Safety Performance of One-Way Arterials

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ABSTRACT

Safety analysts are generally interested in understanding the differences in the safety performance when a two-way street is converted to a one-way operation or vice-versa. Literature exists to understand and predict the safety of two-way streets. However, safety prediction procedures are currently not available for assessing the safety performance of one-way arterials. This research was undertaken to develop the safety prediction models for one-way arterials. To accomplish this objective, data collected in California, Illinois, Michigan, Oregon, and Texas were assembled that included a wide range of geometric design features, traffic control features, traffic characteristics, and crash records. The data were used to calibrate predictive models, each of which included a safety performance function (SPF) and several crash modification factors (CMFs). Separate SPFs were developed for fatal and injury crashes (i.e., fatal, incapacitating injury, non-incapacitating injury, and possible injury crash) and property-damage-only crashes. The SPFs were estimated using the negative binomial modeling structure. Severity distribution functions (SDFs) were also calibrated using the fatal and injury data. These functions can be used with the predictive models to estimate the expected crash frequency for each of four injury severity levels.

Keywords: One-way arterials, Highway Safety Manual, Safety Performance Functions, Crash Modification Factors

BACKGROUND

On urban and suburban arterials, one-way streets are implemented to increase capacity and reduce parking problems (*1*). Similarly, one-way streets are provided to reduce conflicts at intersections, and to provide more parking in residential areas (*1*). It is often believed that one-way streets improve safety by reducing the crash frequency and severity. However, crashes and their severity may still increase due to the increases in speed, volume, trip length, and wrong-way driving.

Safety prediction models are currently unavailable for one-way urban street segments. However, various reports and articles have been published about operational and safety performance changes that have been observed following the conversion of two-way urban streets or frontage road segments to one-way operation. These sources provide some insight into the safety performance that would be expected for one-way urban street segments.

Eisele et al. (*2*) conducted a before-after evaluation of freeway frontage roads that were converted from two-way operation to one-way operation. They proposed a crash modification factor (CMF) of 0.43 for fatal, incapacitating injury, non-incapacitating injury, and possible injury crash (KABC, respectively) segment-related crashes for frontage road conversions, meaning that the average reduction in fatal and injuries (FI) crashes on frontage road segments following a conversion is 57 percent (or 1.00 − 0.43, expressed as percent). Their study included 19.2 mi of frontage road segments that were converted and 22.1 mi of two-way frontage road segments that were used as comparison sites. However, they acknowledged that their results were affected by the crash reduction trends that were observed near freeway entrance or exit ramps that connected to the frontage road segments. They were unable to isolate the ramp-related crashes from other crashes occurring on the frontage road segments. Hence, a 57 percent crash reduction is likely greater than what would occur on a converted urban street where ramp connections do not exist.

In an article about converting urban streets from two-way operation to one-way operation in New York City, Wiley (*3*) reported that pedestrian crashes decreased by about 25 percent following the conversion. He did not specify whether these reductions applied to crossings at intersections, midblock crossings, or both, but he acknowledged that numerous midblock pedestrian crossings occur in New York City.

A comparison by Hocherman et al. (*1*) of crash rates on one-way and two-way urban street segments in Jerusalem yielded mixed results. In their analysis, one-way streets were found to have lower crash rates in central business district areas, particularly for pedestrian crashes, while two-way streets were found to have lower crash rates in non-central business district areas. Their findings are provided in Table 1. Most of the computed relative risk values in the top portion of the table are greater than 1.00, indicating that two-way streets have lower crash rates. However, the relative risk values for pedestrian crashes and total crashes on one-way streets in the central business district are less than 1.00, suggesting that one-way streets are safer for pedestrians and in general (since pedestrian crashes represented over 76 percent of crashes in the central business district). However, Hocherman et al. acknowledged that their findings regarding trends in the central business district must be interpreted cautiously because of the limited number of crashes observed in that area.

In addition to the preceding trends, Hocherman et al. (*1*) also observed a slight difference in crash severity when comparing one-way and two-way streets. In their crash dataset, 18 percent of midblock crashes on one-way streets were severe (AB) or fatal (K), while 22 percent of midblock crashes on two-way streets were severe or fatal. The difference was more noteworthy on streets that were classified as local (rather than arterial or collector). The percentage of severe or fatal midblock crashes on local streets was 16 percent for one-way and 27 percent for two-way streets. As a possible explanation for this trend, they noted that head-on crashes cannot occur on one-way streets unless one driver proceeds in the wrong direction.

Stemley (*4*) and Smith and Hart (*5*) observed that there are fewer conflict points at four-leg intersections of one-way streets than intersections of two-way streets. The number of conflict points for three types of intersections is summarized in Table 2. Note that the number of conflict points decreases notably when comparing an intersection of two two-way streets with an intersection of a two-way street and a one-way street, and the number of conflict points is even fewer for an intersection of two one-way streets.

Table 1. Midblock crash rates and counts on one-way and two-way streets (based on *1*).

Performance Measure	Area Type	Intersection Type	Pedestrian	Vehicle	Total
Midblock Crash Rate (crashes/mvm)	Central Business District	One-Way Streets	0.79	0.29	1.09
		Two-Way Streets	1.00	0.24	1.24
		Relative Risk	0.79	1.20	0.88
	Non-Central Business District	One-Way Streets	1.17	0.72	1.90
		Two-Way Streets	0.60	0.45	1.05
		Relative Risk	1.97	1.61	1.81
Midblock Crash Count	Central Business District	One-Way Streets	25	9	34
		Two-Way Streets	24	6	30
		Total	49	15	64
	Non-Central Business District	One-Way Streets	102	63	165
		Two-Way Streets	477	359	836
		Total	579	422	1001

Table 2. Conflict points at four-leg intersections (based on *5*).

