Quantifying Incident-Induced Travel Delays on Freeways Using Traffic Sensor Data: Phase II

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Quantifying Incident-Induced Travel Delays on Freeways Using Traffic Sensor Data: Phase II

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Traffic incidents cause approximately 50 percent of freeway congestion in metropolitan areas, resulting in extra travel time and fuel cost. Quantifying incident-induced delay (IID) will help people better understand the real costs of incidents, maximize the benefit-to-cost-ratio of investments in incident remedy actions, and facilitate the development of active traffic management and integrated corridor management strategies. Currently, a number of algorithms are available for IID quantification. However, these algorithms were developed with certain theoretical assumptions that are difficult to meet in real-world applications. Furthermore, they have only been applied to simulated cases and have not been sufficiently verified with ground-truth data.

To quantify IID over a regional freeway network using existing traffic sensor measurements, a new approach for IID estimation was developed in this study. This new approach combines a modified deterministic queuing diagram with short-term traffic flow forecasting techniques to overcome the limitation of the zero vehicle-length assumption in the traditional deterministic queuing theory. A remarkable advantage with this new approach over most other methods is that it uses only volume data from traffic detectors to compute IID and hence is easy to apply. Verification with the video-extracted ground truth IID data found that the IID estimation errors with the new approach were within 6 percent for the two incident cases studied. This implies that the new approach is capable of producing fairly accurate freeway IID estimates using volumes measured by existing traffic sensors. This approach has been implemented on a regional map-based platform to enable quick, convenient, and reliable freeway IID estimates in the Puget Sound region.

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EXECUTIVE SUMMARY

Traffic incidents cause approximately 50 percent of freeway congestion in metropolitan areas, resulting in extra travel time and fuel cost. Quantifying incident-induced delay (IID) will help people better understand the real costs of incidents, maximize the benefit-to-cost-ratio of investment in incident remedy actions, and facilitate the development of active traffic management and integrated corridor management strategies.

This study continued a previous research project conducted by the Smart Transportation Applications and Research Laboratory (STAR Lab) at the University of Washington. A new approach for IID estimation based on traffic sensor measurements was developed in this study. The main advantage of this new approach is that it relies only on volume data, available from almost all types of traffic sensors, for IID estimation. Variables such as speed or travel time, required by most existing methods but not directly measurable from most existing sensors, are not needed for IID estimates. Therefore, the new approach is easy to apply and suitable for large-scale applications.

This new approach is based on a modified deterministic queuing diagram and regression techniques for short-term traffic flow forecasting. The modified deterministic queuing diagram utilizes the cumulative traffic volume sequence collected by the loop detectors upstream and downstream of an incident location for total delay estimates. Since recurrent delay at the incident location must be eliminated to result in IID, regression techniques are applied to predict the unobservable downstream volumes under the incident-free scenario. By doing this, the time offset estimation required by previous

methods is no longer needed, and this definitely enables IID to be calculated for locations with only volume measurements.

Two regression techniques, lagged regression and ridge regression, were investigated in this study for downstream volume sequence prediction. Their prediction accuracies were evaluated and compared to help determine the best prediction approach. Ridge regression was chosen for algorithm implementation because it consistently produced better prediction results when compared with observations from traffic surveillance videos. A number of upstream/downstream models were calibrated for application under different scenarios, featured by time of day, number of lanes, route, and direction. The downstream volumes predicted by the ridge regression model were then combined with observed downstream volumes in the modified queuing diagram for IID estimation.

To verify the accuracy of the algorithm, IIDs estimated by the proposed approach were compared with ground-truth IIDs extracted from Washington State Department of Transportation (WSDOT) surveillance video cameras at two study sites, one on I-5 and the other on SR 520. The relative errors associated with the proposed approach were 1.4 percent and -5.6 percent for the I-5 and SR 520 cases, respectively, indicating that the new approach is able to produce fairly accurate IID estimates.

The proposed algorithm was implemented in Java to automate all its computational steps. This application was loaded with all the incidents recorded by the 2009 Washington Incident Tracking System (WITS) database and with loop detector-measured vehicle volumes collected by WSDOT. Incident data were preprocessed to eliminate obvious data errors. After data cleansing, 2,676 incidents remained in the study network and were processed for IID estimates. This demonstration showed that the proposed approach was easy to use, as the computational process took only a very short moment to complete. The proposed algorithm is also flexible in terms of input data aggregation level and time period for the IID analysis. A regional map-based online platform was also developed to help users visualize all the incidents in the 2009 WITS database. For any selected time period in 2009, users can conveniently query for incidents and their associated IIDs with this online application.

On the basis of the estimated IIDs, statistical analyses on frequencies of incident occurrence, incident duration, and IID were conducted in this study. The principal findings of this research are summarized as follows:

- By using the method developed in this study, users can calculate IID with good accuracy for a large-scale freeway network equipped with traffic counters.
- Analysis on 2009 WITS data found that WSDOT responded incidents have longer durations on weekend days and in nights due to the differences in IR resource allocations and response procedures. In general, weekend days and nighttime have lower travel demands and hence lower congestion probability. For some specific corridors, however, weekend travel demand may not be significantly different from weekdays and hence may need similar IR response resource and effectiveness to weekdays. A case study on I-5 incidents revealed that weekend incidents have longer average IIDs than weekday incidents of the same type. This implies that more IR resources may be needed for busy corridors during weekend days.

- Shoulder/median closure corresponds to a much lower median IID compared to other types of lane closure.
- Traffic accidents have significantly longer incident duration than other types of incidents. Longer incident duration tends to result in longer IID. More effective response to traffic accidents will definitely be helpful in IID reduction and congestion mitigation.

This research also revealed the following future research directions and potential applications:

- Accurately predicting the downstream volume sequence under the incident-free scenario is critical for quantifying IID. Since geometric factors, in addition to volume levels, are highly influential to traffic movements, prediction models that take location-specific variables into account are likely to yield better results and should be investigated in future research.
- High quality input data are key to accurate IID estimates. Some of existing incident data and loop detector data are suffering from incomplete or incorrect records (e.g. nonexistent incident location or unrealistic volume). Those errors must be corrected for more accurate IID estimates using the proposed algorithm. This implies the need of methods for improving incident and loop detector data.
- Ramp volumes should be considered in IID estimation. However, this study was not able to consider ramp volumes because the milepost information for on- and off-ramps was missing. Future studies should add milepost the

locations of ramps to the roadway network database so that ramp impacts can be considered in IID calculations.

- The estimated IID can be used to compute the cost induced by IIDs. These data can be used to assess the effectiveness of an IR program. They can also be applied to optimize IR resource allocations.

CHAPTER 1 INTRODUCTION

1.1 Research Background

Aside from their negative impacts on traffic safety, freeway incidents have been identified as one of the major causes for congestion. According to a Federal Highway Administration (FHWA) research report (Cambridge Systematics, Inc., 2005), approximately 50 percent of congestion on freeways is non-recurrent congestion caused by incidents (25 percent), work zones (10 percent), and bad weather (15 percent). The situation is even more severe in urban areas. Approximately one-half to two-thirds of the total travel delay in large metropolitan areas is incident-related (Center for Urban Transportation Research, 2005). Since congestion mitigation and safety enhancement are among the main goals of most transportation agencies, a number of state (and local) departments of transportation have invested in incident response (IR) programs in a variety of forms.

In Washington state, the Washington State Department of Transportation (WSDOT) established its Incident Response Program in collaboration with the Washington State Patrol (WSP) and the Washington State Association of Fire Chiefs (WSAFC), a group called the Washington Traffic Incident Management Coalition (WaTIMCo). Besides prioritizing responder and motorist safety, one of WaTIMCo's goals also involves congestion mitigation when incidents occur. Estimation of IID is highly desirable for the following reasons:

- Measurement of IID is important in assessing the effectiveness of congestion countermeasures.
- IID estimates help engineers understand the impacts of various types of incidents under various traffic and roadway conditions.

- Accurate IID estimates can help in identifying appropriate decisions regarding IR so that limited monetary and labor resources can be allocated to maximize its benefit-to-cost ratio (BCR).
- IID estimates are key components of incident cost calculations and are essential for the development of active traffic management and integrated corridor management strategies.

However, it is not an easy task to quantify IID because existing traffic sensors cannot directly measure IID, and algorithms are needed to estimate IID by using available traffic sensor measurements. Therefore, IID estimation has become a hot research field. Most research efforts have been based on either Deterministic Queuing Theory (DQT) or shock wave analysis. The former calculates IID by using a queuing diagram formed by cumulative vehicle arrival and departure curves. The area enclosed by the two curves represents the total delay. The latter involves several attempts to apply the methods of kinematic waves to explain the characteristics of traffic flow, which lead to the development and application of shock wave analysis for estimating IID.

In Washington state, Hallenbeck et al. (2003) developed a loop-occupancy-based algorithm to identify incident occurrence and to estimate the impacts of incidents on freeways. Although it was easy to apply, this algorithm suffered from false alarms in terms of incident detection because loop-measured lane occupancy is not always a good indicator of actual traffic conditions. Also, IID estimated with this algorithm could be subject to another source of error because of the use of point-sensor measured speeds for sectional travel time calculations. In 2008, Wang et al. (2008) applied a DQT-based approach for estimating IID. This approach improved the accuracy of IID estimates by using traffic data (e.g., vehicle count and loop occupancy) and a Dynamic Volume-Based Background Traffic Profile (BTP) instead of a fixed occupancy background profile to quantify IID. Use of this approach significantly improved the incident detection rate in comparison to results from the loop-occupancy-based method. The accuracy of the DQT-based approach was evaluated by using microscopic traffic simulation models. However, the performance of this DQT-based approach was not stable. Further investigation found that IID estimated from this approach was sensitive to the travel time estimation from the upstream loop station to the incident location.

To improve IID results, the estimation accuracy of the space-mean speed or travel time from the upstream loop station to the incident location had to be enhanced. This would be fairly difficult, given the sporadic deployment of detectors and sensor measurement constraints. Hence, the first challenge to improving IID estimation using DQT methods was that accurate speed or travel time data would be difficult to obtain. Not many traffic sensors deployed on the existing freeway system are capable of measuring traffic speed or travel time. For example, most existing traffic detectors on Washington freeways are single loops. Although Athol's method (Athol, 1965) can be used to estimate traffic speed from single-loop output, the accuracy may not be great when a significant number of long vehicles are present (Wang and Nihan, 2000). Furthermore, capturing each vehicle's speed requires loop event data (high resolution loop status data), which are available only in traffic controllers unless special data collection devices, such as the Advanced Loop Event Data Analyzer (ALEDA) (Cheevarunothai et al., 2006), are used to record the data.

The second challenge to using the DQT-based approaches for quantifying IID was to separate recurrent traffic delay from the total delay under incident scenarios. Wang et al. (2008) applied a BTP matching approach to find a traffic volume series in an incident-free scenario to match the current volume series under incident impact. Once an acceptable match had been found, its volume series at the downstream loop was applied to calculate recurrent delay. The difference between total delay and recurrent delay was IID. However, not all traffic arrival series have an incident-free matching series in the historical database. Also, the matching process is computationally expensive. Therefore, the BTP matching approach may not always be capable of quantifying the delay introduced by an incident. A more robust IID estimation approach was desired. As a continuation of an earlier study (referred to as the Phase I study in this report) by Wang et al. (2008), this study (or Phase II) sought to develop a new IID estimation approach to overcome the two challenges described above.

1.2 Research Objectives

The objectives of this study included the following:

- Improve the IID estimation algorithm and enhance its applicability by limiting the input to traffic volume only. Since volume can be directly measured by single loop detectors, the most common type of traffic sensors in the existing roadway network, an IID estimation algorithm requiring only volume input is highly desirable.
- Implement the new IID estimation approach in a computer program for automatically quantifying IIDs on a regional freeway network.
- Expand the database developed in Phase I to support IID analysis on a larger freeway network, i.e., the Puget Sound regional freeway network.
- Present the incident information together with IID estimates on the Digital Roadway Interactive Visualization and Evaluation Network (DRIVE Net), a regional map-

based online data sharing, modeling, and analysis platform developed by the Smart Transportation Applications and Research Laboratory (STAR Lab).

CHAPTER 2 STATE OF THE ART

IID refers to the extra travel time, in addition to the travel time of an incident-free scenario, which all incident-impacted vehicles take to complete a certain length of trip. This implies that IID quantification is essentially a travel time estimation problem under incident and incident-free conditions. Some studies, e.g., Skabardonis et al. (1996), directly used probe vehicles to measure travel time. However, since the number of probe vehicles on a roadway network is fairly small, travel time obtained this way is subject to a relatively high uncertainty. Calculating travel time with the speed data from dual-loop detectors is another common method in practice (Skabardonis et al., 2003). However, the application of this method is constrained by the fact that dual loop sensors are not widely available. Another issue with the direct travel time estimation method is that it does not provide a travel time for the incident-free scenario that corresponds to an incident case. Obtaining the travel time for the incident-free scenario still requires quantitative models.

Many characteristics of traffic flow are similar to those of fluid flow. Therefore, some researchers have attempted to apply the methods of kinematic waves to explain characteristics of traffic flow. These attempts have led to the development and application of shock wave analysis to estimate IID. Shock wave analysis was first introduced when Lighthill and Whitham (1955) showed how traffic flow can be characterized through the analogy of fluid dynamics. At about the same time, Richards (1956) independently developed a simple model of traffic flow in which individual vehicles were replaced with a continuous fluid density. Therefore, the first shock-wave-based model has been called the Lighthill, Whitham, and Richards model, or the LWR model. Al-Deek et al. (1995) proposed a method based on shock wave analysis for calculating total IID by using loop data and incident data. Mongeot and Lesort (2000) also modeled traffic flow dynamics with the impacts of incidents. In their model, shock waves, perturbation clearing time, and maximum queue length were considered in formulating the model to capture incident-induced flow perturbation variations through space and time. While providing well-defined theoretical estimations, these approaches required intensive data support for implementation, which usually cannot be satisfied by the current traffic data collection infrastructure.

A widely used approach is Deterministic Queuing Theory (DQT). DQT-based methods calculate travel delay as the area enclosed by the arrival and departure curves. However, the calculated delay includes the portion associated with recurrent congestion. To quantify IID, recurrent delay must be separated from total delay (Cheevarunothai et al., 2010). Morales (1987) developed an interactive spreadsheet tool in which DQT was applied to the computation of travel delay caused by freeway incidents. Lindley et al. (1987) applied a similar approach on a national basis and implemented the approach in the FREWAY model they developed. Ten years later, Sullivan (1997) developed the IMPACT model on the basis of the FREWAY model. The incident delay module in IMPACT was still based on the queuing diagram's arrival and departure curves. Fu and Rilett (1997) considered incident duration uncertainty with a probabilistic distribution and combined it with DQT in their model. This enabled their model to estimate each individual vehicle's delay on the basis of its arrival time at the incident site and the distribution of the incident duration. In another study, Fu and Hellinga (2002) applied fuzzy set theory to account for the stochastic characteristics of existing queue condition, future traffic arrival, lane closure, and the vehicle's arrival time, but the essence of their model was still DQT. Li et al. (2006) also combined stochastic incident duration modeling and reduced capacity modeling within the traditional DQT framework.

Traditional DQT methods can be directly applied to simulation data for IID quantification (Fu and Rilett, 1997; Fu and Hellinga, 2002; Li et al., 2006). However, when applied to actual loop detector data, this method must be properly modified to address the physical distance between the upstream and downstream loop stations to avoid bias. This is because a key assumption in DQT is that arrivals and departures occur at the same spatial location (zero vehicle length), whereas in the real world, arrival and departure flows are observed by upstream and downstream loop stations, respectively. In delay calculation applications, the key to addressing this issue is to virtually move the upstream and downstream flow curves along the timeline (the horizontal axis on queuing diagram) to the incident occurrence time, so that the zero vehicle length assumption is not violated. Some researchers (such as Rakha and Zhang, 2005) proposed using speed data to calculate the travel times from the upstream loop location to the incident location and from the incident location to the downstream loop location. However, accurate speed data are usually unavailable because of either an absence of dual loop stations or poor-quality occupancy measurements resulting from single loops with incorrect sensitivities (Cheevarunothai et al., 2006; Wang et al., 2009). Even if quality measurements of point speed are available, the accuracy of travel time estimates may still vary depending on how vehicle speeds change between the upstream and downstream loop stations. Therefore, a method that considers the actual layout of loop detectors on freeways and requires only volume inputs is highly desirable for IID estimates.

As mentioned earlier, IID refers to the travel time that the incident scenario adds to travel time of the incident-free scenario. Because there is no detected data for the incident-free scenario, travel time estimation for the incident-free scenario is essential. To address this issue, Hallenbeck et al. (2003) proposed a Background Traffic Profile (BTP) method for the incident-free scenario. In 2008, Wang et al. developed Dynamic Volume-Based (DVB) extraction of the BTP and used it for the Phase I study funded by WSDOT. Hallenbeck's and Wang's studies provided a good method for IID estimation. However, their methods still faced a challenge in matching the background traffic. To solve this problem, this research used the observed upstream flow curve to predict the downstream flow curve for the incident-free scenario. The feasibility of this approach has been demonstrated in several previous short-term traffic flow forecasting studies, e.g., Hobeika and Kim (1994) and Abdulhai, et al. (1999).

