

Proactive Freeway Crash Prevention Using Real-Time Traffic Control

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Abstract: This paper makes use of a probabilistic model, that predicts the likelihood of crashes (crash potential) on freeways on the basis of traffic flow conditions, in real-time crash prevention. The model was developed using incident logs and loop detector data collected over a 13-month period on the Gardiner Expressway in Toronto. The previous work suggested that an increase in levels of traffic turbulence generally yields high crash potential. Traffic turbulence was defined in terms of a series of crash precursors which represent traffic conditions that were present prior to crash occurrence. To apply the model in crash prevention, the link needs to be established between crash potential and real-time safety intervention. The objective of this paper is to explore this link for different thresholds of crash potential. The paper discusses the guidelines for evaluating the safety benefit of one crash prevention strategy (variable speed limits) and suggests the risk-based evaluation framework for real-time traffic control.

Key words: Crash, Accident, Freeway, Safety, Traffic Flow, Real-Time Control

1. Introduction

So far most work related to traffic safety intervention has used statistical models that do not take into account real-time traffic conditions. Since these models tend to be static, they cannot be used in real-time traffic control. The recent development of driver warning systems highlights deficiency of the existing static crash prediction models. Since traffic conditions change in time and these conditions influence crash potential (Andrey and Yagar 1993), the factors affecting crash potential must be measured in real-time. These traffic conditions that contribute to changes in crash potential in time are referred to as crash precursors. If we understand how crash precursors vary over time, we can also obtain better appreciation of changes in crash potential over time.

In this regard, Lee et al. (2002) developed a probabilistic crash prediction model that estimates real-time crash potential on the basis of the current traffic flow condition. For this task, a number of crash precursors were identified. As a result of model calibration using observed field data, it was found that the model is capable of capturing the effect of crash precursors on crash potential. In agreement with our prior expectation, the model results indicated that high turbulence of traffic flow generally increases crash potential. However, this previous study did not adequately investigate the link between crash potential and safety intervention. Thus, the objectives of this paper are: (1) to describe a method for defining tolerance levels of crash potential as obtained from the crash prediction model; (2) to link these tolerance levels to different types of interventions; and (3) to suggest a framework by which the safety benefit of real-time interventions can be evaluated. This paper mainly focuses on the controls in speed limit.

This paper is composed of five sections. The second section briefly describes the real-time crash prediction model, the data used for the calibration of parameters, and the summary of calibration results. The third section introduces the framework of real-time safety intervention and discusses the method of determining thresholds of crash potential. The section also describes the candidate real-time intervention strategies such as variable speed limits. The fourth section proposes the use of a simulation model to assess the safety benefit of proactive crash prevention. The fifth section presents a summary and suggests future work.

2. Proposed Model

2.1. Model Framework

The proposed real-time crash prediction model defines crash potential as a function of crash precursors and a number of external control factors such as road geometry and the peak/off-peak traffic pattern. Crash precursors represent the factors indicating the degree of turbulence (or stability) of traffic condition, which is closely related to drivers' maneuver and chances of crashes with other vehicles. Thus, in the selection of crash precursors, we initially focused on such traffic factors as speed variance and density that are commonly believed to have an impact on the stability of traffic flow condition. Then, the detailed description of crash precursors was determined such that the distribution of precursor values for traffic conditions at the time of crashes are significantly different from the distribution of precursor values for normal non-crash traffic conditions. For the comparison of the distribution, the data in normal non-crash traffic conditions were collected on the same road section under the same weather condition at the same time period as each of crash data but on different days when crashes did not occur. Using a sample of crash and traffic data, the following three crash precursor variables were

identified: (1) the coefficient of variation of speed (= standard deviation of speed / average speed) at the upstream end of the road section (*CVS*); (2) average density at the upstream end of the road section (*D*); and (3) average difference in speed between the upstream and downstream of a specific location (*Q*). In particular, *CVS* is more preferable to the absolute speed variance because it can better reflect the variation of speed during congested traffic conditions with lower average speeds. A detailed description of these three precursors is provided in Lee et al. (2002, 2003).

In the model, several external traffic and environmental conditions that affect crash potential were considered as control factors. These control factors are (1) road geometry (sections with no ramp and sections with on or off-ramps) and (2) the peak/off-peak traffic pattern (peak period (7-10 am, 4-7 pm) and off-peak period (other than peak period)).

