx Hwy	Northbound	20	5
17	IH 0035	Parmer Lane	Northbound	19	5
18	IH 0035	51st Street	Southbound	18	43
19	IH 0035	51st Street	Northbound	18	45
20	IH 0035	US 290E	Northbound	18	11

Duration < 1 Day; Frequency >=1.25 Collisions per year (50% of All Locations)
Getis-Ord (Gi*) Spatial Statistics: Log Duration; 30-feet Zone of Indifference Clustering; 1-mi Buffer

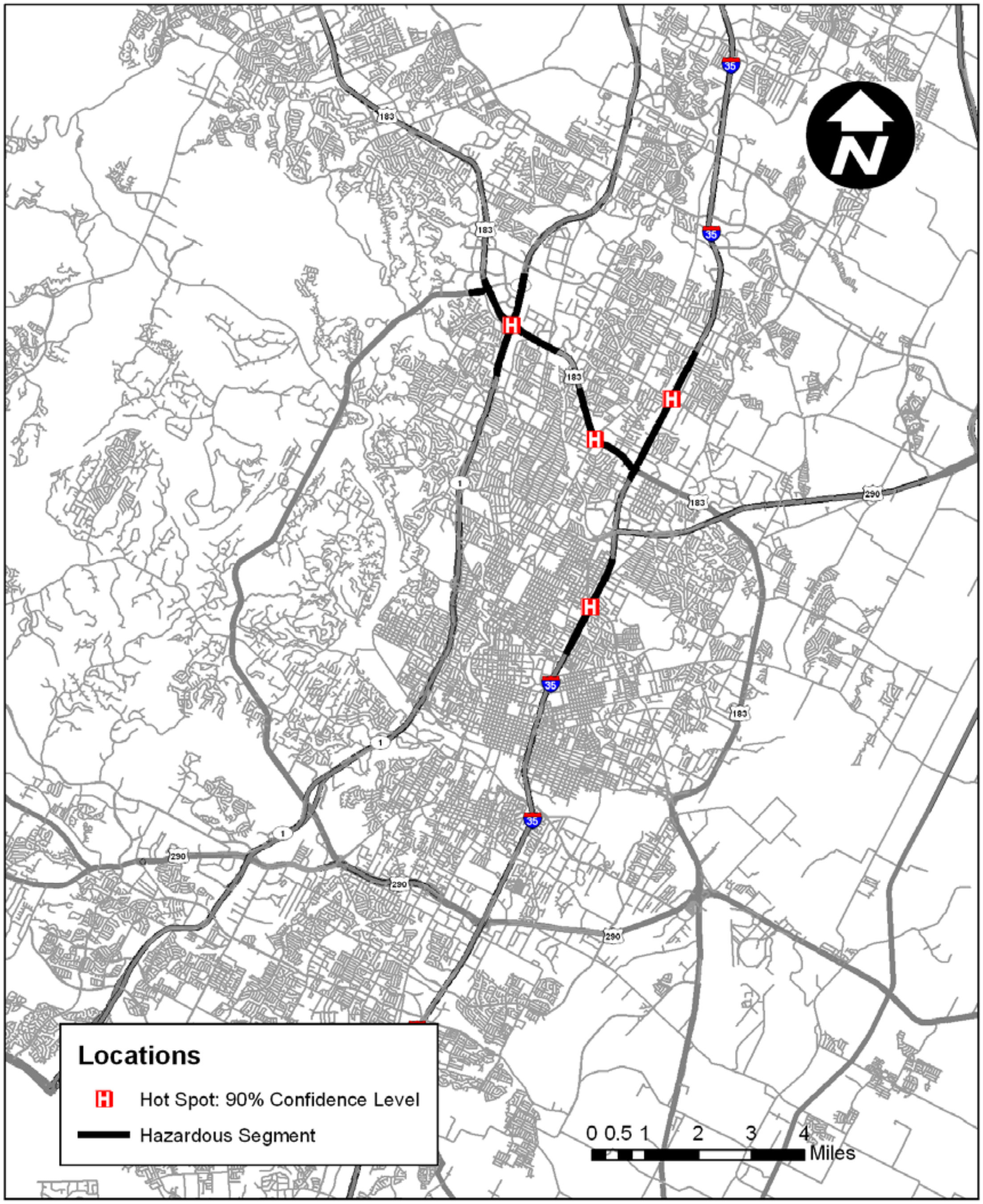


Figure C-26: Collision Hot Spots Using Gi* Spatial Statistics.

Table C-11: Unique Lane-Blocking Stall Locations Using Gi* Spatial Statistics.

Rank	Roadway	Cross Street	Direction	Gi* Scores
1	US 0183	Lamar Blvd./LP 275	Southbound	2.97
2	US 0183	MoPac/Loop 1	Southbound	2.96
3	IH 0035	Rundberg Lane	Southbound	2.05
4	IH 0035	Airport Blvd.	Southbound	1.90

Duration < 1 Day; Frequency >=0.5 Lane-Blocking Stalls per year (50% of All Locations)
Getis-Ord (Gi*) Spatial Statistics: Log Duration; 30-feet Zone of Indifference Clustering; 0.5-mi Buffer

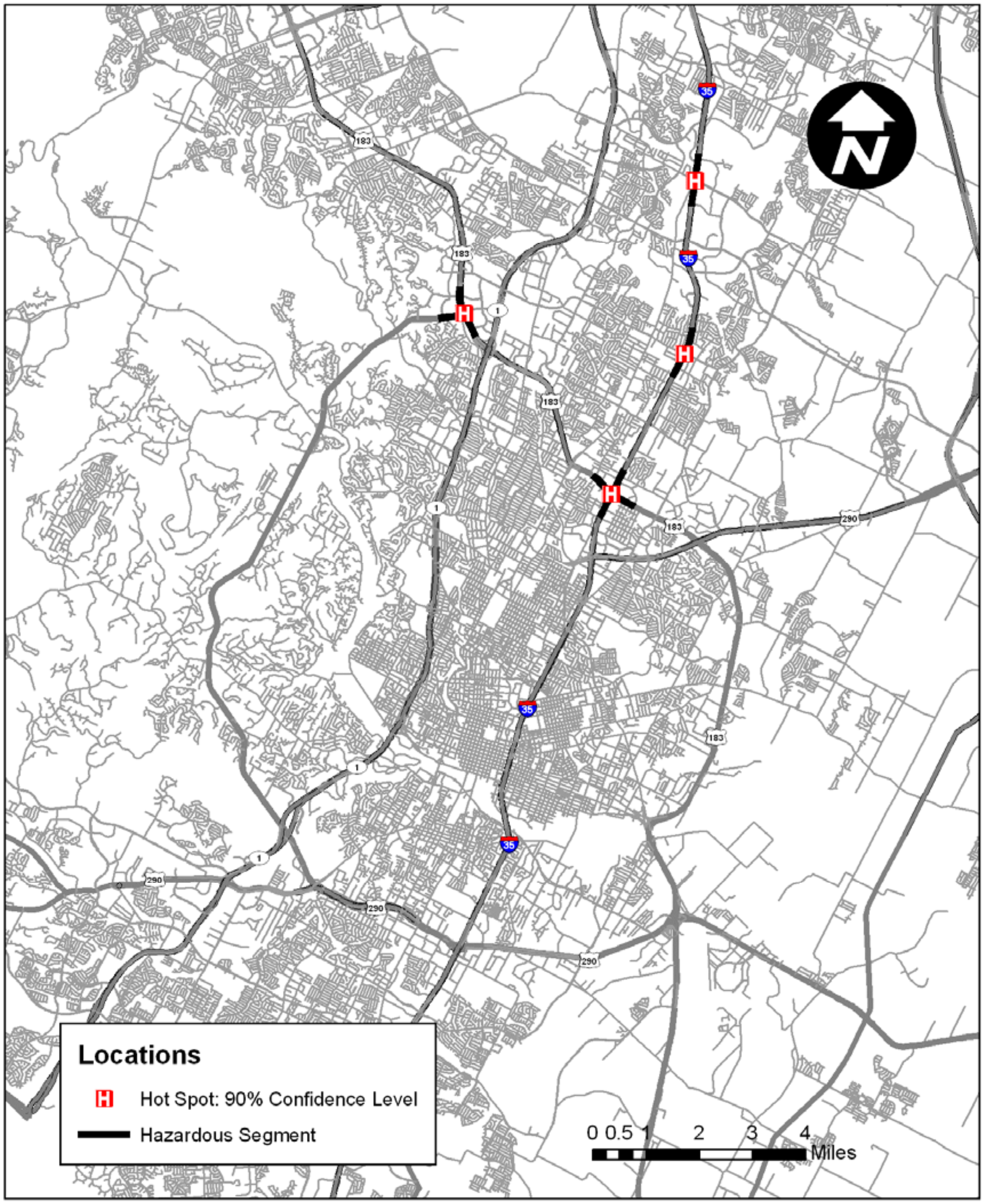


Figure C-27: Lane-Blocking Stall Hot Spots Using Gi* Spatial Statistics.

Table C-12: Lane-Blocking Stall Locations Using Gi* Spatial Statistics.

Rank	Roadway	Cross Street	Direction	Gi* Score
1	IH 0035	Howard Lane	Northbound	2.20
2	IH 0035	Braker Lane	Southbound	2.13
3	US 0183	Cap. Of Tx Hwy./LP 360	Southbound	2.02
4	IH 0035	US 183/Anderson Lane	Southbound	1.94
5	IH 0035	Howard Lane	Southbound	1.69

APPENDIX D. FORT WORTH: DATA ANALYSIS AND RESULTS

Standard Reports of Incident Characteristics

Table D-1: Incident Frequency and Duration by Type (Fort Worth).

