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Primary and Secondary Incident Management: Predicting Durations in Real Time

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Final Report VCTIR 11-R11

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www.VTRC.net

Standard Title Page—Report on State Project

Report No.:	Report Date:	No. Pages:	Type Report:	Project No.:
VCTIR 11-R11	April 2011	81	Final Contract Report	87648
			Period Covered: Sept. 2007-Dec. 2009	Contract No.:

Title:
Primary and Secondary Incident Management: Predicting Durations in Real Time

Key Words:
Traffic incidents, secondary incidents, incident management

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Abstract:

Traffic incidents are a major source of congestion in Virginia. Secondary incidents comprise a relatively small but important portion of all incidents, and relatively little is known about their occurrence, characteristics, and associated delays. The main objectives of this study were to define secondary incidents, understand and analyze the occurrence and nature of such incidents, and develop tools that can comprehensively and continuously analyze primary and secondary incidents at the planning and operational levels, ultimately contributing to congestion management. The scope of the study is limited to freeway incidents in the Hampton Roads (HR) area.

The study found that secondary incidents account for nearly 2% of TOC-recorded incidents, using the 2006 data. Of all accidents, 7.5% had associated secondary incidents, 1.5% of disabled vehicles had secondary incidents, and 0.9% of abandoned vehicles had secondary incidents. Despite their relatively low percentages, on average, two to three secondary incidents occur daily in the HR area. Further, the average durations of secondary incidents in HR are 18 minutes, which is 4 minutes longer than the mean duration of other (independent) incidents, indicating that secondary incidents are not necessarily minor "fender benders." The study also found that a 10-minute increase in primary incident duration is associated with 15% higher odds of secondary incidents.

This study developed and applied a dynamic queue-based tool (SiT) to identify primary and secondary incidents from historical incident data and incorporated the models developed for incident duration, secondary incident occurrence, and associated delays in an online prediction tool (iMiT). Although the tools developed in this study (SiT and iMiT) are currently calibrated using HR data, the methodology is transferable to other regions of Virginia.

The study recommends that (1)VDOT TOC analysts (where available) use primary and secondary incidents as additional performance measures; (2) VDOT TOC analysts (where available) identify secondary incident hot-spots; (3) VDOT's Regional Traffic Operations Managers give priority (in terms of monitoring, patrol coverage, and traveler information dissemination) to secondary incident hot-spots; (4) TOC managers and their staff use the online prediction tool, iMiT; (5) VDOT TOCs continue and expand the use of service patrols to implement aggressive incident clearance procedures (where appropriate), continue and strengthen their outreach to other response agencies using the RCTO or similar mechanisms, and improve incident scene management to avoid distractions from both the same and opposite directions; and (6) VDOT Operations and Security Division staff work to reconstitute the Statewide Incident Management Committee.

The benefit of reducing the number of secondary incidents by 25% (an implication of the stated goal of the HR RCTO) was calculated using two methods. The first method resulted in a benefit in terms of reduced incident delay estimated at $1.11 million per year. The second method used slightly different assumptions and resulted in an estimated delay savings of $1.23 million.

FINAL REPORT

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Virginia Center for Transportation Innovation and Research
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and the University of Virginia since 1948)

Charlottesville, Virginia

April 2011
VCTIR 11-R11

DISCLAIMER

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ABSTRACT

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INTRODUCTION

Urban areas are faced with increasing traffic congestion. Federal regulations require regions to have a congestion management process and associated plans, with the goal of reducing traffic congestion through technology, expanding roadways, and increasing vehicle occupancy. This project focuses on incident-induced congestion and it identifies relevant congestion reduction strategies. Traffic incidents that block lanes or a shoulder can cause a reduction of roadway capacity and create congestion. They are estimated to cause between 30 to 50 percent of the congestion problems on urban roadways (Skabardonis et al. 1995, Ozbay 1999, Kwon et al. 2006), and are also associated with safety, energy, and environmental problems. Incident-induced queues can increase the potential for additional incidents, referred to as secondary incidents. Such incidents further increase the time needed to return the traffic to normal. Together with the primary incident, secondary incidents can become major events that cause substantial disruption and congestion. Therefore, exploring the occurrence of primary and secondary incidents is important from a congestion management perspective.

In urban areas of Virginia, incidents are closely monitored, e.g., in Hampton Roads, the Virginia Department of Transportation (VDOT), produces weekly reports on incident metrics. However, the role of primary and secondary incidents in these reports is unclear, partly because they are not identified by VDOT. Based on past literature, secondary incidents can occur in 2 to 20 percent of the cases after an initial incident (Moore et al. 2004, Hirunyanitiwattana and Mattingly 2006). While some secondary incidents can be relatively minor (e.g., fender benders or vehicles running out of fuel), others can be more severe in terms of their congestion and safety impacts.

Safety service patrols play a key role throughout the Commonwealth and specifically in Hampton Roads. They provide a valuable service by responding to and managing incidents, including primary and secondary. They generate the bulk of data used in this study while providing a nearly 5:1 benefit cost ratio in the Hampton Roads region (Dougald and Demetsky 2008). A related issue is how regional traffic managers can make more informed decisions about allocating safety service patrol resources more effectively, especially when faced with difficult operational situations created by the occurrence of secondary incidents.

PURPOSE AND SCOPE

Managing congestion by reducing incident delays and improving system reliability through better management of incidents were key motivations for the study. The purpose of the study was to understand primary and secondary incidents, and develop operational tools that can help identify, analyze, and deal with such incidents. While primary and secondary incidents are relatively rare, they often represent large-scale events that pose substantial difficulty to the public in terms of congestion, and their management requires substantially more operational resources. The objective was to clearly define and identify secondary incidents, analyze their characteristics, and provide valuable information about how to effectively address such situations.

Using freeway incident and roadway inventory data from Hampton Roads, the study applies modeling and simulation techniques to analyze primary incidents, secondary incidents and their relationships. Two tools are developed based on the models, which allow identifying secondary incidents and predicting incident performance measures in real-time. The first tool, SiT (Secondary Incident Identification Tool), identifies primary and secondary incidents in an archived incident database, based on spatial and temporal criteria. The second tool, iMiT (Incident Management Integration Tool), can be used in a VDOT Transportation Operations Center to predict the remaining duration of an existing incident, the chances of a secondary incident based on the characteristics of the primary incident, and the associated delays. The tool aids in identifying incident management strategies to mitigate the impacts of both primary and secondary incidents. The study also provides insight on the nature of the secondary incident problems in Hampton Roads and recommendations about handling such incidents. Note that the study has generated five research papers, which document the methods and findings (Khattak et al. 2009, Zhang and Khattak 2009, 2010, Khattak et al. 2010, Zhang et al. 2010).

The scope of the study is limited to freeway incidents in the Hampton Roads area. Incidents that occurred on local arterial streets were not examined in this study. The data relate to Hampton Roads and therefore the models calibrated on these data are not directly applicable in other areas. Specifically, the incident duration model (Ordinary Least Squares regression model), secondary incident occurrence model (Probit model) and delay prediction models (Deterministic Queuing model) developed in this study are only appropriate for use in Hampton Roads.

The incident duration model developed in this study was validated by comparing observed incident duration in 2007 data with predicted incident duration using a model estimated with 2006 incident data. Due to the lack of field data, validation of secondary incident occurrence and associated delay was not conducted. The methodology developed in this study can be used in other regions. However, the transferability of the models to other regions of Virginia will require additional work.

METHODOLOGY

Overview

Secondary incidents are those associated with a primary incident, i.e., they occur within the "influence area" of a primary incident. All secondary incidents are associated with a primary incident. However, a primary incident can have one or more secondary incidents associated with them. Figure 1 shows a flow chart that provides an overview of the research methodology.

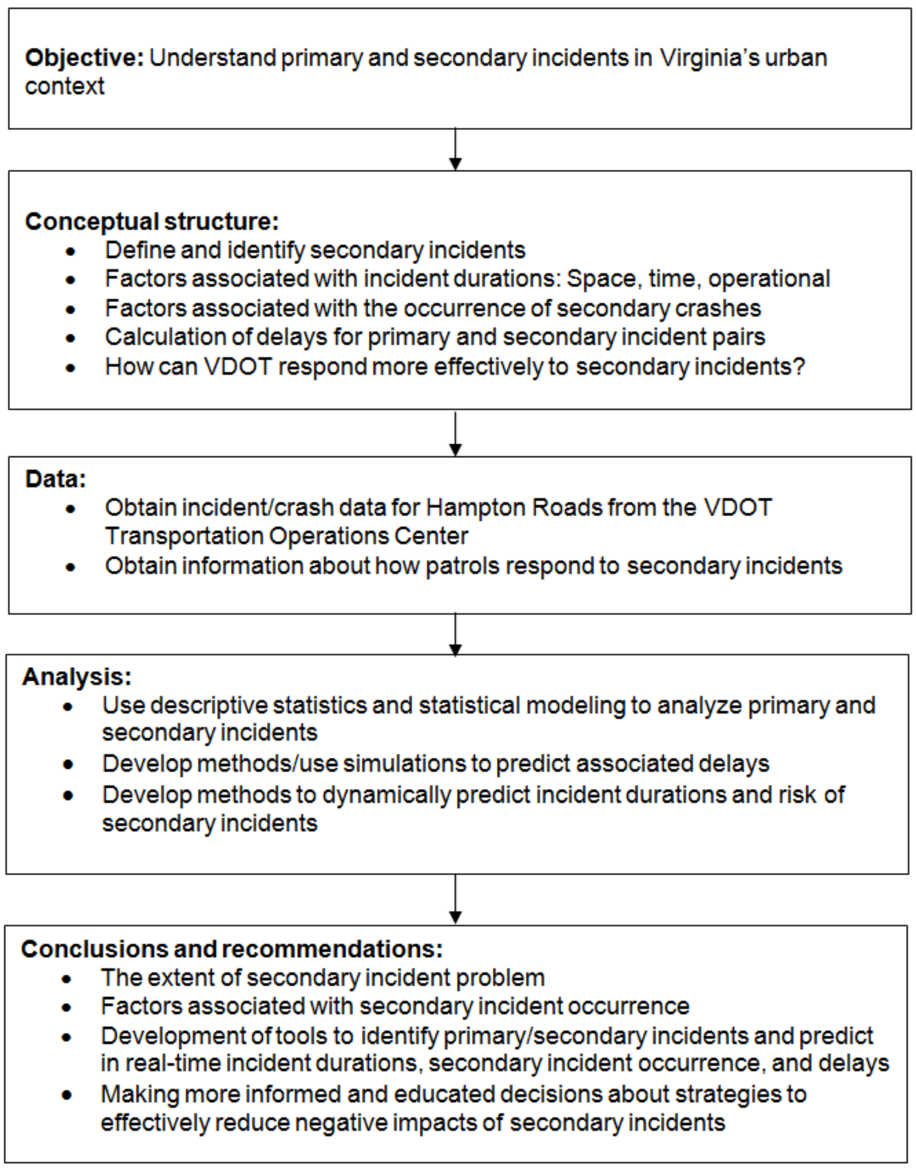


Figure 1: Summary of Research

The key objectives were to define, identify and analyze secondary incidents and develop appropriate identification and prediction tools. The following sections describe the methodologies used for these steps in more detail. The research started with conducting a literature review on how to define secondary incidents and how other states deal with secondary incidents. The review showed major gaps in the literature. After obtaining relevant data on incidents from the Hampton Roads Transportation Operations Center and getting input from TOC staffs about how they manage incident and deal with secondary incident occurrences, the team focused on identifying secondary incidents and analyzed the characteristics of primary and secondary incidents. Although the literature has suggested that secondary incidents can be assumed to occur within 1 or 2 miles and within 1 or 2 hours of the primary incidents, currently, there is no well-established definition for secondary incidents (Moore et al. 2004, Karlaftis et al. 1999, Raub 1997). The difficulty lies in identifying when the secondary incident occurred, and confidently associating it with the primary incident. To fill the gaps in the literature and help VDOT address the issue of secondary incidents, this research used temporal and spatial thresholds to define a secondary incident and then analyzed the characteristics of primary, secondary, and other (independent) incidents. Details of the methodology used to identify secondary incidents and the associated Secondary Incident Identification Tool (SiT) are provided below.

Next, the study team used a host of statistical methods to analyze incidents and explore relationships, as described in detail below. The team disentangled the interdependent relationship between primary and secondary incidents. The issue of “simultaneity” between incident duration and occurrence of secondary incidents was explored-that is, the durations of primary incidents are expected to be longer if secondary incidents occur, and at the same time, the secondary incidents are more likely to occur if the primary incident has a long duration. To account for such simultaneity, appropriate statistical methods were applied. The study further uncovered occurrence of multiple secondary incidents, termed as cascading events, and their event durations. Additionally, spatial analyses of primary/secondary incident frequencies revealed factors associated with higher incident risks.

To analyze delays due to primary and secondary incidents, using deterministic queuing models and simulations, the study developed a framework. Further details regarding the queuing models used in the study are provided below.

Statistical models were estimated to develop the online prediction tool, known as iMiT, which can predict incident duration, secondary incident occurrence and additive delays associated with secondary incidents. The sections below provide further details.

To complete the study, this research project undertook several tasks as listed below:

1. Conduct a literature review. We conducted a comprehensive literature review on traffic incidents in general and secondary incidents in particular.

2. Obtain incident, crash, and road inventory data. The necessary data were obtained from several sources, e.g., incident data (provided by Hampton Roads Traffic Operations Center for 2004-2007), road inventory (provided by the GIS branch of

VDOT), traffic data (obtained from VDOT), and police-reported crash data (obtained from police records, through HRPDC). Using GIS, the data were integrated and a complete picture of the incident problem in the region was developed.

3. Analyze primary and secondary incidents. Descriptive analysis of incident data was conducted. An algorithm for identifying secondary incidents (SiT) was developed, given that incident locations are not precisely identified in the HR incident dataset. The research team used a queue-based method, incorporating secondary incidents that occur on preceding segments and opposite-direction secondary incidents. Statistical models were developed to estimate incident duration and occurrence of secondary incidents. The interdependent relationship between primary incident duration and secondary incident occurrence was explored.

4. Estimate delays associated with primary-secondary incident pairs. Delays associated with primary-secondary incident pairs were estimated using deterministic queuing formulas and simulations of incidents for comparison.

5. Develop real-time incident prediction tools. A tool (iMiT) was developed, which is based on statistical models that predict (in real-time) incident durations, secondary incident occurrence and delays. The inputs are attributes of the roadway/environment and incidents; iMiT allows users to update predictions as new information about incidents is obtained.

Note that most incident duration models in the literature have little operational value since they require knowledge about all incident variables at the time of prediction. A real time prediction tool for incident duration (iMiT) was developed, which is self adaptive to different temporal intervals, as well as different combinations of incident information available. By estimating a set of regression models using different samples, the study captured the temporal dimensions and limited availability of information about incident attributes for real-time prediction. The tool also predicts the chances of a secondary incident and associated delays. The tools can aid in the allocation of limited resources in cases where the chances of secondary incidents increase beyond a given threshold.

Overall, the study provides insights on the extent of the secondary incident problem, and explores factors associated with secondary incident occurrence. It develops tools to identify primary and secondary incidents and predict in real-time incident durations, secondary incident occurrence, and delays. The study facilitates more informed and educated decisions about strategies to effectively reduce negative impacts of secondary incidents. Further information about the benefits of the study and implementation prospects is provided in this report.

Secondary Incident Identification Methodology

Definition and Assumptions

A secondary incident is illustrated in Figure 2.

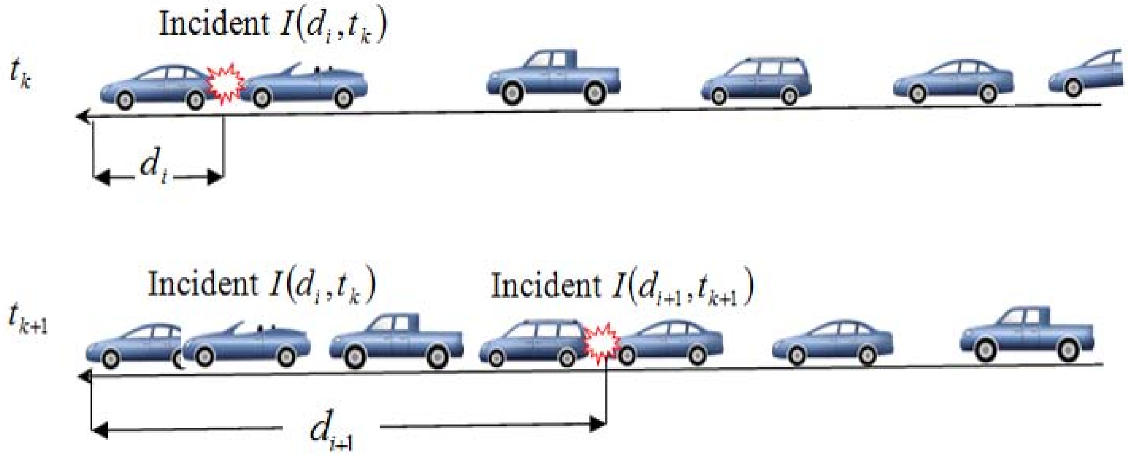


Figure 2: Primary and Secondary Incidents

Suppose that an incident $I(d_i, t_k)$ occurs at distance d_i from the beginning of a road segment at time t_k. If another incident would happen $I(d_{i+1}, t_{k+1})$ at location d_{i+1} and time t_{k+1} partially due to the queue backup of the prior incident $I(d_i, t_k)$, then it is defined as a secondary incident of $I(d_i, t_k)$. Furthermore, $I(d_i, t_k)$ is called the primary incident. $I(d_i, t_k)$ and $I(d_{i+1}, t_{k+1})$ are regarded as a primary and secondary pair. However, it is difficult to identify that the secondary incident is causally related to the prior incident only from historical incident data. Therefore, in this study some assumptions had to be made about temporal and spatial boundaries to capture the likely incident pairs that contain secondary incidents. That is, if two incidents happen within the certain spatial range ($d_{i+1} - d_i < \Delta d$) and temporal period (t_{k+1}-$t_k \leq \Delta t$), they can be considered as associated primary and secondary incidents, without necessarily knowing that they are causally related.

Primary-Secondary Incident Identification Implementation

The primary-secondary incident identification program is designed and implemented to identify and analyze secondary incidents on freeways. The current (beta) version of SiT is applicable to the Hampton Roads incident dataset, but is not necessarily limited to this region.

To run SiT, a standardized incident format for secondary incident identification has been formulated to accommodate different formats. The format converter for the Hampton Roads is currently included in the tool. Based on the methodology mentioned previously, the processing flow chart for secondary incident identification process is illustrated in Figure 3.

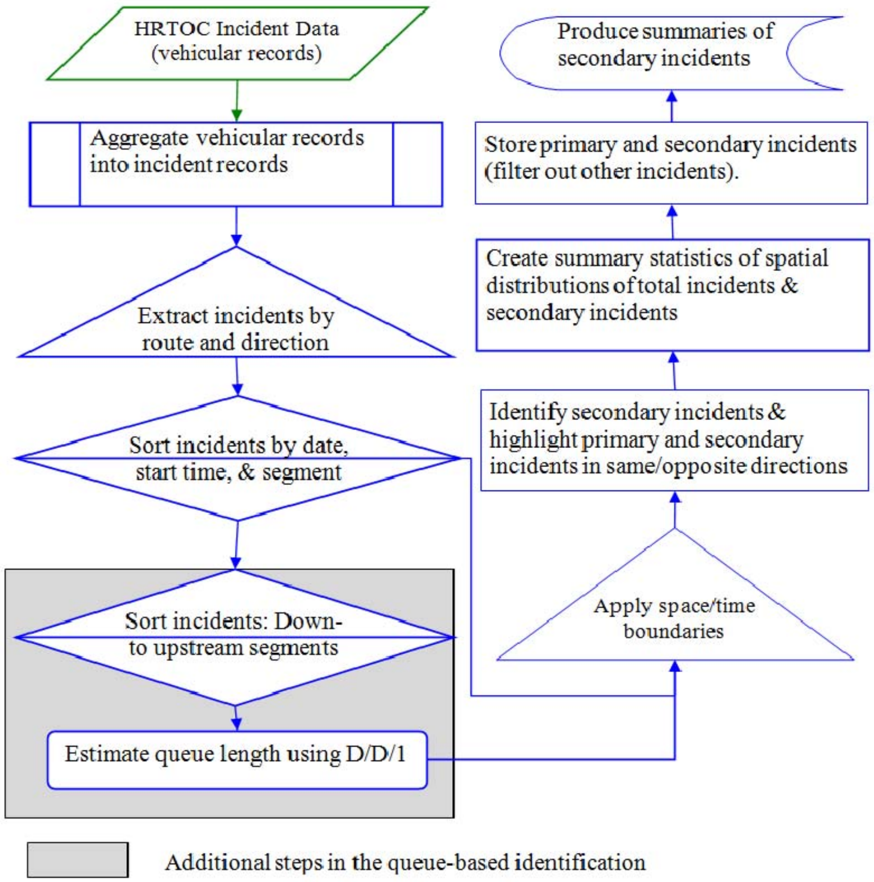


Figure 3: Primary and Secondary Incidents Identification Flow Chart

To identify secondary incident using the queue-based method, the exact position of incidents within a segment are needed. However, due to data limitations, the incident location information available is the code of the segment where the incident occurs. The segment lengths in Hampton Roads are one mile, on average. Therefore, the location of an incident was assigned randomly within the road segment, before applying the queue-based identification. Then the queue length was calculated by using deterministic queuing models. If the queue length exceeded the segment length, then incidents in the adjacent segment were considered as eligible secondary incidents (they should also occur within the primary incident time duration). Thus, queue length is used along with the actual duration to identify secondary incidents. In addition, incident delays were calculated based on the capacity reduction and traffic demand (Havel 2004). Note that one primary incident can be associated with more than one secondary incident.

The determinations of temporal and spatial boundaries are critical for secondary incidents identification. The temporal boundary is typically the recorded duration of the candidate primary incident. The spatial boundary can be the length of the segment where the primary incident occurs. Or it can be the length of the segment where the primary incident occurs plus the length of upstream segments, if the queue due to the primary incident extends to upstream segments. This study provides four methods for secondary incident identification, with different spatial thresholds, as shown in Table 1. Method 1 and 3 are single-segment based, except that method 3 identifies opposite direction incidents. Moreover, methods 2 and 4 are both queue-based, except method 4 identifies opposite direction incidents.

Table 1: Methods used to determine influence area of incidents

ID	Method	Route direction	Spatial Range (Δd)	Temporal Duration (Δt)	Advanced Options
1	Segment-based with actual duration	Same direction only	Single Segment length where primary incident occurred	Actual duration of primary incident	Adding time to incident duration for incidents with lane blockage (Part of the secondary incident identification tool, SiT)
2	Queue-based with actual duration		Queue caused by primary incident (can spill over to upstream segments)		
3	Segment-based with actual duration and including opposite direction	Same and opposite direction	Single Segment length where primary incident occurred		
4	Queue-based with actual duration and including opposite direction		Queue caused by primary incident (can spill over to upstream segments for the same direction), using segment length for opposite direction		

To identify secondary incidents in the opposite direction, the segment length of the opposite direction was set as the spatial boundary. If an incident in the opposite segment occurred within the duration of the primary incident, then it was identified as a secondary incident in the opposite direction. Opposite direction incidents often occur due to visual distractions caused by the primary incident. In this study, there are several predefined conditions which the primary incident must satisfy to be classified as part of a primary-opposite direction secondary combination: 1) the primary incident should be a crash, or 2) a non-crash located on the left shoulder, and 3) it should block at least one lane, or cause a queue backup. In addition there should be no visual barrier in the median.

Among the four identification methods provided in Table 1, method 4 (the dynamic queue-based secondary incident identification method) is the most comprehensive and closest to reality. It captures secondary incidents that may occur on upstream segments and in the opposite direction. Instead of considering only the segments where the primary incident occurred, secondary incidents in the same direction on upstream segments are identified also if a spillback condition is induced by the queue produced by the primary incident. The queue length is calculated using a deterministic queuing model (D/D/1 model), which is illustrated in Figure 4.

If the queue length exceeds the length of the segment where the primary incident occurred, then the spatial boundary used to identify secondary incidents is extended to the adjacent upstream segment; if the queue still overflows this adjacent segment, then the spatial boundary is extended further to the upstream segment. This recursive process stops when the entire queue is accommodated. As shown in the figure, the spatial boundary of the incident in Segment 2 extends to Segment 3. Incidents C_3 and C_4 are covered by the spatial boundary (that includes Segments 2 and 3). If C_3 and C_4 are within the duration of the downstream primary incident C_1, they will be identified as secondary incidents associated with C_1.

