Probability of Secondary Crash Occurrence on Freeways with the Use of Private-Sector Speed Data

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Data available at https://osf.io/em2s3/.

ABSTRACT

A percentage of crashes on freeways are suspected to be caused in part by the congestion or distraction from earlier incidents. Identifying and preventing these secondary crashes are major goals of transportation agencies, yet the characteristics of secondary crashes—in particular the probability of their occurrence—are poorly understood. Many secondary crashes occur when a vehicle encounters non-recurring congestion, yet previous efforts to identify incident queues and their secondary crashes have relied either on deterministic queuing theory, or on data from uniformly-spaced, dense loop detectors. This study is the first analysis of secondary crash occurrence integrating incident timelines and traffic volumes with widely-available (and legally obtained) private sector speed data. Analysis found that 9.2% of all vehicle crashes were secondary to another incident, and that 6.2% of these crashes were tertiary to another primary incident. Secondary crashes occurred on average once every 10 crashes and 54 disabled vehicles. The findings support a fast incident response, as the probability of secondary crash occurrence increases approximately one percentage point for every additional 2-3 minutes spent on-scene in high volume scenarios.

INTRODUCTION

In the United States in 2015, 35,092 people were killed and 2.44 million were injured in motor vehicle crashes *(1)*. A portion of all crashes may be due to the congestion created by an earlier crash or incident, or to drivers distracted by the previous incident scene. These crashes thought to be a product of earlier incidents are referred to as *secondary crashes*, while the precipitating events are referred to as *primary incidents*. Primary incidents can be any unanticipated event that causes non-recurring congestion, and can include such things as crashes, disabled vehicles, and vehicle fires.

The relationship between primary incidents and secondary crashes are not well understood. Previous studies have struggled with limited available data, including minimal or no information on volumes, upstream speeds, and incident durations. The relationship between incident duration and likelihood of secondary crashes is of particular importance, as it may provide traffic incident management personnel with a definite and measurable incentive to quickly clear primary incidents. Establishing a correlation between incident duration and secondary crashes is especially important for emergency responders, as longer clearance times may lead to more secondary crashes, and therefore more time-on-scene and greater overall risk exposure.

The objectives of this study are to develop a methodology to classify crashes as secondary using incident durations and private sector travel time data, and to determine the probability of secondary crash occurrence based on the primary incident's duration, congestion levels, and traffic demand.

LITERATURE REVIEW

Secondary crashes are defined as crashes that are an indirect result of another crash or incident. These can occur in a primary incident's queue, as vehicles encounter unexpected congestion and are unable to brake in time. These can also occur in the immediate vicinity of a crash, as drivers become distracted by the incident scene.

Several studies have attempted to measure the rate and characteristics of secondary crashes. These studies differ on how they define and classify secondary crashes. There are three main approaches to secondary crash classification: crashes that occur within a predefined time and distance of a primary incident *(2–5)*, crashes that occur within a deterministic queue of a primary incident *(6–8)*, and crashes that occur within an observed queue from empirical measurements *(9–11)*. No studies have investigated the prevalence of secondary crashes considering both empirical queues and incident duration. Most empirical queue studies use in-pavement loop detection, which, although they provide high quality data, are being transitioned away from by departments of transportation in favor of private sector travel time data.

One study used crowd-sourced speed data from public-facing web sites *(12)*. The advantage of these data sources are that reported speeds are not limited to the spacing of fixed-point detectors nor the pre-determined segment lengths used by many private sector data providers, but instead are mostly geographically continuous. Unfortunately, the approach recommended in the study—using the application programming interface (API) to pull and store traffic data—violates the terms of use of all three listed providers: Bing in §8.2.b of their terms of use *(13)*, Google in §10.5.d-e *(14)*, and MapQuest in §§ 3.a.vi and 3.c.iii *(15)*.

Previous studies have used different strategies to identify secondary crashes, and these definitions were largely dependent on the available data. The most sophisticated approach was used by Yang et al. *(11)*. In their approach, an incident queue is defined as speeds that are 30%

lower than the historical average speed for that segment at that time of day and day of the week. All incidents are then plotted on a time-space diagram. A crash is considered secondary to another incident if a line can be drawn between them on the time space diagram passing only through segments with non-recurring congestion. Secondary crashes identified in this way are referred to as *queue crashes*. A visualization of this approach is shown in Figure 1.