Incident Type and Duration (Fort Worth: 2004-2006)							
Type	**Counts**	**%**	**Duration Percentile (minutes)**				
			5%	15%	50%	85%	95%
Collision	1769	71.5%	8	21	57	129	256
Disabled	344	13.9%	5	14	65	198	369
Truck	208	8.4%	11	30	82	189	350
Debris	57	2.3%	7	20	65	189	274
Others	49	2.0%	8	16	58	228	1169
Vehicle on fire	41	1.7%	8	23	51	123	171
HAZMAT	19	0.8%	16	21	158	341	783
Emergency	5	0.2%	7	12	283	760	1098
All Types	2475		7	20	58	140	273

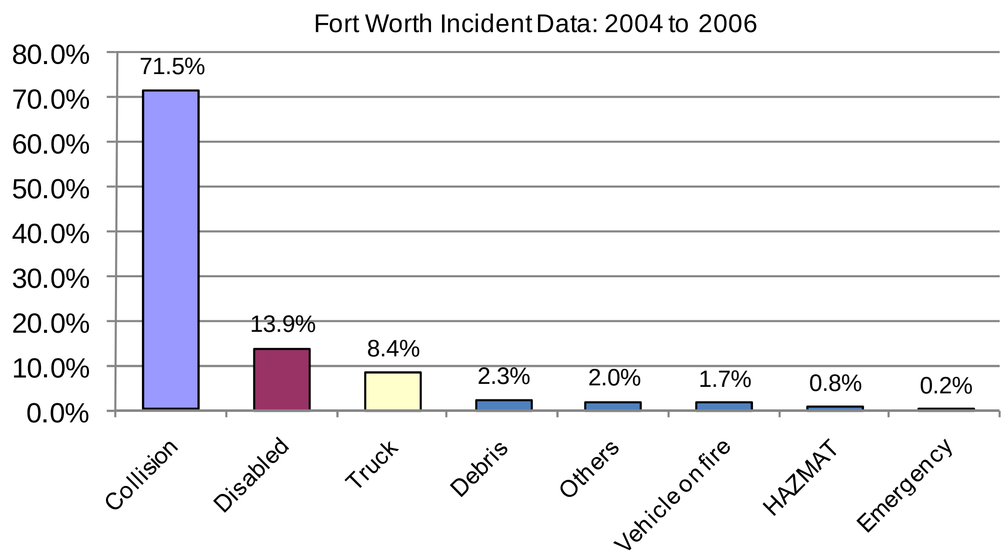


Figure D-1: Distribution of Incident Types (Fort Worth).

Table D-2: Total Number of Incidents per Year (Fort Worth).

Incident Type	2004	2005	2006	Total	% of Total
Collision	609	534	626	1769	71.5%
Disabled	116	99	129	344	13.9%
Truck	80	53	75	208	8.4%
Debris	25	17	15	57	2.3%
Others	19	14	16	49	2.0%
Vehicle on fire	9	15	17	41	1.7%
HAZMAT	5	4	10	19	0.8%
Emergency	2	2	1	5	0.2%
All Types	*848*	*717*	*910*	*2475*	

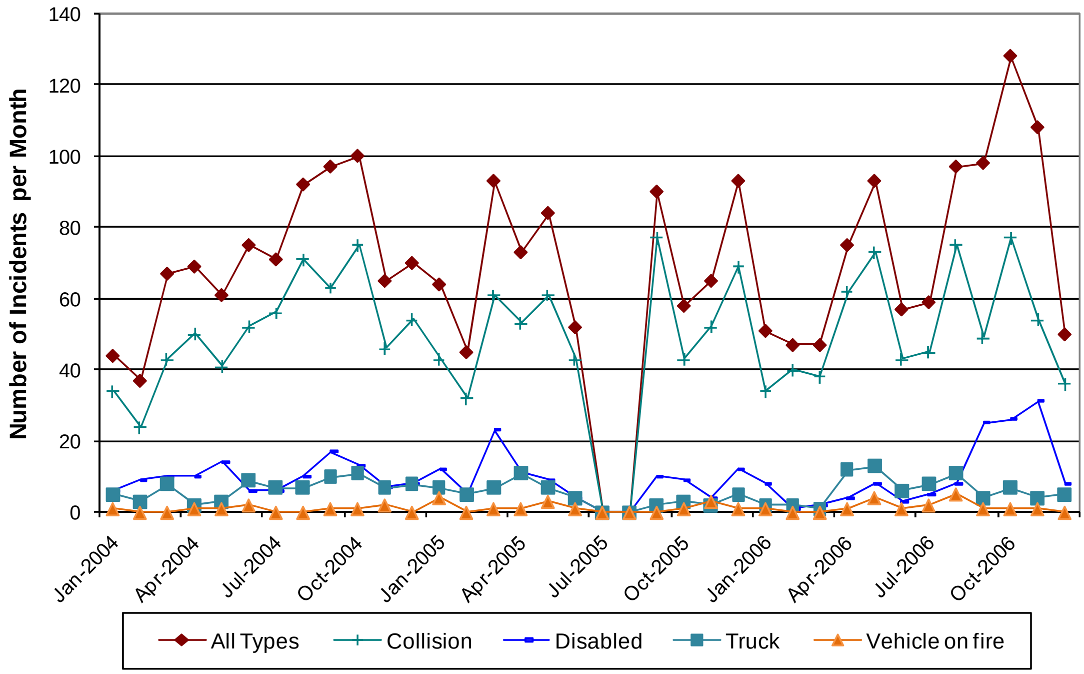


Figure D-2: Monthly Incident Counts over the Analysis Period (Fort Worth).

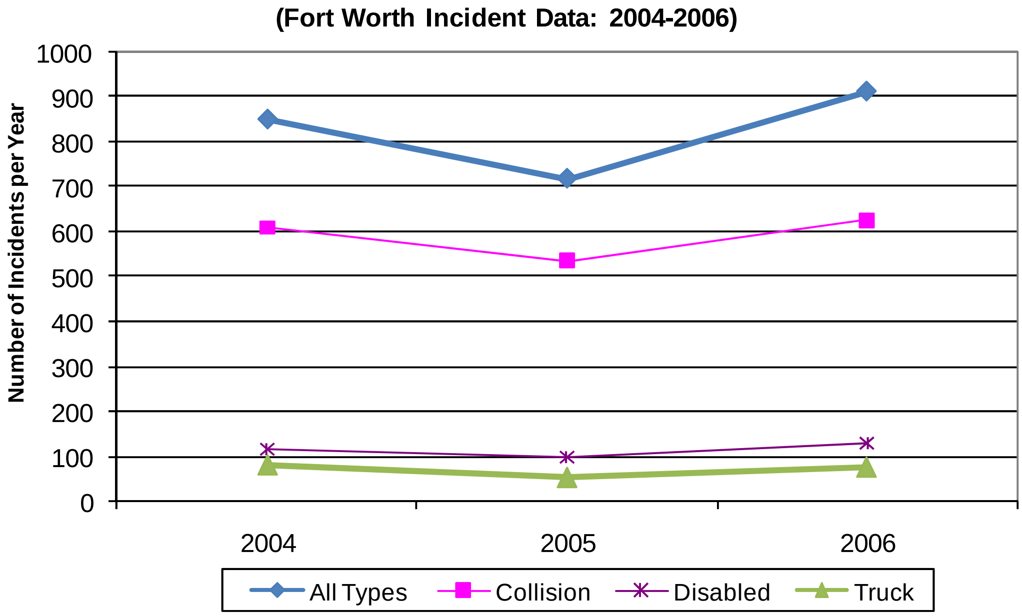


Figure D-3: Yearly Incident Rates by Incident Types (Fort Worth).

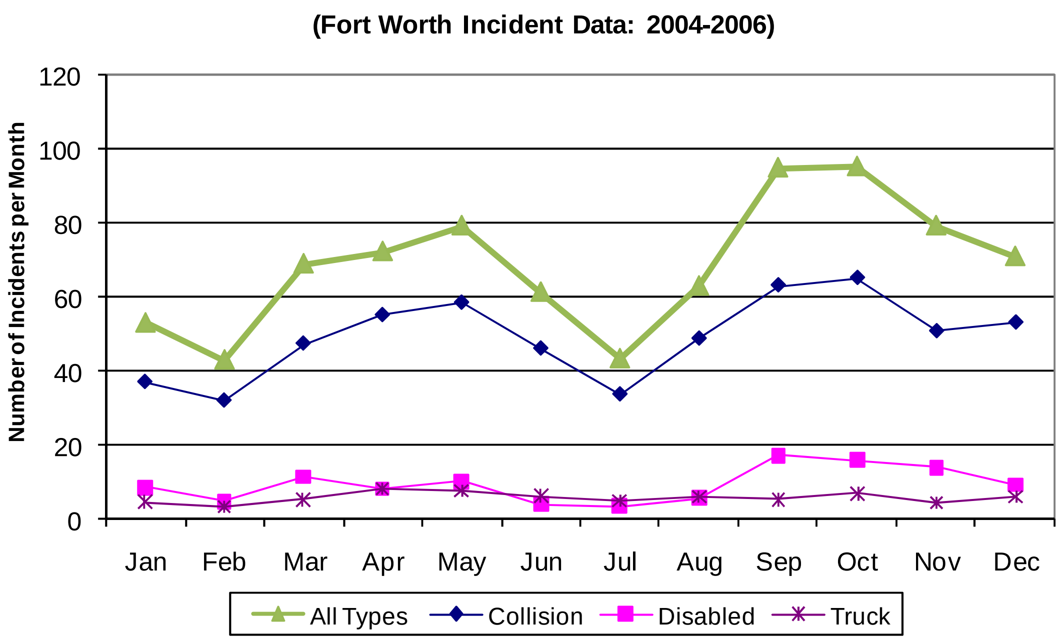


Figure D-4: Monthly Incident Rates by Incident Types (Fort Worth).

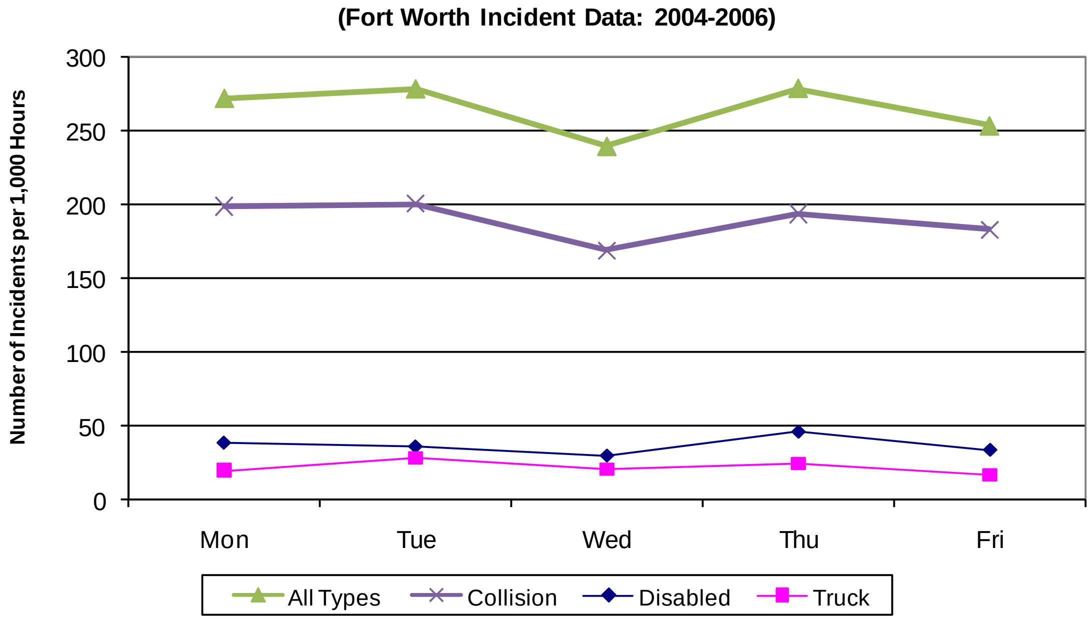


Figure D-5: Daily Incident Rates by Incident Types (Fort Worth).