Intersection Type	Conflict Point Count by Type		
	Crossing	Merge/Diverge	Pedestrian-Vehicle
Two-way/two-way	16	8	16
Two-way/one-way	5	6	10
One-way/one-way	1	4	6

Observations have also been made about human factors issues associated with one-way street traffic operations. Smith and Hart (*5*) illustrated that a driver approaching an intersection of two two-way streets has three areas of concern where he or she needs to look for opposing traffic—to the left, to the right, and (if making a left turn) toward the opposing through vehicles. At an intersection of a two-way street and a one-way street, drivers have two areas of concern (to the left and to the right for drivers on the one-way street, and to one side and toward the opposing through vehicles for drivers on the two-way street). At an intersection of two one-way streets, drivers only need to look for opposing traffic from one direction of the intersecting street. It has been similarly observed that pedestrians crossing a one-way street only have to look for traffic in one direction instead of two (*4*; *6*).

In an analysis of the operational and safety effects of pedestrian signalization alternatives, Zegeer et al. (*6*) reported that intersections of one or more one-way streets experience significantly fewer pedestrian crashes than intersections of two two-way streets. In a branching analysis of mean pedestrian crash frequencies, they found that at intersections with entering volumes of fewer than 27,500 veh/day, the mean pedestrian crash frequency was 0.477 crash/year at intersections of two two-way streets or a two-way street and a one-way street, and 0.241 crash/year at intersections of two one-way streets. In other words, the pedestrian crash frequency at intersections of two one-way streets was roughly half of that at other intersections.

In the same study described above, Eisele et al. (*2*) also conducted a before-after evaluation of intersections that were located on freeway frontage roads that were converted from two-way operation to one-way operation. They proposed the CMFs listed in Table 3 for different subsets of intersection-related KABC crashes. The CMFs show that intersection-related crashes are decreased significantly when two-way frontage roads are converted to one-way operation.

Table 3. Intersection CMFs for two-way to one-way frontage road conversion (based on *2*).

Crash Category	CMF Value
Opposite-direction crashes	0.20
Opposite-direction crashes involving a left-turning vehicle	0.15
Angle and opposite-direction crashes involving a left-turning vehicle	0.23
Minor injury (C) crashes	0.14

DATA DESCRIPTION

The study database was developed using data from five states: Texas, Illinois, California, Michigan, and Oregon (*7*). These states were selected based on the state-owned mileage of one-way streets and the availability of crash data. Crash and roadway data from California and Illinois were obtained from the HSIS, while data from Texas, Michigan, and Oregon were obtained directly from the state highway agencies. The state databases included crash data along with traffic volume and other site characteristics for roadway segments. Additional data variables were collected for each segment mainly by using aerial images and street view. Table 4 provide the summary statistics of the data collected for one-way roadway segments.

Crash data were obtained from Illinois, California, and Oregon for 2006–2010 and from Texas and Michigan for 2008–2012. The entire crash records from these states (and years) were obtained, which included data elements for crash type (single-vehicle, multi-vehicle, vehicle-pedestrian, vehicle-bicycle, etc.) and crash severity (K, A, B, C, or O or property damage only - PDO) and the manner of collision (rear-end, head-on, angle, etc.). Crashes were assigned to roadway segments if they occurred within the boundaries of the segment and were coded as non-intersection-related. Table 5 presents the distribution of roadway segment crashes by jurisdiction and segment type.

Table 4. Descriptive statistics for one-way roadway segment variables.

Stat	Variable	Number of Lanes			Variable	Number of Lanes		
		2	3	4		2	3	4
Min	AADT (veh/day)	316	2,220	200	Posted speed limit (mph)	20	20	25
Max		33,960	29,000	29,000		45	55	45
Mean		7,241	11,590	11,558		32	32	33
StdDev		3,778	5,181	4,460		5	5	4
Min	Segment length (mi)	0.01	0.01	0.01	Railroad crossings	0	0	0
Max		1.326	0.873	1.15		1	1	1
Mean		0.15	0.137	0.194		0.04	0.04	0.05
StdDev		0.16	0.130	0.204		0.19	0.20	0.22
Min	Lane width (ft)	9.0	9.0	9.0	Major commercial driveway density[a] (drive/mi)	0	0	0
Max		27.0	25.0	20.0		58.3	25.0	23.4
Mean		13.7	13.0	12.1		0.52	0.72	0.55
StdDev		2.8	2.7	1.8		3.6	2.96	2.68
Min	Left shoulder width (ft)	0	0	0	Minor commercial driveway density[a] (drive/mi)	0	0	0
Max		20.0	19.0	9.0		83.3	75.0	52.6
Mean		1.5	1.8	1.1		6.4	10.2	8.0
StdDev		3.5	3.5	2.8		10.5	13.1	12.6
Min	Right shoulder width (ft)	0	0	0	Major industrial driveway density[a] (drive/mi)	0	0	0
Max		20.0	20.0	20.0		21.7	51.0	10.0
Mean		2.2	2.4	1.4		0.5	0.5	0.9
StdDev		3.8	4.1	3.4		2.4	3.1	2.2
Min	Bus or HOV lane (1=yes; 0=no)	0	0	0	Minor industrial driveway density[a] (drive/mi)	0	0	0
Max		0	0	1		100.0	50.0	50.0
Mean		0	0	0.03		4.1	4.5	5.7
StdDev		0	0	0.18		8.1	7.2	9.6
Min	Bicycle lane presence (1=yes; 0=no)	0	0	0	Major residential driveway density[a] (drive/mi)	0	0	0
Max		1	0	1		17.9	10.7	0
Mean		0.014	0	0.05		0.05	0.03	0
StdDev		0.12	0	0.24		0.8	0.54	0
Min	Sidewalks	0	0	0	Minor residential driveway density[a] (drive/mi)	0	0	0
Max		2	2	2		58.8	76.3	88.5
Mean		1.45	1.64	1.66		5.3	3.5	7.2
StdDev		0.8	0.73	0.67		10.6	9.7	15.7
Min	Lighting	0	0	0	Other driveway density[a] (drive/mi)	0	0	0
Max		2	2	2		50.0	33.3	14.3
Mean		1.38	1.62	1.74		0.2	0.4	0.3
StdDev		0.72	0.59	0.56		2.2	2.5	1.7
Min	Parallel parking proportion	0	0	0	Roadside fixed-object density (objects/mile)	0	0	0
Max		1.0	0.8	0.6		300.0	240.0	300.0
Mean		0.16	0.13	0.07		80.6	79.2	84.1
StdDev		0.25	0.21	0.14		46.5	40.4	37.9
Min	Angle parking proportion	0	0	0	Roadside fixed-object average offset (ft)	0	0	0
Max		0.6	0.6	X		30.0	30.0	25.0
Mean		0.01	0.01	X		10.4	9.0	8.0
StdDev		0.05	0.04	X		5.2	4.9	3.7