To investigate the relationship between crash potential and crash precursor variables, Lee et al. (2003) developed a crash prediction model using a log-linear expression. The specification of the model is as follows:

$$[1] \quad \ln(F) = \theta + \lambda_{CVS(i)} + \lambda_{D(j)} + \lambda_{Q(k)} + \lambda_{R(l)} + \lambda_{P(m)} + \beta \ln(EXP)$$

where,

F : the frequency of crashes;

EXP : the exposure in vehicle-kilometers of travel;

β : the parameter for the exposure;

θ : constant;

$\lambda_{CVS(i)}$: effect of the crash precursor variable *CVS* having *i* levels;

$\lambda_{D(j)}$: effect of the crash precursor *D* having *j* levels;

$\lambda_{Q(k)}$: effect of the crash precursor Q having k levels;

$\lambda_{R(l)}$: effect of road geometry (control factor) having l levels;

$\lambda_{P(m)}$: effect of the peak/off-peak traffic pattern (control factor) having m levels.

A log-linear expression was selected for two specific reasons: (1) crash precursors must be in the form of categorical variables to control for exposure, and aggregated models are more advantageous in describing the relationship among categorical variables than disaggregate models; and (2) a log-linear model allows us to investigate the interaction between various precursor variables acting alone or in various combinations (Saccomanno and Buyco 1988).

As Hauer (1995) suggested, crash rate is an input to establish crash potential. Thus we need to measure crash rate by controlling for exposure. Crash rate is expressed as the number of crashes over some functions of exposure. In the model, no assumption is made as to the relationship between the number of crashes and exposure. Rearranging Equation 1, we can see that the crash rate is estimated to be F/EXP^β . Unlike the “conventional” crash rate ($= F/EXP$) that implicitly assumes a linear relationship between crash frequency and exposure, the crash rate estimated by the model can take into account non-linearity of the relationship by specifying the parameter β in the expression of F/EXP^β . In other words, if β is not equal to 1, the relationship between crash frequency and exposure is non-linear. Then the expected number of crashes for any given exposure (T) is defined by the product of the crash rate and exposure ($= F/EXP^\beta \times T$). In this study, we assumed the expected number of crashes reflects crash potential at any point in time and location of freeways.

In Equation 1, we introduced three precursors and two control factors. Both of these are defined as categorical inputs in the model. Exposure is defined in terms of vehicle-km of travel

and introduced as a continuous offset term (in log transform). Determining the number of categories and the boundary values for crash precursors depends on the analyst's subjective judgment. Thus, the reliability of the model estimates for different categorizations must be checked.

2.2. Gardiner Expressway Data

To test the performance of the proposed model, this study used incident logs and traffic flow data extracted from 38 loop detectors along a 10-km instrumented stretch of the Gardiner Expressway in Toronto. These data were collected for weekdays over a 13-month period from the beginning of January 1998 to the end of January 1999.

A total of 234 crashes were reported by the traffic control center during the observation period. By definition, crashes are a subset of all incidents that are reported by the center. In this study, only confirmed single-vehicle and multi-vehicle crashes were included in the data because the model only predicts the variation of crash potential that occurs as a result of the vehicle interactions under different traffic conditions. Other incident types, such as stalled vehicles, spilled loads, etc., were excluded in the data. Police reported most crashes were rear-end collisions between vehicles, and single-vehicle crashes rarely occurred in the study area. The incidents are typically first detected by the loop detectors using automated incident detection algorithms and subsequently confirmed visually by an operator at the traffic control center through closed-circuit TV camera feeds.

The traffic flow data from loop detectors contain 20-second average lane-by-lane speed (space-mean speed), volume, and occupancy. The incident logs contain the information on date and time of detection, type of incident, lane block pattern, and the loop detector station immediately *upstream* of the actual crash site.

2.3. Calculation of Crash Precursors

Crash precursors are computed on the basis of a time series static measurement obtained at various points along the road. The measurement of crash precursor values for each specific crash requires that we first specify an appropriate time offset prior to occurrence of the crash. The time offset is determined in relation to the actual time of each crash. The actual time of crashes is not known with any degree of accuracy. In this analysis, this is determined by observing speed profiles of the vehicles traversing upstream and downstream detectors. When a crash occurs, it blocks one or more lanes and a queue forms due to the reduction of capacity. The time at which the speed is observed to drop significantly at upstream detectors corresponds to arrival of shockwave from the downstream crashes. If we can estimate the speed of shockwave, we can determine the actual time of crashes. However, since it is difficult to measure the speed of shockwave that changes over time, we used the time at which the speed at upstream detectors drops as an estimate of the actual time of crashes.

Twenty different time offsets (relative to arrival time of shockwave) were investigated from 1 minute to 20 minutes prior to the crash and precursor values were obtained for CVS , D , and Q as defined previously. The optimal time offsets were determined such that the difference in the distribution of crash precursor values for given offset time between crash data and non-crash data is maximized. The optimal time offsets for CVS , D , and Q were found to correspond to 8, 3, and 2 minutes prior to the crash, respectively.