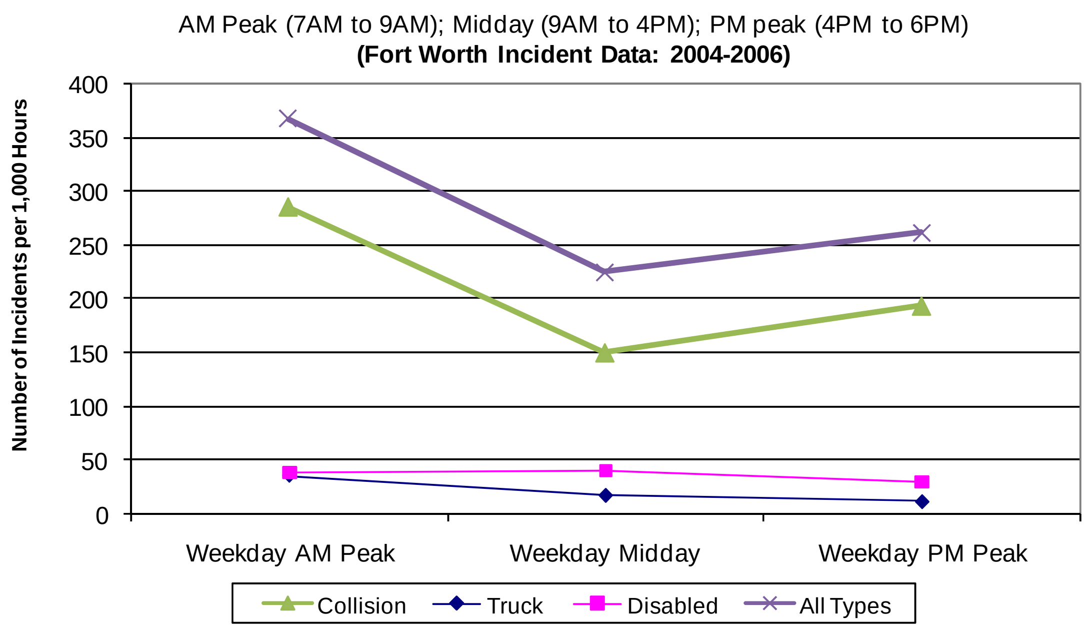


Figure D-6: Incident Rates at Different Times of Day by Incident Type (Fort Worth).

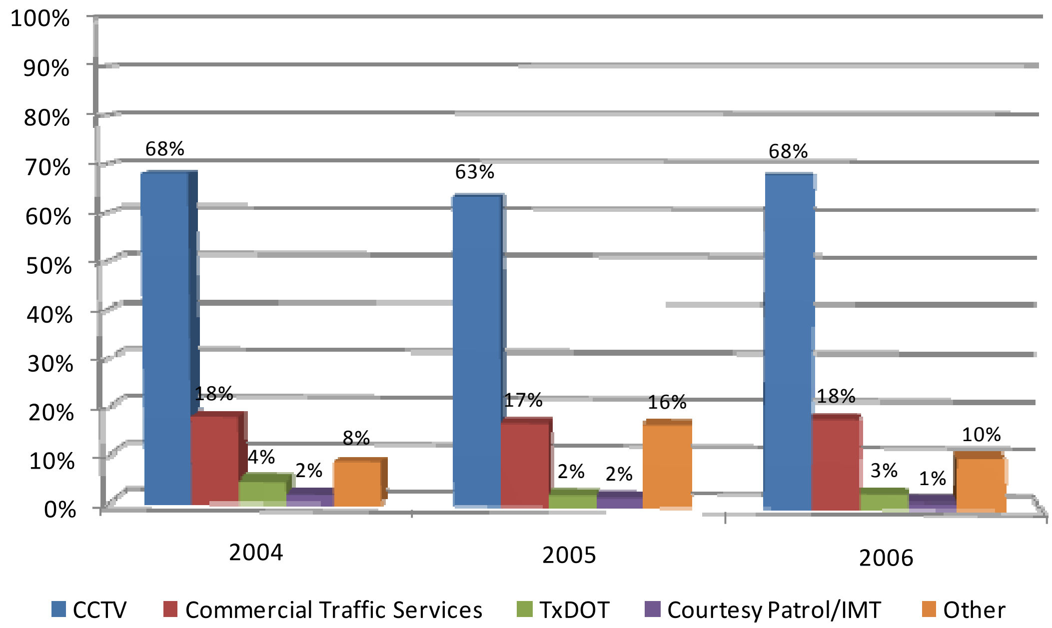


Figure D-7: Distribution of Incident Detection Methods (Fort Worth).

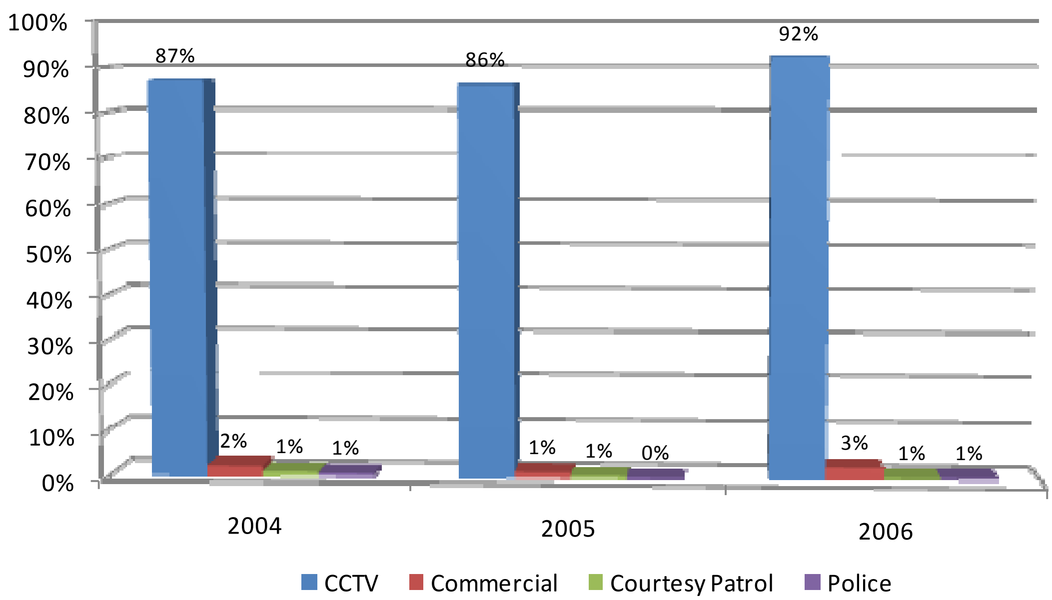


Figure D-8: Distribution of Incident Verification Methods (Fort Worth).

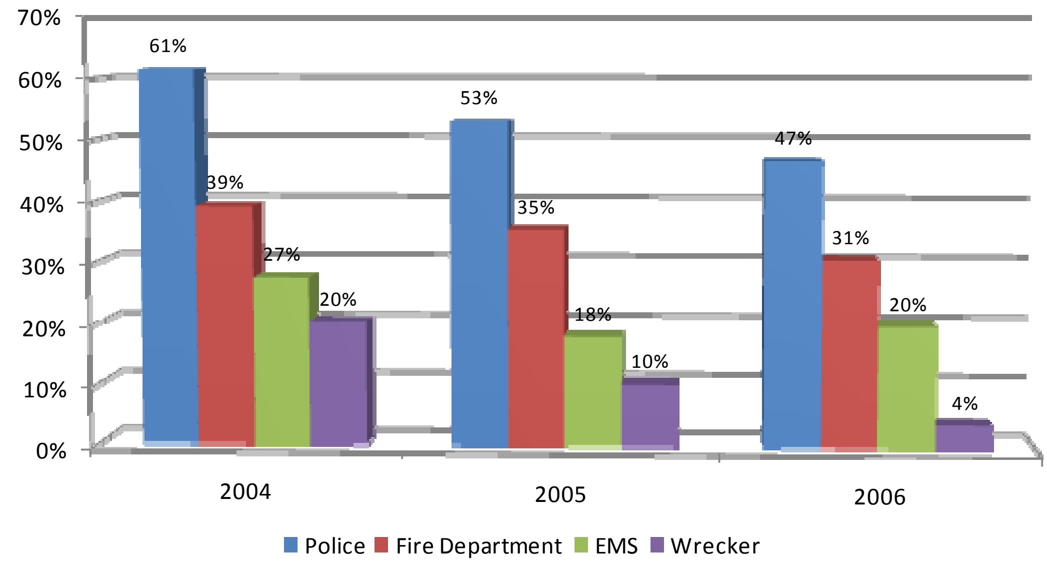


Figure D-9: Distribution of Major Responders (Fort Worth).