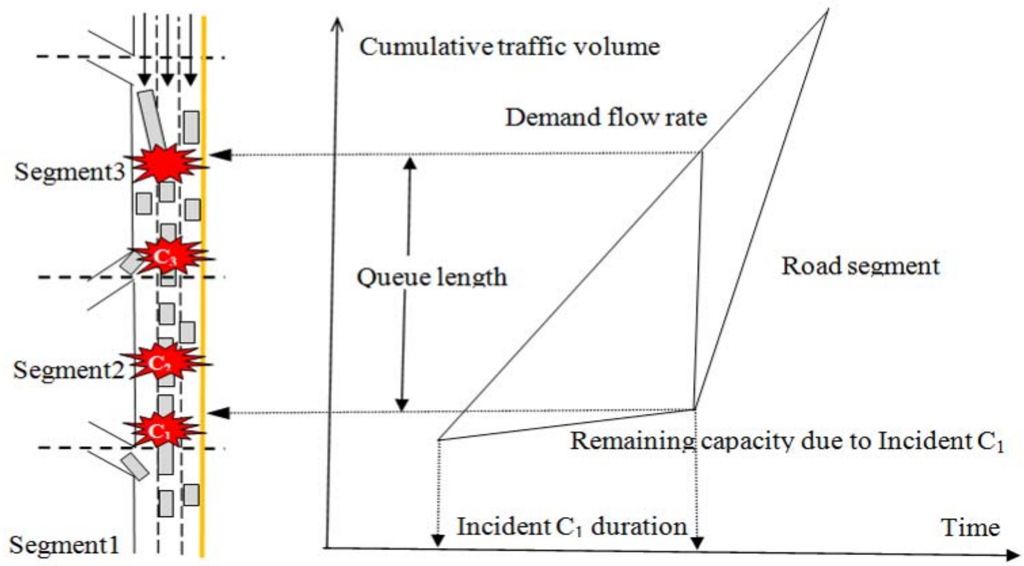


Figure 4: Queue-Based Secondary Incident Identification

Since the queue durations are always longer than incident durations recorded in the incident database, SiT provides users the option to add extra minutes to the primary duration when identifying secondary incidents. Also users can choose to add these extra minutes to all incidents or only to incidents with lane blockage. Detailed information about the secondary incident identification tool can be found in Appendix A.

Statistical Modeling

To explore and understand relationships, various statistical models were estimated:

- Interdependence of primary incident duration and the occurrence of secondary incidents;
- Factors associated with the occurrence of one or more secondary incidents;
- Factors associated with the time difference between secondary incidents and their primary incident (time-gap);
- Factors associated with multiple secondary incident (cascading) event durations;
- Factors associated with higher secondary and non-secondary incident risks, at the road segment level.

Table 2 shows a summary of statistical models used in this study.

Table 2: Summary of Statistical Models

Data used	Secondary incident identification method	Statistical Model	Dependent variables	Independent variables
2006 Incident Data	Actual incident duration plus 15 minutes if lanes were blocked	Probit model with endogenous regressors	Occurrence of secondary events	• Detection source • Incident type • Closure time • Response vehicles • Lanes affected • Time of day • AADT • Number of vehicles involved • Duration of primary incident
2005 Incident Data	Queue-based with actual duration and including opposite direction	Partial Proportional Odds Model	Occurrence of secondary events	• Primary is crash? • Incident duration (minutes) • Truck Involved? • Number of vehicles in primary • Outstate vehicle in primary? • Lane blockage in primary (%) • Segment length • Curve? • AADT/(Lane*1000)
	Queue-based with actual duration and including opposite direction	Heckman Selection Model (Logit)	Time Gaps	• Primary is crash? • Incident duration (minutes) • Truck Involved? • Number of vehicles in primary • Outstate vehicle in primary? • Lane blockage in primary (%) • Segment length • Curve? • AADT/(Lane*1000)
	Queue-based with actual duration	Ordinary linear regressions and truncated linear regressions	Event Durations	• Primary is crash? • Primary lane blockage (%) • # of vehicles involved in primary • Secondary is crash? • Secondary lane blockage (%) • # of vehicles involved • Time-gap (minutes) • On ramp presence? • AADT/(lane*1000) • Service patrol detected? • Response time for service patrol to primary (minutes) • Response time for service patrol to secondary (minutes)
2006 Incident Data	Queue-based with actual duration including opposite direction incidents	Poisson negative Binomial Zero-inflated Poisson	Frequencies of secondary and non-secondary incidents	• Roadway segment length • Number of lanes • Curve or not • AADT • Congestion level (AADT per lane) • Number of on-ramps/off-ramps • Truck volume • Distance to shopping center/ school/tunnel

Figure 5 shows the hypothesis of relationship between primary incident duration and secondary incident occurrence. Evidently, there is a possibility of “simultaneity” between incident duration and occurrence of secondary incidents. That is, incident duration, and the occurrence of secondary incidents may be interdependent. A (primary) incident can result in queuing upstream. This causes speed reductions, and sometimes sudden slowing, surprising some drivers and increasing the possibility of secondary incidents. If a secondary incident occurs shortly after the primary, it will lead to longer primary incident duration due to additional impedance and interference, e.g., with clearance operations of the primary incident and potentially increase the primary incident duration. That is, secondary incidents are more likely to occur if the primary incident lasts long; at the same time, durations of primary incidents are expected to be longer if secondary incidents occur.

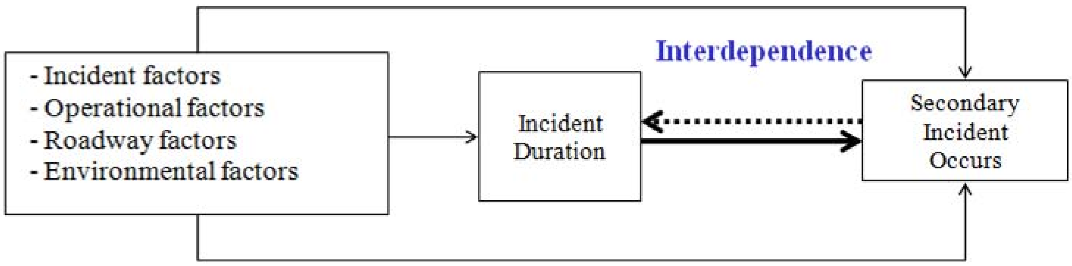
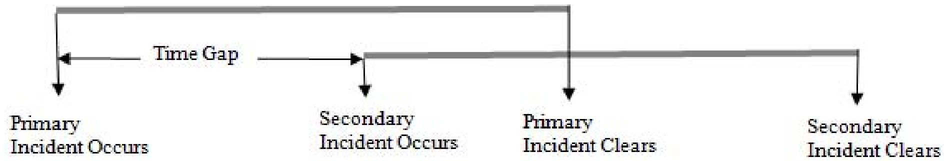


Figure 5: Relationships between Incident Duration and Associated Factors

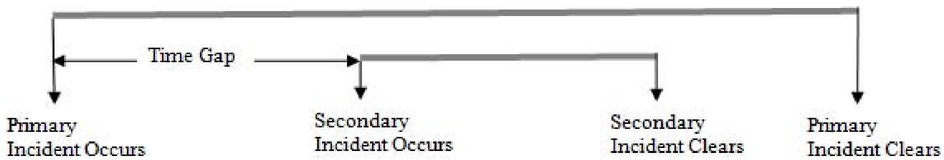
Delays due to primary-secondary incident pairs

To understand the impacts of time gap between the primary and secondary incident on total delays, two deterministic queuing diagrams are provided. In Figure 6 (a) and (b), λ represent a constant arrival rate; μ^* and μ represent the reduced capacity caused by incidents and restored capacity for a roadway, respectively. For demonstration, it is assumed that the reduced capacities caused by a primary incident and related secondary incident are the same (i.e., μ^*). In the figure, t_{1s} and t_{1e} represent the start time and end time of a primary incident respectively. The t_{2s} and t_{2e} denote the start and end times of the associated secondary incident respectively. Clearance time is $t_{d.}$ Figure 6 (a) shows a scenario where the secondary incident occurs at exactly the same time the first incident ends (i.e. $t_{1e} = t_{2s}$). If one were to treat and analyze these two incidents independently, the total delay attributed to both incidents would be equal to the sum of areas enclosed by ABC and CDE (or 2* ABC since these triangles are the same). However, in reality, the total delay would be area ADF. Consequently, the total delay would be underestimated by a value equivalent to BCEF.

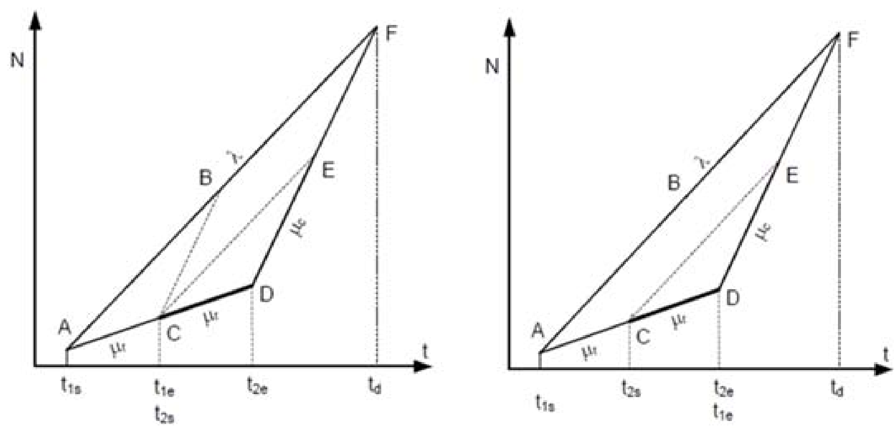
Figure 6 (b) shows another scenario where the secondary incident occurs before the primary incident is cleared (i.e. $t_{2e} < t_{1e}$). Obviously, if the two incidents are analyzed *independently* their total delay would remain the same as before, sum of ABC and GDE or sum of ABC and CDE in Figure 6 (a). In this case, the actual total delay is less than the first case and equal to area ADF. The total delay would then be underestimated (or overestimated depending on the time gap) by a value equivalent to BHEF – GCH. If the time gap (t_{2s}-t_{1s}) is such that BHEF is equal to GCH then, the estimated delays, whether the two incidents are modeled jointly or independently, would be the same. In the extreme case when the time gap is zero, the actual total delay will be equal to ABC, half of what would be estimated by independent analysis of incidents.



(a) Extended event



(b) Contained event



(a) **(b)**

Figure 6: Illustration of primary-secondary incident events

Based on the observation made above, it can be hypothesized that the time gap plays a critical role in calculating total delays of secondary incidents. Depending on the value of the critical gap, total delays estimated by treating associated incidents as independent events may result in over or under estimation of the actual delays. To further analyze delays due to secondary incidents, simulations were used.

Some secondary incidents add substantial network delays, while others do not. Figure 6 illustrates two scenarios. Figure 6(a) shows an extreme case of extended event, when the time gap between two incidents equals the primary duration (i.e. a secondary incident occurs exactly the same time its primary incident ends) and the distance between them is zero. Figure 6(b) represents a contained secondary event, when a secondary starts and ends within its primary incident duration and the distance between two incidents are very small.

iMiT: Real-time incident prediction tool

Tool framework

The online incident prediction tool iMiT includes three major components: incident duration prediction module, secondary incident probability prediction module, and delay (and queue length) predication module. Microsoft Visual Basic for Applications (VBA) in Excel was used to develop the tool. The framework of the tool is shown in Figure 7. A User's Manual for iMiT can be found in Appendix B. A beta version of iMiT was provided to VDOT.

Given that an incident has occurred, the key iMiT inputs include incident information such as start time, weather conditions, and incident location; additional inputs include type of incident (crash, disabled, abandoned, other), lanes closed, number of vehicles involved, detection sources, whether EMS (Emergency Medical Service) is present, and the start and end time of lane closure. The key outputs include predicted incident duration, the chances of a secondary incident and associated delays caused by the incident.

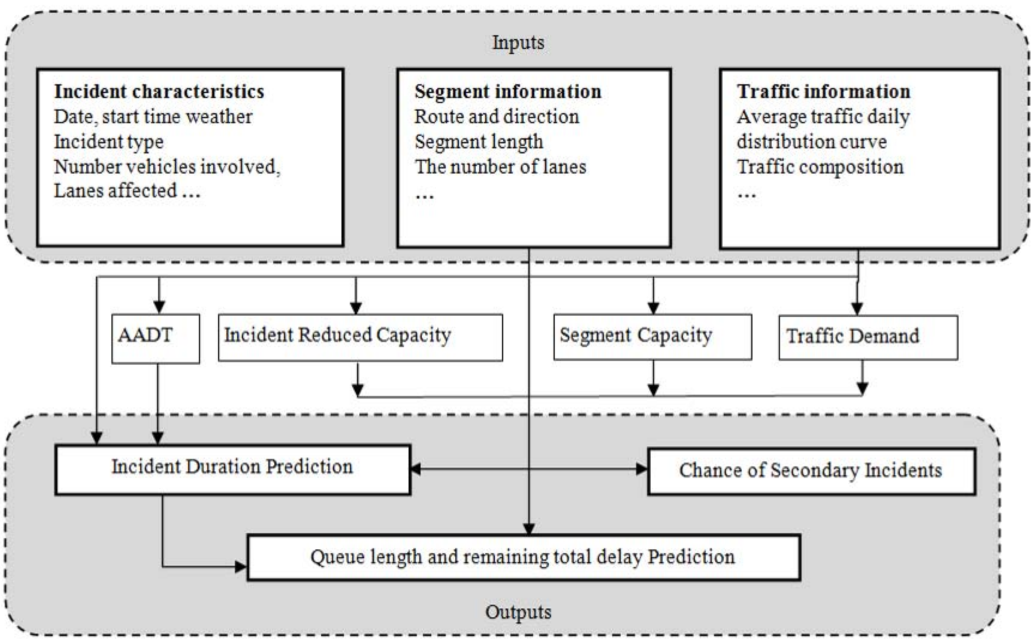


Figure 7: Framework for iMiT, the Real-Time Incident Prediction Tool

Incident duration prediction

The prediction of incident duration can facilitate incident management, but most incident duration models have limited operational value since they require knowledge about all incident variables at the time of prediction. However, in most real-time situations, incident information cannot be obtained at the same time, instead, information is acquired sequentially, which makes it difficult to do predictions, and reflect the time dimension in a model (Khattak, 1995). Also, the independent variables requested for the model are not always available. For instance, for a certain incident with few available details, operations managers may only know the incident location, time of day and detection source. An incident duration prediction model can be used, based on known incident information available at this time. But when more information about the incident becomes available, e.g., the incident type (crash or disabled, etc), and multiple vehicles involved, the incident duration needs to be updated. In some situations, the incident type, number of vehicles involved, etc., may be known at the outset. As a result, the developed tool must be capable of accepting various levels and combinations of data. The variables used in the tool are listed in Table 3.

Table 3: Variables used in models for incident duration and secondary incident occurrence

Variable name	**Variable explanation**	**Detailed info.**
TOD *	Time	1: peak hours; 0: off-peak hours
Badweather *	Weather	1: bad weather (rain, snow, hurricane, etc.) 0: good weather
Route *	Categorical variable for location	I-64, I-264, I-464, I-564, I-664
AADT *	AADT	Num
AADT_dummy*	Dummy variable for AADT	1: if AADT for this section is not available 0: if AADT for this section is available
Detection*	Detection source of incidents Categorical variable	SSP, CCTV, VSP, Phone, Other
Vehicles	Number of vehicle involved	Num
Incident type	Type of incidents Categorical variable	Accident, Abandoned, Disabled
EMS	Whether Emergency Management Service responded	1: Yes, 0: No.
Laneclose	Whether lanes were closed	1: Yes, 0: No.
Right_Shou	Whether right shoulder was affected	1: Yes, 0: No.
Left_Shou	Whether left shoulder was affected	1: Yes, 0: No.
Ramp	Whether ramp was affected	1: Yes, 0: No.

Note: * are those variables requested in initial model

The structure of the duration prediction module is shown in Figure 8. To develop such operational models (for use in TOCs) which can adapt to different temporal and variable combinations, statistical techniques were used to estimate a set of OLS models using different variable combinations (note that truncated regression models with equivalent specification were estimated, but they were not used in the tool, owing to their under-prediction of incident durations). In iMiT, there are five temporal stages (counting past the start of the incident). These include the initial incident occurrence stage, longer than 10 minutes, longer than 20 minutes, longer than 30 minutes, and longer than 45 minutes. For each stage, there are 28 models to deal with different variable combinations. The tool uses an initial model from the beginning based on the available variables at that time. Within each temporal stage, if more information arrives, then the user can insert it and update the duration prediction. Even without additional information, the user can update the prediction as time goes by since iMiT will automatically switch from the initial (or previous) model to the next stage model. The longer than 10 minutes model is based on the historical incident data that excludes those incidents whose duration is less than 10 minutes.

The detailed model structures and variables used can be found in Appendix B.

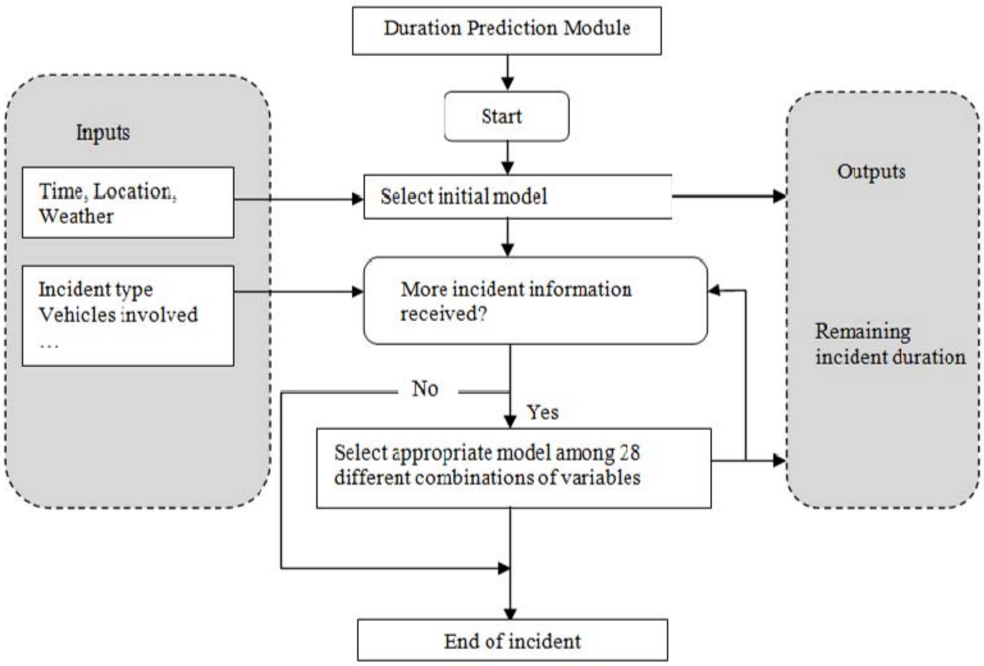


Figure 8: Frameworks for Incident Duration Prediction

The tool (iMiT) will show a remaining duration based on the current time. It will keep counting down the remaining duration until the user updates the inputs. This is typically when new information about the incident arrives. The tool predicts incident duration successively more accurately since TOCs often acquire more information about an incident as it progresses. The methodology accounts for the dynamic nature of the information acquisition process at a TOC. Both Ordinary Least Squares and truncated regression models were used for prediction. Truncated regression models were found to under-predict durations. Therefore, OLS models were embedded in iMiT. In this study, the real-time models are based on data from the Hampton Roads area for 2006.

Secondary incident probability prediction

Given all or partial independent variables (incident characteristics such as type, lane blockage, truck involved, road geometry and traffic information), the possibility of secondary incident is estimated from the binary Logit model developed in the project. The real-time model provides the probability of a secondary incident occurring when a limited set of variables are available. Similarly, 28 models with the same data structure as in the duration prediction module are used for secondary incident occurrence prediction. Note that one additional independent variable is added into the secondary incident probability model, which is the predicted duration from the incident duration prediction module (for details, see Appendix B).

Incident delay prediction (Queuing model)

To assess incident-induced delays, a delay prediction model was developed that can be used in real-time. The main inputs to the model are: 1) incident severity which is directly related to incident reduced capacity, 2) incident duration, which affects the length of time it takes to clear the incident, 3) arrival rate (traffic demand) and road geometry information such as the number of lanes. The predictions include: clearance time, total delay, and maximum queue length. Currently, a simple D/D/1 (deterministic queuing) model has been implemented in iMiT.

The queue length at a given time and the remaining total delays on a specified freeway segment are illustrated in Figure 9. Traffic arrives at the incident location according to curve $A_c(t)$. The departure curve $D_c(t)$ shows the departure from the incident bottleneck. The departure flow rate is initially μ^*, the reduced capacity of the bottleneck and then after the incident is cleared at time T_c, is the restored capacity, u. The variables t_{n-1}, t_n represent the (n-1)th and nth time intervals from the incident start (the time interval usually is 15 minutes, representing the minimum period when a traffic arrival rate remains steady). The traffic arrival curve consists of a number of small time-dependent arrival rates at small time intervals.

The current queue length for a given time t_i can be expressed as:

$$q(t_i) = q(t_{n-1}) + (t_i - t_{n-1})(\lambda_n - \mu^*) \qquad \text{for } t_{n-1,} t_i < T_c$$

$$q(t_i) = q(t_{n-1}) + (t_i - t_{n-1})(\lambda_n - \mu) \qquad \text{for } t_{n-1,} t_i > T_c$$

As long as all of the queue lengths for $t_i, t_n, \cdots t_e$ are calculated, the remaining total delay for a given time t_i is the shaded area between t_i and T_e, (in the figure) which is the summation of small trapeziums between arrival and departure curve right after t_i. The areas of the first three trapeziums can be written as:

$$A_1 = \frac{1}{2}(q(t_n) + q(t_i)) \times (t_n - t_i) \qquad A_2 = \frac{1}{2}(q(t_{n+1}) + q(t_n)) \times (t_{n+1} - t_n)$$

$$A_3 = \frac{1}{2}(q(t_{n+2}) + q(t_{n+1})) \times (t_{n+2} - t_{n+1}) \qquad \cdots$$

Thus the remaining total delay at t_i is equal to $\sum_{k=1} A_k$

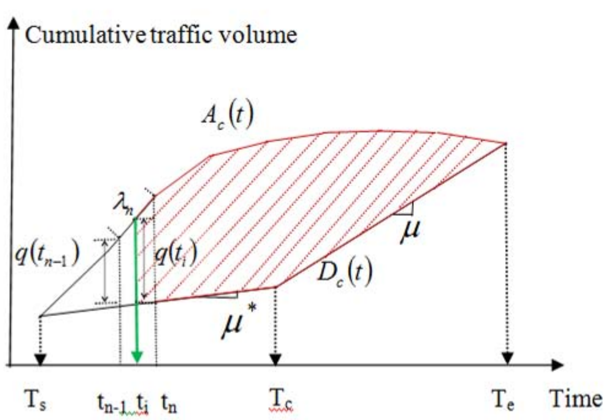


Figure 9: Illustration of the Queue Length and Remaining Total Delay at Time t_i.

RESULTS

Literature Review

The identified literature was reviewed to assess a variety of issues related to definition of secondary incidents, the factors influencing secondary incident occurrence, calculation of delay caused by primary and secondary incidents and how state DOTs deal with primary and secondary incidents.

Defining a secondary incident

To define secondary incidents, the literature review showed the following results (See Table 4 for a summary). Raub (1997) defined secondary crashes using fixed temporal and spatial parameters. He assumed that secondary crashes are those occurring within 15 minutes plus the initial duration of the primary event and within a distance of less than 1 mile. More than 15% of the crashes reported by police may be secondary in nature according to this study. The average secondary crash occurred within 36.4 min and about 0.25 miles from primary accident. Karlaftis et al. (1999) also adopted this fixed threshold to identify secondary crashes. Using a crash database for Borman Freeway in Indiana (N = 741 over 5 years), their study found that more than 15% of all crashes in Indiana might have resulted from an earlier incident based on this research. In more recent research, Chang et al. (2003) adopted a definition for secondary incident accounting for rubbernecking effects- incidents incurred within two hours from the onset of a primary incident and also within two miles downstream of the primary incident location; or incidents incurred in the opposite direction that are within a half-hour from the onset of a primary incident and lie within a half-mile either downstream or upstream of the primary incident location. The study showed that 6.8% of all incidents with lane blockage are identified as secondary incidents. Moore et al. (2004) extended the boundary criteria to two hours and two miles and concluded that secondary accidents are considerably rarer events with lower frequencies (secondary crashes per primary crash ranged between 0.015 and 0.030). Hirunyanitiwattana et al. (2006) defined secondary crashes as any crash that results from the non-recurring congestion or emergency response associated with a primary crash, as any crash that occurs in the same direction within 60 minutes of a primary crash and no more than two miles upstream. Zhan et al. (2008) defined a secondary incident as a crash that occurs at most two miles upstream of the primary incident location in the same direction of travel and within the period from the start of the primary incident to 15 minutes after the clearance of the primary incident. Meanwhile, they assumed that only incidents with lane blockages can potentially cause secondary incidents. In their study, of all lane blockage incidents, 7.9% were identified as primary incidents (Note that a majority of incidents are neither primary nor secondary.)

All of above methodologies of classifying secondary accidents seem to use the static thresholds. Sun (2005, 2007) proposed an improved dynamic threshold methodology to extract secondary accidents from an incident fusion database. The dynamic spatial threshold is derived from a master incident progression curve. The analysis shows that the static and dynamic methods can differ by over 30% in terms of identifying secondary incidents. Also, Zhan et al. (2009) developed a method to identify secondary incidents based on estimating the maximum queue length and the associated queue recovery time for incidents with lane blockages. They used a cumulative arrival and departure traffic delay model. In this case, 4.98% were identified as primary incidents, which are substantially lower than the 7.94% incidents identified by the static method in their previous study (Zhan, 2008).

Factors associated with the occurrence of secondary incidents

Studies have found that various factors are associated with the occurrence of a secondary incident. The peak hour and weekdays are associated with more secondary incidents, and the clearance time is also associated with secondary incidents occurrence (Raub, 1997). In the study by Karlaftis et al. (1999), clearance time, season, vehicle type (car, tractor-trailer) and lateral location are the most significant factors for higher secondary incident likelihood. Odds of a secondary crash increase by 2.8% for each minute the primary incident is not cleared. Chang (2003) stated that the likelihood of having secondary incidents increases consistently with the primary incident duration and congestion level based on statistical data. Hirunyanitiwattana (2006) found that secondary crashes occur more often during rush hour and rear end collision is the predominant secondary collision type, which accounts for about two thirds of all secondary crashes. He also found that the typical secondary crash on the State of California Highway System is a rear-end, property damage only crash on a greater than a four lane urban freeway that occurs during one of the peak periods and is caused by excessive speed. Zhan et al. (2008) identified five major factors influencing secondary incidents, which include the number of involved vehicles (in the primary incident), the number of lanes, the duration of primary incident, the time of day, and the primary vehicle rolling over. In a later paper, Zhan et al. (2009) found four factors were associated with likelihood of secondary crashes: primary incident type, primary incident lane blockage duration, time of day, and whether the incident occurred on northbound I-95. Khattak et al. (2009) demonstrated that primary incident duration and secondary incident occurrence are statistically interdependent.

