IMPACT OF TIME PERIOD ON SAFETY PERFORMANCE FUNCTION DEVELOPMENT FOR INTERSECTIONS

Wen Cheng, College of Engineering, California State Polytechnic University, Pomona, 3801 W. Temple Ave., Pomona, CA 91768, 909-869-2957, wcheng@csupomona.edu
Steve Avon, College of Engineering, California State Polytechnic University, Pomona, 3801 W. Temple Ave., Pomona, CA 91768, 714-860-2556, savon@csupomona.edu

ABSTRACT

Network screening is the process of identifying intersections or stretches of road as candidates for further study and possible mitigation. The identification methods rely on a function which relates accidents to characteristics of the roadway or intersection, or, safety performance functions (SPF). This paper examines how the amount of crash data added to develop safety performance functions affects the identification results. It is illustrated that four to six years of the most recent crash history be used when using the alternative methods for network screening.

INTRODUCTION

Safety is commonly referred to as the number of accidents (crashes), or accident consequences, by kind and severity, expected to occur on the entity during a specified period [2]. The entity can be either a stretch of roadway or an intersection. The job of a traffic engineer and the goal of a traffic safety study are to improve the safety of the entity. To that end traffic studies are composed of three major parts. These parts are: Identification, Implementation, and Improvement.

In the identification stage, transportation engineers look at the big picture, network screening. The goal of network screening is to identify intersections or stretches of road that require further study. These entities will have been labeled as having safety issues and also have the good possibility of safety improvement. Network screening methods range from the simple, frequency count and crash rate, to the more statistically complex, level of service of safety (LOSS) and Empirical Bayes (EB. These methods all have the same goal which is to rank entities. The way that these methods rank entities is what makes them different. For instance, a frequency count ranks intersections by simply adding up either the total accidents and accident severity while the EB method ranks intersections with the difference between the EB estimated crashes and the SPF predicted crashes. This difference is called the potential for safety improvement and is more meaningful than ranking entities based on totals.

Implementation is a micro look at the entities which are flagged by network screening. In this stage an appropriate countermeasure is suggested and implemented with the goal being to reduce accidents. Improvement, the final part of a traffic safety study, measures the safety of the entity before and after the implementation of the countermeasure. The purpose of a before and after study is to determine the affect the countermeasure had on the safety of the entity. One popular method is the Empirical Bayes method which can measure the safety of the entity. The empirical Bayes method for the estimation of safety increases the precision of estimation and corrects for the regression to- mean bias [3] [4] [5].

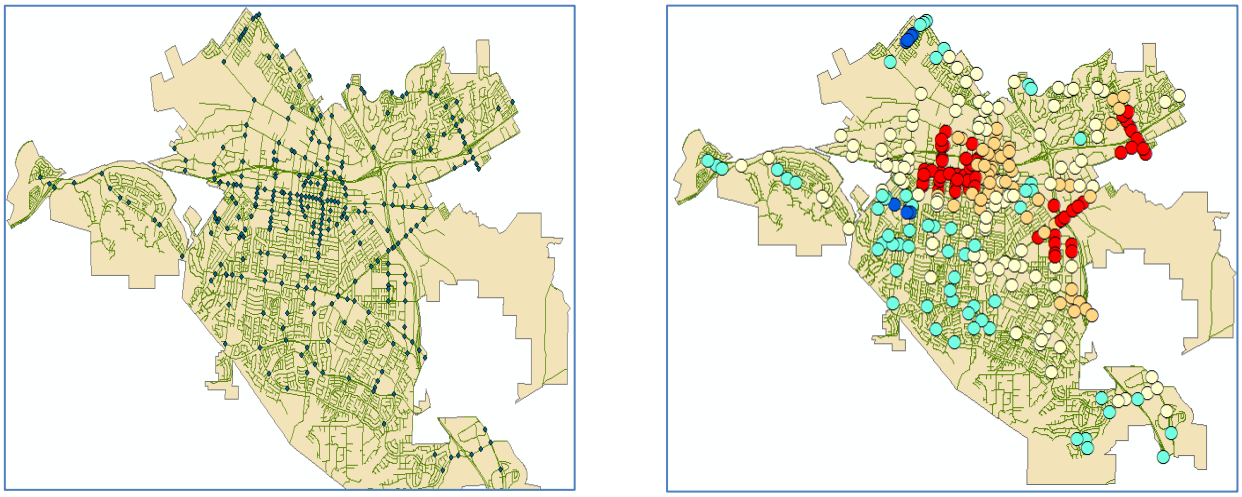
Methods such as the Empirical Bayes need functions to relate accidents to roadway characteristics. These functions are collectively known as safety performance functions (SPF). In order to develop safety performance functions the user needs crash data and characteristics to relate the crash data to. Some characteristics that are used to predict accidents are annual average daily traffic (AADT), major and minor approach speed, number of lanes, and many more. These characteristics vary depending geographic location and the culture of the area. While these predictor variables are relatively known and largely studied, it is less known what the effect of years of crash data added to develop a SPF has on the EB rankings. Different studies have come to different conclusions in this matter but the general consensus is that anywhere from three to six years of crash data is needed in order to adequately develop a statistical defendable SPF. However, it has been shown that in certain cases five years of data is not enough to account for regression to the mean [6] [7] [8].

