Dynamic Incident Progression Curve for Classifying Secondary Traffic Crashes

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ABSTRACT

The classification of secondary crashes is a useful performance measure of incident management systems. Previous classification methodologies used a static threshold for classifying secondary crashes. Such a threshold represents the spatial and temporal influence of a primary incident, such as 3.2 km upstream (2 miles) and 2 hours after the incident. The dynamic methodology described herein improves upon existing static methodology by marking the end of the varying queue throughout the entire incident using incident progression curves. The four steps in the development of incident progression curves are: 1) the processing of intranet incident reports, 2) the filling in of incomplete incident reports, 3) the non-linear regression of incident progression curves, and 4) the merging of individual incident progression curves into a master curve. The result from a 640 sample validation set shows the dynamic methodology reduces type I error by 24.38% and type II by 3.13%. And the application to a 5514 freeway crash dataset shows the results from using dynamic versus static methodology can differ by more than 30%.

CE DATABASE SUBJECT HEADINGS

Traffic Crashes, Data Processing, Traffic Management, Traffic Safety

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INTRODUCTION

Traffic incidents adversely affect traffic safety and operations. Such primary incidents could be as trivial as a vehicle breakdown or as severe as a multi-vehicle crash. Secondary crashes are crashes which result from an existing primary incident. The use of the term “secondary crash” instead of “secondary accident” is intentional to emphasize the potential for reducing such crashes due to improved incident management. It is arguable that incident management would have any effect on primary incidents because many of these crashes are caused by driver error such as fatigue, intoxication, or aggressive driving. Therefore traditional analysis of primary crashes and crash rates will not reveal the full potential of such systems. Thus the number of secondary crashes reduced can be a good performance measure for evaluating incident management programs such as traffic management centers, freeway service patrols or emergency management services.

The goal of this paper is to describe a readily deployable methodology for classifying secondary crashes from a crash database. The temporal and spatial region of influence of a primary incident is delineated by the queue length resulting from a primary incident throughout the duration of an incident. Since a queue often persists after an incident has been cleared, the incident normalization time is required in addition to the incident clearance time. This temporal and spatial region of influence of a primary incident is bounded by what the authors call an “Incident Progression Curve (IPC)”. Detailed incident data is required for creating IPCs, but such data is difficult to obtain because incidents are random events and most agencies do not track queue lengths in real time. The Traffic Management Centers (TMCs) in Missouri involve a private partnership with traffic news networks, thus traffic data from news sources such as helicopters and reporters are used in conjunction with data from freeway surveillance cameras and freeway service patrol. The TMCs generate intranet traffic reports that track the end of the queue during an incident. Some crash reports, however, lack the time of incident normalization. For such reports,
the normalization time is extended using the clearance time and the rate of queue shrinkage. Once IPCs are developed for individual incidents using intranet traffic reports, master IPCs are produced by combining individual IPCs. Such master IPCs are easy to use and are suited for producing an aggregate measure of secondary crashes by classifying the number of secondary crashes over a significant time period, e.g. multiple years. The master IPCs control for differences in the severity of crashes and in the level of congestion (volume over capacity ratio). Police crash databases are often used for highway safety studies and the master IPCs can be easily applied on such databases to classify the number of secondary crashes.

This research built upon previous work in the area of crash analysis and safety. Raub presented a methodology for the temporal and spatial analysis of incidents on urban arterials to identify secondary crashes (Raub 1997). Raub found that more than 15% of the crashes reported by police may be secondary in nature. He also found that such crashes resulted from external distractions instead of internal distractions or driver perception errors. For his analysis, he assumed a crash effect duration of 15 minutes plus the clearance time. He also assumed an effect distance of less than 1600 meters (1 mile). Thus if a crash occurred within these temporal and spatial boundaries, then the crash was considered to be secondary.