2.4. Results of Calibration

Having determined all the crash precursors and external control factors, the log-linear model was calibrated. Crash precursors were categorized for different boundary values by visual inspection of the observed frequency distributions of precursor values. For example, suppose that

we arrange the observed precursor values in typical daily traffic conditions in an order from the smallest to the largest. Then if we classify the first 50% of precursor values into low level, the next 30% into intermediate level, and the last 20% into high level, the resultant category boundaries for the three crash precursors can be determined as follows:

Categories (CVS): low: $CVS \leq 0.056$, intermediate: $0.056 < CVS < 0.74$, high: $CVS \geq 0.74$

Categories (D): low: $D \leq 16.4$, intermediate: $16.4 < D < 20.8$, high: $D \geq 20.8$

Categories (Q): low: $Q \leq 2.7$, intermediate: $2.7 < Q < 8.3$, high: $Q \geq 8.3$

For this categorization, a log-linear model of crash potential was fit to the crash data and the results are summarized in Table 1. The results imply that the combination of high coefficient of variation of speed, high density and high speed difference between successive loop detectors create the most hazardous traffic condition leading to crashes. The results agree with our expectation in a sense that when drivers have to adjust their speed frequently due to high speed variance, they are more likely to make a misjudgment in controlling speed to avoid crashes. The abrupt speed change within the road sections captured by precursor variable Q , also contributes to high crash potential for the same reason. On the other hand, when the traffic density is high, the average spacing between vehicles is small and there is also a greater likelihood of collisions. The model also shows that control factors (R , P) have statistically significant effect on crash potential.

The goodness of fit of the log-linear model was measured by comparing the distributions of expected number of crashes and the crash frequency in the observed data, and the similarity of distributions can be evaluated using a chi-square test. For the case of three categories, it was

found that the models consistently fit to the observed data very well for different combinations of boundary values, based on the results that all chi-square values were lower than the critical value for a 95% confidence level. Also, the model results displayed the consistent relationship between crash potential and the levels of crash precursors - high-level crash precursors indicate higher crash potential than low-level precursors. This result shows that the model performance is robust, not being affected by subjective determination of boundary values for a given number of categories.

To illustrate the calculation of crash potential in details, the following example is considered. Suppose that at current time t^* (during peak period), $CVS(t^*) = 0.04$, $D(t^*) = 10$ veh/km, and $Q(t^*) = 2$ km/hr. For the given boundaries as defined earlier, CVS , D , and Q are classified into low level (Category 1) at t^* . Then crash potential at the merging road section with exposure of 1×10^9 vehicles-km of travels over a 13-month period can be estimated as follows.

$$\begin{aligned}
 F(t^*) &= \exp(\theta + \lambda_{CVS=1} + \lambda_{D=1} + \lambda_{Q=1} + \lambda_{R=1} + \lambda_{P=1} + \beta \ln(EXP)) \\
 &= \exp(2.6569 - 3.3065 - 2.3797 - 2.6859 + 0 + 0 + 0.0964 \cdot \ln(1)) = 0.0033 \text{ crashes}
 \end{aligned}$$

$$\begin{aligned}
 \text{Crash Potential } (t^*) &= F(t^*) / EXP^\beta \times T \text{ (any given exposure)} \\
 &= 0.0033 / (1)^{0.0964} \times T = 0.0033 T \text{ crashes}
 \end{aligned}$$

If CVS , D , and Q all increase to high level (Category 3) at the next time interval, t^*+1 , and exposure decreases to 0.5×10^9 vehicles-km, reflecting rare occurrence of high-level precursors (risky condition) relative to low-level precursors (normal condition), crash potential is calculated as follows:

$$\begin{aligned}
F(t^*+1) &= \exp(\theta + \lambda_{CVS=3} + \lambda_{D=3} + \lambda_{Q=3} + \lambda_{R=1} + \lambda_{P=1} + \beta \ln(EXP)) \\
&= \exp(2.6569 + 0 + 0 + 0 + 0 + 0 + 0.0964 \cdot \ln(0.5)) = 13.3 \text{ crashes}
\end{aligned}$$

$$\text{Crash Potential } (t^*+1) = F(t^*+1) / EXP^\beta \times T = 13.3 / (0.5)^{0.0964} \times T = 14.2 T \text{ crashes}$$

From the above calculation, it can be seen that crash potential increases significantly after the levels of crash precursors increase from low levels to high levels. In general, the increase in crash potential is mainly influenced by changes in crash precursor values while other control factors remain the same.

3. Framework of Real-Time Safety Intervention

Having established a real-time crash prediction model, this section discusses how the model can be used for the implementation of proactive freeway crash prevention. In order to use the model for decision-making of implementing intervention, we must determine a set of rules for different values of crash potential. This can be achieved by the categorization of crash potential into separate decision-making regimes that are defined by some given threshold values (for example, no action is required, action is required at all costs, etc.).

