Predicting Annual Intersection Accidents with Conflict Opportunities

A. R. KAUB
J. A. KAUB
Traffic Safety Software, LLC
6941 Cohasset Circle
Riverview, FL 33569
www.Traf-Safe.com

ABSTRACT

Validation and the general algorithm are presented for a conflict opportunity-based annual accident prediction software for both signalized and unsignalized intersections over a wide variety of volume, geometry, speed, signal timing and phasing, and other variables. Validation to numerous intersections indicates an average prediction accuracy of 90 percent compared to the historical annual reported accident average at any individual intersection.

INTRODUCTION

"The pruf's in the puddin' " is an old adage that says, if you think your cooking is really good, the proof isn't in talking about the ingredients, or about how to mix it, or how good you think it is. The real proof lies in tasting the pudding. Any "taste test" should be done by someone other than the chef, and all the chef can hope for is that other tasters are connoisseurs of pudding! And while there's no substitute for letting everyone taste to find out just how good the pudding is, if the bowl isn't big enough you could sample a hundred people and plot their responses. That's called a validation study, and the plot of the data would tell the story about how good the pudding really is.

Predicting accidents is no different. If an approach exists that predicts intersection accidents with both accuracy and precision, then the "pruf" rests with those who are connoisseurs of accident analysis and with the plots of the validation that would tell the story. And here is the point: *if accidents really are predictable, then they are also correctable,* just like the ingredients in the pudding. With this new predictability engineers can begin to prevent the over 6,000 deaths and 725,000 disabling injuries that occur each year at U.S. signalized and stop-controlled intersections (*1*). So rather than presenting the ingredients or the directions for this traffic accident prediction technology, let's save that for last and let the validation results tell the story.

SIGNALIZED INTERSECTION ACCIDENT VALIDATION USING CONFLICT OPPORTUNITIES

Rather than giving all the data from the original signalized intersection validation,which may confuse and muddle any presentation and most readers, Tables 1–2 and Figures 1–5 present 25 randomly selected comparisons of predicted and actual DOT reported accident histories from the original validation study (*2*). The original validation was comprised of numerous randomly selected intersections from a pool of over 800 signalized urban intersections within one typical major metropolitan urban area. Often comparisons of actual to predicted accidents only compare *total* annual accidents, but if a true comparison is made, all predictions should also conform to the major accident types including *angle*, *rear-end*, *sideswipe*, and *single-vehicle/fixed-object(other)* accidents. In this comparison, total accidents should reflect a very short event horizon such as 1 year before and after the traffic data collection (for a total of a 3-year history), while angle, rear-end, sideswipe and other accidents should reflect an expanded data collection horizon since these accidents are often "rare events" that require more data and a longer collection timeframe.

With this background, Tables 1–2 and Figures 1–5 present the results of the 25 samples and compare accident predictions against accident histories. Each of the separate elements of the validation is presented as follows:

1. *Total Annual Accident Comparison*—Given a 3-year accident history, each site is able to develop a mean and standard deviation to which the predicted accident response can be compared as presented in Table 1. The comparison of total accidents indicates the average prediction is within approximately 12 percent of the historical average (range 1–28 percent) or conversely that the average accuracy may be defined as 88 or approximately 90 percent. In comparison to the historical standard deviation at each site, 95 percent of the predictions are within 1 standard deviation of the 3-year mean, over 50 percent are within ½ standard deviation, and no predictions are beyond 2 standard deviations from the historical mean. Using identical cubic linear regression models of the predicted and actual data, a visual comparison of the regression models in Figure 1 indicates how closely the models track one another and just how well, in the absence of actual historical data, the conflict opportunity software is able to predict total annual accidents before they occur.
2. *Angle Accident Comparison*—Given a 5-year accident history, a mean and standard deviation of the historical data can be developed to which the predicted angle accident response can be compared. Table 2 presents a comparison of the angle (and other) event types for each of the 25 sites. The angle comparison indicates a relatively close correspondence between actual and predicted events with an approximate 80 percent accuracy when comparing mean responses. Over 70 percent of the predictions are within 1 standard deviation of the 5-year historical mean. Using identical linear regression models of the predicted and actual data, a visual comparison in Figure 2 indicates how closely the angle accident predictions and regression model track the historical data and its regression model, and how well the software predicts angle accidents.
3. *Rear-End Accident Comparison*—Given a 5-year accident history for rear-end accidents, a comparison of historical and predicted accidents is presented above in Table 2. Both the table and Figure 3 indicate a close correspondence between actual and predicted rear-end events with an accuracy of approximately 85 percent when comparing mean responses. Over 75 percent of the predictions are within 1 standard deviation of the historical mean. Using identical linear regression models of the predicted and actual data, a visual comparison in Figure 3 indicates how closely the rear-end accident predictions and regression model track the historical data and model, and how well conflict opportunity software predicts rear-end accident events.