Moore et al. (2004) examined secondary crash rates on Los Angeles freeways using crash records from the California Highway Patrol’s First Incident Response Service Tracking system as well as data from loop detectors on Los Angeles freeways. They defined secondary crashes as crashes occurring upstream of the initial incident in either direction within or at the boundary of the queue formed by the initial incident. A static threshold of 3.2 km (2 miles) and 2 hours was used as an initial necessary condition. Several levels of filters served to eliminate erroneous data. Another example of the use of static threshold was Hirunyanitiwattana and Mattingly (2006) who used a threshold of 3.2 km (2 miles) and 1 hour in the same direction. Zhan et al. (2008) examined
the characteristics of secondary crashes and concluded that incident visibility and lane blockage durations of the primary incidents were significant contributing factors for determining the severity of secondary crashes. Khattak et al. (2009) used a threshold of 1.6 km (1 mile) in length plus the actual duration of the primary incident adjusted for lane blockage. The thrust of their study was on analyzing the interdependence between incident duration and secondary incident occurrence. Zhang and Khattak (2009) examined the role of secondary incidents in traffic operations because complicated large scale events could involve multiple secondary incidents.

Most of these studies exemplify the use of static (fixed) thresholds for classifying secondary crashes. Figure 1 shows a hypothetical graph of the progression of an incident. The origin represents the onset of the primary incident. The horizontal axis represents time elapsed since the incident occurred. The vertical axis represents the growth of the queue from the location of the incident. The letters A through F, represent 6 crashes that occurred after the onset of the primary incident and upstream from the incident. If a crash falls within the influence of the primary incident, i.e. the crash happened within the queue of the primary, then the crash is considered to be secondary. The static/fixed thresholds of queue length and time are superimposed on this progression. Progression refers to the growth and decline of the queue length as the incident progresses through the various stages. In general, the various stages of an incident include the onset, the arrival of response teams, the clearance to the shoulder, the completion of clearance, and the normalization of traffic. Not every incident includes all the aforementioned stages. The progression is also a function of both the demand (traffic) and the supply (road capacity). With the demand changing constantly, it is clear that the assumption of static thresholds would not capture field conditions as well as dynamic thresholds. Some would argue that on average the total number of secondary crashes can still be estimated accurately with static thresholds if the area of the static threshold rectangle is the same as the area under the progression curve. For example, Figure 1
shows the same number of crashes (three) is classified as secondary using either a static threshold or an actual IPC. However, by definition, secondary crashes differ in cause from primary crashes. Therefore even if the average number of crashes is captured accurately with static thresholds, the crashes themselves are still misclassified. Referring back to the example and looking at the static thresholds, the total number of secondary crashes is estimated correctly even though crash B is a false positive (should have been excluded) and crash E is a false negative (should have been included). The elimination of such type I and type II classification errors is one primary motivation for the development of dynamic thresholds. It is intuitive that crashes that occur near the time of the onset of the primary crash but far away from its location should be not classified as secondary since the queue growth is limited by the speed of the shockwave. However, this mistake can occur if a static threshold is used.

< Insert Figure 1 here>

Other articles were related to secondary crash analysis but did not address the secondary crash classification process directly. Karlaftis et al. (1999) examined the primary crash characteristics that influenced the likelihood of secondary crash occurrence. They suggested that clearance time, season, type of vehicle involved, and lateral location of the primary crash were the most significant factors. They also presented the economic benefit of secondary crash reduction for the Hoosier Helper freeway service patrol program. There were several articles that addressed the estimation of impact of incident delays. These included Garib et al. (1997), Giuliano (1989), Skabardonis et al. (1996), Morales (1997), Sullivan (1997), Smith et al. (1987), Lindley (1987), and Lee et al. (2003). In contrast to estimation techniques, this research advances the direct measurement of crash impacts (queue lengths over time) from intranet traffic reports.
RESEARCH METHODOLOGY

Police Crash Database

The primary source of data used in this research is the crash database obtained from the highway patrol in Missouri, U.S.A. The crash database for freeways is compiled by police agencies and consolidated by the state highway patrol. Table 1 shows an example of a crash record snippet from I-70 in Missouri. The complete crash records contain much more information than what is shown in Table 1. In addition, images of the four-page crash reports are also kept in the crash database. The primary fields that are used in this analysis include name, direction, continuous log, date, severity, time, image number, and traffic condition.

