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Roadway Safety Management in Small Municipalities

--Manuscript Draft--

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ROADWAY SAFETY MANAGEMENT IN SMALL MUNICIPALITIES

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ABSTRACT

Roadway safety management consists of network screening, diagnosis, countermeasure selection, economic appraisal, prioritization, and safety effectiveness. Applications of the safety management process is limited in small municipalities due to data, statistical expertise, and resources required. This paper addresses the challenges faced by small jurisdictions and implementation of the safety management process for Madison metropolitan area in Wisconsin. Jurisdiction specific crash prediction models were developed by intersection type using data from over 4,000 intersections. Performance measures included the Equivalent Property Damage Only (EPDO) average crash frequency with Empirical Bayes adjustments and the Level of Service of Safety (LOSS). Wisconsin Crash Outcome Data Evaluation System (CODES) data was used to estimate local crash costs by severity and type. Sites were provisionally ranked in network screening, and diagnosis was conducted based on intersection observed crash types and distributions. Treatments were selected for each intersection and costs of treatments were obtained from local estimates and available literature. Crash cost benefit and treatment cost were used to estimate benefit-cost ratio by site. A combination of sites that had the greatest overall cost effective safety benefit on the network were selected through an incremental optimization process. This paper contributes to exiting literature by providing guidance for development of jurisdiction specific crash prediction models, integration of pedestrian and cyclist crashes, application of EPDO and LOSS performance measures, and selection of sites with promise through an incremental optimization process for a given budget in a small jurisdiction.

Keywords: Safety, network screening, EPDO, LOSS, optimization, management, small municipality.

INTRODUCTION

Roadway safety management is a process that consists of network screening, diagnosis, countermeasures selection, economic appraisal, prioritization, and safety effectiveness (*1*). In network screening, a list of sites with promise for safety treatment are ranked. Diagnosis focuses on engineering studies to select appropriate countermeasures. Economic appraisals are conducted with cost benefit analysis to identify potential benefits. Based on the economical appraisal, projects are prioritized for implementation. After selected treatments are implemented, effectiveness of treatments is evaluated over time (*1*). Including all the steps of the roadway safety management cycle, the process was automated with the *Safety Analyst* software—developed for state and local agencies (*2*). Unfortunately, adoption has been slow due to stringent data requirements, resources, and software yearly licensing cost (*3*).

Safety initiatives have mainly been implemented at the state level which has indirectly benefited small jurisdictions (*4*). However, small jurisdictions have their own needs, management, policy, and practices. In this paper, the implementation of the roadway intersection safety management process is illustrated for a small municipality—Madison, Wisconsin. The Madison metropolitan area has a population of 435,430 over an area of 446.1 square miles (including lakes). The city has a well-established transit system and over 61-mile network of bike paths and 117-mile bike routes. Madison is one of the only five cities in the United Sates with platinum-level bicycle friendly community status from the League of American Bicyclist. Madison intersection safety management consisted of assessing 4,062 intersections through network screening, diagnosis, selection of countermeasure, economic appraisal, and prioritization.

For network screening, Madison jurisdiction specific crash prediction models were developed by intersection type. Performance measures included Equivalent Property Damage Only (EPDO) average crash frequency with Empirical Bayes adjustments and Level of Service of Safety (LOSS) (*1*). In collaboration with several local agencies, diverse datasets were integrated including geometric, operational, crash, and hospital data. For the EPDO method, severity equivalent crash weights were required, so the Wisconsin Crash Outcome Data Evaluation System (CODES) was used to estimate local crash costs by severity (KABCO scale) and crash type (motor vehicle, motor vehicle-pedestrian, and motor vehicle-bicycle crashes). Sites were provisionally ranked and an automated diagnosis was conducted based on intersections observed crash distributions (angle, nighttime, pedestrian crashes, etc.). Twelve proven intersection countermeasures were identified, and Crash Modification Factor (CMF) were obtained from the CMF clearinghouse (*4*). Countermeasures costs were obtained from local estimates and available literature (*6*). Through an optimization process, a combination of sites that had the greatest overall safety benefit on the network were selected following the "most bang for the buck" principle (*7*).

In roadway safety management process, network screening gets the most attention as a measure of the state of safety of the system, and ranking of facilities with descriptions such as "collision-prone", "high crash", "most dangerous", or "top 30 riskiest" locations are commonly found. Consequently, attention is emphasized on locations that may require significant investment and time for the implementation of a safety treatment; or the safety issues may not even be completely addressed because it may not be economically viable. Focusing on the results of network screening alone is counterproductive since only the sites are highlighted and not the overall optimal solution for safety improvement in the network. Completing the safety management process up to the stage of project prioritization provides a more effective message for safety improvement and resource allocation. This paper provides a clear pathway of the entire safety management process to effectively use jurisdiction specific data, implement the Highway Safety Manual (HSM) to its fullest potential, and obtain the greatest overall safety improvement for the system with the resources available in a small jurisdiction such as Madison metropolitan area in Wisconsin.

LITERATURE REVIEW

The literature review section focuses on the implementation of the HSM in small jurisdictions including model development, crash costs, EDPO weights, and intersection countermeasures.

Model Development

There is evidence that developing jurisdiction specific crash prediction models instead of calibrating existing models significantly improve the accuracy of estimates (*8*-*13*). Young and Park (*8*) conducted a study for the City of Reina, Saskatchewan, Canada in which network screening jurisdiction specific models were developed and compared with calibrated models from the HSM. The database consisted of 387 intersections. The results showed that jurisdiction specific models outperformed calibrated models and similar effort and resources were required in the process—development of models is feasible and economically viable for small jurisdictions. Similarly, Persaud et al. (9) found mixed results with the transferability of models from other jurisdictions to Toronto, Canada. Sacci et al. (*10*) evaluated transferability of the HSM prediction models to Italian two-lane undivided rural roads by comparing the calibrated predictions with local data estimates. The results showed that the models differed significantly with increasing exposure, and the CMFs revealed some bias to site characteristics. Claros et al. (*13*) found that calibration factors for signalized intersections had a disproportional difference between the observed data in Missouri and the HSM models. Thus, the calibration was deemed inappropriate and the development of Missouri-specific models was warranted.

Crash Costs and EPDO Weights

Network screening included the EPDO performance measure which requires crash cost estimates to determine property damage equivalent weights by crash severity. There are no nationally standardized crash costs for safety analysis and jurisdictions independently adjust or estimate crash costs. However, there is guidance and procedures for crash cost estimation (*14*). Comprehensive crash costs consist of economic and loss of quality of life costs. Economic costs are measured in terms of goods and services related to emergency response, property damage, and medical costs. Loss of quality of life costs consist of the monetized value of pain and suffering due to death or injury. Crash cost estimates may differ based on the severity levels and definitions considered. Table 1 provides values of crash costs and corresponding EPDO weights in the HSM and selected studies. The HSM's recommended crash costs follow the KABCO severity scale. In contrast, crash costs of combined severities may use fatal and serious injury crashes such as MORCP (*18*) in Table 1. Assumed crash costs have a direct effect on the magnitude and distribution of EPDO weights. Specific EPDO weights for bicycle or pedestrian crashes were not available in the literature.