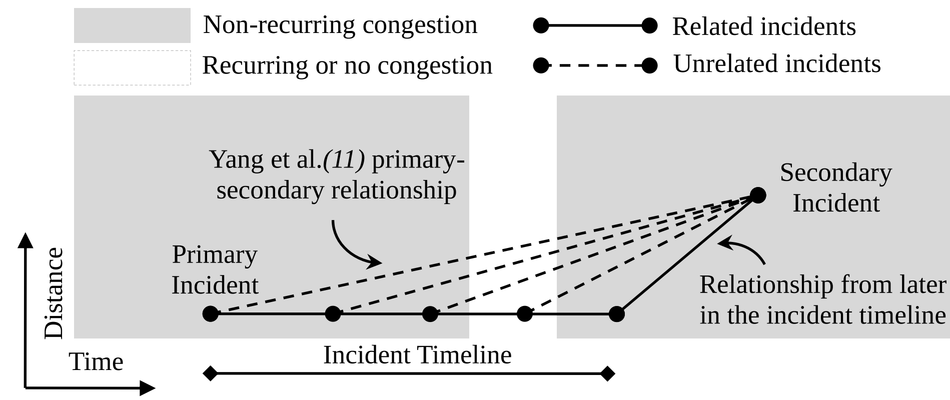

FIGURE 1 Identifying secondary incidents from the primary incident-only vs. multiple points along the primary incident timeline.

There are two major shortcomings with this approach. First, if the line between the primary incident and secondary crash passes through even a single segment not considered as non-recurring congestion, then the incidents are considered unrelated. In practice, however, there may be small segments within the time-space diagram where speeds do not meet the definition for non-recurring congestion, yet are clearly within the larger queue. The second shortcoming is that only the beginning of the incident is used to connect the primary and secondary. For incidents which do not cause congestion until later in their duration, the connecting line between primary and secondary may not experience much non-recurring congestion.

In addition to crashes that occur within the incident queue, secondary crashes may also occur in the physical proximity of a primary incident, due to rubbernecking. The secondary crashes are referred to as *proximity crashes*. To capture these crashes, Yang et al. classified any crash occurring within 30 minutes of the start of the primary incident and within 0.5 miles in the upstream direction when occurring in the same direction as a secondary crash *(11)*. They further defined secondary crashes as occurring in the opposite direction within 1 hour of the start of the primary and within 1 mile upstream. Yang et al. was forced to use a time window as they did not have access to incident duration data. In this study, the definition of secondary crashes occurring within proximity of a primary incident is any crash within 0.5 miles and within the duration of the primary incident.

There are several factors that can contribute to the risk of a secondary crash, and influence the model of secondary crash probability. For example, as upstream vehicles approach an unexpected queue, sudden braking behaviors may increase the crash risk for distracted drivers. With each driver that encounters this queue, the risk for a secondary crash may increase slightly. The number of vehicles encountering the end-of-queue has been investigated in simulation as a surrogate measure for freeway safety *(6)*. Several studies of secondary crash occurrence have used surrogates for real-time volume such as time of day *(7)* or unadjusted average annual daily traffic (AADT) *(4, 8)*. No studies have investigated the relationship between empirical demand and secondary crash rate.

IDENTIFICATION OF SECONDARY CRASHES

As part of this research, a new study of secondary crashes was initiated using incident data from the Regional Integrated Transportation Information System (RITIS) *(16)* and speed data from the RITIS Vehicle Probe Project. Unlike the detector-based speed data used in other studies *(10, 11)*, RITIS uses probe speed data collected from private sources. Speeds are provided in 5-minute intervals over irregularly shaped freeway segments, ranging in length from several feet to several miles. Similar data has been available to states via the Federal Highway Administration's National Performance Management Research Data Set (NPMRDS) *(17)*.

Incident information in RITIS is pulled from the Virginia 511 feed *(18)*, in which events are manually entered by VDOT transportation management center operators in real-time. Operators determine incident location in terms of mile markers either from Virginia State Police's computer-aided dispatch system, from VDOT field staff such as safety service patrol drivers, or from video coverage of the incident. Spatial accuracy of the incident has not been formally evaluated, but from anecdotal experience is typically within 0.1 miles of the true incident location.

The study covered the entire 75-mile I-66 corridor in both directions from January 1, 2014 to December 31, 2014. The corridor, shown in Figure 2, consists of a mix of rural sections in the west and highly-congested urban section in the Washington, DC suburbs to the east.

FIGURE 2 Map of the I-66 study corridor with mile markers.