CHAPTER 3 DATA COLLECTION

3.1 Data for IID Estimates

To quantify IID, three types of data are required:

- Incident data provide detailed information on each incident, including incident location, start time, and end time.
- Traffic volume data, collected by loop detectors, are required to characterize traffic conditions along segments at times with incidents as well as without incidents.
- Traffic surveillance video data of the roadway segments being analyzed are also needed for the purpose of algorithm verification.

3.1.1 Incident Data

Freeway incident data are available from three sources in Washington State: the WSDOT IR teams, the Washington State Patrol (WSP), and the WSDOT Transportation Systems Management Center (TSMC). Data collected by the WSDOT IR teams are stored in the Washington Incident Tracking System (WITS). This data set contains only information pertaining to the incidents for which WSDOT IR teams were present. Washington State Patrol data are stored in its Computer Aided Dispatch (CAD) database. This database contains information on all incidents reported to and handled by the WSP. The TSMC maintains its own incident log file with incidents observed by traffic surveillance video cameras.

When the researchers determined which set of incident data would best serve the purposes of this study, three pieces of information were considered critical: incident start time, end time, and location. While both the CAD database and the WITS database contain these data items, the WITS database is preferable because of its higher data quality. Although the CAD data set has more data items than the WITS data set, it frequently misses critical pieces of information such as the beginning and clear times. Furthermore, the CAD data set is more difficult to obtain, as it includes drivers' private data.

Incidents recorded in the 2009 WITS database were therefore used in this study. *State Route ID*, *direction*, and *mile post* jointly define an incident's location. *Notification time* records the time when an incident was reported to the IR program. Since most incidents were reported through mobile phones nowadays, notification time should be very close to the start time of an incident in metropolitan areas. *Arrival time* stores the time when an IR truck arrived at the incident location. *All lanes open time* is the time when all lanes became open to traffic. *Clear time* is the time when the incident had been fully cleared and the IR teams left the incident scene. In this study, an incident's duration was defined as the time when traffic is under the impact of the incident. In the 2009 WITS data, this is labeled as *Clearance Time*. This can also be easily checked by periodically calculating IID with the proposed approach. When IID stops growing, impacts from the incident have ended.

3.1.2 Loop Detector Data

Loop detector data required for this study were acquired from WSDOT and archived on a data server hosted by the STAR Lab at the University of Washington. Required loop detector data primarily consist of single loop measurements, i.e., traffic volume and lane occupancy, aggregated every 20 seconds for all the major routes in the central Puget Sound region, including I-5, I-405, I-90, and SR 520. Loop detector stations are spaced approximately every half a mile in the central Puget Sound region.

Although loop detectors are located at a relatively high frequency along freeways, the quality of the data from many of these loop detectors renders them unusable. One major issue of loop data is the inaccuracy of occupancy indication caused by wrong sensitivity levels (Wang et al., 2009). Another issue that degrades loop data quality is missing data, due to bad communication or loop failure.

3.1.3 Video Data

Video data were used in this study to validate the IID algorithm. The STAR Lab has access to all the 400+ WSDOT traffic surveillance video cameras deployed along the freeway corridors. These cameras cover I-5, I-405, I-90, SR 167, SR 520, and others. To capture ground-truth travel delay data, two cameras are needed, one at each end of the link being monitored. To facilitate a comparison with loop data-based IID estimates, these cameras' fields of view are best centered at the loop stations bounding the freeway link. However, very few freeway links have both surveillance video cameras and inductance loops located at approximately the same places.

The STAR Lab's fiber connection can support two live video streams simultaneously, which satisfied the video data collection need for this project. Two video streams, one at each end of a freeway link, were recorded simultaneously to collect vehicle arrival and departure data for the link. Because the research team could not predict when an incident would occur, the video streams were recorded for long periods to ensure the capture of traffic volumes under incident impacts.

3.2 Site Selection

To validate the accuracy of the IID algorithm proposed in this research, test sites for delay quantification and video verification were selected. The selection of sites was not easy because multiple factors had to be properly considered to ensure the quality of data and analysis results. The criteria used for site selection were as follows:

1) **No entry or exit points –** The selected freeway link should not have any on- or off-ramps between the upstream and downstream loop stations because there are no sufficient cameras to capturing all the entering and exiting traffic.
2) **Suitable video surveillance –** Not only did video cameras have to be present at these locations, but their viewing ranges had to cover all possible vehicle paths. No vehicles could pass the camera without being seen, or the counts would be inaccurate. The video cameras also had to be of high enough quality to allow for visual identification and matching of vehicles at both ends of a test segment. If unique vehicle properties could not be identified because of poor visual quality, the camera could not be used. Cameras along a specific segment also had to be spaced far enough apart to allow vehicle queuing to form but not extend beyond the visual limits of the upstream camera.
3) **High accident probability –** To validate the new IID estimation approach, vehicles entering and exiting the segment during an incident had to be captured. Incident data have shown that the number of incidents between different locations varies greatly. Many incidents occur at some locations while nearly none occurs at others. To increase the possibility of capturing video of an incident, locations with a greater tendency for incidents were preferable over those with fewer incidents.
4) **Quality loop detector data –** To mitigate the impacts of data errors on IID estimates, loop detectors at the test sites had to be in good working condition. The quality of loop detector measurements had to pass a quality check before a segment could be chosen as a study site.

Four locations were chosen as the study sites through the selection process. These locations were as follows:

1) I-90 Bridge westbound, from milepost (MP) 4.53 to 5.45

2) I-405, near Everett Mall, in both directions, from MP 189.98 to 191.88

3) I-5 northbound, near Boeing Field, from MP 158.45 to 160.64

4) SR 520 Bridge westbound, from MP 1.58 to 4.1.

CHAPTER 4 STATISTICAL ANALYSIS OF INCIDENTS

4.1 Occurrence Frequency

This section discusses an investigation of the statistical patterns of incident occurrence frequency and incident duration based on the 2009 WITS data. Statistical analysis of incidents can provide not only a better quantitative description of incidents for traffic operators but also help for them to develop countermeasures against traffic incidents and incident-induced congestion.

Table 4-1 and Figure 4-1 present the statistical results for the monthly frequency of incidents on Washington state freeways in 2009. We can see that fewer incidents occurred in winter than in summer, but the difference was not significant. The three months with the highest incident frequencies were June, July and August, while those with the lowest frequency were January, February, and November.

Table 4-1. Incident Frequency by Month

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Incident Frequency	3,104	3,164	3,693	3,897	3,724	4,100	4,574	3,917	3,450	3,481	3,148	3,534
Total	**43,786**											

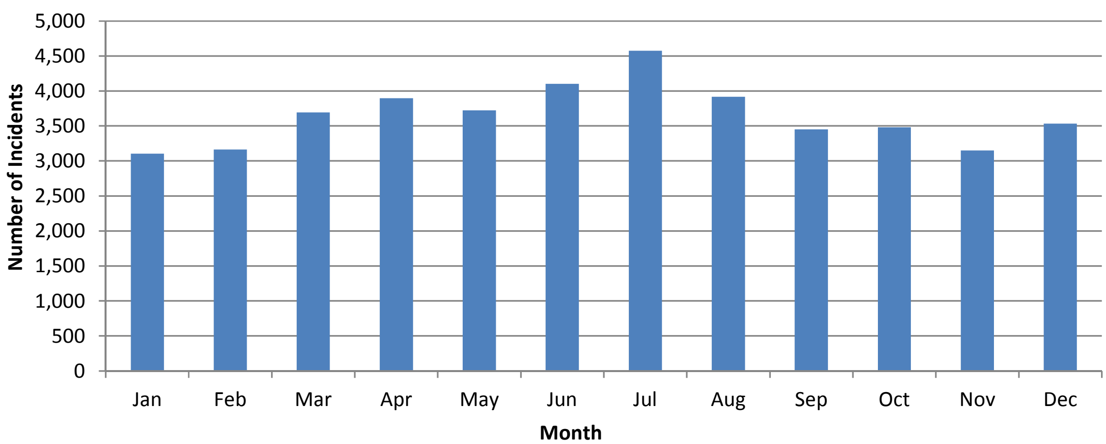


Figure 4-1. Number of Incidents by Month

Table 4-2 and Figure 4-2 show the number of incidents by the day of week. In Table 4-2, it can easily be observed that the incident frequency on weekdays was two to three times higher than that on weekends. This may have been due to the volume difference, as a similar trend was observed between weekday and weekend volumes. Also, IR teams are deployed more lightly on weekends, so some incidents might have gone unrecorded since WSDOT IR personnel were not present at them.

Table 4-2. Number of Incidents by Day of Week

Day of Week	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Incident Frequency	7,135	7,817	7,708	7,676	8,069	2,764	2,617
Daily Average			**Weekdays: 7,681**			**Weekends: 1,191**	

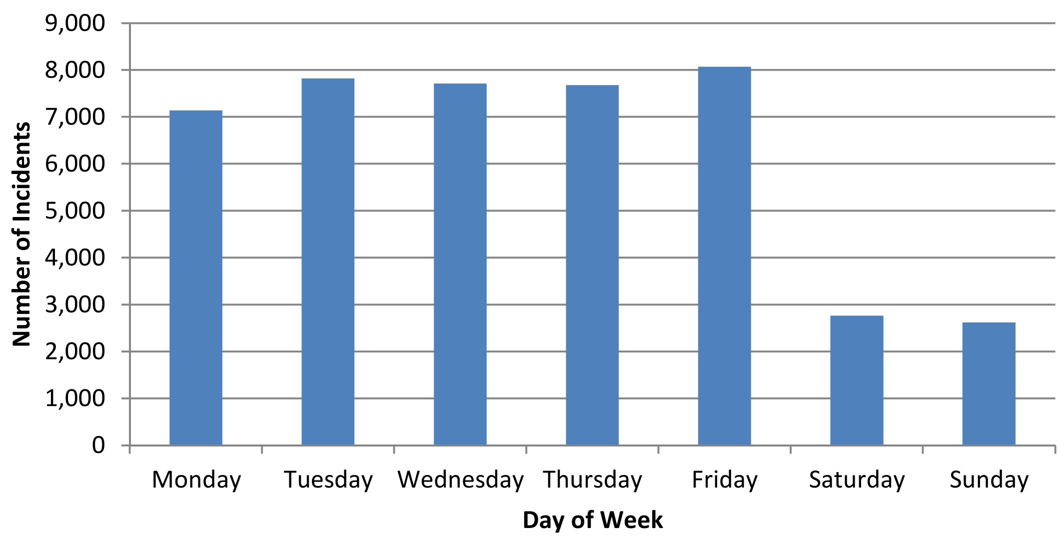


Figure 4-2. Number of Incidents by Day of Week

The number of incidents by time of day is summarized in Table 4-3 and Figure 4-3. The whole time period for one day was divided into four periods: 6:00 to 9:00 AM, 9:00 AM to 4:00 PM, 4:00 to 7:00 PM, and 7:00 PM to 6:00 AM of the next day. The statistical results show that the second time period had the most incidents, with over 56 percent of all incidents occurring in this time period. The incident frequencies per hour for each period were 2,651, 3,533, 3,146, and 151. The incident frequency for the midnight phase was much lower than those of the other three phases, likely due to the low traffic volume as well as the low priority for the WSDOT to apply congestion management countermeasures such as IR when traffic volume is low. Also since WSDOT's IR resource is more likely deployed in the high traffic volume time periods, some incidents might have gone unrecorded in the WITS database, because WSDOT IR personnel were not present at them during the nighttime.

Table 4-3. Number of Incidents by Time of Day

Quarter	06:00-09:00	09:00-16:00	16:00-19:00	19:00-6:00
Q1	1,975	5,663	1,944	379
Q2	2,108	6,614	2,535	464
Q3	2,044	6,613	2,801	483
Q4	1,826	5,843	2,157	336
Total	**7,953 (18.16%)**	**24,733 (56.49%)**	**9,437 (21.55%)**	**1,663 (2.77%)**
Incidents / hr	**2,651**	**3,533**	**3,146**	**151**

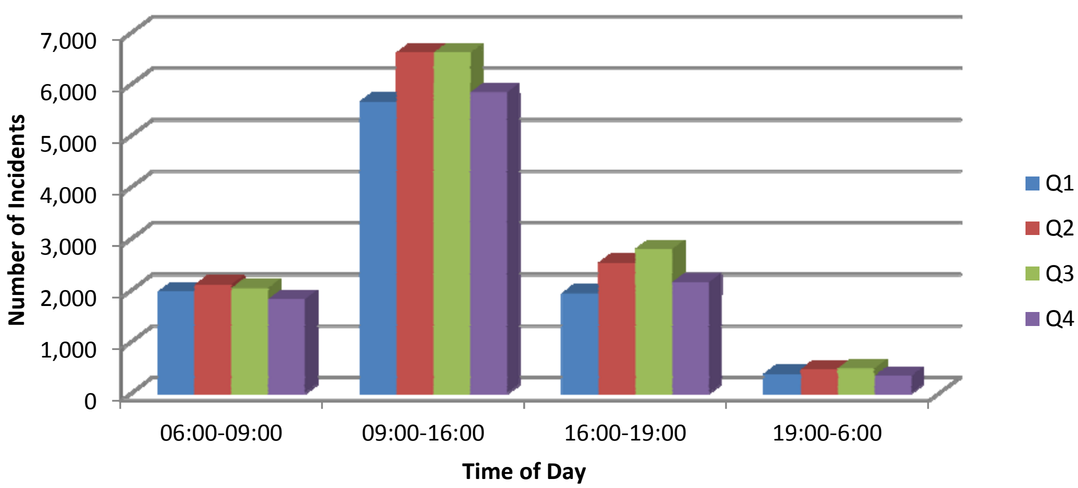


Figure 4-3. Number of Incidents by Time of Day

According to the results of incident classification by route, we can see that the five corridors with the highest occurrence frequency statewide were I-5, I-90, I-405, SR 167, and SR 520, in descending order. The rate of incidents was also calculated as the number of incidents per mile. Incidents that occurred in the Puget Sound region are summarized in a similar way to reflect a comparison with statewide data. The numbers of incidents and incident rates for these main corridors are listed in Table 4-4 and Figure 4-4. It is especially noteworthy that the I-5 corridor in the Puget Sound region should be the focus of incident management, given that incidents in this section accounted for more than 70 percent of the whole corridor, whereas in terms of mileage this section was only 40 percent of the full length. Also note that since Table 4-4 is based on the WITS data, it could be skewed by the deployment of WSDOT's IR team on each main corridor. Due to the fact that WSDOT's IR teams are not evenly deployed on all the corridors, incidents occurring on the corridor with less IR coverage might not be recorded and thus not summarized by Table 4-4.

Table 4-4. Number of WSDOT Responded Incidents and Incident Rate by Route

Route		I-5	I-90	I-405	SR 167	SR 520
Statewide	Incident Frequency	23,009	5,823	5,297	2,072	1,787
	Length/mi	276.56	297.88	30.32	27.28	12.83
	Incidents per Mile	83	20	175	76	139
Puget Sound Region	Incident Frequency	16512	1416	5297	2072	1787
	Length/mi	108	19.41	30.32	27.28	12.83
	Incidents per Mile	153	73	175	76	139

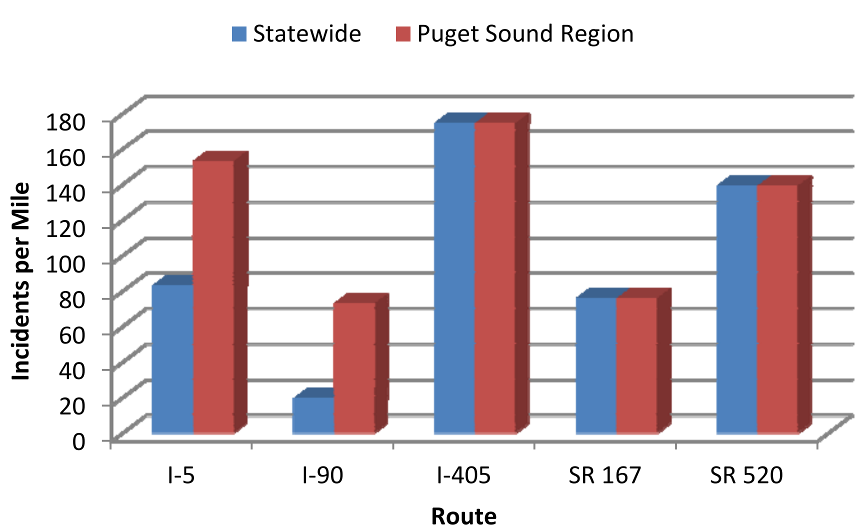


Figure 4-4. Incident Rate by Route

On the basis of primary lane closure, incidents were divided into eight categories: total closure (TC), all travel lanes (ATL), multiple lanes (ML), a single general purpose lane (SL), the HOV lane (HOV), a shoulder/median closure (SM), and other kinds of incidents (Other). Table 4-5 and Figure 4-5 indicate the frequency of incidents by primary lane closure. The top three categories were shoulder/median, single lane, and multiple lanes. Among them, shoulder/median was identified as the category with the highest incident frequency, accounting for more than 75 percent of the total closures. Note that shoulder/median closures have less influence on main lane traffic flows, so they cause lower delays than other closure types. Meanwhile, this finding also provides a statistical piece of evidence for the importance of road shoulder and median barrier configurations.

