Systematic Approach to Hazardous-Intersection Identification and Countermeasure Development

Xuesong Wang, Ph.D.[1]; Kun Xie, S.M.ASCE[2]; Mohamed Abdel-Aty, Ph.D.[3]; Xiaohong Chen, Ph.D.[4]; and Paul J. Tremont, Ph.D.[5]

Abstract: Safety performance functions (SPFs) are commonly used to correlate geometric, traffic, and environmental characteristics with total crashes, and to identify hotspots that have excessive overall crash frequencies. However, different crash types are associated with different vehicle maneuvers and therefore different risk factors. At signalized intersections, geometric design, signal control, traffic flow, and traffic crash occurrences vary across different approaches of a single intersection. This study developed approach-level SPFs using a full Bayesian method to assess the safety effects of specific risk factors for rear-end, left-turn, right-angle, and sideswipe crash types, and for total crashes. Based on these approach-level SPFs, a systematic method that efficiently integrated the procedures of hotspot identification and countermeasure development was proposed. The method can be used to identify high-risk intersection approaches with specific safety problems and can serve as a useful complement to general hotspot analyses that use expected crash totals. It was found that some variables, including the number of through lanes, median presence, and left-turn protection, could have contrary effects on the occurrence of certain crash types. The proposed method can provide insights to aid in the development of countermeasures aimed at reducing certain crash types and an improved ability to identify deficiencies related to geometric and traffic characteristics for each intersection approach. **DOI:** 10.1061/(ASCE)TE.1943-5436.0000660.

Author keywords: Signalized intersection; Approach level; Crash type model; Bayesian method; Hotspot identification; Countermeasure development.

Introduction

The exploration of risk factors associated with signalized intersections is complicated by numerous potential conflicts and by the many different intersection features, including geometric design, traffic control, and traffic characteristics. Safety performance functions (SPFs) are typically used to correlate intersection features with total crashes and then to identify hotspots with excessive overall crash frequencies. However, each crash type has its own conflicting patterns and consequently is differentially associated with certain risk factors. As a result, some intersections that do not have an excessive amount of total crashes should still be flagged as hazardous because they have an overrepresentation of specific crash types. Total crash models are less helpful in investigating risk factors related to particular crash types and in identifying high-risk intersections with specific safety problems. To more accurately estimate the relationships of geometric, traffic, and environmental characteristics to crash causes, it is necessary to develop SPFs based on specific crash types. The greater explanatory power of these crash type models can then be used to develop more effective countermeasures aimed at reducing those specific crash types that account for most of the crash problem at signalized intersections.

It should be noted that at signalized intersections, geometric design, signal control, and traffic flow vary across the different approaches at a single intersection. Moreover, and at any given intersection, crashes are usually not evenly distributed among approaches. It follows that SPFs, at the overall intersection level, may obscure the real relationships between the crash antecedents and outcomes. SPFs developed at the approach-level models can remedy this shortcoming by identifying the specific deficiencies related to geometric and traffic factors for each intersection approach.

The framework of intersection safety analysis proposed in this study is illustrated below in Fig. 1. Initially, approach-level crash type models for signalized intersections were developed, and risk factors for particular crash types identified. Then, expectations of various crash types were calculated for each intersection approach. Next, if excessive crash totals or excessive crashes of certain types were present, such hazardous approaches were flagged. At this point, effective countermeasures that can address specific crash problems for those approaches can be identified. The objective of this study is to present a systematic method for intersection safety analysis that focuses on improvements to hotspot identification and countermeasure development based on approach-level crash type models.

[1]Associate Professor, School of Transportation Engineering, Tongji Univ., Shanghai 201804, China (corresponding author). E-mail: wangxs@tongji.edu.cn

[2]Graduate Research Assistant, Dept. of Civil and Urban Engineering, New York Univ., Brooklyn, NY 11201. E-mail: kun.xie@nyu.edu

[3]Professor, Dept. of Civil, Environmental and Construction Engineering, Univ. of Central Florida, Orlando, FL 32816. E-mail: M.Aty@ucf.edu

[4]Associate Professor, School of Transportation Engineering, Tongji Univ., Shanghai 201804, China. E-mail: chenxh@tongji.edu.cn

[5]Visiting Professor, School of Transportation Engineering, Tongji Univ., Shanghai 201804, China. E-mail: pjtremont@hotmail.com

Note. This manuscript was submitted on March 12, 2013; approved on January 6, 2014; published online on April 1, 2014. Discussion period open until September 1, 2014; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Transportation Engineering***, © ASCE, ISSN 0733-947X/04014022(12)/$25.00.

Literature Review

Crash Type Models

Most previous studies focus on the SPFs for overall crash frequencies of intersections (Chin and Qudds 2003; Maher and

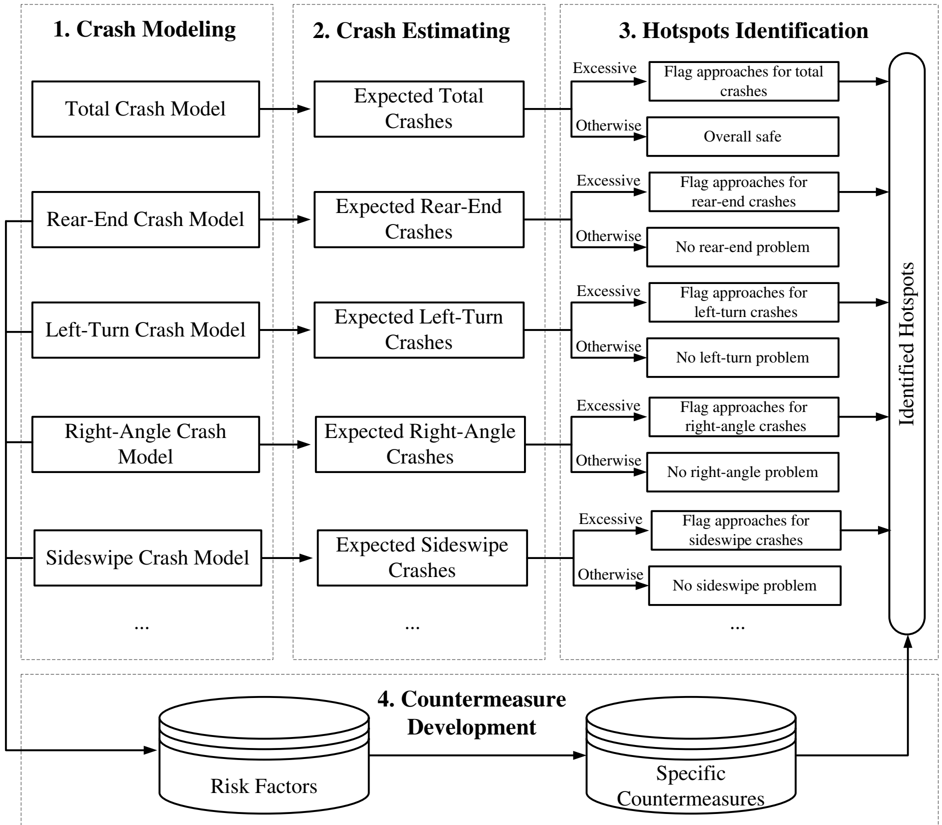

Fig. 1. The intersection safety analysis framework

Summersgill 1996), whereas studies specifically focusing on crash type models are less common. In one such study, Hauer et al. (1988) classified initial crashes into 15 types by vehicle maneuvers before collisions and modeled each type for different time periods (morning peak, afternoon peak, and daily) using conflicting flows. Similar research was conducted for signalized intersections in Ontario, Canada, by Persaud and Nguyen (1998). Crash type models disaggregated by time period, crash severity, and environment class were fitted using traffic flows. In those studies, traffic flow was the only predictor included in each model. The safety effects of other intersection characteristics were not explored.