Of the incidents logged in 2014, 156 were removed as they had no associated mile marker, 2,292 "general congestion" events were removed, and 131 events with longitudes that fell beyond the bounds of the roadway were discarded. After filtering, 8,772 incidents remained, of which 2,466 were crashes. Summary statistics of the filtered incident database are shown in Table 1.

TABLE 1 Summary Statistics of Incident Database

Incident Type	Duration (minutes)					Sample Size
	Mean	Median	Standard Dev.	Maximum	Minimum	
Collision	55.6	52	31.9	369	1	2466
Disabled Vehicle	26.7	18	27.4	518	1	5882
Fire	49.3	54	37.7	82	7	4
Vehicle Fire	53.5	43	41.5	214	7	46
Incident	23.7	18	23.8	190	1	374

To identify secondary queue crashes, the techniques developed by Yang et al. *(11)* were used with a few variations. In Yang et al.'s approach, a speed contour map of the time and space surrounding an incident is first developed. The cells on the contour map are assigned either non-recurring congestion (30% slower than historical average speed) or not. Crashes that occur upstream and after a primary, and that can be linked to a primary on a straight line through the contour map passing only through non-recurring congestion cells are considered to be secondary queue crashes. In this study, only 90% of the connecting line must pass within non-recurring congestion, to allow for small gaps in non-recurring congestion, and to capture crashes that may occur at the tail end border of a queue but not necessarily within a queue. Figure 1 shows a hypothetical example of how the approach used in this study might identify a secondary crash that was missed in Yang et al. *(11)*. Figure 3 shows an actual incident that would have been rejected when 100% of the connecting line must be within non-recurring congestion, but is classified as secondary when only 90% is required.