TABLE 1 Crash Costs and EPDO Weights

Reference	Severity	Crash Cost[1]	Weight
HSM (*1*)	Fatal (K)	$4,008,900	542
	Disabling injury (A)	$216,000	29
	Evident injury (B)	$79,000	11
	Possible injury (C)	$44,900	6
	Property Damage (O)	$7,400	1
Ma et al. (*15*)	Fatal	$4,113,956	607
	Injury	$144,291	21
	No-injury	$6,783	1
Washington et al. (*16*)	Fatal	$3,366,388	1,330
	Major injury	$2,402,997	949
	Minor injury	$27,852	11
	Property damage	$2,532	1
Flores et al. (*17*)	Fatal	$5,543,800	509
	Injury	$134,600	12
	Property Damage	$10,900	1
MORPC (*18*)	Fatal and serious injury	$315,578	38
	Visible injury	$54,470	7
	Possible injury	$36,920	4
	Property damage	$8,320	1

Notes: [1] Crash costs may differ according to the reference year. For instance, the HSM crash costs are in 2001 dollars.

Intersection Countermeasures

Crash modification factors (CMF) are adjustment factors that account for geometric or operational variations at a site. CMFs are multiplied by the base Safety Performance Function (SPF). In the case of countermeasures, CMFs greater than 1.0 indicate an expected increase of crashes and a value less than 1.0 indicates an expected reduction in crashes after the implementation of the treatment. Reliable CMF estimates provide strong evidence of the effectiveness of treatments. Table 2 provides selected CMFs for stop controlled, signalized intersections, and corresponding treatment cost estimates.

TABLE 2 Intersection Countermeasures Crash Modifications Factors and Costs (*5*, *14*)

Intersection Countermeasure		CMF[1]	Cost[2]		Safety Target
			Min	Max	
Stop Controlled	Systemic signing and marking	0.92	$5,000	$8,000	Overall safety
	LED beacons	0.95	$5,000	$15,000	Speed/running sign crashes
	Transverse rumble strips	0.82[3]	$3,000	$10,000	Speed/running sign crashes
	J-turn	0.65	$75,000	$125,000	Angle crashes, divided road
	Roundabout	0.56	$250,000	$500,000	Site specific
	Install traffic signal	0.76	$200,000	$500,000	Site specific
Signalized	Systemic signing and marking	0.96	$5,000	$30,000	Overall safety
	Adaptive signal control	0.83	$10,000	$70,000	Overall operations/safety
	Pedestrian treatments	0.91	$5,000	$15,000	Pedestrian safety
All	Lighting	0.84[3]	$10,000	$15,000	Nighttime crashes
	Skid resistance surface	0.83[3]	$20,000	$50,000	Wet, ice, and snow crashes
	Dynamic speed warning	0.95	$10,000	$20,000	Speed related crashes

Notes: [1] Crash modification factors that apply to all crash types and all severities were considered (*5*); [2] local estimates and costs found in the literature (*14*); [3] CMFs may apply to diverse roadway facility types.

Based on the study design and data availability, CMFs are ranked with a five-star level rating in the CMF Clearinghouse (*5*). There are instances in which reliable CMFs are not available for specific treatments or facility types (difficult to capture safety effect, limited data available). Available CMFs may be used for different applications at discretion.

METHODOLOGY

The methodology follows established roadway safety management process of the HSM including network screening, diagnosis, countermeasure selection, economic appraisal, and prioritization. Before initiating network screening, crash prediction models, crash costs, and EPDO weighs were obtained with local data. Figure 1 summarizes the safety management process methodology and considerations of this study. Each section of the safety management process is covered in detail in the following sections.

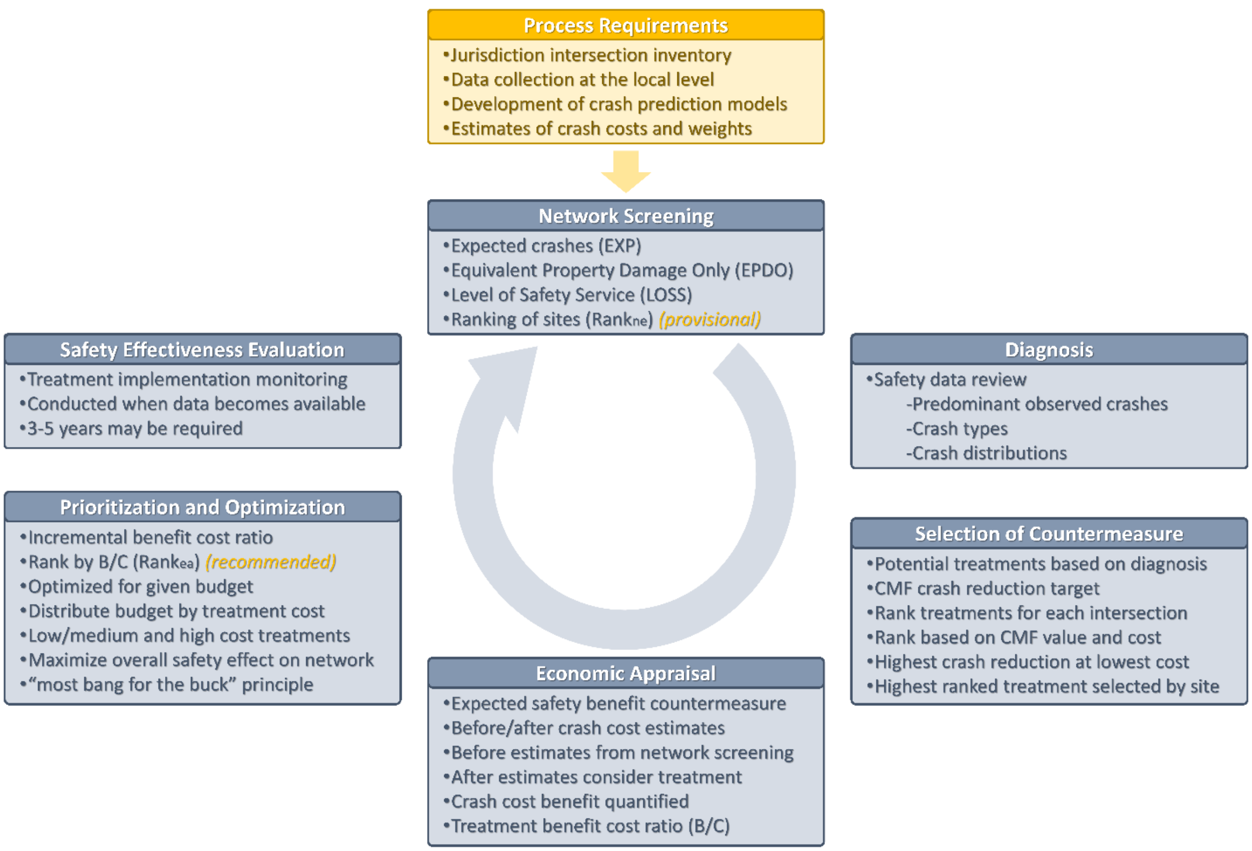

Figure 1 Safety management process methodology and considerations

Jurisdiction Specific Crash Prediction Models

Development of crash prediction models consisted of data collection, modeling, and model diagnostics.