[a] Equivalent number of full driveways where a partial driveway is given half the weight of a full driveway.

Table 5. Summary of crash frequency and exposure data for roadway segments.

Segment Type	Number of Roadway Segments	Total Length (mi)	Total Number of Crashes[a]	AADT (veh/day)	Total Exposure[a] (10^6 veh-mi)	Average Crash Rate[a] (per 10^6 veh-mi)
TEXAS						
2-lane	247	52.41	988	6602	0.35	1.448
3-lane	85	19.99	498	8847	0.18	2.008
4-lane	49	12.96	279	11,382	0.15	1.077
Total	1141	453.4	26,144			
ILLINOIS						
2-lane	488	59.11	2092	7267	0.43	2.703
3-lane	261	28.94	1662	11,145	0.32	2.730
4-lane	68	9.85	427	11,430	0.11	2.249
Total	1932	204.16	19,946			
CALIFORNIA						
2-lane	42	6.93	153	10,990	0.08	1.289
3-lane	81	9.30	591	15,976	0.15	2.308
4-lane	1	0.09	10	29,000	0.00	2.032
Total	441	79.31	7461			
OREGON						
2-lane	260	14.67	283	14,236	0.21	1.267
3-lane	109	6.37	244	20,789	0.13	1.662
4-lane	18	1.02	60	17,037	0.02	3.670
Total	387	22.06	587			
COMBINED						
2-lane	1037	133.11	3516	9007	1.20	1.987
3-lane	536	64.59	2995	13,472	0.87	2.335
4-lane	136	23.92	776	12,284	0.29	2.013
Total	3901	758.91	54,138			

Note: Shaded cell = not applicable.
[a] In the five years of the study period.

MODELING RESULTS

The NLMIXED procedure in the SAS software (*8*) was used to estimate the proposed model coefficients. This procedure was used because the proposed predictive model is both nonlinear and discontinuous. The log-likelihood function for the NB distribution was used to determine the best-fit model coefficients.

Safety Performance Functions

Different variable combinations and various model forms were examined to identify the best possible relationship between number of crashes and independent variables. The model presented below was informed by findings from several preliminary regression analyses. This model form includes variables that are intuitive, in-line with previous findings and best fits the data.

$$N_j = (N_{mv} I_{mv} + N_{sv} I_{sv}) \times CMF_{rsw} \quad (1)$$

with,

$$N_{mv} = N_{spfmv} \times CMF_{pk\_par} \times CMF_{pk\_ang} \times CMF_{dwc\_mj} \times CMF_{dw\_mn} \quad (2)$$

$$N_{sv} = N_{spfsv} \times CMF_{fo} \quad (3)$$

$$N_{spfmv} = L \times n \times e^{b_{mv}+b_{mv1}\ln(AADT)+b_{ca}I_{ca}+b_{il}I_{il}+b_{or}I_{or}} \quad (4)$$

$$N_{spfsv} = L \times n \times e^{b_{sv}+b_{sv1}\ln(AADT)+b_{ca}I_{ca}+b_{il}I_{il}+b_{or}I_{or}} \quad (5)$$