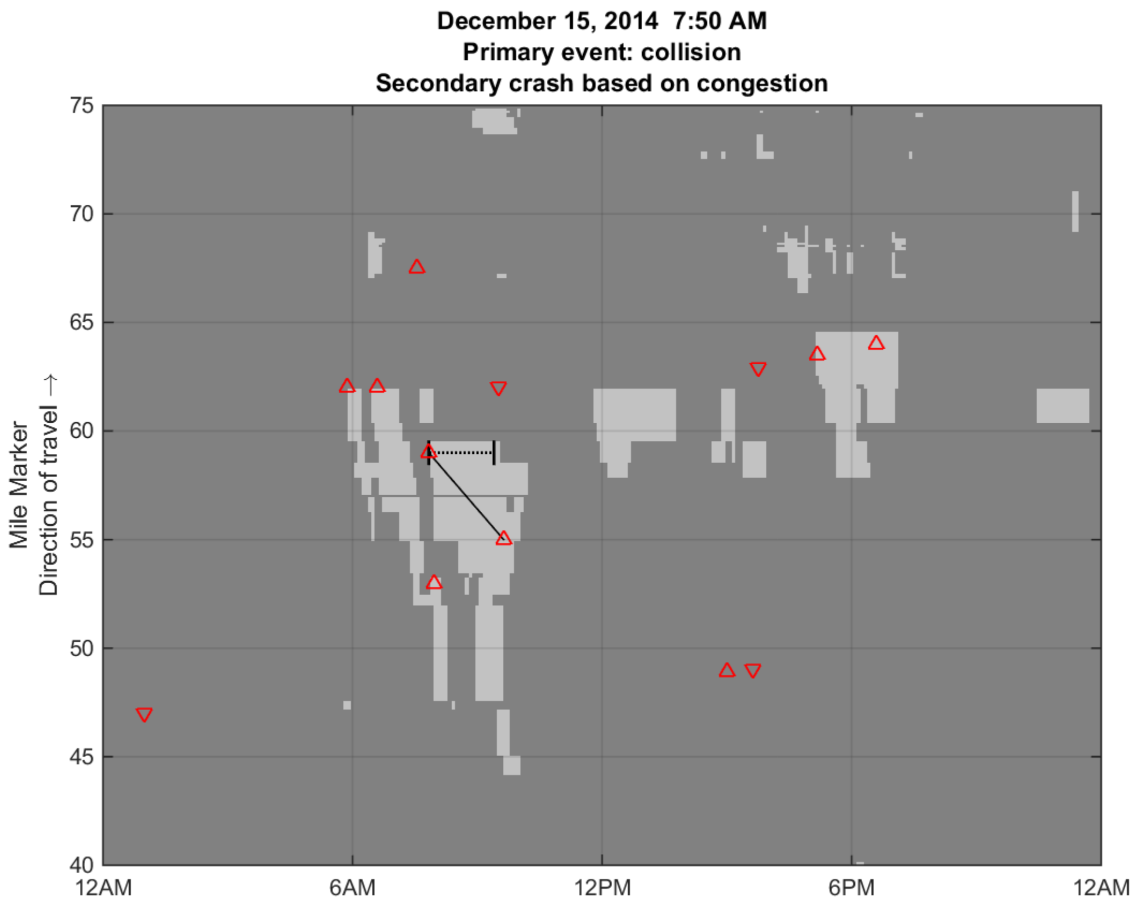

FIGURE 3 Example of a secondary crash where less than 100% of its line passes through non-recurring congestion.

The second difference between the approach used in this study and that used in Yang et al. *(11)* involves the incident duration. In their approach, the secondary crash is connected to the start of the incident. In our approach, the secondary crash can be connected to the primary incident at any point along the primary incident timeline. This allows the identification of secondary crashes where a primary incident may not have generated congested until later in the incident timeline. Figure 1 again shows a hypothetical example of a secondary crash that can only be detected by connecting the secondary crash to a point farther along on the primary incident timeline. Figure 4 shows an example of a secondary crash that would have been missed using Yang et al.'s approach. The congestion appears to be a result of the primary incident, but does not begin until well into the incident timeline. From the original record of the incident, the primary incident (a vehicle crash) occurred at 5:32 PM blocking a lane and the shoulder. Emergency responders closed a second lane at 5:59 PM, which generated more congestion. The record of the incident timeline as recorded in RITIS can be seen in Figure 5. By linking the primary and secondary crashes via any point along the incident duration timeline, the approach laid out in this paper accounts for incidents which may not generate congestion immediately, but rather at a later point in their timelines.

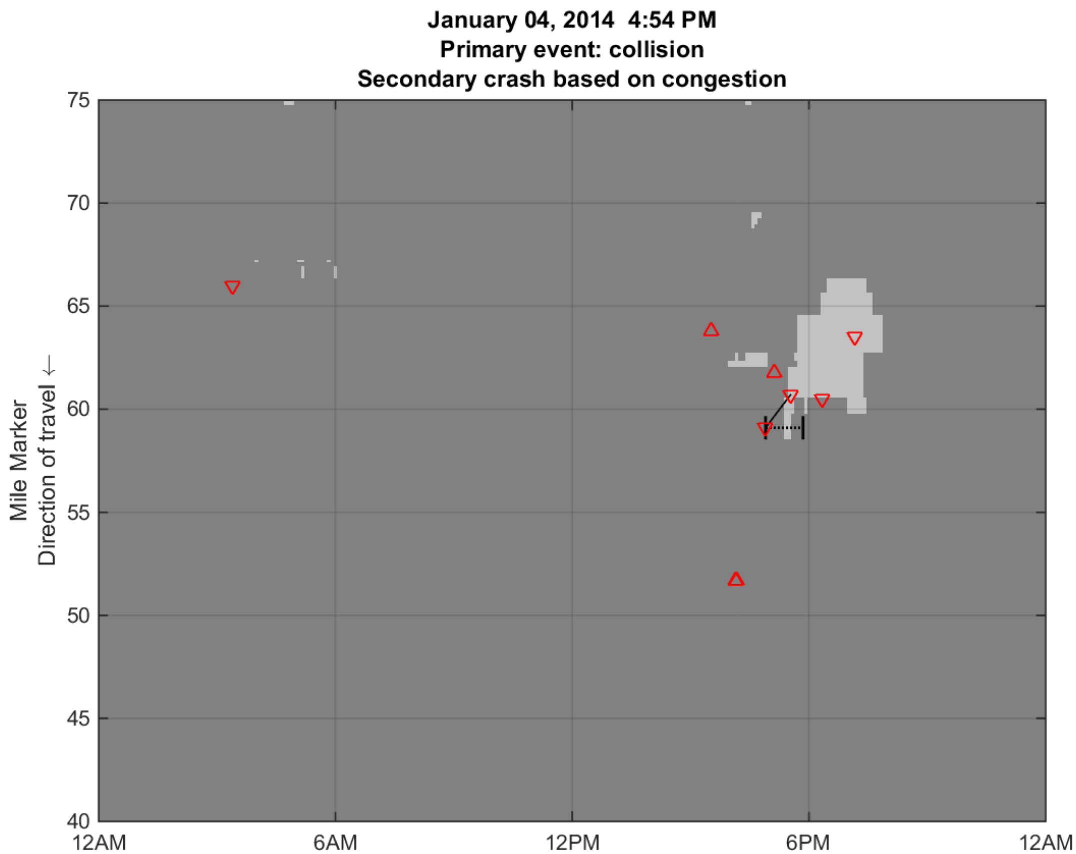

FIGURE 4 A primary incident with late-forming congestion, linking to a secondary crash.

