REAL-TIME SAFETY PERFORMANCE FUNCTIONS FOR SIGNALIZED INTERSECTIONS

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ABSTRACT

Existing advanced traffic management and emerging connected vehicles (CVs) technology can generate considerable amount of data on vehicle positions and trajectories. This data can be used for real-time safety optimization of signalized intersections. To achieve this, it is essential to first understand how changes in signal control affect safety in real-time. This study develops real-time conflict-based safety performance functions (SPFs) for signalized intersections. The developed SPFs relate various dynamic traffic parameters to the number of rear-end conflicts at the signal cycle level. The traffic parameters include: the maximum queue length, the shock wave speed and area, and the platoon ratio. Traffic video-data collected from six signalized intersections in British Columbia and Alberta was used in the analysis. The SPFs were developed using the generalized linear models (GLM) approach. The results showed that all the developed SPFs have good fit with all explanatory variables being statistically significant and have logical signs. In other words, the number of traffic conflicts is expected to increase during the signal cycles that have long queues, bigger shock waves, and lower platoon ratios. Finally, the outcomes of this study can be used most beneficially in real-time safety optimization of signalized intersection.

1. BACKGROUND

The emerging connected vehicles (CVs) technology is expected to produce considerable amount of real-time data on vehicle positions and trajectories using wireless communication between vehicles, infrastructure, and other road users (U.S. Department of Transportation, 2015). These data can potentially be used to improve road safety at signalized intersections in real-time. For instance, using real-time CVs data throughout the functional area of a signalized intersection, the signal controller can be adapted in real-time to minimize vehicle interactions and improve the level of safety. However, the existing methods used to evaluate safety of signalized intersections do not support the real-time safety evaluation.

Therefore, with the increasing emergence of the CVs technology, there is needfor developing real-time safety models that can utilize CVs data to evaluate traffic safety in real-time. The most beneficial use of these safety models is to predict, evaluate and proactively optimize road safety in real-time. Real-time safety models differ from traditional SPFsin two main aspects. First, traditional SPFs predict the number of collisions in several years, while real-time safety models can predict a surrogate safety measure, such as the crash risk or the number of traffic conflicts, in considerably shorter time periods, usually few minutes. Second, traditional SPFs consider only the traffic flow, which is usually aggregated to the annual average daily traffic (AADT). On the other hand, real-time safety models consider several traffic characteristics and their recurrent variation.

Considering the importance of the real-time safety evaluation, several studies have recently developed real-time safety models for freeways (Lee, et al., 2003; Ahmed and Abdel-Aty, 2013; among others). Comparatively, very limited research has consideredreal-time safety models for signalized intersections (Theofilatos, et al., 2017; Yuan and Abdel-Aty, 2018). Thus, given the lack of existing tools to evaluate real-time safety of signalized intersections, there is a growing need for developing real-time safety models for signalized intersections, considering the effect of various traffic variables on safety within very short time periods, few seconds.

The main objective of this study was to develop real-time SPFs for signalized intersections. The models relate the number of rear-end conflicts occurring in each signal cycle to various traffic variables. The traffic variables includedthe traffic volume, the maximum queue length, the shock wave area, and the platoon ratio. The developed models can give insight about how changes in the signal cycle design affect

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the safety of signalized intersections. The overall goal is to use the developed models for optimizing traffic signals in real-time for safety.

2. DATA

Data from six signalized intersections in in the City of Edmonton, Alberta, and the City of Surrey, British Columbia, were used in this study. For all six sites, video cameras were installed to record video-data. The camera scenes were mainly focused on the intersection approaches where most of the rear-end conflictsoccur. The video data were analyzed to track vehicles and extract their trajectories. Detailed trajectories of more than 2500 vehicles were extracted. The data were divided into hundreds of traffic signal cycles. At each signal cycle, the space-time diagram was plotted using vehicle trajectories and the actual signal timing; then different traffic parameters were extracted. The extracted traffic parameters included: the traffic volume (V), the maximum queue length (Q), the shock wave area (A), the platoon ratio (P), and the number of rear-end conflicts. **Figure 1** illustrates the extracted traffic parameters from the cycle's space-time diagram.