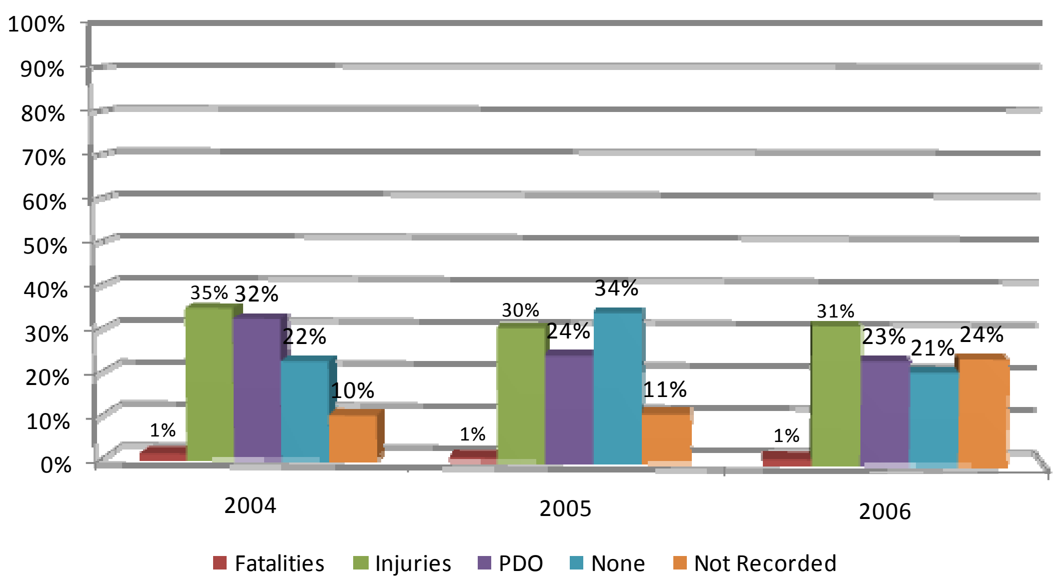


Figure D-10: Distribution of Incident Severity (Fort Worth).

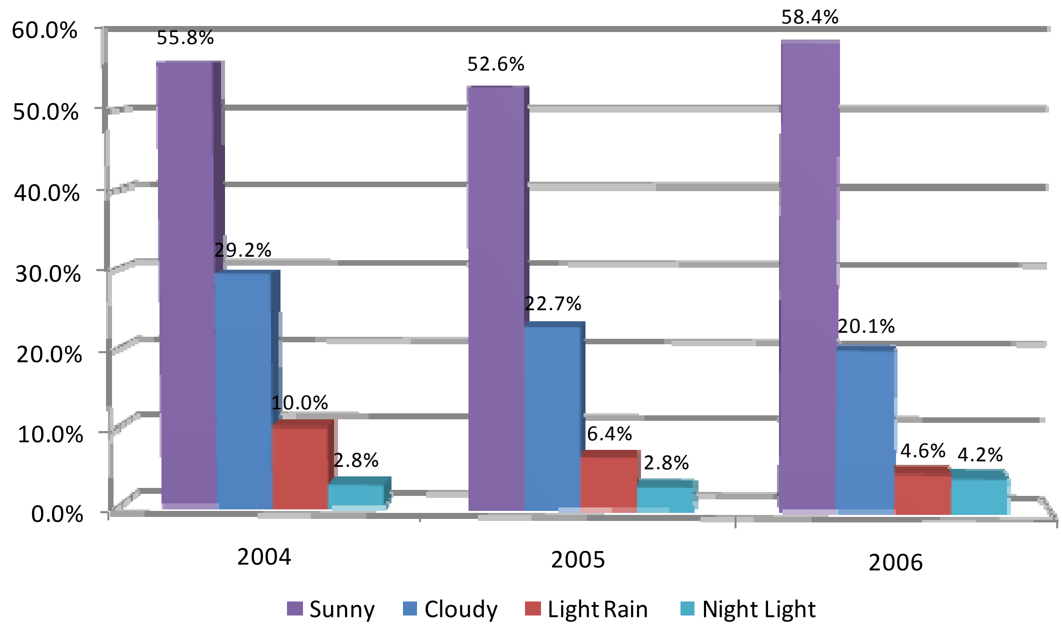


Figure D-11: Distribution of Major Weather Conditions (Fort Worth).

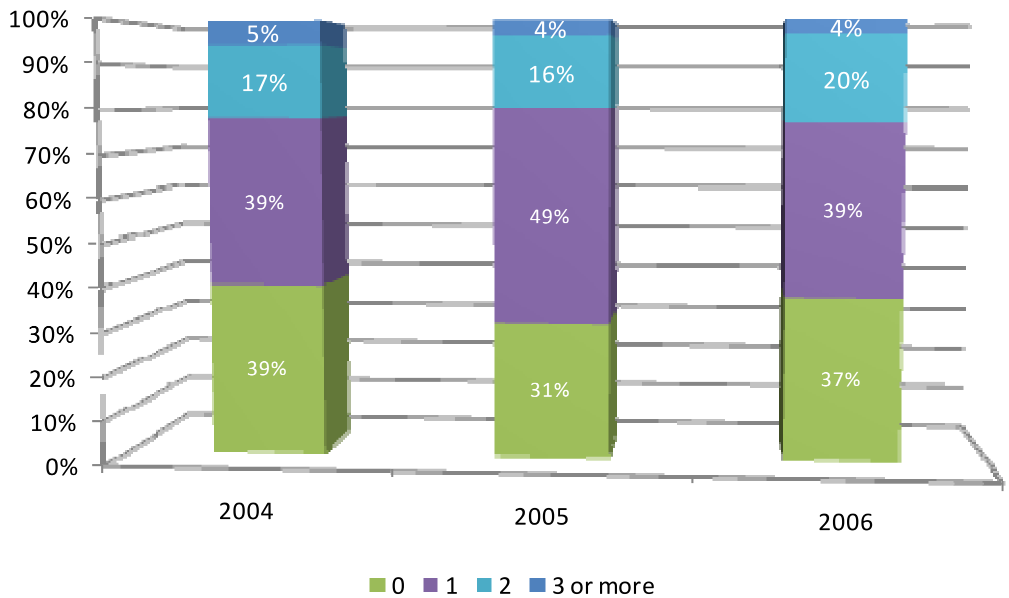


Figure D-12: Distribution of Number of Mainlanes Blocked (Fort Worth).

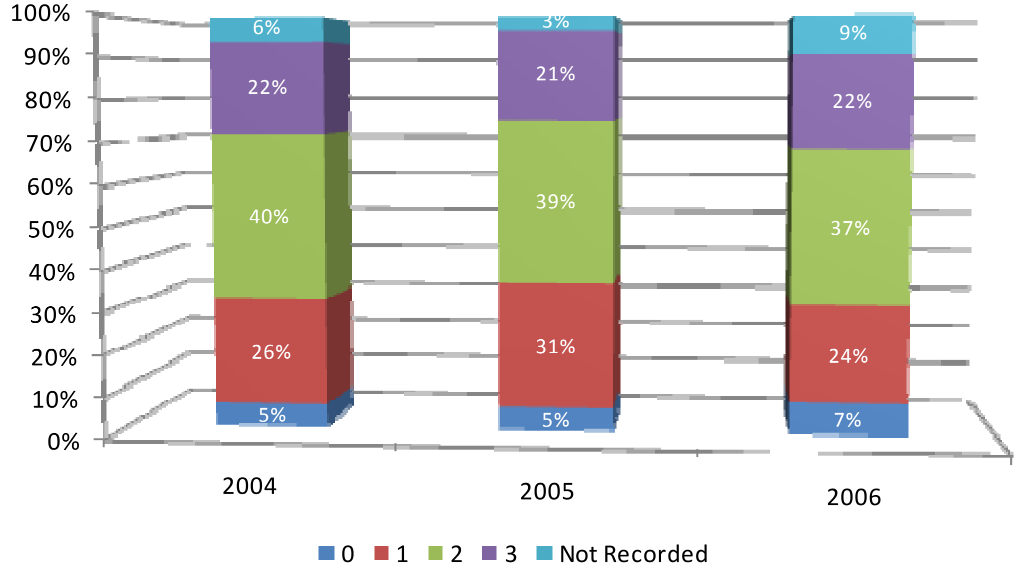


Figure D-13: Distribution of Number of Vehicles Involved (Fort Worth).

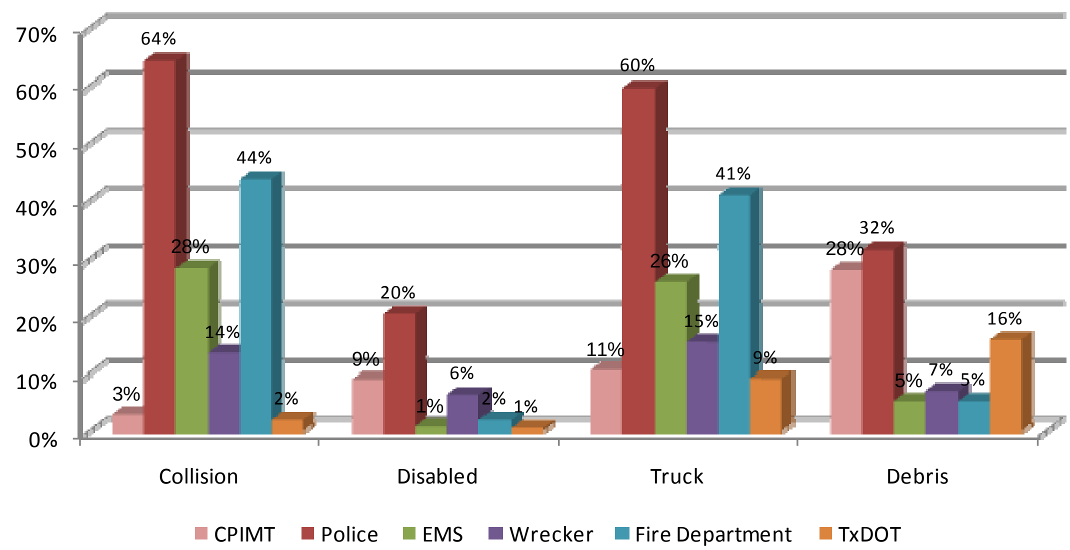


Figure D-14: Distribution of Major Responders by Incident Types (Fort Worth).