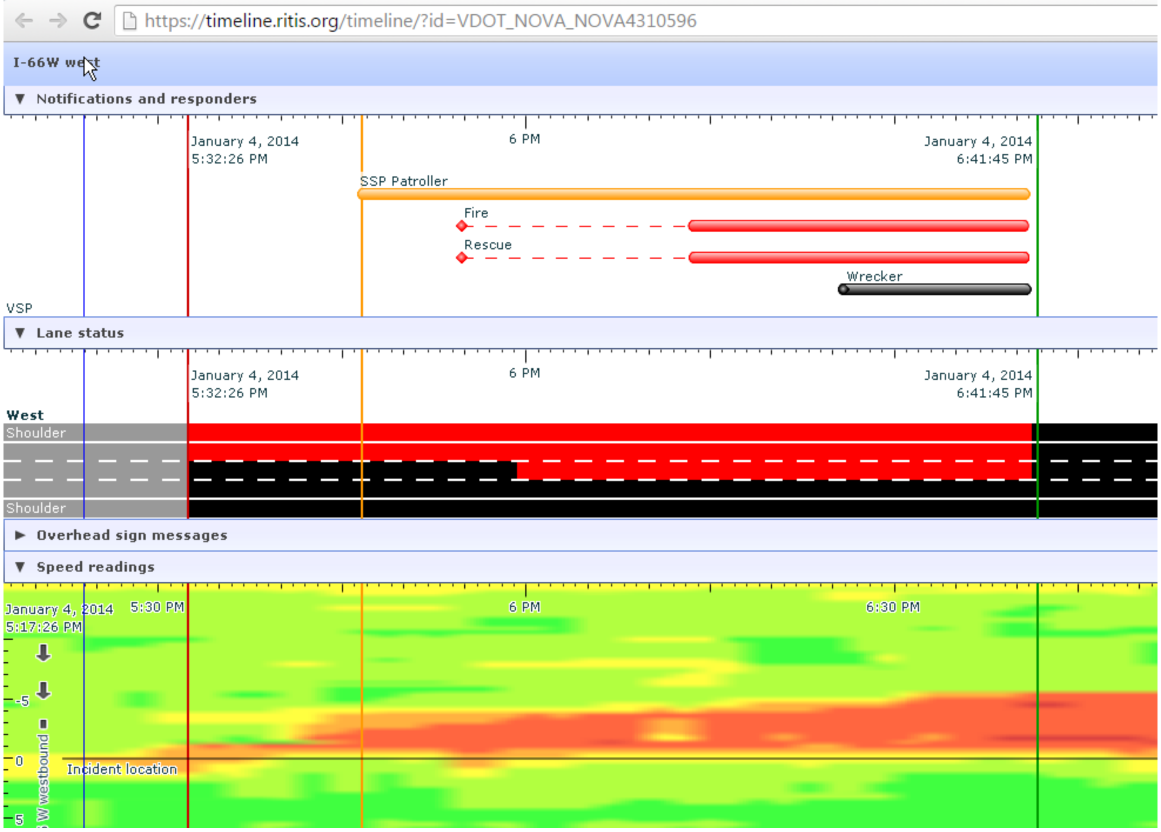

FIGURE 5 Record of the incident time line for the January 4, 2014 primary incident.

Proximity crashes are identified as occurring within 0.5 miles of the primary incident and within the duration of the primary incident. The secondary crash can occur in either direction, but must always occur when upstream of the primary incident from the perspective of the secondary vehicle. Once a vehicle has passed the primary incident, it is no longer a secondary crash.