Data Collection

Data required for modeling included intersection traffic volumes, traffic control, geometry, and crashes. Traffic data consisted of total entering vehicles ($AADT_{ent}$) to the intersection per day (vpd). Total entering vehicles were obtained through the summation of entering AADTs from all approach legs to the intersections. Street segments in a GIS database file had total traffic volume for all directions of travel. The volume of all legs in the intersection was totaled and divided in half to get an estimated entering traffic volume. The dataset included signal, stop, yield, and no control intersections. The main geometric parameter was the number of legs or approaches to the intersections. Crashes within 250 feet from the center of the intersection were collected. Crashes were mapped using available lat/long coordinates. Only 6.2% of crash records did not have coordinate information available and were not considered. Crash data was collected between 2005 and 2016. Data used for modeling was different than the data used for network screening. Data from 2005-2011 (7 years) was used for model development and 2012-2016 (5 years) was used for network screening. In the case of roundabouts, a completely separate database with 75 sites across the state were used (excluding Madison area roundabouts). Since there were not enough roundabouts and crash data for model development in the Madison area, sites and data collection were expanded at the state level.

Model Development

Network screening crash prediction model development consisted of exploratory data analysis, intersection category designation, and statistical modeling using the Negative Binomial formulation. Crash distribution factors were obtained by crash type and severity. Crash types considered were motor vehicle, motor vehicle-bicycle, and motor vehicle-pedestrian crashes. Crash severity consisted of conventional KABCO scale.

Exploratory Data Analysis (EDA) The analysis consisted of evaluating intersection crash distribution by signal control type over total entering vehicles ($AADT_{ent}$). Figure 2(a) illustrates the EDA plot for intersections in the Madison area during 2005-2011. The results showed a distinct distribution of crashes by signal control type in which signalized intersections had a higher number of crashes and traffic volume compared to the other intersection types, as one might expect. Also, all-way stop controlled intersections displayed an increasing orderly crash distribution over total entering vehicles. The rest of intersections had lower crash occurrence and showed similar distribution along total entering traffic (mainly two-way stop-controlled intersections). Figure 2(b) illustrates crash data distribution for roundabouts over total entering vehicles (crashes per year since date of implementation varies).

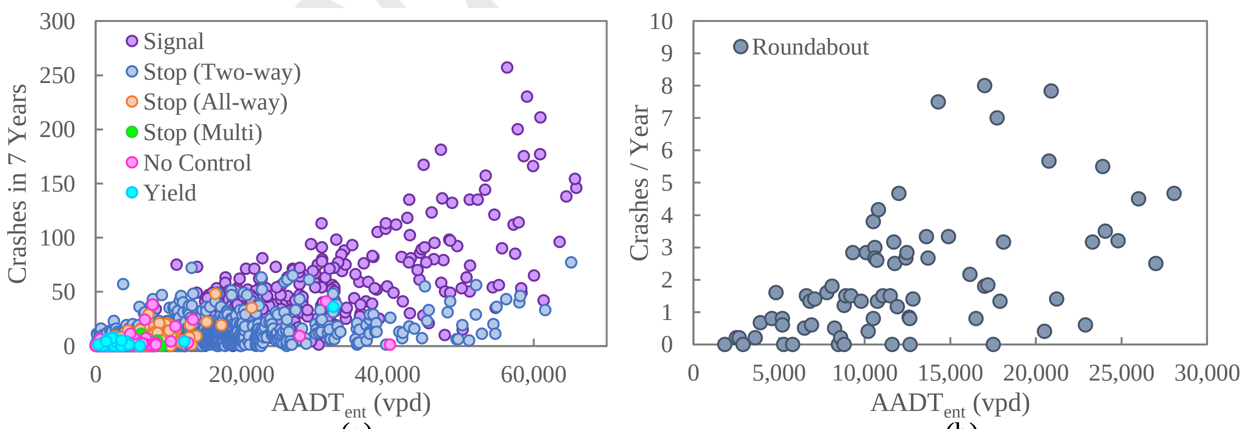

Figure 2 EDA of crashes versus $AADT_{ent}$ for (a) conventional intersections and (b) roundabouts

For model development, four intersection categories were designated: 1) Signal, 2) Stop (All-way), 3) Roundabouts, 4) Stop (Two-way), Stop (Multi), Yield, and No Control. In Table 3, descriptive statistics for each intersection category are provided. Stop (Multi) refers to stop control intersections that may have one-way streets or approach legs for exclusive use of cyclist.

TABLE 3 Descriptive Statistics by Intersection Category

Cat.	Description	Sites	Variable	Minimum[1]	Maximum	Average	St. Deviation
1	Signal	423	$AADT_{ent}$ (vpd)	4,475	65,825	25,388	13,606
			Number of Legs	1	6	3.70	0.51
			Crashes (in 7 years)	0	257	41.04	38.76
2	Stop (All Way)	170	$AADT_{ent}$ (vpd)	440	11,800	4,517	2,759
			Number of Legs	3	5	3.72	0.48
			Crashes (in 7 years)	0	21	3.64	4.45
3	Roundabout	75	$AADT_{ent}$ (vpd)	1,830	28,076	12,333	6,382
			Number of Legs	3	4	3.40	0.49
			Crashes / Year	0	8	2.04	1.93
4	Stop (Two-way), Stop (Multi), Yield, No Control	3,382	$AADT_{ent}$ (vpd)	35	33,538	6,865	6,102
			Number of Legs	2	5	3.27	0.45
			Crashes (in 7 years)	0	65	4.35	6.88

Notes: [1] one leg intersections were considered for one-way roads with mid-block pedestrian crossings and traffic controllers.

The average $AADT_{ent}$ was 50,775 vpd, 9,033 vpd, 12,333 vpd, and 13,730 vpd for intersection categories 1, 2, 3, and 4 respectively. The number of legs showed that there were some intersections with only one leg and up to six legs. Intersections with the number of legs less than 2 (176 sites) and more than 4 (110 sites) were individually reviewed and validated. One leg intersections were considered for one-way roads with mid-block pedestrian crossings and traffic controllers. Intersections with inconsistent number of legs were corrected and included in the data. The number of crashes provided in Table 3 were for crashes in a seven-year period. As expected, intersection category 1 (signalized) with 41.04 crashes over seven years had on average more crashes than the other categories. In the case of roundabouts, the periods of analysis were different, so crashes per year were provided in Table 3 (average of 2.04 crashes/year).