Relationships among geometric, traffic, and environmental features and specific types of crashes were also investigated in several other studies. Mitra et al. (2002) divided crashes occurring at four-legged signalized intersections in Singapore into a head-to-side type and a head-to-rear type. Geometric and traffic factors affecting the two crash types were identified. In a study by Kim et al. (2006), based on 837 crashes occurring on two-lane rural intersections in the U.S. state of Georgia, SPFs for total, angle, head-on, rear-end, sideswipe, and pedestrian-involved crashes were developed. However, because of differences across intersection approaches, modeling crash occurrences for the full intersection sample cannot reveal the relationships between the crashes and their causes.

With most prior research focused on the association between crash frequencies and overall intersection features, only a few SPFs at the intersection approach level have been developed. Hall (1986) built Poisson models for 14 crash types at the approach level for 199 intersections in urban areas in Great Britain. Poch and Mannering (1996) estimated approach-level negative binomial models for three crash types: angle, rear-end, and turn crashes. They investigated the relationships between approach-related geometric and traffic features, and crash frequencies. Shankar et al. (1995) developed negative binomial models for specific accident types. Qin et al. (2004) developed zero-inflated Poisson models for four different crash types. Nevertheless, these prior studies did not account for correlations among approaches at the same intersection. In a more recent study, Wang and Abdel-Aty (2007) developed right-angle crash models at the approach level using generalized estimation equation (GEE) models to deal with the correlated approach data. In another study by Wang and Abdel-Aty (2008), left-turn crashes were classified into nine patterns based on vehicle maneuvers, and the crash frequencies of each pattern were fitted at the approach level using GEE models.

Hotspot Identification in Terms of Crash Types

Heydecker and Wu (1991) proposed a proportional method to identify hotspots by considering overrepresentation of specific crash types at similar sites. Crash occurrence was regarded as a sequence of infinite and independent Bernoulli trials. A Bayesian posterior beta-binomial probability distribution of the crash rate was used to prioritize hazardous sites according to the probability that the observed proportion of a crash type at a site was above a given critical proportion. Lyon et al. (2007) compared the proportion method and the widely accepted empirical Bayes method, and their results showed the proportion method was a reasonable alternative when SPFs were not available. Based on the same assumption of a Bernoulli distribution for crash occurrence, Kononov (2002) used direct diagnostics and pattern recognition methods for hotspot identification. Kim et al. (2006) screened out high-risk intersections for each crash type using crash type models; however, the regression-to-the-mean issue (Hauer 1980; Cheng and Washington 2005;

Cheng and Washington 2008) was not taken into consideration in these studies.

Risk Factor Analysis

Previous studies have evaluated the safety effects of intersection risk factors on various crash types including rear-end (Hall 1986; Hauer et al. 1988; Kim et al. 2006; Mitra et al. 2002; Persaud and Nguyen 1998; Poch and Mannering 1996; Roess et al. 2003; Wang and Abdel-Aty 2006), left-turn (Hall 1986; Hauer et al. 1988; Joshua and Saka 1992; McCoy et al. 1992; Persaud and Nguyen 1998; Poch and Mannering 1996; Upchurch 1991; Wang and Abdel-Aty 2006), right-angle (Hall 1986; Hauer et al. 1988; Kim et al. 2006; Persaud and Nguyen 1998; Poch and Mannering 1996; Shankar et al. 1995; Songchitruksa and Tarko 2006; Wang and Abdel-Aty 2007), and sideswipe (Hall 1986; Hauer et al. 1988; Kim et al. 2006, 2007; Persaud and Nguyen 1998). Hauer et al. (1988), and Persaud and Nguyen (1998) found that the frequencies of collisions were significantly associated with the traffic flows to which the colliding vehicles belonged. The impacts of geometric features on intersection safety were also investigated. For example, median width was positively associated with left-turn crashes, possibly because wide medians impaired the sight distance for left-turning vehicles (Joshua and Saka 1992; McCoy et al. 1992). They also found that the traffic control and the operational features of intersections could affect crash occurrence. For example, Roess et al. (2003) found that installing a signal could cause an increase in rear-end crashes due to cyclical stopping of the traffic flows. In the research of Wang and Abdel-Aty (2007), the speed limit was identified to be positively correlated with right-angle crashes, possibly because it was related to the running of red lights by drivers at high-speed approaches.

The current study was designed to address some of the limitations of the prior research on intersection crashes by identifying predominant crash types and linking them to geometric design features, traffic control and operational features, and traffic flows at the approach level. Random effects models capable of accounting for the correlation among observations were applied to deal with the correlated approach data. To overcome the regression-to-the-mean problem, a full Bayesian method was used for making crash predictions (Miranda-Moreno and Fu 2007; Lan and Persaud 2011; Persaud et al. 2010). Hazardous intersection approaches were then identified using estimations from crash type models. Based on the identified risk factors that affect specific safety problems, several countermeasures were proposed.

Data Preparation

This study required extensive efforts to collect datasets since all the data was organized at the approach level. The data availability of some variables (such as the left-turn flow and the right-turn flow for approaches) restricted the sample selection. Therefore, one important criterion of sampling was to select the intersections with all the data obtainable. Compared with the four-legged intersections, the traffic organization of three-legged intersections results in less potential conflicts between vehicles and thus three-legged intersections tend to exhibit lower crash rates than four-legged intersections (Wang and Abdel-Aty 2006; Xie et al. 2013). To get more accurate estimated crash frequencies, only four-legged intersections were included into the datasets for modeling. A sample of 177 four-legged signalized intersections was selected from Orange and Hillsborough counties in Central Florida for study. For the 708 approaches to these intersections, geometric design features, traffic control and operational features, traffic flows, and crash frequencies, by type of crash, for the years 2000 to 2005 were collected. Each four-legged intersection was split into four approaches. Crashes occurring on receiving lanes were rare and not considered in this study. The approach-related variables were categorized as entering, near-side crossing, far-side crossing, and opposing.

Approach Characteristics

Geometric design features for each intersection approach were extracted using the high-resolution aerial and satellite imagery provided by software *Google Earth*. The number of through lanes, left-turn lanes, right-turn lanes, the types of left-turn lane offset (negative, zero, or positive), the angle of intersecting roadways, the presence of a median, and the direction of each intersection roadway were identified.

Traffic control and operational features were retrieved by inspecting signal plans of the county traffic engineering departments. The type of left-turn control (*permissive*, *compound*, or *protected*), whether the signal control was coordinated, the yellow and all-red intervals, and the speed limits, were retrieved for each intersection approach. Some intersections controlled by normal signals in the day time transfer to a flashing mode operation during the late night, and the use of a flashing operational mode was also obtained for each intersection.

In Hillsborough County, the daily traffic volumes for each intersection approach were available for only a single year over the study period. Approach annual average daily traffic (AADT) was calculated using the growth rates provided by the traffic department. In Orange County, traffic volume for roadway segments (in both approaching and departing directions) is counted annually by the county traffic engineering department. The approach AADT was obtained by averaging the roadway segment AADT for the period 2000 to 2005. In both counties, the approach daily turning movements (right-turning, left-turning, and through) were derived from the approach AADT supplemented by the proportion of approach turning movements at the peak hours. It is a limitation of this study that actual daily turning movements could not be obtained.

Since each approach will be taken as entering, near-side crossing, far-side crossing, or opposing approach alternatively, the descriptive statistics of variables for entering near-side crossing, far-side crossing, and opposing approach are exactly the same. Therefore, only the descriptive statistics of variables for entering approaches are tabulated in Table 1.