Incident durations: associations with spatial, temporal, and operational factors

Studies of incident durations are plentiful (Golob et al. 1987, Giuliano 1989, Jones et al. 1991, Nam and Mannering 1998). Incident durations have been estimated using a variety of techniques, broadly classified as:

- Standard regressions including log-normal distributions (Golob et al., 1987; Garib et al. 1997; Sullivan 1997), analysis of variance (Giuliano, 1989), truncated linear regression (Khattak et al. 1995), and discrete choice models (Lin et al. 2004).

- Hazard-based models (Jones et al. 1991; Nam and Mannering 1998).

- Decision trees (Ozbay and Kachroo 1999), classification trees (Smith and Smith 2001; Kim et al. 2008) and Bayes classifier (Ozbay and Noyan 2006, Boyles et al. 2007).

Each approach has its own advantages and shortcomings. Standard regression offers more intuitive and easier interpretation. Hazard-based models show advantages in terms of recognizing that the likelihood of ending an incident depends on the elapsed time from the start of incident (Mannering 1998). Decision Tree or Classification Trees can be effectively used to discover patterns with or without considering probabilistic distributions. However, if the classification categories increase, relatively large amounts of data are required. Appropriate use of these methods depends on specific research needs.

In general, the incident duration is associated with incident characteristics, temporal characteristics, environmental effects, geographic information, and operational factors. Variables that are positively associated with longer incident durations are: longer response times, accidents (as opposed to other types of incidents), lane blockage, adverse weather, more heavy vehicles involved in an incident (Khattak et al. 1995; Ozbay and Kachroo, 1999; Kim and Gang-Len Chang, 2008), injury or fatality, occurrence during peak hour (Nam and Mannering 1998; Ozbay and Kachroo 1999; Kim and Gang-Len Chang, 2008), incident located farther away from a transportation operations center (partly due to longer response times), and more vehicles responding from various agencies (Kim and Gang-Len Chang 2008). Several of these variables are simply associative and not necessarily causal.

Delays for secondary incidents

Generally accepted methods for delay calculations are: deterministic queuing (Moskowiz and Newman 1963) and shock-wave analysis (Lighthill and Whitham 1955, Richards 1956). The deterministic queuing method requires a cumulative arrival curve, representing normal traffic demand in a freeway segment and a departure curve, representing the traffic volume passing through the location. If demand is less than capacity, then the departure curve exactly follows the arrival curve. If demand exceeds capacity, the two curves will split. The area between the two curves is the total vehicle hours of delay. The shock-wave analysis utilizes the fluid dynamic theory to define flow, density and speed for the description of traffic flow behavior and develop a formula for calculating total delay.

Many studies calculated delays using either of these two methods. Morales (1987) first developed a deterministic queuing method to calculate the incident delay on a freeway. Wirashinghe (1978) used shock-wave analysis to determine individual and total delay upstream of incidents. To check the interrelationship and consistency of these two models, Chow (1974) and Rakha and Zhang (2005) conducted their investigations and both studies found the results from these methods to be identical if a unique flow-density relationship is applied in the shock-wave analysis. However, both methods are limited by static demands, which is unrealistic under peak hour or flow fluctuation situations. Khattak et al. (2004) used the FREEVAL model, which faithfully replicates the freeway facility methodology in Chapter 22 of the 2000 Highway Capacity Manual (HCM 2000) to estimate incident induced delay for prioritizing and expanding freeway safety patrol service. The two important improvements of the FREEVAL model are: first, it allows analyzing an entire freeway facility consisting of basic, ramp and weaving segments with time-varying demands and capacities at multiple intervals. Second, this model can handle both undersaturated and oversaturated traffic conditions (Eads et al. 2000). Since the above-mentioned methods do not consider dynamic route diversion that would be expected in practice, Al-Deek et al. (1995) proposed a loop-detector based method to estimate single incident or multiple incident induced delays on freeways by capturing traffic demand variation due to diversion of traffic. With the development of more sophisticated car-following and lane change models, microscopic simulation can be easily used to estimate the incident-induced delays.

Few studies have examined the delay relating to the primary and secondary incident pairs. Only one recent study (Sun and Chilukuri 2005) uses accident data from Missouri and focuses on analyzing the safety impacts. For incidents of various sizes, clearance times can have a relatively wide range (from a few minutes to several hours), depending on the incident type, number of vehicles involved, time of day, and response by various agencies.

How state DOTs deal with secondary incidents

An extensive Internet search of various state DOTs was conducted, focusing on information about secondary incidents. The information obtained is summarized in Table 5. Traffic Incident Management is an important component for state DOTs. The U.S. DOT, FHWA and many state DOTs such as the Florida DOT, the California DOT, the Colorado DOT, the Minnesota DOT, the Wisconsin DOT, VDOT, and the Michigan DOT proposed that primary and secondary incidents are key factors impacting traffic safety and congestion. Reducing secondary incidents would effectively improve operational performance of freeways.

Few DOTs have defined secondary incidents based on their own experiences and standard. Most of them either referred to research papers when defining secondary incident or their definitions are usually qualitative. For instance, the Minnesota DOT stated: "A crash that occurs because of the congestion or distraction from a prior incident is referred to as a 'secondary crash'." The Kentucky DOT stated: "Secondary crashes occur as a result of a previous crash," etc. "Secondary crashes," "secondary collisions," "secondary incidents," "secondary accidents" are used by DOTs. Moreover, in most existing incident databases, secondary incident identification information is usually missing which makes it difficult to determine the linkage between two incidents after the fact, based on crash reports (the Florida DOT). Therefore, due to the limited secondary incident databases available for analysis purposes, the definition and identification of secondary incidents is primarily based on assumptions.

Presence of non-recurrent congestion is believed to be the important factor associated with most secondary incidents. Quick response to the primary incidents and clearing the incidents as soon as possible is the main approach used by DOTs in order to reduce the risk of secondary incident occurrence. Furthermore, many state DOTs have applied intelligent transportation systems to accelerate incident clearance. By employing comprehensive methods dealing with incident detection, verification, response, clearance, and information dissemination, significant improvements have been achieved in reducing primary incident duration and mitigating secondary incident occurrence.

The Coordinated Highways Action Response Team (CHART) system deployed by the Maryland DOT is composed of traffic monitoring, traveler information, incident management, and traffic management systems to help to improve real-time operations of Maryland's highway system through teamwork and technology. According to estimates, the CHART incident management program resulted in an estimated 377 fewer secondary crashes in 2002 (Chang et al. 2003).

The Hoosier Helpers system by Indiana DOT make driving safer by clearing incidents quickly, reducing the number of secondary crashes—those that occur in traffic backups created by traffic incidents (Latoski et al. 1999). Indiana DOT has also implemented a SHSP (Strategic Highway Safety Plan) to address ways to expedite crash clearance to reduce secondary crashes. Strategies include promoting “four Es”- engineering, education, enforcement, and emergency medical responders to work in harmony with each other, and Hoosier SAFE-T (Safety Acting for Everyone—Together) is designed to provide interoperable communications among local, state, and federal public safety agencies during emergency response (Strategic Highway Safety Plan, INDOT).

The Georgia DOT’s Intelligent Transportation System, known as NaviGAtor, is a freeway incident and traffic management program as well as a traveler information system. It reduced secondary crashes from an expected 676 to 210 in the twelve months ending April 2004 (Guin et al. 2006).

The TransGuide system in San Antonio, Texas, was designed to provide information to motorists about traffic conditions, such as accidents, congestion, and construction with the use of cameras, message signs, and fiber optics (TransGuide website). It is estimated to have achieved a 35% reduction in primary accidents and a 30% reduction in secondary accidents (Hank 1997).

SmartWay by the Tennessee DOT is an intelligent transportation system designed to reduce traffic congestion by reducing incident clearance time and decreasing the number of secondary incidents. It provides warning messages on dynamic message signs to drivers approaching a crash or disabled vehicle. These warnings allow traffic to divert to other routes while also reducing the potential for secondary crashes caused by drivers running into unanticipated backups (TDOT Smartway Website).

The USDOT has proposed Quick Highway Incident Detection and Incident Warning Systems. The proposed system uses low-cost speed sensors spaced at 100 feet or less. Sensors spaced at such intervals can detect changes in vehicle speeds and track each vehicle and the speed differentials between them. As a result the system can quickly determine incident situations and provide warnings to upstream traffic using LED flashers preventing secondary crashes. This is also referred to as end of queue management (USDOT).

The California DOT (Caltrans) has proposed a responder system to track and share incident information between at-scene responders and the secondary responders, facilitating management of the incident scene and improving the effectiveness of response activities. Collection and transmission of digital photographs are stressed in this project to enhance incident management and help to clear incidents more quickly (Galarus 2005).

Table 4: Secondary Incident Literature Review Summary

		Raub (1997)	Karlaftis et al. (1999)	Chang (2003)	Moore et al.(2004)
Definition of secondary incident	Temporal parameter	Clearance time+15 minutes	Clearance time+15 minutes	Two hours for the same direction ½ hours in the opposite direction	Clearance time < 120 minutes
	Spatial parameter	<1 mile	<1 mile	< 2 miles downstream for the same direction or <0.5 mile downstream or upstream in the opposite direction	Queue length< 2 miles
	Other cond-itions		Excluded non-accidents & secondary crashes in the opposite direction		Excluded secondary crashes in the opposite direction
Factors associated with secondary incident occurrence		Peak hour Weekdays Clearance time	Weekdays Clearance time Vehicle type Primary incident location Season	Primary incident duration	Clearance time Speed High density traffic
Data collection sources		Police reports	Indiana DOT	CHART(Coordinated Highways Action Response Team) actual operation data	California Highway Patrol's First Incident Response Service ; Loop detectors on Los Angeles freeway
Data collection period		1995	1992-1995	2002	March, May, July 1999 and December 1998
Study location		Northern Chicago	Borman expressway		Los Angeles freeway
Sample size		1796		13752 lane-closure related incidents	84,684
Main findings		1. More than 15% of the crashes may be secondary. 2. Average secondary crash occurs within 36.4 min and 600 meters after primary accident. 3. Average Primary accident duration is 45 min, Added delay 69 min.	1. Clearance time, Car-passage car, semi-truck, and WKD increase the secondary incident likelihood, WNT and RMPMS decrease the chance. 2. More than 15% of all crashes might have resulted from an earlier crash.	1. 6.8% of all incidents with lane blockage are identified as secondary incident. 2.Secondary incidents have positive correlation with the primary incident duration	Secondary accidents are considerably rarer events than previous studies suggest, lower frequency of secondary crashes (secondary crashes per primary crash range between 0.015 and 0.030)

Table 4: Secondary Incident Literature Review Summary (Continued)

		Hirunyanitiwattana (2006)	Sun et al. (2005, 2007)	Zhan et al. (2008)	Zhan et al. (2009)
Definition of secondary incident	Temporal parameter	Clearance time < 60 minutes	Incident duration	Clearance time+15 minutes	Maximum possible queue Length upstream
	Spatial parameter	Queue length< 2 miles Same direction	Not available	Two miles upstream of the primary incident	The queue dissipation time of the primary incident
	Other conditions		Dynamic thresholds		
Factors associated with secondary incident occurrence		Peak hour Clearance time Speed Urban area Route number		Number of vehicles involved; Number of lanes; Incident duration; Time-of-day; Whether or not vehicle rollover occurs during the primary incident.	Primary incident type Primary incident lane Blockage duration Time of day
Data collection sources		Federal highway administration	Highway patrol in St. Louis, Missouri	FDOT D4	FDOT D4
Data collection period		1999 and 2000	2002	January 2005 to January 2007	January 2005 to January 2007
Study location		California highway system	I-70 in Missouri	I-95, I-75, I-595	I-95, I-75, I-595
Sample size		170,866 in 1999 and 183,988 in 2000	5,514	4,435 lane blockage incidents	4,435 lane blockage incidents
Main findings		1. Secondary crashes occur more often during rush hour traffic in the morning and evening. 2. Rear-end collision is the predominant secondary collision type, accounting for about two-thirds of all secondary crashes. 3. Secondary incidents on urban freeways and four lanes are higher.	The static and dynamic methods can differ by over 30% in terms of identifying secondary incidents	1. Secondary crashes are usually much less severe than other crashes. 2. Traveler sight conditions (visibility) and the lane blockage durations of primary incidents are significant contributing factors for determining the severity of secondary crashes.	1. Longer lane blockage durations increase the likelihood of secondary crashes. 2. The likelihood of secondary crashes is higher for the weekday morning and afternoon peaks and midday. 3. Secondary crashes are more likely to occur when the primary incident type is "Accident."

Table 5: Information about Secondary Incidents Gleaned from State DOTs

	System used	Secondary incident reduction method	Benefit achieved
US DOT (USDOT website)	Quick Highway Incident Detection and Incident Warning Systems	Detect vehicle speeds, quick determine incident situation and distribute warning information	
California DOT (Caltrans) (Galarus 2005)	Responder system	Track and share incident information between responders	
Indiana DOT (Latoski, et al., 1999) (SHSP website)	Hoosier Helpers system SHSP	Share information to clear incidents quickly	
Georgia DOT (Guin et al. 2006)	NaviGAtor system	a freeway incident and traffic management program and a traveler information system	reduced secondary crashes from an expected 676 to 210 within one year ending 2004
Maryland DOT (Chang et al. 2003)	CHART system	Comprised of a number of sub-systems, including traffic monitoring, traveler information, incident management, and traffic management.	377 fewer secondary crashes in 2002
Tennessee DOT (TDOT Smartway Website)	SmartWay system	Clear incident quickly; provides warning messages on dynamic message signs	
San Antonio Texas DOT (Hank 1997)	TransGuide	Provide information to Road User	35% reduction in primary accidents; 30% reduction in secondary accidents

Summary

Incidents are a major source of congestion, imposing substantial social and personal costs on road users and they negatively impact traffic operations. Substantial efforts have been made by researchers and management agencies to understand incident duration, secondary incidents and their impacts. Several strategies have been applied in the field to mitigate the impacts of both primary and secondary incidents.

Researchers and practitioners generally agree that secondary incidents are those occurring in the temporal and spatial vicinity of primary incidents. The main factors that are associated with secondary incident occurrence can be summarized into four types:

1. Primary incident attributes, e.g., incident type, and number of vehicles involved
2. Traffic condition, e.g., speed distribution, and traffic density
3. Roadway condition (e.g., obstructions, inadequate lighting, curvature, and certain routes
4. Environmental factors, e.g., time of day, and weather conditions

The properties of primary incidents are believed to be the main factors that are associated with secondary incident occurrence. However, certain gaps are apparent:

- There is still no standard definition of secondary incidents. The identification of primary and secondary incidents in Virginia and corresponding analysis are non-existent.

- Many studies only deal with crashes only rather than the entire spectrum of incidents.

- Most studies focus on single incidents, but few of them focus on understanding the complex interrelationship between incident durations and the occurrence of secondary incidents. Compared with two single incidents, the combination of primary and secondary incidents may have larger impacts on traffic operations and incident management. Analyzing the characteristics of secondary incidents themselves and the joint impacts of primary and secondary incidents is important.

- The existing delay estimation models are suitable for analysis of single incidents. The delay caused by multiple associated incidents, i.e. primary-secondary incident pairs, has not been analyzed fully.

- There is still no efficient practical planning tool to help transportation operations centers identify secondary incidents by using existing historical databases.

- Despite methods based on regression and other methodologies, there is no practical online tool to help incident managers and operators predict incident duration, secondary incident occurrence, and associated delay, which can support the real-time operations. The results of research on secondary incidents still need to be translated into practical planning and operational tools.

Finally, most of the relevant literature relies on fixed temporal and spatial thresholds for identifying secondary incidents, e.g., secondary incidents are those occurring within 1 mile and 1 hour of the primary incidents. However, there is a need to identify secondary incidents based on queuing associated with a primary incident, as the study by Sun and Chilukuri (2007) indicates that secondary accidents identified by dynamic versus static thresholds can differ by more than 30%.

Analysis

Secondary Incident Definition and Identification

Data overview

The incident data collected for this study are from two sources: The Hampton Roads Transportation Operations Center (HRTOC) and the Virginia State Police (VSP). There are a number of known discrepancies between those two sources. The HRTOC data are based primarily on Safety Service Patrol (SSP) records. SSP provide incident management and offer assistance to motorists experiencing problems on freeways. At the time of the study, they covered more than 110 miles, from Newport News to Virginia Beach, 24 hours a day, and 7 days a week. The VSP data are more reliable but they only relate to crashes and do not contain crash duration information.

There are two main limitations of the HRTOC incident database: first, the exact positions of these archived incidents are not provided. The only available location information is the code of road segment where the incident occurred. This creates difficulties in the secondary incident identification process since these segments are typically 1 mile in length. Secondly, the incident duration reported in the database is when the TOC staff opened/closed an "incident window." This is not the "true" incident duration (it is the clearance time) since SSPs typically need response time before arriving on an incident scene. Note that the incident duration data may have measurement error in the detection of short incidents. Incidents may not be detected for some time after they occur and it may take 2 to 3 minutes on average (of course longer in some cases) to detect them. The detection time is not fully captured in the incident duration.

The VSP crash data were obtained with the assistance of staff from the Hampton Roads Transportation Planning Organization. The VSP data are restricted to crashes involving injury and/or property damage exceeding $1000. The crash database from VSP has milepost information, which is helpful in precisely identifying crash locations. But there is a serious disadvantage of the VSP data: this database does not include information about the duration of a crash and lane blockage information, and it only records crashes involving injury and/or property damage exceeding $1000, which cannot provide the complete data needed. Therefore it is not possible to identify secondary crashes using the VSP data alone.

The incident database provided by HRTOC has a field indicating whether VSP responded to the incident, which makes it possible to compare crashes in HRTOC incident database with those in police reports in the VSP database. Table 6 shows the comparison. Firstly, it shows that a significant number (1,946) of police reported crashes were not included in the HRTOC database. This implies that a substantial portion of police reported crashes occurring on freeways are missed by service patrols. Also, the crashes recorded by police have higher severity than those recorded by SSP. That is, they are longer duration crashes and more vehicles are involved, on average, as shown the table. Further data checks show that only 10% of the crashes recorded in the VSP database can be traced in the incident database. This raised the possibility that some of the HRTOC recorded crashes may be crashes that do not meet the criteria for police reporting, i.e., injury or $1000 or more in property damage.

Table 6: Comparison of 2006 HRTOC and VSP crash data

Data source		**Observed crashes**	**Number of vehicles involved in crash**			
			Mean	**Std. Dev.**	**Min**	**Max**
HRTOC data	All crashes	3026	1.86	0.94	1	10
	VSP was on scene	2071	1.91	1.00	1	10
	VSP was not on scene	955	1.75	0.78	1	6
VSP data		4817	2.01	0.88	1	10

Note: VSP = Virginia State Police; HRTOC = Hampton Roads Transportation Operations Center

Besides the difference between HRTOC and VSP data, discrepancies were found between HRTOC and VDOT data for bridge-tunnels, e.g. the Hampton Roads Bridge Tunnel. Specifically, data on stoppages are collected separately in VDOT's bridge tunnel complexes for Hampton Roads Bridge Tunnel-HRBT (I-64), Monitor Merrimac Bridge Tunnel-MMBT (I-664), James River Bridge (Route 17), Downtown Tunnel (I-264), and the Midtown Tunnel (Route 58). The study team obtained data on total stoppages in the bridge tunnels, their locations and incident types (whether crashes or disablements). However, the raw data on each incident were not available. Analysis showed that the HRTOC data includes only a fraction of all incidents that occur at bridge tunnels. For instance, the HRBT bridge tunnel complex recorded 2652 incidents, which are far higher than the 154 incidents recorded in the HRTOC database for HRBT during 2006. Clearly, the data from the bridge-tunnels mini-transportation operations centers are not integrated with the HRTOC incident data.

Detailed comparisons between HRTOC data and VSP data are available from the authors. While the incident data are not ideal, they were deemed fit for further analysis and modeling. Details of incidents and descriptive statistics for the data were examined and are available from the authors. The descriptive statistics provided information on outliers and obvious errors. As a result, a few unreasonable values were purged from the dataset.

Road inventory data and historical traffic count data are relevant for the analysis. Road inventory data were obtained from the Hampton Roads Transportation Planning Organization (HRTPO). Traffic flow data were provided by staff of the Virginia Center for Transportation Innovation & Research from an earlier study on Hampton Roads. The GIS Manager, VDOT—Transportation and Mobility Planning Division, also provided detailed count data in GIS format. In addition, traffic data were obtained from HRTPO. Traffic counts are collected continuously by embedded sensors (loop detectors). The daily traffic data for 2006 showed substantial directional differences in traffic counts across freeways.

Identification results

Primary and Secondary Incident Pair Frequency. Incident data collected by HRTOC were vehicular based, covering the period from January 2004 to June 2007. For analysis, they were converted to incident-based records, i.e. incidents involving multiple vehicles were aggregated into only a single event record with a unique incident ID. The number of involved vehicles was treated as a separate variable.

A total of 38614 incidents were recorded in 2006 HRTOC database, among which 38,086 records have valid spatial location and incident duration information used for secondary incidents identification. By using the different identification methods listed in Table 1, the secondary incident identification results for I-64 west bound (42 miles in the Hampton Roads area, from I-264-I 664 interchange to US 17 J Clyde Morris Blvd.) are shown in Table 7 to explore the differences between different identification methods.

Table 7: Comparing Secondary Incidents Using Different Assumptions of incident influence area (I-64 West Bound)

Method	**Primary Incidents**	**Secondary incidents identified in the same/opposite directions**		
		Same direction	**Opposite direction**	**Total (% increase)**
Segment-based with actual duration	160	180	-	180 (Base)
Queue-based with actual duration	198	218	-	218 (21%)
Segment-based with actual duration and including opposite direction	200	180	43	220 (22%)
Queue-based with actual duration and including opposite direction	198	218	43	261 (45%)

NOTES: When using different spatial and temporal selection criteria, e.g., adding opposite direction secondary incidents may result more tertiary incidents. In such cases, those secondary incidents which cause tertiary incidents are (re)identified as both primary incidents and secondary incidents.

The results from this limited analysis indicate that the difference between identified secondary incidents is substantial when applying the queue-based method and when opposite direction secondary incidents are considered. Method 2 (and 4) is queue-based and considers secondary incidents occurring on the upstream segments due to spillbacks. Therefore, the number of secondary incidents identified by method 2 is larger than method 1 (21% higher). When opposite direction incidents are included, the secondary incidents identified by method 4 are 18.6% higher than method 3. Note that the queue-based methods require more input data than method 1 and 3, including traffic data and incident-reduced capacity information. Importantly, the secondary incidents that occurred in the opposite direction of primary incidents account for nearly 20% (=43/218) of all secondary incidents identified using queue based method. It is possible that distractions from incidents in the opposite direction may be an important factor in secondary incidents.

Using appropriate thresholds (Method 2 with 15 minutes added to primary incidents with lane blockage without considering opposite direction), 736 incidents were identified as primary incidents, which are 1.93% of all incidents recorded by SSPs; 764 incidents were identified as secondary which accounts for 2.01% of all incidents. The remaining 36,633 incidents are independent incidents (neither primary nor a secondary incident). Note that some secondary incidents can be tertiary incidents; although few, some incidents are identified as both primary and secondary in the database.

The distribution of identified secondary incidents by month is shown in Figure 10 and Table 8. Relatively higher secondary incidents are observed during summer months, which is when traffic increases substantially in the region. On average, 2 to 3 secondary incidents occur daily.

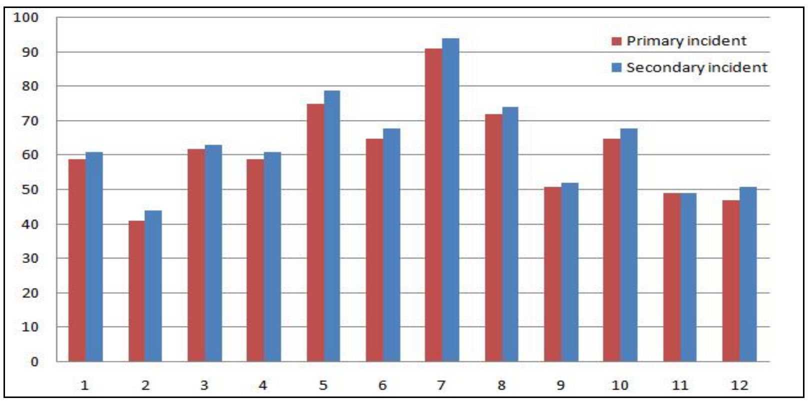


Figure 10: Secondary Incident Pair Frequency by Month (2006 incident data).

Note: This figure is based on HRTOC data only. Some of the secondary crashes might be missing, as the HRTOC data does not capture all crashes on freeways in HR.