Model Parameter Estimation Maximum likelihood was used for model parameter estimation. The log-likelihood function based on the Negative Binomial is illustrated in Equation 1 (*19*). Statistical software was used to optimize the function and obtain model coefficients.

$$ln[\mathcal{L}(a,b,\dots,\mathcal{b})] = \sum_{i=1}^{n}[ln\Gamma(obs_i + \mathcal{b}) - ln\Gamma(\mathcal{b}) + \mathcal{b}\, ln(\mathcal{b}) + obs_i\, ln(pred_i) - (\mathcal{b} + obs_i)l\,n(\mathcal{b} + pred_i)] \qquad (1)$$

The letter i denotes units (intersections). The mean incident count for unit i over period of time y_i is u_i. The traits of i define population of units that are assumed to be Gamma distributed with mean $E(u_i)$ and variance $E(u_i)^2/\mathcal{b}$. The value $1/\mathcal{b}$ is called the overdispersion parameter which is also commonly denoted by the letter k. The parameter estimates of the model coefficients are $a, b, \dots, \mathcal{b}$. The log-likelihood function that maximizes the estimates are those that maximize the sum of $ln[\mathcal{L}(a,b,\dots,\mathcal{b})]$ (*19*). Crash prediction models were developed by intersection category provided in Equations 2-7.

Intersection Category 1:

$AADT_{ent}$ < 35,000 vpd

$$N_1 = 0.450 \times \left(\frac{AADT_{ent}}{10{,}000}\right)^{1.199} \times Legs^{1.059} \qquad \left(\frac{crashes}{year}\right),\, k = 0.364 \qquad (2)$$

35,000 vpd ≤ $AADT_{ent}$ < 70,000 vpd

$$N_1 = 0.143 \times \left[6.746 \times \left(\frac{AADT_{ent}}{10{,}000}\right) - 10.778\right] \times Legs^{1.059} \qquad \left(\frac{crashes}{year}\right),\, k = 0.364 \qquad (3)$$

Intersection Category 2:

$AADT_{ent}$ < 12,500 vpd

$$N_2 = 0.761 \times \left(\frac{AADT_{ent}}{10{,}000}\right)^{1.229} \times Legs^{0.416} \qquad \left(\frac{crashes}{year}\right),\, k = 0.522 \qquad (4)$$

Intersection Category 3:

$AADT_{ent}$ < 30,000 vpd

$$N_3 = \left[\frac{0.540}{1+23.409\times\exp\left(-2.901\times\frac{AADT_{ent}}{10{,}000}\right)}\right] \times Legs^{1.576} \qquad \left(\frac{crashes}{year}\right),\, k = 0.473 \qquad (5)$$

Intersection Category 4:

$AADT_{ent}$ < 7,500 vpd

$$N_4 = 0.017 \times exp\left(2.136 \times \frac{AADT_{ent}}{10{,}000}\right) \times Legs^{1.737} \qquad \left(\frac{crashes}{year}\right),\, k = 0.785 \qquad (6)$$

7,500 vpd ≤ $AADT_{ent}$ < 35,000 vpd

$$N_4 = 0.143 \times \left[0.737 \times \left(\frac{AADT_{ent}}{10{,}000}\right) + 0.063\right] \times Legs^{1.737} \qquad \left(\frac{crashes}{year}\right),\, k = 0.785 \qquad (7)$$

Where,

N_n , crash prediction model for intersection category n in crashes per year [n=1, Signal; n=2, Stop (All-way); n=3, Roundabout; n=4 Stop (Two-way), Stop (Multi), Yield, No Control];
$AADT_{ent}$, total entering vehicles in vehicles per day (vpd);
$Legs$, number of approaching legs to intersection;
k , model Overdispersion parameter.

Predictions beyond specified $AADT_{ent}$ ranges for each model should be used with caution. Two models were developed for intersection categories 1 and 4 since crash distribution was different by ranges of $AADT_{ent}$.

Distribution Factors Crash type (CDF) and Severity Distribution (SDF) Factors were obtained for different crash types and corresponding severity levels. Distribution factors are essentially proportions of each crash type and severity of the overall intersection crashes (*1*). Table 4 provides a summary of all distribution factors obtained.

TABLE 4 Crash Distribution Factors

CDF_i	All	Ped	Bike	Veh
	1.000	0.016	0.023	0.960
$SDF_{i,j}$	K	0.026	0.004	0.001
	A	0.157	0.088	0.013
	B	0.455	0.487	0.080
	C	0.322	0.331	0.178
	O	0.040	0.090	0.727
	All	1.000	1.000	1.000

Notes: i = crash type, j = crash severity, Ped = motor vehicle-pedestrian crashes, Bike = motor vehicle-bicycle crashes, Veh = motor vehicle crashes, KABCO severity scale.

Model Diagnostics

Three goodness-of-fit measures were used to determine the performance of crash prediction models: Log-likelihood, overdispersion parameter, and Cumulative Residuals (CURE) plots (*19*). Model parameters that maximize the Negative Binomial likelihood function (Equation 1) are those that maximize the sum of $ln[\mathcal{L}(a, b, \ldots, \mathscr{b})]$ resulting in the Log-likelihood. An increase in Log-likelihood is desired when predictor variables with specified functional forms are introduced in the model. The overdispersion parameter indicates the variability of the model in comparison with a Poisson distribution with the same mean. The reliability of the resulting models is likely to be higher with a smaller value of the overdispersion coefficient ($k = 1/\mathscr{b}$). The larger the dispersion term ($\mathscr{b}$), the smaller the overdispersion. In contrast with a single goodness-of-fit measure that reflects overall model performance for all values of a variable, CURE plots track model performance throughout the range of values as provided in Figure 3 (by $AADT_{ent}$ ranges).

A satisfactory CURE plot is one that follows a symmetric random walk to the horizontal axis. Large vertical changes represent large residuals (outliers), and long increasing or decreasing runs represent regions of consistent under- or overestimation (*19*). As mentioned previously, two prediction models were developed for categories 1 and 4, so the CURE plots by range of $AADT_{ent}$ were combined in Figures 3(a) and 3(d). Throughout the process of adding variables and trying different functional forms, all measures of goodness of fit were continuously evaluated for each resulting model. CURE plots showed satisfactory measures of goodness of fit along AADT ranges for all models developed.