Table 4-5. Number of Incidents by Primary Lane Closure

Quarter	Total Closure	All Travel Lanes	Multiple Lanes	Single Lane	HOV Lane	Shoulder/ Median	Other
Q1	55	19	291	1,822	198	7,535	41
Q2	45	30	332	2,085	198	8,990	41
Q3	43	34	329	2,071	179	9,231	54
Q4	31	27	272	1,843	159	7,772	59
Total	**174 (0.40%)**	**110 (0.25%)**	**1,224 (2.80%)**	**7,821 (17.86%)**	**734 (1.67%)**	**33,528 (76.57%)**	**195 (0.45%)**

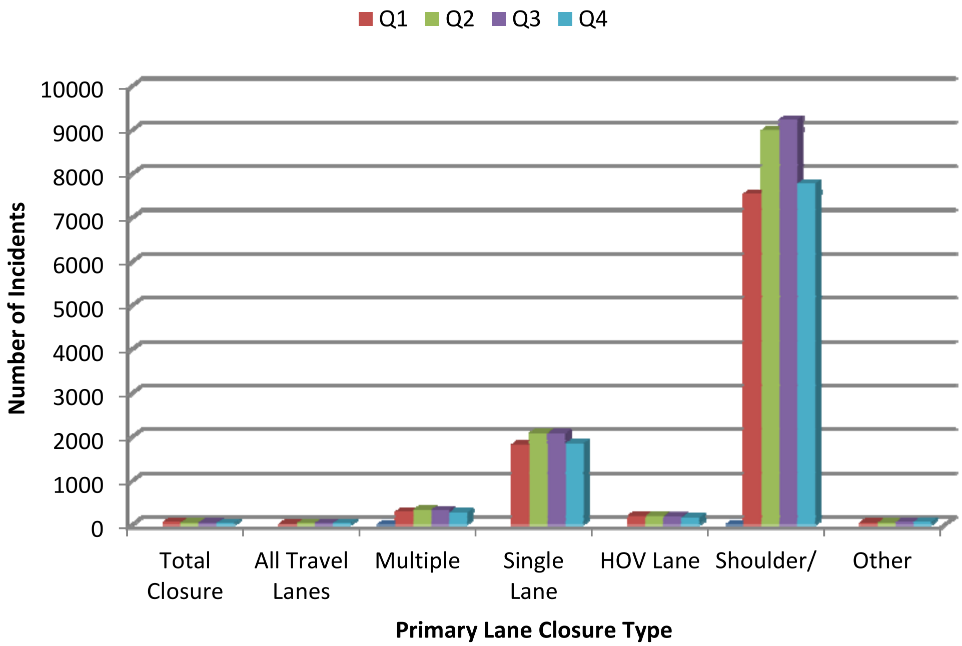


Figure 4-5. Number of Incidents by Primary Lane Closure

In WITS, all incidents can be classified into eight categories by their nature: fatality collision (FC), injury collision (IC), non-injury collision (NIC), abandoned vehicle (AV), disabled vehicle (DV), debris, police activity (PA), and other kind of incidents (Other). From Table 4-6 and Figure 4-6, it is apparent that *disabled vehicles*, *abandoned vehicles*, and *debris* were the top incident categories. As the most frequent incident type, *disabled vehicles* accounted for more than 50 percent of the total in 2009, while the other two top categories jointly accounted for more than 25 percent. This fact indicates that WSDOT may consider maintaining and further strengthening the vehicle towing capability to facilitate the incident clearance process.

Table 4-6. Number of Incidents by Incident Type

Quarter	Fatality Collision	Injury Collision	Non-Injury Collision	Abandoned Vehicle	Disabled Vehicle	Debris	Police Activity	Other
Q1	27	279	877	1,626	5,287	1,082	16	767
Q2	18	358	919	1,718	6,286	1,528	19	875
Q3	23	339	869	1,706	6,602	1,557	17	828
Q4	27	324	1,059	1,611	5,414	983	22	723
Total	**95 (0.22%)**	**1,300 (2.97%)**	**3,724 (8.51%)**	**6,661 (15.21%)**	**23,589 (53.87%)**	**5,150 (11.76%)**	**74 (0.17%)**	**3,193 (7.29%)**

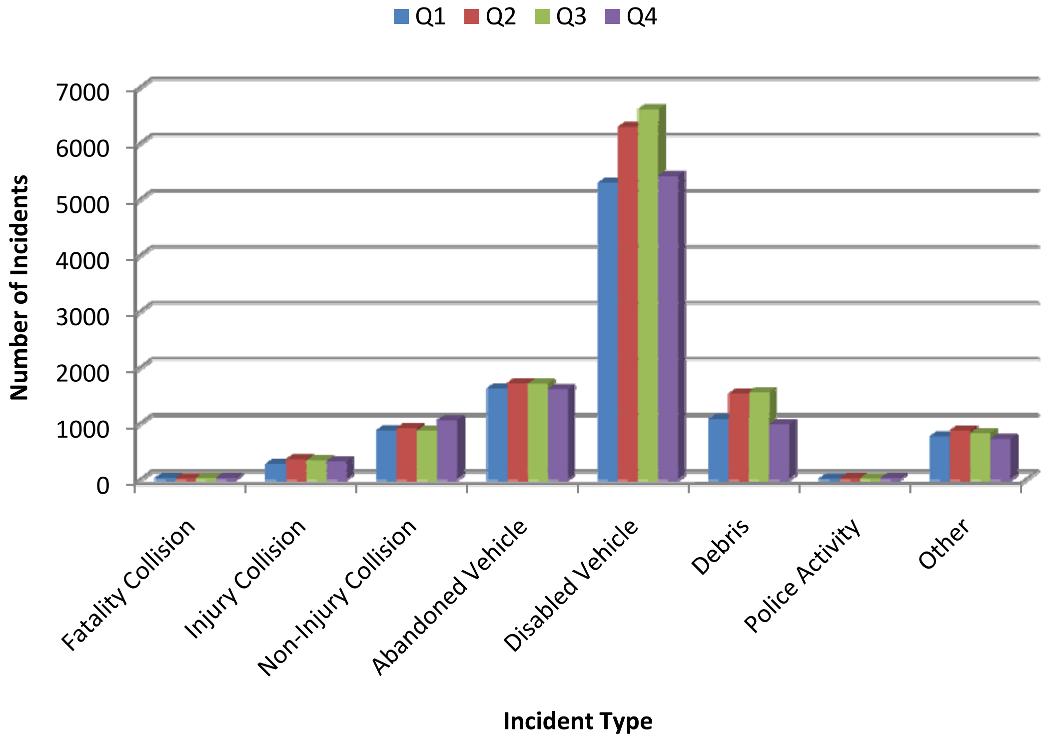


Figure 4-6. Number of Incidents by Incident Type

Actions taken for emergency management include nine categories: advised the WSP (AWSP), changed a flat tire (CFT), minor repair (MR), provided fuel (PF), pushed, removed debris (RD), towed, provided traffic control (TC), and other kinds of action (Other). Because the action taken for several incidents was not provided on the incident reports, we summarize these incidents under Unknown in Table 4-7 and Figure 4-7. The most common action was *advised WSP*, which covered more than 60 percent of all the actions taken.

Table 4-7. Number of Incidents by Action Taken

Quarter	Advised WSP	Changed Flat Tire	Minor Repair	Provided Fuel	Pushed	Removed Debris	Towed	Traffic Control	Other	Unknown
Q1	6,216	279	167	247	238	580	62	1,066	1,056	50
Q2	7,386	369	164	316	221	817	54	1,070	1,272	52
Q3	7,570	350	198	320	177	853	66	988	1,390	29
Q4	6,463	276	142	332	190	598	56	887	1,192	27
Total	**27,635 (63.11%)**	**1,274 (2.91%)**	**671 (1.53%)**	**1,215 (2.77%)**	**826 (1.89%)**	**2,848 (6.50%)**	**238 (0.54%)**	**4,011 (9.16%)**	**4,910 (11.21%)**	**158 (0.36%)**

Note: IR teams can perform multiple actions at one incident, so total actions taken will be more than total incidents.

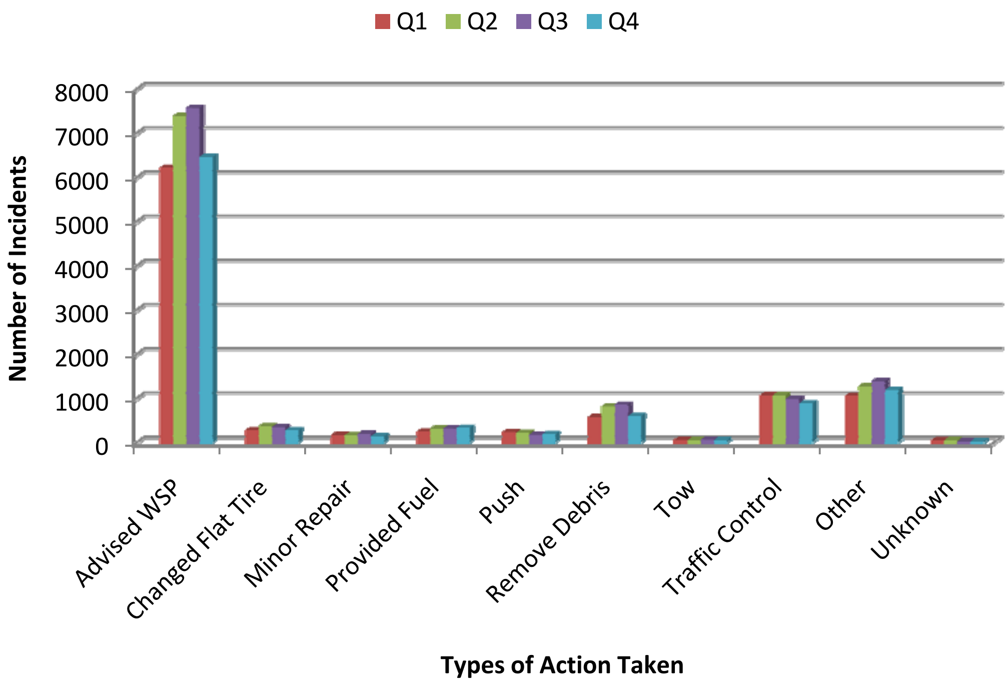


Figure 4-7. Number of Incidents by Action Taken

4.2 Incident Duration

In 2009 WITS data, four timestamps are recorded for a typical incident: notification time (when the incident was notified to the IR team), arrival time (when the IR team arrived at the incident site), lane open time (when all lanes became open to traffic), and clear time (when the incident had been cleared and full departure capacity of the roadway section became available). Note that the actual start time of an incident might be some time before the incident is notified; however, unless the person involved in the incident could provide accurate information, there is uncertainty to determine when the incident actually started. Fortunately, due to the widely-used wireless communication, notification time is a good estimate of the actual start time of an incident, which is considered as the "start time" of an incident in 2009 WITS data (WSDOT, 2008). Correspondingly, the incident duration consists of three typical intervals: arrival (the interval between the notification and arrival times), clearance (the interval between arrival and all lanes open times), and recovery (the interval between all lanes open and clear). The arrival interval depends on and reflects the ability of the IR teams to respond to an incident. The clearance interval measures the performance of the IR teams to clear an incident with the 90-minute goal (WSDOT, 2008). The recovery interval reflects the time for the traffic to operate at full departure capacity from the incident impact. As mentioned in Section 3.1.1, following WSDOT's convention the period from the notification time to the clear time (labeled as Clearance Time in WITS data) of an incident is referred as the duration of the incident.

All of the 2009 incident records in WITS were classified by month, with the incident duration shown in Table 4-8. The three months with the highest average incident durations were January, March, and May. Meanwhile, April, July, and June had the shortest average incident durations. On average, incidents last longer in winter than in summer.

Table 4-8. Incident Duration (in minutes) by Month

		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Clearance Time	Mean	14.7	13.2	14.2	12.4	13.8	12.5	12.4	13.6	12.7	13.6	13.7	13.6
	SD	27.0	21.7	28.3	23.9	32.7	22.9	20.9	25.9	21.3	23.8	22.8	27.7
	Median	7	7	7	6	7	6	6	6	6	6	7	6
	Max	407	360	570	866	1,020	567	377	505	370	402	300	542

		Winter Quarter	Spring Quarter	Summer Quarter	Autumn Quarter
Clearance Time	Mean	14	12.9	12.9	13.6
	SD	25.93	26.69	22.76	24.93
	Median	7	6	6	6
	Max	570	1,020	505	542

		Total
Clearance Time	Mean	13.3
	SD	25.09
	Median	6
	Max	1,020

While there were fewer incidents on weekends than on weekdays, as mentioned in Section 4.1, incidents on weekends had durations approximately 32 percent longer than on weekdays, as shown in Table 4-9 and Figure 4-8. This finding is consistent with the deployment of WSDOT's IR teams. There are fewer IR teams scheduled on weekends; additionally, with the collaboration with WSP, on the weekends WSDOT is more likely to be called to more severe incidents, which tend to last longer. To better evaluate the overall IR performance on the weekends compared to weekdays, both the WITS data by WSDOT's IR teams and the CAD data by WSP need to be taken into consideration for future investigation.

Table 4-9. Incident Duration (in minutes) by Day of Week

Quarter		Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Weekdays	Weekends
Q1	Mean	15.23	13.07	12.62	12.94	13.99	15.39	19.17	13.57	17.13
	SD	27.43	22.66	24.28	22.83	23.31	30.76	39.53	24.13	35.11
	Median	7	6	6	6	7	7	8	7	7
	Max	394	526	570	407	341	491	360	570	491
Q2	Mean	12.42	12.62	12.12	12.35	12.82	14.37	16.94	12.48	15.62
	SD	20.01	25.92	19.39	27.07	27.20	41.35	34.72	24.38	38.30
	Median	7	6	6	6	7	6	7	6	7
	Max	351	567	263	866	898	1.020	450	898	1,020
Q3	Mean	13.50	12.14	12.07	12.38	11.81	16.29	17.69	12.34	16.99
	SD	24.22	19.59	21.82	21.99	17.35	33.29	32.03	21.05	32.67
	Median	6	6	6	6	6	7	8	6	7
	Max	377	330	505	455	270	478	344	505	478
Q4	Mean	12.81	12.21	12.90	13.50	13.75	21.43	15.95	13.03	18.67
	SD	21.08	22.80	20.82	21.94	25.16	45.58	33.38	22.42	40.01
	Median	6	6	6	6	6	7	7	6	7
	Max	324	482	267	354	542	402	382	542	402
Total	Mean	13.45	12.50	12.39	12.76	13.02	16.48	17.47	12.81	16.96
	SD	23.28	22.86	21.57	23.65	23.52	37.87	34.99	22.99	36.50
	Median	7	6	6	6	6	7	7	6	7
	Max	394	567	570	866	898	1,020	450	898	1,020

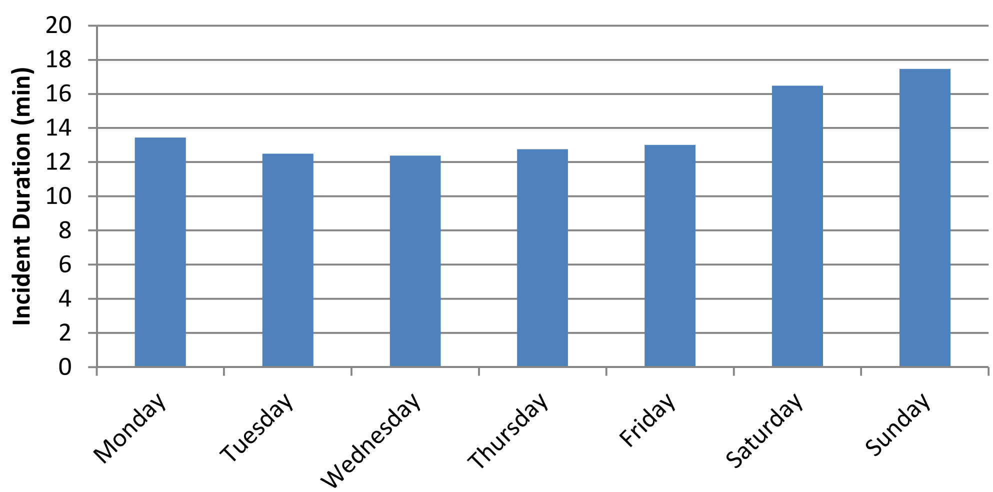


Figure 4-8. Average Incident Duration (in minutes) by Day of Week

Table 4-10 and Figure 4-9 show the incident duration for four periods: 6:00 to 9:00 AM, 9:00 AM to 4:00 PM, 4:00 to 7:00 PM, and 7:00 PM to 6:00 AM the next day. It is obvious that the average incident duration for the midnight period was much longer than the other periods. The main reason for longer incident durations at night lies in that there is no regular IR team scheduled from 8 PM to 5: 30 AM of the next day, according to the current IR deployment plan. IR teams provide an on-call service during the nighttime so it takes longer for the IR driver to reach the incident scene. Also WSDOT's IR teams are responding to more severe incidents at night, which results in a longer incident duration.