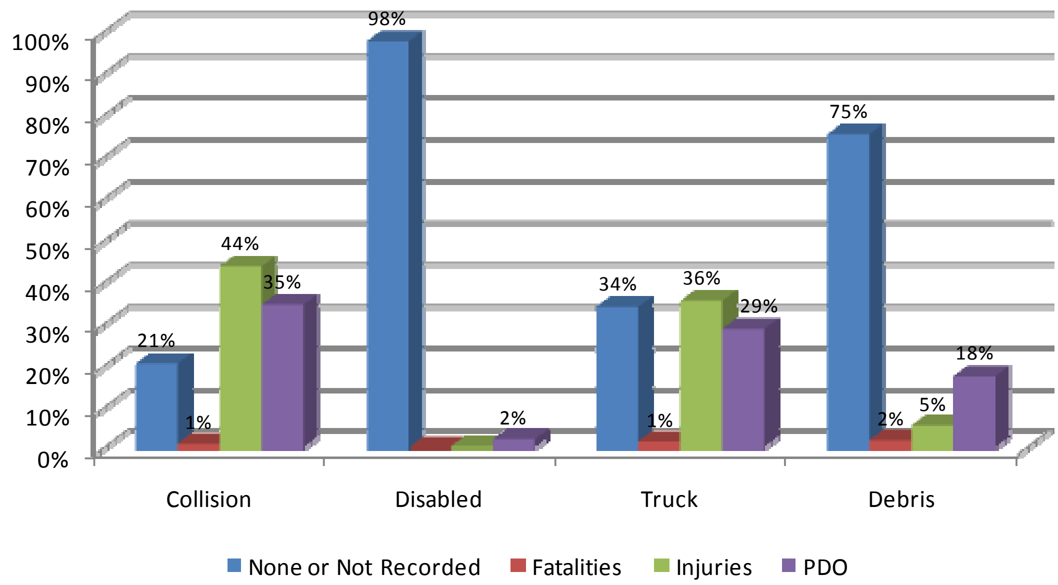


Figure D-15: Distribution of Severity by Incident Types (Fort Worth).

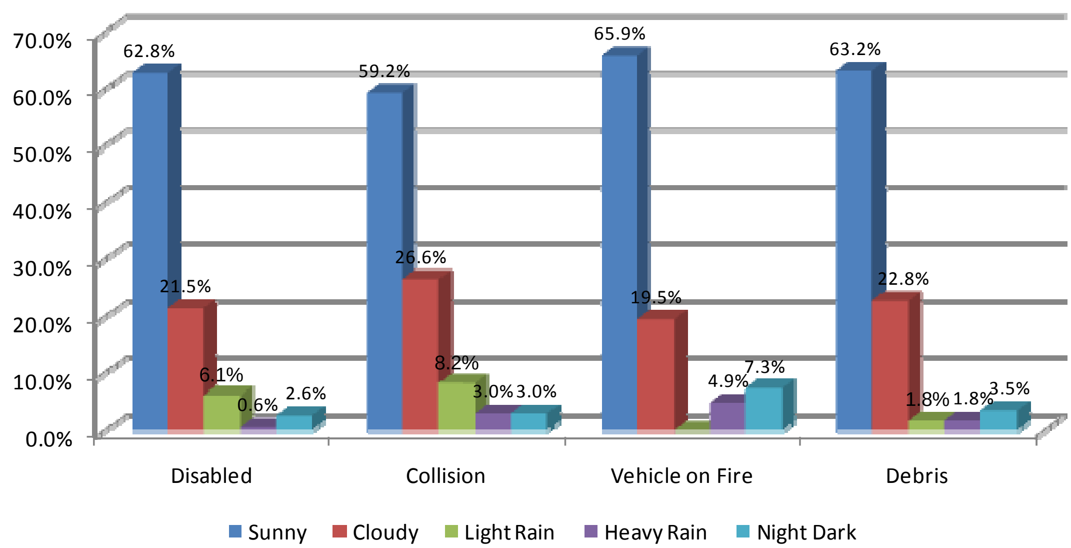


Figure D-16: Distribution of Weather Conditions by Incident Types (Fort Worth).

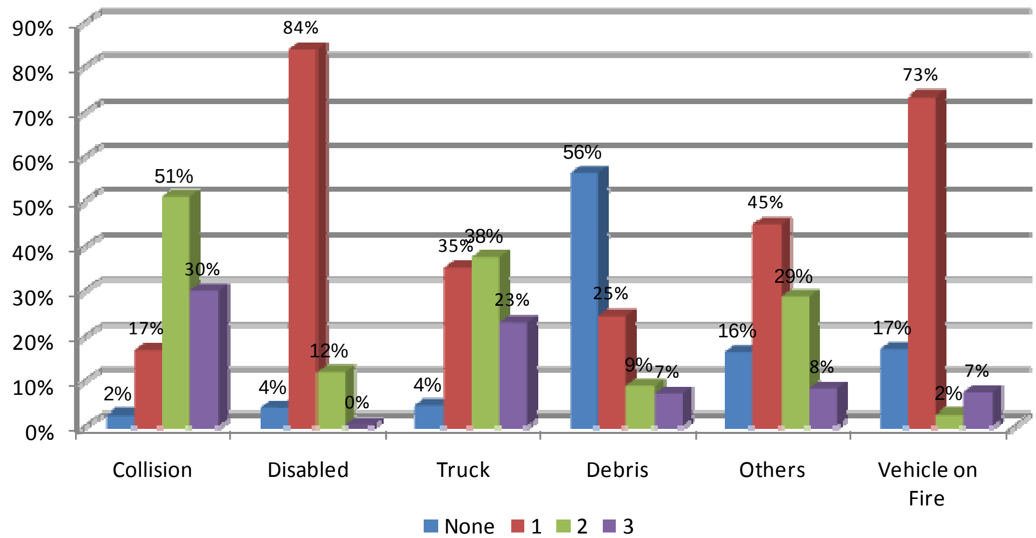


Figure D-17: Distribution of Vehicles Involved by Incident Types (Fort Worth).

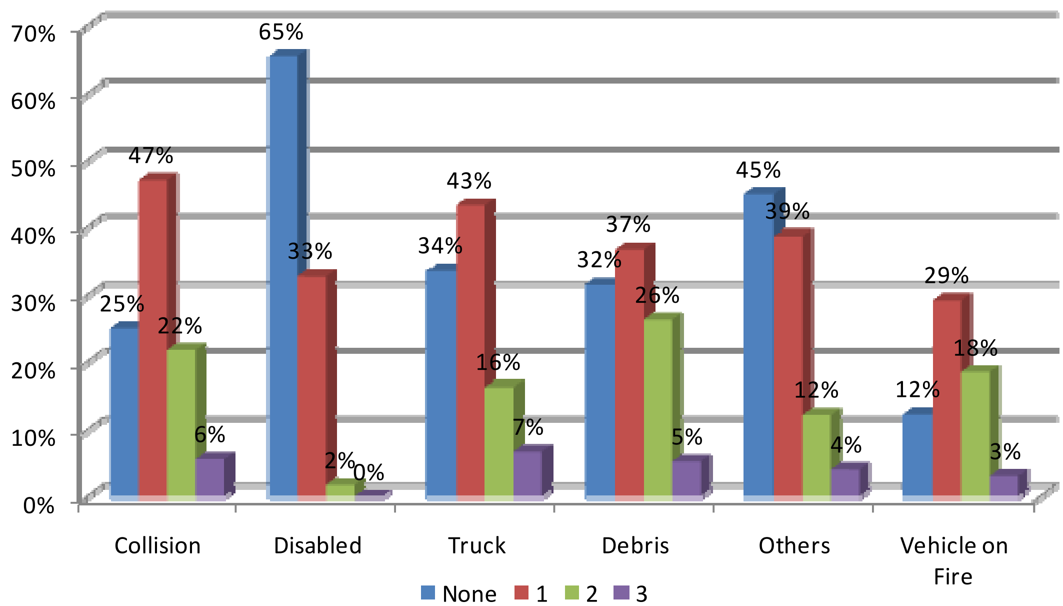


Figure D-18: Distribution of Lane Blockage by Incident Types (Fort Worth).

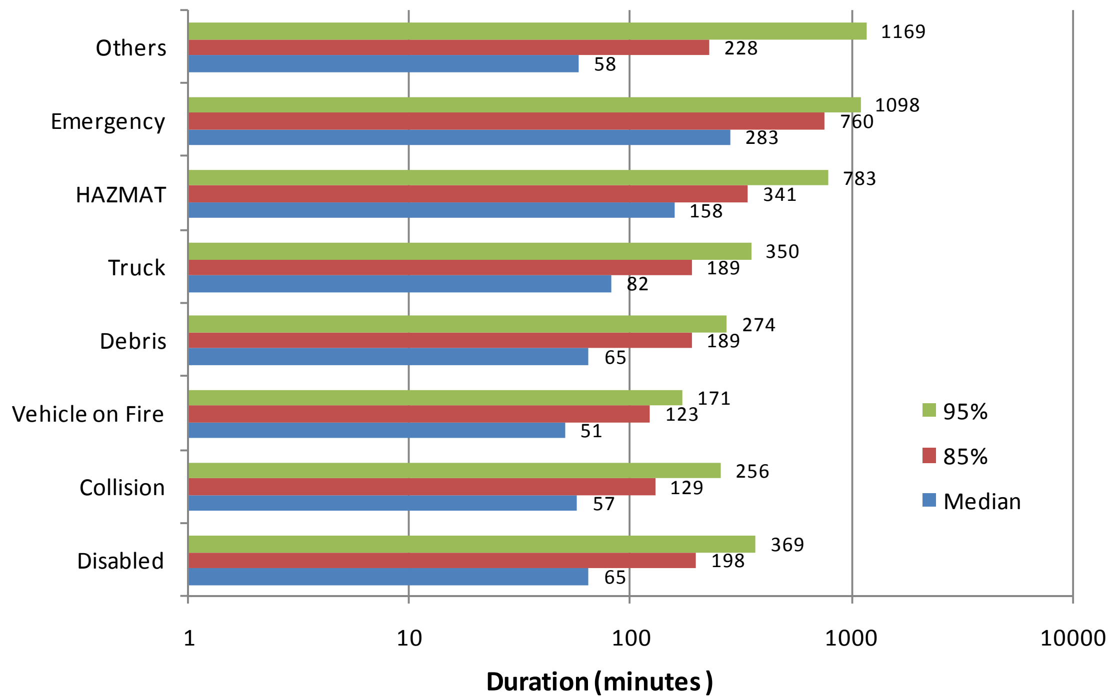


Figure D-19: Incident Duration Percentile Statistics (Fort Worth).