Crash Data

The crash analysis reporting (CAR) system maintained by the Florida Department of Transportation (FDOT) was used to retrieve crashes occurring at the selected intersections for the 2000–2005 6-year period. Crashes were determined to be intersection related based on a method of dynamic identification of the safety influence area proposed by Wang et al. (2008). According to the safety influence areas identified for each intersection, and the crash location distances from the intersection centers, 1940 crashes previously coded as *not at intersection* were reclassified as intersection-related crashes. This resulted in a total of 12,318 intersection related crashes that we then linked to the 177 selected signalized intersections.

Specific crash information such as the initial crash type (e.g., rear-end and left-turn), vehicle movement (e.g., straight ahead and making left turn) and travel direction (e.g., east and west) of crash involved vehicles are available in the crash database of FDOT. In this study, crashes were assigned to intersection

Table 1. Descriptive Statistics of Approach-Level Variables

Variables	Mean	Minimum	Maximum	Standard deviation
Entering approach AADT (vehicles)	13,042.33	51	50,763	10,201.57
Entering approach through AADT (vehicles)	9,280.59	10	50,464	9,190.20
Entering approach left-turn AADT (vehicles)	2,075.08	10	13,005	2,148.97
Entering approach right-turn AADT (vehicles)	1,686.68	3	1,1653	1,717.87
Total number of lanes on entering approach	3.32	1	7	1.32
Number of through lanes on entering approach	1.76	1	5	0.81
Number of left-turn lanes on entering approach	1.06	0	2	0.52
Number of right-turn lanes on entering approach	0.50	0	2	0.51
Median on entering approach (1 if with median; 0 if without median)	0.53	0	1	0.50
Left-turn offset on entering approach (1 if having positive offset; 0 if having no offset; −1 if having negative offset)	0.40	−1	1	0.69
Angle of intersecting approaches (degree)	90.12	36	144	13.05
Signal coordination (1 if coordinated; 0 if isolated)	0.38	0	1	0.49
Left-turn protection on entering approach (2 if protected; 1 if compound; 0 if permissive)	0.94	0	2	0.85
Yellow time for through movement on entering approach (s)	2.46	0	5.5	2.11
All-red time for through movement on entering approach (s)	1.67	0.5	5.1	0.65
Flashing operation (1 if with flashing; 0 if without flashing	0.08	0	1	0.27
Speed limit on entering approach (mph)	41.82	15	60	6.95
Pavement friction on entering approach	35.68	24.19	46.07	4.01
County (1 if Orange County; 0 if Hillsborough County)	0.36	0	1	0.48

approaches near the crash sites. Some records of initial crash type were not consistent with the movement and traveling direction of involved vehicles. By inspecting the crash reports through the state crash report image retrieval system, 1,523 left-turn crashes that were originally recorded as some other crash type, were determined to be left-turn crashes since at least one of the involved vehicles was turning left when the crash occurred. Also, 97 crashes were reclassified as right-angle crashes according to the movement of the crashed vehicles.

The conflict patterns preceding left-turn crashes often vary; however, the two most frequent patterns of left-turn crashes account for 86.6% of all the left-turn crashes, and these two patterns were considered in this paper. For pattern 1, left-turning traffic collides with the opposing through traffic, and for pattern 2, left-turning traffic collides with near-side crossing through traffic. A total of five prominent crash types were identified for modeling in this study: rear-end, left-turn pattern 1, left-turn pattern 2, right-angle, and sideswipe. The sum of these five crash types was 11,386, and accounted for 92.4% of the total crashes. Fig. 2 below illustrates each of these crash types.

Model Development

Methodology

Approaches to a given intersection are correlated with each other because their traffic flows and signalized operations are interactive. Therefore, if basic count models are used based on the assumption of independent observations, biased estimations will result from these correlations. To correct for correlated approach observations, Bayesian random effects models were used in this study. The deviance information criterion (DIC), a widely accepted measure for fitting and complexity of Bayesian models, was used to identify the most appropriate models.

Random Effects Model

To account for dependency and heterogeneity attributable to the unobserved characteristics among observations, random effects models have been frequently been used in previous research (Johansson 1996; Shankar et al. 1998; Xie et al. 2013). In this study, because approaches at the same intersections are correlated and likely to share an unobserved cause, a random intersection-specific effect term was incorporated into each SPF. The overdispersion of crash data was handled by using a negative binomial model. The random effects model can be expressed as follows:

$$y_{ij} \sim \text{Negbin}(\theta_{ij}, r) \tag{1}$$

$$\log(\theta_{ij}) = \beta X_{ij} + \varepsilon_i \tag{2}$$

where y_{ij} is the crash frequency of approach j at intersection i, θ_{ij} is the expectation of y_{ij}, and r is the overdispersion coefficient of negative binomial distribution. X_{ij} is the explanatory variable associated with approach j at intersection i, and β is the vector of regression parameters. The random effect across intersections is ε_i, where $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$.

Full Bayesian Method

Schluter et al. (1997) were among the first to use the full Bayesian method to estimate the posterior mean of a crash frequency and to use it as the criterion for ranking hazardous sites. In the application of the Bayesian method, a prior distribution of likely values was generated and then combined with the observed data to create a site-specific posterior distribution. The theoretical framework for the full Bayesian method (Carlin and Louis 2009) can be expressed as

$$\pi(\theta|y) = \frac{L(y|\theta)\pi(\theta)}{\int L(y|\theta)\pi(\theta)d\theta} \tag{3}$$

where y is the vector of observed data, θ the vector of parameters required for the likelihood function, $L(y|\theta)$ the likelihood function, $\pi(\theta)$ the prior distribution of θ, $\int L(y|\theta)\pi(\theta)d\theta$ the marginal distribution of observed data, and $\pi(\theta|y)$ the posterior distribution of θ given y.