SECONDARY CRASH RATES

Secondary crashes were identified from the RITIS database over a segment of I-66 in 2014. Of the 2466 crashes, 340 (13.8%) were classified as secondary crashes. Of these secondary crashes, 233 (69%) occurred within the incident queue and 107 (31%) were in proximity. Of those occurring in the queue, 159 (69%) were in the same direction as the primary incident, while 74 (31%) were in the opposite direction. Of those occurring in proximity, 70 (66%) were in the same direction, while 37 (34%) were in the opposite direction. A secondary crash occurred on average once every 24.8 incidents, although this rate varies based on the type of primary incident. For example, a secondary crash occurs on average once every 9.9 crashes, 54 disabled vehicles, and 7.8 vehicle fires.

Additionally, several of the crashes were found to have primary crashes that were themselves secondary to another incident. These crashes can be defined as tertiary to the initial incident, and represent cascading incidents *(19)*. A total of 21 crashes were classified as tertiary, representing 6.2% of all secondary crashes, and 0.9% of all crashes.

The approach specified in Yang et al. *(11)* was applied to the 2014 I-66 data set for a direct comparison. Several variations of their approach and the approach described here were developed. In some cases, the percentage of the primary-secondary connecting line was required as 100% in non-recurring congestion, other times only greater than 90%. In some cases a static time boundary for classifying proximity crashes was used, other times a dynamic boundary equal to incident duration was used. The results are shown in Table 2. The secondary crashes as a percentage of total crashes found in this study, 13.79%, is within the range of findings from past studies, but on the high end. Similar studies have found percentages from 15% *(20–22)* to 2-3% *(4, 7, 19)*. On applying their approach to a data set on a New Jersey freeway, Yang et al. found that 8.42% of crashes were secondary *(10)*.

TABLE 2 Comparison of Yang et al. and Proposed Classification Approaches

Approach	**Primary Incident Type**	**Prim.-Sec. Non-recurring Congestion**	**Proximity Crash Times Boundary**	**Number Secondary Crashes**	**Secondary Crashes as Percentage of Total Crashes**
Yang et al.	Crashes-only	100%	Static	104	4.19%
	Any	100%	Static	200	8.05%
Goodall	Crashes-only	100%	Static	161	6.48%
	Any	100%	Static	267	10.75%
	Crashes-only	> 90%	Static	183	7.37%
	Any	> 90%	Static	306	12.32%
	Crashes-only	> 90%	Incident Duration	228	9.16%
	Any	> 90%	Incident Duration	342	13.79%

Visualizing such a range of crashes over time and space is challenging. Figure 6a shows all secondary and tertiary crashes in 2014 on a single chart, with all primary incidents plotted at the origin for direct comparison. The x-axis represents the time after the initial incident, while the y-axis represents the distance from the initial incident (negative distances are upstream, while positive distances are downstream and generally represent secondary crashes in the opposite direction lanes). Histograms on both axes show the distribution of secondary crashes. From the figure, one can see that despite the wide-range of time and space between some primary-secondary pairs, the vast majority occur within a mile and within one hour of the primary. For comparison, Figure 6b shows the same chart but with only secondary queue crashes, ignoring proximity crashes.