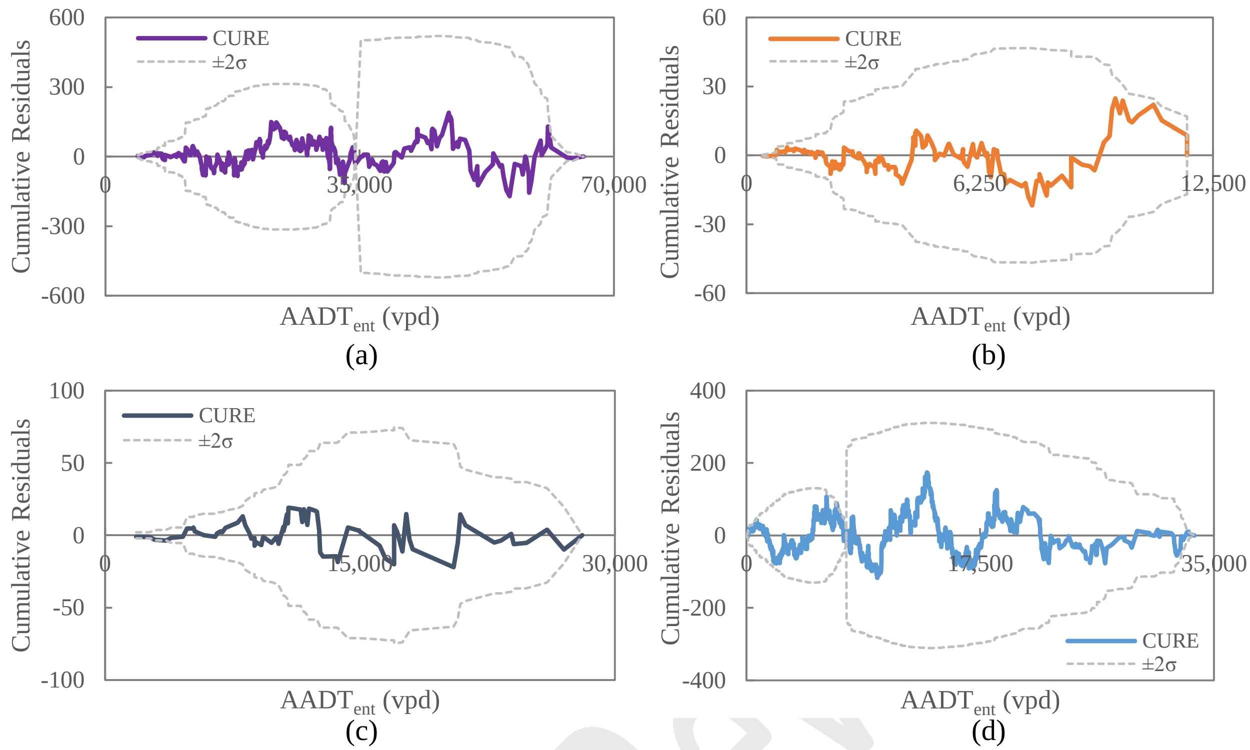

Figure 3 CURE Plots for model (a) category 1, (b) category 2, (c) category 3 and (d) category 4

Crash Costs and EPDO Weights

Wisconsin CODES data was used to estimate jurisdiction specific intersection crash costs by crash type and severity. Crash costs were used to estimate EPDO weights. CODES database provides cost estimates for medical, societal, and quality of life costs by person injured in a crash. Crash and hospital databases were linked to categorize injuries by part of the body, fracture involvement, and threat to life. Cost estimates were also provided for non-hospitalized crash cases using the Bureau of Labor Statistics data. Costs were adjusted for inflation (standard CPI changes) (*14*, *21*, *22*).

Records of persons injured in crashes were used to estimate crash costs by type and severity. Types of crashes were classified by motor vehicle, motor vehicle-bicycle, and motor vehicle-pedestrian crashes. Crash severity classification adopted was conventional KABCO scale. Person injured crash costs had to be translated to costs per crash. Each person injured was linked to the corresponding crash report. Since police crash reports are designated by the highest injury severity observed from one of the persons injured in the crash, multiple individuals with different injury severities may be involved in the crash. Crash costs of all persons injured were included in the calculation of the overall crash costs with the designated maximum severity.

EPDO weights were obtained as a function of crash types and severities. The base property damage cost was $24,322, which corresponds to the motor vehicle property damage crash cost. The analysis showed that 11.4% of people involved in property damage crashes did receive medical attention which was not expected for crashes designated as property damage only. Table 5 provides a summary of crash costs and EPDO weights by crash type and severity. Crash costs data at the state level (Wisconsin) for intersection cases between 2009-2016 were used. A total of 921,782 persons injured in 348,731 crashes at urban intersections were recorded at the state level. Crash cost were estimated with state level data because there were not enough data available at the local level, especially for pedestrian/bicycle fatal and injury crashes.

Reduced number crashes with specific severities have a direct influence in the magnitude and variability of crash cost, so expanding the crash cost analysis at the state level was required to obtain reliable estimates.

TABLE 5 Crash Costs and EPDO Weights by Crash Type and Severity

Severity		Crash Cost			EPDO Weight		
		Ped	Bike	Veh	Ped	Bike	Veh
K	Fatal	$3,305,922	$3,147,627	$3,782,512	135.9	129.4	155.5
A	Incapacitating	$433,383	$362,759	$389,169	17.8	14.9	16.0
B	Non-Incapacitating	$113,100	$90,303	$107,674	4.7	3.7	4.4
C	Possible Injury	$73,539	$60,060	$56,365	3.0	2.5	2.3
O	Property Damage	$35,692	$49,042	$24,322	1.5	2.0	1.0

Notes: Ped = motor vehicle-pedestrian crashes, Bike = motor vehicle-bicycle crashes, Veh = motor vehicle crashes, KABCO severity scale.

Network Screening

Network screening is the examination of the population to select sites that merit attention and further assessment. The result of the network screening process is a list of sites ranked in order of priority. Safety network screening was conducted for arterial/collector intersections for Madison metropolitan area in Wisconsin. A total of 4,062 intersections were evaluated. EPDO with Empirical Bayes adjustments and the LOSS were used as safety performance measures to identify and rank intersections for potential safety improvements.