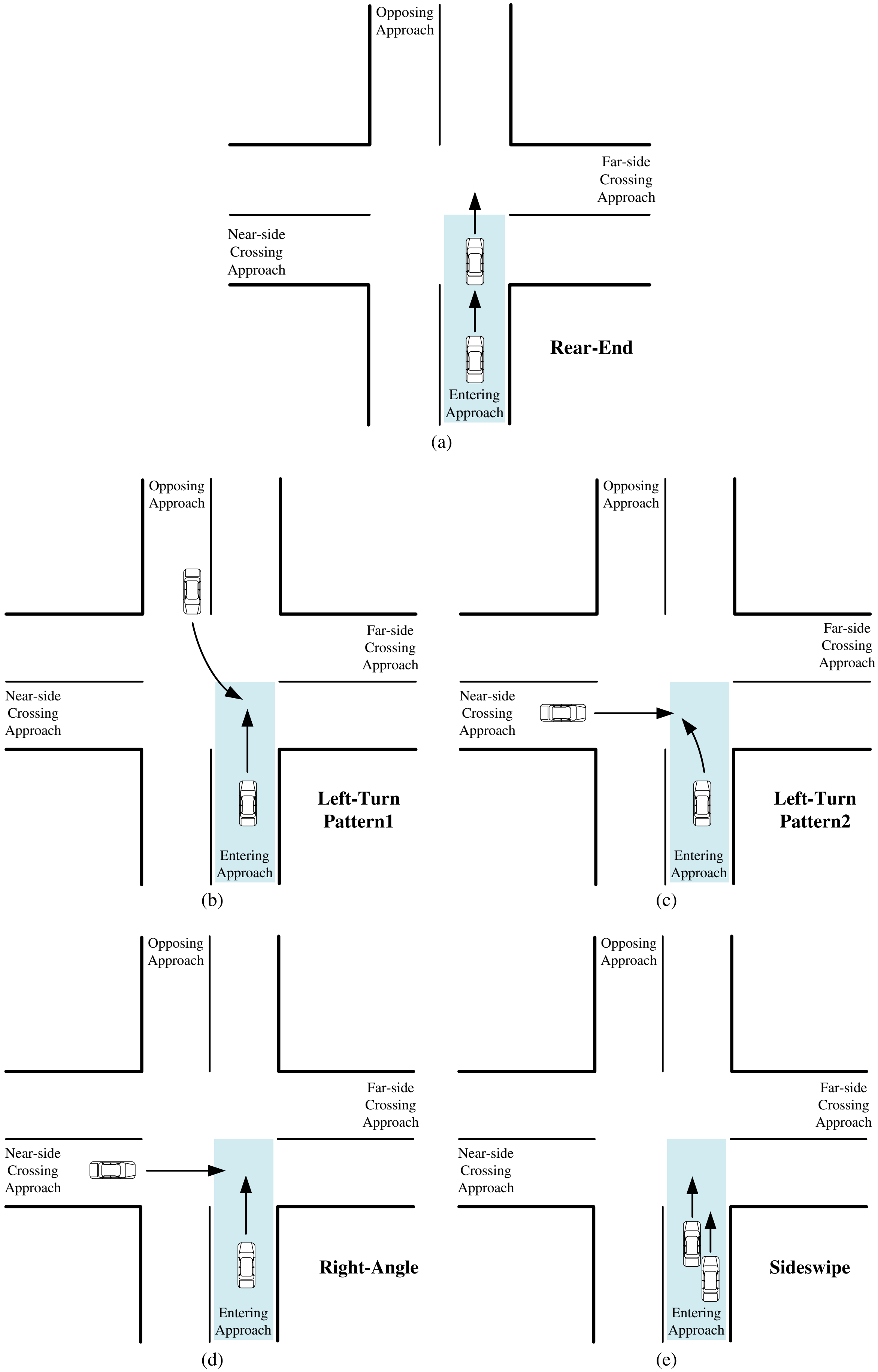

Fig. 2. Crash types classified by conflicting vehicle maneuvers: (a) rear-end; (b) left-turn pattern 1; (c) left-turn pattern 2; (d) right-angle; (e) sideswipe

Table 2. Model Comparisons using DIC

Crash type	Negative binomial models $\overline{D(\theta)}$	Negative binomial models p_D	Negative binomial models DIC	Random effects models $\overline{D(\theta)}$	Random effects models p_D	Random effects models DIC
Total crash	4,809.474	8.983	4,818.457	4,258.960	156.103	4,415.063
Rear-end	4,161.088	9.934	4,171.022	3,815.000	134.093	3,949.093
Left-turn pattern 1	2,889.461	8.987	2,898.448	2,689.300	109.062	2,798.362
Left-turn pattern 2	1,262.087	8.998	1,271.085	1,187.280	63.586	1,250.866
Right angle	2,070.913	7.962	2,078.875	1,907.140	99.629	2,006.769
Sideswipe	1,739.779	9.009	1,748.788	1,567.400	100.362	1,667.762

Deviance Information Criterion

The DIC is widely used as a Bayesian measure of model fitting and complexity (Speigelhalter et al. 2003a). DIC is defined as

$$\mathrm{DIC} = \overline{D(\theta)} + p_D \tag{4}$$

where $D(\theta)$ is the Bayesian deviance of the estimated parameter θ and $\overline{D(\theta)}$ denotes the posterior mean of $D(\theta)$. $\overline{D(\theta)}$ can be taken as a measure of model fitting. p_D is the effective number of parameters and indicates complexity of models. Models with smaller DIC are preferred.

Modeling Results

Bayesian inference is usually implemented using a Markov chain Monte Carlo (MCMC) algorithm (Gilks et al. 1995). Open source software *WinBUGS* (Spiegelhalter et al. 2003b) was used to calibrate the Bayesian models using MCMC. Without credible prior information, uninformative priors were assumed for all regression coefficients with the Normal distributions (0, 10^5). The variance of the random effect and the overdispersion coefficient for the negative binomial distribution were assumed with the inverse-gamma distribution (10^{-3}, 10^{-3}).

The proposed random effects models were used to develop SPFs for total, rear-end, left-turn pattern 1, left-turn pattern 2, right-angle, and sideswipe crashes in the Bayesian framework. Negative binomial models for various crash types were also calibrated as comparisons. As shown in Table 2, lower DIC values of the random effects models indicate that they perform better than the negative binomial models by including a random effect term, although it is penalized by higher p_D values that reflect the increasing complexity of random effects models.

Posteriors summary and goodness of fit statistics for the six random effects models are reported in Tables 3–5. Traffic volume was

Table 3. Posterior Summary of Total and Rear-End Crash Models

Variables		Total crash Mean	Total crash Standard deviation	Rear-end Mean	Rear-end Standard deviation
Intercept		−1.853	0.2324	−4.378	0.5967
Logarithm of the traffic volume involved[a]		0.3957	0.0273	0.6542	0.0478
Number of through lanes on entering approach		—	—	—	—
Number of left-turn lanes on entering approach		0.1042	0.0522	—	—
Number of right-turn lanes on entering approach		0.1855	0.0462	0.2514	0.0608
Number of through lanes on opposing approach		—	—	—	—
Median on entering approach	With median	—	—	—	—
	Without median	—	—	—	—
Signal coordination	Yes	—	—	0.2426	0.0756
	No	—	—	0	—
Left-turn protection on entering approach	Protected	0.3648	0.0775	0.6937	0.0985
	Compound	0.259	0.0682	0.3831	0.09
	Permissive	0	—	0	—
Speed limit on entering approach		0.011	0.0037	—	0.0056
Speed limit on near-side crossing approach		—	—	—	—
Difference between the real value and the standard yellow time		—	—	—	—
Difference between the real value and the standard all-red time		—	—	—	—
Flashing operation	With flashing	—	—	—	—
	Without flashing	—	—	—	—
Pavement friction of entering approach		—	—	−0.0156	0.0087
County	Orange	−0.3683	0.0953	−0.4225	0.102
	Hillsborough	0	—	0	—
Dispersion		0.1203	0.0141	0.2319	0.0257
Random effect		0.3138	0.0438	0.2816	0.0464
Summary statistics	Intersection number	177		177	
	Observation number	708		708	
	Crash number	12,318		7279	

[a]Logarithm of traffic volumes on the entering approaches in the total crash model; logarithm of traffic volumes on the entering approaches in the rear-end crash model.

Table 4. Posterior Summary of Left-Turn Patterns 1 and 2 Crash Models

Variables		Left-turn pattern 1		Left-turn pattern 2	
		Mean	Standard deviation	Mean	Standard deviation
Intercept		−5.9730	0.5970	−6.3950	1.0020
Logarithm of the traffic volume involved[a]		0.2797	0.0361	0.3681	0.0483
Number of through lanes on entering approach		0.2053	0.0904	—	—
Number of left-turn lanes on entering approach		—	—	—	—
Number of right-turn lanes on entering approach		—	—	—	—
Number of through lanes on opposing approach		—	—	−0.6285	0.1482
Median on entering approach	With median	0.3934	0.1455	−0.1549	0.0826
	Without median	0	—	0	—
Signal coordination	Yes	—	—	—	—
	No	—	—	—	—
Left-turn protection on entering approach	Protected	−0.5397	0.1742	0.2882	0.1865
	Compound	0.4366	0.1511	0.1940	0.1952
	Permissive	0	—	0	—
Speed limit on entering approach		0.0438	0.0077	—	—
Speed limit on near-side crossing approach		—	—	0.0177	0.0135
Difference between the real value and the standard yellow time		—	—	—	—
Difference between the real value and the standard all-red time		—	—	—	—
Flashing operation	With flashing	—	—	—	—
	Without flashing	—	—	—	—
Pavement friction of entering approach		—	—	—	—
County	Orange	−0.7686	0.1485	−0.4034	0.1731
	Hillsborough	0	—	0	—
Dispersion		0.7083	0.0851	0.5690	0.1934
Random effect		0.4600	0.1020	0.3341	0.1408
Summary statistics	Intersection number	177		177	
	Observation number	708		708	
	Crash number	2,059		393	

[a]Logarithm of the product of the entering through and opposing left-turning traffic volumes in the left-turn pattern 1 crash model; logarithm of the product of the entering left-turning and near-side crossing through traffic volumes in the left-turn pattern 2 crash model.