Hot Spot Analysis

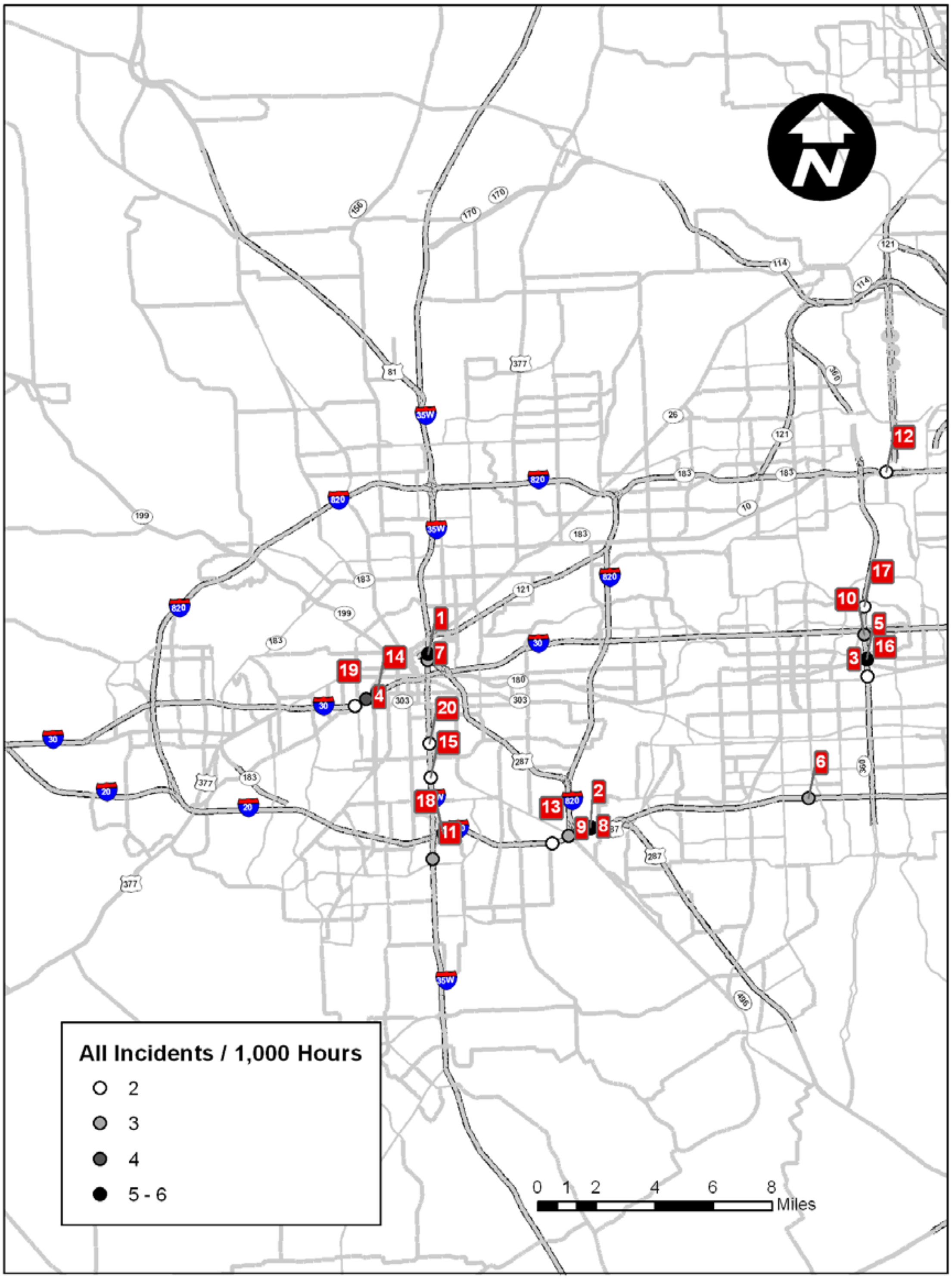


Figure D-20: Frequency-Based Hot Spots during All Times of Day.

Table D-3: Locations with Highest Incident Frequencies during All Times of Day.

Rank	Roadway	Cross Street	Direction	Total	Avg*
1	I35	SPUR 280	Northbound	54	5
2	I20	BOWMAN SPRINGS RD	Westbound	48	5
3	SH360S	DIVISION ST/US-180	Northbound	46	5
4	I30	FOREST PARK BLVD	Eastbound	37	4
5	SH360S	DIVISION ST/US-180	Southbound	33	3
6	I20	S COLLINS ST	Westbound	31	3
7	I35	SPUR 280	Southbound	30	3
8	I20	BOWMAN SPRINGS RD	Eastbound	29	3
9	I20	MANSFIELD HWY/US-287	Eastbound	29	3
10	SH360S	SIX FLAGS	Southbound	25	2
11	I35	ALTAMESA BLVD	Northbound	25	2
12	SH183	AMON CARTER BLVD	Westbound	22	2
13	I20	ANGLIN DR	Eastbound	22	2
14	I30	FOREST PARK BLVD	Westbound	22	2
15	I35	RIPY ST	Southbound	22	2
16	SH360S	ABRAM ST	Northbound	21	2
17	SH360S	BROWN/AVE K	Southbound	20	2
18	I20	OAK GROVE RD	Westbound	20	2
19	I30	UNIVERSITY DR	Eastbound	20	2
20	I35	MORNINGSIDE DR	Northbound	20	2

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

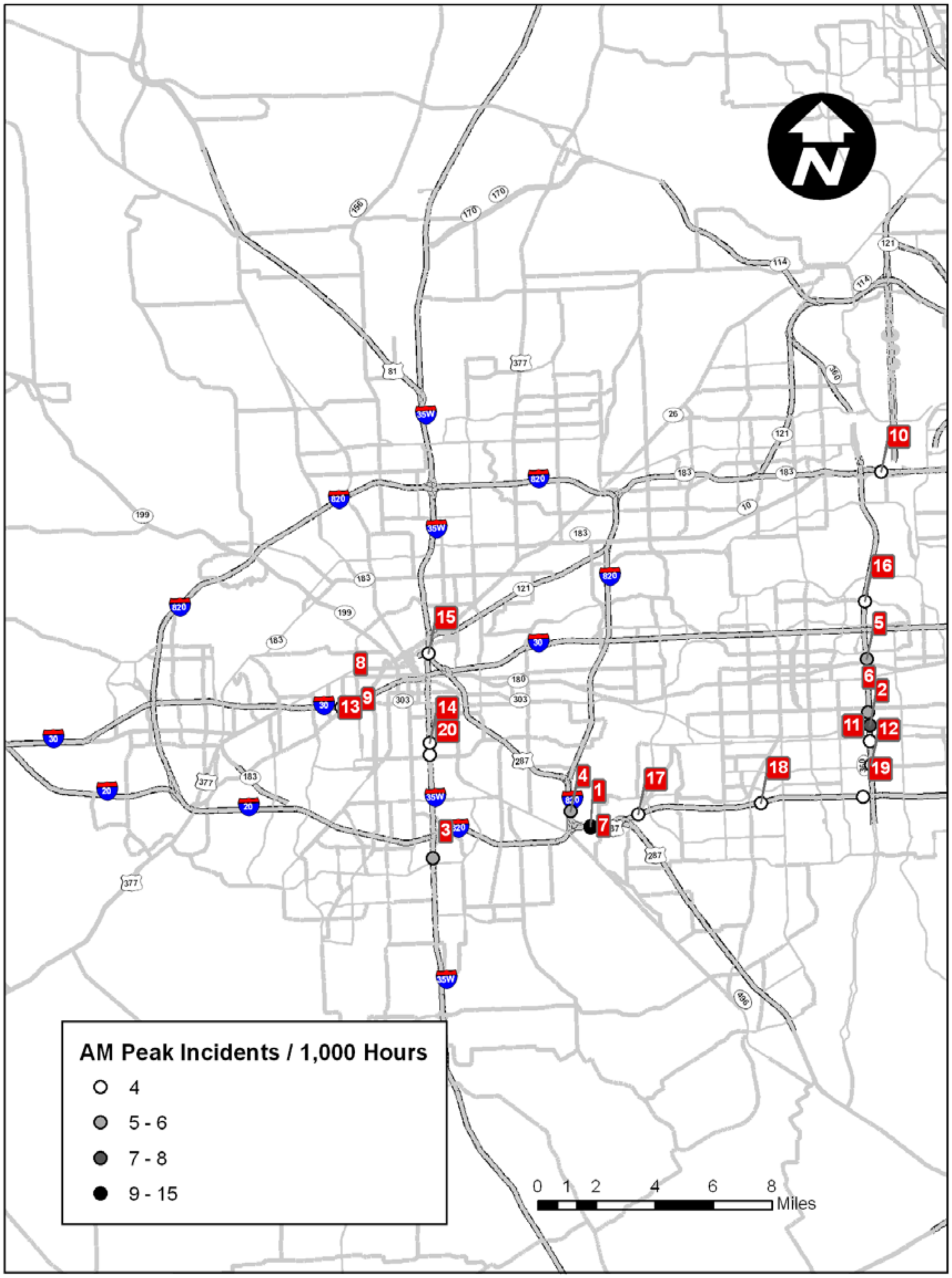


Figure D-21: Weekday AM Peak Frequency-Based Hot Spots.

Table D-4: Locations with Highest Incident Frequencies during AM Peak.

Rank	Roadway	Cross Street	Direction	Total	Avg*
1	I20	BOWMAN SPRINGS RD	Westbound	24	15
2	SH360S	SPUR 303/PIONEER PKWY	Northbound	12	8
3	I35	ALTAMESA BLVD	Northbound	10	6
4	I820E	SUN VALLEY DR	Northbound	10	6
5	SH360S	DIVISION ST/US-180	Northbound	8	5
6	SH360S	PARK ROW DR	Northbound	8	5
7	I20	BOWMAN SPRINGS RD	Eastbound	8	5
8	I30	FOREST PARK BLVD	Eastbound	8	5
9	I30	UNIVERSITY DR	Eastbound	8	5
10	SH183	AMON CARTER BLVD	Eastbound	7	4
11	SH360S	ARKANSAS LN	Northbound	7	4
12	SH360S	MAYFIELD RD	Northbound	7	4
13	I30	MONTGOMERY ST	Eastbound	7	4
14	I35	MORNINGSIDE DR	Northbound	7	4
15	I35	SPUR 280	Northbound	7	4
16	SH360S	BROWN/AVE K	Northbound	6	4
17	I20	LITTLE/SCHOOL RD	Westbound	6	4
18	I20	S COOPER ST	Eastbound	6	4
19	I20	SH-360	Eastbound	6	4
20	I35	BERRY ST	Northbound	6	4