Table 4-10. Incident Duration (in minutes) by Time of Day

Incident Duration		06:00-09:00	09:00-16:00	16:00-19:00	19:00-6:00
Q1	Mean	12.90	12.46	15.52	36.07
	SD	21.87	21.45	24.86	67.66
	Median	6	7	8	10.5
	Max	407	570	326	526
Q2	Mean	10.86	12.07	13.24	32.02
	SD	15.71	19.40	21.63	91.63
	Median	5	6	7	8
	Max	219	403	567	1,020
Q3	Mean	10.55	12.37	12.99	29.17
	SD	15.87	19.63	21.23	59.57
	Median	5	6	7	8
	Max	230	505	455	478
Q4	Mean	13.08	12.25	14.26	36.29
	SD	22.21	20.11	24.62	68.82
	Median	6	6	8	10
	Max	381	382	482	542
Total	Mean	11.80	12.29	13.87	32.96
	SD	19.07	20.11	22.94	73.50
	Median	5	6	7	9
	Max	407	570	567	1,020

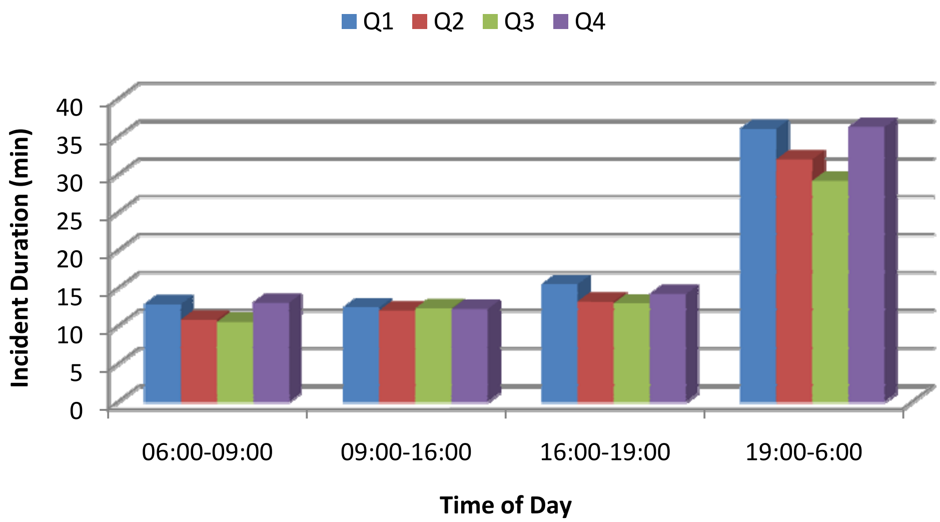


Figure 4-9. Average Incident Duration (in minutes) by Time of Day

Table 4-11 and Figure 4-10 display the durations of incidents occurring on the main corridors for each quarter and the whole year. It is clear that significant differences existed among different corridors. For instance, the duration of a US 2 incident was almost twice as long as the duration of an SR 167 incident (not shown in Table 4-11). The differences could be caused by various factors, e.g., the distance from the incident site and the response team, the length and traffic condition of corridors, or others.

Table 4-11. Incident Duration (in minutes) by Route

Quarter		I-5		I-90		I-405		SR 167		SR 520	
		NB	SB	EB	WB	NB	SB	NB	SB	EB	WB
Q1	Mean	12.68	11.67	15.36	17.00	11.96	12.58	9.09	10.85	12.89	15.74
	SD	23.15	18.87	20.30	29.86	14.56	15.40	13.13	15.38	14.21	17.27
	Median	6	6	8	9	7	8	5	5	8	10
	Max	526	285	181	326	130	118	159	153	106	115
Q2	Mean	11.50	10.45	14.47	13.59	11.93	11.86	9.02	11.22	12.42	11.82
	SD	22.94	14.85	23.59	22.62	16.48	14.42	12.71	30.00	12.19	9.92
	Median	6	6	8	7	6	7	4	4.5	9	10
	Max	898	266	392	385	270	123	140	402	81	57
Q3	Mean	10.89	11.28	13.95	14.23	12.17	11.97	10.49	7.74	12.35	13.56
	SD	14.93	19.63	19.26	18.95	13.64	14.73	19.14	9.40	12.67	16.99
	Median	6	6	7	7	7	7	4	4	8	9
	Max	259	370	211	188	89	134	192	89	95	200

Q4	Mean	11.49	11.92	12.91	13.55	11.93	11.89	12.78	10.24	13.76	16.38
	SD	20.18	20.56	20.13	17.14	17.66	13.58	36.22	15.78	12.76	21.35
	Median	6	6	7	8	6	7	5	5	9	9
	Max	542	382	321	125	183	101	482	143	70	227
Total	Mean	11.57	11.30	14.20	14.51	12.00	12.07	10.25	9.95	12.82	14.33
	SD	20.38	18.56	21.08	22.63	15.64	14.56	21.81	19.20	12.97	16.96
	Median	6	6	7.5	8	6	7	5	5	9	10
	Max	898	382	392	385	270	134	482	402	106	227

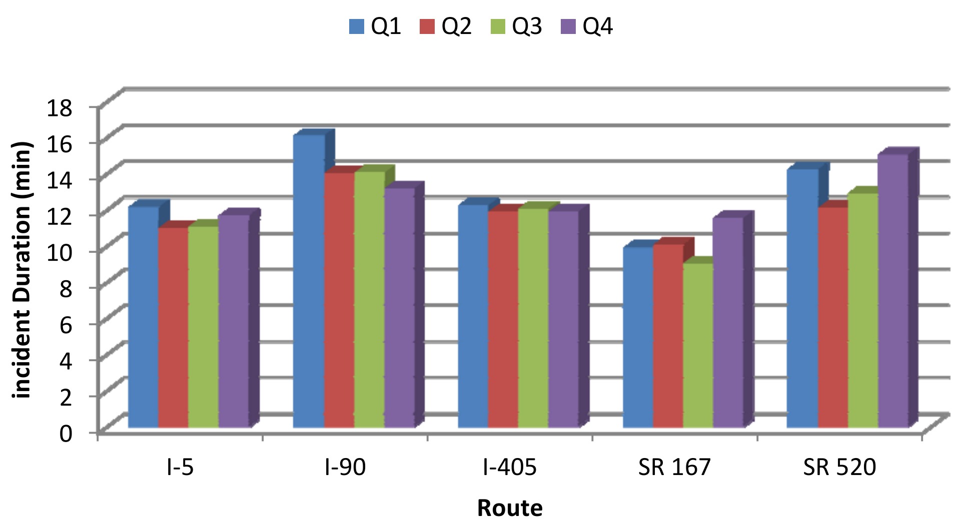


Figure 4-10. Average Incident Duration (in minutes) by Route

Figure 4-11 shows that the average incident duration of a “total closure” or “all travel lanes closure” incident was far longer than the duration of any other kind of incident. “Total closure” and “all travel lanes closure” indicate more severe incidents and also represent more difficult scenarios for IR trucks trying to access the incident scene.

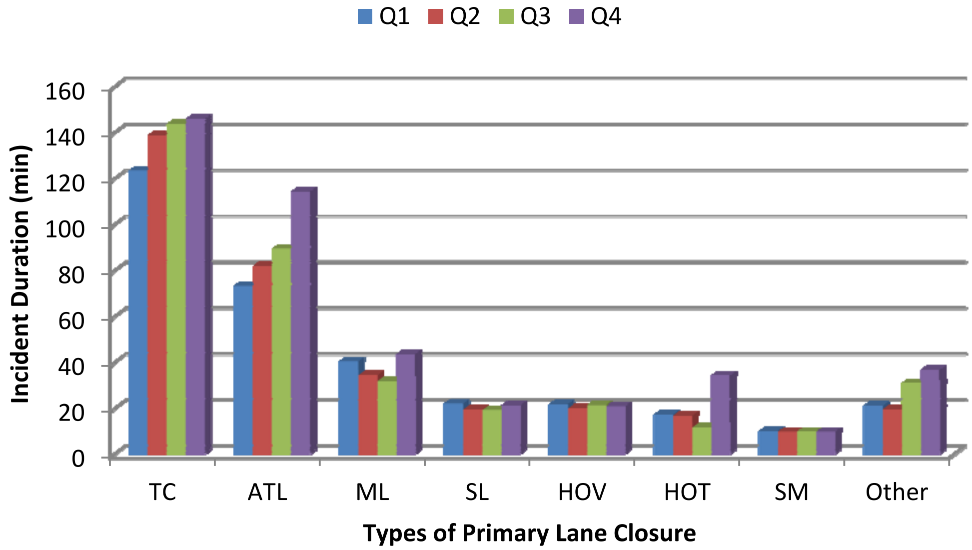


Figure 4-11. Average Incident Duration (in minutes) for by Primary Lane Closure

The average incident durations for different incident categories are summarized in Table 4-12 and Figure 4-12. The top three categories associated with the longest incident duration were fatal collisions, injury collisions, and police activity. Generally speaking, a positive relationship exists between the severity of incidents and the incident duration. For example, collisions involving fatalities or injuries are the most severe and consequently require the longest time to process and clear.

Table 4-12. Incident Duration (in minutes) by Incident Type

Quarter		Fatality Collision	Injury Collision	Non-Injury Collision	Abandoned Vehicle	Disabled Vehicles	Debris	Police Activity	Other
Q1	Mean	188.11	56.70	31.50	5.91	11.13	10.50	57.81	13.89
	SD	85.58	49.46	41.65	15.39	12.40	11.66	96.58	36.24
	Median	172	44	21	3	7	8	23	3
	Max	491	394	570	350	242	235	407	360
Q2	Mean	230.56	57.09	29.22	5.64	10.58	9.06	53.11	9.92
	SD	92.02	50.73	59.48	10.28	11.97	9.01	90.11	27.89
	Median	234.5	42	19	3	7	6	16	3
	Max	403	392	1,020	186	266	93	351	567
Q3	Mean	210.22	61.87	26.87	5.47	10.46	10.05	32.35	12.21
	SD	101.47	55.69	32.00	8.43	11.18	14.56	29.46	28.78
	Median	192	45	19	3	7	7	23	3
	Max	455	478	505	104	230	259	121	329
Q4	Mean	195.56	65.00	29.10	4.96	9.95	10.62	61.32	10.53
	SD	87.38	67.78	32.56	6.49	10.05	14.88	76.87	19.41
	Median	194	45	20	3	7	7	28	4
	Max	482	542	382	84	161	240	324	155
Total	Mean	203.62	60.22	29.18	5.50	10.53	9.96	51.80	11.60
	SD	92.65	56.56	42.72	10.66	11.44	12.63	78.61	28.83

Median	195	45	20	3	7	7	23	3
Max	491	542	1,020	350	266	259	407	567

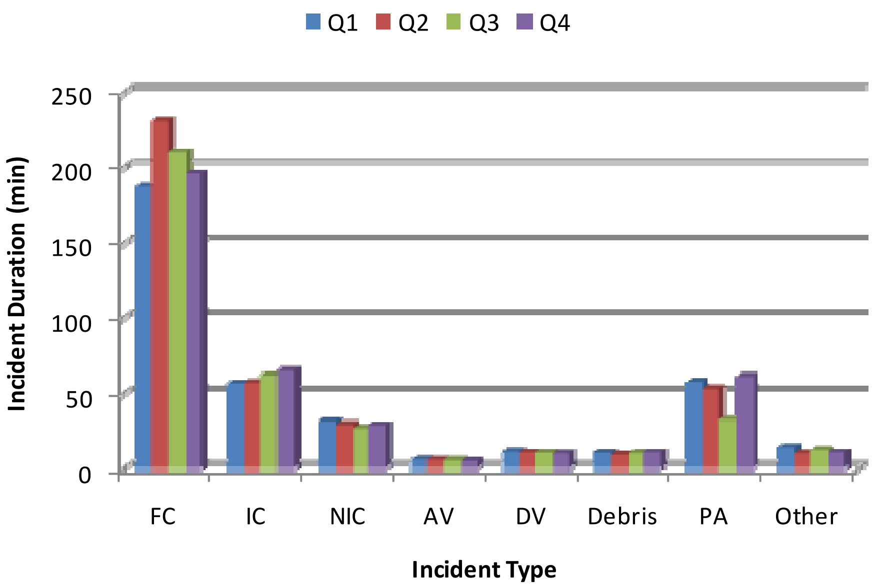


Figure 4-12. Average Incident Duration (in minutes) by Incident Type

Statistical analysis of traffic incidents is essential for estimating incident-induced congestion and for emergency management. It can help for traffic operators better understand non-recurrent congestion caused by incidents, as it identifies the time periods and locations with a higher probability of accidents. Additionally, traffic operators can take advantage of statistical analysis results to develop effective countermeasures against incident-induced congestion. A pressing issue is to optimize the IR team configuration and schedule. With a better understanding of the roadway spots and time periods that have higher incident frequencies, traffic operators can better address these time periods and locations with improved patrol schedules and IR team configurations.

CHAPTER 5 RESEARCH APPROACH

5.1 Review of the Phase I Approach

IID refers to the extra travel time, in addition to the travel time of an incident-free scenario, which all incident-impacted drivers take to complete a certain length of trip. Therefore, in the Phase I study, Wang et al. (2008) calculated IID as $IID = VD_{WI} - VD_{WOI}$, where VD_{WI} refers to the travel delay with an incident, and VD_{WOI} refers to the travel delay without an incident.

As mentioned earlier, a DQT-based approach was developed to quantify VD_{WI}. To overcome the zero-vehicle length assumption in traditional DQT, the approach introduced two time offsets, as indicated in Figure 5-1, i.e., the travel time from the upstream loop station to the incident location (t_{UI}) and the travel time from the incident location to the downstream loop station (t_{ID}). Time offsets are essential for moving the arrival and departure curves to the incident location so that the area enclosed by the relocated arrival and departure curves can be calculated as IID.

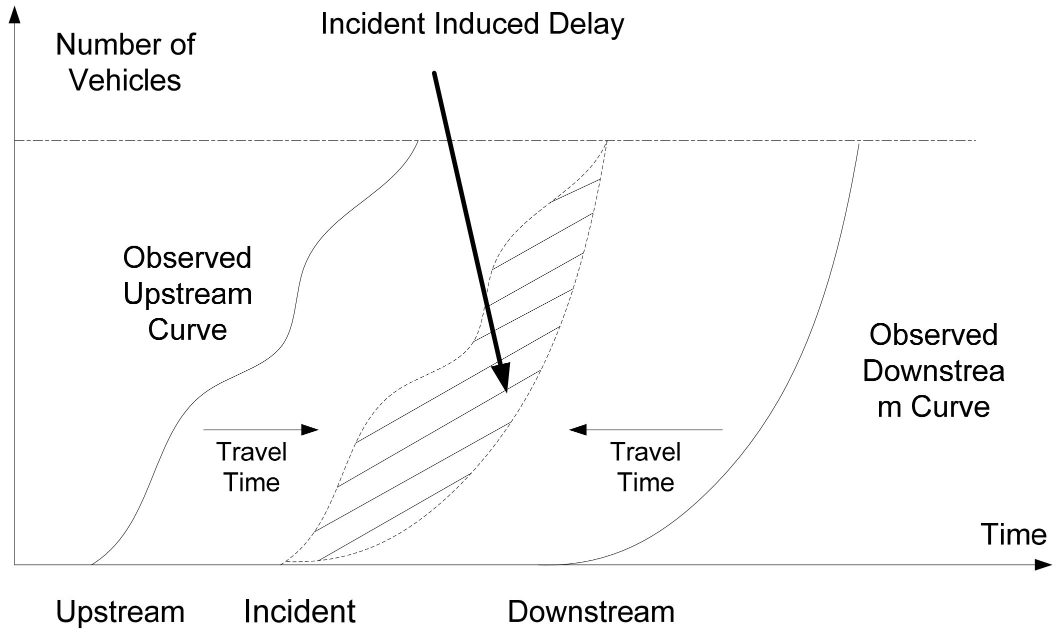


Figure 5-1. DQT with Time Offsets

To quantify VD_{WOI}, a Background Traffic Profile (BTP) matching process was designed, as shown in Figure 5-2. This process uses the vehicle arrival volume series under the incident scenario as the current pattern and searches the historical data for a match series under the incident-free scenario. Mean square error is used as the measure of similarity between two volume patterns. If the error of the most similar pattern is in an acceptable range, a match is identified. Then, the match pattern's downstream departure volume series is used as the departure sequence of the current arrival pattern as if the incident had not happened. With the observed arrival curve and the virtual departure curve of the incident-free scenario, delay due to recurrent congestion (VD_{WOI}) can be estimated. If all the historical patterns are compared but none has an error in the acceptable range, the search fails to find a match, and VD_{WOI} cannot be computed for the current arrival pattern.

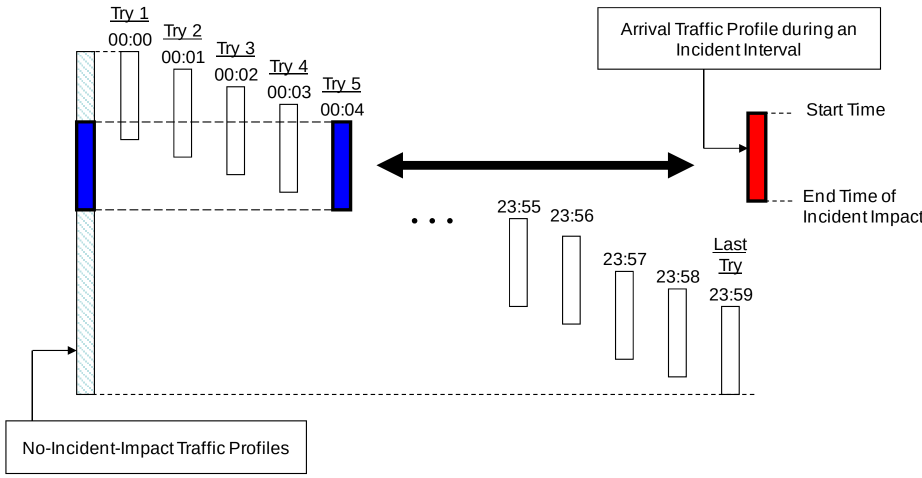


Figure 5-2. BTP Matching

To verify the accuracy of this approach, a preliminary study was conducted to compare estimated delay with ground-truth delay extracted manually from surveillance video of vehicle movements. The incident used for this preliminary study was a lane-blocking incident that occurred at 10:42 AM on the Evergreen Point Floating Bridge of SR 520 on December 19, 2007. Because there is no entrance or exit on the three-mile-long bridge, travel times for all incident-influenced vehicles were collected. The ground-truth total vehicle delay caused by this incident was compared with that estimated by the DQT-based approach. Surprisingly, the analysis results showed that the DQT estimated delay was very sensitive to the time offsets (travel times from the upstream counter location to the incident location and from the incident location to the downstream counter location at the moment when the incident occurred) used in calculations. The DQT-based approach may significantly overestimate or underestimate travel delays if inappropriate time offsets are applied.