$$CMF_{rsw} = e^{b_{rsw}(W_{rs}-4)} \quad (6)$$

$$CMF_{pk\_par} = 1 + p_{pk\_par} \times (b_{pk\_par} - 1.0) \quad (7)$$

$$CMF_{pk\_ang} = 1 + p_{pk\_ang} \times (b_{pk\_ang} - 1.0) \quad (8)$$

$$CMF_{dwc\_mj} = e^{b_{dwc\_mj}(n_{dwc\_mj}-2)} \quad (9)$$

$$CMF_{dw\_mn} = e^{b_{dw\_mn}(n_{dw\_mn}-10)} \quad (10)$$

$$CMF_{fo} = 1.0 + \frac{0.01D_{fo}}{e^{b_{fo}(O_{fo})}} \quad (11)$$

where,

N_j	=	predicted annual average crash frequency for model *j* (*j*=*mv*, *sv*).
N_{mv}	=	predicted annual average multiple-vehicle crash frequency.
N_{sv}	=	predicted annual average single-vehicle crash frequency.
I_{mv}	=	crash indicator variable (= 1.0 if multiple-vehicle crash data, 0.0 otherwise).
I_{sv}	=	crash indicator variable (= 1.0 if single-vehicle crash data, 0.0 otherwise).
L	=	segment length, mi.
n	=	number of years of crash data.
$AADT$	=	average annual daily traffic, veh/day.
I_{ca}	=	California state indicator variable (= 1.0 if site is in California, 0.0 if not).
I_{il}	=	Illinois state indicator variable (= 1.0 if site is in Illinois, 0.0 if not).
I_{or}	=	Oregon state indicator variable (= 1.0 if site is in Oregon, 0.0 if not).
CMF_{rsw}	=	right shoulder width CMF.
CMF_{pk_par}	=	on-street parallel parking CMF.
CMF_{pk_ang}	=	on-street angle parking CMF.
CMF_{dwc_mj}	=	major commercial driveways CMF.
CMF_{dwi_mj}	=	major industrial driveways CMF.
CMF_{dw_mn}	=	minor driveways CMF.
CMF_{bar}	=	median barrier CMF.
CMF_{fo}	=	roadside fixed-object CMF.
W_{rs}	=	right shoulder width, ft.
p_{pk_par}	=	proportion of curb length with on-street parallel parking = (0.5 L_{pk_par}/L).
p_{pk_ang}	=	proportion of curb length with on-street angle parking = (0.5 L_{pk_ang}/L).
L_{pk_par}	=	sum of curb length with on-street parallel parking for both sides of road combined, mi.
L_{pk_ang}	=	sum of curb length with on-street angle parking for both sides of road combined, mi.
n_{dwc_mj}	=	major commercial driveway density, driveways/mile.
n_{dw_mn}	=	minor driveway density, driveways/mile.
O_{fo}	=	roadside fixed-object offset, ft.
D_{fo}	=	roadside fixed-object density, fixed objects/mile.
p_{fo}	=	roadside fixed-object collisions as a proportion of total crashes.
b_i	=	calibration coefficient for variable *i*.

The inverse dispersion parameter K (which is the inverse of the overdispersion parameter k) is allowed to vary with the segment length. The inverse dispersion parameter is calculated using Equation 12.

$$K = L \times e^{\delta,j};\ j = mv, sv \quad (12)$$

where,

K	=	inverse dispersion parameter.
δ	=	calibration coefficient for inverse dispersion parameter.

The predictive model calibration process consisted of the simultaneous calibration of multiple-vehicle and single-vehicle crash models and CMFs using the aggregate model represented by the equations above. The simultaneous calibration approach was needed because the right shoulder CMF was common to multiple-vehicle and single-vehicle crash models and other variables had different effects on these two crash types. The database assembled for calibration included two replications of the original database. The dependent variable in the first replication was set equal to the multiple-vehicle crashes. The dependent variable in the second replication was set equal to the single-vehicle crashes.

Separate models were developed for FI and PDO crashes. Experience with regression-based calibration of SPFs and CMFs using total crashes and using only FI crashes indicates that the calibration coefficients often vary between two models for common variables. Some of this variation is likely due to the fact that geometric elements often have a different effect on FI crashes than on PDO crashes. As a result, the search for correlation and possible causation is challenged when using total crash data to build total crash prediction models because total crashes combine FI and PDO crashes. It is widely recognized that PDO crash counts vary widely on a regional basis due to significant variation in the reporting threshold. The FI regression model structure was developed first and then used as a starting point for the development of the PDO regression model. By doing this, the research team could estimate the PDO crashes at the same base conditions. Table 6 and Table 7 summarize the modeling results for one-way arterial segments for FI and PDO, respectively. The variables with the corresponding p-values less than 0.05 can be considered statistically significant (at the significance level $\alpha = 0.05$). For those few variables where the p-value was greater than 0.05, it was decided that the variable was important to the model, and its trend was found to be consistent with previous research findings (even if the specific value was not known with a great deal of certainty when applied to this database).

Table 6. Calibrated coefficients for FI crashes.

Coefficient	Variable	Facility	Estimate	Std. Error	t-statistic	p-value
b_{mv}	Intercept for MV crashes	2-lane	−11.4766	0.7694	−14.92	<0.0001
		3-lane	−11.4871	0.7999	−14.36	<0.0001
		4-lane	−11.7375	0.8067	−14.55	<0.0001
b_{mv1}	AADT on MV crashes	All	1.2559	0.0839	14.98	<0.0001
b_{sv}	Intercept for SV crashes	2-lane	−5.3153	1.1314	−4.70	<0.0001
		3-lane	−4.9291	1.1859	−4.16	<0.0001
		4-lane	−4.9291	1.1859	−4.16	<0.0001
b_{sv1}	AADT on SV crashes	All	0.4179	0.1259	3.32	0.0009
b_{rsw}	Right shoulder width	All	−0.0201	0.0098	−2.05	0.0403
b_{pk_par}	On-street parallel parking on MV crashes	2-lane	1.1116	0.2515	4.42	<0.0001
		3-/4-lane	1.3586	0.3087	4.40	<0.0001
b_{pk_ang}	On-street angle parking on MV crashes	2-/3-lane	4.3644	2.4706	1.77	0.0774
b_{dwc_mj}	Major commercial driveway density on MV crashes	2-/3-lane	0.0177	0.0113	1.56	0.1186
b_{dw_mn}	Minor driveway density on MV crashes	2-/3-lane	0.0046	0.0026	1.76	0.0793
b_{fo}	Roadside fixed-object density on SV crashes	All	0.0938	0.0838	1.12	0.2629
b_{il}	Added effect of Illinois	All	−0.1732	0.0803	−2.16	0.0311
δ_{mv}	Inverse dispersion parameter for MV crashes	2-lane	2.1203	0.1659	12.78	<0.0001
		3-lane	2.5670	0.1931	13.29	<0.0001
		4-lane	2.4619	0.4102	6.00	<0.0001
δ_{sv}	Inverse dispersion parameter for SV crashes	2-lane	1.1900	0.3160	3.77	0.0002
		3-lane	1.9423	0.4244	4.58	<0.0001
		4-lane	1.9423	0.4244	4.58	<0.0001
	Observations	1709 segments (2-lane=1037; 3-lane=536; 4-lane=136)				