Table 8: Incident Frequency in Hampton Roads by Month (2006 data)

	Primary incidents		Secondary incidents		**Total incident frequency**
Month	frequency	Percentage	frequency	percentage	
1	59	1.90%	61	2.03%	3,162
2	41	1.81%	44	1.99%	2,312
3	62	2.20%	63	2.30%	2,881
4	59	1.88%	61	2.01%	3,204
5	75	2.14%	79	2.34%	3,579
6	65	1.75%	68	1.91%	3,774
7	91	2.48%	94	2.67%	3,762
8	72	2.01%	74	2.14%	3,657
9	51	1.74%	52	1.84%	2,976
10	65	2.14%	68	2.31%	3,098
11	49	1.62%	49	1.67%	3,066
12	47	1.52%	51	1.70%	3,143
Total	736		764		38,614

Incident Durations. The incident durations (clearance times) for each type are shown in Table 9. The average duration for all recorded incidents in the data is 14.3 minutes, noting that this does not include response time. However, the average duration for independent incidents (neither primary nor secondary incidents) is less than 14 minutes, while the average duration for primary incidents is nearly 37 minutes, indicating that larger incidents are likely to result in secondary incidents, as expected. Interestingly, the average duration for secondary incident is slightly more than 18 minutes, which is still longer than the mean for independent incidents. This indicates that secondary incidents are, on average, relatively large events in terms of their durations, i.e., they may not be minor rear-end fender benders.

Table 9: Incident Durations by Incident Type in Hampton Roads

Sample size	Min	Max	Mean	Stand. Dev.
38,086 (All incidents)	1	728	14.27	20.22
736 (Primary)	1	728	36.75	48.64
764 (Secondary)	1	320	18.37	25.77
36,633 (Independent)	1	651	13.78	18.88

Note: Segment-based method with actual incident duration + 15 minutes (no opposite direction).

Event Durations. Owing to the spatial and temporal proximity of primary and secondary incidents, they can be considered collectively as an event. Based on the incident duration and start times, two distinct types of incident events can be categorized as follows:

1. Contained Event Duration: The durations of all secondary incidents are included within the primary incident duration. As a result, the entire event duration will be equal to the duration of primary incident.

2. Extended Event Duration: The duration of one or more secondary incidents partially overlaps with primary incident duration but extends beyond the duration of primary incident.

Also, one primary incident may be associated with one secondary incident or with multiple secondary incidents, which are termed large-scale incident events. The durations for primary incident, secondary incident and incident pairs are shown in Figure 11. The values shown in the figure are averages for identified primary and secondary incidents. The numbers of one-pair contained and extended events are nearly equal, (about 50% each). Surprisingly, the mean event durations for extended events are shorter than the contained events. Furthermore, the mean event duration of large-scale events is 1.5 times longer than the durations of one pair events. The figure also shows the time-gap between a primary incident and its secondary incidents. On average the time gap for extended secondary incidents is shorter than the contained incidents. Major factors associated with longer multiple secondary incident event durations can be found in a project related paper by Zhang and Khattak (2010).

Time Gaps between Primary and Secondary Incidents. To investigate how soon a secondary incident happens after a primary incident, the time gaps between identified secondary incidents and their primary incidents were calculated. A simple curve fitting model was estimated to obtain the best fitting equations for time gap between primary and secondary incidents.

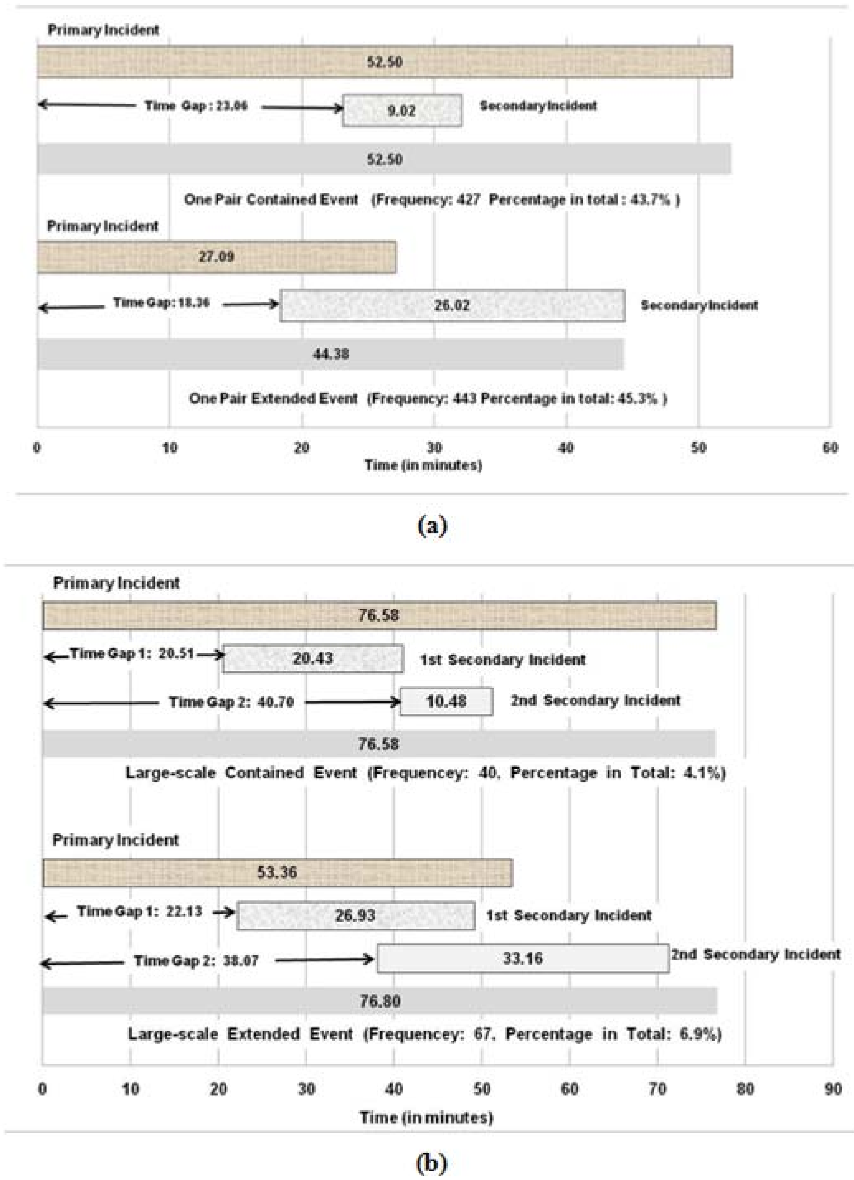


Figure 11: Summaries of Contained and Extended Events. (a) One Pair and (b) Large-scale

Based on goodness of fit, the second order Gaussian model was selected. Mathematically it can be expressed as:

$$y = a_1 \times e^{\left(-\left(\frac{x-b_1}{c_1}\right)^2\right)} + a_2 \times e^{\left(-\left(\frac{x-b_2}{c_2}\right)^2\right)}$$

Where y is the probability density of time-gaps x; a_i represent the Gaussian curve peak height; b_i denote the x-axis locations of the peak maximum; c_i are the width of the peak at half-maximum. All parameters are used to mathematically express the non-linear relationship between the dependent variable y and time gaps.

The distributions were fitted to time-gaps shown in Figures 12-14. There are three graphs in each figure. The first graph shows the percentage of frequency versus time gap. The middle one displays the frequency distribution and a non-linear curve fitted to the data. The bottom one provides a cumulative probability plot of secondary incidents. The distributions for three categories: 1) the first secondary incident in the same direction, 2) the first secondary incident in the opposite direction, and 3) the second secondary incident in the same direction, it indicate that more than one-half of the incidents in the first two categories occurred within 20 minutes of the primary incident occurrence. Furthermore, the time gap distribution for additional secondary incidents was relatively widely spread. This implies that the time gaps of second secondary incidents are more difficult to ascertain and predict.

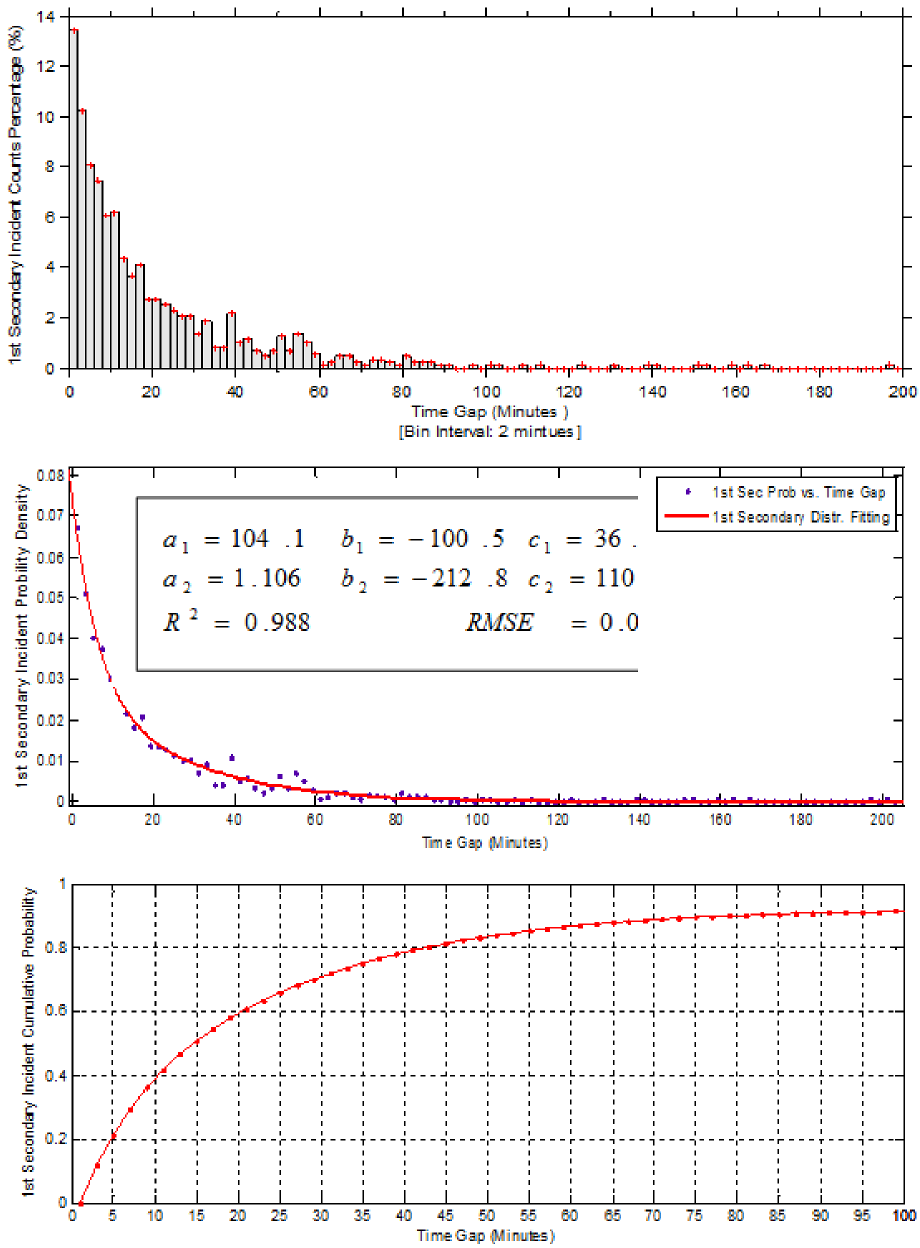


Figure 12: Time Gap of 1st Secondary Incident in the same direction

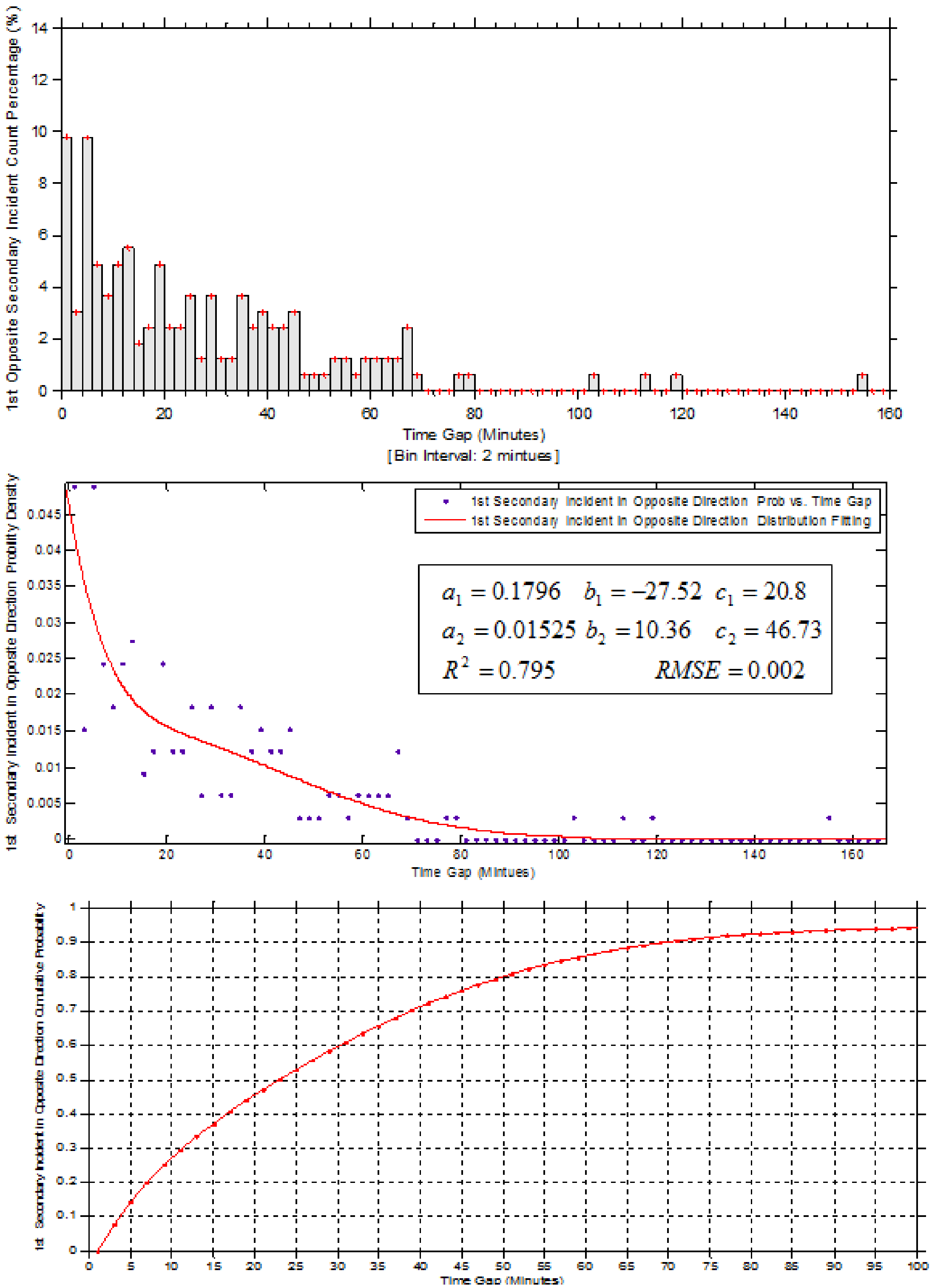


Figure 13: Time Gap for 1st Secondary Incident in the opposite direction

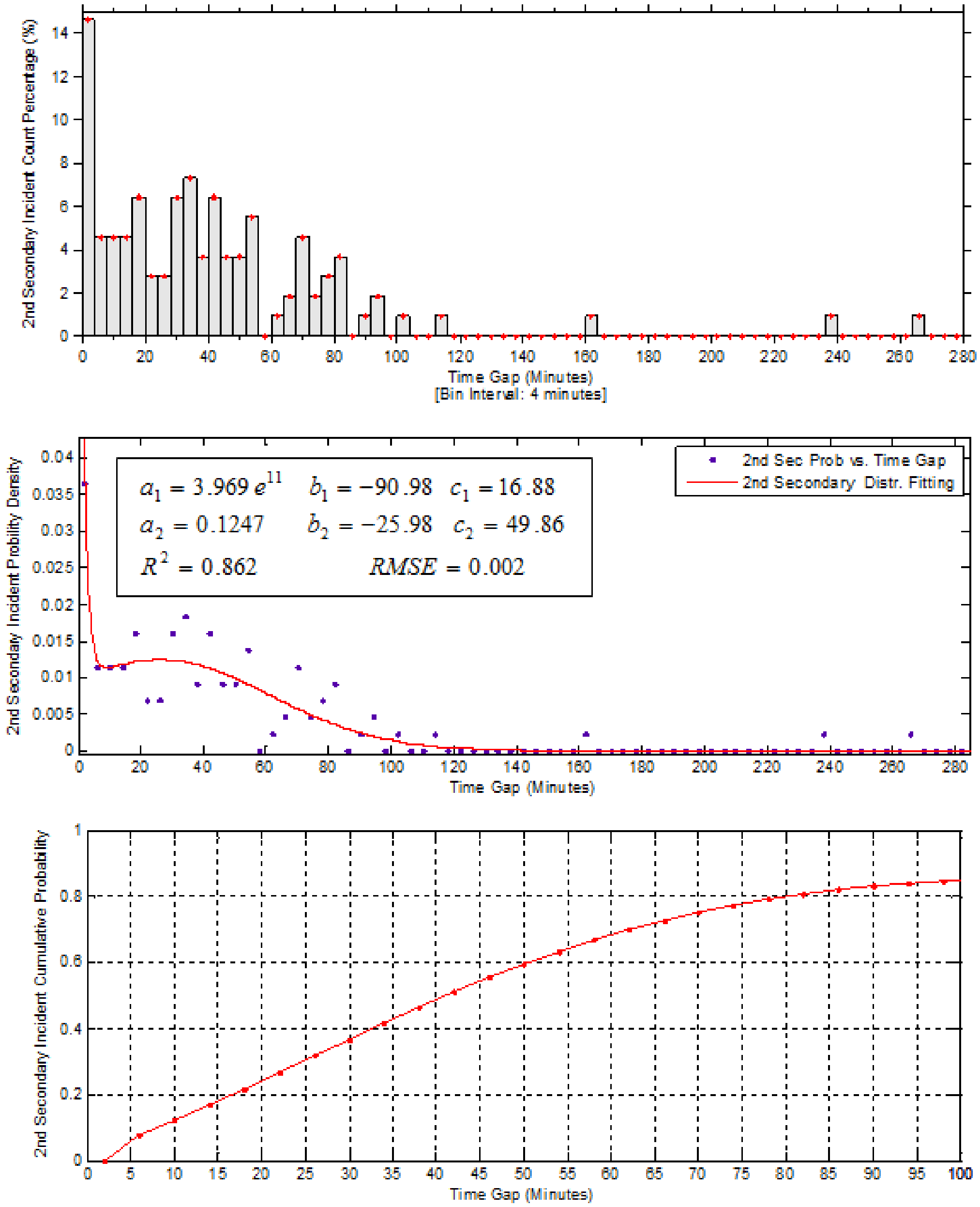


Figure 14: Time Gaps for 2nd Secondary Incident in the same direction

Spatial Distribution of secondary incidents. Figure 15 shows the frequency of secondary incident pairs by different route segments. Secondary incidents shown are based on Method 2—identification of same direction incidents using queues and actual primary incident duration.

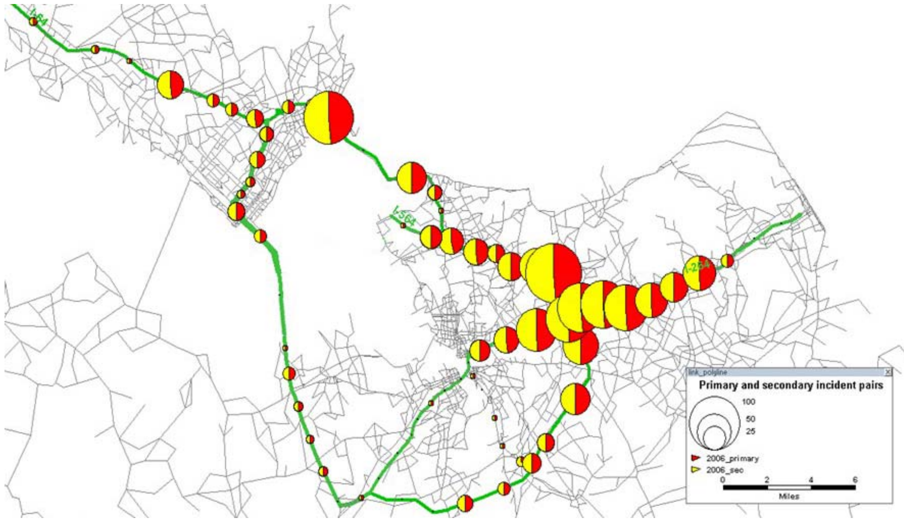
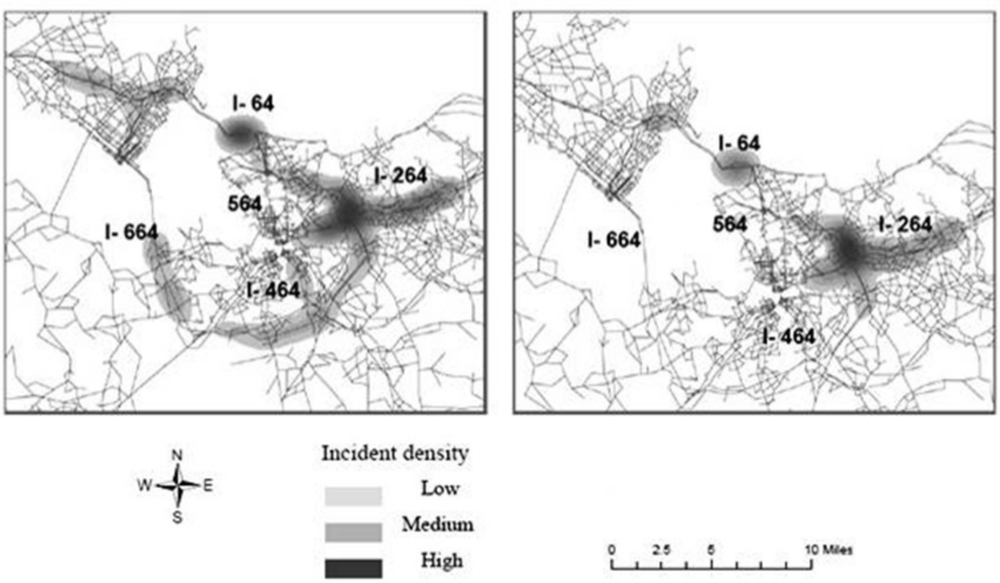


Figure 15: Spatial Distribution of Primary Incidents and Secondary Incidents (2006 Data)

The size of circles indicates incident frequency, with the ratio of the red and yellow representing the relative proportion of primary and secondary incidents. Generally, the proportion of primary and secondary incidents is 1:1, which means that one primary incident is associated with one secondary incident. On some segments, one primary incident was associated with multiple secondary incidents, e.g., the segment north of Hampton Roads Bridge Tunnel. The figure identifies locations where secondary incidents are more likely to occur and consequently higher service patrol, police and tow coverage may be needed (in order to respond to secondary incidents more effectively).

Figure 16 shows the kernel density distribution of secondary and non-secondary incidents of 2006.



(a) **(b)**

Figure 16: Spatial Distributions of Incident Density
(a) Non-Secondary Incident Density (b) Secondary Incidents

Visual comparison reveals that not all locations with high non-secondary incidents necessarily have high secondary incidents, such as segments on I-664, I-464, and south of I-64, while the density clusters of non-secondary incidents are more widely distributed across roadway segments. This indicates that the spatial distribution of secondary and non-secondary incidents is different. Furthermore, a chi-square test showed that the spatial distribution of secondary incidents is significantly different from that of non-secondary incidents. This implies that higher risks of secondary incidents in certain roadway segments do not necessarily correlate with relatively higher risk of non-secondary incidents. Spatial analysis of primary and secondary incident frequencies will appear in a project-related paper by Khattak et al. (2010), forthcoming in the Transportation Research Record.

Modeling of secondary incidents

Interdependence between incident duration and secondary incident occurrence

Based on the identified secondary incidents, statistical models were estimated to explore the interdependent relationships between duration and secondary incident occurrence. To account for such interdependence, with respect to the secondary incident variable, appropriate statistical methods are available and are applied. Specifically, the Two-Stage Least Squares (2SLS) method is used with the advantage that a secondary incident occurrence model is estimated with duration as endogenous variable. Statistical software STATA is used to estimate the model using conditional maximum likelihood estimator, fully accounting for the information in the data. The first stage is Ordinary Least Squares (OLS) model of duration and the second stage is a binary probit model of secondary incident occurrence. Further information about interdependence between primary incident duration and secondary incident occurrence can be found in a project related paper by Khattak et al. (2009), published in the Transportation Research Record.

Three secondary incident occurrence models are reported in Table 10. Model 1 is a binary probit model estimated with observed duration. Model 2 is a binary Probit model using observed duration without the closure time variables and a related dummy. Model 3 is a Probit model estimated with endogenous regressors, instrumenting incident duration (and it is directly comparable to Model 2-1). Note that lane closure times and a dummy variable for no lane closure are used as instruments in the first stage only, and duration is used as endogenous explanatory variable in the first stage. The model results confirmed interdependent relationship. This means that secondary incident occurrence is associated with longer durations of primary incidents; meanwhile higher secondary incident occurrence is associated with longer primary incident duration. Other factors associated with longer incident durations are detection by non-SSP sources, crashes, more vehicles involved, severe injuries, if the incident affects the left shoulder or ramp, and longer lane closure times.