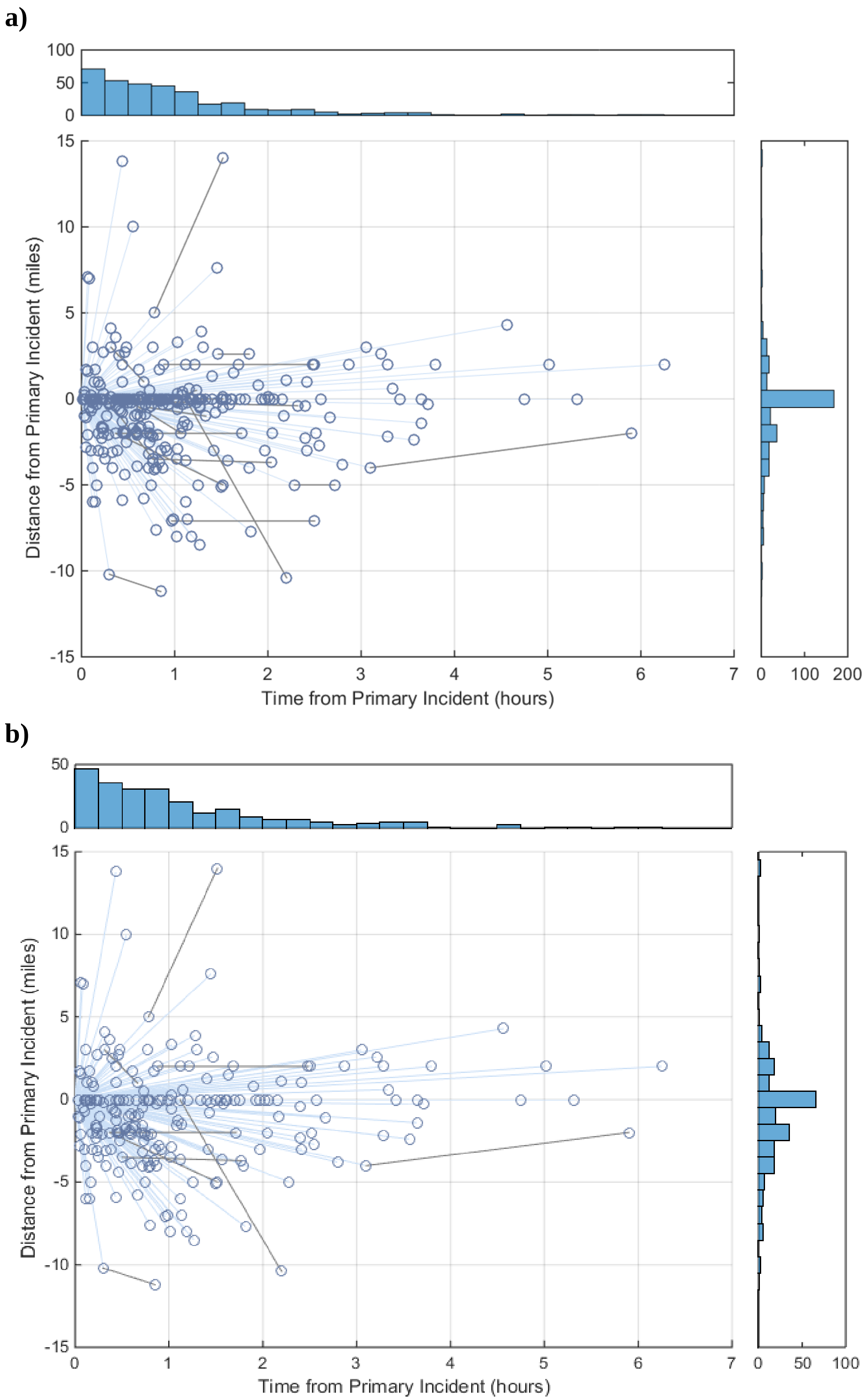

FIGURE 6 Secondary and tertiary crashes according to the time and distance from the primary incident: a) all secondary crashes, b) queue crashes only

MODELS OF SECONDARY CRASH PROBABILITY

Model Development

A model was developed to determine the probability of a secondary crash occurring over time. The model considers three factors: whether or not the incident generated congestion, the duration of the incident in minutes, and the estimated number of vehicles that encountered either the incident in the same direction (if no congestion) or the queue (if congestion was present). The factors were fitted to a binary logistic regression model using Minitab software.

Number of Vehicles Encountering the Queue

There are several factors that can contribute to the risk of a secondary crash. As vehicles upstream approach an unexpected queue, sudden braking behaviors may increase the crash risk for distracted drivers. With each driver that encounters this queue, the risk for a secondary crash may increase slightly. The number of vehicles encountering the end-of-queue has been investigated in simulation as a surrogate measure for freeway safety *(6)*. Several studies of secondary crash occurrence have investigated the effect of volume, but only using surrogate measures for volume such as time of day *(7)* or unadjusted average annual daily traffic (AADT) *(4, 8)*.

Real-time volumes were estimated as part of this study to determine the effect of the number of vehicles encountering non-recurring congestion on secondary crash occurrence. AADT values were obtained from the Virginia Department of Transportation *(23)* and adjusted into hourly volumes using data from continuous count stations. As continuous volume measurements are collected somewhat sparsely on most freeways, some geographic extrapolation was required.

Two continuous count stations deployed on I-66 were used in this study. One was located at mile marker 72, approximately two miles from the eastern terminus of the study area. The other was located at mile marker 30, approximately 6 miles beyond the western terminus. I-66 is restricted to high-occupancy vehicles only on all lanes during peak hours on sections east of I-495. Therefore, hourly volumes often decrease during peak hours, in contrast to sections of I-66 west of I-495. The continuous count station at mile marker 72 was used to estimate hourly adjustment factors for sections of I-66 east of mile marker 65 (I-495), while the station at mile marker 30 was used to develop hourly adjustment factors for I-66 west of mile marker 65.