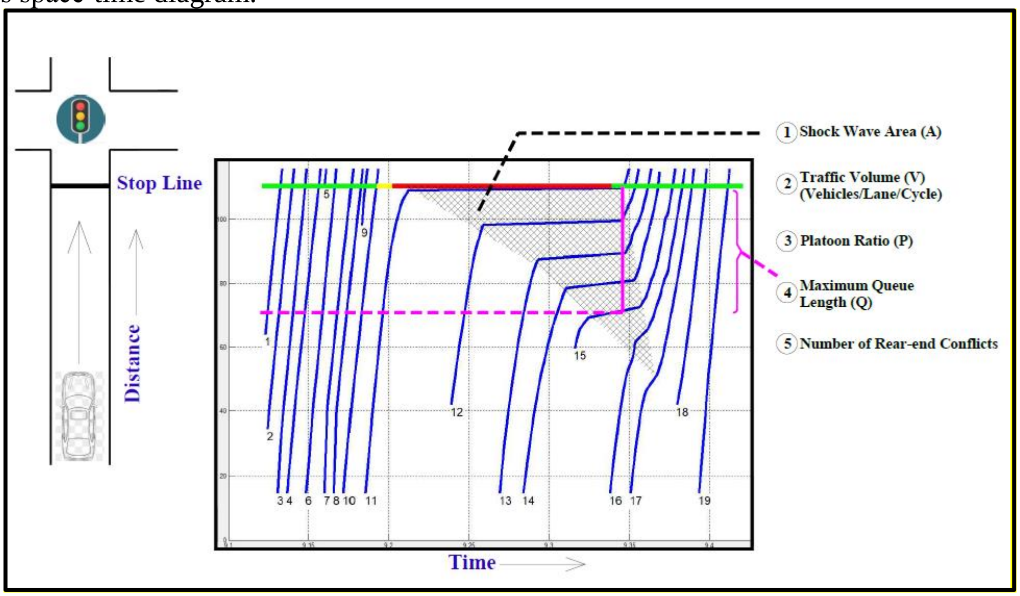

Figure 1: Extracted traffic parameters from the cycle's space-time diagram

The video-analysis procedure was based on a set of MATLAB codes. The procedure started with identifying actual traffic signal timing and cycles for each intersection by detecting the changes in the signal colors from video scenes. Afterwards, moving vehicles in through lanes were tracked and the space-time diagram for each cycle was plotted. Finally, different traffic parameters and the number of rear-end conflicts at each cycle were estimated. The Time-to-Collision (TTC), with a threshold of 1.5 s, was selected as a traffic conflict indicator. The TTC is generally recognized as the most frequently used indicator to identify rear-end conflicts and is defined as "*the time required for two vehicles to collide if they continue at their present speeds and on the same path*" (Hayward, 1972). More details on the video analysis procedure can be found in (Essa and Sayed, 2018a, 2018b). **Table 1** provides summary of statistics of the data used in the analysis.

Table 1: Summary of data statistics

Variable	Description	Unit	Mean	SD	Min	Max
V	Traffic Volume per lane per cycle	---	11.58	3.56	2	22
A	Shock wave area	km. seconds	1.05	0.96	0	3.93
Q	Maximum queue length	meter	40.42	24.54	0	97.46
P	Platoon ratio	---	1.26	0.40	0	2.27
$TTC_{1.5}$	Number of rear-end conflicts (TTC≤ 1.5 s)	---	1.88	1.88	0	7

3. METHODOLOGY

After obtaining the measurements (V, A, Q, P, and the number of rear-end conflicts) for each traffic cycle, the next step was todevelop real-time conflict-based safety models. The models relatedifferent traffic variables within a signal cycle to the number of rear-end conflicts that occurred at the same cycle.The models are developed using the GLM approach.The GLM approach has been widely used in literature for the development of collision and conflict prediction models (e.g. Sawalha and Sayed, 2001; Persaud et al., 2010).The conflict prediction models used in this paper can be expressed mathematically as**Eq.1**.