TABLE 1 Comparison of Actual and Predicted Signalized Total Annual Accidents[1–4]

Site #	Daily Entering Volume (1,000's)	Historical Average Accidents/Year	Standard Deviation	Predicted Accidents/Year	Precision of the Prediction (Std. Deviations from Mean)	Percent Difference* (Ave.- Pred) Prediction
1	90	42.3	2.52	39.1	< 2 Std	8.1
2	38	6.0	1.72	7.2	<1 Std	16.7
3	43	4.7	1.53	5.7	<1 Std	18.1
4	22	11.3	3.51	13.2	<1 Std	14.1
5	66	26.3	1.15	26.6	<1/2 Std	1.0
6	80	35.6	3.06	36.5	<1/2 Std	2.3
7	25	6.3	3.21	8.9	<1 Std	28.8
8	23	7.6	4.04	10.1	<1 Std	24.1
9	20	10.0	3.61	9.3	<1/2 Std	7.5
10	73	29.3	5.86	29.8	<1/2 Std	1.6
11	70	55.0	9.54	47.5	<1 Std	15.8
12	62	26.6	5.86	28.7	<1/2 Std	7.1
13	52	11.6	2.52	13.7	<1 Std	14.8
14	49	6.0	1.00	6.9	<1 Std	13.0
15	54	10.7	7.37	14.5	<1 Std	26.4
16	97	27.3	5.51	27.3	<1/2 Std	0.1
17	86	35.3	1.15	36.0	<1 Std	1.9
18	5	1.7	0.58	0.4	<1/2 Std	0
19	92	29.6	4.62	28.4	<1/2 Std	4.5
20	25	9.6	2.52	9.3	<1/2 Std	3.9
21	48	8.3	3.51	9.6	<1/2 Std	13.2
22	46	17.0	6.93	20.3	<1/2 Std	16.3
23	30	4.3	1.53	4.2	<1/2 Std	3.2
24	52	14.0	8.19	11.9	<1/2 Std	17.6
25	49	7.3	3.06	10.0	<1 Std	26.7

* Percent Differences exclude annual events less than 2.0, assumed as "rare events" with 0.0 difference. Average = 12 %

1. Intersection Speeds: 30 – 55 mph; 2. Intersection Geometries: 3 and 4 leg with 2, 3 and 4 through lanes;
3. Turn Bays: Single and dual left and right turn lanes; 4. Actuated signal timing and phasing selected by the software for each hour of the day with minimums and maximums from site data.