EPDO with Empirical Bayes Adjustments

The Empirical Bayes (*20*) is a rigorous statistical method that accounts for regression to the mean and utilizes model predictions. The method estimates expected crashes (EXP) as a function of weighted average of observed (OBS) and predicted (PRED) crashes (Equation 8). Predicted crashes are estimated with prediction models and distribution factors (Equation 9). The weighted value (w) is a function of the overdispersion (k) and magnitude of predicted crashes (Equation 10) (*20*). Thus, the variability of the prediction model serves as a parameter to adjust the quality of estimates in relation to the amount of observed data. Expected crashes were estimated by crash type and severity. Since roundabouts were implemented in different years, predictions were adjusted to reflect a 5-year period comparable with other intersection types in the study.

$$EXP_{n,i,j} = w_{n,i,j} \times PRED_{n,i,j} + \left(1 - w_{n,i,j}\right) \times OBS_{n,i,j} \quad (8)$$

$$PRED_{n,i,j} = CDF_i \times SDF_{i,j} \times N_n \quad (9)$$

$$w_{n,i,j} = \frac{1}{1 + k_n \times PRED_{n,i,j}} \quad (10)$$

Where,

$EXP_{n,i,j}$, expected crashes for intersection category n [n=1, Signal; n=2, Stop (All-way); n=3, Roundabout; n=4 Stop (Two-way), Stop (Multi), Yield, No Control], crash type i (Ped = motor vehicle-pedestrian crashes, Bike = motor vehicle-bicycle crashes, Veh = motor vehicle crashes), and crash severity j (KABCO scale);

$PRED_{n,i,j}$, predicted crashes for intersection category n, crash type i, and crash severity j;

$OBS_{n,i,j}$, observed crashes for intersection category n, crash type i, and crash severity j;
$w_{n,i,j}$, weight for intersection category n, crash type i, and crash severity j;
k_n , model Overdispersion parameter intersection category n;
CDF_i , Crash Type Distribution Factor by crash type i;
$SDF_{i,j}$, Severity Distribution Factor by severity j;
N_n , crash prediction model for intersection category n.

Overall EPDO of intersections was calculated as the sum of the product of expected crashes and corresponding EPDO weight by crash type and severity (weights provided in Table 5). Equation 11 provides the intersections overall EPDO (*1*). Intersections were ranked according to the magnitude of the EPDO. Although the EPDO ranking may suggest locations with high crash occurrence, practitioners should not consider that all intersections are equal. Intersections in a network have distinct differences of geometry, traffic volume, traffic control, and surrounding environment. Hauer (*7*) argued that a good network screening is the one that ranks highly those sites at which the most cost-effective treatment can later be implemented. EPDO ranking is not a definite ranking to select sites with promise for safety improvement, it is a step in the roadway safety management process to select sites and identify corresponding treatments that would provide the most safety benefit in the overall system with the resources available.

$$EPDO = \sum_{n,i,j} EXP_{n,i,j} \times EPDO_{weight,i,j} \tag{11}$$

Where,

$EPDO$, overall intersection EPDO estimate;
$EXP_{n,i,j}$, expected crashes for intersection category n [n=1, Signal; n=2, Stop (All-way); n=3, Roundabout; n=4 Stop (Two-way), Stop (Multi), Yield, No Control], crash type *i* (Ped = motor vehicle-pedestrian crashes, Bike = motor vehicle-bicycle crashes, Veh = motor vehicle crashes), and crash severity *j* (KABCO scale);
$EPDO_{weight,i,j}$, EPDO weight by crash type *i* and severity *j*.

Level of Service of Safety (LOSS)
Crash prediction model estimates were compared to observed crashes and the degree of deviation from the model prediction was quantified and categorized in four LOSS classes (*1*). The variability of the model prediction was calculated in Equation 12 with the overdispersion parameter and predicted crashes:

$$\sigma_{n,All,All} = \sqrt{k_n \times PRED_{n,All,All}{}^2} \tag{12}$$

The following limits apply to the LOSS evaluated with the prediction standard error, observed, and predicted crashes (*1*):

LOSS I:	Low potential for crash reduction	$\sigma < OBS_{n,All,All} < PRED_{n,All,All} - 1.5\sigma$
LOSS II:	Low to moderate potential for crash reduction	$PRED_{n,All,All} - 1.5\sigma \leq OBS_{n,All,All} < PRED_{n,All,All}$
LOSS III:	Moderate to high potential for crash reduction	$PRED_{n,All,All} \leq OBS_{n,All,All} < PRED_{n,All,All} + 1.5\sigma$
LOSS IV:	High potential for crash reduction	$OBS_{n,All,All} \geq PRED_{n,All,All} + 1.5\sigma$

Diagnosis

The diagnosis process serves to identify contributing factors and potential safety concerns. The HSM recommends a three-step process: 1) safety data review, 2) assess supporting documentation, and 3) assess field conditions (*1*). Diagnosis requires review of crash types, severities, environmental conditions, past studies and plans in the vicinity, and site visit. However, in a network screening process, thousands of intersections are considered and it is not reasonable to believe that a systematic and rigorous diagnosis is feasible in a timely manner even for a subset of intersections. Thus, for this study, the diagnosis was limited to the safety data review of the three-step recommended process.

Safety Data Review

Review of the observed safety data was automated to identify crash types that are predominant at each intersection. The process consisted of calculating the proportion of left turn, right angle, running signal, failed to yield, speed, bike, pedestrian, weather (wet, ice, snow), and nighttime related crashes from the overall observed crashes. Crash types were divided in such categories to match the specific applications of the countermeasures for intersections mentioned in Table 2. Proportion of crash types were then used to selected potential countermeasures.

Selection of Countermeasure

A countermeasure is a roadway strategy aimed at decreasing frequency and/or severity of crashes at a site (*1*). As part of the countermeasure selection process, contributing factors should be identified. Unless, a detailed examination of highly ranked sites in the network screening process is conducted, there is not a practical way to identify contributing factors at each intersection considered. Thus, anticipation of future safety benefits due to unspecified treatments must be based on assumptions (*7*). In this study, based on the results of the diagnosis step, potential countermeasures were identified based on the magnitude of the proportion of crash types related to the CMF crash target. In many cases, there were intersections with more than one potential countermeasure, so treatments were ranked for each intersection considering the CMF magnitude and cost of implementation (most potential for crash reduction at lowest cost). As a result, the highest ranked countermeasure for each intersection was identified.

Economic Appraisal

Safety economic appraisals are performed to quantify the benefits of potential countermeasures in relation to the treatment cost. The economical appraisal was conducted after network screening, diagnosis, and countermeasure selection was completed. To quantify the expected benefit of the countermeasure after implementation, before crash cost estimates were required. Estimates for the before period were already available from the network screening process, so expected crashes and crash cost estimates in the after period were calculated. Assuming that the only change in the intersection conditions was the countermeasure implementation, predicted crashes (Equation 9) were multiplied by the selected countermeasure CMF (Table 2) to obtain predicted crashes in the after period (Equation 13). In Equation 14, the expected crashes in the before period were adjusted to reflect the effect of the countermeasure in the after period. The expected crashes in the after period were then used with the EPDO weight to obtained the overall intersection EPDO for the after period, illustrated in Equation 15. The crash cost benefit was estimated by subtracting the EPDO for the before and after period and multiplied by the base property damage cost of $24,322 (severity O, motor vehicle crash) (Table 5). In Equation 17, the benefit-cost ratio was obtained with the crash cost benefit and treatment cost.