Table 7. Calibrated coefficients for PDO crashes.

Coefficient	Variable	Facility	Estimate	Std. Error	t-statistic	p-value
b_{mv}	Intercept for MV crashes	2-lane	−8.2598	0.5140	−16.07	<0.0001
		3-lane	−8.2735	0.5376	−15.39	<0.0001
		4-lane	−8.6803	0.5443	−15.95	<0.0001
b_{mv1}	AADT on MV crashes	All	1.0194	0.0569	17.92	<0.0001
b_{sv}	Intercept for SV crashes	2-lane	−4.7133	0.7891	−5.97	<0.0001
		3-lane	−4.7189	0.8323	−5.67	<0.0001
		4-lane	−4.7189	0.8323	−5.67	<0.0001
b_{sv1}	AADT on SV crashes	All	0.4269	0.0885	4.82	<0.0001
b_{rsw}	Right shoulder width	All	−0.0047	0.0076	−0.61	0.5390
b_{pk_par}	On-street parallel parking on MV crashes	2-lane	1.2587	0.1695	7.42	<0.0001
		3-/4-lane	1.9568	0.3013	6.49	<0.0001
b_{pk_ang}	On-street angle parking on MV crashes	2-/3-lane	4.2811	1.5850	2.70	0.0069
b_{dwc_mj}	Major commercial driveway density on MV crashes	2-/3-lane	0.0303	0.0100	3.02	0.0025
b_{dw_mn}	Minor driveway density on MV crashes	2-/3-lane	0.0015	0.0019	0.76	0.4450
b_{fo}	Roadside fixed-object density on SV crashes	All	0.2545	0.1436	1.77	0.0764
b_{il}	Added effect of Illinois	All	0.7450	0.0580	12.85	<0.0001
δ_{mv}	Inverse dispersion parameter for MV crashes	2-lane	2.4635	0.0955	25.80	<0.0001
		3-lane	2.4531	0.0952	25.77	<0.0001
		4-lane	2.5184	0.2164	11.64	<0.0001
δ_{sv}	Inverse dispersion parameter for SV crashes	2-lane	2.1203	0.2287	9.27	<0.0001
		3-lane	1.9771	0.2265	8.73	<0.0001
		4-lane	1.9771	0.2265	8.73	<0.0001
	Observations	1709 segments (2-lane=1037; 3-lane=536; 4-lane=136)				

Indicator variables were included for the states of California, Oregon, and Illinois. However, only the coefficient for Illinois was statistically significant. This means that the magnitude of the crashes between Texas, Oregon, and California are about the same, but Illinois experiences fewer FI crashes and more PDO crashes for the same conditions and exposure. It is likely that the differences between states are due to unobserved variables such as vertical grade, signing, pavement condition, weather, reporting accuracy, and speed limit.

Crash Modification Factors

Several CMFs were calibrated in conjunction with the SPFs. All of them were calibrated using FI crash data. Collectively, they describe the relationship between various geometric factors and crash frequency. The models developed for this project include several CMFs that are calibrated for a specific crash type.

This section presents the CMFs developed from the regression models described above for one-way arterials. The CMFs for one-way arterials are compared with the CMFs for two-way arterials because there are no CMFs available in the literature for one-way arterials.

Right Shoulder Width CMF

The right shoulder width CMF is described using Equation 13.

$$CMF_{osw} = e^{-0.0201(W_{os}-4)} \tag{13}$$

The base condition for this CMF is a 4-ft outside shoulder width. The shoulder width used in this CMF is measured at places where parking is not present. For places with parking, the shoulder width is 0 ft. The right shoulder width CMF is shown in

Figure 1 using a thick, solid trend line. This CMF is applicable to both multi-vehicle and single-vehicle crashes. The right shoulder width CMF is compared with the outside shoulder width CMF for two-way arterials with six or more lanes (*7*) in

Figure 1 (note that the outside shoulder width was not included as a significant factor in influencing crashes for roadways with less than 6 lanes in the HSM). A dotted line is used to differentiate this CMF from the one developed for one-way arterials. The CMF values suggest that the right shoulder on one-way streets has a more significant effect on crashes than the outside shoulder width on two-lane streets.

Figure 1. Right shoulder width CMF.