Table 10: Modeling Secondary Incident Occurrence in Hampton Roads

Number of observations: 37,369		Model 1: Probit model		Model 2: Probit model		Model 3: Probit model: Endogenous	
		Observed Duration as independent		Observed Duration as independent		Duration as Instrumented	
Independent variables		Coef.	Marg. eff.	Coef.	Marg. eff.	Coef.	Marg. eff.
Detection source (Base: SSP)	CCTV	0.291***	0.014	0.342***	0.017	0.362***	0.019
	VSP_radio	0.049	0.002	0.086	0.003	0.106	0.004
	Phone_call	-0.141	-0.004	-0.101	-0.003	-0.073	-0.002
	Other_dete	0.182	0.008	0.132	0.005	0.204	0.009
Incident type (Base: Other)	Crash	0.589**	0.037	0.667***	0.045	0.649***	0.044
	Disabled	0.404*	0.011	0.384	0.011	0.343	0.010
	Abandoned	0.340	0.017	0.304	0.014	0.247	0.011
Closure time	Durationclos	-0.004***	-0.0002				
Nonlaneclosure	Dummy_close	-0.404***	-0.021				
Vehicle involved	Vehicles	0.114***	0.004	0.127***	0.005	0.135***	0.005
Resp. vehicles	Re_veh	-0.011	-0.0004	0.008	0.0003	0.035	0.001
AADT (per 1000)	AADT	0.002***	0.0001	0.003***	0.0001	0.002***	0.0001
	AADT_dummy	-0.179	-0.005	-0.166	-0.005	-0.169	-0.005
Affects left shoulder?	Left_shoul	0.038	0.001	0.062	0.002	0.072	0.003
Affects ramp?	Ramp	-0.078	-0.003	-0.058	-0.002	-0.051	-0.002
Duration	Duration	0.009***	0.0002	0.007***	0.0002	0.005***	0.0002
in peak hours?	TOD	0.159***	0.006	0.162***	0.006	0.160***	0.006
	Constant	-2.839***		-3.226***		-3.195***	
Independent variables						Duration instrument	
Detection source (Base: SSP)	CCTV					7.688	0.000***
	VSP_radio					8.357	0.000***
	Phone_call					9.381	0.000***
	Other					4.605	0.001***
Incident type (Base: Other)	Crash					6.254	0.000***
	Disabled					-1.265	0.131
	Abandoned					-8.065	0.000***
Response vehicles	Re_veh					2.919	0.000***
AADT(per 1000)	AADT					0.005	0.002***
	AADT_dummy					0.400	0.740
Affects left shoulder?	Left_shoul					3.835	0.000***
Affects ramp?	Ramp					2.955	0.000***
In peak hours?	TOD					0.071	0.665
Vehicle involved	Vehicles					1.946	0.000***
Closure time	Durationclos					0.836	0.000***
nonlaneclose	Dummy					10.231	0.000***
	Constant					-3.780	0.000***
Prob > chi2		0		0		0	
Log likelihood		-3214.43		-3240.66		-157,389	
Pseudo R2		0.11		0.10		NA	
Wald Test		NA		NA		Rho=0.049; Prob > Chi^2 = 0.0048	

Note: * p<0.10; ** p<0.05; *** p<0.01; The marginal effects listed are at the means of the independent variables.

The relationships between explanatory factors, primary incident duration and secondary incident occurrence are shown in Figure 17.

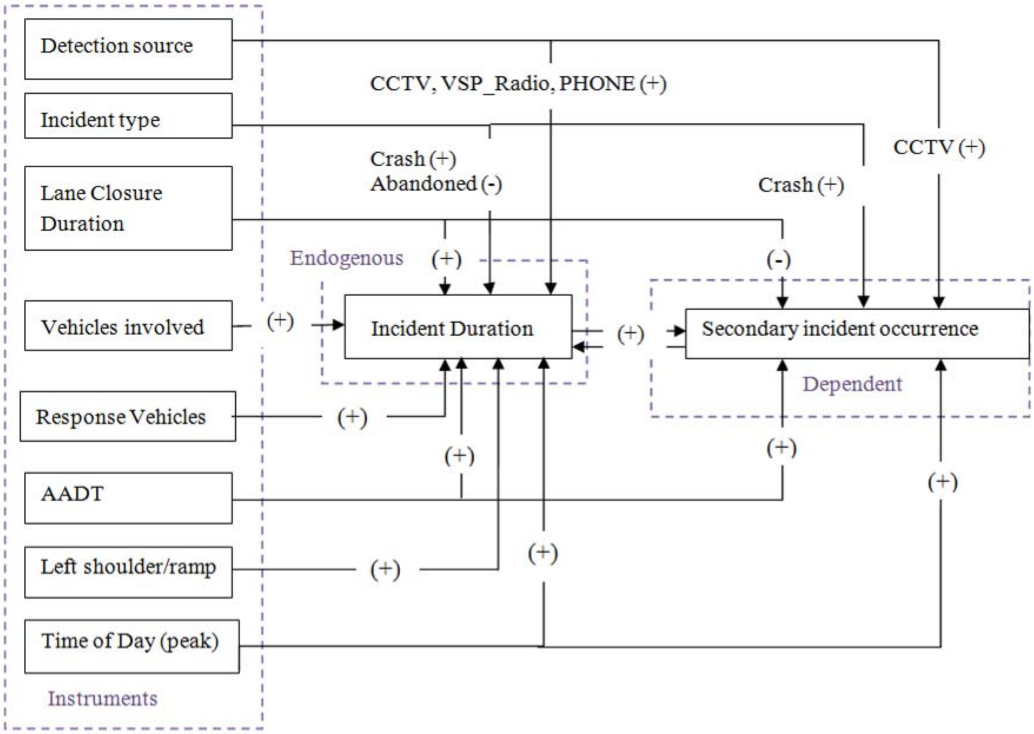


Figure 17: Relationships between Dependent, Endogenous Variable and Instruments.

Note: A + sign indicates positive association between the variables, and a – sign indicates the opposite.

The factors associated with higher occurrence of secondary incidents include: if the incident is a crash, detection source (source other than SSP), occurrence of incident in peak hours, multiple vehicles involved, and higher AADT in the incident location. A key result worth noting is that an additional minute of primary incident duration is associated with 1.5% higher odds of a secondary incident occurrence. Note that the direct association of lane closure duration with secondary incident occurrence is negative (incidents resulting in a longer lane closure durations had a lower chance of having a secondary incident than those shorter lane closure durations), though this (somewhat counter-intuitive relationship) might be due to multi-collinearity of lane closure duration with incident duration. Furthermore, note that lane closure duration has a positive indirect correlation with secondary incident occurrence through longer incident durations.

Multiple secondary incidents and their event durations

The study team uncovered multiple secondary incidents that occur sequentially, and termed them cascading events. Such cascading events, i.e., two or more secondary incidents associated with a primary incident are often large-scale events. They are relatively rare, yet they can stretch the resources of responding agencies, especially transportation agencies. Roadways that are likely to have multiple secondary incidents were identified. An ordered Logit model, shown in Table 11, is estimated to explore the associations of cascading event adversity with various factors.

Table 11: Partial Proportional Odd Model for Ordinal Scale of Events

Parameters	Coefficients		Marginal effects		
	Primary-secondary pair	**Multiple secondary incidents**	**Indep. incidents**	**Primary-secondary pair**	**Multiple secondary incidents**
Primary Incident Characteristic					
Primary is crash?	0.7781**	0.7781**	-0.0215	0.0197	0.0018
Incident duration	0.0222**	0.0222**	-0.0004	0.0004	0.0000
Truck involved in primary?	-0.0423	-0.0423	0.0009	-0.0008	-0.0001
Number of vehicles in primary	0.2783**	0.5145**	-0.0055	0.0047	0.0008
Outstate vehicle in primary?	-0.0531	-0.0531	0.0011	-0.0010	-0.0001
Lane blockage in primary (%)	0.0092**	0.0179**	-0.0002	0.0002	0.0000
Road Geometry					
Segment length	-0.0825*	-0.0825*	0.0016	-0.0015	-0.0001
Curve?	0.0748	0.0748	-0.0015	0.0014	0.0001
Traffic					
AADT/(Lane*1000)	0.0880**	0.0880**	-0.0018	0.0016	0.0002
Constant	-6.2193**	-9.0388**			
Summary Statistics					
Generalized ordered logit model significance Number of observations = 36272 Log likelihood function = -4600.2501 Pseudo R^2 = 0.1471			LR Chi^2 (11) = 1587.12 Prob > Chi^2 = 0.0000		

Notes: * p<0.05, **p< 0.001; Marginal effects in the two tables represent the changes in the dependent variable with a unit change in the independent variable. STATA software procedure gologit2 was used with autofit. A Chi-squared test showed that the assumption of parallel lines is violated.

The dependent variable was measured on an ordinal scale as 1) single incident with no secondary incidents, 2) one secondary incident (primary-secondary pairs), and 3) two or more secondary incidents (multiple secondary incidents). This scale captures event adversity from a traffic management perspective, with the last category capturing multiple secondary events. The results indicate that longer duration crashes, shorter segments, and heavy traffic are associated with higher propensity for secondary incidents. More importantly, multiple-vehicle involvement and lane-blockage had a different contribution to the occurrence of secondary incidents, and they are particularly associated with more secondary incidents.

A Heckman model, shown in Table 12, was estimated to investigate the relationship between time-gap and primary incident characteristics. Based on the results, the time to the first secondary incident is shorter if the primary incident is a crash, the primary incident has a long duration, lane blockage occurs, or there are multiple lanes, and higher traffic levels. The model can be used to predict time to the first secondary incident, given parameters of an incident.

Table 12: Heckman Model for Time Gap

Parameters	Heckman Selection Model (Logit Link)		
	Coefficients		Marginal effects
	Outcome	Selection	Pr(Sec1=1)
	LN(Time Gap)	P(Sec1=1)	
Primary Incident Characteristics			
Primary is crash?	-0.24137	.0933572*	.0045283
Incident Duration	-0.01008 ***	.0116952***	.0005225
Truck Involved in primary	-0.00129	.0054804	.0002449
Number of vehicles in primary	0.58004 ***	.1571563***	.0070217
Out of state vehicle in primary?	0.047175	-.0212049	-.0009474
Lane Blockage	-1.06316 ***	.3030384***	.0180753
Road Geometry			
Segment Length	-0.11721*	.0401892***	.0017956
Number of Lane	-0.26308**	.0773715**	.0034569
Curve	-0.00558	.0010218	.0000456
Traffic characteristics			
AADT/1000	-0.01084***	.0032279***	.0001442
Constant	12.53511***	-2.957001***	
Summary Statistics			
Number of obs = 37015		Censored obs = 36059	
Log likelihood = -5185.16		Uncensored obs = 956	
Wald chi-squared(10) = 212.32		Prob > chi-squared = 0.00	
LR test of independence of equations. (Rho = 0), chi-squared = 794.9, Prob>chi-squared = 0.000			

Note: * p <0.10, ** p<0.05, ***p<0.001

Cascading incidents can be grouped into an event due to their spatial and temporal proximity. Events consisting of a primary and its secondary incidents are expected to have longer durations than single incidents. Cascading events were analyzed and the following groupings were developed: One-pair events (one primary and one secondary incident) and large-scale events (one primary and multiple secondary incidents). As mentioned previously, event durations were categorized as either "contained" or "extended." If the duration of the secondary incident plus the time-gap between primary and secondary incident start times is less than or equal to the primary incident duration, then this event is categorized as a contained event; otherwise, it is categorized as an extended event. Correlates of event durations are identified through a set of rigorous statistical models. Specifically, regression models are estimated to quantify associations with key factors that include incident characteristics, roadway geometry and traffic flows. Table 13 shows three linear and truncated regression models (including their marginal effects) for event durations. All models are statistically significant. The goodness of fit, R^2 for the linear regression and a roughly estimated equivalent R^2 value for truncated regression are reasonable. Both models show consistent and similar empirical results, although theoretically we would recommend the truncated model. The major factors associated with longer cascading incident events are: the primary incident is a crash, longer time-gap between a primary incident and related secondary incident/s, longer response time of service patrol on primary and secondary incident sites, and police presence on primary and secondary incident sites. Furthermore, Primary incident characteristics are dominant in contained events, while secondary incident characteristics play a substantial role in extended events, requiring substantial resources from response agencies (Zhang and Khattak, 2009, 2010).

Table 13: Event Duration Regression Models using Hampton Roads Incident and Road Inventory Data

Independent Variables	Total Models					Contained Event Models					Extended Event Models				
	OLS		Truncated			OLS		Truncated			OLS		Truncated		
	Coef.	P-value	Coef.	P-value	Marg. Effect	Coef.	P-value	Coef.	P-value	Marg. Effect	Coef.	P-value	Coef.	P-value	Marg. Effect
Primary is crash?	6.625	0.018**	11.443	0.001**	9.976	7.999	0.024**	14.667	0.001**	13.153	3.429	0.431	6.687	0.267	5.734
Primary lane blockage (%)	0.057	0.333	0.075	0.450	0.065	0.105	0.148	0.152	0.205	0.135	-0.093	0.408	-0.199	0.157	-0.168
# of vehicles involved in primary	-1.461	0.279	-1.393	0.403	-1.195	-2.063	0.210	-2.087	0.270	-1.857	-0.183	0.945	-0.127	0.972	-0.107
Secondary is crash?	9.134	0.005**	14.346	0.010**	12.687	3.204	0.593	4.055	0.672	3.640	14.483	.000**	21.852	0.002**	9.215
Secondary lane blockage (%)	0.083	0.304	0.078	0.524	0.067	-0.002	0.986	-0.057	0.678	-0.051	0.137	0.169	0.174	0.279	0.147
# of vehicles involved in secondary	4.626	0.023**	6.169	0.029**	5.292	5.050	0.278	7.452	0.266	6.630	4.919	.027**	6.246	0.038**	5.269
Time-gap (minutes)	1.150	0.000**	1.370	0.000**	1.175	1.211	0.000**	1.399	0.000**	1.244	1.030	.000**	1.299	0.000**	1.096
On ramp presence?	0.312	0.907	0.220	0.956	0.189	2.677	0.494	3.986	0.520	3.512	-2.550	0.487	-4.004	0.403	-3.422
AADT/(lane*1000)	0.260	0.282	0.495	0.259	0.424	0.212	0.547	0.275	0.642	0.245	0.250	0.448	0.571	0.378	0.482
Service patrol detected?	-1.068	0.689	-2.441	0.625	-2.107	-3.312	0.393	-4.681	0.440	-4.200	1.616	0.663	1.713	0.929	0.601
Response time for service patrol to primary (minutes)	0.394	0.002**	0.574	0.009**	0.492	0.361	0.023**	0.526	0.066*	0.468	0.508	0.035**	0.704	0.007**	0.594
Response time for service patrol to secondary (minutes)	0.546	0.035**	0.824	0.008**	0.706	1.341	0.019**	1.852	0.060**	1.648	0.392	0.164	0.645	0.035**	0.544
Constant	9.979	0.149	-17.085	0.155		11.034	0.293	-13.391	0.428		8.759	0.369	-18.758	0.295	
Summary Statistics															
Number of observations	870					427					443				
Test statistic	F(12,857) =105.05		Wald chi2(12) = 326.77			F(12,414) =64.07		Wald chi2(12)=264.32			F(9,500)=40.45		Wald chi2(12)=191.03		
Prob. > F / Waldchi^2	0.000		0.000			0.000		0.0000			0.0000		0.0000		
R^2 / Equivalent R^2	0.595		0.562			0.650		0.553			0.530		0.532		

Note: * p<0.10; ** p<0.05

Frequencies of primary-secondary incidents

To explore factors associated with secondary incidents, Poisson and Negative Binomial regression models were estimated combining traffic exposure, road segment characteristics, and spatial/land use information. Table 14 shows the model results. Both the Poisson and Negative binomial models for non-secondary incidents are statistically significant. The Poisson model has a substantially higher goodness of fit. Furthermore, the performance of negative binomial and Zero Inflated Poisson (ZIP) models for secondary incidents is similar.

The models show that greater secondary incident frequency was associated with longer freeway segments, higher traffic volumes and more on-ramps on freeway segments. Additionally, more secondary incidents occur on roadways that are close to bridge-tunnels. Segments with more lanes were linked with lower non-secondary incidents.

Overall, the ZIP model is recommended for analysis of secondary incident frequencies, and the Poisson model is recommended for the analysis of non-secondary incident frequencies. See Khattak et al. (2010) for further details.

Simulation of delays due to primary-secondary incident pairs

A 6-mile basic section of a three lane freeway with 60 mph speed limit was simulated as a test network. Using microscopic simulation software, PARAMICS, the effects of three critical parameters on incident delays were explored: time gap, spatial distance between primary and secondary incidents, and traffic demand levels. In all incident scenarios, it is assumed that one lane is blocked for the duration of the incident. Other relevant characteristics of the simulated primary and secondary incidents are shown in Table 15. If the secondary incident duration is contained within the duration of the primary incident and it is not more severe or restrictive (in terms of lane blockage) than the primary incident, then the simulation results suggest that the secondary incident does not cause additional delays. In such cases the total delay caused by the primary incident is dominant. However, if a contained secondary incident blocks more lanes than the primary incident, then this incident will cause additional delays.

Simulation results for extended primary- secondary incidents are shown in Figure 18. Results indicate that total delays substantially increase as the time gaps between primary and secondary incidents increase. Delays also increase for those secondary incidents that end after their associated primary incidents, as expected. Furthermore, increasing distance is associated with declining delays.

Based on simulation results, certain issues should be given consideration. In calculating delay impacts/costs of incidents, it is important to identify secondary incidents and analyze them jointly with their primary counterparts. This is because delay impacts of secondary incidents depend on their relationship (in terms of time and space) to the associated primary incidents. For traffic operations, incident managers and responders need to be concerned with extended primary-secondary incidents, because in such situations, the contribution of secondary incidents to delays is substantial. See Zhang et al. (2010) for more details.

Table 14: Regression Models for Secondary and Non-Secondary Incidents using Hampton Roads Data

Independent variable	**Secondary incidents**						**Non-secondary incidents**			
	Poisson Model 1		**Negative binomial Model 1**		**Zero-inflated Poisson Model**		**Poisson Model 2**		**Negative binomial Model 2**	
	Coefficient *(P* value)	**Marg. Effects**	**Coefficient *(P* value)**	**Marg. Effects**	**Coefficient *(P* value)**	**Marg. Effect**	**Coefficient *(P* value)**	**Marg. Effects**	**Coefficient *(P* value)**	**Marg. Effects**
Constant	0.047(0.948)		-0.315(0.788)		0.998(0.183)		6.065(0.000)		6.120(0.000)	
Length	0.693(0.000)	2.015	0.650(0.000)	1.835	0.638(0.000)	2.279	0.419(0.000)	87.711	0.462(0.000)	94.443
Lanes	-0.009(0.966)	-0.027	0.060(0.868)	0.170	-0.219(0.320)	-0.791	-0.443(0.000)	-92.788	-0.510(0.055)	-104.257
Curve	-0.379(0.000)	-1.089	-0.331(0.044)	-0.926	-0.387(0.000)	-1.092	-0.231(0.000)	-47.962	-0.172(0.179)	-34.987
AADT/1000	0.060(0.000)	0.175	0.055(0.004)	0.155	0.063(0.000)	0.221	0.057(0.000)	11.957	0.056(0.000)	11.354
AADT/1000Lanes	-0.036(0.287)	-0.103	-0.009(0.887)	-0.025	-0.060(0.083)	-0.215	-0.090(0.000)	-18.902	-0.079(0.117)	-16.111
On Ramp	0.180(0.001)	0.522	0.141(0.164)	0.399	0.157(0.003)	0.556	0.066(0.000)	13.826	0.015(0.860)	3.111
Off Ramp	-0.112(0.033)	-0.327	-0.074(0.455)	-0.209	-0.112(0.036)	-0.373	-0.014(0.052)	-3.013	0.072(0.450)	14.633
Police	-0.092(0.002)	-0.268	-0.076(0.105)	-0.215	-0.105(0.001)	-0.372	-0.079(0.000)	-16.566	-0.102(0.005)	-20.845
School	0.001(0.980)	0.003	-0.082(0.295)	-0.232	0.016(0.707)	0.056	-0.075(0.000)	-15.625	-0.160(0.009)	-32.687
Super-center	0.076(0.007)	0.222	0.074(0.133)	0.208	0.093(0.001)	0.328	0.038(0.000)	8.035	0.039(0.302)	7.936
Bridge-Tunnel	-0.071(0.000)	-0.206	-0.073(0.000)	-0.208	-0.046(0.000)	-0.167	-0.037(0.000)	-7.794	-0.041(0.000)	-8.471
Truck volume	-0.609(0.000)	-1.771	-0.559(0.000)	-1.579	-0.633(0.000)	-2.236	-0.261(0.000)	-54.711	-0.206(0.034)	-42.088
Summary statistics										
Dependent variable	Secondary incidents (Number of obs.=154, Non-zero obs.=110, Zero obs.=44)						Non-secondary incidents (Number of obs.=154)			
Prob. > Chi-sq	0.00		0.00		0.00		0.00		0.00	
Pseudo-R^2	0.55		0.177		-		0.606		0.058	
LR Chi-sq	921.27		146.41		544.44		19017.7		117.34	
Prob. Alpha ( )	-		0.00		-		-		0.00	
Notes: ZIP binary model Y = 5.624(0.073)-2.473*Length(0.026)-2.241*lane(0.017)-6.871*curve(0.022)-1.881*offramp(0.012)+0.367*tunnel(0.001)give (p-values in parentheses). Variables with high p-values are kept in the model for demonstration (typically they will be dropped from the final models).										

Table 15: Scenarios Analyzed for Contained and Extended Incidents

Demand (veh/hr)	Incident Durations (minutes)				Correlations	
	Contained Incidents		Extended Incidents		Time Gap (minutes)	Distance (feet)
	Primary	Secondary	Primary	Secondary		
4000	45	15	30	30	10	660
						1320
						1980
						2640
					20	660
						1320
						1980
						2640
					30	660
						1320
						1980
						2640
5000					10	660
						1320
						1980
						2640
					20	660
						1320
						1980
						2640
					30	660
						1320
						1980
						2640

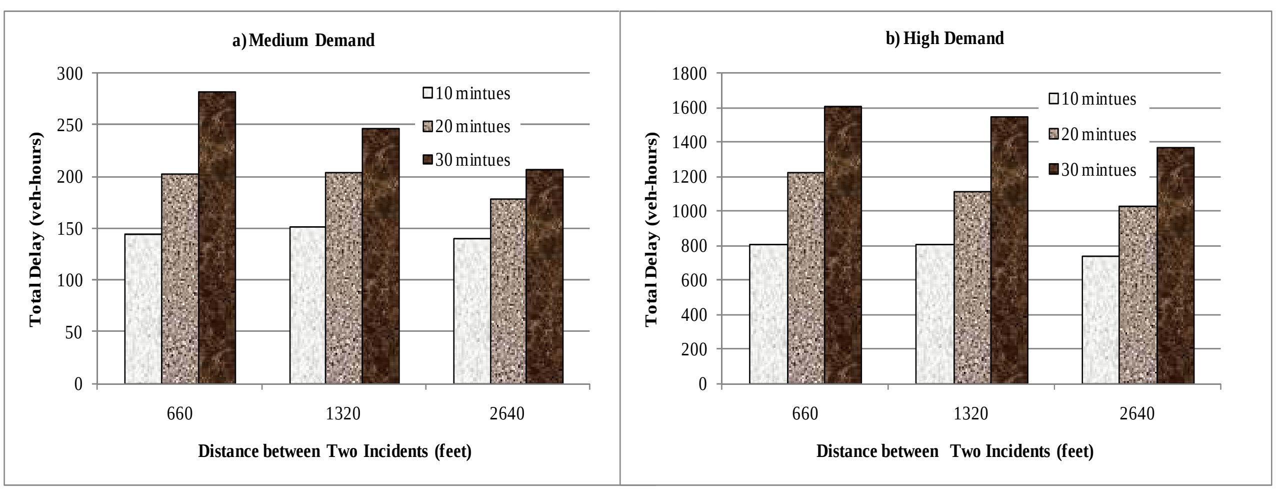


Figure 18: Total Delays for (a) Medium Demand, and (b) High Demand (extended case)

STUDY LIMITATIONS

Several limitations of this study are recognized. The database did not provide exact locations of the incidents. Instead, a segment code was used to identify secondary incidents. This may have missed primary and secondary incident pairs if two incidents occurred near the segment boundary but were located on separate segments. No actual secondary incident data could be used to validate the identification of secondary incidents (which is also the case in almost all studies of secondary incidents to date). Consequently, the identified secondary incidents are not necessarily causally related to the primary incident, while other incidents that might be related could have been missed. Another limitation of the study is the model specifications, as some of the excluded variables can have strong associations with the dependent variables. For example, the number of personal injuries and the number of vehicles responding from each agency could be important factors in incident duration, but were not available in the database obtained.

Comparing the incident data and crash data collected by police revealed that incidents recorded by HRTOC do not include a considerable number of crashes on area freeways. This implies that a portion of crashes were probably not responded to by SSP vehicles. If some of the crashes not responded to were secondary crashes, then they would have been missed from the analysis provided in this report. Given that crashes are strongly associated with secondary incident occurrence, it will be prudent for traffic operations personnel to detect and respond to a greater larger number of crashes. Furthermore, incidents that occur in bridge tunnels (e.g., HRBT) are not integrated in the HRTOC database. Therefore, a complete picture of the incidents at bridge-tunnels was not available, and some associated secondary incidents in bridge-tunnels could not be identified. This impacts the accuracy of secondary incident identification and prediction, as well as incident duration prediction.

A critical question is whether the models suitably represent the behaviors of real world systems? That is, are predictions of incident durations, secondary incident occurrence, and related delays reasonable? Based on availability of data, this study can empirically validate incident duration. The validation was done by comparing observed and predicted values. Specifically, validation of the incident duration models was conducted as follows: The incident duration model estimated by using 2006 incident data were used to predict the incident duration for 2007 incident data. The predicted incident durations for 2007 were compared with the observed incident duration, as shown in Table 16. As expected the duration model does not predict extreme values very well. This is partly because statistical models are based on capturing the central tendency in the data, rather than outliers. RMSE (Root Mean Squared Error) can be used to compare observed and predicted values and it was calculated to examine differences. The RMSE for 2007 predicted duration is 16.4, which is reasonable, and indicates that the incident models will provide realistic predictions for most incidents.