$$PRED_{n,i,j,after} = PRED_{n,i,j} \times CMF_z \quad (13)$$

$$EXP_{n,i,j,after} = EXP_{n,i,j,before} \times \frac{PRED_{n,i,j,after}}{PREDn,i,j,_{before}} \quad (14)$$

$$EPDO_{after} = \sum_{n,i,j} EXP_{n,i,j,after} \times EPDO_{weight,i,j} \quad (15)$$

$$Crash\ Cost\ Benefit = \left(EPDO_{before} - EPDO_{after}\right) \times \$24{,}322 \quad (16)$$

$$B/_C = \frac{Crash\ Cost\ Benefit}{Countermeaure\ Cost} \quad (17)$$

Where,

$PRED_{n,i,j,k}$, predicted crashes for intersection category n, crash type *i*, crash severity *j*, *k* period;
CMF_z , Crash Modification Factor for treatment z,
$EXP_{n,i,j,k}$, expected crashes for intersection category n [n=1, Signal; n=2, Stop (All-way); n=3, Roundabout; n=4 Stop (Two-way), Stop (Multi), Yield, No Control], crash type *i* (Ped = motor vehicle-pedestrian crashes, Bike = motor vehicle-bicycle crashes, Veh = motor vehicle crashes), crash severity *j* (KABCO scale), and *k* period;
$EPDO_k$, overall intersection EPDO estimate for *k* period;
$EPDO_{weight,i,j}$, EPDO weight by crash type *i* and severity *j*;
$B/_C$, benefit-cost ratio.

Project Prioritization and Optimization

The method selected for project prioritization was the incremental benefit-cost optimized for a given budget (*1*). The method consisted of ranking sites based on the magnitude of the B/C ratio. For a given budget, sites that maximized the overall B/C were selected. As expected, sites treated with low and medium cost treatments ($5,000-$70,000) would yield the best outcome—maximum overall safety effect to the system. Alternatively, with a separate budget, jurisdictions may decide to conduct an independent prioritization and optimization process for sites with high cost treatments which may include implementation of j-turns, roundabouts, or signalized intersections ($75,000-$500,000).

RESULTS

Results are presented for optimal site selection with treatments that provide the overall maximum safety benefit in the network of intersections in the Madison metropolitan area in Wisconsin. A summary of the results is presented in Table 6. A hypothetical budget of $3,000,000 was assumed. Since low and medium cost treatments would provide the maximum overall benefit, selection of higher cost treatments may also be specified with the budget distributed in two groups—low/medium and high cost treatments. The optimization proposed allocates resources based on two subset budgets according to the cost of the treatments; however, other conditions may be specified by number of locations, intersection type, or crash types. Ranking from network screening ($Rank_{ne}$) was used provisionally to identify potential countermeasures in the diagnosis and countermeasure selection steps. As a result of the economical appraisal, a second ranking ($Rank_{ea}$) was developed based on the magnitude of the B/C ratio. Based on the economical appraisal ranking, sites were sorted from the highest to lowest B/C for the optimization process.

TABLE 6 Summary of Results

Budget[1]			**$3,000,000**			
Proposed Distribution[1]	Low/Medium	**33.00%**	$990,000	Crash Cost Benefit	Low/Medium	$17,905,385
	High	**67.00%**	$2,010,000		High	$4,709,099
Adjusted Distribution[2]	Low/Medium	36.67%	$1,100,000	Overall Crash Cost Benefit		$22,614,485
	High	63.33%	$1,900,000	Benefit-Cost Ratio (B/C)	Low/Medium	**16.3**
Actual Distribution[3]	Low/Medium	36.63%	**$1,099,000**		High	**2.5**
	High	63.33%	**$1,900,000**	Overall Benefit-Cost Ratio (B/C)		**7.5**
Budget - Treatment Cost	Low/Medium	0.03%	$1,000	Intersection Treatments	Low/Medium	59
	High	0.00%	$0		High	9

Intersection			**Network Screening**				**Diagnosis/Countermeasure**					**Economic Appraisal**			**Prioritization/Optimization**		
Site	Category	$AADT_{ent}$ (vpd)	$EPDO_{before}$	LOSS	Crash $Cost_{before}$	$Rank_{ne}$ [4]	CMF_z	Treatment Cost Level	Treatment Cost	$EPDO_{after}$	Crash $Cost_{after}$	Crash Cost Benefit	B/C	$Rank_{ea}$ [5]	Selected[6]	Incremental Treatment Cost (Low-Medium)	Incremental Treatment Cost (High)
1	4	58,038	94	III	$2,284,555	86	1	Low	$6,500	86	$2,101,791	$182,764	28.1	1	Yes	$6,500	$0
2	4	65,125	92	III	$2,236,743	93	1	Low	$6,500	85	$2,057,804	$178,939	27.5	2	Yes	$13,000	$0
3	4	58,150	87	III	$2,122,922	101	1	Low	$6,500	80	$1,953,088	$169,834	26.1	3	Yes	$19,500	$0
4	1	65,650	250	III	$6,084,027	6	8	Medium	$40,000	208	$5,049,742	$1,034,285	25.9	4	Yes	$59,500	$0
:															:	:	:
57	1	40,800	175	IV	$4,245,583	23	7	Medium	$17,500	167	$4,054,532	$191,051	10.9	57	Yes	$1,075,000	$0
58	1	48,825	174	III	$4,240,441	24	7	Medium	$17,500	166	$4,049,621	$190,820	10.9	58	Yes	$1,092,500	$0
59	1	63,550	171	II	$4,170,460	25	7	Medium	$17,500	164	$3,982,790	$187,671	10.7	59	No	$0	$0
60	1	51,300	171	III	$4,154,957	26	7	Medium	$17,500	163	$3,967,984	$186,973	10.7	60	No	$0	$0
61	1	33,200	103	III	$2,500,127	71	8	Medium	$40,000	85	$2,075,105	$425,022	10.6	61	No	$0	$0
62	4	31,558	35	III	$860,288	344	1	Low	$6,500	33	$791,465	$68,823	10.6	62	Yes	**$1,099,000**	$0
63	1	42,950	169	III	$4,113,725	27	7	Medium	$17,500	162	$3,928,608	$185,118	10.6	63	No	$0	$0
:															:	:	:
117	4	16,625	27	III	$662,069	452	1	Low	$6,500	25	$609,103	$52,965	8.1	117	No	$0	$0
118	4	22,285	96	IV	$2,340,897	82	4	High	$100,000	63	$1,526,265	$814,632	8.1	118	Yes	$0	$100,000
119	1	20,575	79	IV	$1,913,931	115	8	Medium	$40,000	65	$1,588,562	$325,368	8.1	119	No	$0	$0
:															:	:	:
1329	4	948	2	III	$39,560	3,568	3	Low	$6,500	1	$32,439	$7,121	1.1	1,329	No	$0	$0
1330	4	26,975	66	IV	$1,594,851	153	6	High	$350,000	50	$1,212,087	$382,764	1.1	1,330	Yes	$0	**$1,900,000**

Notes: [1] Hypothetical budget and proposed distribution were data entries; [2] redistribution of resources from high to low-median cost treatments to optimize use of resources; [3] final distribution of resources based on optimization; [4] ranking based on network screening; [5] ranking based on economical appraisal; [6] sites with highest potential for treatment.