Table 5. Posterior Summary of Right-Angle and Sideswipe Crash Models

Variables		Right-angle		Sideswipe	
		Mean	Standard deviation	Mean	Standard deviation
Intercept		−2.305	0.4603	−7.641	0.7139
Logarithm of the traffic volume involved[a]		0.1677	0.0287	0.6564	0.087
Number of through lanes on entering approach		−0.097	0.0547	0.1972	0.0874
Number of left-turn lanes on entering approach		—	—	0.3827	0.1106
Number of right-turn lanes on entering approach		—	—	0.2684	0.1033
Number of through lanes on opposing approach		—	—	—	—
Median on entering approach	With median	—	—	—	—
	Without median	—	—	—	—
Signal coordination	Yes	—	—	—	—
	No	—	—	—	—
Left-turn protection on entering approach	Protected	—	—	0.5367	0.1782
	Compound	—	—	0.4652	0.16
	Permissive	—	—	0	—
Speed limit on entering approach		—	—	—	—
Speed limit on near-side crossing approach		—	—	—	—
Difference between the real value and the standard yellow time		−0.3867	0.1265	—	—
Difference between the real value and the standard all-red time		−0.1169	0.0774	—	—
Flashing operation	With flashing	0.5059	0.1942	—	—
	Without flashing	0	—	—	—
Pavement friction of entering approach		—	—	—	—
County	Orange	−0.5791	0.138	−0.229	0.1348
	Hillsborough	0	—	0	—
Dispersion		0.1238	0.0657	0.064	0.0518
Random effect		0.2908	0.0681	0.3677	0.0879
Summary statistics	Intersection number	177		177	
	Observation number	708		708	
	Crash number	848		807	

[a]Logarithm of the product of the through traffic volumes on the entering and crossing approaches in the right-angle crash model; logarithm of traffic volumes on the entering approaches in the sideswipe crash model.

Table 6. Identify Hazardous Intersection Approaches Based on Individual Crash Type Estimates

Ranking criteria	Rank				
	First	Second	Third	Fourth	Fifth
Total crash					
Approach ID	*4494-1*	*4494-3*	*506-3*	*1443-3*	*4129-2*
Predictions	125	104	86	74	69
Rear-end					
Approach ID	***4494-1***	***4494-3***	***506-3***	***1443-3***	**506-1**
Predictions	103(< 0.001)	78(< 0.001)	78(< 0.001)	64(< 0.001)	54(< 0.001)
Left-turn pattern 1					
Approach ID	**474-1**	*4494-3*	**174-1**	**458-1**	**6215-3**
Predictions	33(< 0.001)	18(0.489)	15(0.031)	15(< 0.001)	13(0.001)
Left-turn pattern 2					
Approach ID	**6003-2**	881-1	**1449-4**	**3710-3**	**1461-4**
Predictions	4(0.004)	4(0.054)	3(< 0.001)	3(< 0.001)	3(< 0.001)
Right-angle					
Approach ID	**497-2**	**497-4**	**2333-2**	**2333-4**	**2333-3**
Predictions	4(0.015)	4(0.002)	4(0.002)	4(0.002)	4(0.005)
Sideswipe					
Approach ID	*4494-1*	*4494-3*	**1454-3**	1653-2	**1644-2**
Predictions	8(0.552)	7(0.501)	7(0.018)	6(0.138)	6(0.012)

Note: Approaches in italics are ranked as the top five by predicted crash totals. Approaches in bold are those with overrepresentation of specific crash types. Numbers in parentheses indicate the probabilities obtained by the direct diagnostic method.

included as an explanatory variable in crash predictions, since it has been confirmed that the frequencies of accidents are related to conflicting traffic flows, and not to the sum of the entering flows (Hauer et al. 1988). The forms of traffic volume included in these models are listed in the note below each table.

The random effect variances (e.g., 0.2816 in the SPF for rear-end crashes) were statistically significant and affirmed the presence of between-intersection heterogeneity. The estimated dispersion values (e.g., 0.2319 in the SPF for rear-end crashes) provided strong evidence that crash data are overdispersed. This overdispersion would result in the underestimation of the standard errors in the Poisson model formulation.

Improvements to Hotspot Identification

In this section, hazardous intersection approaches were identified based on posterior means of each crash type by the full Bayesian method and were compared with approaches identified by the predicted crash totals.

Hotspot Identification Based on Crash Type Estimates

A direct diagnostics method proposed by Kononov (2002) was used to examine whether a particular crash type was overrepresented in an intersection approach. Instead of using observed data in the original direct diagnostics method, Bayesian posterior estimations were applied to make the determinations of crash type overrepresentations. The advantage of using posterior estimations over raw crash observations is that it is able to address the regression-to-the-mean issue. The regression-to-the-mean is a statistical phenomenon that makes natural variation in repeated observed data (Barnett et al. 2004). Since crashes are rare and random events, sites with high crash frequencies in one period can experience lower crash frequencies subsequently even if no treatment is implemented. Identifying hotspots by raw crash observance is likely to confound the natural variation with the *should-be* crash occurrence.

The following example shows the Bayesian posterior means of left-turn pattern 1 and total crashes for approach #1 at intersection #458 (denoted as #458-1) to be 15 and 30, respectively, while the predicted average proportion for left-turn pattern 1 crashes is 17.0%. If we assume that each crash that occurred at approach #458-1 as an independent Bernoulli trial, then the probability of 15 or more left-turn pattern 1 crashes out of 30 total crashes can be calculated as follows:

$$P(X \geq x|\theta, n) = \sum_{i=x}^{n} \frac{n!}{(n-i)!i!}\theta^i(1-\theta)^{n-i} \tag{5}$$

$$P(X \geq 15|0.170, 30) = \sum_{i=15}^{30} \frac{30!}{(30-i)!i!}0.170^i(1-0.170)^{30-i} = 3.34 \times 10^{-5} \tag{6}$$

As shown in Eq. (6), the probability of 15 or more left-turn pattern 1 crashes out of 30 total crashes is extremely low at 3.34×10^{-5}. Therefore a deficiency must be present in approach #458-1 that increases the risk of left-turn pattern 1 crashes.

Table 6 below lists the top five hazardous approaches for each crash type ranked by predicted crash frequencies. The direct diagnostics method mentioned above was used to check those top ranked approaches. If $P <= 0.05$, it can be viewed as an evidence of overrepresentation of that crash type. The results show that approaches #4494-1, #4494-3, #506-3, #1443-3, and #506-1 are overrepresented in rear-end crashes; approaches #474-1, #174-1, #458-1, and #6215-3 have excessive left-turn pattern 1 crashes; approaches #6003-2, #1449-4, #3710-3, and #1461-4 have excessive left-turn pattern 2 crashes; approaches #497-2, #497-4, #2333-2, #2333-4, and #2333-3 have excessive right-angle crashes; and approaches #1454-3 and #1644-2 have excessive sideswipe crashes.