On-Street Parking CMF

The on-street parking CMF is determined using Equations 14 and 15. The base condition is the absence of on-street parking on a roadway segment. This CMF is applicable to multi-vehicle crashes only.

$$CMF_{pk\_par} = \begin{cases} 1 + \left(0.5\, L_{pk\_par}/L\right) \times (0.112) & if\ 2 - lanes \\ 1 + \left(0.5\, L_{pk\_par}/L\right) \times (0.359) & if\ 3\ or\ 4 - lanes \end{cases} \tag{14}$$

$$CMF_{pk\_ang} = 1 + \left(0.5\, L_{pk\_ang}/L\right) \times (3.364) \quad (15)$$

Driveway CMF

This CMF is applicable to multiple-vehicle crashes only. Major commercial and minor driveways are found to be significant in influencing the crashes. Minor driveways include all driveway types. Major driveways are those that serve sites with 50 or more parking spaces. Minor driveways are those that serve sites with fewer than 50 parking spaces. Commercial driveways provide access to establishments that serve retail customers.

The major commercial driveway CMF is described using Equation 16.

$$CMF_{dwc\_mj} = e^{0.0177(n_{dwc\_mj}-2)} \quad (16)$$

The base condition for commercial driveway CMF is two driveways per mile. The CMF is compared with the commercial driveway CMF for two-way arterials (*7*) and is shown in

Figure 2. It can be seen that commercial driveways on two-way arterials are associated with more multiple-vehicle crashes than on one-way arterials. On one-way arterials, there are fewer conflict points with the vehicles entering or exiting the driveways than on the two-way arterials.

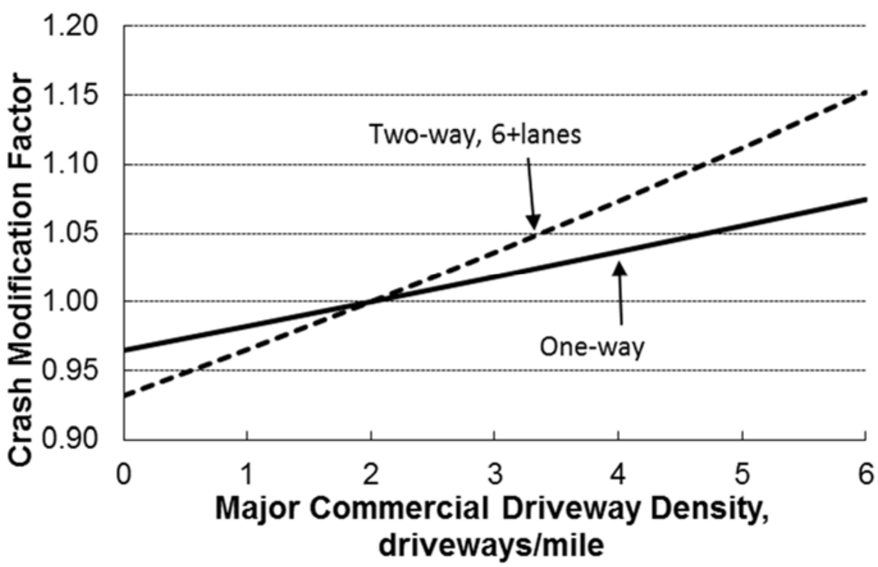

Figure 2. Major commercial driveway CMF, one-way arterials.

The minor driveway CMF is described using Equation 17.

$$CMF_{dw\_mn} = e^{0.0046(n_{dw\_mn}-10)} \quad (17)$$

The base condition for the minor driveway CMF is 10 driveways per mile. The CMF is compared with the minor driveways CMF for two-way arterials (*7*) and is shown in Figure 3. It can be seen that minor driveways on two-way arterials are associated with more multiple-vehicle crashes than on one-way arterials. On one-way arterials, there are fewer conflict points with the vehicles entering or exiting the driveways than on the two-way arterials.

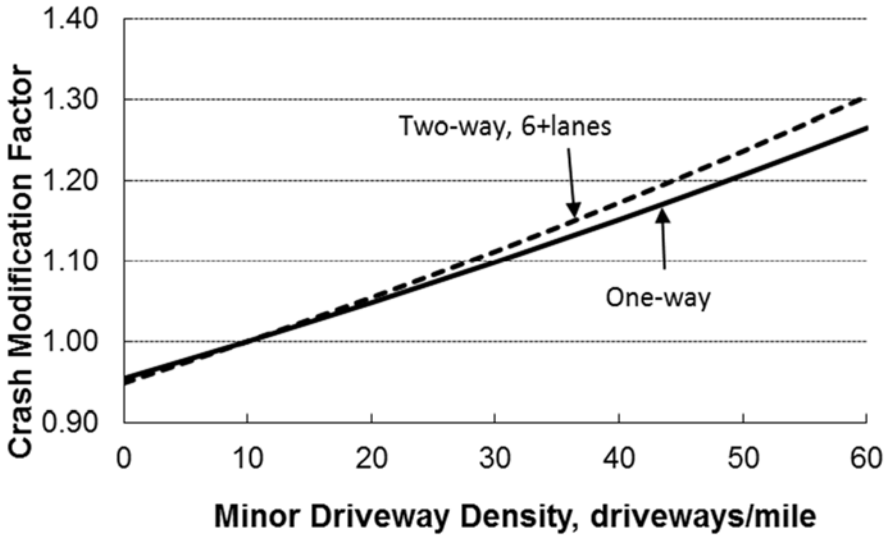

Figure 3. Minor driveway CMF, one-way arterials.