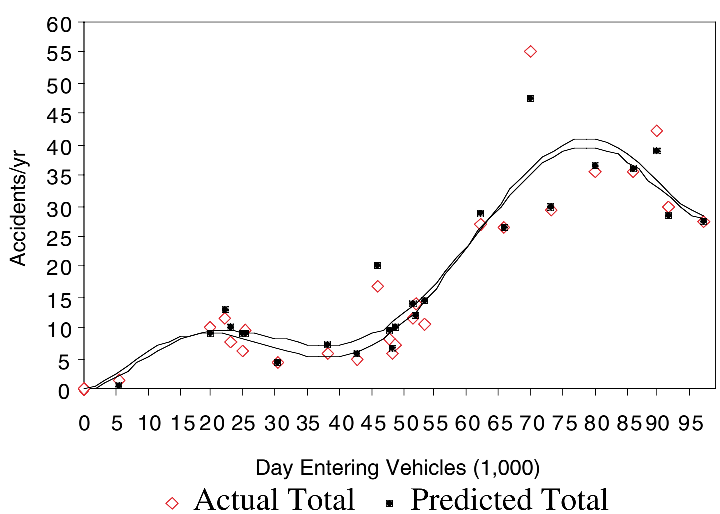

FIGURE 1 Comparison of actual and predicted signalized total annual accidents.

TABLE 2 Comparison of Actual and Predicted Signalized Accident Events by Type

Daily Entering Volume (1,000)	Angle Accidents		Rear-End Accidents		Sideswipe Accidents		Single Vehicle (Other) Accidents	
	Historical Average	Predicted	Historical Average	Predicted	Historical Average	Predicted	Historical Average	Predicted
90	16.0	12.5	19.2	20.9	1.8	2.7	1.8	3.0
38	2.4	1.3	1.6	4.1	1.0	0.4	0.4	1.3
43	0.8	0.7	1.0	3.3	0.2	0.5	1.2	1.1
22	5.0	3.8	3.8	7.8	0.4	0.0	2.8	1.6
66	8.8	7.5	15.6	16.0	3.4	1.1	1.0	1.9
80	8.2	5.2	19.4	21.1	1.6	6.5	1.0	3.7
25	3.4	1.7	2.6	5.5	0.0	0.0	0.8	1.7
23	0.6	0.4	7.2	7.6	0.0	0.0	0.8	2.0
20	6.0	5.3	1.8	2.5	0.4	0.0	0.0	1.5
73	6.0	8.0	15.8	17.1	3.0	2.4	2.4	2.1
70	32.4	29.4	15.4	13.4	2.2	2.0	2.8	2.4
62	10.6	4.5	13.8	17.9	3.8	3.8	2.0	2.6
52	2.0	3.5	6.8	7.6	0.6	1.1	1.0	1.5
49	0.6	0.9	4.6	4.3	0.8	0.4	0.8	1.2
54	0.8	3.0	7.0	8.3	0.6	1.8	1.6	1.4
97	4.4	7.5	15.2	13.9	3.6	3.5	1.0	2.4
86	15.8	14.9	22.6	16.5	5.6	3.0	3.4	2.5
5	1.6	0.1	0.2	0.1	0.0	0.0	0.2	0.2
92	4.2	6.8	16.6	17.7	3.4	1.9	2.8	2.1
25	2.4	1.9	5.4	5.7	1.0	0.7	1.8	1.0
48	1.6	2.9	3.8	5.0	1.2	0.4	2.0	1.2
46	6.8	8.3	6.4	6.4	1.4	3.8	3.4	1.8
30	1.4	1.5	1.6	1.1	0.4	0.4	0.2	1.3
52	2.8	1.4	10.2	7.2	0.0	1.5	1.0	1.9
49	1	3.9	6.0	4.1	0.4	0.8	0.2	1.3

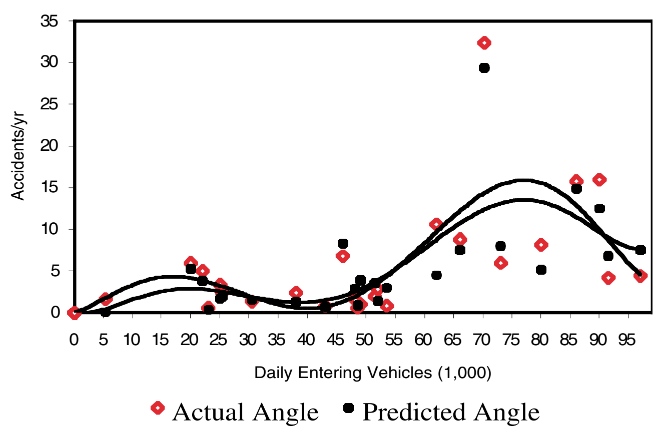

FIGURE 2 Comparison of actual and predicted signalized angle accidents.