Because most existing traffic sensors cannot measure travel time or even speed, obtaining accurate time offsets was a very challenging issue. Another major problem with the Phase I approach was finding the BTP match. Therefore, the current pattern recognition approach as computationally expensive and could not perform at a satisfactory level.

5.2 Algorithm Design for Quantifying IID

This study proposed a modified DQT to address the time offset issue. Figure 5-3 shows an example of IID quantification in a modified queuing diagram, in which the horizontal axis is time and the vertical axis is the accumulated number of vehicles. In Figure 5-3, the arrival and departure flow curves are drawn at the moments they are measured, so that the horizontal distance between the two curves represents the travel time from the upstream loop station to the downstream one, and the vertical distance between two curves is the number of vehicles between the two loop stations. Thus the area enclosed by the upstream arrival and downstream departure curves is the total travel time for all the incident-affected vehicles on the freeway segment bounded by the two loop stations.

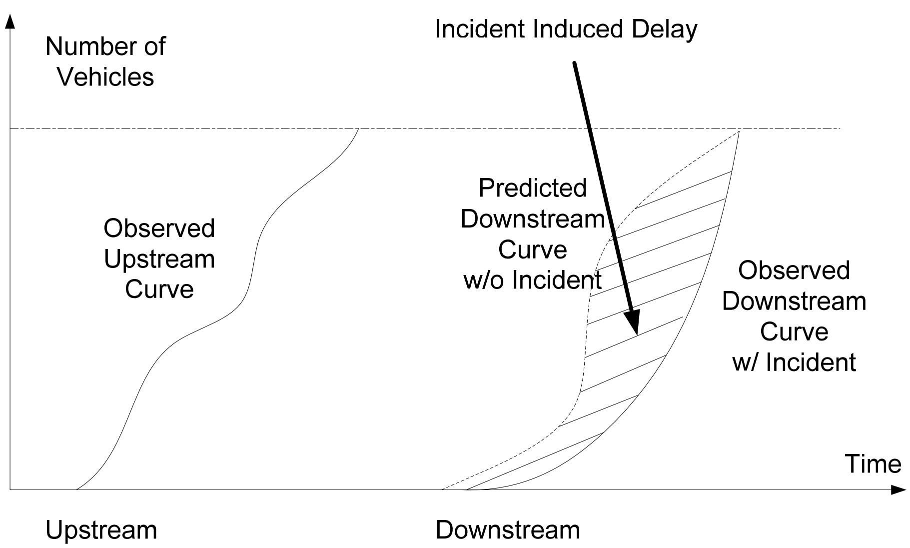


Figure 5-3. Illustration of the Modified Queuing Diagram

Some previous studies also utilized similarly modified queuing diagrams for link travel time estimations (Woensel *et al*. 2008, Nam and Drew, 1996). However, IID cannot be directly retrieved from the modified queuing diagram because it only reflects the total travel time between two loop stations. Total travel time consists of three components: free-flow travel time, extra travel time caused by recurrent congestion (recurrent delay), and extra travel time caused by non-recurrent congestion (IID in this case). To estimate IID, both recurrent delay and free flow travel time need to be excluded from the observed total travel time. As mentioned above in the second challenge, however, this is not easy because given a specific arrival curve for an incident condition, the departure curve for the incident-free scenario remains unknown. If this unobservable departure curve can be virtually created, then it would be straightforward to estimate IID using the modified DQT. Therefore, the key is how to construct the departure curve under the incident-free scenario.

When there is no incident, traffic is either under free flow conditions (with zero delay) or recurrently congested conditions (with predictable congestion locations and times). In either condition, the relationship between the upstream flow and the downstream flow should be relatively stable and predictable. Therefore, the research team used the observed upstream flow curve to predict the downstream flow curve of the incident-free scenario. The feasibility of this approach has been demonstrated in previous short-term traffic flow forecasting studies (Hobeika, and Kim, 1994; Abdulhai, et al., 1999).

The modified DQT approach shown in Figure 5-3 needs three curves for IID estimation: the observed upstream arrival curve, observed downstream departure curve of the incident scenario, and the predicted downstream departure curve of the incident-free scenario. IID corresponds to the area enclosed by the observed downstream departure curve of the incident scenario and the predicted downstream departure curve of the incident-free scenario. A mathematical expression of the total vehicle travel time with the incident impact, VD_{WI}, and total vehicle travel time without the incident impact, VD_{WOI}, can be defined as in equations (5-1) and (5-2), respectively.

$$VD_{WI} = \int_{i=t_I} \left(\int_{i=t_I - t_{UI}} n_{U,i} dt - \int_{i=t_I + t_{ID}} n_{D,i} dt \right) dt \tag{5-1}$$

$$VD_{WOI} = \int_{i=t_I} \left(\int_{i=t_I - t_{UI}} n_{U,i} dt - \int_{i=t_I + t_{ID}} n^{WOI}{}_{D,i} dt \right) dt \tag{5-2}$$

where $n_{U,i}$ and $n_{D,i}$ are the upstream and downstream vehicle counts during period i; $n_{D,i}^{WOI}$ is the predicted downstream vehicle count during period i assuming no incident; t_I is the time when the incident occurred; t_{UI} is the travel time from the upstream loop station to the incident location, and t_{ID} is the travel time from the incident location to the downstream loop station.

Then IID can be calculated as the difference between VD_{WI} and VD_{WOI}:

$$IID = VD_{WI} - VD_{WOI} = \int_{i=t_I} \left(\int_{i=t_I + t_{ID}} n^{WOI}{}_{D,i} dt - \int_{i=t_I + t_{ID}} n_{D,i} dt \right) dt \tag{5-3}$$

$\int_{i=t_I + t_{ID}} n^{WOI}{}_{D,i} dt$ corresponds to the predicted downstream curve, and $\int_{i=t_I + t_{ID}} n_{D,i} dt$ corresponds to the observed downstream curve. During the period t_{ID}, $n^{WOI} \approx n_{D,i}$ because vehicles between the incident location and the downstream loop station are not influenced by the incident. Equation (5-3) can be rewritten as

$$\begin{aligned} IID &= \int_{i=t_I} \left(\int_{i=t_I + t_{ID}} n^{WOI}{}_{D,i} dt - \int_{i=t_I + t_{ID}} n_{D,i} dt + \int_{i=t_I}^{t_{ID}} n^{WOI}{}_{D,i} dt - \int_{i=t_I}^{t_{ID}} n_{D,i} dt \right) dt \\ &= \int_{i=t_I} \left(\int_{i=t_I} n^{WOI}{}_{D,i} dt - \int_{i=t_I} n_{D,i} dt \right) dt \end{aligned} \tag{5-4}$$

Equation (5-4) indicates that the proposed approach successfully eliminates the need for time offsets (t_{UI} and t_{ID}) for IID estimation and thus significantly eases the data collection process.

5.3 Regression Techniques for Short-Term Traffic Flow Forecasting

The downstream vehicle departure curve of the incident-free scenario is essential for IID estimation. However, it is not observable and must be estimated on the basis of historical data and current upstream arrivals. The Phase I approach utilized BTP matching to identify an incident-free matching series of arrival traffic at the same location and then used the corresponding downstream volume series to form the departure curve of the no-incident scenario. As mentioned earlier, BTP matching itself is a challenging research issue, and the mean square error approach employed in Phase I is computationally expensive. Therefore, the research team attempted to use a different approach to construct the departure curve of the incident-free scenario.

All vehicles entering a freeway segment should be observed by the upstream loop station and then by the downstream loop station after traversing the segment. Depending on the traffic conditions and the length of the segment, it may take several time intervals (loop detector data reporting intervals are typically 20 to 60 seconds) for a vehicle to complete the journey. Given that the upstream and downstream traffic volumes are typically correlated, the research team was inclined to use regression techniques for this short-term traffic flow forecasting problem. In this research, two forecasting techniques were investigated and compared.

5.3.1 Lagged Regression and Ridge Regression

Lagged regression is a time series analysis technique. It investigates the correlations between the downstream flow count series from time step *i* and the upstream flow count series from time steps *i-r*. Here, *r* is the time lag between two series that takes values of *r=1, 2, 3, …* and evaluates which *r* value corresponds to a correlation stronger than a user-specified level. The lagged regression model used for this study is shown in Equation (5-5).

$$y_t = \beta_0 + \sum_{r=l_1}^{l_k} a_r x_{t-r} + \omega_t \tag{5-5}$$

where y_t represents the downstream flow count series; x_{t-r} denotes the upstream flow count series with a time shift of *r* intervals from the downstream series; β_0 is the constant; l_1 to l_k are the lags at which correlations between inputs and outputs are above the correlation threshold; and ω_t is white noise.

Ridge regression is a nonparametric regression technique. Unlike multiple linear regression, it uses goodness of prediction as the parameter estimation criterion rather than goodness of fit. As shown in Equation (5-6), ridge regression shares the same mathematical expression as multiple linear regression.

$$y_i = \beta_0 + \sum_{j=1}^{k} x_{ij}\beta_j + \varepsilon \tag{5-6}$$

An important distinction between ridge regression and multiple linear regression is that ridge regression applies a different procedure for model parameter estimation. Equations (5-7) through (5-11) show the parameter estimation procedure with ridge regression. Note that a penalty term, λ, called the smoothing parameter, is added to constrain the parameters $\beta_1, \beta_2, \cdots, \beta_k$ in Equation (5-7).

$$\sum_{i=1}^{n}\left(y_i-\beta_0-\sum_{j=1}^{k}x_{ij}\beta_j\right)^2+\lambda\sum_{j=1}^{k}\beta_j^2 \tag{5-7}$$

For a specific λ, minimizing Equation (5-7) is equivalent to minimizing

$$\sum_{i=1}^{n}\left(y_i-\beta_0-\sum_{j=1}^{k}x_{ij}\beta_j\right)^2 \text{ subject to } \sum_{j=1}^{k}\beta_j^2\le s \tag{5-8}$$

where *s* is the constraint to $\beta_1,\beta_2,\cdots,\beta_k$, which plays a similar role as λ. Solving Equation (5-8) yields

$$\hat{\beta}=(x^Tx+\lambda D)^{-1}x^TY \tag{5-9}$$

where D is an identity matrix. For smoothing parameter selection, cross validation techniques are applied: a sample of data is partitioned into two complementary datasets, one for model training and the other for validation. Then values of ordinary cross-validation (OCV) and generalized cross-validation (GCV) are calculated by using Equations (5-10) and (5-11), respectively:

$$OCV^{\lambda}=\frac{1}{n}\sum_{i=1}^{n}\frac{(y_i-\hat{y}_i)^2}{(1-S_{ii})^2} \tag{5-10}$$

$$GCV^{\lambda}=\frac{1}{n}\sum_{i=1}^{n}\frac{(y_i-\hat{y}_i)^2}{\left(1-tr(S^{\lambda})/n\right)^2} \tag{5-11}$$

where $S^{\lambda}=(x^Tx+\lambda D)^{-1}x^T$. The λ value with the lowest OCV or GCV score will be chosen. In this way, cross-validation essentially compares different models and selects the one with the best predictions on the basis of the training data set.

As illustrated above, in comparison to multiple linear regression, ridge regression skips the variable selection process but applies a smoothing parameter to constrain all parameters. The estimation goal is to minimize cross validation scores (OCV and GCV) rather than the sum of the squared residuals. Therefore, ridge regression can accommodate more input variables. In this study, *k* was chosen to be 15, meaning that the downstream volume count was estimated by the upstream volume counts over the past 15 intervals, or 5 minutes. The research team chose 5 minutes because in IID quantification applications, the distance between upstream and downstream loop stations usually ranges from 0.5 to 1.5 miles. Even in congested periods (e.g., vehicles traveling at 20 mph), travel time over such a distance would still be under 5 minutes, and the regression model can capture the relationship between upstream and downstream flows.

5.3.2 Prediction Accuracy Evaluation

Since the downstream departure volume prediction under the incident-free scenario is a key component in the proposed methodology framework, the prediction accuracies for the two proposed short-term traffic forecasting techniques had to be compared to find the better one for IID estimates. The measures used for the comparison are Mean Squared Error (MSE) and Index of Agreement (IA).

Mean Squared Error (MSE) is widely used as a measure for quantifying the difference between the estimated value and the observed value. It is defined as

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \qquad (5\text{-}12)$$

where n is the number of observations, $\hat{y}_i$ is the estimated value, and y_i is the observed value. Despite its widespread use, MSE has been criticized because its value is highly related to the magnitude of the observed values. One remedy for this problem would be to take the mean of observed values into consideration. Index of Agreement (IA) was proposed by Willmott (1981) as a quantitative indication of the quality of model prediction. It is defined as

$$IA = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(|\hat{y}_i - \overline{y}| + |y_i - \overline{y}|)^2} \qquad (5\text{-}13)$$

where n, $\hat{y}_i$, and y_i are as defined in Equation (5-12), and $\bar{y}$ is the mean of observed values. IA is dimensionless and ranges between 0 and 1. When IA=1, perfect agreement is achieved between the estimated and observed values.

Prediction accuracy tests were conducted for two locations, one on I-5 northbound between mileposts 157.92 (upstream) and 158.92 (downstream), and the other on SR 520 westbound between mileposts 1.58 (downstream) and 4.10 (upstream). For each location, an interval free of incidents was randomly chosen, and the corresponding upstream and downstream 20-second loop volume data retrieved from the database server at the STAR Lab were employed for parameter estimation using both regression techniques.

The calibrated model for each location was then applied to three testing data sets, representing three different scenarios: (1) the same location on another date, (2) the same date at another location, and (3) at another location on a different date. All the locations and dates were chosen randomly to test the calibrated model's spatial and temporal transferability, i.e., how well it can be applied to different dates or locations. Detailed information about the training data, test data, and test results are summarized in Table 5-1.

Table 5-1. Prediction Accuracy Test Results

Training Data			Testing Scenario			Prediction Method			
Time	Location		Time	Location		Ridge Regression		Lagged Regression	
	Upstream Milepost	Downstream Milepost		Upstream Milepost	Downstream Milepost	IA	MSE	IA	MSE
10/15/2009	I-5 157.92	I-5 158.92	11/11/2009	157.92	158.92	0.64	38.2	0.38	65.4
			10/15/2009	139.69	140.64	0.74	38.8	0.38	79.2
			11/11/2009	189.98	190.9	0.77	39.7	0.6	65.7
11/18/2009	SR 520 4.1	SR 520 1.58	10/14/2009	4.1	1.58	0.52	15.4	0.27	19
			11/18/2009	7.98	6.01	0.47	43.8	0.47	43.7
			10/14/2009	7.98	6.01	0.44	37.6	0.44	37.7

For the I-5 location, ridge regression performed better than lagged regression in terms of prediction accuracy. IA for ridge regression at the I-5 location ranged from 0.64 to 0.77, meaning that the predicted values agreed 64 percent to 77 percent with the observed values. MSE values for ridge regression at the I-5 location were half those for lagged regression. For the SR 520 location, ridge regression also outperformed lagged regression when applied to a different date, with a higher IA and a lower MSE. In the other two scenarios, ridge regression and lagged regression both had lower prediction accuracies at approximately the same level. IA values for these two scenarios were less than 50 percent. One reason might be that the training data set for SR 520 case was from both ends of a floating bridge, where the traffic characteristics were different from those at the location for training scenarios 2 and 3, which was a regular freeway section.

From this comparison, the researchers concluded that ridge regression had a better or equivalent prediction accuracy than lagged regression at these two test sites. This result would also be found at other locations because the parameter estimation for ridge regression is designed for better prediction: it uses cross-validation for smoothing parameter selection, a technique to evaluate how well the predictions from the trained model can be generalized to other independent data sets.

Additionally, ridge regression can accommodate more variations in traffic than lagged regression. Lagged regression calculates cross-correlation function to find the most correlated previous time steps. Once the model is formulated, only time steps with correlations higher than the threshold will be kept in the model. Ridge regression keeps all the upstream volumes from the previous 15 time steps, so it captures more of the traffic dynamics that occurred in the last five minutes.

Last but not least, in comparison to lagged regression, ridge regression is more flexible in terms of choosing upstream and downstream loop stations. The most correlated time steps picked up by lagged regression are strongly influenced by the distance between the upstream and downstream loop stations. When traffic flow stays stable, vehicles will take a certain time to travel from upstream to downstream locations. This travel time is mainly determined by the distance between the upstream and downstream loop stations. However, when the trained model is applied to another upstream/downstream pair along a specific corridor, with a longer or shorter distance than that in the training data set, the trained model will fail to perform well. Ridge regression is a nonparametric regression technique, which does not rely on specific parameters but shrinks the input data to best fit the relationship between input and output. Therefore, within the scope of this study the research team chose ridge regression over lagged regression for methodology implementation.