Using conditional functions, sites with the highest B/C ratio that maximized the use of budget allocated for the treatment cost group were selected as illustrated in Table 6. For instance, in column “Incremental Treatment Cost (Low-Medium)”, sites 59-61 were not selected since the cost of treatment at any of those sites would go over the allotted budget; those sites were skipped until site 62 with a treatment cost that complied with the remaining budget (maximizing the use of resources). The same process was conducted for high cost treatments. As anticipated, the B/C ratio of low and medium cost treatments was significantly higher than high cost treatments (16.3 compared to 2.5). With low and medium cost treatments, 59 intersections were selected for systemic signing and marking improvements, adaptive signal control for signalized intersections, transverse rumble strips, and pedestrian improvement treatments. Intersections selected with high cost treatments were 9 overall—J-turns, roundabouts, or signalized intersections.

Safety management process should be completed up to the project prioritization process. Usually, network screening results are released before further analysis is conducted. For instance, in Figure 4(a), using the EPDO results from network screening, the top 100 sites were selected as sites with promise. However, the approach is biased towards intersections with high number of crashes and AADT. Additionally, evaluating the EPDO by intersection type in Figure 4(b) clearly illustrates that most of those top 100 sites were signalized intersections, not including other intersections types. Using the LOSS measure in Figure 4(c), we can visualize that the distribution of sites with lower LOSS included a wide array of signal types and AADT ranges. Thus, through the optimization process, we can observe in Figure 4(d) that sites that maximized the overall safety benefit of the network were sites from varied LOSS, AADT ranges, and intersections types.

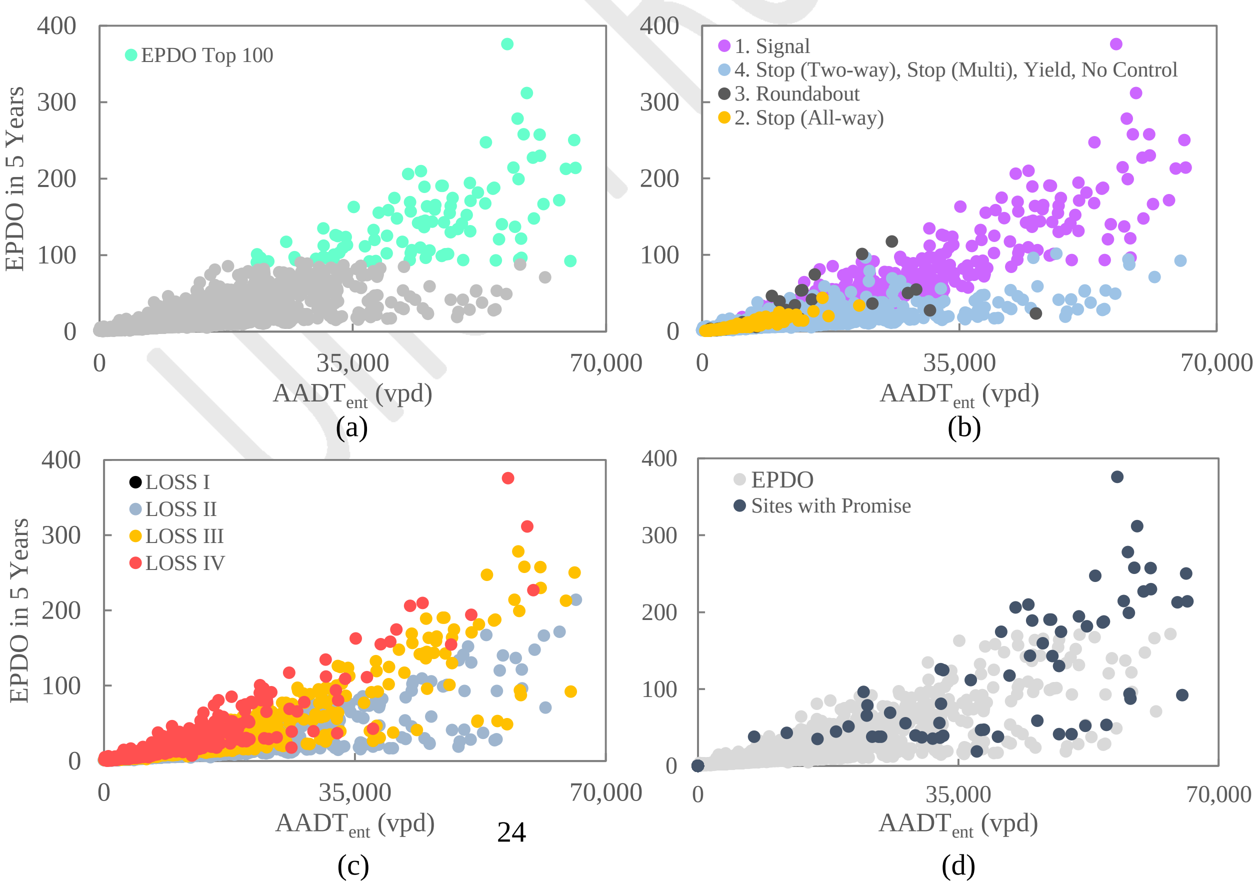

Figure 4 EPDO/AADT$_{ent}$ (a) top 100, (b) by intersection type, (c) by LOSS, and (d) with optimization

CONCLUSIONS

Safety initiatives have mainly been implemented at the state level (*4*). However, application of the safety management process is limited in small municipalities due to data, statistical expertise, and resources required. In this paper, the implementation of intersection safety management process for a smaller transportation agency is illustrated.

Since the first step of the safety management process is network screening, ranking of facilities have a negative connotation and disseminate inconclusive information of the process. Attention is drawn to locations that may require significant investment and time for the implementation of a safety treatment; or the safety issues at the location may not even be completely addressed because it may not be economically viable. Focusing and disseminating results of network screening alone is counterproductive and should be used provisionally until project prioritization, in the safety management process, is completed. Through an optimization process, a combination of sites that have the greatest overall safety benefit to the network should be selected following the "most bang for the buck" principle (*7*).

This paper provides a clear implementation of the entire safety management process to effectively use jurisdiction specific data for model development, integrate pedestrian and cyclist crashes, application of EPDO and LOSS performance measures, and selection of sites with promise through an incremental optimization process to obtain the greatest overall safety improvement for the network with the resources available in a small jurisdiction.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: Boris Claros, Madhav Chitturi, Andrea Bill, and David A. Noyce; analysis and interpretation of results: Boris Claros, Madhav Chitturi, and Andrea Bill; draft manuscript preparation: Boris Claros and Madhav Chitturi. All authors reviewed the results and approved the final version of the manuscript.

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