Roadside Fixed-Object CMF

The roadside fixed-object CMF is applicable to single-vehicle crashes only and is described by Equation 18:

$$CMF_{fo} = 1.0 + \frac{0.01D_{fo}}{e^{0.0938(O_{fo})}} \tag{18}$$

The base condition for the roadside fixed-object CMF is the absence of roadside objects. The change in the CMF with the increase in the offset distance for a segment with 50 roadside objects per mile is shown in Table 8.

Table 8. Roadside fixed-object CMF.

Offset to Fixed Objects (O_{fo}) (ft)	CMF (Proposed)
0	1.50
2	1.41
5	1.31
10	1.20
15	1.12
20	1.08
25	1.05
30	1.03

Severity Distribution Function

The severity distribution functions (SDFs) were developed to be used with a predictive model to estimate the expected crash frequency for each severity level. They were calibrated using a highway safety database that combines crash data with road inventory data. The database assembled for calibration included crash severity level as a dependent variable and the geometric variables of each site as independent variables. Each row (site characteristics) is repeated to the frequency of each severity level.

Thus, a segment with *n* crashes will be repeated *n* number of times. It should be noted that the segments with no injury crashes are not included in the database. The total sample size of the final dataset for model calibration will be equal to the total number of injury (and fatal) crashes in the original dataset. During the model calibration, the "possible injury" category is set as the base scenario, with coefficients restricted at zero.

The multinomial logit (MNL) model is used to predict the probability of crash severities. Given the characteristics of the data, the MNL is the most suitable model for estimating an SDF. A linear function is used to relate the crash severity with the operational variables. SAS's non-linear mixed modeling procedure is used for the evaluation of MNL model.

The probability for each crash severity category is given by the following equations:

$$P_{K+A} = \frac{e^{V_{K+A}}}{1 + e^{V_{K+A}} + e^{V_B}} \tag{19}$$

$$P_B = \frac{e^{V_B}}{1 + e^{V_{K+A}} + e^{V_B}} \tag{20}$$

$$P_C = 1 - (P_{K+A} + P_B) \tag{21}$$

With

$$V_j = ASC_j + \sum_{k=1}^{K} b_{k,j} X_k \tag{22}$$

where,

P_j = probability of the occurrence of crash severity *j* (*j=1,…,J*).

J = total number of crash severities to be modeled.

V_j = systematic component of crash severity likelihood for severity *j*.

ASC_j = alternative specific constant for crash severity *j*.

$b_{k,j}$ = regression coefficient for crash severity *j* and variable *k*, *k* =1,...,K.

X_{ki} = independent variable *k*.

The database included 1,615 FI crashes reported in California, Illinois, Oregon, and Texas. Initially, a multinomial logistic regression model was developed to predict the proportion of crashes in each severity category (i.e., K, A, B, and C). However, due to a small number of reported fatal crashes, the model provided unreliable and insignificant estimates. Thus, the fatal and incapacitating injury crashes were combined into one category during the final model calibration. The results of crash severity models are summarized in Table 9. Although many variables were considered, the results presented in Table 9 show the variables that are significant in influencing crash severities. An examination of the coefficient values and their implication on the corresponding crash severity levels are documented in a subsequent section. In general, the sign and magnitude of the regression coefficients in Table 9 are logical and consistent with previous research findings.

Table 9. SDF Calibrated Coefficients

Variable	Fatality (K)+Incapacitating Injury (A)		Non-incapacitating Injury (B)	
	Coefficient	t-value	Coefficient	t-value
Alternative specific constant	0.2933	0.54	−0.381	−3.8
Lane width	−0.1226	−3.01		
Right shoulder width	−0.126	−4.53	−0.05755	−3.7
Area type (urban=1)	−0.3994	−2.38		
Bike lanes (yes =1)	0.9969	2.19	0.8691	3.01
Illinois	0.5035	4.03	0.5035	4.03
Observations	1615 crashes (K=17; A=154; B=611; C=833)			

Note: Possible injury is the base scenario, with coefficients restricted at zero. Shaded cell means coefficient is highly insignificant.

In addition to the variables included in the calibrated model, there may be differences between states, such as weather and driver behavior, that were not included in the model. Thus, indicator variables for the states of California, Oregon, and Illinois were included in the calibrated model to account for the overall differences between the states, which could not be explained with the variables included in the model. The coefficients for Oregon and California were very small and not statistically significant, suggesting that the state effects are very similar among Texas, Oregon, and California. The positive coefficient for Illinois in Table 9 shows that a crash occurring on roads in Illinois is likely to be more severe than a crash in other states, when all other variables are controlled. The differences may be explained by different highway design practices (e.g., use of different roadside design features, etc.), terrain, weather pattern, driver behavior, and reporting accuracy or criteria.

The coefficients in Table 9 were combined with Equation 22 **Error! Reference source not found.**to obtain the deterministic component of each crash severity level for crashes on six-or-more-lane segments. The form of each model is described by Equations 23 and 24.

$$V_{K+A} = 0.2933 + (-0.1226 \times W_l) + (-0.126 \times W_{rs}) + (-0.3994 \times I_{urban}) + (-0.9969 \times I_{bike}) \quad (23)$$

$$V_B = -0.381 + (0.0000 \times W_l) + (-0.05755 \times W_{rs}) + (0.0000 \times I_{urban}) + (0.8691 \times I_{bike}) \quad (24)$$

where,

W_l	=	lane width (ft).
W_{rs}	=	shoulder width on the right side (ft).
I_{urban}	=	area type indicator variable (= 1.0 if urban, 0.0 if suburban).
I_{bike}	=	bike lane presence indicator variable (= 1.0 if present, 0.0 otherwise).