Figure 1 shows the framework for real-time safety intervention. First, traffic surveillance systems collect traffic flow data in real-time from road sensors such as loop detectors. From these data, we obtain appropriate crash precursors. Second, based on these precursors, the real-time crash prediction model estimates crash potential at different time intervals. Third, we compare these estimates of crash potential to pre-specified threshold values and, if they exceed the thresholds, safety intervention measures are introduced. These measures are expected to affect traffic conditions and the corresponding crash precursor values. The changes in precursor

values, in turn, affect crash potential in the next time intervals and so on. The process is repeated such that if crash potential drops below the threshold values, intervention module is by-passed, otherwise, the intervention remains in effect.

Within this framework, the important question that needs to be addressed is how to determine practicable threshold values for different intervention strategies. To answer this question, the two basic issues need to be discussed. At what values of crash potential (CP* in Figure 1), should we intervene? What form should this intervention take?

A number of researchers have investigated how changes in values of risk (crash potential) trigger different types of safety intervention. HSE (1996) in UK defined the three risk regimes for the transportation of dangerous goods: (1) the intolerable regime, (2) the ALARP (as low as reasonably practicable) regime, and (3) the broadly acceptable regime. Similar decision-making approach was adopted by Mao (2002) in his analysis of Blackspots along Highway 401 in southern Ontario. Blackspots were defined as locations where risks exceeded certain preset thresholds for intervention. Unlike HSE, the nature of intervention was not clearly discussed in his study.

In this paper, we define CP* as some threshold measures for which intervention measure is suggested. Figure 2 shows a plot of crash potential in real-time at given location. The solid line represents crash potential with no intervention and the dashed line illustrates crash potential in post intervention (when crash potential exceeds CP*). So far, we have discussed intervention in general terms and the detailed intervention strategies will be discussed later in this section.

The critical issue in determining thresholds of crash potential is how long we should maintain intervention strategies in effect. This depends on the benefit of intervention *vis a vis*

changes in crash potential profiles as illustrated in Figure 2. The benefit can be estimated using the following expression:

$$[2] \quad B = \int_{t'}^T [CP_{ni}(t) - CP_i(t)] dt$$

where,

B : benefit associated with reduction in crash potential (difference in crash potential with and without intervention);

t' : time when intervention starts (i.e. when $CP_{ni}(t) >$ threshold of crash potential);

T : end time of comparison;

$CP_{ni}(t)$: estimated crash potential at time t in the case without intervention.

$CP_i(t)$: estimated crash potential at time t in the case with intervention.

However, we can expect that as the benefit of intervention increases, the cost of intervention will also increase. Thus the benefit needs to be compared to additional cost of traffic delay and the cost of intervention measure. From the comparison, we can identify the point where the rate of increase in benefit for additional cost becomes less pronounced and intervention becomes less cost-effective. The situation is explained schematically as in Figure 3. Each point in the figure represents the benefit and the cost of intervention for the specified threshold value. However, it is difficult to determine precisely the point at which the intervention ceases to be cost-effective. Due to uncertainty, the cost-effective intervention region is shown as an interval in Figure 3.

The second issue to be addressed is what form intervention strategy should take. As noted above, a number of different intervention strategies can be considered, such as variable speed

limits, ramp metering, lane control signals, and route guidance, can be considered. In this paper, we confine the scope of the study to changes in speed limits as an initial step.

In fact, a number of European studies have shown both theoretically and empirically that the use of variable speed limits can stabilize traffic flow in congestion and thereby decrease the probability of crashes (Hines 2002). Variable speed limits were found to have positive effect on crash reduction.

Before the implementation of variable speed limits, we need to understand how drivers normally react to change in speed limits and how driver's behavior changes traffic flow characteristics. For this purpose, it is worthwhile to review the past experimental analysis. Over the years, many researchers have attempted to identify the relationship between speed limits and changes in traffic flow. For instance, there are a few studies on the relationship between different levels of the "fixed" speed limit and speed variance.

Aljanah et al. (1999) found that enforcing lower speed limit reduced the spread of speeds and substantially reduced the number of accidents. Similarly, Garber and Gadiraju (1990) observed that lower posted speed limits reduced mean speed and speed variance.

There are also some work done on the relationship between "variable" speed limits and the variation of traffic flow. Rämä (1999) found that when the variable speed limits are enforced, mean speed and standard deviation of speed were reduced due to a drop in the highest speeds. Also, Smulders (1990) observed that there was a significant reduction in the percentage of small time headways (≤ 1 second) on the fast lane when the variable speed signaling displayed advisory speed signals to oncoming traffic. These are common characteristics that were observed in many other works on the variable speed limits.

In summary, the observed change in traffic flow in these studies is the reduction in mean speed, speed variance, and the proportion of short time headways. This result implies that speed limit changes homogenize individual drivers' speeds and maintain the stable traffic flow.

The observed changes in traffic flow as a result of speed limit changes are the fundamental elements of estimating changes in crash potential. Therefore, the safety benefit of variable speed limits strongly depends on the accurate estimation and prediction of traffic flow changes in real-time.