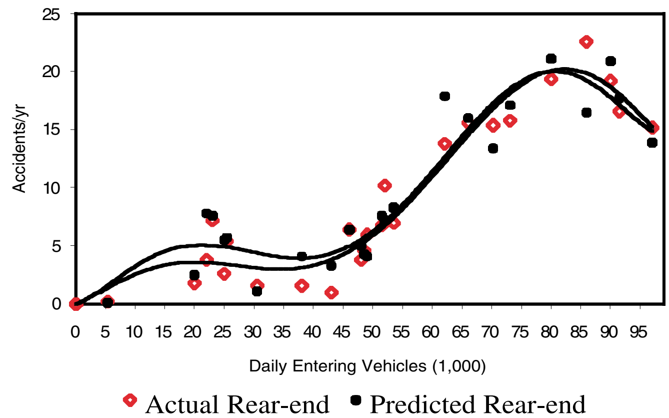

FIGURE 3 Comparison of actual and predicted signalized rear-end accidents.

4. *Sideswipe Accident Comparison*—Similarly, a comparison of historical and predicted sideswipe accidents is presented in Table 2 and Figure 4 and indicates a close correspondence between actual and predicted events with an approximate 80 percent accuracy comparing mean responses. Over 80 percent of the predictions are within 1 standard deviation of the historical mean with the visual comparison in Figure 3 indicating how closely the sideswipe accident predictions and regression model track the historical data and model.

5. And lastly, a comparison of historical and predicted *fixed-object/single-vehicle accidents* is presented above in Table 2 and in Figure 5 and indicates a slightly weaker correspondence between actual and predicted events caused by the use of a simplified volume and speed-based exposure (rate-based) prediction model within the software. While the software was designed to accommodate fixed-object prediction, collection of the input data was found to be too time-intensive for the marginal loss of accuracy compared to the use of exposure (or rate-based) prediction techniques that required no extensive data collection. This approach continues to provide an approximate 70 percent accuracy when comparing mean responses with 70 percent of the predictions within 1 standard deviation

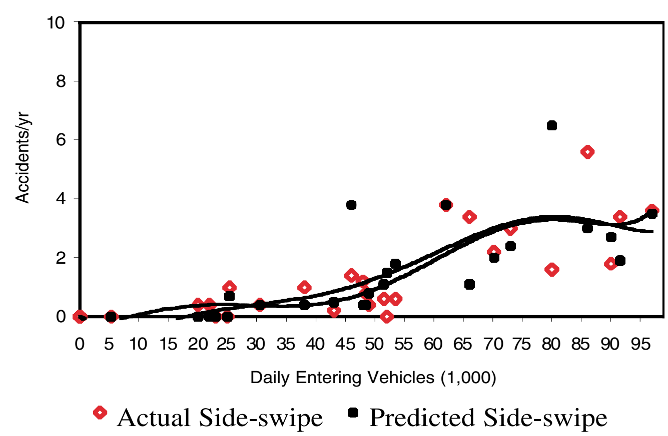

FIGURE 4 Comparison of actual and predicted signalized sideswipe accidents.