In the absence of field data regarding secondary incident occurrence and delays, tests of validity include reasonableness and theoretical consistency of the results and interpretation. The results explained above are largely consistent with a-priori expectations and with findings from earlier studies (e.g., Zhan et al. 2008). This also points to the criticality of TOCs expanding their efforts to collect data on secondary incidents occurrence, and record their physical locations and associated queues. The lack of knowledge regarding exact physical locations of incidents also precludes using traffic data from loop detectors or other sources to get speed, flow, and density measures.

Table 16: Incident validation results

	year	Number of Obs*	Mean	Std. Dev.	Min	Max
Observed duration	2006	37934	14.27	20.2	1	728
Predicted duration	2006	37934	14.27	10.22	2.13	83.05
Observed duration	2007	21870	14.00	19.4	1	541
Predicted duration (using 2006 model)	2007	21870	13.97	9.95	2.25	76.87

*Outliers are excluded from sample used in incident duration model

Despite these limitations, the findings and tools can help transportation operations centers reduce incident durations and the adverse impacts of events involving secondary incidents. Furthermore, the work provides a framework for combining operations with planning in the context of secondary incidents.

SUMMARY

With the overall goal of congestion management, this research focused on ways to deal with traffic incidents. The main focus was to define, identify, and analyze secondary incidents using Hampton Roads incident and inventory data, which was provided by HTROC. The attributes of primary and secondary incidents (in terms of their frequency and durations) were analyzed in detail, and associations with various incident and roadway characteristics were explored. Rigorous statistical models were estimated and appropriate simulations were used to comprehensively explore the occurrence and role of primary and secondary incidents in Hampton Roads. A key aspect of the study was the development of a primary-secondary incident identification tool (SiT) for planning purposes and an online incident prediction tool (iMiT) for operations management.

Currently available incident data posed substantial challenges in terms of extracting primary and secondary incidents, e.g., the exact locations of incidents were not available. Nevertheless, the research team was able to develop software that identifies secondary incidents based on the influence area of primary incidents.

CONCLUSIONS

- Clearly, primary and secondary incidents pose a substantial problem, and they can potentially cascade into larger-scale events.

- The team used traffic incident data to identify secondary incidents, which account for nearly 2% of TOC recorded incidents. Furthermore, 7.5% (N = 230/3,050) of accidents had associated secondary incidents, 1.5% (N = 479/32,673) of disabled vehicles had secondary incidents and 0.9% (N = 24/2,543) of abandoned vehicles has secondary incidents. Analysis of secondary incidents indicates that they are, on average, relatively large incidents in terms of their durations. Thus they pose significant operational challenges for incident managers.

- Spatial distributions of secondary and non-secondary incidents were identified. They show that certain locations have higher chances of secondary incidents. In many cases secondary incidents occur at hotspot locations of non-secondary incidents, e.g., the intersection of I-64 and I-264 and entrance of the Hampton Roads Bridge Tunnel are secondary incident hot-spots in Hampton Roads. Consequently higher service patrol, police and tow coverage may be considered in these regions, in order to effectively respond to secondary incidents. In rare cases, secondary incident hotspots did not coincide with non-secondary incident hotspots. Clearly, better planning decisions can be made based on information about the spatial distribution of secondary incidents. It is important to emphasize that safety service patrol availability is critical in management of primary and secondary incidents.

- A deeper understanding of the primary and secondary incident problem in Virginia was developed. Specifically, the study found that some secondary incidents are contained within the duration of the primary incident, while others extend beyond the duration of the primary incident. Nearly one-half of the secondary incidents extend beyond the duration of the primary incident, which may cause substantial system delays. Furthermore, in some cases, multiple secondary incidents happen. If multiple secondary incidents occur (typically these would be larger-scale events), their durations are typically longer (nearly 1.5 times) than the durations of one pair primary-secondary events. This study analyzed the issue of cascading secondary incidents in detail and found that such events need special attention by incident managers.

- Using statistical regression techniques, the study explored factors associated with longer incident durations and secondary incident occurrence. Some of the key factors associated with longer incident durations were crashes (as opposed to other types of incidents), freeway facility damage, more vehicles involved in incident, severe injuries, when incident affects the left shoulder or ramp, and longer lane closure times. Key factors associated with higher occurrence of secondary incidents included longer primary incident duration, primary incident is a crash and occurs during peak hours, with more vehicles involved, and on higher AADT roadways. These models enhance our understanding of secondary incident occurrence, and form the basis for predicting the durations of incidents and chances of secondary incidents.

- The study was able to untangle the complex relationship between primary incident duration and secondary incident occurrence. The study found that while the primary incident duration and secondary incident occurrence are statistically significantly interdependent, the magnitude of interdependence is relatively small. This translates to simpler model estimation, i.e., separate models for duration and secondary incident occurrence can be estimated.

- The study found that some secondary incidents add substantial network delays, while others do not. Simulation results show that total delays substantially increase as the time gaps between primary and secondary incidents increase; and for those secondary incidents that end after their associated primary incidents, increasing the distance between the locations of primary and secondary incidents lessens the delays.

- This study produced research that is implementable. This study developed and applied the dynamic queue-based tool (SiT) to identify primary and secondary incidents from historical incident data, and 2) incorporated the models developed for incident duration, secondary incident occurrence, and associated delays in an innovative online prediction tool (iMiT). The primary and secondary incident identification method can be used on incident data from other years (or data from other regions), as long as the fields are consistent with the 2006 Hampton Roads data format. This tool (SiT) allows users to identify primary and secondary incidents in the same and opposite directions. (Results showed a substantial number of opposite direction secondary incidents.) Also, multiple secondary incidents over segments associated with one primary incident can be identified through a queue-based module. However, users have the opportunity to use fixed or variable spatial and temporal boundaries, based on data availability. The online tool can predict the duration of an incident, chances of secondary incidents, and associated delays in real-time, given certain inputs about the incident.

- Although the tools developed in this study (SiT and iMiT) are currently calibrated using Hampton Roads data, the methodology is transferable to other regions of the Commonwealth. Ultimately, these tools are intended for use in transportation operations centers throughout the Commonwealth.

RECOMMENDATIONS

1. *VDOT should pay particular attention to managing incident congestion by comprehensively and continuously identifying primary and secondary incidents and using real-time and predictive information to improve operations by responding effectively to incidents and avoiding occurrence of secondary incidents.* This assumes the availability of incident management resources that include service patrols. A number of improvements can be identified, based on the study results. These can be broadly categorized as data collection/integration, planning/operational response, and further research. Specific actionable recommendations follow.

2. *In preparing performance measures reports, VDOT Transportation Operations Center analysts (where available) should use primary and secondary incidents as additional performance measures.* Secondary incidents should be reported and monitored closely. Specifically, a baseline should be first established for primary and secondary incidents, in terms of their frequency, durations, and spatial distributions. Subsequently, secondary incident reduction targets should be established. The primary and secondary incident identification tool (SiT) developed in this study should be applied to incident data collected by the transportation operations centers. A logical next step will be to identify and analyze secondary incidents throughout the Commonwealth of Virginia.

3. *VDOT Transportation Operations Center analysts (where available) should identify secondary incident hot-spots.* Based on the Hampton Roads incident data, these would include the entrance to HRBT, and I-64/I-264 interchange. Other choke points, especially at bridge-tunnels should be monitored for occurrence of secondary incidents. This study has

generated valuable information about the locations of secondary incident hot-spots in Hampton Roads, which can be viewed as initial input to quantifying the problem.

4. *After primary and secondary incidents are identified and analyzed for a region, VDOT's Regional Traffic Operations Managers should give priority (in terms of monitoring, patrol coverage, and traveler information dissemination) to secondary incidents hot-spots.* Priority should be given to secondary incident hot-spots because they can extend the duration of a primary incident, causing longer delays.

5. *To make informed operational response decisions, transportation operations center managers and their staff should use the online prediction tool, iMiT.* Prior to initiating use of the tool however, it should be fully validated for the region in which it will be used. Real-time incident information can be generated by iMiT, the online tool developed in this study. After proper testing, validation, and integration, it can help allocate resources effectively to where they are most needed. In particular, when an incident occurs, transportation operations center staff should pay particular attention to predicted durations, chances of secondary incidents, and associated delays; if these predictions cross certain thresholds (e.g., higher than 10% chance of a secondary incident), then additional resources, if available, should be allocated to handle that incident. Also, after further testing and validation, predicted incident duration and delay information (obtained by applying iMiT) can be disseminated to roadway users via changeable message signs and highway advisory radios to encourage safer lane changing and detouring, where appropriate.

6. *To minimize incident clearance times and chances of secondary incidents, VDOT transportation operations centers should a) continue and expand the use of service patrols to implement aggressive incident clearance procedures (where appropriate), b) continue and strengthen their outreach to other response agencies using the Regional Concept of Transportation Operations or similar mechanisms, and c) improve incident scene management to avoid distractions from both the same and opposite directions.* Quick clearance of major incidents should receive priority, and it is critical to have service patrols for this purpose. Moreover, the Regional Concept of Transportation Operations (RCTO) in Hampton Roads has facilitated stakeholders to collectively work on collaborative incident management solutions. Support for such mechanisms should continue and be strengthened. Furthermore, transportation operations centers should monitor the end of incident-related queues, where possible, and provide motorists with information and warnings about the length and tail of the queue such that approaching motorists are not forced to stop or change lanes abruptly when the end of queue is encountered.

7. *VDOT Operations and Security Division staff should work to reconstitute the Statewide Incident Management Committee.* By bringing together various agencies involved with incident management, the activities of this group helped to foster a common goal of quick clearance of roadway disturbances.

8. *VDOT's Transportation Operations Centers should flag secondary incidents within the incident database whenever possible.* In terms of incident data collection and archiving, the lack of information about secondary incidents limits the ability to clearly identify and

understand primary and secondary incidents and their impacts. The provision of geo-location incident information that VDOT has recently started collecting will be valuable from the perspective of analyzing primary and secondary incidents and designing better strategies for secondary incident avoidance. Furthermore, incident data coverage should be expanded to integrate various databases. For the Hampton Roads region, this includes 1) incidents recorded by the transportation operations centers, 2) incidents recorded by the bridge-tunnel traffic control centers, and, 3) crashes recorded by the police. This will help develop a complete picture of incidents in the region.

BENEFITS AND IMPLEMENTATION PROSPECTS

Clearly, traffic incidents are a major source of delays, system unreliability, and inefficiency. Cascading secondary incidents further complicate operations and stretch VDOT response resources. By developing tools that identify and analyze secondary incidents, this research contributes toward potentially improving network efficiency. Specifically, using the identification tool (SiT) to locate secondary incident hot-spots can help monitor and more effectively respond to secondary incidents.

A key product of this research is iMiT, a tool capable of predicting (short-term) primary incident durations, the probable occurrence of secondary incidents, and associated delays. These predictions can be updated in real-time while the incident is active. Use of the online prediction tool will allow VDOT to better manage incidents. The predictive information can be used by regional traffic managers to make more informed decisions and to allocate safety service patrol/other resources more effectively.

After further testing and verification/validation in a transportation operations center, the tools can be used to generate valuable incident information which can then be disseminated to the general public. This has the potential to divert travelers to alternate routes, when major incidents occur. Application of the tools can potentially reduce primary incident durations and reduce the chances of secondary incident occurrence. The study also provides information that can support VDOT’s future investment decisions regarding incident management strategies/technologies in addition to the operational decisions about effectively dealing with primary and secondary incidents. The incident management strategies that are recommended in the report for VDOT’s consideration can enhance safety and roadway efficiency. Additional benefits can accrue in terms of potentially reducing incident durations, associated delays, fuel consumption, and emissions.

Based on communications with HRTOC, the prospects for implementation of SiT and iMiT are promising. Even though the models were developed based on archived incident datasets and existing roadway inventory, actual field testing was not performed in this study to evaluate how well models will predict incident durations and delays in real-time. After the capabilities of the tools are verified and validated with field data, the tools will need to be integrated within the traffic operations software. This will involve making the data fields in the archived and incoming traffic data consistent with the software requirements. The data required include vehicular incident records and freeway segment characteristics. The vehicular incident records must contain a unique incident identification number, start date, start time, duration, route name and direction, a segment location code, and affected lanes.

Assuming that TOC staff is willing to use the new tools, the research team recognizes that the software interface will need improvement. It will be valuable to know how well the tools perform in terms of estimation and predictions and the consequences of the tools' poor (or good) performance, and needed improvements. Special training on using the tool is not needed—a simple demonstration should be sufficient.

The tools offer to quantify various performance measures (incident durations, secondary incident occurrence, and delays) that the Hampton Roads TOC staff has confirmed will be valuable to them. In addition, the Regional Concept of Transportation Operations (RCTO) effort in Hampton Roads attempts to improve incident management on freeways throughout the region. One of the six objectives of the RCTO is to decrease secondary incident occurrences, with a target of a 25% reduction over three years. To estimate secondary incident occurrence, a simple version of the secondary incident identification tool was provided to the consultants working on RCTO. Furthermore, the knowledge and tools developed in this study was used to quantify the implications of a 25% reduction. It was decided to estimate the costs incurred by travelers due to secondary incident congestion. The estimated secondary incident delays were verified using delay data published in the 2009 edition of the Urban Mobility Report produced by the Texas Transportation Institute.

All secondary incidents from the 2006 incident data (N=899, identified using the queue-based method with actual duration and including opposite direction secondary incidents) were analyzed further by calculating delays using deterministic queuing (D/D/1). Specifically, total delays and monetary costs associated with delays, fuel consumption and emissions were calculated (details on these calculations are available from the authors). In a few cases, extreme delay values were truncated based on realistic assumptions, e.g., length of the queue associated with an incident was capped at 15 miles. In some cases, multiple secondary incidents occurred, but for delay calculations, they were treated independently. As pointed out earlier, a significant number of police-reported crashes were not contained in the incident database, resulting in potential underestimations of costs. For incidents that last longer than one hour, the delay calculations used time-varying arrival profiles instead of constant arrival rate during the hour. Hourly traffic profiles based on available 2006 traffic data (i.e., traffic profiles by time of day for freeway segments) in Hampton Roads were used. However, the average traffic profile used in this analysis may not necessarily be reflective of the traffic pattern on the day of the incident. In some cases, traffic demand exceeded normal capacity of the roadway at the time of the incident, indicating the presence of recurrent congestion. Note that the 2006 incident data shows that they occur more frequently during peak periods. In such cases, recurrent congestion was calculated separately from incident-induced congestion. Fuel costs were calculated assuming 0.87 gallons/hour of delay, and a cost of $2.50 per gallon. The emission calculations and associated costs were based on values available from the federally-sponsored STEAM model.

The number of secondary incidents contained within the primary were 51% (N=454) and the extended events were 49% (N=435). The value of time for motorists was assumed to be

$15.47 per hour of delay and for commercial trucks $102.12 per hour (TTI mobility study, 2009). Vehicle occupancy was assumed to be 1.25, based on the TTI report. The overall delay, fuel and emission costs due to secondary incidents alone (not counting the delays associated with primary incidents) are estimated to be $4.46 Million in Hampton Roads; this relatively conservative estimate is based on 14% of the secondary incidents resulting in delays. A 25% reduction of secondary incident delays, which is an implication of the stated goal of Hampton Roads RCTO, can be estimated at $1.11 Million ($0.95 Million if we consider the costs of delay alone). This also provides an estimate of the potential benefits from implementing the recommendations of this study.

To verify these results, data from another source was used. The 2009 edition of the Urban Mobility Report produced by the Texas Transportation Institute provides estimates of total delay for many urban areas. These estimates include both recurring (congestion) delay and non-recurring (incident) delay. For the Hampton Roads region, delay caused by non-recurring congestion is estimated to be 2.1 times that of delay resulting from recurring congestion. Using the tables presented in the Urban Mobility Report and incident data presented in this report, the potential benefits of implementing the recommendations of this study can be estimated. Parameter values used in the calculation are presented in the Table 17.

Table 17: Parameter values used for benefit calculation

Parameter	Source	Value
Total annual delay for Hampton Roads (As presented in the UMR):	UMR	25,906,000 person-hours
Delay attributable to freeways (based on % of VMT)	UMR	11,785,600 person-hours
Freeway Incident Delay Ratio (UMR)	UMR	2.1
Annual freeway incident delay (UMR)	UMR	7,983,794 person-hours
Percent of incident delay attributable to secondary incidents* (this study)	This study	3%

* Used as a surrogate for % of delay attributable to secondary incidents

Using the values above, the benefit of reducing the number of secondary incidents by 25% (an implication of the stated goal of the HR RCTO) can be calculated as follows:

- Reduced delay estimate = Annual freeway incident delay x 25% of secondary incident delay
- Reduced delay estimate = 7,983,794 person-hours x 0.25 x 0.03
- Reduced delay estimate = 59,878 person-hours

In terms of a monetary benefit, using the values of time indicated above (and 3% commercial trucks), the overall delay, fuel, and emission costs due to secondary incidents alone are estimated to be $4.93 Million, which is close to the estimate obtained earlier. A 25% reduction of secondary incident delays can be estimated at $1.23 Million. Therefore, reducing delays associated with secondary incidents in Hampton Roads can result in a monetary benefit to users. Overall, substantial benefits are expected from implementing the recommendations given in this study and preventing incidents from cascading into larger events.

ACKNOWLEDGMENTS

Special thanks are extended to the Virginia Center for Transportation Innovation and Research, Virginia Department of Transportation, for sponsoring the study and Ms. Cathy McGhee for ably managing the project. Ms. Kaixin Yang and Ms. Libin Zheng contributed in the early part of the project. Transportation Research Institute at Old Dominion University provided additional financial support. The authors are very thankful to Dr. Camelia Ravanbakht, and Mr. Stephany Hanshaw of VDOT for their help and support. Also, our sincere thanks to Mr. Keith Nichols and Mr. Matt Merrill for their help with the data and project implementation.

We are thankful to reviewers of project related papers. Specifically, the project has received national attention and recognition, as reflected in presentation of five technical papers at the 2009 and 2010 Annual Meetings of the Transportation Research Board, Washington, D.C. Three of these papers will appear in Transportation Research Record, Journal of Transportation Research Board and one in the ASCE Journal of Transportation Engineering. Two more related papers were submitted to the 2011 Annual Meeting of the Transportation Research Board. Additionally, the project has benefited greatly from the TRB peer-review process and comments received during presentations of project results in several forums.

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APPENDIX A
SECONDARY INCIDENT IDENTIFICATION TOOL

Introduction

The Secondary Incident Identification Tool (SiT) is designed and implemented to identify and analyze secondary incidents on freeways by utilizing vehicular incident records, freeway segment characteristics, representative traffic distribution curves on critical segments, and capacity reduction parameters from HCM 2000. The tool was developed by using Visual Basic for Application (VBA) scripts, embedded in a Microsoft Excel worksheet. The current (Beta) version applies to the Hampton Roads incident dataset; it can be modified for other regions, if needed. A standardized format for secondary incident identification was developed. The format converter for Hampton Roads dataset is available upon request.

Definition and Assumptions

Theoretically, a secondary incident can be described with the aid of Figure A-1. Suppose that an incident $I(d_i, t_k)$ occurred at distance d_i from the beginning of a road section at time t_k. If another incident would happen $I(d_{i+1}, t_{k+1})$ at location d_{i+1} and time t_{k+1} due to partially queue backup of the prior incident $I(d_i, t_k)$, then it is defined as a secondary incident of $I(d_i, t_k)$. Furthermore, $I(d_i, t_k)$ is called the primary incident. $I(d_i, t_k)$ and $I(d_{i+1}, t_{k+1})$ are regarded as a primary and secondary pair.

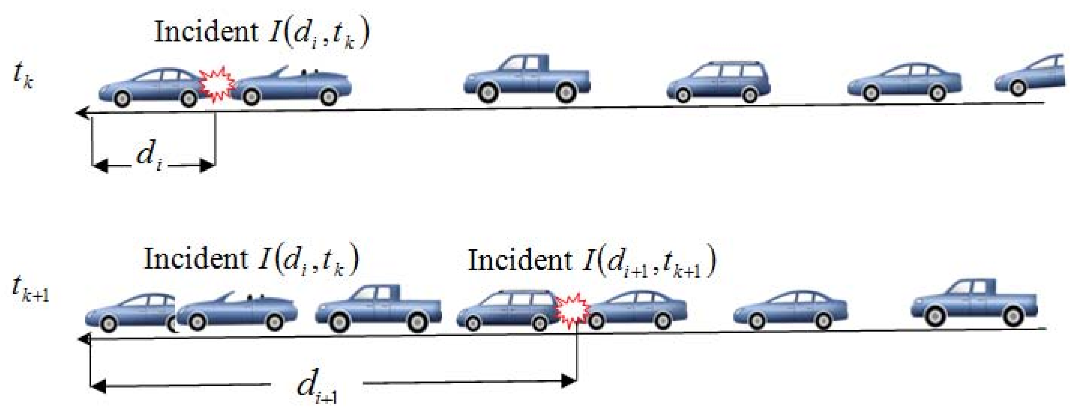


Figure A-19 Primary and Secondary Incident Scenario

It is difficult to say that a secondary incident is causally related to a prior incident using the available historical incident and road inventory data. In this regard, certain assumptions were made about the associative relationship, based on relative time and space of secondary incidents from their primary incidents. If two incidents occurred within a certain spatial range ($d_{i+1} - d_i < \Delta d$) and a temporal period ($t_{k+1} - t_k \leq \Delta t$), then they can be considered a primary and secondary incident pair.

Boundary criteria

To identify secondary incidents, temporal and spatial boundaries are needed. These boundaries can be fixed or dynamic, based on data availability. The boundaries are constraints, which are applied in the secondary incidents identification process. The tool provides various options to users who wish to identify secondary incidents that occur in the same and opposite directions. Four methods are implemented in the secondary incident identification software, as summarized in Table A-1.

Table A-18 Methods used to derive influence area of an incident, i.e., spatial and temporal boundaries $(\Delta d, \Delta t)$

ID	Method	Route direction	Spatial Range (Δd)	Temporal Duration (Δt)	Advanced Options
1	Segment-based with actual duration	Same direction incidents identified as secondary	Single Segment length where primary incident occurred	Actual duration of primary incident	Adding time to incident duration for incidents with lane blockage (These options are available in the secondary incident identification tool)
2	Queue-based with actual duration		Queue caused by primary incident (can spill over to upstream segments)		
3	Segment-based with actual duration, includes opposite direction incidents	Same and opposite direction incidents identified as secondary	Single Segment length where primary incident occurred		
4	Queue-based with actual duration, includes opposite direction incidents		Queue caused by primary incident (can spill over to upstream segments); use segment length to identify opposite direction incidents		

After determining the spatial and temporal boundaries, secondary incidents are identified as those that satisfy the defined spatial and temporal constraints. Note that some secondary incidents may have more than one associated “primary incident.”

Implementation

The process flow chart for secondary incident identification is illustrated in Figure A-2.

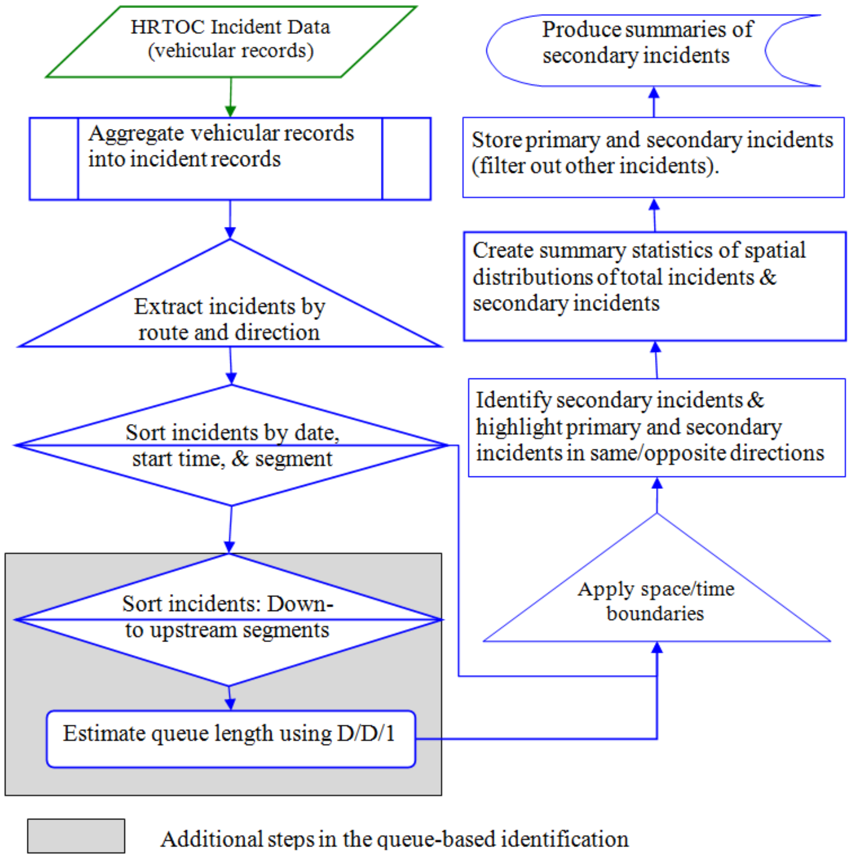


Figure A-20 Primary and Secondary Incidents Identification Flow Chart

System Requirements

To run the secondary incident identification tool, the user should have Microsoft Excel (2003 or later versions) running under Windows XP or VISTA. The program does not require separate installation as it is executed within MS Excel.