4. Evaluation of Variable Speed Limits

To evaluate the effectiveness of variable speed limits in the reduction of crash potential, the relationship between speed limits and speed variance must be examined. This relationship can be observed either from field experiment or simulation. However, to avoid the complexity, cost, and safety issues associated with staging field experiment and directly measuring drivers' reaction especially under the condition of change in speed limits, microscopic traffic simulation models can be used instead. In using a microscopic traffic simulation model, the following conditions must be met. First, the model should permit changes in posted speed limits without resetting the simulation to produce crash potential profiles in real-time. Second, the model should provide instantaneous traffic flow data for individual vehicles and drivers, which can be aggregated to give speed profile and density of entire traffic stream. These aggregated data will yield crash precursor estimates that can be input to crash prediction model.

To ensure the reality of the simulation results, we must validate the simulation model. In this study, the microscopic traffic simulation model INTEGRATION (Van Aerde 1998) was selected for the validation. In validation of the model, a 4-km section of the Gardiner

Expressway (Figure 4) was selected for which we estimated the parameters such as speed, speed variance and density. The study area is a three-lane roadway section and all the parameters are averaged over three lanes at the location of six detector stations. The profiles of speed, speed variance and density were obtained for a two-hour period (3 – 5 pm) at the current posted speed limit of 90 km/hour. In a similar fashion, the profiles were obtained using INTEGRATION. In INTEGRATION, the input parameters associated with macroscopic traffic flow relationship such as free-flow speed, speed at capacity, capacity and jam density were chosen to reflect the prevailing traffic conditions in the study area.

Figure 5 (a), (b) and (c) illustrate the observed and simulated speed, speed variance and density profiles, respectively, at the detector station 70 along the test section. Speed variance is assumed to be the standard deviation of speed for the past five minutes. As shown in the figure, it appears that the profiles in the observed data and simulation results are reasonably similar. This result indicates that a simulation model could yield a good representation of changing traffic conditions affected by speed limits. Since the simulation model produced promising results, we can apply the simulation model to examine the effect of changing speed limits, the intervention strategy of interest in this paper.

Following the validation of the simulation model, the appropriate intervention strategy (in this case, the reduction of speed limits) must be determined when crash potential exceeds thresholds. For this task, different estimates of total crash potential are obtained for different scenarios of speed limits for the given duration of intervention. In each scenario, the total crash potential is compared with the total crash potential without intervention to estimate the benefit of speed limits reduction. Finally, the speed limit where the benefit of speed limits reduction is cost-effective is selected as the optimal speed limit as discussed in Section 3.

Finally, in the implementation of intervention, some real-world problems such as compliance of drivers with variable speed limits need to be addressed. Since it is impossible to realistically predict driver's compliance in the simulation model, the analysis is undertaken for different simplified assumptions – e.g. only 50% of total drivers conform to speed limit changes. Then the sensitivity of the estimated crash potential to different compliance rates is examined. However, in reality, driver's compliance cannot be controlled externally and this still remains an unsolvable issue in predicting traffic flow changes.

5. Summary and Recommendation

This paper has described the development of a real-time crash prediction model and discussed the application of the model to real-time traffic control to reduce crash potential. The model overcomes the limitations of many existing static crash prediction models that relate crashes to fixed geometric and aggregated traffic flow characteristics. Crash potential estimated by the model is sensitive to short-term variation of traffic flow and can be incorporated into a large framework of real-time traffic safety management systems.

For the practical application of the model, there are two issues to consider: (1) how to determine thresholds of the estimated crash potential; and (2) how to perform real-time traffic control on the basis of the model estimates. In this paper, we suggest using the reduction in crash potential as the benefit of intervention and traffic delay as the cost of intervention. From the comparison of benefit and cost, the optimal threshold of crash potential is determined at the point where the benefit of intervention is no longer cost-effective.

In discussing proactive crash prevention strategies, the study suggests the use of the variable speed limits because the restriction of speed is effective in leading to stable traffic

condition by reducing speed variance. In discussing the effectiveness of the model in real-time crash prevention, it is important to examine whether crash precursors are greatly affected by the speed limit changes and how the change in values of crash precursors has an impact on crash potential.

For the evaluation of variable speed limits, a microscopic traffic simulation model can be used since it enables us to diagnose the effect of different speed limits on temporal variation of traffic flow, and furthermore the variation of crash potential. The simulated traffic conditions were validated by comparing with the observed data and they were found to be reasonably close. This result indicates a simulation model can be used as a good tool in analyzing safety benefit of real-time traffic control.

In future work, the issues that need to be addressed are whether the model is robust or accurate in realistically reflecting crash potential in real world, and the real-time traffic control interventions (variable speed limits) integrated with the model are effective in inducing driver's response. Although it is hard to make a conclusion until variable speed limits are actually implemented in the field, we can tackle the issues as follows.