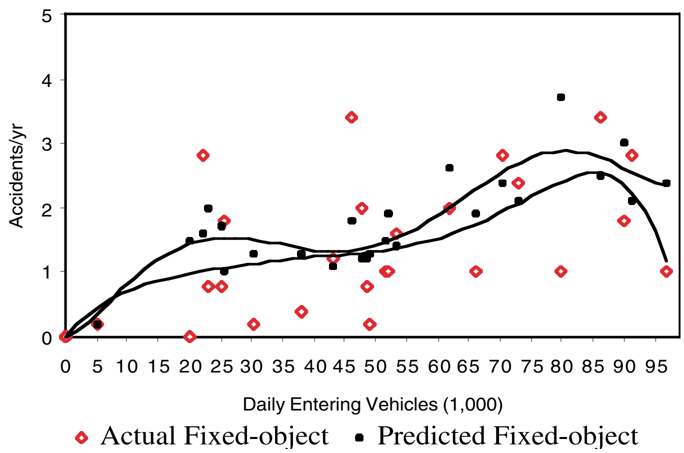

FIGURE 5 Comparison of actual and predicted signalized fixed-object/single vehicle other accidents.

of the historical mean. Using identical linear regression models of the predicted and actual data, a visual comparison in Figure 5 indicates how closely the fixed-object accident predictions and regression model track the historical data and model, and how well conflict opportunity software predicts fixed-object/single vehicle (other) accident events.

UNSIGNALIZED INTERSECTION ACCIDENT VALIDATION USING CONFLICT OPPORTUNITIES

Defining accidents at unsignalized intersections raises a number of new issues for accident prediction because, while the complexities of a signalized intersection with its myriad of timing and phasing options throughout the day are eliminated, the complexity of modeling “rare-event” accidents enters the picture. At signalized intersections, sufficient accident samples often exist to estimate actual historical accidents, but at stop-controlled intersections traffic volumes entering from the sidestreet are often very small in comparison to the mainline volume, with a resulting accident history that is almost always less than 5 per year and generally less than 2–3 per year. That’s why the intersections remain unsignalized, and this lack of reliable data is what causes unsignalized intersection accident events to be considered “rare.” Predicting anything that can be considered a rare event was always a challenge, and thus there should be little expectation that accident prediction capability will surpass that of signalized intersections. With this understanding, 65 unsignalized two-way stop-controlled intersections were selected, with all selections and data provided by the Florida DOT and collected by consulting traffic engineers (*3*). As with the signalized intersections, these intersections were composed of a wide variety of cross-sections and geometry, volumes, and speeds, all with generally flat terrain.

The results of this analysis are presented in Figure 6 and indicate as expected that the number of annual accidents is generally below 2–3 per year, but include several sites where the actual history (or erred history?) reaches 5 accidents per year and in one case (not displayed) 6 per year. Using special FDOT (Turns software) techniques to balance

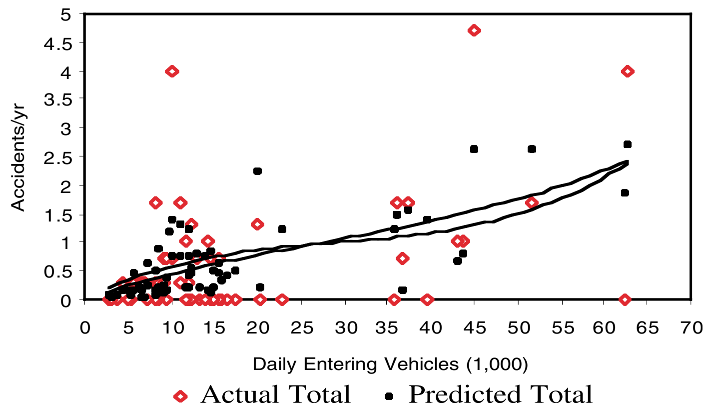

FIGURE 6 Comparison of actual and predicted unsignalized total annual accidents.

approach volumes on a daily basis along with a 5-year accident history, a comparison of historical and predicted total accidents shown in Figure 6. The results indicate a good correspondence between actual and predicted events with over 50 percent of the predictions within ½ standard deviation of the historical average accident history, 70 percent of the predictions within 1 standard deviation, 90 percent within 2 standard deviations, and over 96 percent within 3 standard deviations of the historical mean at each individual site. As with signalized intersections, using identical linear regression models of the predicted and actual data, a visual comparison indicates how closely the conflict opportunity predictions and regression model track the historical data and its regression model, and how well conflict opportunity software predicts unsignalized accidents. Interestingly, the R^2 for the actual data is only 5 percent while the R^2 for the predicted data is 55 percent.