<Insert Table 1 here>

There are difficulties in only using the police crash database for classifying secondary crashes. The police crash report contains a field that describes downstream conditions as “accident ahead” or “congestion ahead”. The difficulty with the police determining whether a crash is primary or secondary is that they are limited spatially (at one location) and temporally (responding to the current crash). Since the effect of primary crashes can persist long after it has been cleared, it is difficult to determine at the scene of a crash if it is due to recurrent or non-recurrent congestion. The use of the category “accident ahead” for classifying secondary crashes would undercount the number while adding the category “congestion ahead” would severely over-count the number. Therefore the crash reports themselves do not contain enough information for classifying secondary crashes accurately.
Intranet Incident Reports

Traffic management centers and traffic news agencies provide wide spatial coverage of incidents as well as track the incident queues over time. They use information from aircrafts, elevated traffic cameras, freeway service patrol, emergency management (fire, police, ambulance, and HAZMAT), and motorist calls. They also monitor and update this information throughout the course of an incident. Such intranet traffic information complements the police crash database. Data fusion helps to incorporate both available information sources: the intranet traffic reports and the police crash database. The fused data includes the reporting times of the incident and the dynamic locations of the back of the queue. The difference between the initial and final reporting times gives an estimate of the total duration of the incident.

The intranet reports, however, need to be processed significantly in order for them to be in a usable format. The methodology for processing such reports is as follows. Pages of traffic reports are downloaded daily at regular intervals, say 3 minutes, using an automated computer script. These reports are then consolidated and parsed so that pieces of information are extracted into specific fields such as incident reporting time, incident type, and incident description. A major task is to extract the traffic information for a particular highway along a particular direction in the sequence they are reported in the files on a particular day. A computer program saves the information pertaining to a single incident through multiple reports in a single day. Since there is no unique identifier associated with the information pertaining to a particular incident, the lines containing information related to a particular incident need to be extracted through the use of keywords present in those lines and absent in other lines. There can be difficulties in this process, since traffic reports are human-generated and can include syntax variability as well as errors. As
an example, consider the primary route eastbound interstate 70. In the reports, eastbound can also be expressed as “EB”, “E/B”, or “east”, and interstate 70 as “70”, “I70”, or “I-70”. There can also be descriptions of the route expressed in phrases such as “eastbound lanes of 70” or “east and westbound lanes of 70”.

**Filling in Incomplete Incident Data**

A total of 480 incidents were extracted from traffic reports for freeways I-70 and I-270 in St. Louis, Missouri. These incident reports contained some sort of backup or queue information. For these reports the extent of traffic information varied from covering the incident progression for the entire duration to reporting the incident with only an initial report. The reports can be classified into three types based on the completeness of coverage. These types are characterized by (1) complete incident information through normalization, (2) incomplete incident information containing information on decreasing queue lengths, and (3) incomplete incident information containing ascending queue lengths only.

Since detailed incident data is difficult to obtain, it would be desirable to make use of the incomplete traffic reports instead of discarding them. One way of accomplishing this, is to fill in the incomplete incident reports by estimating the duration of the incident. The duration of incidents that do not have descending queue information is difficult to estimate, since neither the clearance time nor the rate of the queue reduction is known. However, if the incident is cleared and the backup queue is descending then the queue dissipation time can be estimated. Thus incident report types (1) and (2) are used while type (3) is discarded. Out of 480 reports, 49 have complete incident information while 97 incidents have some traffic information after incident clearance. The resulting dataset of 146 incidents have 119 incidents that match police crash
reports. A chi-squared test shows that the distributions of the complete and incomplete incident reports are not statistically different.

To fill in or model incomplete incident reports, second, third and fourth order polynomials were used. These models were evaluated using a ground truth dataset that replicated the incomplete incidents. This dataset was constructed by taking the complete incidents and then eliminating data samples after the clearance time. The third order polynomial model provided the best fit as compared to the second and fourth order polynomials. The third order model reproduced the total delay estimates (areas under the queue length/time curves) to within ±10% with an average difference of 1.4%. In comparison, the average difference for second order was 5.3% and for fourth order was 6.5%. The third order model also produced the best R² value.

**Master Incident Progression Curves**

A master IPC was an IPC that was unified from individual incident IPCs in order to simplify the application of the methodology to a large dataset. Two approaches were initially considered for the development of master IPCs. The first approach was to perform regression on an entire database of incidents. Thus every data point from every incident was used in the regression. This approach was eliminated because the resulting IPC would not look like a real incident, thus any traffic flow intuition would be lost in the application. The second approach was to capture the central tendency of incidents. The median was chosen over the mean and the mode because it was less sensitive to extreme values and was not affected by the number of modes. Each individual incident produced an IPC similar to the one shown in Figure 1. To join IPCs to form one IPC, the IPCs were divided into equal increments. For each increment, the median values of incident duration and queue length were calculated. The result was an IPC that looked like an actual IPC from a single incident.
As was previously discussed, a threshold was used to separate secondary crashes from primary crashes. A crash falling within the bounds of the threshold meant that the crash occurred inside the queue of the primary crash and within the duration of the primary crash. Two types of thresholds were compared in this research: static and dynamic. Each type was a function of both time and distance. The static threshold determined from the intranet incident reports was 42 minutes in duration and 5.7 km (3.53 miles) in queue length. These values were the median values of the maximum queue length and the time at which the maximum queue length occurred.