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

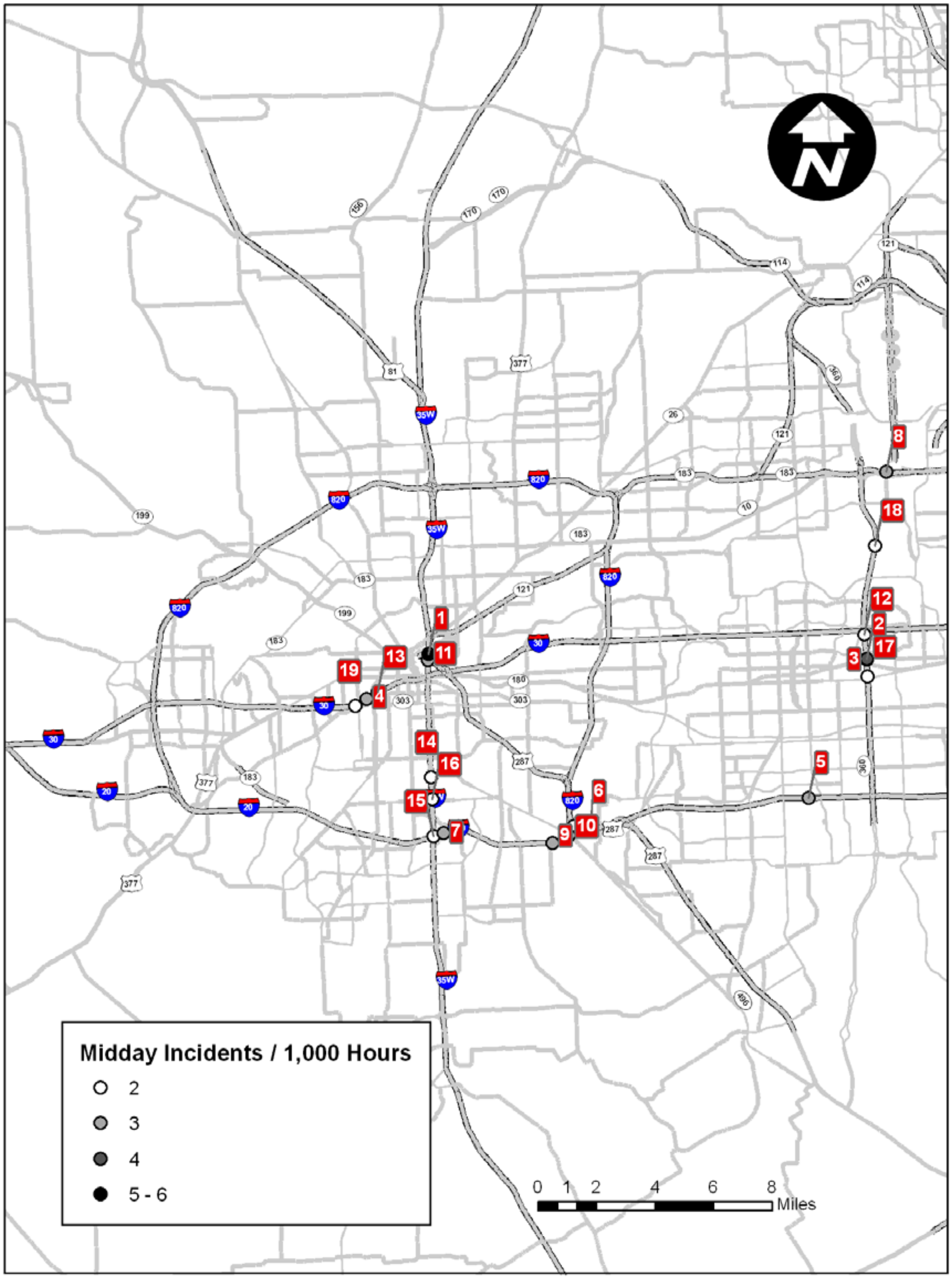


Figure D-22: Weekday Midday Frequency-Based Hot Spots.

Table D-5: Locations with Highest Incident Frequencies during Midday.

Rank	Roadway	Cross Street	Direction	Total	Avg*
1	I35	SPUR 280	Northbound	35	6
2	SH360S	DIVISION ST/US-180	Southbound	20	4
3	SH360S	DIVISION ST/US-180	Northbound	19	3
4	I30	FOREST PARK BLVD	Eastbound	19	3
5	I20	S COLLINS ST	Westbound	18	3
6	I20	BOWMAN SPRINGS RD	Westbound	15	3
7	I20	OAK GROVE RD	Westbound	15	3
8	SH183	AMON CARTER BLVD	Westbound	14	3
9	I20	ANGLIN DR	Eastbound	14	3
10	I20	MANSFIELD HWY/US-287	Eastbound	14	3
11	I35	SPUR 280	Southbound	14	3
12	SH360S	SIX FLAGS	Southbound	13	2
13	I30	FOREST PARK BLVD	Westbound	13	2
14	I35	RIPY ST	Southbound	13	2
15	I20	I-35 W	Westbound	12	2
16	I35	SEMINARY DR	Southbound	12	2
17	SH360S	ABRAM ST	Northbound	11	2
18	SH360S	RIVERSIDE PKY	Northbound	11	2
19	I30	UNIVERSITY DR	Eastbound	11	2
20	I20	I-820 EAST LOOP	Westbound	10	2

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

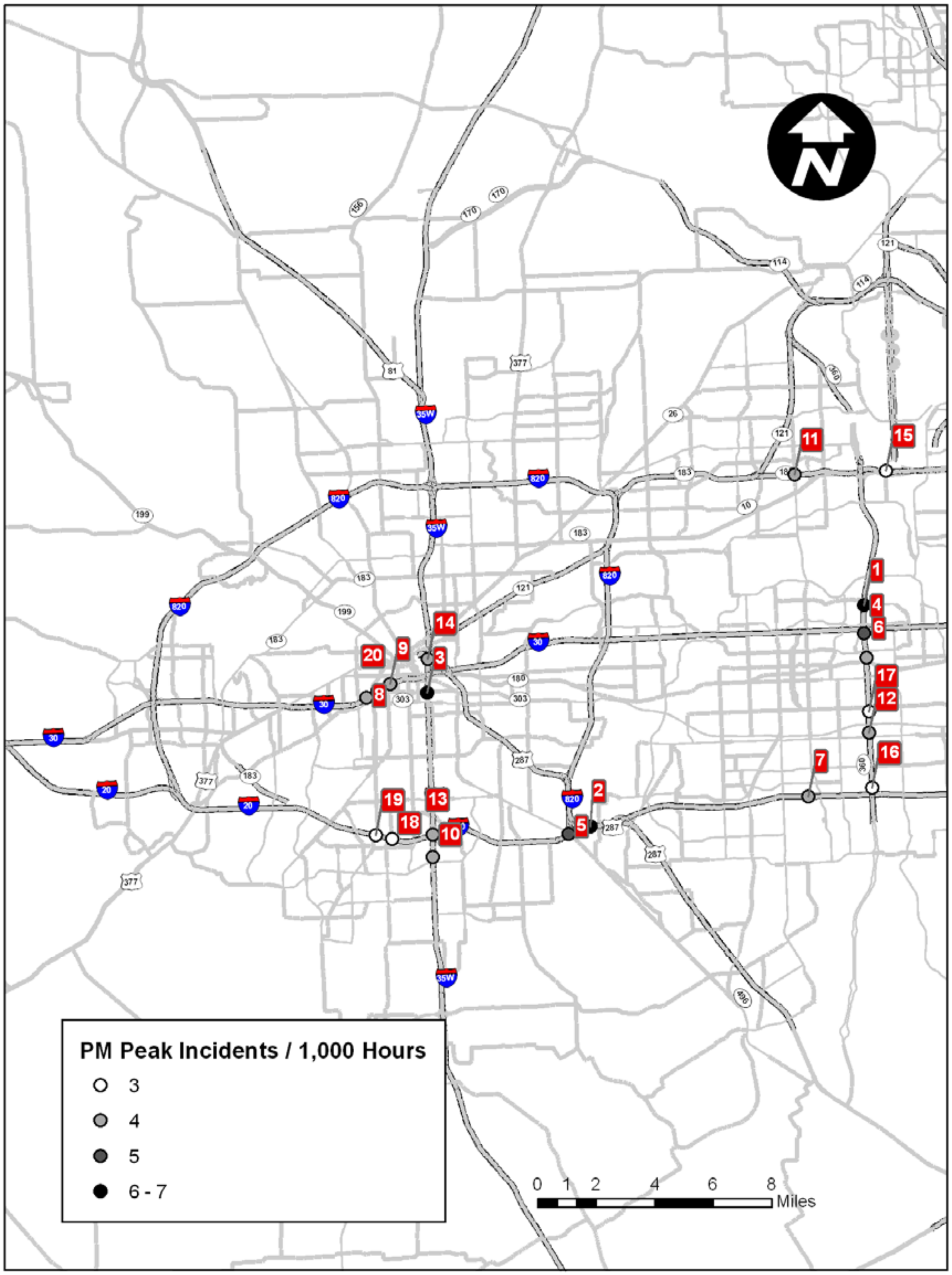


Figure D-23: Weekday PM Peak Frequency-Based Hot Spots.

Table D-6: Locations with Highest Incident Frequencies during PM Peak.

Rank	Roadway	Cross Street	Direction	Total	Avg*
1	SH360S	BROWN/AVE K	Southbound	11	7
2	I20	BOWMAN SPRINGS RD	Eastbound	11	7
3	I35	HATTIE ST	Southbound	9	6
4	SH360S	SIX FLAGS	Southbound	8	5
5	I20	MANSFIELD HWY/US-287	Eastbound	8	5
6	SH360S	DIVISION ST/US-180	Southbound	7	4
7	I20	S COLLINS ST	Westbound	7	4
8	I30	FOREST PARK BLVD	Eastbound	7	4
9	I30	SUMMIT AVE	Westbound	7	4
10	I35	ALTAMESA BLVD	Northbound	7	4
11	SH183	INDUSTRIAL BLVD	Westbound	6	4
12	SH360S	ARKANSAS LN	Southbound	6	4
13	I35	I-20	Southbound	6	4
14	I35	SPUR 280	Southbound	6	4
15	SH183	AMON CARTER BLVD	Westbound	5	3
16	SH360S	CUMMINS ST	Southbound	5	3
17	SH360S	PARK ROW DR	Southbound	5	3
18	I20	JAMES/CROWLEY AVE	Westbound	5	3
19	I20	MCCART AVE	Westbound	5	3
20	I30	FOREST PARK BLVD	Westbound	5	3