[1]

$$E(Y) = V^{a_1}\, exp\left[a_0 + \sum_j b_j x_j\right]$$

Where:
$E(Y)$:The predicted number of rear-end conflicts per cycle;
V: The traffic volume per lane per cycle (exposure);
x_j: Any other explanatory variables (such as A, Q, or P);
a_0, a_1, b_j: The model parameters.

Four various models were developed in this paper using different combinations of the explanatory variables (V, A, Q, and P). The goodness of fit of the developed models was assessed using twomain statistical measurements: the scaled deviance (SD), and the Pearson chi-squared (χ^2). In addition, different developed models were compared using Akiake's Information Criterion (AIC). The free software environment for statistical computing "R" was used to develop the GLM models and to estimate different statistical measurements.

4. RESULTS

The results of the developed models are provided in **Table2**. The first model represents the exposure only. In addition to the first model, the table shows threemodels that consider the exposure and one additional variable. The significance of the explanatory variables, the goodness-of-fit statistics, and the error structure for all models are provided in the table.

Table 2: Conflict-based real-time safety models

Model# $\boldsymbol{E(Y)}$ = Number of Rear-end Conflicts =	**Variables***	**Error Structure**	**K****	**SD**	**df**	$\boldsymbol{\chi^2}$	**AIC**
One Variable (Exposure only):							
Model 1:$V^{1.563} exp(-3.231)$	V	NB	3.05	249	220	356	775
(Two Variables):							
Model 2:$V^{0.706} exp(-1.797 + 0.501\, A)$	V, A	NB	14.9	244	219	241	702
Model 3:$V^{0.65} exp(-2.046 + 0.0122\, Q)$	V, Q	NB	8.73	243	219	253	716
Model 4:$V^{1.571} exp(-1.768 - 1.266\, P)$	V, P	Poisson	---	276	219	281	706

**All variables are significantly different from zero at 95% confidence level*
***K: Dispersion parameter for Negative binomial family*

The developed models showed good fit with all explanatory variables being statistically significant at the 95% confidence level. All coefficientshave logical signs. In other words, higher number of conflictsis expected during the signal cycles that have longer queues,bigger shock waves, and lower platoon ratios.

For the exposure-only model (**model 1**), the coefficient of V is statistically significant at 95% confidence level. This model shows a good fit in terms of the (SD)value which is close to the degree of freedom (df). However, the model has a large value of the Pearson chi-squared (χ^2) compared to the (df). This model also has the largest value of AIC comparing to the other models. Thus, despite of the significance of the exposure variable V, more explanatory variables are still needed to provide a better prediction of the conflict occurrence beyond what can be expected from the exposure only.

M**odels 2, 3, and 4** are noted to have a better statistical fit comparing to **model 1**. Also, the additional explanatory variable is significant at 95% confidence level. **Model 2** (volume and shock wave area) represents the best model in terms of AIC, (χ^2), and (SD) values. **Model 3** (volume and maximum queue length) shows a good fit in terms of the(χ^2)and (SD) values. This model shows a value of AIC significantly lower than **model 1** and slightly higher than **model 2**. **Model 4** has a value of AIC very close to **model 2** and significantly better than **model 1**. Thus, the shock wave area, the maximum queue length, and the platoon ratio are shown to be important characteristics that affect the number of rear-end conflicts at the signal cycle. Incorporating one of these characteristics, along with the traffic volume, in the conflict-based safety models of signalized intersections is recommended to improve the model fit.

5. CONCLUSION

The main objective of thisstudywas to develop conflict-based real-time safety models for signalized intersections. Traffic video-data were recorded for six signalized intersections located in two cities in Canada. A video analysis procedure was performed to collect rear-end conflicts and various traffic variables at each signal cycle from the recorded videos. The TTC was used as a traffic conflict indicator. The traffic variables include: the traffic volume, the maximum queue length, the shock wave area, and the platoon ratio.

The safety models were developed using the GLMapproach. The results showed that all the developed models had good fit with all explanatory variables being statistically significant. The shock wave area, the maximum queue length, and the platoon ratio were shown to be important characteristics that affect the number of rear-end conflicts at the signal cycle. Finally, the developed models in this paper can be used most beneficially in real-time safety optimization of signalized intersection.

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