The goal of this paper is to develop a set of safety performance functions and see how the function coefficients change when more years of crash data are added. Current state of the art practice recommends three to six years of accident data to develop a SPF but there are no intensive studies as to how the amount of data affects the Empirical Bayes ranking of sites. This paper will show the EB rankings of the top 10 sites for each SPF developed and for each year of crash data added. It is the hope of this paper to settle down on a range of acceptable years of crash data one would need to develop a defendable safety performance function.

METHODOLOGY

The data for this project was gathered from the City of Corona for the years 2000 through 2009. The data contained a count of accidents for each year and for varying severities (fatal, injury, and non-injury). In addition, the data set including some roadway characteristics such as major and minor AADT, major and minor right and left turn lanes, number of lanes etc. The first thing that was done was visualization of the data. This was accomplished with ArcGIS and an address locator which plotted a point at every intersection (see left panel in Figure 1). The advantage of using ArcGIS is that we were able to take advantage of the cluster analysis tools. This allowed for the visualization of hotspots within our analysis zone (see right panel in Figure 1).

FIGURE 1: ArcGIS Address Locator and Hotspot Analysis Results



The high/low cluster program in ArcGIS, otherwise known as Getis-Ord, concentrates on high and low values for a study area. A high value means that high values are clustered in an area and vice versa. Positive Z values mean that high values are clustered while negative Z values mean that low values are clustered. Hot-spot analysis is just the Getis-Ord mapped out. Given a set of weighted data points, this tool identifies those points higher in magnitude than you might expect to find by random chance, and vice versa. Those that are statistically significant, a Z-value score larger than 1.96 (Red points) or lower than -1.96 (Blue points) are highlighted.

From left panel in Figure 1 it can be seen that there are three areas which are highlighted in red (high accident cluster). These areas were looked at more closely and it was found that they are centered on on/off ramps. This fact provides a few clues as to what may be causing accidents and ultimately lead us to choose the factors that are in our SPF. These areas have a high truck percentage and large speed differences between cars and trucks which may contribute to accidents [17]. On and off ramps are also characterized as having large AADT's and high turning volumes. For this reason we developed two separate SPFs. The first SPF contains only AADT as a predictor while the second contains AADT and whether or not the major and minor road has left or right turn lanes. Each SPF will predict total accidents for the entity.

Each SPF was initially developed with the most recent year of data. Once the general equation was accepted, the next year of crash data was added to develop each SPF until all 10 years of data were used. Once the two SPFs were developed for each of the ten years of accident data the coefficients were then plotted against time their respective time. In order to rank the intersections we used R program to get the EB estimated accidents for each intersection for each year and for each SPF. The intersections were ranked for each year and for each SPF based on their PSI. The PSI is the difference between the intersections SPF predicted accidents and the EB estimated accidents.

DATA DESCRIPTION AND SPFs DEVELOPMENT

As mentioned previously, the data for this study was provided by the City of Corona for the years 2000 through 2009. There are a total of 300 intersections in the data set but 22 could not be used due to a lack of data. Each row of data corresponds to a different intersection within our area of interest. Each intersection has variables such as major and minor speed limit, AADT, turn lane information, pedestrian crossings, and number of driveways on each approach. Furthermore, the accident data for each intersection is broken up by accident severity for each year.