5.4 Algorithm Implementation

The IID estimation approach developed in this study is straightforward. However, it is very challenging to perform the calculations manually. Therefore, the entire procedure was implemented in an online system to automate the calculations. Implementation consisted of three components: incident and loop data cleansing, model training (parameter estimation), and IID calculation.

Both incident duration and incident location are indispensable information for IID estimation. However, applying the proposed approach to inaccurate data would generate wildly biased IID estimates. Because of communication problems and loop malfunctions, some loop stations could not produce any useful data, and in the WITS database, the information for some incidents was either incomplete or missing. Therefore, incidents without complete, good quality data were excluded from IID calculations.

When traffic flow conditions change, the upstream/downstream relationship will change correspondingly. Therefore, it is desirable to develop individual prediction models for different locations and flow conditions to ensure downstream flow prediction accuracy. The research team applied ridge regression to different traffic flow conditions from location to location over different time periods. They identified traffic flow levels and traffic volume trends as two main factors that influence prediction accuracy. They also found that almost all the locations experienced four phases of traffic dynamics. These four phases are based on traffic flow levels and volume trends and are as follows:

1. Free flow phase: low volume and high speed, usually from midnight to early morning

2. Travel growing phase: the transition phase from free flow to morning peak, with consistently increasing volume until morning peak volume is reached

3. Daytime phase: even though it might experience morning or afternoon peak, traffic demand remains at a high level over a long period during the day

4. Travel decreasing phase: the transition phase from daytime flow to free flow phase, with consistently decreasing volumes. An example of traffic flow variation in one day free of incidents on I-5 northbound between mileposts 158 and 160 is shown in Figure 5-4. There were five lanes in the section, and both upstream and downstream volumes were aggregated into 5-minute intervals. In Figure 5-4, the free flow, travel growing, daytime, and travel decreasing phases roughly correspond to midnight to 4:00 AM, 4:00 to 7:00 AM, 7:00 AM to 6:00 PM, and 6:00 PM to midnight. The research team went through 22 locations along main corridors including I-5, I-405, I-90, and SR520. For each location, four traffic phases within one day were identified. For each phase, a specific prediction model was calibrated.

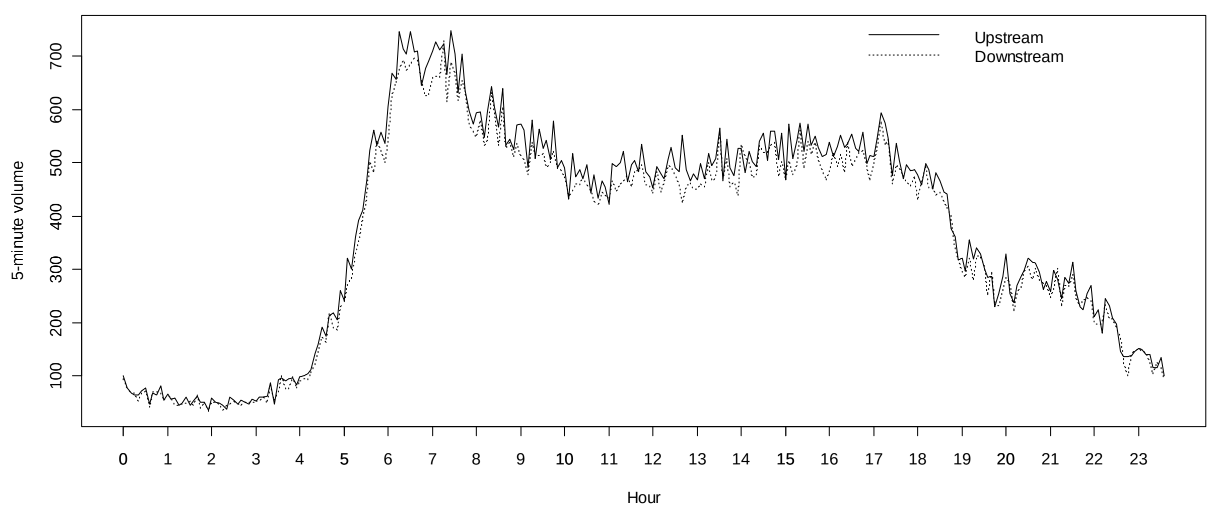


Figure 5-4. Typical Traffic Variations over a Day

While traffic phases defined different flow levels and volume trends, four other factors were used to represent flow direction and location: route, milepost, direction, and number of lanes. Once a new combination of the factors was determined, a new set of model parameters needed to be estimated. This was straightforward to do for freeway segments with traffic counters. In this study, 88 different models were estimated, representing a variety of scenarios.

Once an incident has been identified, its duration and location information can be retrieved. On the basis of that information, a corresponding calibrated model and upstream/downstream 20-second volume data are obtained. With the calibrated model and upstream volumes, predicted downstream volumes can generated instantly. The predicted downstream volumes can then be used with the observed downstream volumes in the modified DQT for IID estimation.

The procedure described above is summarized in Figure 5-5. After the IID is calculated for the incident, the result, together with the incident description information, is stored in a Microsoft SQL database hosted in a Dell Edge server operating Windows Server 2008 at the Star Lab. All of the IID results are integrated into the database, whose access and query are supported by a regional map-based online platform called Digital Roadway Interactive Visualization and Evaluation Network (DRIVE Net) (Ma et al., 2010). The current implementation is on Google Maps. However, it should be fairly easy to transplant DRIVE Net to other digital map systems.

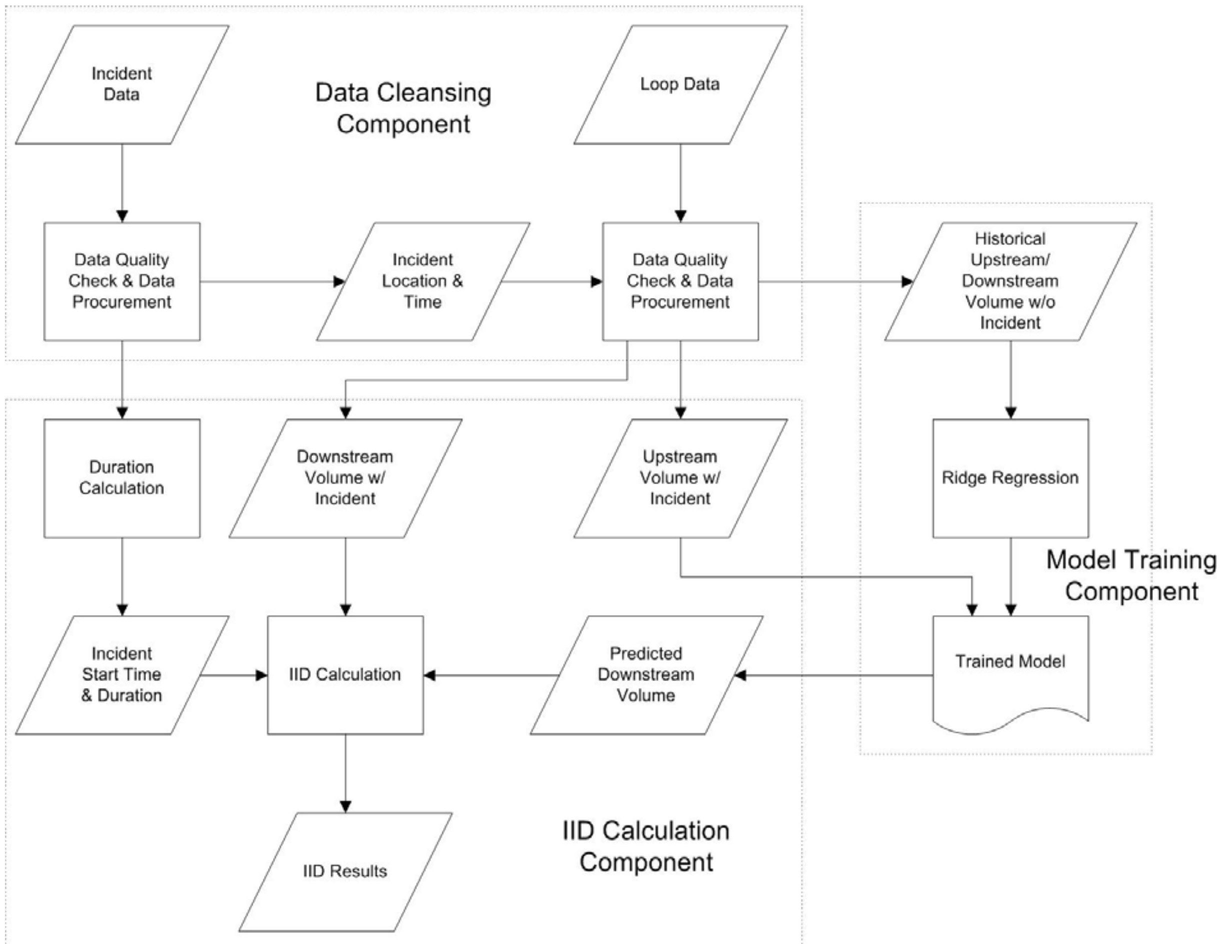


Figure 5-5. Implementation Process

Through the regional map-based user interface, practitioners can configure queries on the incident database by using the tools provided by DRIVE Net. For example, a user can specify the time period (note: only 2009 incident data have been loaded at this time) and routes to define the kinds of incidents to show. All incidents that fit the query criteria will be marked by a balloon symbol on the regional map. If the user is interested to know details of an incident, he or she can click the corresponding balloon and see the fundamental data of the incident in a callout textbox. To calculate the IID, users can click on a "Calculate Delay" button on the bottom of the callout. Figure 5-6 shows a snapshot of an example incident on I-5.

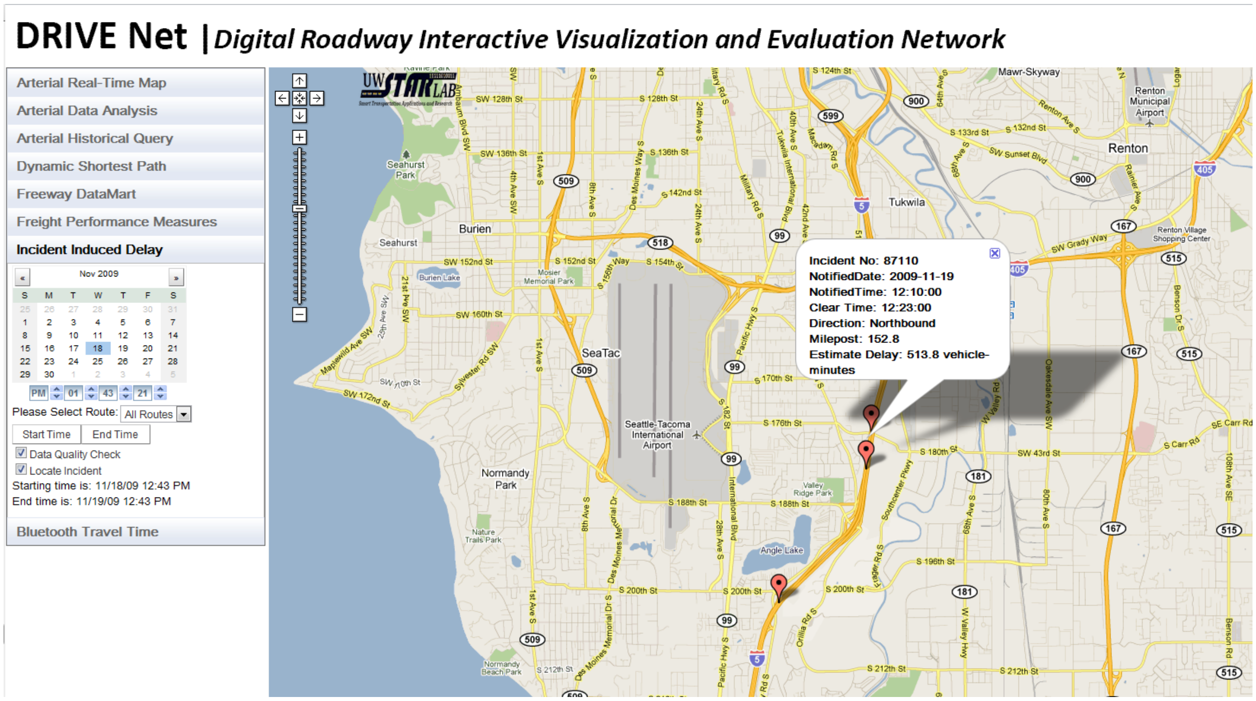


Figure 5-6. Snapshot of the Online System

CHAPTER 6 RESULTS AND DISCUSSION

6.1 Case Studies for Algorithm Verification

To validate the accuracy of the IID algorithm, IID estimates calculated by the algorithm were compared to ground-truth IIDs. However, data regarding vehicle travel delay are not easy to obtain. Therefore, surveillance video camera-captured traffic data were chosen as a means for extracting ground-truth travel delays for validating the algorithm results in this study.

The Phase I methodology used a simulation-based approach for algorithm validation. VISSIM simulation software was used to simulate 18 incidents occurring on eastbound SR 520 along the Evergreen Point Floating Bridge in January 2003. Although the simulations produced similar results to those calculated with the Phase I methodology, the use of simulation software has several disadvantages, including the constraints of the built-in driver behavior models and a lack of data and methodology for thorough calibration of a microscopic simulation model.

Therefore, validation with field observed travel data is highly desirable. The research team recorded a large amount of video data and eventually fully captured two incidents under the monitoring range of the surveillance video cameras. The first recorded incident occurred on January 26, 2010, at 7:53 AM on I-5 near Boeing Field in Seattle, Washington. The second recorded incident occurred on April 9, 2010, at 4:43 PM on the SR 520 Bridge. The ground-truth travel delay associated with each incident was manually determined.

6.1.1 Video Validation Methodology

Test sites for the video validation were selected on the basis of the criteria described in Chapter 3. Each test site consisted of a freeway segment with one camera at the upstream end of the segment and another camera at the downstream end. Each camera’s field of view covered the corresponding inductance loop station so that the volume data extracted from the video footage were ground-truth data at the loop detector location. In order for the delay from an incident to be calculated properly, the incident and the queue induced by the incident had to be located between the two cameras.

The two video streams for each chosen study site were recorded continuously until an incident had been captured. A Really Simple Syndication (RSS) Web feed from WSDOT was used to determine when an incident had occurred at the study site. The RSS feed provides information for all incidents occurring within the Northwest Region of WSDOT. Data included in the RSS feed are incident time, location, and a brief description. The recording was then analyzed to determine whether the incident had been captured and if IID could be calculated from the recording.

To determine IID from the video recording, a baseline travel time for the segment was calculated. Timestamps for a sample of eight vehicles were recorded at both the upstream and downstream cameras minutes before the occurrence of the incident. The difference between the two time stamps of a vehicle provided the travel time for the vehicle to traverse the segment right before the incident. The travel times for all the eight vehicles was averaged to determine the mean travel time of the segment without the incident.

The duration of the incident was then broken into 30-second intervals. For each interval, a single vehicle with visually identifiable features was tracked to determine its travel time through the segment. This provided a representative travel time for all vehicles within the interval. By taking the difference of the travel time for the given interval and the travel time without the incident and multiplying it by the total number of vehicles within the given interval, the cumulative delay for all vehicles in the interval was determined. By adding the delay for each

30-second interval throughout the duration of the incident, the total incident induced delay was calculated.

In some intervals, a featured vehicle may not have been available for easy manual tracking because of either poor video quality or the absence of featured vehicles. While a vehicle count could be determined for these intervals, a representative travel time could not be obtained. In this case, the average travel time of the adjacent time intervals was used to calculate the IID of the interval.

6.1.2 Case Study 1: I-5 Boeing Field

The first recorded incident used to calculate delay occurred on January 26, 2010, at 7:53 AM on I-5 near Boeing Field in Seattle, Washington, in the northbound direction, as shown in Figure 6-1. The southern camera was located at the Albro Place overpass (MP 159.05), and the northern camera was located at mid-Boeing Field (MP 158.05). This gave a segment length of one mile. Calculation for this incident yielded an IID of 9,332 vehicle-minutes. The screen shots in Figures 6-2 and 6-3 provide examples of the video used for ground-truth IID extraction.

Figure 6-1. I-5 Northbound Boeing Field Camera Locations

Figure 6-2. Jan. 26, 2010, Downstream of Incident

Figure 6-3. Jan. 26, 2010, Upstream of Incident

6.1.3 Case Study 2: SR 520 Bridge

The second recorded incident used in the IID algorithm validation occurred on April 9, 2010, at 4:43 PM on the SR 520 Bridge in the westbound direction. This study site is illustrated in Figure 6-4. The cameras used at this location were at MP 1.58 at the Lake Washington Blvd exit and MP 4.1 at the 76th Ave NE overpass (see Figures 6-5 and 6-6 for a snapshot at each location).

The methodology for verification was slightly altered for this incident. Because of the nature of the study segment, queues forming as a result of incidents near the downstream camera exceeded the video extents of the upstream camera. After the point in time when the queue had passed the upstream camera, delay estimations were no longer accurate, as vehicles had already experienced a significant amount of delay before entering the view of the camera. The quantification of this incident was cut short, ending at the point in time when the queue reached the upstream camera. This shortening of the validation methodology did not affect its accuracy, as the time adjustment was considered in the calculation methodology as well.