However, among those aforementioned approaches, none of the approaches with excessive left-turn pattern 1, left-turn pattern 2, right-angle, and sideswipe crashes were listed in the top five approaches that had high expected crash totals. A number of approaches with problems such as approaches #474-1, #6003-2, #497-2, which were respectively ranked first by estimations of left-turn pattern 1, left-turn pattern 2, and right-angle crashes, and had overrepresentation of these types that had been previously ignored because of their relatively few total crashes.

Comparisons of Ranked Hazardous Approaches

Comparisons of the ranks of hazardous approaches between predicted crash totals and numbers of each crash type are shown below in Fig. 3. For each panel, the X-axis represents the rank in decreasing order of predicted total crashes, and the Y-axis represents the rank in decreasing order of estimations for each crash type. The spread of points around the diagonal line shows the difference in identifying hazardous approaches with a greater spread of points indicating great difference. It can be seen that the ranking difference between predicted total crashes and predicted left-turn pattern 1 [Fig. 3(b)], left-turn pattern 2 [Fig 3(c)], and right-angle crashes [Fig. 3(d)], is greater than that between predicted total crashes and predicted rear-end [Fig. 3(a)], and sideswipe crashes [Fig. 3(e)]. According to FDOT summary of crash injury severity for each crash type, around 14.3% of left-turn (patterns 1 and 2) crashes, 13.5% of right-angle crashes involve incapacitating and fatal injuries, while the percentages of rear-end and sideswipe crashes which caused incapacitating and fatal injuries are only 5.1% and 2.3%,

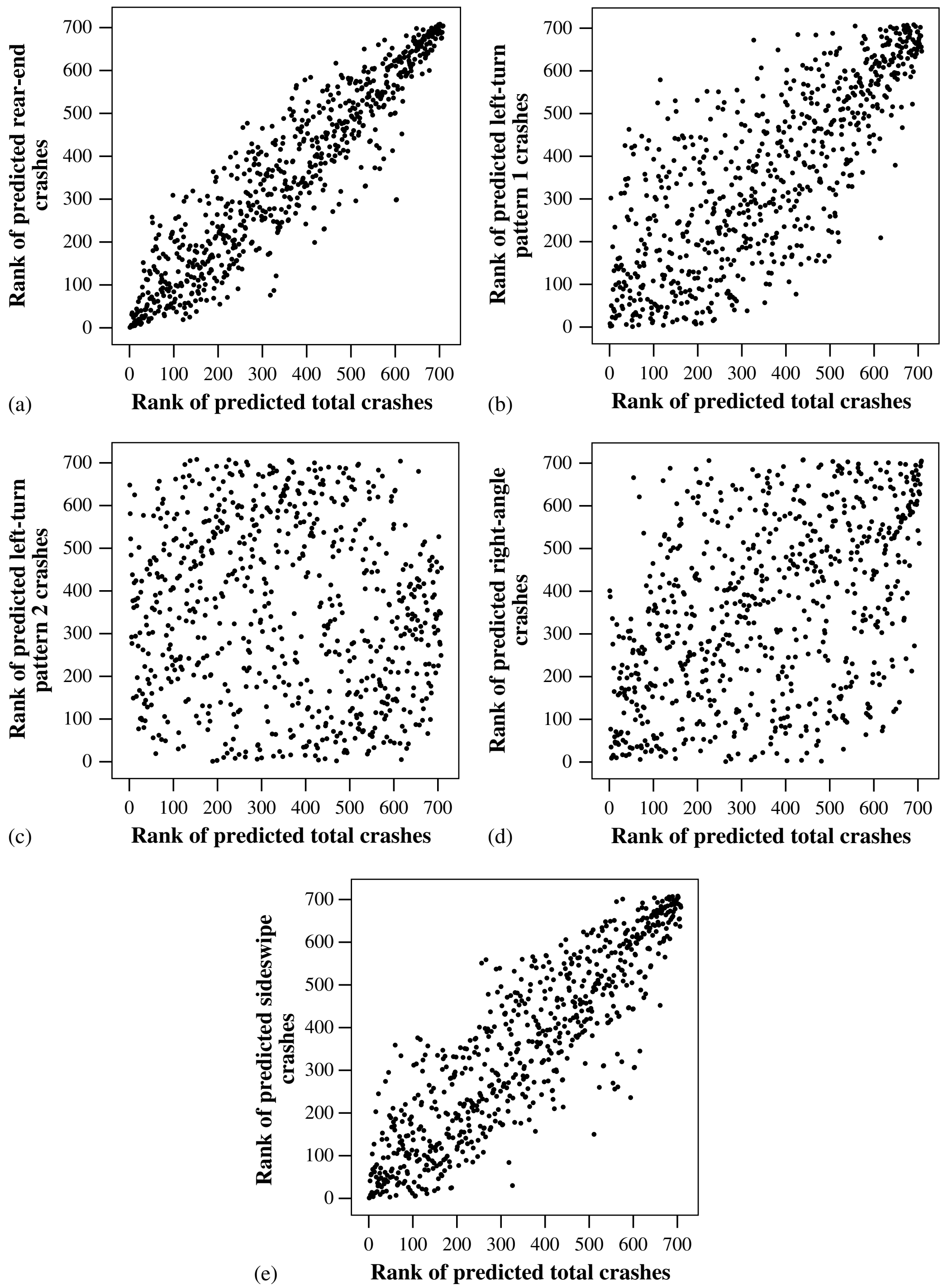

Fig. 3. Comparisons of high-risk approach ranking between predicted crash total and each crash type: (a) rear-end versus crash total; (b) left-turn pattern 1 versus crash total; (c) left-turn pattern 2 versus crash total; (d) right-angle versus crash total; (e) sideswipe versus crash total

respectively. In this case, hotspot identification based on overall crash totals (rather than types) screened out approaches with high frequencies of rear-end and sideswipe crashes, and were more likely to miss the approaches with more serious crash types such as left-turn and right-angle. The method adopted in this study reduces the likelihood of making this kind of error.

Improvements to Countermeasure Development

Crash type models at the approach level lead to an improved ability to develop countermeasures in two ways. First, since risk factors are different for different crash types, treatments can be aimed at reducing those specific crash types that are causing the most problems. Second, by modeling crash occurrence with approach-related factors, specific deficiencies can be identified for each intersection approach.

Treatments Aimed at Specific Crash Types

The quantified safety effects of geometric features, traffic control and operational features, and traffic flows on specific crash types were presented in Tables 3–5. A specific case to consider is one where a single approach-related variable might have contrary effects on the occurrence of different crash types. An example would be left-turn protection. Compared with the permissive phase, the protected phase reduces the left-turn pattern 1 crashes (coefficient = −0.5397), but is associated with more left-turn pattern 2 (coefficient = 0.2882), rear-end (coefficient = 0.6937), sideswipe (coefficient = 0.5367), and total crashes (coefficient = 0.3648). In addition, the presence of a median increases the frequencies of left-turn pattern 1 crashes (coefficient = 0.3934), but is associated with fewer left-turn pattern 2 crashes (coefficient = −0.1549). Furthermore, the number of through lanes on entering approach has a negative association with right-angle crashes (coefficient = −0.0970), but a positive association with left-turn pattern 1 (coefficient = 0.2053), and sideswipe crashes (coefficient = 0.1972).

More specific and efficient treatments can be developed to improve safety at intersections based on the identified factors that affect the precise problem. For instance, if an intersection has excessive left-turn pattern 1 crashes, but fewer rear-end crashes, a protected phase would be recommended for left-turn protection at this intersection. This example shows specifically how crash type models can provide an improved ability to investigate the real effects of risk factors for certain type of crashes and to help identify effective countermeasures.