In contrast to the static threshold, the dynamic threshold was the master IPC described previously. The dynamic threshold was expressed by the following third order polynomial equation:

\[ Q = a_3 t^3 + a_2 t^2 + a_1 t + a_0 \]  

(1)

where \( Q \) was the queue length of the primary incident in miles and \( t \) was the time after the occurrence of the primary incident in minutes. The coefficients were 0.013873, 0.12652, -0.00094363, and -0.000007826 for \( a_0, a_1, a_2, \) and \( a_3 \). The total duration of the master IPC was 80.5 minutes and the maximum queue was 5 km (3.09 miles) which occurred at 43.5 minutes.

**Extension to Multiple Master Incident Progression Curves (IPC)**

Even though incident databases typically do not contain information on queue lengths, crash durations or volumes, they often include severity and time-of-the-day of incidents. Thus different master IPCs could be developed based on such additional information. The time-of-the-day could be used as a surrogate for the volume over capacity ratio (v/c). The procedure for estimating the v/c ratio is explained in the Highway Capacity Manual (HCM 2000) and is not repeated here. Thus the effects of incidents can be differentiated by the severity and the traffic conditions or v/c ratio. Due to the small sample size of fatal crashes, only PDO (property damage
only) and INJ (injury) categories are used. For each severity, three different IPCs are developed based on the v/c ratio. Figure 2 is the plot of the IPC Based on PDO crashes and v/c. Figure 3 is the plot of the IPC Based on injury crashes and v/c. The injury crashes intuitively show larger effects than PDO crashes. Similarly, an increase in v/c also results in greater crash effects. Table 2 shows the parameters resulting from the IPCs shown in Figures 2 and 3. Table 3 shows the model coefficients of the IPCs shown in Figures 2 and 3.

<Insert Table 2 and 3 here>

<Insert Figures 2 and 3 here>

RESULTS

One challenge in comparing the dynamic threshold or IPC with the static is the fact that accurate ground truth data is not readily available. There are several reasons for this. First, it is typical that the agencies that record crash reports are different than the parties that record the traffic and incident data. For example, police agencies typically produce the crash reports at the crash site while departments of transportation and media track and report on the impact of primary incidents and the resulting traffic conditions. Thus the police managing the incident could have marked the contributing circumstance as “congestion ahead” instead of “accident ahead” because they either were not aware of the primary incident upstream, or could not estimate the length of the queue. A local police agency responsible for a section of I-70 would probably not be aware of the traffic conditions in the jurisdictions that are downstream from theirs. Second, even if the crash reports, incident reports, and traffic conditions were perfectly synchronized among all agencies and parties, there would still be difficulty in determining perfectly the time when traffic is normalized especially during periods of congestion. This is because it is difficult to determine precisely how much the secondary crash has contributed to an existing peak hour congestion. One viable option is to generate a validation set using actual primary incident data but randomly generated crashes in
the vicinity of those incidents. Another option is to examine the movement of shockwaves from the primary incident queues, and to compare the differences in classification produced by the static versus dynamic thresholds.

For the first option, a validation set of 640 crashes was generated using primary incidents. The details of the primary incidents were fully reconstructed by fusing the police crash reports with the intranet crash reports. For each primary incident from Missouri, 10 crashes were randomly generated using a uniform distribution. If the generated crash was inside the reported queue at the time the incident information was reported via intranet, then the crash would be considered a secondary crash. The results of the classification using the static and dynamic thresholds were compared to this ground truth.

One reason the generation of crashes was necessary was because fully reconstructed incidents were difficult to obtain. Thus the value of each available primary incident data was maximized by focusing on the temporal and spatial scope of the crashes that truly tested the effectiveness of the dynamic threshold. The physical boundary of the generated crashes was constrained to be within 120% of the median of the maximum queue lengths observed. If the boundary was not constrained, then the classification methodology would produce a high accuracy even if it would classify very few crashes as secondary. This validation set was developed to investigate both Type I (false positives) and Type II errors (false negatives). Therefore, the reader should be cautious in interpreting the absolute error percentages since the validation set was intentionally made to be challenging. Table 4 shows the results from the validation data. The use of the dynamic threshold produced 24.38% less Type I error and 3.13% less Type II error. This result was unsurprising since the dynamic threshold tried to mimic the location of the end of queues over time.