Data Requirements

To perform secondary incident identification, the first step is to ensure that all necessary input tables for the selected method are available. The spreadsheets needed for secondary incident identification are described as follows:

- Vehicular incident spreadsheet. The incident worksheet is required by all methods described above. The HRTOC collected vehicular incident records during the years analyzed in this study. A yearly table can be created, containing all incident involvements for that year. The data fields generally include: incident identification number, start date, weekday, start time, weather, route name and direction, location code and safety service patrol response variables, etc.
- Route summary spreadsheet. The route summary sheet is required for all methods. The table lists roadway segment information. It is organized according to route direction. Each record contains a segment code, segment length, whether the segment has a curve or

not, AADT, etc. Segments in one route direction are organized according to their spatial distribution order starting from the downstream end and going toward the upstream end.

- Traffic distribution worksheet. The traffic worksheet is required only for the queue-based methods; it includes different representative traffic profiles for critical segments during different days of the week along freeways (by direction). If the traffic distribution profile is not specified, a default regional average daily traffic distribution profile is used by the program.

- Capacity reduction worksheet. The capacity reduction sheet is required for application of the queue-based method. The table is taken from HCM2000 Exhibit 22-6: “Proportion of Freeway Segment Capacity Available under Incident Conditions”.

All worksheets have their own specific format. Particular care should be taken when updating these sheets with new data, ensuring that appropriate format is preserved.

Identification Procedure

The major steps taken for secondary incident identification basically follow the process flow chart (Figure A-2) presented above. Integrated with the Graphic User Interface (GUI), the steps are described as follows:

- Step 1: The user can run the identification tool from the FrontPage sheet by enabling the Marco and pressing the button “Run Identification Tool” (following the order indicated in the red circles shown in Figure A-3).

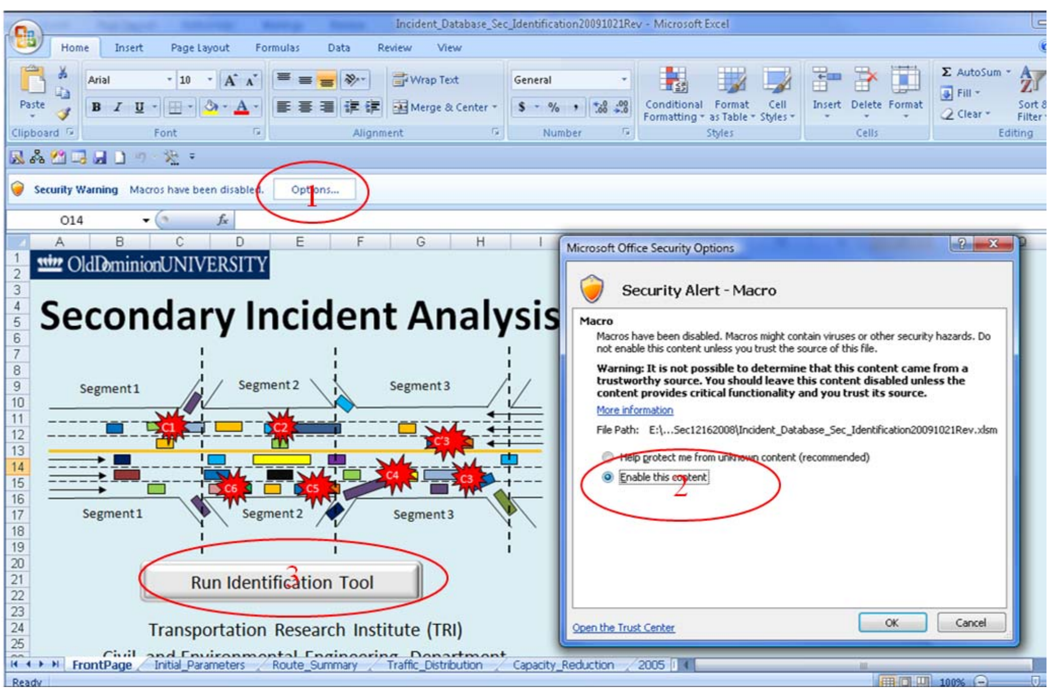


Figure A-3 FrontPage for Running Identification Tool

- Step 2: The user can run the conversion and removal module (this needs to be run only once, and it can be skipped subsequently, see Figure A-4). The main function of this module is to convert multiple vehicular incident records with the same “TMS-Call Number” into only one record with a unique incident ID. Essentially, the tool converts a vehicle file into an incident file. Incidents with multiple vehicles will become one row in the spreadsheet. New variables are created including vehicles involved in the same incident, truck involved in the incident, and whether out of state vehicle is involved in incident. Selected key variables (shown in Table A-2) are used to identify secondary incidents. After this step, an incident sheet named “YYYY_Incident” is created.

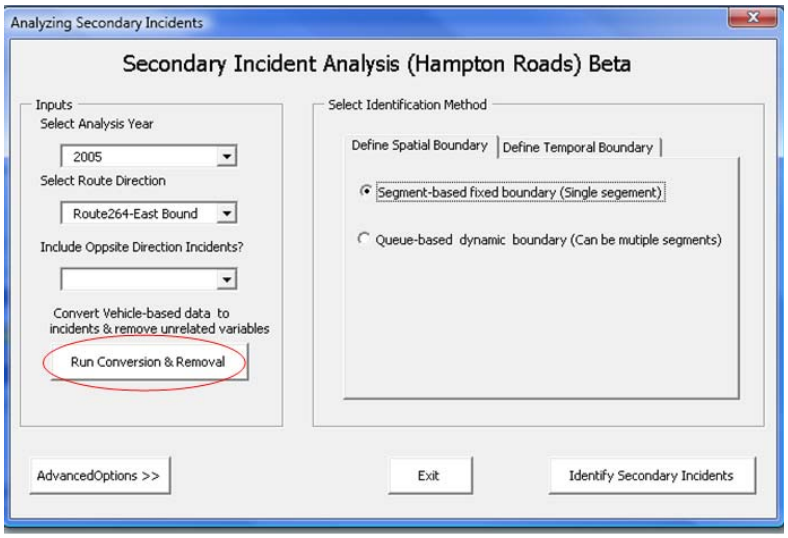


Figure A-4 Running Incidents Data Conversion and Removal Module

Table A-2 Selected Key Variables in the Incident Records

Key variable	**Definition**	**Category**
TMS_Call_Number	Incident ID	Incident Info
Start_Date	Occurrence Date	
Start_Time	Occurrence Time	
Duration	Incident Duration	
Type	Incident Type	
Number of Involved	Number of vehicles involved in incident	
TypeofInvolvedVehicles	Vehicular types involved in incident	
StatesofInvlovedVehicles	In state or out of state vehicle involved	
Weather	Weather at time of incident	Weather Info
Road Name	Name of roadway	Road Info
Direction	Roadway direction	
Location_Code	Name of Roadway Section	
Lanes Affected	Number of lanes sffected	
Lane blockage	Number of lane blocked by incident	
LaneColsureStart	Time when SSP closed the lane	Service Info
LaneColsureEnd	Time when SSP reopened the lane	

- Step 3: The user can select the route direction and specify the identification method (option for including the opposite direction incidents is shown in Figure A-5 and Figure A-6).

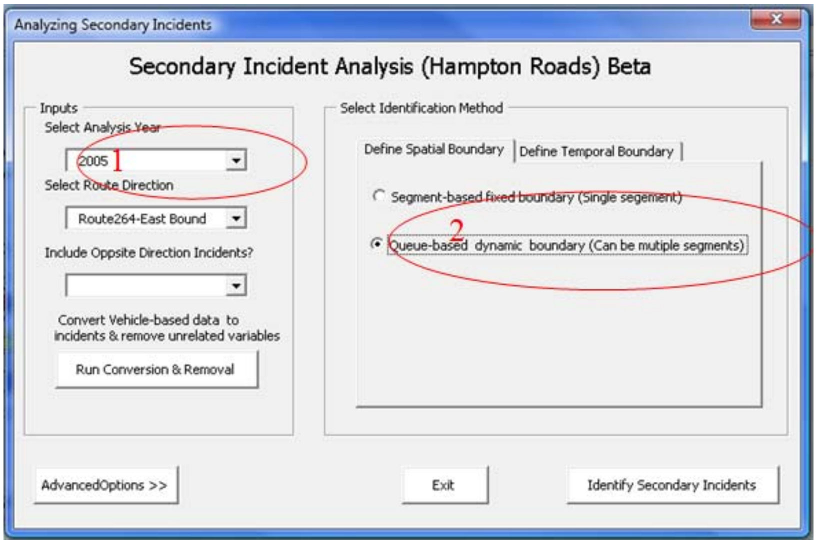


Figure A-5 Select Route Direction (1) and Define Spatial Boundary (2)

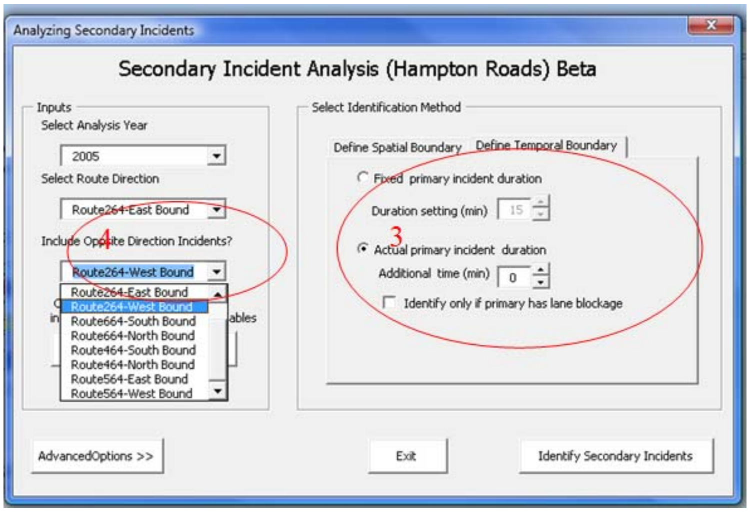


Figure A-6 Define the Temporal Boundary (3) and Include Opposite Direction (4)

- Step 4: The user can extract the incident data for each route direction. This step will be automatically performed after pressing the button “Identify Secondary Incidents.” This step queries key variables from the original dataset by route and direction. The sheet name for extracted incident data will be automatically named “YYYY_RouteXXX-West/East/South/North Bound”. Note that “YYYY” indicates the year in four digit format and “XXX” represents the route number. For example, “2005_Route264-East Bound” represents the extracted secondary incidents for route I-264 Eastbound, during 2005.

- Step 5: The user can sort the incident records by date, start time and road segment. The main function available at this step is to sort the extracted incident data according to the date, time, and segment code of freeways. The output records are grouped by route segments and sorted by date and start time (shown in Figure A-7).

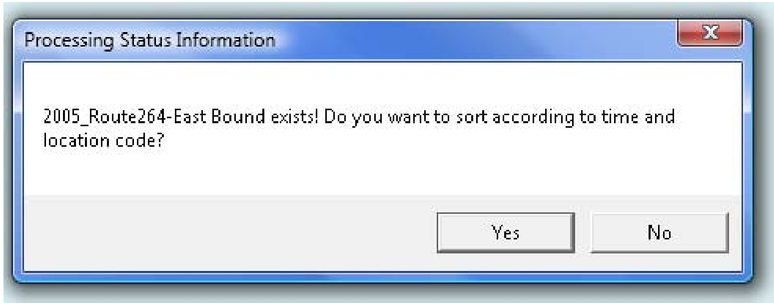


Figure A-7 Sorting Incident Data according to Time and Segment Code

- Step 6: The user can sort the incident records by roadway segments in spatial order (shown in Figure A-8). Specifically, this step sorts the incident records by adjacent route segment, which starts from downstream and progresses upstream. The purpose of doing this is to determine the extended spatial boundary (for secondary incident identification) due to queue back-ups. Note that if the identification method is not queue-based, then this step can be skipped.

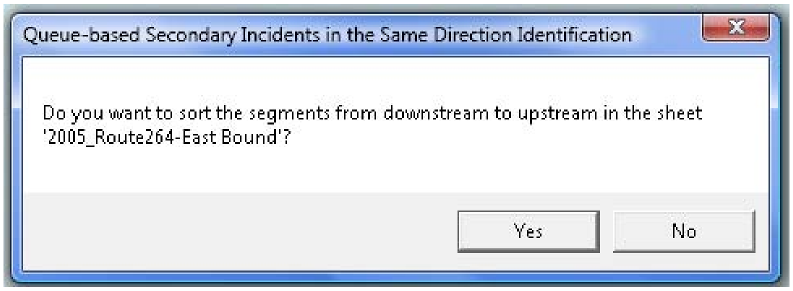


Figure A-8 Sort the incidents according to segment spatial distribution order

- Step 7: The user can run the secondary identification process by confirming through a pop-up window (shown in Figure A-9).

Figure A-9 Run Secondary Incidents Identification

- Step 8: The user can generate a summary sheet of the results containing the route geometric information (shown in Figure A-10), frequencies of incidents and different categories of secondary incidents along each segment, and average durations for independent, primary and secondary incidents (shown in Figure A-11). The tool automatically produces or updates this output sheet, and names it "Result-YYYY-RouteXXX-East/West/North/South Bound."

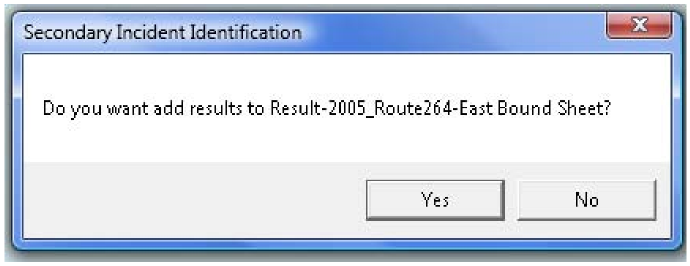
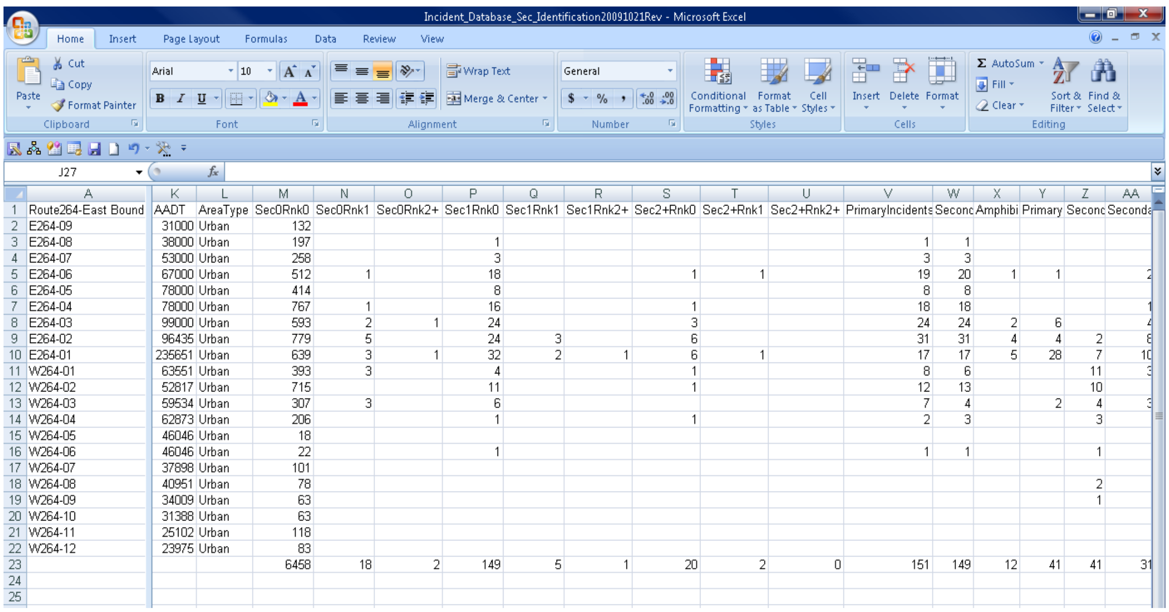


Figure A-10 Generate the Result Summary Sheet



	A	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA
1	Route264-East Bound	AADT	AreaType	Sec0Rnk0	Sec0Rnk1	Sec0Rnk2+	Sec1Rnk0	Sec1Rnk1	Sec1Rnk2+	Sec2+Rnk0	Sec2+Rnk1	Sec2+Rnk2+	PrimaryIncidents	Seconc	Amphibi	Primary	Seconc	Seconda
2	E264-09	31000	Urban	132														
3	E264-08	38000	Urban	197			1						1	1				
4	E264-07	53000	Urban	258			3						3	3				
5	E264-06	67000	Urban	512	1		18			1	1		19	20	1	1		2
6	E264-05	78000	Urban	414			8						8	8				
7	E264-04	78000	Urban	767	1		16			1			18	18				1
8	E264-03	99000	Urban	593	2	1	24			3			24	24	2	6		4
9	E264-02	96435	Urban	779	5		24	3		6			31	31	4	4	2	8
10	E264-01	235651	Urban	639	3	1	32	2	1	6	1		17	17	5	28	7	10
11	W264-01	63551	Urban	393	3		4			1			8	6			11	3
12	W264-02	52817	Urban	715			11			1			12	13			10	
13	W264-03	59534	Urban	307	3		6						7	4		2	4	3
14	W264-04	62873	Urban	206			1			1			2	3			3	
15	W264-05	46046	Urban	18														
16	W264-06	46046	Urban	22			1						1	1			1	
17	W264-07	37898	Urban	101														
18	W264-08	40951	Urban	78													2	
19	W264-09	34009	Urban	63													1	
20	W264-10	31388	Urban	63														
21	W264-11	25102	Urban	118														
22	W264-12	23975	Urban	83														
23				6458	18	2	149	5	1	20	2	0	151	149	12	41	41	31
24																		
25																		

Figure A-11 Identified Results Summary Sheet

- Step 9: The user can delete all independent incidents from the database and keep only the primary incidents and the associated secondary incident records (shown in Figure A-12). This will delete information from a new worksheet that is created, while keeping original worksheet in-tact with all the records.

Figure A-12 Delete All of Independent Incidents

One example of outputs from the secondary incident identification tool using the queue-based spatial boundary method is shown in Figure A-13. Secondary incidents occurring in the opposite direction are also identified in this example, and marked with different color than same direction secondary incidents.

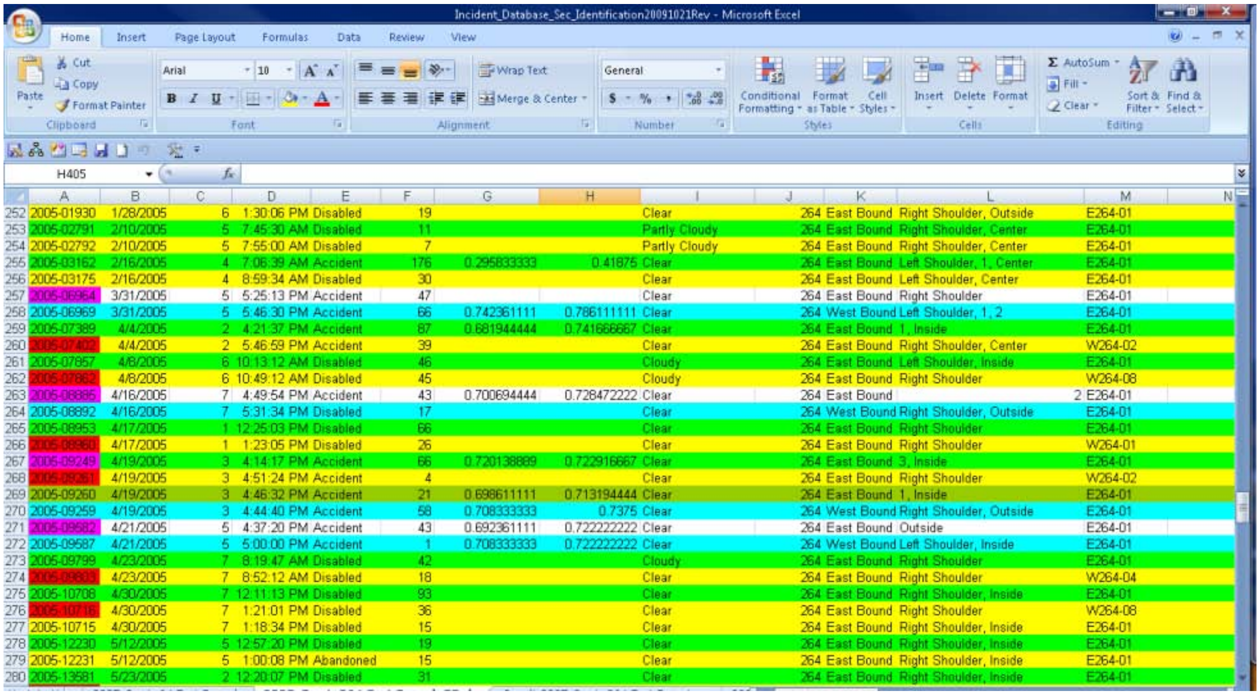


Figure A-13 Samples of Identified Secondary Incidents

Primary incidents are highlighted as green and are immediately followed by their secondary incidents, colored yellow. The pink-colored cells in the first column indicate that this incident had a secondary incident in the opposite direction. A red color in the first column means that this secondary incident occurred on an upstream segment due to a queue backup. The primary-secondary incidents are linked. The primary incident IDs and variables are added into the associated secondary incidents' record, and vice-versa (that is, the secondary incidents' IDs and frequency are identified in their primary incidents' row). A dark green row means that some incidents play dual roles of being both primary and secondary incidents. After the user completes all the steps, the finish message box appears (shown in Figure A-14).

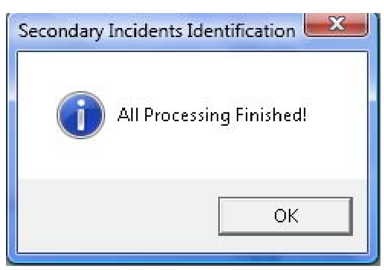


Figure A-14 Processing Finished Reminder

To summarize, the Secondary Incident Identification (SiT) tool identifies secondary incidents based on their spatial and temporal proximity to the primary incident. That is, primary-secondary incidents can be identified and analyzed separately by using spatial and temporal boundaries, which can be controlled by the user. The tool uses different colors to represent primary incidents, secondary incidents and in rare cases, incidents that are both primary and secondary. The identified primary and secondary incidents can then be summarized in a results table.

APPENDIX B
ONLINE PREDICTION TOOL FOR INCIDENTS

Introduction

The online Incident Management Integration Tool (iMiT) includes three major components: Incident duration prediction module, secondary incident probability prediction module, and delay (and queue length) predication module. The tool is developed using Microsoft Visual Basic for Applications (VBA) in MS Excel.

Figure B-1 below shows the conceptual structure for this tool. Given that an incident has occurred, the required inputs to the tool include incident information such as start time, weather conditions, and location. Desirable inputs include type of incident (accident, disablement, abandonment, other), lanes affected, and number of vehicles involved. The key outputs are predictions of incident duration, the chances of secondary incident occurrence, and associated delays caused by the incident.

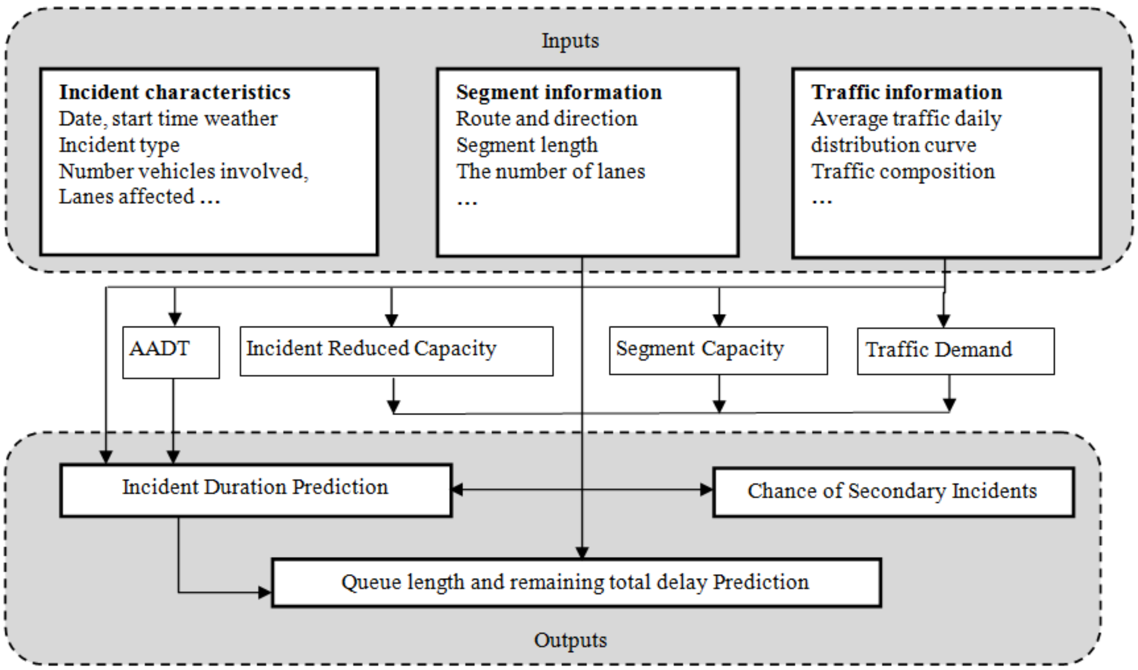


Figure B-1 Framework for Real-Time Incident Prediction Tool

Prediction of incident duration and chance of secondary incident

The short-term prediction of incident duration can facilitate incident management, but most incident duration models have limited operational value since they require knowledge about all incident variables at the time of prediction. However, in most real-time situations, incident information cannot be obtained simultaneously. Instead, information is acquired sequentially over time, which makes it difficult to do predictions, and reflect the time dimension in incident duration models. Also, all the variables needed for accurate incident duration prediction are not always available. For instance, at the start of an incident, TOC managers may only know the incident location, time of day, and detection source. An incident duration prediction model can be used at this stage, based on known incident information. When more information about the incident arrives, e.g., the incident type (crash or disabled vehicle), and multiple vehicles involved, the incident duration can be updated. However, in some situations, detailed incident information may be available at the beginning of the incident. That means various situations with different variable combination may exist. In this regard, a duration model with a fixed number of explanatory variables cannot satisfy the need, and a more comprehensive set of models are needed in order to deal with different incident situations. Table B-1 shows 28 different variable combinations used to develop the incident prediction tool.