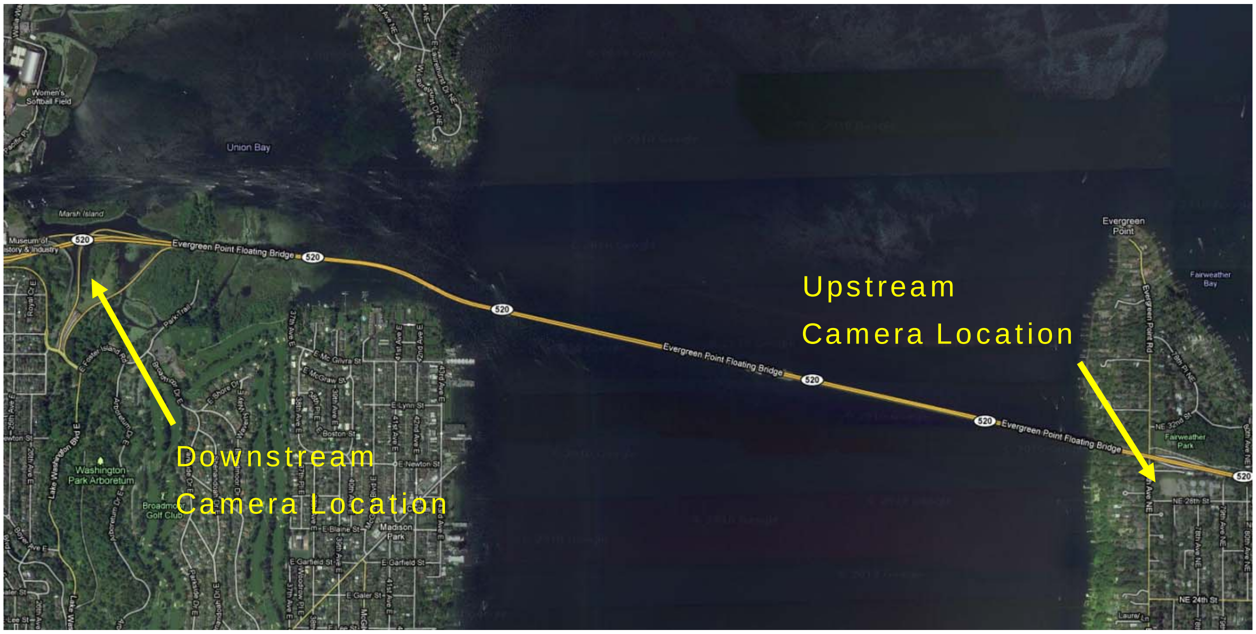


Figure 6-4. SR 520 Bridge Camera Locations

Figure 6-5. Apr. 9, 2010, Downstream of Incident

Figure 6-6. Apr. 9, 2010, Upstream of Incident

6.2 Statistical Analysis on IID

The improved DQT-based IID estimation algorithm was coded in JAVA as a module of the DRIVENet system. Currently, only the 2009 WITS data set has been loaded and is ready for users to access and query. There are 2,676 incidents with complete incident records and good-quality loop data in the databases and all of them were processed. Of the total incidents processed, 2,028 (75.8 percent) incidents were found to have caused travel delays. In the following sections, these 2, 028 incidents are summarized based on primary lane closure type and incident type; then the relationship between the incident duration time and calculated IID is analyzed in detail; finally, the difference of IID on weekdays and weekends is investigated.

6.2.1 Summarization of IID estimation results

IID estimation results for those 2, 028 incidents are summarized in Tables 6-1 and 6-2. In each table, the descriptive statistics, including frequency, mean, standard deviation (SD), median, and maximum, are shown for different categories.

Table 6-1 shows aggregated IID statistics by primary lane closure type. On the basis of the mean IIDs of lane closure types, one can tell that multiple lane closures are the most severe, followed by HOV lane closures, and then single lane closures. Shoulder/median closures are the least severe. Since the mean IID for shoulder/median closure is much lower than that for any other primary lane closure types, closing the shoulder or median for necessary incident investigations is a good incident management strategy for mitigating incidents' impacts to traffic.

Table 6-1. Statistics of Incident-Induced Delays (in vehicle-hours)

Primary lane closure type	Frequency	Mean	SD	Median	Max
HOV	69	169	15	628	4685
Multiple Lane	60	609	26	2871	22045
Shoulder/Median	1642	17	2	68	1667
Single Lane	253	75	11	271	3094

Table 6-2 presents IIDs grouped by incident type. From Table 6-2, it can be found that collision-related incidents, especially incidents with injury, were associated with longer delay than other types. Note that in both Table 6-1 and Table 6-2, the mean values are significantly smaller than the corresponding median values. The reason lies in that of all the 2,028 incidents associated with a non-zero IID, there are 68.2 percent of them (1,384 incidents) have an IID of less than 10 vehicle-hours, implying a non-symmetrical distribution of IIDs. In this case the median value provides more statistically meaningful information than the mean value. For example in Table 6-2, for incident type "Disabled Vehicle", half of the sampled incidents were associated with delay longer than 90 vehicle-hours, although the mean value for this category is only 20 vehicle hours.

Table 6-2. Statistics of Incident-Induced Delays (in vehicle-hours)

Incident type	Frequency	Mean	SD	Median	Max
Abandoned Vehicle	359	7	1	39	454
Debris Blocking Traffic	193	21	5	56	591
Disabled Vehicle	1218	20	2	90	1993
Injury Collision	38	544	186	1030	4685
Non-Injury Collision	100	168	37	361	2460

6.2.2 Relationship between the incident duration time and calculated IID

In terms of the incident duration of these 2,028 incidents, 80.9 percent (1,640 incidents) of them lasted less than 15 minutes, 18.9 percent (384 incidents) of them stayed between 15 and 90 minutes, and only 0.2 percent (4 incidents) of them had duration of over 90 minutes. Figures 6-7 and 6-8 show the percentage of different IID significance levels (on a log scale, in the unit of vehicle-hour) for those with durations of less than 15 minutes and between 15 and 90 minutes respectively. By comparing Figure 6-7 and Figure 6-8, one can find that the IID tends to increase when the duration increases. On one hand, the percentage of IID greater than 100 vehicle-hour grows from 0 percent to 31 percent and the percentage of IID between 10 and 100 vehicle-hour grows from 15 percent to 46 percent when the incident duration changes from less than 15 minutes to between 15 and 90 minutes; on the other hand, the percentage of IID stayed for less than 10 vehicle-hour decreases when the duration increases.

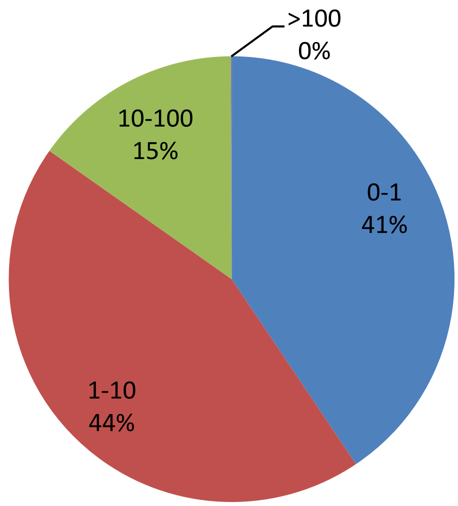


Figure 6-7. IID significance levels for incidents lasting less than 15 minutes

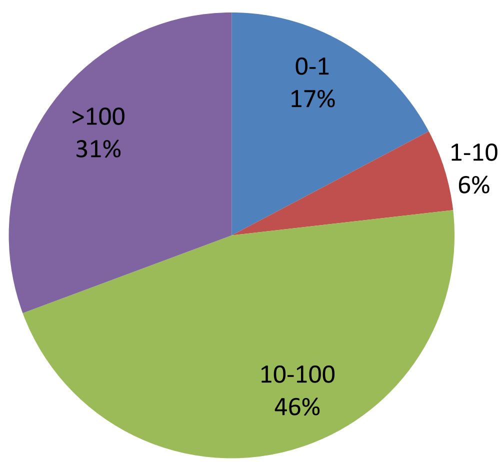


Figure 6-8. IID significance levels for incidents lasting between 15 and 90 minutes

Table 6-3 shows the information of the four incidents with duration of over 90 minutes. All these four incidents are related to lane closure. Two of them (the first and the fourth) are injury collisions; the third one is a non-injury collision; and the incident type of the second one is not available in the WITS database.

Table 6-3. Duration over-90-minute incidents within the 2,028 incidents

Date	Notification Time	Duration (minute)	Location	Description	IID (vehicle-hour)
5/13/2009	2:00 PM	124	I5 MP:151.2	Injury Collision, HOV lane closed	4,685
7/29/2009	1:13 PM	215	I5 MP:151.8	Multiple Lane closed	22,045
9/4/2009	12:14 PM	96	I5 MP:146.8	Non-injury Collision, Single Lane closed	945
12/21/2009	7:23 AM	381	I5 MP:142	Injury Collision, Single Lane closed	3,094

Figure 6-9 uses a log scale on the IID-axis to show the frequency of different incident types. From Figure 6-9, one can find:

- The incident types with IID less than 10 vehicle-hours are mostly disabled vehicles and abandoned vehicles.
- The IID is usually higher than 10 vehicle-hours when collision-related incident types (injury collision and non-injury collision) happen.

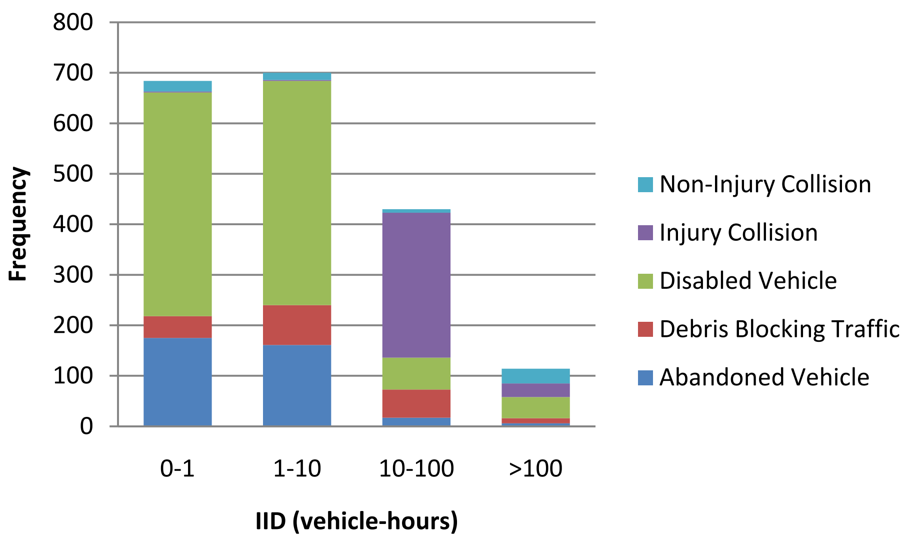
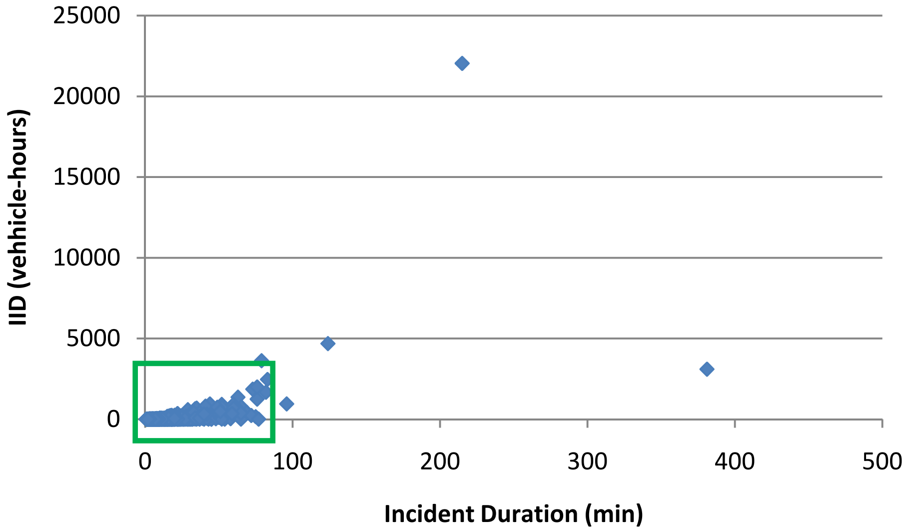


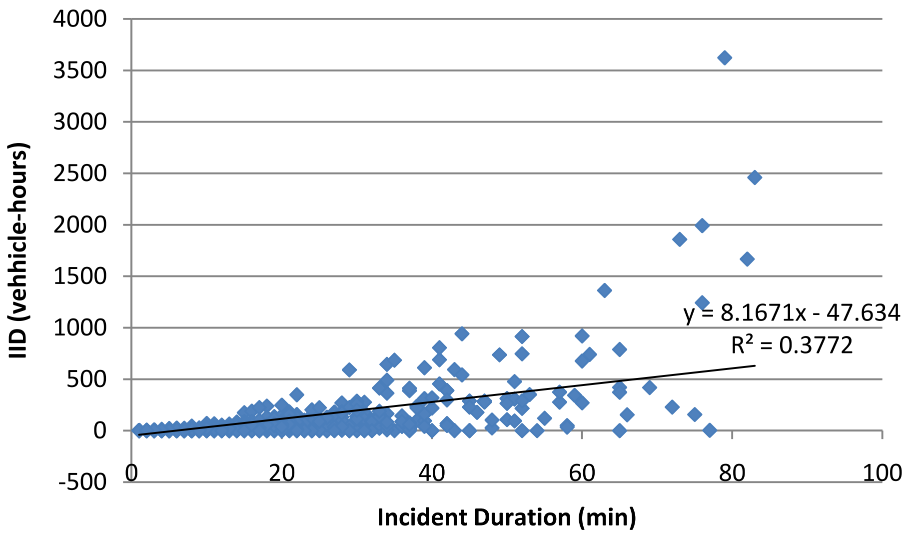
Figure 6-9. Frequency of different incident type uses a log scale on the IID-axis

The scatter plot in Figure 6-10 (a) shows the relationship between the incident duration time and calculated IID for these 2,028 incidents. Figure 6-10 (b) is an enlarged chart for the green box in Figure 6-10 (a) which displays IIDs caused by incidents lasted less than 90 minutes. From Figure 6-10, one can find that the calculated IID tends to increase with the incident duration time. However, this may not always be the case, since IID is also affected by many other factors, such as the traffic demand on the freeway and lane closure type. In Figure 6-10, a linear model was calibrated to establish a best-fit relationship between the incident duration time and IID. The positive slope of 8.167 indicates that IID increases as incident duration increases. However, the square of the correlation coefficient is only 0.377, indicating a relatively weak correlation between the two variables. That indicates that IID is not a simple linear function of incident duration. The IID can be affected by incident duration time, as well as other factors, such as traffic volume when the incident happens and the roadway configuration.

Additionally, 33.7 percent of the WSDOT IR team responded incidents are associated with IIDs of less than one vehicle-hour. A closer look at those incidents revealed that most of them had incident duration of less than 10 minutes and occurred at a period with relatively low traffic volume. Very likely, the reduced capacities resulting from these incidents were still higher than the demands, and hence these incidents did not result in any significant travel delays in relation to the incident-free scenarios.



(a)



(b)

Figure 6-10. The Relationship between Incident Duration Time and Calculated IID - Linear Scale

6.2.3 Investigation on the IID difference between weekdays and weekends

The magnitude of IID is dependent on the effectiveness of incident response, as well as the severity of the incidents and the traffic conditions. In order to investigate in these impact factors, we need to compare IIDs on weekdays and those on weekends of the similar incident types. A case study on I-5 was conducted. In this case study, all the I-5 incidents with IID calculated were categorized according to the incident types.

For each incident type, corresponding incidents were further divided into two groups, one for weekday incidents and the other for weekend incidents. For each group, a box plot was drawn to show the lower quartile, the median, and the upper quartile. As shown in Figure 6-11, the gold and green box plots were used to summarize weekday and weekend IIDs, respectively. In each box plot, the bottom and top of the box represent the 25^{th} and 75^{th} percentiles (the lower and upper quartiles, respectively), and the band near the middle of the box shows the 50^{th} percentile (the median).

In total, there were 2,355 incidents on I-5 in 2009 had IIDs calculated. Of these incidents, 429 (18.2 percent) were due to Abandoned Vehicles, 225 (9.6 percent) were due to Debris, 1438 (61.1 percent) were due to Disabled vehicles, 38 (1.6 percent) were due to Injury Collisions, 129 (5.5) were due to Non- Injury Collisions, and 96 (4.1 percent) were due to other reasons.

For Abandoned Vehicle, the midspread (range from 25^{th} to 75^{th} percentile) for weekday and weekend were similar. For Debris, Disabled, Non- Injury Collisions, and other reasons, weekend midspreads were all bigger than weekday midspreads. Midspread is a robust statistic measuring the statistical dispersion, therefore in general it can be concluded that there are more variations in weekend IIDs than weekday IIDs. Additionally, excluding the Injury Collision category (with a relatively small sample size), for all the other incident types, median and 75^{th} percentile IID values were higher on weekends than weekdays. A general indication revealed from this case study is that weekend incident response needs to be enhanced for busy corridors like I-5. Enhancement may include improving the procedure for IR or increasing IR resources during weekend days.

Because of the variations of traffic flow dynamics, roadway geometry, and traffic regulations over time and locations, a calibrated model may not transfer well to another location and time period. The new approach developed in this study performed fairly well in both spatial and temporal transferability tests (details of these tests can be found in Table 5-1). This implies that the new IID estimation approach is reasonably robust to location and time changes. To achieve the best IID estimation accuracy, however, location-specific models are preferable. Given the ease of using the online implementation of the proposed approach, parameter estimation for each location should be convenient and straightforward for large-scale network applications.