< Insert Table 4 here>
For the second option for testing the dynamic threshold, a year’s worth of I-70 and I-270 crash data in Missouri (5514 crashes) was used. Out of 5514 crashes, 397 were classified as secondary based on the dynamic threshold IPC and 390 were classified as secondary crashes based on the static threshold. The areas under the static and dynamic thresholds were 238.7 km-minutes (148.3 mile-minutes) and 265.2 km-minutes (164.8 mile-minutes) respectively. On the surface, these numbers seemed to imply that the use of static or dynamic thresholds produced similar results since the areas under the curves and the total number of secondary crashes classified were similar. In reality, the two thresholds yielded very different results and could be seen in Figure 4 and Table 4. In Figure 4, the origin was the time and location at which a primary incident occurred. So the y-axis represented the upstream queue displacement from the location of the primary incident and the x-axis represented the time after the onset of the primary incident. For simplicity, the movement of the shockwave that represented the front of the queue was not considered. X-axis had units of minutes and, y-axis had units of miles. Figure 4 shows graphically a significant number of crashes that were not common to the application of both the static and dynamic thresholds. Table 4 shows 125 crashes were classified as secondary by the dynamic threshold but not by the static. Conversely, 118 crashes were classified as secondary by the static threshold but not by the dynamic. So the classification results actually differed by more than 30%. This difference could be significant since crash costs could differ significantly based on the severity of the crash. Based on an analysis of 72,687 St. Louis freeway crashes from 2000 to 2008, the proportions of different crash severities were found to be statistically different between primary and secondary crashes. The proportions were 0.337% and 0.829% for primary and secondary fatal crashes, 24.28% and 21.29% for primary and secondary minor injury crashes, and 73.20% and 75.25% for primary and secondary PDOs. The difference in the proportion of disabling injury crashes was not statistically significant. Lastly, Table 4 also shows that the results are similar for daytime only versus all-day.
CONCLUSIONS

This paper described a readily deployable methodology for classifying secondary crashes through the use of crash and incident data fusion. The effort in deployment will depend on the format and availability of intranet traffic reports. In cases where the report format is standardized, the deployment is much easier as human generation errors are minimized. IPCs can be applied easily by agencies who are interested in estimating the number of secondary crashes in their jurisdiction. IPCs can be used directly if severity of the primary incident, or segment volume and capacity (or time-of-day) are known. In addition, if an agency knows the average duration of incidents in their jurisdiction, then an IPC can be calibrated by re-scaling according to the average duration.

The practical applications of IPCs are many and include both short term and long term programs and of both large and small geographical scales. One application, for example, is incident management. Incident management cannot eliminate most primary incidents, but has the potential to eliminate and mitigate secondary crashes. Having accurate secondary crash numbers can assist in the planning and staffing of incident management programs both regionally and locally. Furthermore, the use of the dynamic thresholds or IPCs for computing secondary crashes can produce a quantitative measure of the operational performance of incident management programs that goes beyond the recording of the number or duration of incidents serviced. The use of such secondary crash statistics can help to better quantify and monetize the safety value of incident management programs. Another application is improving public education and awareness of secondary crashes through the greater use of secondary crash statistics. With the increasing
availability and use of real time traffic and incident information, there can be a greater awareness of travelers’ impact on primary incidents if secondary crashes are differentiated from primary.

The method presented improves upon the existing method of static threshold since it does not make the assumption that the queue length is constant. The analysis of the validation set shows the dynamic threshold produces 24.38% less type I error and 3.13% less type II error. The analysis of 5514 freeway crashes shows that these two methods can differ by over 30%. To derive the dynamic threshold, 480 intranet incident reports are analyzed and 119 incident reports are used for calibrating the master IPC. Some of these incident reports are incomplete, therefore the missing data is modeled using a third order polynomial. The polynomial model produces an average error of 1.4% in representing the total delay of an incident. A chi-squared test shows that the frequency distributions of the complete and incomplete incident reports are not statistically different.