Approach-Specific Deficiencies

Crash expectations for each approach can be obtained from SPFs at the approach level. These expectations can provide useful insights when diagnosing specific safety problems and identifying relevant deficiencies for each approach. Taking intersection #474 as an example, according to Table 6 above, a problem of excessive left-turn pattern 1 crashes is expected to occur at its eastbound approach #474-1. Predictions of each of the various crash types were calculated for the #474 intersection's four approaches, and the results are shown below in Fig. 4.

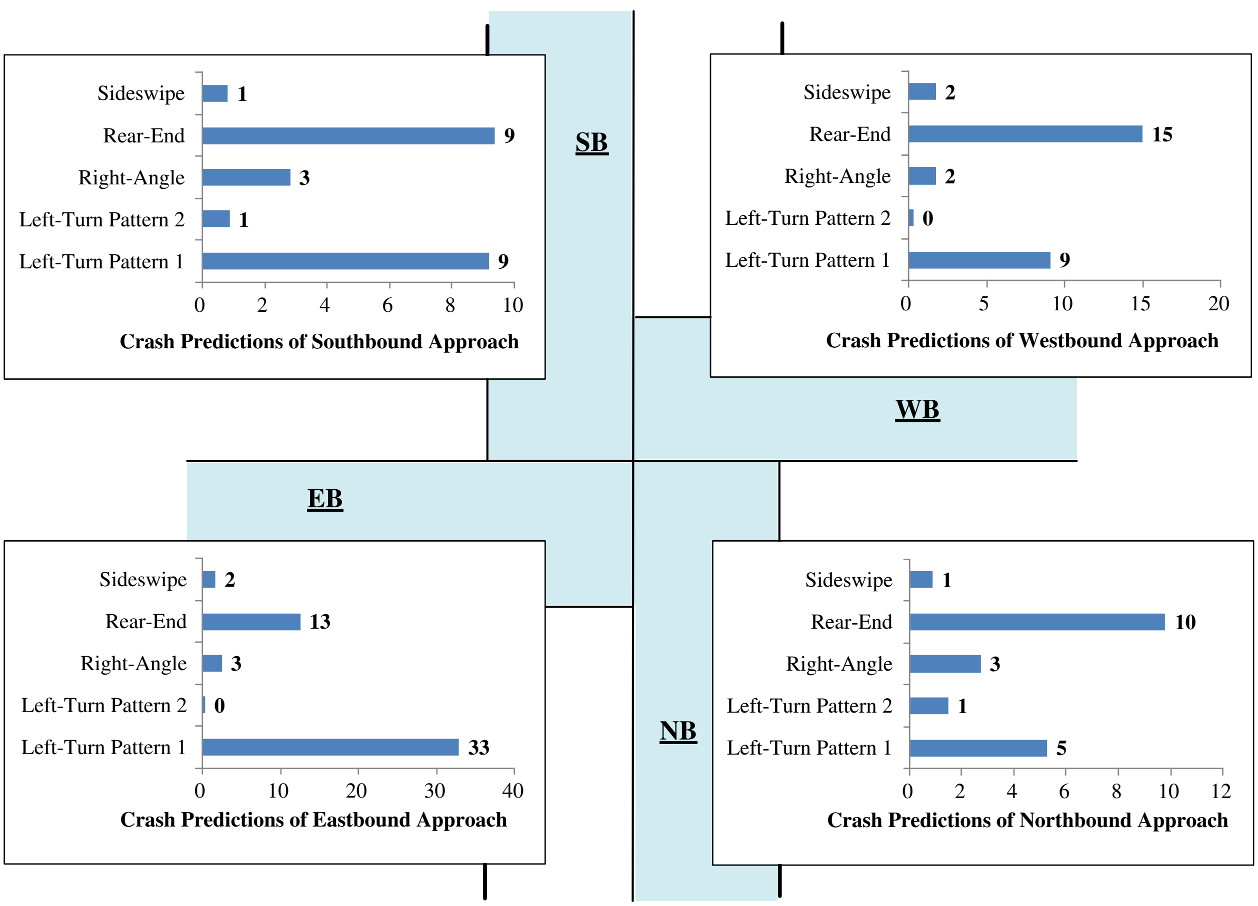

Fig. 4. Crash predictions for each approach of one hazardous intersection (intersection ID = 474)

Observe that for the eastbound approach, there are 33 left-turn pattern 1 crashes expected and only 13 rear-end crashes expected. If the left-turn protection in the eastbound approach is changed from a permissive phase to a protected phase, according to the coefficients in Tables 3 and 5, the left-turn pattern 1 crashes can be expected to decrease by 41.7% (1-$e^{-0.5397}$), i.e., from 33 to 19; the rear-end crashes are expected to increase by 100.1% ($e^{0.6937} - 1$), i.e., from 13 to 26; and the sideswipe crashes are expected to increase by 71.0% ($e^{0.5367} - 1$), i.e., from 2 to 3. Considering the higher proportion of serious left-turn pattern 1 crashes than those of rear-end and sideswipe crashes, it is recommended to change the left-turning protection phase.

For the northbound approach, however, the recommendation would be to keep the permissive phase because the most predominant crash type is rear-end (10 rear-end crashes out of 20 total crashes), and protected or compound phases would increase the overall risk of crashes. These examples illustrate how approach-level SPFs can provide specific suggestions for safety improvements by identifying the geometric and traffic characteristics that predict specific crash types for the approaches being considered.

Summary and Conclusions

The main focus of this study is to present a systematic approach that integrates the procedures of hotspot identification and countermeasure development based on approach-level crash type models.

A total of 177 four-legged signalized intersections were selected from the Orange and Hillsborough counties in the Central Florida area for study. Bayesian random effects models for five crash types (i.e., rear-end, left-turn pattern 1, left-turn pattern 2, right angle, sideswipe) and total crashes were developed at the approach level. The correlations among approaches at the same intersection were accounted for by incorporating a random intersection-specific effect term into each SPF.

A direct diagnostics method was used to examine whether there was overrepresentation of certain crash types for the top ranked intersection approaches. Approaches with specific problems were then flagged, as a good complement to hotspots identified using crash totals. In addition, comparisons of hazardous approach ranks between predicted crash totals and frequencies of each crash type using the full Bayesian method were conducted in this study. The results showed that hotspot identification based on crash totals tended to screen out approaches with high frequencies of rear-end and sideswipe crashes, rather than the ones with more serious crash types such as left turn and right angle.

Approach-level crash type models provide a powerful method for quantifying the effects of risk factors. It was found that certain variables (e.g., number of through lanes, median, and left-turn protection all on the entering approach) can have differential effects on the occurrence of different crash types. This finding leads to the recommendation that countermeasures specific to the crash type be developed where overrepresentation of a particular crash type is identified. In addition, approach-level SPFs should be used because they improve the ability to diagnose specific safety problems compared to an overall intersection-level model, as they are capable of identifying the deficiencies with respect to geometric and traffic characteristics for each approach.

In most previous studies, SPFs were developed for special purposes such as estimation of crash frequencies, identification of hazardous locations, and analysis of risk factors. This study adds to the safety literature by presenting an integrated framework for multiple purposes by developing more specific SPFs for crash types at the approach level. Using the same SPFs as the basis of analysis, procedures of hotspot identification and countermeasure development in safety management can be efficiently coordinated. For future research, more factors such as crash injury severity will be considered to be incorporated into this safety framework.

Acknowledgments

The authors acknowledge the comments and suggestions of the anonymous reviewers. This study was jointly sponsored by the Chinese National Science Foundation (51008230), the program for New Century Excellent Talents in University (NCET-11-0387), and the Fundamental Research Funds for the Central Universities. The authors would like to thank Florida Department of Transportation for providing the data.

References

Barnett, A. G., van der Pols, J. C., and Dobson, A. J. (2004). “Regression to the mean: What it is and how to deal with it.” *Int. J. Epidemiol.*, 34(1), 215–220.