The probability of each severity level is obtained by combining Equations 23 and 24 with Equations 19–21.

Predicted Probabilities

The subsections below provide the influence of variables on crash severities for one-way arterials.

Lane Width. The lane width used in this research was an average for all through lanes on the segment. The average lane width in the dataset was 13 ft. The negative coefficients for the lane width variable for fatal and non-incapacitating crashes in Table 9 suggests that as the lane width increases, the likelihood of these severity levels decreases. As seen in Table 10, the likelihood of fatal and incapacitating injury crashes (i.e., K and A) changes from 18.2 percent for 10-ft lanes to 9.6 percent for 16-ft lanes. For every 1-ft increase in lane width, an average reduction of 1.4 percent in K and A crashes can be expected. The relative effect of lane width reduces at the higher widths. Generally, the lane width is positively correlated with safety because it allows drivers more room to maneuver within the lane.

Right Shoulder Width. The effect of both left and right shoulders on crash severity was initially considered in the calibrated model. However, only the right shoulder width was statistically significant. The average right shoulder width in the dataset was 3 ft. The negative model coefficients in Table 9 indicate that as right shoulder width increases, probability of fatal and incapacitating injury crashes decreases. As seen in Table 10, the likelihood of fatal and incapacitating injury crashes (i.e., K and A) changes from 17.1 percent with no right shoulder to 6.7 percent with 10-ft right shoulder. For every 1-ft increase in right shoulder width, an average reduction of 1.0 percent in K+A crashes can be expected. The relative effect of right shoulder width reduces at the higher widths. Generally, the right width is positively correlated with safety because it prevents drivers from hitting the roadside fixed objects.

Area Type. The sites considered in the project were located in both urban and suburban areas. About 68 percent of crashes occurred in urban areas. The negative coefficient for the area type shown in Table 9 indicates that a crash occurring in an urban area is generally less severe than a crash in a suburban area. The possible reason for this influence could be due to higher speeds on roads located in suburban areas. As seen in Table 10, the likelihood of a fatal and incapacitating injury changes from 11.9 percent in urban areas to 16.7 percent in suburban areas. The trend with area type can be attributed to higher operating speeds in suburban areas. A crash that occurs at a higher speed typically has higher severity than a crash at a lower speed.

Bike Lanes. The effect of bike lane presence on crash severity was also considered in the calibrated model. About 4 percent of crashes occurred on segments with bike lanes. The positive coefficients for high severe crashes in Table 9 indicate that a crash on a road with bike lanes is generally more severe than on a road without bike lanes. As seen in Table 10, the likelihood of a fatal and incapacitating injury changes from 13.0 percent on segments without bike lanes to 21.1 percent on segments with bike lanes. It is important to note that this result does not suggest that the bike lanes increase the crash severity. It is a proxy for the presence of more bicycle volume. If the bike lanes are not physically separated from the vehicular lanes, then the chances of vehicle-bicycle collisions increase and are much more severe than vehicle-vehicle crashes.

Table 10. Crash severity distribution.

Variable	Value	Crash Severity		
		K+A	B	C
Lane Width	10	18.2%	30.5%	51.3%
	11	16.4%	31.2%	52.4%
	12	14.8%	31.8%	53.4%
	13	13.3%	32.4%	54.3%
	14	12.0%	32.9%	55.1%
	15	10.8%	33.3%	55.9%
	16	9.6%	33.7%	56.6%
Right Shoulder Width	0	17.1%	34.3%	48.6%
	2	14.4%	33.0%	52.5%
	4	12.0%	31.6%	56.4%
	6	9.9%	30.0%	60.1%
	8	8.2%	28.3%	63.5%
	10	6.7%	26.5%	66.8%
Area Type	Urban	11.9%	32.9%	55.2%
	Suburban	16.7%	31.1%	52.2%
Presence of Bike Lanes	No	13.0%	31.8%	55.2%
	Yes	21.1%	45.7%	33.2%

CONCLUSIONS

Currently, safety prediction procedures are not available for assessing the safety performance of one-way arterials. A safety prediction method for this facility type was developed for 2-, 3- and 4- lanes urban one-way segments. It included CMFs that describe the observed relationship between crash frequency and the following variables:

- On-street parking.
- Roadside fixed objects.
- Major commercial driveways.
- Minor driveways.
- Right shoulder width.

A safety prediction method for estimating the proportion of crashes by severity levels was also developed. The SDFs developed in this research included various factors that influence the severity of collisions such as lane width, right shoulder width, area type, and presence of bike lanes.
The following future research recommendations have been developed based on the research conducted in this study:

- A small number of one-way segments with one lane or five lanes do exist. However, the sample size was too small. Hence, additional research is needed to include such facilities in safety prediction methodologies.
- Since speed limits are higher in suburban areas, the geometric variables may have a different effect in suburban areas than in urban areas. Although the SDFs capture the overall safety performance difference, more research is needed to capture the performance of each geometric feature by area type.

The next step consists of developing a safety prediction methodology for estimating the safety performance of unsignalized and signalized intersections located on urban one-way arterials. This will be the subject of a future paper.

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AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: Srinivas Geedipally, Dominique Lord, and Kay Fitzpatrick; data collection: Srinivas Geedipally, Mike Pratt; analysis and interpretation of results: Srinivas Geedipally, Dominique Lord, Kay Fitzpatrick, Eun Sug Park; draft manuscript preparation: Srinivas Geedipally, Dominique Lord, Kay Fitzpatrick. All authors reviewed the results and approved the final version of the manuscript.

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