For the SPFs developed in this paper the power family was used. They are presented in general form and the variables for each SPF and for each year can be seen in the results section. It is known that SPF1 includes only the most important independent variable, while SPF 2 also contains other variables.

SPF 1:

$$e^{\ln(y_i)} = e^{(\propto + \beta_1 \log(AADT))}$$

$$y_i = e^{\propto} x AADT^{\beta_1}$$

SPF 2:

$$e^{\ln(y_i)} = e^{((\alpha+\beta_1 \log(AADT))+\beta_2 MajRT+\beta_3 MajLT+\beta_4 MinRT+\beta_5 MinLT)}$$

$$y_i = e^{\alpha} x AADT^{\beta_1} x e^{\beta_2 MajRT} x e^{\beta_3 MajLT} x e^{\beta_4 MinRT} x e^{\beta_5 MinLT}$$

RESULTS

Two safety performance functions were developed for this paper. The general equation for each SPF was shown previously. Table 1 shows the coefficient values for α and β1. Each of these respective values was then plotted against time, see Figures 2 and 3.

TABLE1: Coefficient Values for SPFs

SPF 1 - AADT Only				SPF 2 - AADT + Turn Lanes			
Years of data	α	β1	Standard Error	Years of data	α	β1	Standard Error
2009	0.000466	0.86395	1.02	2009	0.001276	0.74644	1.17
2009-2008	0.000937	0.86452	0.7	2009-2008	0.00187	0.7882	0.733
2009-2007	0.000973	0.91035	0.602	2009-2007	0.001432	0.86983	0.652
2009-2006	0.000592	0.99323	0.48	2009-2006	0.00096	0.941827	0.519
2009-2005	0.00051	1.02972	0.417	2009-2005	0.00081	0.9807	0.445
2009-2004	0.000541	1.0412	0.366	2009-2004	0.000853	0.99228	0.388
2009-2003	0.000525	1.05812	0.327	2009-2003	0.0008143	1.01001	0.343
2009-2002	0.000566	1.0633	0.295	2009-2002	0.0009276	1.00764	0.308
2009-2001	0.000546	1.07706	0.278	2009-2001	0.0008666	1.02464	0.29
2009-2000	0.000561	1.08172	0.268	2009-2000	0.0008527	1.03359	0.278

FIGURE 2: Plot of Coefficient α versus Time Periods

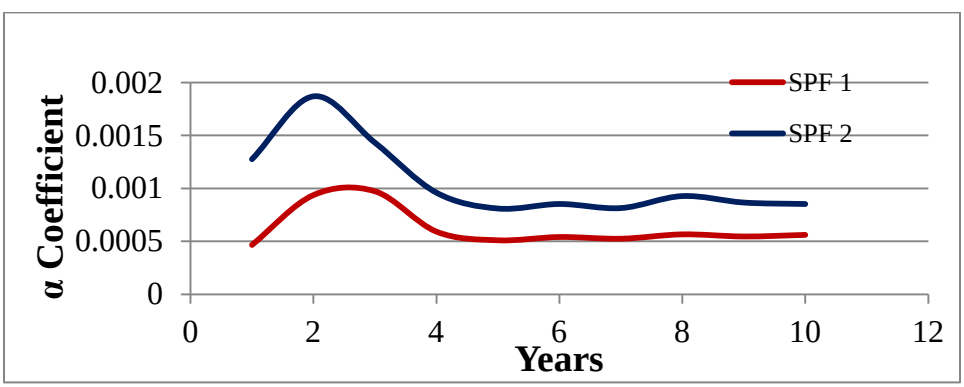
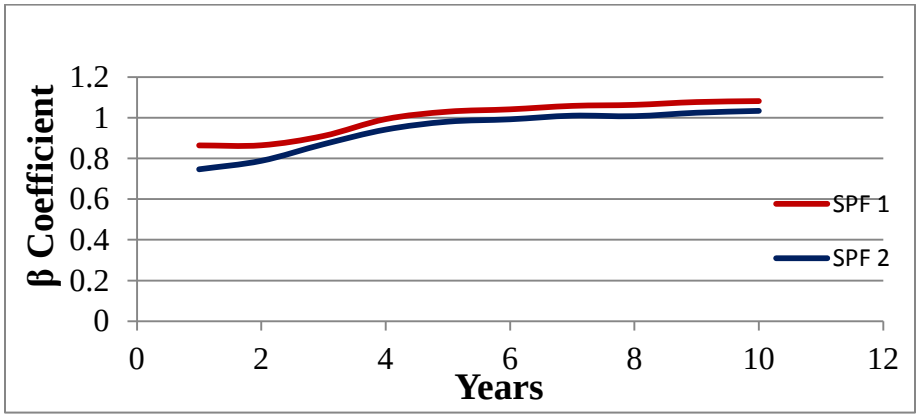