First, the robustness of the model can be evaluated by validating the performance of the model against different data set (collected from different freeways) that was not used in the calibration of the model. Second, the effectiveness of inducing driver's response can be examined through the observation of changes in driver behavior when the speed limits change from the past experimental studies. Then the effect of their response on traffic condition and safety can be analyzed on the basis of interaction among individual vehicles which comply and do not comply with variable speed limits in the simulation model.

This paper presents a conceptual framework for the evaluation of safety benefits of variable speed limits. This framework will be used to quantify the safety benefits of proactive freeway crash prevention using real-time traffic control.

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Table 1. Estimated parameters of log-linear model.

Parameters	Estimate	Standard Error ^a	Z-Value ^b
Constant (θ)	2.6569	0.1394	19.06
$\lambda_{CVS=1}$ ($CVS \leq 0.056$)	-3.3065	0.3430	-9.64
$\lambda_{CVS=2}$ ($0.056 < CVS \leq 0.74$)	-1.8415	0.2181	-8.44
$\lambda_{CVS=3}$ ($CVS > 0.74$) ^c	0	.	.
$\lambda_{D=1}$ ($D \leq 16.4$)	-2.3797	0.2982	-7.98
$\lambda_{D=2}$ ($16.4 < D \leq 20.8$)	-0.7088	0.1693	-4.19
$\lambda_{D=3}$ ($D > 20.8$) ^c	0	.	.
$\lambda_{Q=1}$ ($Q \leq 2.7$)	-2.6859	0.3094	-8.68
$\lambda_{Q=2}$ ($2.7 < Q \leq 8.3$)	-1.4794	0.1883	-7.86
$\lambda_{Q=3}$ ($Q > 8.3$) ^c	0	.	.
$\lambda_{P=0}$ ($R = 0$)	-0.9916	0.1773	-5.59
$\lambda_{P=1}$ ($R = 1$) ^c	0	.	.
$\lambda_{R=0}$ ($P = 0$)	-0.4929	0.1476	-3.34
$\lambda_{R=1}$ ($P = 1$) ^c	0	.	.
β (Exposure)	0.0964	0.0119	8.13

^a A measure of the dispersion of the coefficient.

^b A standardized measure of the parameter coefficient.

^c This cell serves as the basis against which log-linear parameters are applied to obtain crash frequency for any combination of crash precursors. The cell is called the “aliased” cell.

Description of Parameters:

θ : Constant;

$\lambda_{CVS=1}$, $\lambda_{CVS=2}$, $\lambda_{CVS=3}$: Effect of CVS (=1 (low), =2 (intermediate), =3 (high));

$\lambda_{D=1}$, $\lambda_{D=2}$, $\lambda_{D=3}$: Effect of D (=1 (low), =2 (intermediate), =3 (high));

$\lambda_{Q=1}$, $\lambda_{Q=2}$, $\lambda_{Q=3}$: Effect of Q (=1 (low), =2 (intermediate), =3 (high));

$\lambda_{R=0}$, $\lambda_{R=1}$: Effect of road geometry (=0 (straight section), =1 (merge/diverge section));

$\lambda_{P=0}$, $\lambda_{P=1}$: Effect of the peak/off-peak traffic pattern (=0 (off-peak), =1 (peak));

β : Coefficient for exposure.

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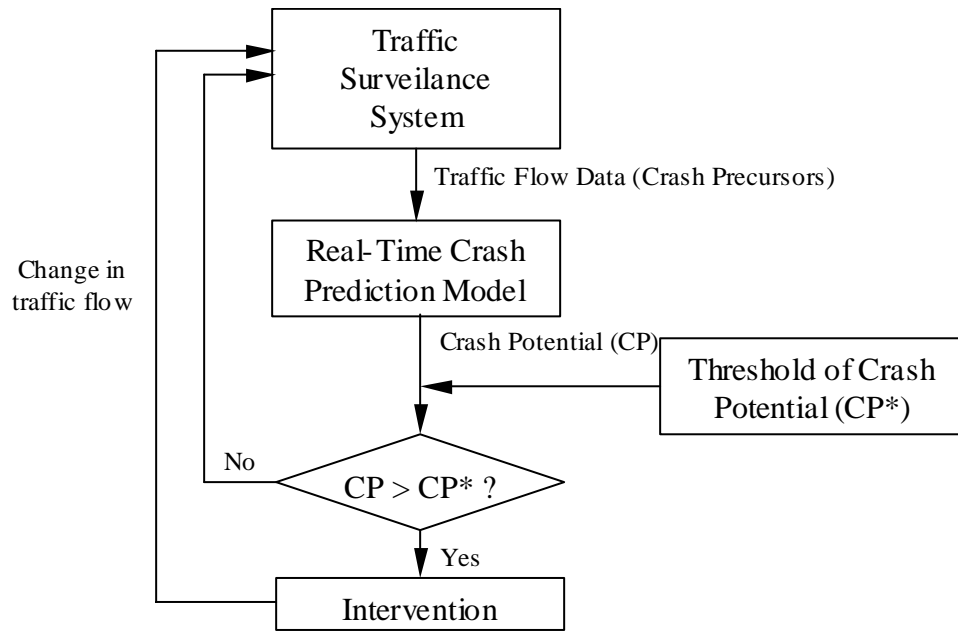


Figure 1.