Secondary Crash Occurrence Probability Model

The resulting binary logistic regression model of secondary crash probability is shown in the following equation.

$$P(s) = \frac{e^Y}{1 + e^Y}$$

where *P(s)* is the probability of a secondary crash occurring, and Y is defined as:

$$\text{For } \begin{cases} C = 0; Y = -4.459 + 0.006985t + 0.000162d \\ C = 1; Y = -2.836 + 0.006985t + 0.000162d \end{cases}$$

and where *C* = 1 indicates congestion, *t* is incident duration in minutes, and *d* is the total number of vehicles that have encountered the incident or its queue. For the development of the model, congestion was defined as the road segment with the primary incident having a speed of 30% lower than the historical average across 90% or more of the incident timeline. The model can be adapted for hypothetical incidents, where the presence of a queue is not known. In this approach, one can define congestion as any period where estimated demand is greater than or equal to estimated capacity. Demand can be estimated from AADT using seasonal, time-of-day, and day-of-week adjustments, while capacity can be estimated using the Highway Capacity Manual's capacity adjustment factors due to incidents, found in Exhibit 10-17 in Chapter 10 of the 2010 Highway Capacity Manual *(24)*.

For all model terms, $p < 0.01$. A representation of the probability of secondary crash occurrence for a roadway with an estimated demand of 2000 vehicles per hour is shown in Figure 7.

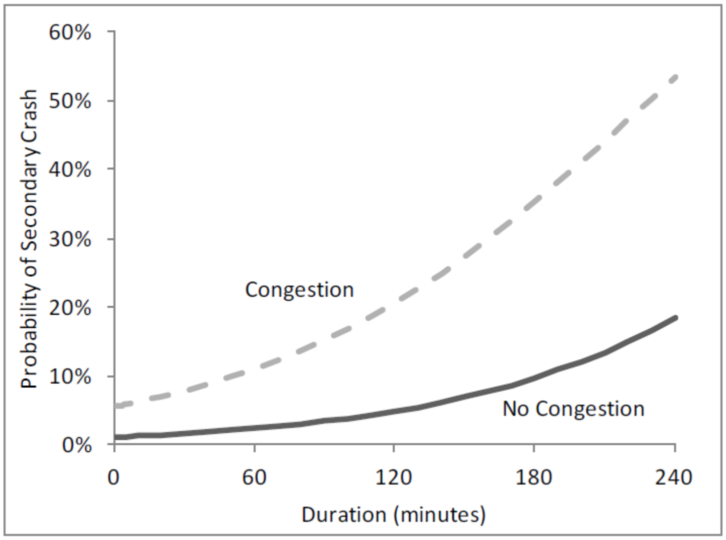

FIGURE 7. Estimated probability of a secondary crash at 2000 vehicle per hour demand.

Emergency responders are often curious to know the relationship between incident duration and probability of secondary crashes. First responders, in particular, often find it useful to have a rule-of-thumb for training new staff on the importance of quickly clearing an incident. While the relationship between incident duration and secondary crashes is complicated by several factors, a reasonable principle from the model is that during peak periods on urban freeways (maximum AADT on I-66 is 93,000), every two to three minutes on-scene increases the probability of a secondary crash by 1%. On low-volume sections and during evenings, risk increases by about one percentage point every five minutes. The baseline likelihood of a secondary crash once arriving on scene at all is about 5%.

Model Limitations

As observed incidents rarely had durations longer than three hours, the predictive performance of the model may suffer at longer primary incident durations.

CONCLUSIONS

This paper proposed a technique to classify crashes as secondary to other incidents on the roadway, and developed a model to predict secondary crash probabilities based on empirical queuing and estimated volumes using data from I-66 in Northern Virginia. The study's contributions were:

1. The development of a secondary crash classification strategy that accommodates widely-available private sector travel time data.
2. Methodological improvements on previous secondary crash classification techniques, mainly the emphasis on empirical queues and incident durations, as well as the tendency of incidents to generate congestion (and therefore secondary crashes) at later stages in the incident timeline.
3. A simple model of crash probability using the most relevant factors.
4. A rule-of-thumb estimate of increased secondary crash risk with time on-scene, which can be used by incident responders as a training tool.

The study found that 9.2% of all vehicle crashes were secondary to another incident, and that 6.2% of these crashes were tertiary to another primary incident. The findings support a fast incident response, as the models predicts that the probability of secondary crash occurrence increases approximately one percentage point for every additional 2-3 minutes spent on-scene in high-volume scenarios.

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