FIGURE 3: Plot of Coefficient β versus Time Periods



Looking at Figure 2, the first three years of data have a lot of variability. The coefficients from Table 1 and Figure 2 show that α starts off low, shoots up, then drops off sharply after the third year. The coefficients start to stabilize around the fourth and fifth year. The coefficients for β1 are more linear and the variability is a bit less dramatic than the α coefficient. We can still see that the coefficients for β1 start to stabilize at about four years.

These two SPFs were then used in the Empirical Bayes method to rank the top ten intersections in terms of total number of accidents. Further investigation was also conducted to focus on the top ten rankings for each SPF for 4, 5, and 6 years of data, respectively. These rankings are compared to a frequency ranking of total accidents. In the case of 4 years of crash data, we found that SPF 1 and 2 identify the same first 4 intersections. However, we also found that the control identifies the same 4 intersections but two of which have their ranking swapped. It also reveals that 9 out of 10 intersections are identified by both SPF 1 and 2. The case of 5 years of crash data shows a similar stability of rankings between SPF 1 and 2. Again, SPF 1 and 2 have 9 common intersections while the control has only 6 common intersections with both. While for 6 years of crash data, we can see that SPF 1 and 2 have the same rank for the top 6 intersections and they share 9 similar intersections.

CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER STUDY

It can be seen in Figures 2 & 3 that the alpha and beta coefficients begin to level out around four years. In between four and six years the data starts to normalize and the standard error begins to level out. This suggests that using accident counts for the most recent four to six years will provide more stable results.

Turning attention to the Empirical Bayes rankings we can conclude that the amount of years used does have an impact on the rankings. Table 5 shows the rankings for SPF 1 for 4, 5, and 6 years of crash data. We can see that 9 of the same intersections are identified for each year. Also, years 5 and 6 have the same ranking for the first 7 intersections.

It is the conclusion of this paper that using four to six years of accident data to develop safety performance functions will provide more stable results. It should also be noted that if less data is used the EB rankings of intersections are more sensitive to changes in rankings.

For future study, it would be pertinent to see if the results of this study are repeatable for other data sets. Also, safety performance functions should be developed to predict accident severities so rankings can factor in cost.

REFERENCES

[1] Cheng, Wen, and Simon Washington. "New Criteria for Evaluating Methods of Identifying Hot Spots." *Journal of the Transportation Research Board*, 2008: 76-85.

[2] Elvik, Rune. "New Approach to Accident Analysis for Hazardous Road Locations." *Journal of the Transportation Research Board*, 2006: 50-55.

[3] Garber, Nicholas J., and Griselle Rivera. *Safety Performance Functions for Intersections on Highways Maintained by the Virginia Department of Transportation.* Final Contract, Richmond: Virginia Transportation Research Council, 2012.

[4] Hauer, Ezra. *Observational Before-After Studies in Road Safety.* Oxford, U.K.: Pergamon, 1997.

[5] Hauer, Ezra, Bryan K. Allery, Jake Kononov, and Michael S. Griffith. "How Best to Rank Sites with Promise." *Journal of the Transportation Research Board*, 2004: 48-54.

[6] Hauer, Ezra, Douglas W. Harwood, Forrest M. Council, and Michael S. Griffith. "Estimating Safety by the Empirical Bayes Method: A Tutorial." *Transportation Research Record*, n.d.: 126-131.

[7] Jang, Hakjin, Soobeom Lee, and Seong W. Kim. "Bayesian analysis for zero-inflated regression models with the power prior: Applications to road safety countermeasures." *Accident Analysis and Prevention*, August 24, 2009: 540-547.

[8] Wang, Xuesong, Mohamed Abdel-Aty, and Patrick A. Brady. "Crash Estimation at Signalized Intersections: Significant Factors and Temporal Effect." *Journal of the Transportation Research Board*, 2006: 10-20.