Certainly, it could be concluded that the 4 percent of unsignalized sites that did not conform to the software predictions for two-way stop-controlled intersections may have been errors due to incorrect reporting, record-keeping or other factors, or may have actually been hazardous locations or even violated the assumptions of the software, which of course leads to the next question of how does the conflict opportunity technology work.

THE CONFLICT OPPORTUNITY ACCIDENT PREDICTION ALGORITHM

Numerous studies have reported on the impacts, effects, and correlation of actual on-site conflicts to accidents at specific intersections, but generally these studies reported only a 20% predictability of the models to actual on-site annual accidents (*4*). This is not really unexpected in the modeling of actual on-site events because the definition and observation of any on-road event are subjectively unique among both drivers and observers and influenced and confounded by human, vehicle, environmental and other conflicting factors and effects, not to mention the accident data itself, which remains only 65–75% reliable, including unreported minor accidents (*5*). Given these format and data inconsistencies, it becomes desirable to replace actual on-road conflicts with a more precise conflict surrogate of “Statistically Probable Conflict Opportunities” (SPCO).

One of the first attempts in the formulation of objective and quantifiable SPCOs began with Perkins and Harris of General Motors who introduced the concept for discrete types of conflicts. This study was later followed by other theoretically specific conflict event formations (*6–12*). But while specific conflict event formulations are useful, the integration of these probable event formulations into a mathematical algorithm to predict annual accidents was introduced by Kaub using uniquely competing probable event elements to form an annual accident expectation based on the assumed mutually exclusive event probabilities and their calibration to actual annual reported accidents using a "Nested Regression" approach with a general algorithm for intersections as follows for a variety of conflict events (*13*, *14*):

$$\text{SPCO (Conflict type)}_t = E(\text{Movement Opportunities})_{ij} * P(\text{Arrival of Opposition to Movement})_{kl}$$

where:

- t = Specific Conflict Type such as passing on two-lane highway, intersection angle conflicts, merging/diverging sideswipe conflicts, rear-end conflicts, fixed object vehicle conflicts, etc., per unit time,
- i = Arrival Movement Type such as the vehicle desiring to pass, the vehicle(s) desiring to turn left, the vehicle(s) desiring to change lanes, the vehicle(s) desiring to stop, etc. per unit time,
- j = Arrival Approach such as one lane of a two-lane highway, or one lane of a specific intersection approach which may have two, three or more approaches,
- k = Opposition Movement Type such as the vehicle opposing the passing vehicle on a two-lane highway, or the vehicle opposing an angle movement(s) within an intersection, the vehicle opposing a merge/diverge sideswipe movement(s) on a specific approach, the vehicle opposing a vehicle(s) desiring to stop (rear-end), etc., per unit time, and
- l = Opposition Approach such as the opposing one lane of a two-lane highway in a passing maneuver, one lane of a specific intersection approach which is in opposition to a movement produced in another lane or on another approach.

E (Movement Opportunities)$_{ij}$ = Expected number of vehicles per unit time from a specific movement type "i" (such as number of vehicles desiring to pass/hour in a given segment on a two-lane highway or the number of vehicles desiring to turn left or right on an approach to an intersection/hour or any other arriving movement) which may be exposed to an opposition movement on any particular roadway segment or intersection approach or adjacent lane "j," where each expectation follows the form:

$E = P$(Movement Opportunity/unit time) ∗ (Vehicles performing this movement/ unit time)

Often the probability of movement opportunity may be 1.0 where the conflict can occur at any particular time such as at a signalized intersection approach, or the probability may be a discrete unit as where there exists a finite probability that a following vehicle may desire to pass on a two-lane highway and this probability depends on the volume of traffic in one direction on the advancing roadway segment.