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

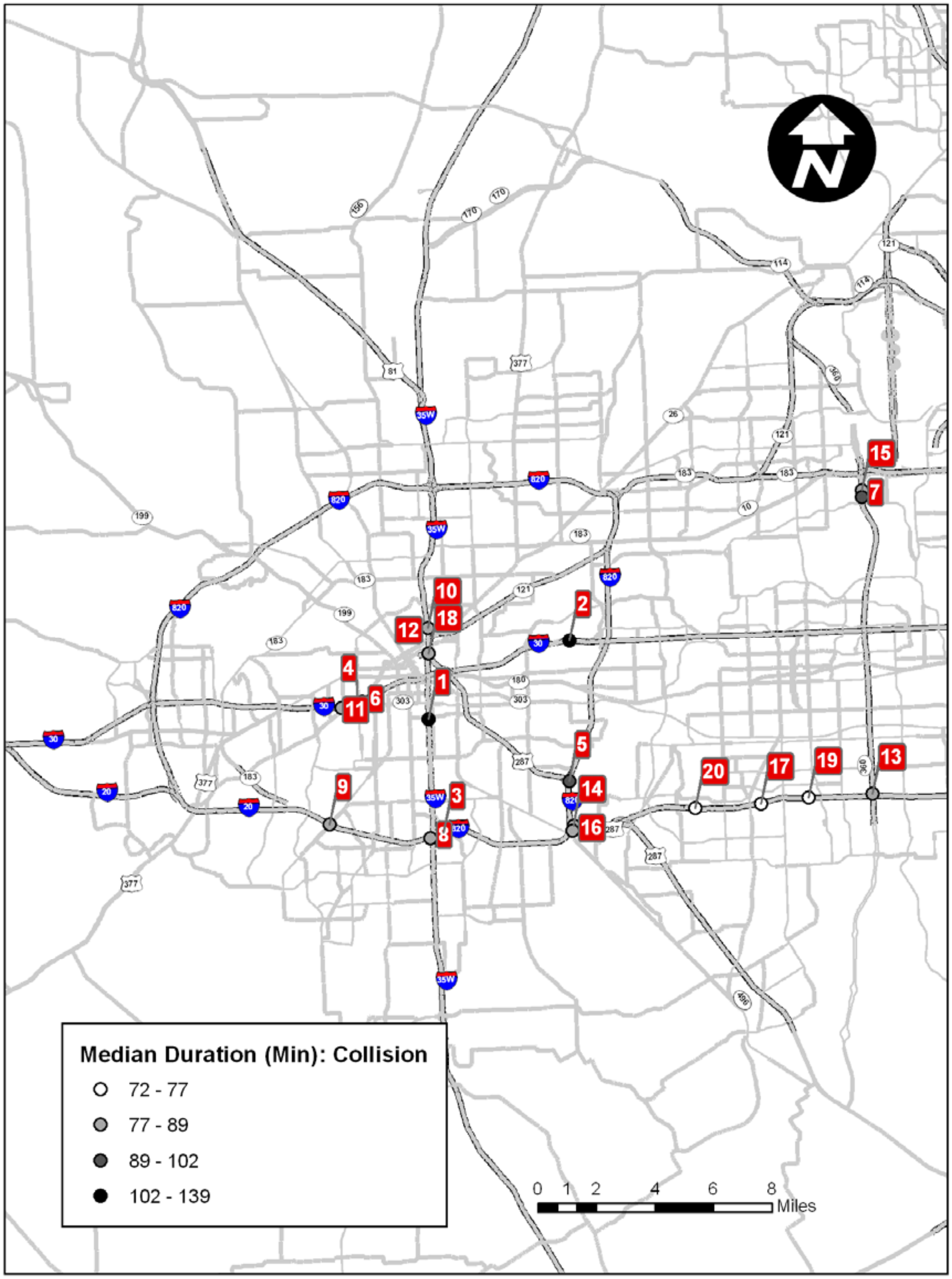


Figure D-24: Median-Duration Based Collision Hot Spots.

Table D-7: Collision Locations with Highest Median Duration.

Rank	Roadway	Cross Street	Direction	Median Duration (min)	# of Incidents
1	I35	ALLEN AVE	Northbound	139	7
2	I30	COUNTRY CLUB	Westbound	127	7
3	I20	OAK GROVE RD	Westbound	117	9
4	I30	UNIVERSITY DR	Eastbound	103	10
5	I820E	US-287/MLK	Northbound	102	9
6	I30	UNIVERSITY DR	Westbound	101	9
7	SH360S	TRINITY BLVD	Southbound	93	8
8	I20	I-35 W	Eastbound	89	8
9	I20	GRANBURY RD	Eastbound	88	7
10	I35	PHARR ST	Northbound	87	8
11	I30	MONTGOMERY ST	Eastbound	86	10
12	I35	SPUR 280	Southbound	84	12
13	SH360S	I-20	Southbound	82	7
14	I20	I-820 EAST LOOP	Westbound	81	16
15	SH360S	F A A BLVD	Northbound	81	12
16	I20	I-820 EAST LOOP	Eastbound	80	13
17	I20	S COOPER ST	Eastbound	77	11
18	I35	SPUR 280	Northbound	76	43
19	I20	S COLLINS ST	Westbound	73	26
20	I20	PARK SPRINGS BLVD	Westbound	72	7

Duration < 1 Day; Frequency >=1 Collisions per year (50% of All Locations)
Getis-Ord (Gi*) Spatial Statistics: Log Duration; 30-feet Zone of Indifference Clustering; 1-mi Buffer

Figure D-25: Collision Hot Spots Using Gi* Spatial Statistics.

Table D-8: Unique Collision Locations Identified Using Gi* Spatial Statistics.

Rank	Roadway	Cross Street	Direction	Gi* Score
1	I20	S BOWEN RD	Westbound	3.29
2	I35	ALLEN AVE	Northbound	2.97
3	I35	HATTIE ST	Northbound	2.57
4	I35	SPUR 280	Southbound	2.42
5	I20	S COLLINS ST	Westbound	2.41
6	SH360S	TRINITY BLVD	Southbound	2.33
7	I20	I-820 EAST LOOP	Westbound	2.29
8	I820NE	HOLIDAY LN	Westbound	2.14
9	I30	BALLPARK WAY	Westbound	2.14
10	SH360S	GREEN OAKS/NORTH CARRIER PKY	Northbound	2.10
11	I20	BOWMAN SPRINGS RD	Westbound	2.07
12	I20	MCCART AVE	Westbound	2.01

Duration < 1 Day; Frequency >=0.33 Disablements per year (50% of All Locations)
Getis-Ord (Gi*) Spatial Statistics: Log Duration; 30-feet Zone of Indifference Clustering; 0.5-mi Buffer

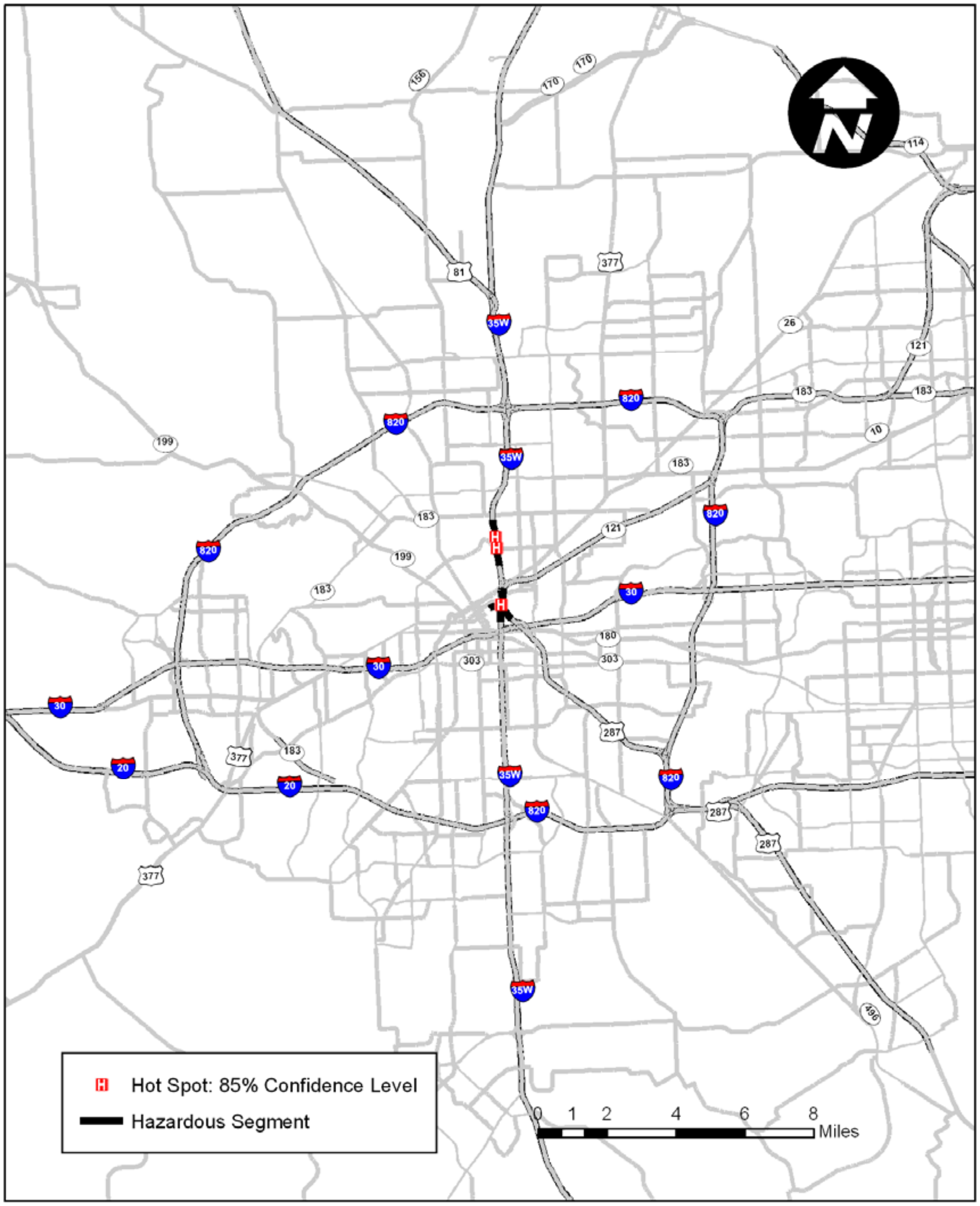


Figure D-26: Lane-Blocking Disablement Hot Spots Using Gi* Spatial Statistics.

Table D-9: Lane-Blocking Disablement Locations Using Gi* Spatial Statistics.

Rank	Roadway	Cross Street	Direction	Gi* Score
1	I35	NORTHSIDE DR	Southbound	2.21
2	I35	NORTHSIDE DR	Northbound	1.97
3	I35	SPUR 280	Southbound	1.44