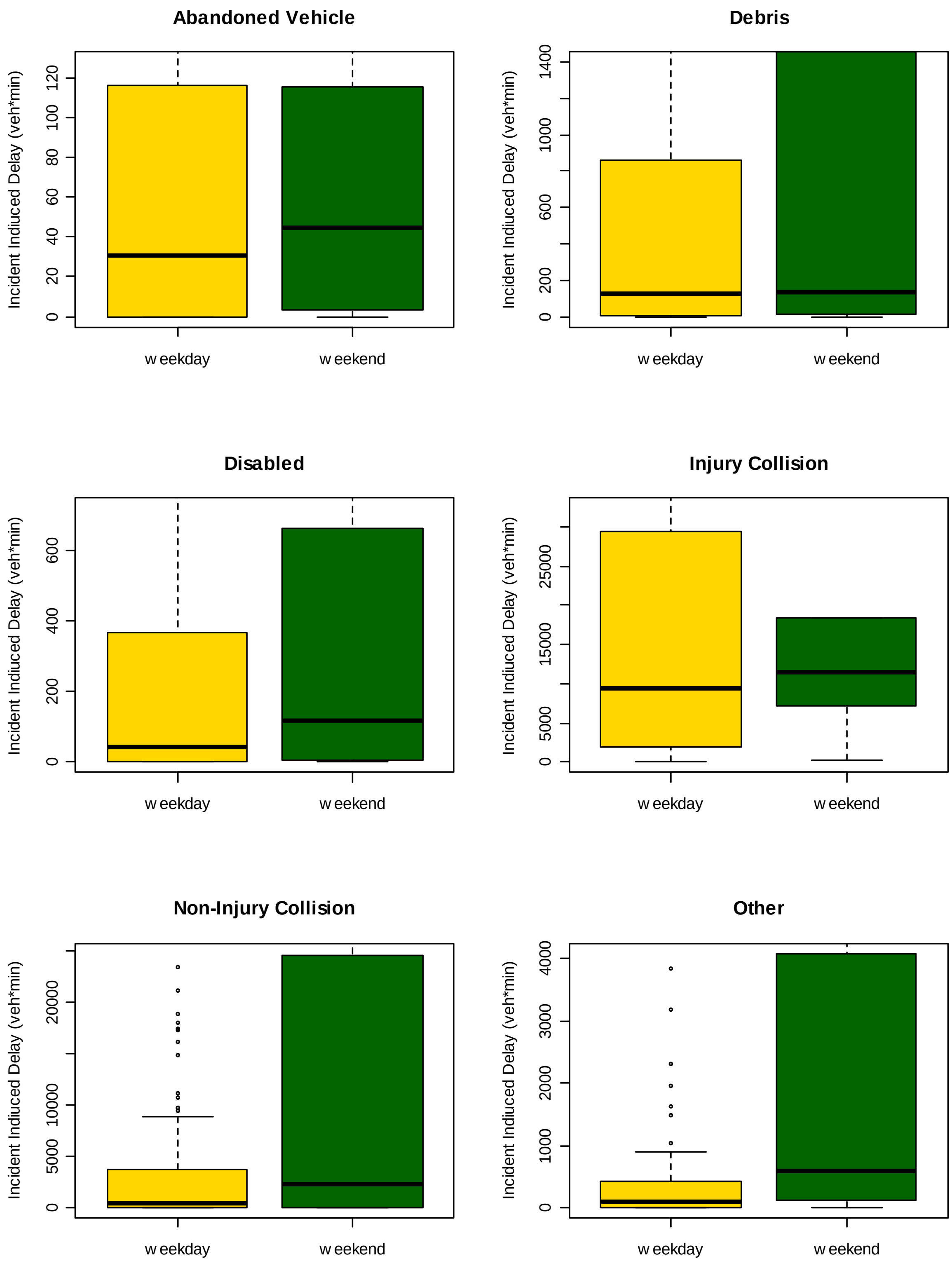


Figure 6-11. I-5 Case Study: IID on Weekdays and Weekends by Incident Types

CHAPTER 7 CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusions

Incidents are one of the major causes of urban freeway congestion. IID quantification helps traffic practitioners and policy makers better evaluate their investment in congestion mitigation measures and develop more effective IR strategies.

In this study, a new approach based on the modified deterministic queuing diagram and short-term traffic flow forecasting was developed for quantifying IID on freeways. The proposed approach utilizes only traffic volume data for estimating IID, making it appealing for most transportation agencies because of its simplicity in implementation. The key to enabling such an approach is to accurately predict the unobservable downstream volumes under the incident-free scenario. Two regression techniques, lagged regression and ridge regression, were investigated in this study for downstream volume prediction. Their prediction accuracies were evaluated and compared. Ridge regression was chosen for algorithm implementation because it produced better prediction results. The downstream volumes predicted by the ridge regression model were then combined with observed downstream volumes in the modified queuing diagram for IID estimation. To facilitate the calculations, the proposed algorithm was implemented online on a regional map-based system.

Results from the proposed approach were verified by using video-captured ground truth data at two locations. The percentage of errors using the proposed approach was under 5.6 percent, indicating that the new approach is able to produce fairly accurate IID estimates. To test the online system of the proposed approach, IIDs were estimated for 2,676 incidents that occurred on the Washington state freeways in 2009 and 2,028 incidents were found associated with IID. This test demonstrated that the proposed approach is easy to use, and the computational process took only a very short moment to complete. The proposed algorithm is also flexible in terms of input data aggregation level and time period for the IID analysis. Its online implementation system provides a great platform for a variety of possible future applications.

Statistical analysis was conducted on the frequency of incident occurrence and incident duration. Incident frequency peaks in June, July, and August. More incidents were responded by the WSDOT IR team on weekdays, while those responded incidents occurred during weekend days have longer average incident durations. Over 50 percent of incidents are related to disabled vehicles. Collision-related incidents have longer durations, especially for injury accidents. At night, it takes more than twice as long to clear an incident as it does during the day. These findings reflect the current deployment of the WSDOT's IR teams. The weekend incidents takes longer to clear because the WSDOT's IR teams are on call to address only severe incidents on weekends. Thus the recorded weekend incidents have much longer average duration than those responded during weekdays. The similar relationship was also found in the analysis on incident occurrence and incidents duration when comparing daytime and nighttime. In terms of incident type, *disabled vehicles*, *abandoned vehicles*, and *debris* were the most frequently occurring incident categories, indicating that an efficient and capable towing task power is necessary to ensure effective IR. In terms of incident duration, collision related incidents were generally associated with longer duration.

Statistical analysis was also conducted on the 2,028 incidents with non-zero IID according to the calculation results. Some findings include: 1) shoulder/median closure corresponds to a much lower median IID compared to other types of lane closure (Table 6-1); 2) 88.3 percent of incidents with IID less than 10 vehicle-hours were due to disabled vehicles or abandoned vehicles, and 61.7 percent of incidents with IID longer than 10 vehicle-hours were due to non-injury collision or injury collision; 3) longer incident duration tends to result in a longer IID. Although they are not highly correlated, a trend still exists showing that longer incident duration tends to result in a longer delay; and 4) weekend incident response needs to be enhanced for busy corridors like I-5.

In summary, this research proposed a new algorithm that only requires loop volume as input to yield reasonably accurate IID estimates. The wide availability of volume data definitely extends the scope of its application. The algorithm has been verified by two real-world incidents whose ground-truth IIDs were extracted from the upstream and downstream video sequences captured by the traffic surveillance cameras. Such ground-truth data based verifications were rarely done in previous studies. In both cases, the new algorithm estimated IIDs matched the ground-truth IIDs reasonably well. The algorithm for IID quantification provided great potential for future incident analysis and IR effectiveness evaluations. If an hourly value is applied, IID cost can be easily calculated. However, there are two issues must be properly addressed before applying this algorithm:

(1) Loop data quality. This algorithm relies on loop volume as input and bad quality of loop data would certainly deteriorate the accuracy of IID estimates; and

(2) Location specific calibration. Road and driver characteristics at each location may not be similar to the study sites used in this study and hence affect the accuracy of the short-term flow forecasts at the downstream sensor locations for the incident-free scenarios. It is highly desirable to ensure that model parameters are properly suitable to apply at each application site.

Although this research well sampled over the main corridors in Puget Sound region, attained 88 location-specific models for IID calculation, cleared loop data errors, and tested the temporal-spatial transferability of those models. In the future these efforts need to be expanded and strengthened for large-scale applications in the entire state of Washington.

7.2 Recommendations for Future Study

To facilitate future research, the following recommendations are made:

- Accurately predicting the downstream volume sequence under the incident-free scenario is critical for quantifying IID in this new approach. Since geometric factors, in addition to volume levels, are highly relevant to traffic movements, prediction models that take location-specific variables into account are likely to yield better results and should be investigated in future research. Further study should address this and develop more general models capable of taking location-specific characteristics into account for improved IID estimates.
- Traffic detectors may subject to various errors. A general approach that can automatically check the quality of volume data and correct data errors, if possible, is highly desirable. Improvement of data quality in the incident database will help further enhance the IID estimation.
- Incidents with duration longer than 15 minutes are likely to associate with higher delay. Collisions tend to have longer duration, especially those with person injuries.
- The new approach relies on volumes upstream and downstream of the incident location for IID calculation; therefore, once the locations of ramps have been defined, IID can be calculated correspondingly. Unfortunately, ramp milepost information is currently missing in the loop detector database, so the algorithm cannot determine whether ramp volumes are affecting upstream or downstream volumes. In the future,

the milepost locations for on- and off-ramps should be added to the loop database so that the proposed algorithm can incorporate ramp volumes.

- With IID estimated by this new algorithm, travel delay cost induced by an incident can be derived with value of time information. This enables the potential for economic analysis on incident cost and IR resource allocations. Such an analysis shall be able to answer important questions for congestion management, for example, given the characteristics of traffic and incident distributions on a corridor, what is the best IR team configuration and work schedule? Accurately quantifying travel delays are also essential for evaluating the benefit of infrastructure investments.

REFERENCES

Abdulhai, B., H. Porwal and W. Recker (1999). Short Term Freeway Traffic Flow Prediction Using Genetically-Optimized Time-Delay-Based Neural Networks. California PATH Working Paper UCB-ITS-PWP-99-1. Institute of Transportation Studies, Department of Civil and Environmental Engineering, University of California Irvine..

Al-Deek, H. M., A. Garib, and A.E. Radwan. New Method for Estimating Freeway Incident Congestion (1995). In Transportation Research Record: Journal of the Transportation Research Board, No. 1494, Transportation Research Board of the National Academies, Washington, D.C., pp. 30-39.

Athol, P. (1965). Interdependence of certain operational characteristics within a moving traffic Stream. Highway Research Record 72, 58-87.

Cambridge Systematics, Inc. (2005). *Traffic Congestion and Reliability: Trends and Advanced Strategies for Congestion Mitigation*. Research Report for Federal Highway Administration. Available online at http://www.ops.fhwa.dot.gov/congestion_report/congestion_report_05.pdf. (Accessed Feb. 20, 2010).

Center for Urban Transportation Research. *Best Practices for Traffic Incident Management in Florida*, (2005). Available online at http://www.iacptechnology.org/IncidentManagement/BestPracticesFLDOT.pdf. Accessed Jul. 2, 2010.

Cheevarunothai, P., G. Zhang, and Y. Wang (2010). Quantifying Freeway Incident-Induced Delays Using Loop Detector Measurements. Proceedings CD-ROM for the 89th Annual Meeting of Transportation Research Board, Washington, D.C.

Cheevarunothai, P.,Y.Wang, and N. L. Nihan (2006). Identification and Correction of Dual-Loop Sensitivity Problems. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1945, Transportation Research Board of the National Academies, Washington, D.C., pp. 73-81.

Fu, L., and B. Hellinga (2002). Real-Time Adaptive Prediction of Incident Delay for Advanced Traffic Management Systems. Proceedings of the 2002 Annual Conference of Canadian Institute of Transportation Engineers, Ottawa, Canada, May 12-15.

Fu, L., and L.R. Rilett (1997). Real-Time Estimation of Incident Delay in Dynamic and Stochastic Networks. In Transportation Research Record: Journal of the Transportation Research Board, No. 1603, Transportation Research Board of the National Academies, Washington, D.C., pp. 99-105.

Hallenbeck, M.E., J.M. Ishimaru, and J. Nee (2003). Measurement of Recurring versus Non-Recurring Congestion: Technical Report. Research Report for Washington State Department of Transportation. WA-RD 568.1. Seattle

Hobeika, A G and Kim, Changkyun (1994). Traffic-Flow-Prediction Systems Based On Upstream Traffic. The 1994 Vehicle Navigation and Information Systems Conference, Yokohama, Japan, 1994, pp. 345-350.

Li, J., C. J. Lan, and X. Gu (2006). Estimation on Incident Delay and Its Uncertainty on Freeway Networks. In Transportation Research Record: Journal of the Transportation Research Board, No. 1959, Transportation Research Board of the National Academies, Washington, D.C., pp. 37-45.

Lighthill, M. J., and G. B. Whitham (1955). On Kimematic Waves. II. A Theory of Traffic Flow on Long Crowded Roads. Proceedings of the Royal Society of London. Series A, Mathematical and Physical Sciences, Vol. 229, No. 1778, pp. 317-345.

Lindley, J. A. (1987). A Methodology for Quantifying Urban Freeway Congestion. In Transportation Research Record: Journal of the Transportation Research Board, No. 1132, Transportation Research Board of the National Academies, Washington, D.C., pp. 1-7.

Ma, X., Y. Wu, and Y. Wang (2010). DRIVE Net: An E-Science of Transportation Platform for Data Sharing, Visualization, Modeling, and Analysis. Paper 11-4106. Proceedings CD-ROM for the 90th Annual Meeting of Transportation Research Board, Washington, D.C.

Mongeot, H., and J.B. Lesort (2000). Analytical Expressions Of Incident-Induced Flow Dynamic Perturbations Using The Macroscopic Theory And An Extension Of The Lighthill And Whitham Theory. In Transportation Research Record: Journal of the Transportation Research Board, No. 1710, Transportation Research Board of the National Academies, Washington, D.C., pp. 58-68

Morales, M. J (1987). Analytical Procedures for Estimating Freeway Congestion. ITE Journal, Vol. 57 (1), pp. 45-49.

Nam, Do H., and D.R. Drew (1996). Traffic Dynamics: Method for Estimating Freeway Travel Times in Real Time from Flow Measurements. Journal of Transportation Engineering. Vol. 122, No. 3, pp. 185-191.

Rakha, H., and W. Zhang (2005). *Consistency of Shock-Wave and Queuing Theory Procedures for Analysis of Roadway Bottlenecks*. Proceedings CD-ROM for the 84th Annual Meeting of Transportation Research Board, Washington, D.C.

Richards, P. I. (1956). Shock Waves on the Highway. Operations Research, Vol. 4, No. 1, pp. 42-51.

Skabardonis, A., K. Petty, H. Noeimi, D. Rydzewski, and P. P. Varaiya (1996). I-880 Field Experiment: Data-Base Development and Incident Delay Estimation Procedures. In Transportation Research Record: Journal of the Transportation Research Board, No. 1554, Transportation Research Board of the National Academies, Washington, D.C., pp. 204-212.

Skabardonis, A., P. Varaiya and K. Petty. Measuring Recurrent and Nonrecurrent Traffic Congestion (2003). In Transportation Research Record: Journal of the Transportation Research Board, No. 1856, Transportation Research Board of the National Academies, Washington, D.C., pp.118-124.

Sullivan, E. C (1997). New Model for Predicting Freeway Incidents and Incident Delays. Journal of Transportation Engineering, Vol. 123 (4), pp. 267-275.

Wang, Y. and N.L. Nihan (2000). Freeway traffic speed estimation using single loop outputs, Transportation Research Record 1727, TRB, National Research Council, Washington, D.C., 120-126.

Wang, Y., J. Corey, Y. Lao, and Y.J. Wu (2009). *Development of a Statewide Online System for Traffic Data Quality Control and Sharing*. Research Report for TransNOW and Washington State Department of Transportation. Available online at http://www.transnow.org/publication/final-reports/documents/TNW2009-12.pdf. (Accessed Sep. 16, 2010)

Wang, Y., M. Hallenbeck, and P. Cheevarunothai (2008). Quantifying Incident-Induced Delay Using Traffic Sensor Data. Research Report for Washington State Department of Transportation and Transportation Northwest (TransNow), USDOT University Center for Federal Region 10.

Washington State Department of Transportation (2008). *Measures, Markers and Mileposts: The Gray Notebook for the quarter ending March 31, 2008*. Available online at www.wsdot.wa.gov/NR/rdonlyres/BFF201B6.../GrayNotebookMar08.pdf. (Accessed Dec. 05, 2010)

Washington State Department of Transportation (2008). *Strategic Plan for Traffic Incident Management*. Available online at www.wsdot.wa.gov/NR/rdonlyres/B79A29B1-2F56.../IRStrategicPlan.pdf

Willmott, C. (1981). On the Validation of Models. Physical Geography, Vol. 2, pp. 183–194.

Woensel, T.V., L. Kerbache, H. Peremans, and N. Vandaele (2008). Vehicle routing with dynamic travel times: A queueing approach. European Journal of Operational Research. Volume 186, Issue 3, pp. 990-1007