Multiple IPCs are developed to capture differences in crash and traffic conditions using crash severity and time-of-day, a surrogate for v/c.

REFERENCES


Transportation Research Record: Journal of Transportation Research Board No. 1554, TRB, National Research Council, Washington, D.C.


**TABLES**

**TABLE 1 Sample Crash Record of I-70 in Missouri**

<table>
<thead>
<tr>
<th>NAME</th>
<th>DIR</th>
<th>CONT LOG</th>
<th>DATE</th>
<th>CRASH TYPE</th>
<th>CRASH CLASS</th>
<th>SEVERITY</th>
<th>TIME</th>
<th>VEHICLE NO</th>
<th>VEHICLE TYPE</th>
<th>CIRCUMSTANCE</th>
<th>TRAFFIC COND</th>
</tr>
</thead>
<tbody>
<tr>
<td>70</td>
<td>E</td>
<td>223.409</td>
<td>1/1/02</td>
<td>MOTOR VEHICLE IN TRAFFIC</td>
<td>REAR END</td>
<td>PROPERTY DAMAGE ONLY</td>
<td>350</td>
<td>1 PASSENGER CAR</td>
<td>DRINKING</td>
<td>NORMAL</td>
<td></td>
</tr>
<tr>
<td>70</td>
<td>E</td>
<td>223.409</td>
<td>1/1/02</td>
<td>MOTOR VEHICLE IN TRAFFIC</td>
<td>REAR END</td>
<td>PROPERTY DAMAGE ONLY</td>
<td>350</td>
<td>1 PASSENGER CAR</td>
<td>INATTENTION</td>
<td>NORMAL</td>
<td></td>
</tr>
<tr>
<td>70</td>
<td>E</td>
<td>223.409</td>
<td>1/1/02</td>
<td>MOTOR VEHICLE IN TRAFFIC</td>
<td>REAR END</td>
<td>PROPERTY DAMAGE ONLY</td>
<td>350</td>
<td>1 PASSENGER CAR</td>
<td>NOT STATED OR UNKNOWN</td>
<td>NORMAL</td>
<td></td>
</tr>
<tr>
<td>70</td>
<td>E</td>
<td>250.312</td>
<td>1/1/02</td>
<td>MOTOR VEHICLE IN TRAFFIC</td>
<td>REAR END</td>
<td>PROPERTY DAMAGE ONLY</td>
<td>1110</td>
<td>1 PASSENGER CAR</td>
<td>IMPROPER PASSING</td>
<td>NORMAL</td>
<td></td>
</tr>
<tr>
<td>70</td>
<td>E</td>
<td>250.312</td>
<td>1/1/02</td>
<td>MOTOR VEHICLE IN TRAFFIC</td>
<td>REAR END</td>
<td>PROPERTY DAMAGE ONLY</td>
<td>1110</td>
<td>2 PASSENGER CAR</td>
<td>NOT STATED OR UNKNOWN</td>
<td>NORMAL</td>
<td></td>
</tr>
<tr>
<td>70</td>
<td>E</td>
<td>15.57</td>
<td>1/2/02</td>
<td>MOTOR VEHICLE IN TRAFFIC</td>
<td>REAR END</td>
<td>INJURY</td>
<td>815</td>
<td>1 PICKUP</td>
<td>FOLLOWING TOO CLOSELY</td>
<td>NORMAL</td>
<td></td>
</tr>
<tr>
<td>70</td>
<td>W</td>
<td>15.57</td>
<td>1/2/02</td>
<td>MOTOR VEHICLE IN TRAFFIC</td>
<td>REAR END</td>
<td>INJURY</td>
<td>815</td>
<td>2 PASSENGER CAR</td>
<td>NOT STATED OR UNKNOWN</td>
<td>CONGESTION AHEAD</td>
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<tr>
<td>70</td>
<td>E</td>
<td>234.229</td>
<td>1/2/02</td>
<td>RAN OFF ROAD-FIXED OBJECT</td>
<td>OUT OF CONTROL</td>
<td>PROPERTY DAMAGE ONLY</td>
<td>847</td>
<td>1 PASSENGER CAR</td>
<td>NOT STATED OR UNKNOWN</td>
<td>NORMAL</td>
<td></td>
</tr>
</tbody>
</table>
### TABLE 2 IPC Parameters and Static Thresholds Based on Severity and v/c Ratio