Carlin, B. P., and Louis, T. A. (2009). *Bayesian methods for data analysis*, Chapman & Hall/CRC, Boca Raton, FL.

Chin, H. C., and Quddus, M. A. (2003). “Applying the random effect negative binomial model to examine traffic accident occurrence at signalized intersections.” *Accid. Anal. Prev.*, 35(2), 253–259.

Cheng, W., and Washington, S. P. (2005). “Experimental evaluation of hotspot identification methods.” *Accid. Anal. Prev.*, 37(5), 870–881.

Cheng, W., and Washington, S. P. (2008). “New criteria for evaluating methods of identifying hot spots.” *Transp. Res. Rec.: J. Transp. Res. Board*, 2083,76–85.

Gilks, W. R., Richardson, S., and Spiegelhalter, D. J. (1995). *Markov chain Monte Carlo methods in practice*, Chapman & Hall, New York.

Google Earth [Computer software]. Google.

Hall, R. (1986). “Accidents at four-arm single carriageway urban traffic signals.” *Publication CR65*, Transport Research Laboratory, U.K.

Hauer, E. (1980). “Bias-by-selection: Overestimation of the effectiveness of safety countermeasures caused by the process of selection for treatment.” *Accid. Anal. Prev.*, 12(2), 113–117.

Hauer, E., Ng, J. C. H., and Lovell, J. (1988). “Estimation of safety at signalized intersections.” *Transportation Research Record 1185*, Transportation Research Board, Washington, DC, 48–61.

Heydecker, B. J., and Wu, J. (1991). “Using the information in road accident records.” *Plann. Transp. Res. Comput.*, 350, 241–255.

Johansson, P. (1996). “Speed limitation and motorway casualties: A time series count data regression approach.” *Accid. Anal. Prev.*, 28(1), 73–87.

Joshua, S. C., and Saka, A. A. (1992). “Mitigation of sight distance problem for unprotected left-turning traffic at intersections.” *Transportation Research Record 1356*, Transportation Research Board, Washington, DC, 73–79.

Kim, D. G., Washington, S., and Oh, J. (2006). “Modeling crash types: New sights into the effects of covariates on crashes at rural intersections.” *J. Transp. Eng.*, 10.1061/(ASCE)0733-947X(2006)132:4(282), 282–292.

Kim, D., Lee, Y., Washington, S., and Choi, K. (2007). “Modeling crash outcome probabilities at rural intersections: Application of hierarchical binomial logistic models.” *Accid. Anal. Prev.*, 39(1), 125–134.

Kononov, J. (2002). “Identifying locations with potential for accident reductions: Use of direct diagnostics and pattern recognition methodologies.” *Transportation Research Record 1784*, Transportation Research Board, Washington, DC, 153–158.

Lan, B., and Persaud, B. (2011). “Fully Bayesian approach to investigate and evaluate ranking criteria for black spot identification.” *Transportation Research Record 2237*, Transportation Research Board, Washington, DC, 117–125.

Lyon, C., Gotts, B., Wong, W. K. F., and Persaud, B. (2007). “Comparison of alternative methods for identifying sites with high proportion of specific accident types." *Transportation Research Record 2019*, Transportation Research Board, Washington, DC, 212–218.

Maher, M. J., and Summersgill, I. (1996). "A comprehensive methodology for the fitting of predictive accident models." *Accid. Anal. Prev.*, 28(3), 281–296.

McCoy, P., Navarro, U., and Witt, W. (1992). "Guidelines for offsetting opposing left-turn lanes on four-lane divided roadways." *Transportation Research Record 1356*, Transportation Research Board, Washington, DC, 28–36.

Miranda-Moreno, L. F., and Fu, L. (2007). "Traffic safety study: Empirical Bayes or full Bayes?" *Transportation Research Board 86th Annual Meeting 1680*, Transportation Research Board, Washington, DC.

Mitra, S., Chin, H. C., and Quddus, M. A. (2002). "Study of intersection accidents by maneuver type." *Transportation Research Record 1784*, Transportation Research Board, Washington, DC, 43–50.

Persaud, B., and Nguyen, T. (1998). "Disaggregate safety performance models for signalized intersection on Ontario Provincial roads." *Transportation Research Record 1635*, Transportation Research Board, Washington, DC, 113–120.

Persaud, B., Lan, B., Lyon, C., and Bhim, R. (2010). "Comparison of empirical Bayes and full Bayes approaches for before-after road safety evaluations." *Accid. Anal. Prev.*, 42(1), 38–43.

Poch, M., and Mannering, F. (1996). "Negative binomial analysis of intersection-accident frequencies." *J. Transp. Eng.*, 10.1061/(ASCE)0733-947X(1996)122:2(105), 105–113.

Qin, X., Ivan, J. N., and Ravishanker, N. (2004). "Selecting exposure measures in crash rate prediction for two-lane highway segments." *Accid. Anal. Prev.*, 36(2), 183–191.

Roess, G. P., Prassas, E. S., and McShane, W. R. (2003). *Traffic engineering*, 3rd Ed., Pearson Prentice Hall, Upper Saddle River, NJ.

Schluter, P. J., Deely, J. J., and Nicholson, A. J. (1997). "Ranking and selecting motor vehicle accident sites using a hierarchical Bayesian model." *The Statistician*, 46(3), 293–316.

Shankar, V., Mannering, F., and Barfield, W. (1995). "Effect of roadway geometric and environmental factors on rural freeway accident frequencies." *Accid. Anal. Prev.*, 27(3), 371–389.

Shankar, V. N., Albin, R. B., Milton, J. C., and Mannering, F. L. (1998). "Evaluating median cross-over likelihoods with clustered accident counts: An empirical inquiry using random effects negative binomial model." *Transportation Research Record 1635*, Transportation Research Board, Washington, DC, 44–48.

Songchitruksa, P., and Tarko, A. P. (2006). "Practical method for estimating frequency of right-angle collisions at traffic signals." *Transportation Research Record 1953*, Transportation Research Board, Washington, DC, 89–97.

Speigelhalter, D. J., Best, N. G., Carlin, B. P., and Linde, V. D. (2003a). "Bayesian measures of model complexity and fit." *J. Royal Stat. Soc. (Ser. B)*, 64(4), 583–616.

Spiegelhalter, D. J., Thomas, A., Best, N. G., and Lunn, D. (2003b). *WinBUGS version 1.4.1 user manual*, MRC Biostatistics Unit, Cambridge, U.K.

Upchurch, J. (1991). "Comparison of left-turn accident rates for different types of left turn phasing." *Transportation Research Record 1324*, Transportation Research Board, Washington, DC, 33–40.

Wang, X., Abdel-Aty, M., and Nevarez, A. (2008). "Investigation of safety influence area for four-legged signalized intersections: Nationwide survey and empirical inquiry." *Transp. Res. Rec.: J. Transp. Res. Board*, 2019, 86–95.

Wang, X., and Abdel-Aty, M. (2008). "Modeling left-turn crash occurrence at signalized intersections by conflicting pattern." *Accid. Anal. Prev.*, 40(1), 76–88.

Wang, X., and Abdel-Aty, M. (2007). "Right-angle crash occurrence at signalized intersections." *Transportation Research Record 2019*, Transportation Research Board, Washington, DC, 156–168.

Wang, X., and Abdel-Aty, M. (2006). "Temporal and spatial analyses of rear-end crashes at signalized intersections." *Accid. Anal. Prev.*, 38(6), 1137–1150.

Xie, K., Wang, X., Huang, H., and Chen, X. (2013). "Corridor-level signalized intersection safety analysis in shanghai, china using Bayesian hierarchical models." *Accid. Anal. Prev.*, 50, 25–33.