P (Arrival of Opposition to Movement)$_{kl}$ = the probability of arrival of one or more vehicles during the specific time period of exposure to a particular type of conflict "k" (or the probability of opposition during the time of exposure of the arriving vehicle to a conflict situation "k"), on any particular roadway segment or intersection approach or adjacent lane "l," where using the Poisson Distribution each probability function follows the general form:

$$P(1 \text{ or more}) = 1 - P(0) = 1 - \frac{e^{-m}m^{x}}{x!} = 1 - \frac{(e^{-m} * m^{0})}{0!} = 1 - e^{-m}$$

where: for example in angle conflicts

m = angle conflict average arrival rate:
= [(q veh/hour per lane per approach) ∗ (t seconds of exposure time)]/3600.
For practical purposes, the angle conflict exposure or clearance times of the arrival vehicles are based upon the 1985 *Highway Capacity Manual* critical gap times for unsignalized intersections, under the assumption that these times adequately estimate vehicle exposures, even though new research continually improves exposure predictions (*15*, *16*). For through movements, exposure times are calculated using safe stopping distances for through vehicles exposed to sidestreet conflicts (such as for an entering sidestreet vehicle stalling on acceleration). And theoretically, t seconds of exposure or clearance time may also be replaced by a continuous distribution of the form: $P(h \geq t_{Li})$ and $P(h \leq t_{Ui})$ where:
t_{Li} = Lower bound of exposure time on approach "i" (sec)
t_{Ui} = Upper bound of exposure time on approach "i" (sec).

With the above general formulation of competing probable events for each conflict type and their finite element expansion to multiple lanes of one approach and then to all approaches of an intersection, an annual SPCO expectation can be developed representing the summation of individual conflict types of angle, rear-end, sideswipe and fixed-object/single-vehicle (other) events. And with the summation of all hours and days in a year, the process of predicting annual intersection accidents may be expressed as:

$$\text{Annual Accidents} = \left[\sum_{1}^{n} \text{SPCO (Conflict Type/hour)}_{t}\right] * [\text{MODEL SPCOs/Accident}]$$

where:

n = hours of the year;
Conflict Type = Angle, Rear-end, Sideswipe and Fixed Object/Single Vehicle SPCO;
[MODEL SPCOs/Accident] = a speed-based stable, calibrated relationship between all summed annual conflict opportunities and annual accidents for each traffic control device over typical volumes, speeds, geometry, environments, drivers and vehicles.

To formulate the above theoretical formats into a practical working process for an intersection, a finite element analysis approach to intersection accidents is used which breaks the accident models and each intersection into discrete elements based in part on the following assumptions:

1. Each access opening or intersection is assumed to be sufficiently separated from adjacent openings so that the driveway or intersection under study is an isolated, mutually exclusive entity.
2. The terrain is assumed as level on all approaches so that no driveway aprons, sidewalks, valley gutters, or other obstructions interfere with normal operational maneuvers.
3. Sight distance is assumed as sufficiently clear on all approaches so as not to interfere with normal operational maneuvers.
4. All vehicles are normalized as typical vehicles used in AASHTO driveway, intersection and/or roadway planning and design, and conform to typical vehicle physical and performance characteristics so that the intersections or driveways where the software is used have normal amounts of vehicle-induced accidents (e.g., no excessive number or character of vehicle failures such as numerous "bald tires" or "vehicle fires").
5. All drivers and passengers are normalized as typical drivers and passengers used in AASHTO driveway, intersection, and/or roadway planning designs so that the physical, mental, and emotional characteristics required to safely and efficiently accomplish the basic driving tasks of Control, Guidance, and Navigation are performed, and locations where this software is used have normal amounts of human-induced accidents (e.g., no excessive human failures such as alcohol or drug abuse, or excessive age or handicap impairments that may affect operational abilities, either of which may produce nonnormal accident expectations).
6. The environment is normalized as the typical environment used in AASHTO driveway, intersection and/or roadway planning and design so that the driveways, intersections and/or roadways where the software is used have normal amounts of environmentally induced accidents (e.g., no unusual weather conditions such as consistently icy roads in Florida, which may produce nonnormal accident expectations).
7. Other normalizing assumptions pertinent to each particular driveway, intersection or roadway and traffic control type (e.g., drivers perception/reaction time, vehicle length, stop sign setback, turning radii, turn bays, speeds, signal timing, etc.), which are user-defined within the software.
8. In the formulation of the conflict/accident relationships, and because existing accident databases generally segregate accident occurrence into the four major categories of sideswipe, rear-end, and fixed-object/single-vehicle accidents, only these four accident types are used. Thus each of the following (assumed) mutually exclusive types of accidents is taken as additive, given the use of a common statistical (Poisson) format within each term (Nested Regression):

$$\text{Accidents/year} = f\{\text{Conflicts}[(\text{Angle}) + (\text{Rear-end}) + (\text{Sideswipe}) + (\text{Fixed Object})]\}.$$

9. And last, given the formation of annual accidents, a stable relationship is assumed between speeds, annual accidents, and injury and fatality occurrence of the following form (*17*, *18*):

Severities/year = f {Accidents/yr., speed, accident:injury and injury:fatality ratios}.

Note that the violation of any one or more of the above assumptions should generally lead to an increase in annual accident and injury predictions, and thus the estimates of annual accidents and involvements from conflict opportunity software should be generally conservative, which on review of Figures 1–6 is occurring frequently.

To assure conformance to these assumptions and to examine the predicted vs. actual accident expectancies at individual intersections, it is necessary to validate the conflict opportunity software either to individual intersections or to general areas such as Cities, Counties or State Highway Districts where the above assumptions are expected to remain relatively stable at the local level. For instance, since the software was calibrated using national data, the model may respond more accurately in locations such as the Midwest where environmental conditions include both icy and dry weather accidents as opposed to southern Florida where few, if any, icy accidents occur. In southern Florida, the software may overestimate annual accidents because icy accidents are included in the software response, yet those types of accidents are extremely rare.

CONCLUSIONS

Tables 1–2 and Figures 1–6 speak for themselves to show that "the pruf's in the puddin' " and that total annual reported accidents at typical intersections can be predicted within approximately 12 percent of the 3-year historical average, or more generally with an accuracy of approximately 90 percent. And with such predictability comes a viable new source of information for traffic engineers, as well as for planning and land use professionals involved in the management and design of urban and rural traffic environments. Such new information can also be the catalyst for new Federal Highway initiatives such as a Topics 2000 Program, for emerging AASHTO Safety Management Programs, for ITE Safety Audit Programs, for new University Traffic Safety Design Thesis Programs, and for Continuing Education Certificates. More importantly, such new safety predictions can also be a catalyst for new thinking about the nature of the relationship between traditional intersection management, using delay-based methodologies, and a new intersection management technology that uses daily and annual intersection safety design, thereby assuring the public of reasonably safe and efficient intersection design before projects are built and new access permits issued.

In addition, for those developers and municipalities involved in Impact Fee assessment, such accurate accident estimates also offer an exciting new opportunity to protect the public from unwarranted intrusions into the safety of their environment, along with an opportunity to protect developers from unwarranted exactions and fees where public safety may not be impacted but in fact improved.

And although conflict opportunity software is only intended as a decision support tool, at last Traffic Engineers can also begin to document how much the public may benefit from their safety knowledge and expertise; with this technology, they can continue to increase the respect and admiration of the motoring public as well as to achieve appropriate salary levels for their expertise.

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