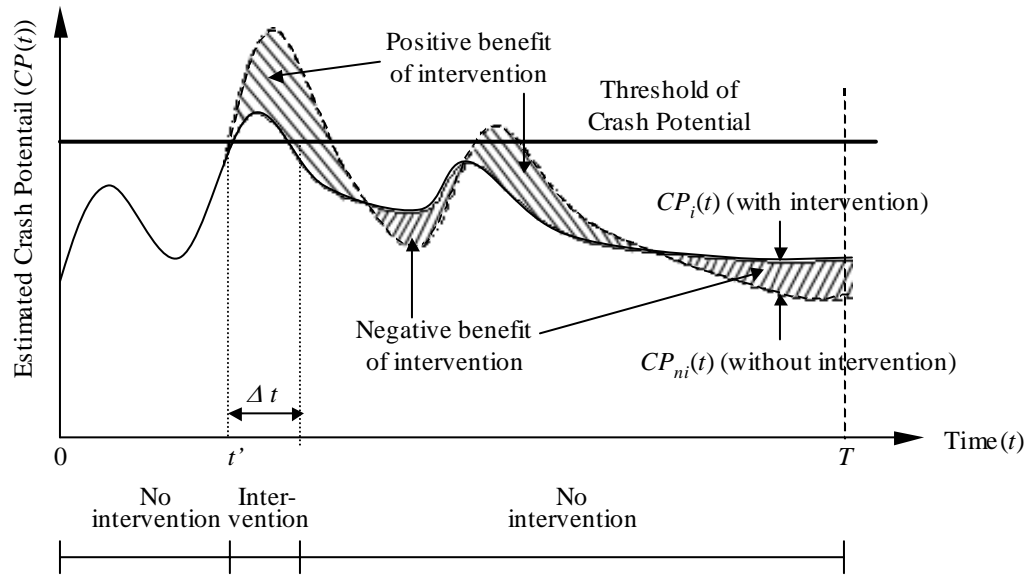


Figure 2.

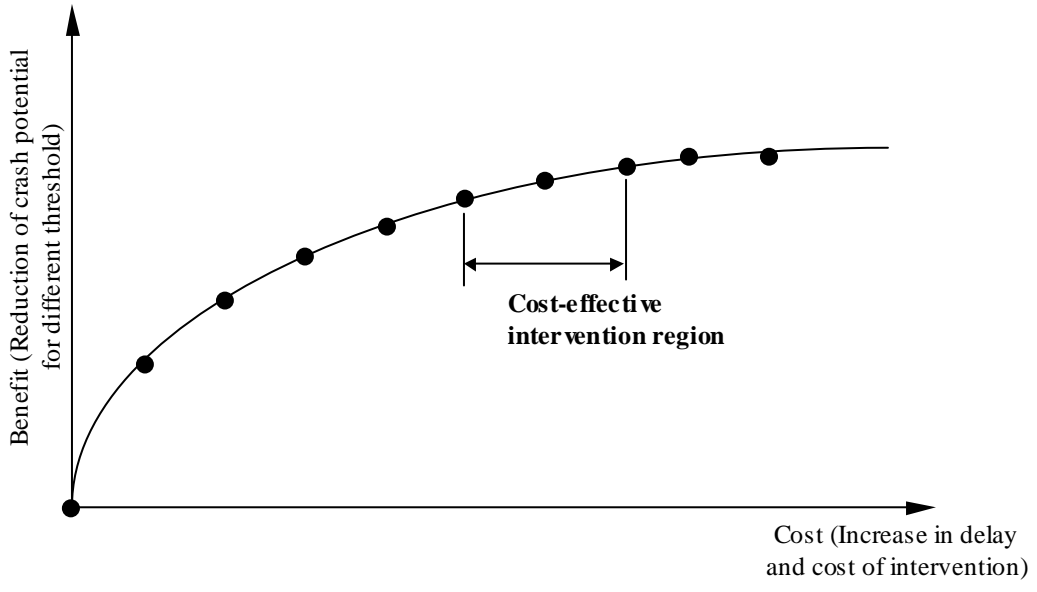


Figure 3.