The prediction tool developed shows a duration prediction when the user presses the "update" button which starts the incident duration prediction. Note that the displayed duration is the remaining duration based on the start time of the incident and the duration keeps coming down with the passage of time, until the user enters new relevant information and presses "update" or if the user chooses to update this prediction every ten minutes even if no new information is entered. The structure of the duration prediction module is shown in the Figure B-2.

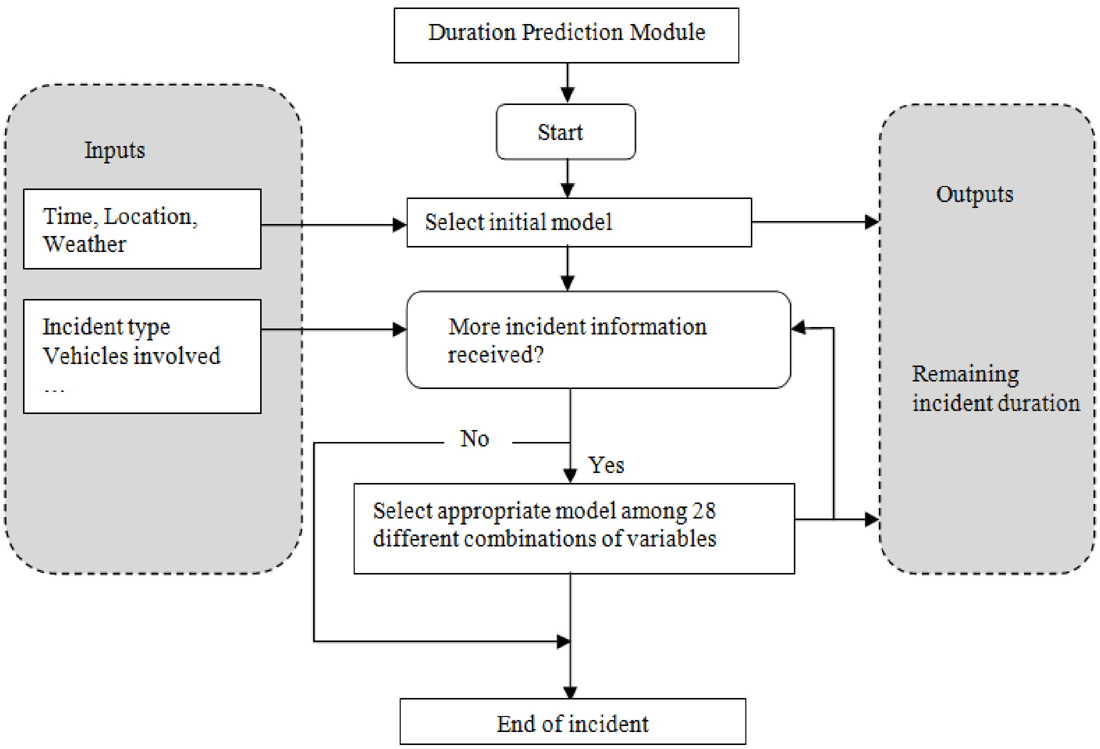


Figure B-2 Framework for Incident Duration Prediction Tool

Table B-1 Variable combination for incident duration model

	Cons.	time	Weather	Location				AADT		Detection souce				# of veh involve	Incident type			Lane close	EMS	Lane affected		
	_cons	tod	Bad weather	I264	I464	I564	I664	aadt	aadt_dy	cctv	vsp_radio	phone	other	vehicles	Dis.	Acci.	Aband.	laneclose	ems	Right shoulder	ramp	Left shoulder
1																						
2																						
3																						
4																						
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Mandatory input   Optional input   Note: Cells with white color means that the corresponding variable is not included

To develop incident duration models that can adapt to different variable combinations, statistical techniques were applied. A set of models were estimated to capture various temporal stages of incidents. Specifically, there are five temporal stages, which are the initial stage, longer than 10 minutes stage, longer than 20 minutes stage, longer than 30 minutes stage, and longer than 45 minutes. For each stage, there are 28 models that deal with different variable combinations. The tool functions in the following way: it uses an initial model from based on the available variables at that time of incident detection. Within each temporal stage, if more information becomes available, the user can update the duration prediction. Or in the next temporal stage-longer than 10 minutes stage for instance, the user can also update the prediction since the tool will automatically switch from initial model to next stage model. The longer than 10 minutes models are based on historical incident data which excludes incidents that lasted less than 10 minutes.

The tool developed allows users to predict incident durations since it uses new incident information as an incident progresses. The methodology used to develop iMiT accounts for the dynamic nature of the information acquisition process at a TOC. In this study, the real-time models are based on the 2006 incident data in the HR area. Ordinary least squares models of duration were estimated and used to make duration predictions.

Given all or a partial set of independent variables (incident characteristics such as type, lane blockage, truck involved, road geometry, and traffic information), the possibility of secondary incident is estimated from binary Logit models. The online model provides the probability of a secondary incident occurring when a limited set of variables are available. Similar to the incident duration models, 28 models with the same data structure as in the duration prediction module are used for secondary incident occurrence prediction. Note that one additional independent variable is added into the secondary incident model, which is the predicted duration from the incident duration prediction module.

Determination of current queue length and remaining total delays

The queue length at a given time and the remaining total delays on one specified freeway segment are illustrated in Figure B-3. Traffic arrives at the incident location according to curve $A_c(t)$. The departure curve $D_c(t)$ shows the departure from the incident bottleneck. The departure flow rate is initially μ^*, the reduced capacity of the bottleneck, and after the incident is cleared at time T_c, the restored capacity is μ. Times t_{n-1}, t_n represent the n-1 and nth time intervals from the incident start time (the time interval is usually15 minutes, representing the minimum period during which the arrival rate is assumed to be constant). The traffic arrival curve consists of a number of small time-dependent vehicle arrivals. The queue length for a given time t_i can be expressed as:

$$q(t_i) = q(t_{n-1}) + (t_i - t_{n-1})(\lambda_n - \mu^*) \qquad \text{for } t_{n-1,} t_i < T_c$$
$$q(t_i) = q(t_{n-1}) + (t_i - t_{n-1})(\lambda_n - \mu) \qquad \text{for } t_{n-1,} t_i > T_c$$

As long as all of the queue lengths for $t_i, t_n, \cdots t_e$ can be calculated, the remaining total delay for a given time t_i is the shaded area between t_i and T_e, which is the summation of small trapeziums between arrival and departure curves right after t_i. The areas of the first three trapeziums can be written as:

$$A_1 = \frac{1}{2}\left(q(t_n) + q(t_i)\right) \times (t_n - t_i)$$

$$A_2 = \frac{1}{2}\left(q(t_{n+1}) + q(t_n)\right) \times (t_{n+1} - t_n)$$

$$A_3 = \frac{1}{2}\left(q(t_{n+2}) + q(t_{n+1})\right) \times (t_{n+2} - t_{n+1})$$

$$\ldots$$

Thus the remaining total delay at t_i = $\sum_{k=1} A_k$

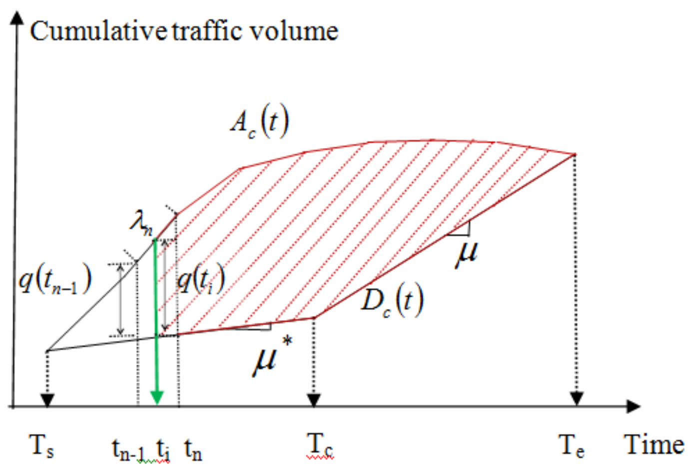

Figure B-3 Illustration of the queue length and remaining total delay at time t_i

System Requirements

To run iMiT, the user needs to have Microsoft Excel (2003 or later versions) running in Windows XP or VISTA. The program does not need installation. The user can directly copy the worksheet with the program into a destination directory, and run the tool.

Data Requirements

The data requirements are summarized below:

- Route summary worksheet. This worksheet is required for extracting freeway segment information. This table lists all available information about road segments. It is organized according to route direction. Each record contains a segment code, segment length, and AADT. Segments in one route direction are organized from downstream to upstream.

- Traffic distribution worksheet. This worksheet is required for determining the traffic demand, which includes different historical traffic distribution profiles for specified segments during different days of the week along each route (by direction). If the traffic distribution profile is not specified, a default regional distribution profile is used by the tool.

- Capacity reduction worksheet. This sheet is used to obtain the remaining proportion of the capacity due to an incident. This table is from HCM2000 Exhibit 22-6: "Proportion of Freeway Segment Capacity Available under Incident Conditions."

Online Prediction Procedure

The following steps can be used to run iMiT.

- Step 1: The user can open the Excel worksheet and enable the Marcos. The following screenshot will appear (shown in Figure B-4). The user can press "Run Program" button to activate iMiT.

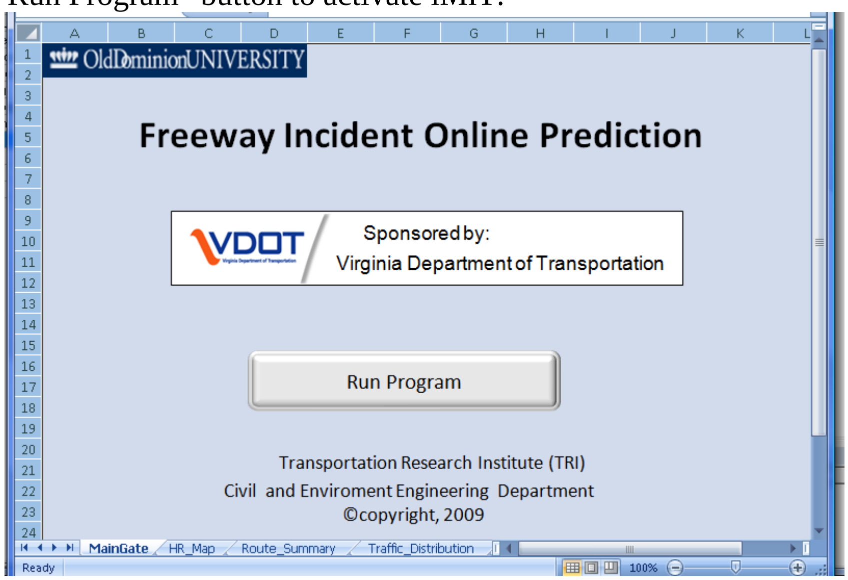

Figure B-4 Front Page of Online Prediction Tool for Incidents

- Step 2: The user is provided a map of the Hampton Roads area. There are several shortcuts (yellow circles shown in the Figure B-5) for the seven major choke points in this region including the interchange of I-64 and I-664, Hampton Roads Bridge Tunnel (HRBT), I-564 near Granby Street, the interchange of I-64 and I-264, Downtown Tunnel, High-Rise Bridge, and the Monitor Merrimac Memorial Bridge Tunnel (MMMBT). The user can click on any one of them to directly access the prediction tool's primary data entry screen. If the incident of interest is not at any of the choke points, then the user can press the button "Non-Choke Point Incident, Click Here" in the top right corner of the screen and a primary data entry screen will appear.

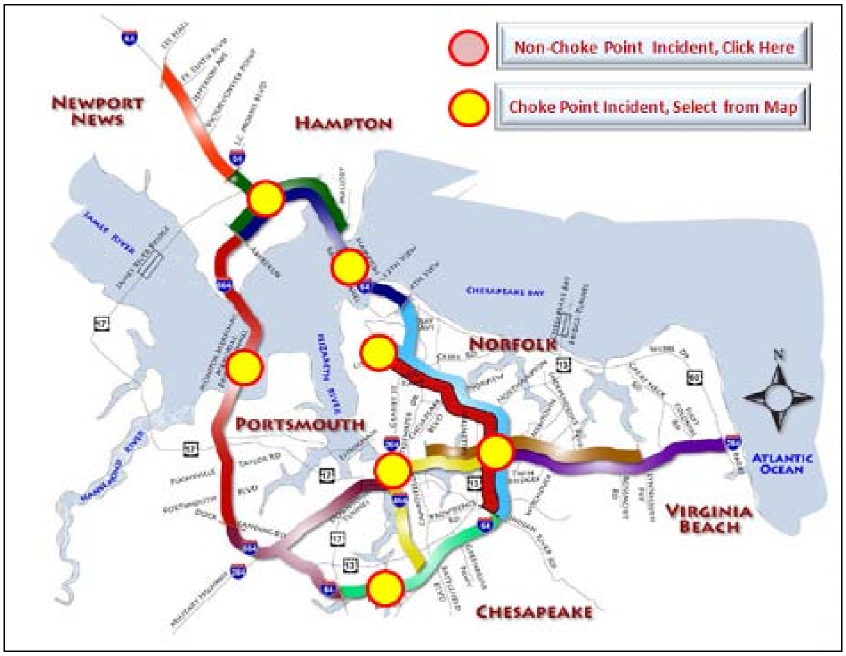

Figure B-5 Hampton Roads Area Road Map with Choke Points

- Step 3: The user can enter the primary incident input data as shown in Figure B-6. There are six major groups in the input section. They are date and time when the incident occurred and the present time. There should be no need to change anything in this portion. The next group is weather condition, which is shown in the following section. The user needs to choose any of the pre-coded weather conditions according to the prevailing conditions. The third group is incident characteristics which include incident ID, incident type, the number of vehicles involved, and lanes affected. After finishing the third group, the user can move into the incident location information, where the user can choose the route number, route direction, and segment code. Output information such as segment length, the number of roadway lanes, segment description, and AADT will be extracted from the route summary sheet and will be shown as read-only fields. After this, the user needs to verify the traffic information such as the traffic demand; they can adjust the road capacity and the proportion of capacity remaining due to incident, if needed. Finally, the user needs to select the detection source. They can then press the "REC" button to record time for the lane closure start or end time, if the incident or patrol closes a lane (or a closed lane opens up). In addition, the user can check if Emergency Medical Service is present or not, and input the number of agencies responding to the incident (when this information becomes available).

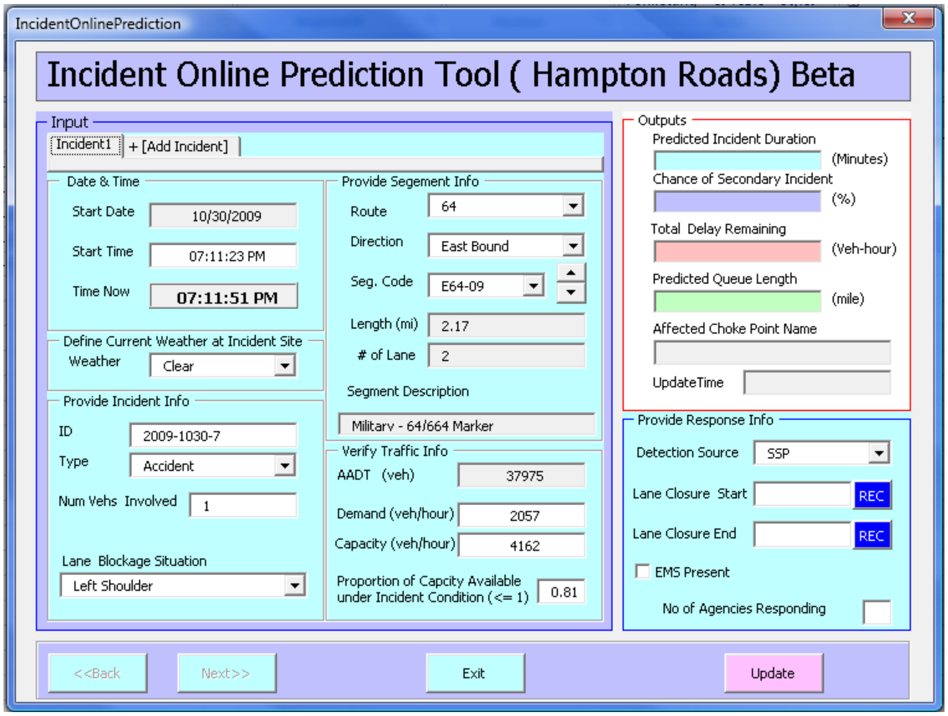

Figure B-6 Incident Prediction Tool Primary Data Entry Screen

- Step 4: After users verify all of the inputs, they can press the “Update” button and the predicted incident duration, chances of secondary incident, the remaining total delay and current queue length, and updated time will appear in the output section (as shown in the right corner of Figure B-7).

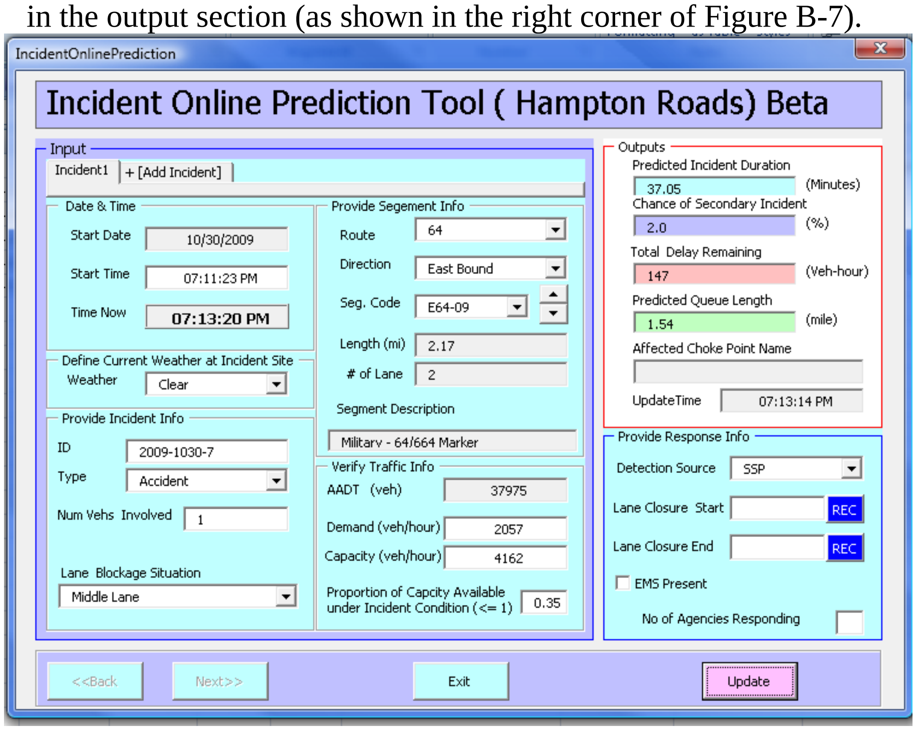

Figure B-7 Predicted Results Output Display

The predicted results will change with the passage of time. In the mean time, the incident prediction record will be archived into an "incident archive" worksheet. Users can always review the saved results by pressing the "back" and "next" button. Updated results around choke points in Hampton Roads will be structured for display in bar charts. Users can press "exit" and reopen the data entry window and repeat the above steps for another incident.

- Step 5: The user can display predictions of durations, and secondary incident occurrence according to the selected category. Four different kinds of graphs generated by iMiT are shown in Figure B-8 to Figure B-11. Note that these graphs are for demonstration only and do not reflect the actual conditions at these choke point locations.

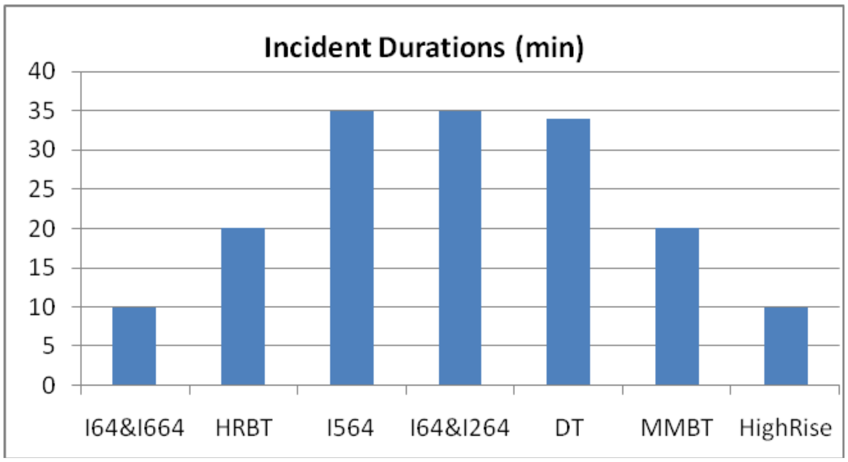

Figure B-8 Predicted Incident Durations

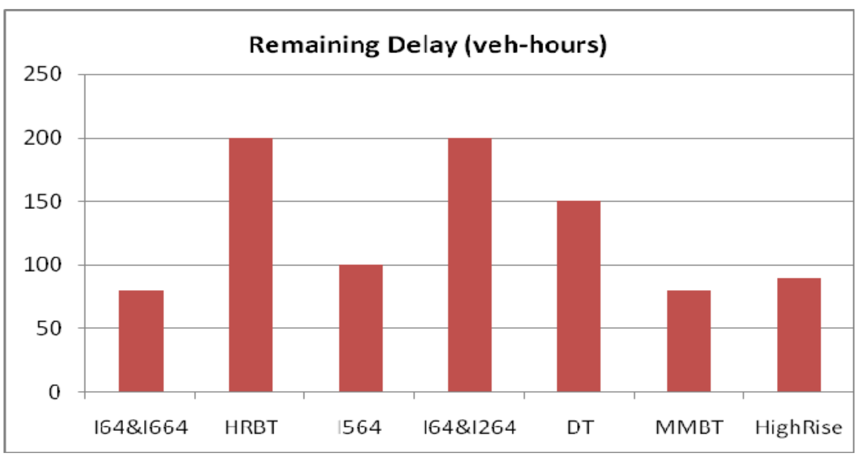

Figure B-9 Predicted Remaining Total Delay

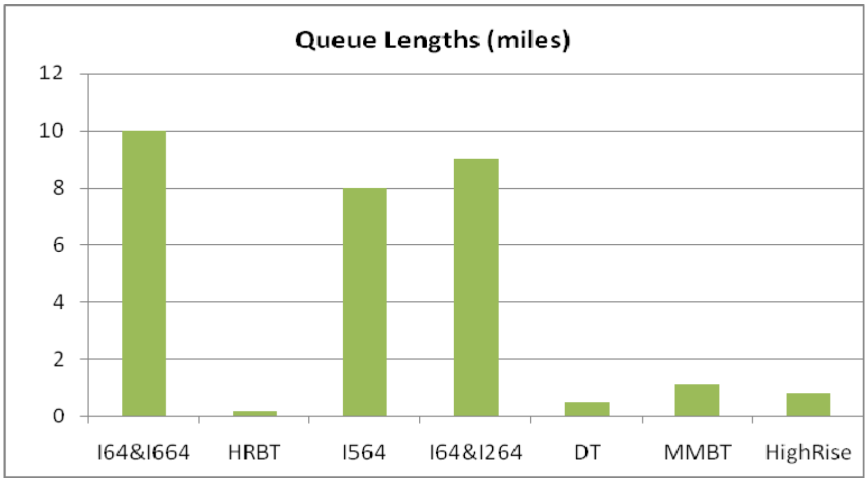

Figure B-10 Predicted Queue Lengths at Choke Points

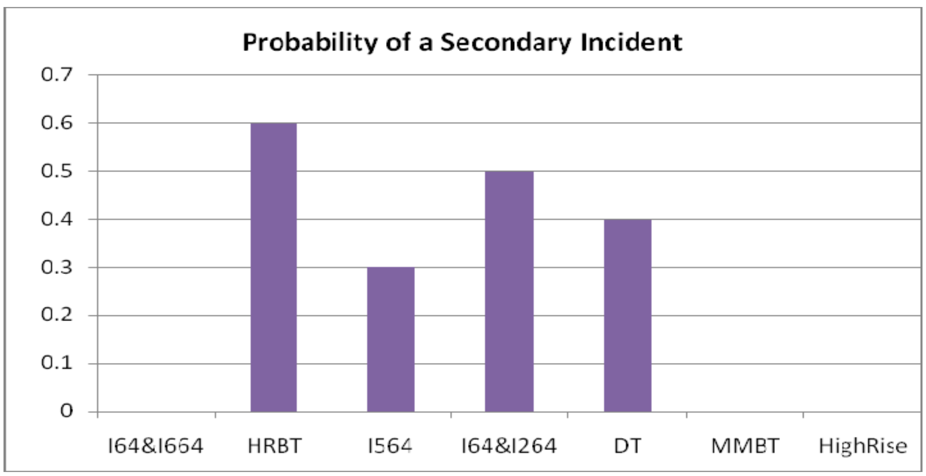

Figure B-11: Predicted Probability of Secondary Incidents