<table>
<thead>
<tr>
<th>Description</th>
<th>Criteria</th>
<th>Maximum Queue (km)</th>
<th>Time of Max. Queue (min)</th>
<th>Time to Normal. Queue (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Light PDO, v/c &lt; 0.4</td>
<td>4.86 (3.02 mi)</td>
<td>42</td>
<td>78</td>
<td></td>
</tr>
<tr>
<td>Medium PDO, 0.4 &lt; v/c &lt; 0.7</td>
<td>7.21 (3.48 mi)</td>
<td>48</td>
<td>90</td>
<td></td>
</tr>
<tr>
<td>Heavy PDO, v/c &gt; 0.7</td>
<td>7.35 (4.57 mi)</td>
<td>64</td>
<td>118</td>
<td></td>
</tr>
<tr>
<td>Light INJ, v/c &lt; 0.4</td>
<td>5.09 (3.16 mi)</td>
<td>44</td>
<td>82</td>
<td></td>
</tr>
<tr>
<td>Medium INJ, 0.4 &lt; v/c &lt; 0.7</td>
<td>5.92 (3.68 mi)</td>
<td>51</td>
<td>95</td>
<td></td>
</tr>
<tr>
<td>Heavy INJ, v/c &gt; 0.7</td>
<td>7.90 (4.91 mi)</td>
<td>68</td>
<td>127</td>
<td></td>
</tr>
<tr>
<td>Criteria</td>
<td>a0</td>
<td>a1</td>
<td>a2</td>
<td>a3</td>
</tr>
<tr>
<td>-----------------</td>
<td>-----</td>
<td>--------</td>
<td>--------</td>
<td>--------</td>
</tr>
<tr>
<td>PDO, v/c &lt; 0.4</td>
<td>0</td>
<td>0.1174</td>
<td>-0.0006</td>
<td>-1E-05</td>
</tr>
<tr>
<td>PDO, 0.4 &lt; v/c &lt; 0.7</td>
<td>0</td>
<td>0.1252</td>
<td>-0.0008</td>
<td>-7E-06</td>
</tr>
<tr>
<td>PDO, v/c &gt; 0.7</td>
<td>0</td>
<td>0.1125</td>
<td>-0.0003</td>
<td>-6E-06</td>
</tr>
<tr>
<td>INJ, v/c &lt; 0.4</td>
<td>0</td>
<td>0.1171</td>
<td>-0.0006</td>
<td>-1E-05</td>
</tr>
<tr>
<td>INJ, 0.4 &lt; v/c &lt; 0.7</td>
<td>0</td>
<td>0.1157</td>
<td>-0.0004</td>
<td>-8E-06</td>
</tr>
<tr>
<td>INJ, v/c &gt; 0.7</td>
<td>0</td>
<td>0.1219</td>
<td>-0.0005</td>
<td>-4E-06</td>
</tr>
</tbody>
</table>
### TABLE 4 Comparison of Dynamic versus Static Thresholds

<table>
<thead>
<tr>
<th>Validation</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>n = 640</td>
<td>Dynamic</td>
<td>Static</td>
</tr>
<tr>
<td>Type A Error (%)</td>
<td>14.84</td>
<td>39.22</td>
</tr>
<tr>
<td>Type B Error (%)</td>
<td>9.06</td>
<td>12.19</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Application</th>
<th>Number of Secondary Crashes</th>
</tr>
</thead>
<tbody>
<tr>
<td>n = 5514</td>
<td>Dynamic Only</td>
</tr>
<tr>
<td>Time Period</td>
<td></td>
</tr>
<tr>
<td>Day Time (5:30 A.M - 6:30 P.M)</td>
<td>106</td>
</tr>
<tr>
<td>All-day</td>
<td>125</td>
</tr>
</tbody>
</table>
FIGURE AND TABLE CAPTIONS

FIGURE 1 Static threshold versus actual incident progression.

FIGURE 2 IPC Based on PDO crashes and v/c.

FIGURE 3 IPC Based on injury crashes and v/c.

FIGURE 4 Secondary crashes based on static and dynamic thresholds.

TABLE 1 Sample Crash Record of I-70 in Missouri

TABLE 2 IPC Parameters and Static Thresholds Based on Severity and v/c Ratio

TABLE 3 IPC Polynomial Coefficients Based on Severity and v/c Ratio

TABLE 4 Comparison of Dynamic versus Static Thresholds
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