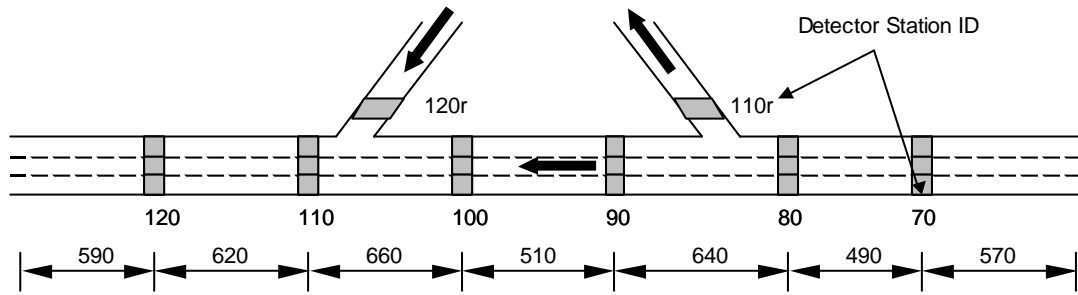
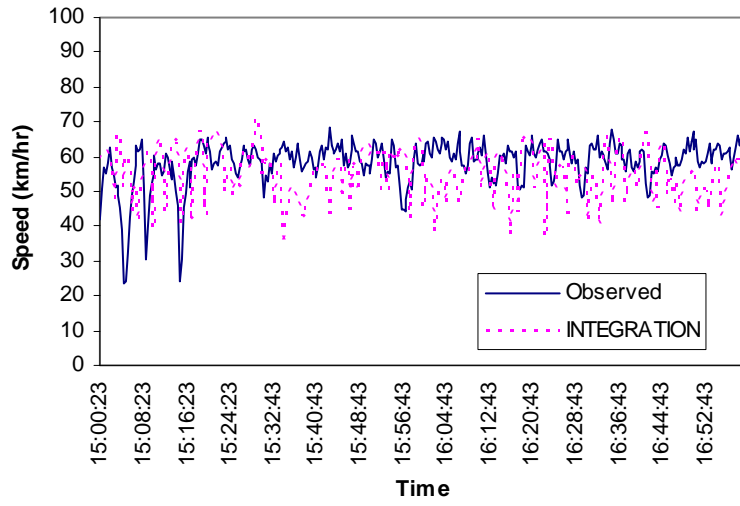
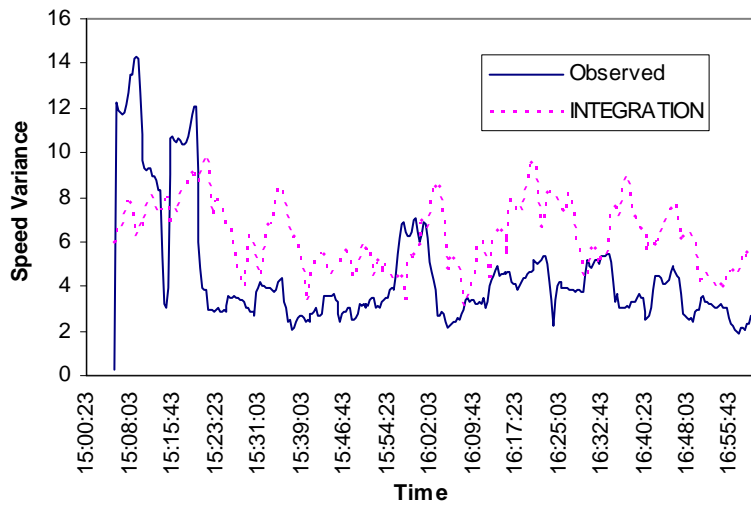


Figure 4.

(a)



(b)



(c)

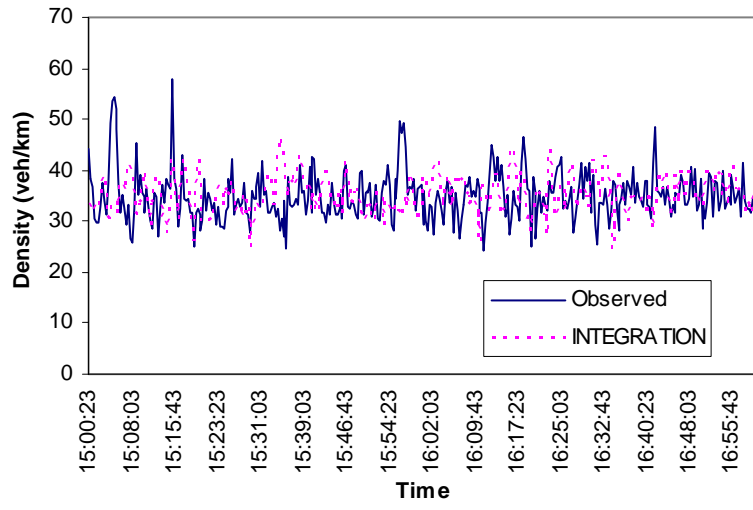


Figure 5.