INVESTIGATING DIFFERENCES IN THE PERFORMANCE OF SAFETY PERFORMANCE FUNCTIONS ESTIMATED FOR TOTAL CRASH COUNT AND FOR CRASH COUNT BY CRASH TYPE

Thomas Jonsson
Research Fellow, Lund University, Dept. of Technology & Society
Box 118, 221 00 Lund, Sweden
Voice +(46) 46 222 91 39 / FAX +46 46 12 32 72
thomas.jonsson@tft.lth.se

Craig Lyon
Principal, Persaud and Lyon Inc.
87 Elmcrest Road, Toronto, Ontario, Canada
Voice (613) 422-2542
craig.lyon@rogers.com

John N. Ivan
Professor, Civil & Environmental Engineering
University of Connecticut, Unit 2037, Storrs, CT 06269-2037
Voice (860) 486-0352 / FAX (860) 486-2298
johnivan@engr.uconn.edu

Simon Washington
Professor, Department of Civil and Environmental Engineering
Arizona State University, Room ECG252, Tempe, AZ 85287-5306
Voice (480) 965-2220 / FAX (480) 965-0557
simon.washington@asu.edu

Ida van Schalkwyk
Assistant Professor, School of Civil and Construction Engineering
Oregon State University, 220 Owen Hall, Corvallis OR 97331-3212
Voice (541) 737-8874 / FAX (541) 737-3052
idavan@engr.oregonstate.edu

Dominique Lord
Assistant Professor, Zachary Department of Civil Engineering
Texas A&M University, College Station, TX 77843-3136
Voice (979) 458-3949 / FAX (979) 845-6481
d-lord@tamu.edu

Words: 3080 +250*4 +250*12 = 7080
NOVEMBER 15, 2008
In recent years the development and use of crash prediction models for roadway safety analyses have received substantial attention. These models, also known as Safety Performance Functions (SPFs), relate the expected crash frequency of roadway elements (intersections, road segments, on-ramps) to traffic volumes and other geometric and operational characteristics.

A commonly practiced approach for applying intersection SPFs is to assume that crash types occur in fixed proportions, e.g., rear-end crashes make up 20% of crashes, angle-crashes 35%, etc., and then apply these fixed proportions to crash totals to estimate crash frequencies by type. As demonstrated in this paper, this practice makes questionable assumptions and results in considerable error in estimating crash proportions.

Using rudimentary safety performance functions based solely on major and minor road AADTs, the homogeneity-in-proportions assumption is shown to not hold across AADT, because crash proportions vary as a function of both major and minor road AADT. For example, with minor road AADT of 400 vpd, the proportion of intersecting direction crashes decreases from about 50% with 2000 major road AADT to about 15% with 82,000 AADT. Same direction crashes increase from about 15% to 55% over this same comparison.

The homogeneity-in-proportions assumption should be abandoned and crash type models should be used to predict crash frequency by crash type. SPFs using additional geometric variables would only exacerbate the problem quantified here. Comparing models for different crash types using additional geometric variables remains the subject of future research.
MOTIVATION AND OBJECTIVES

In recent years, the development and use of crash prediction models for roadway safety analyses has made substantial progress. These models, also known as Safety Performance Functions (SPFs), relate the expected crash frequency of a roadway element such as an intersection or road segment to the traffic volume and other characteristics of that element. Typically, traffic volumes account for the majority of the variability in crash frequencies. In addition, models with AADT as only predictor variable are often used by transportation safety analysts. They are generally considered for use over models that include several covariates because they can be easily re-calibrated when they are developed in one jurisdiction and applied to another. In fact, this type of model is likely to be the kind of model used for estimating the safety performance of rural and urban highways as well as for intersections in the forthcoming Highway Safety Manual (HSM). Although such models will suffer from an omitted variables bias (because many non-flow related factors are known to affect the frequency of crashes) and the possibility of being subjected to a structured variance, the empirical assessment carried out in this work still provides valuable insight into the comparison analysis, particularly when models are built for use at national level and across a number of states.

SPFs are normally developed for different types of facilities, e.g., separate models for four-legged signalized intersections, three-legged stop controlled intersections, two-lane rural road segments, etc. However, for any facility, the purpose of the model would usually be to predict the total number of crashes, ignoring the fact that the severity distributions differ by crash type and the mechanism and dynamics of how the severity distribution arises, e.g., a rear-end crash involves two vehicles traveling in the same direction and generally only results in slight injuries, while an angle crash can only occur when there is intersecting traffic and its consequences (i.e., occupant deceleration and compartmental intrusion) are often more severe than that of the rear-end crash.

An unresolved issue in the development and use of SPFs is whether it is more compelling statistically to develop models for total crashes or separately for specific crash types. There are at least three important and defensible reasons for estimating models separately by crash type. One is to identify sites with high risk for specific crash types, but with fairly typical total crash counts. A second is to learn more about how various crash types are associated with road geometry, the environment, and traffic variables differently from one another. Finally, different crash types typically are associated with different distributions of crash severity due to the relative speed and dynamics of the colliding vehicles. Predicting crashes by crash type can promote advancement in knowledge about road safety in all three of these ways.

While considerable research has concentrated on the estimation of crash prediction models at intersections (see for a more complete review of this literature), limited effort has been devoted to investigating the safety effects of roadway geometric, traffic, and environmental factors on different crash types. An early study by Hauer et al. developed crash type prediction models for 15 different crash patterns at urban and suburban signalized intersections in Toronto, Canada. The inclusion of turning movements significantly improved the predictive ability of these models. Another study on Canadian roads developed two levels of models based on data inputs. The Level 2 models were similar to the model developed by Hauer et al., while the Level 1 models developed ‘aggregate’ prediction models for crash types rear-end, right-angle, and turning movement crashes. Another study by Shankar et al. focused on identifying the safety effects of environmental variables on crash types rather than identifying the safety effects of roadway geometric variables, and concluded that allowing coefficient
estimates to vary by the type of crash has the potential for providing greater explanatory power relative to a single overall frequency model. Kim et al. (10) describes an estimation of crash prediction models for angle, head-on, rear-end, sideswipe (same direction and opposite direction) and pedestrian-involved crash types, and compared their results with a model estimated for total crashes. They found that the best fitting model covariates are related to crash types in varying capacities, suggesting that crash types are associated with different pre-crash conditions and that modeling total crash frequency may not be helpful for identifying specific countermeasures. Kononov and Allery (14) acknowledge this fact noting that some, but not all, normative parameters (including crash types percentage) within the same SPF change with AADT. For instance, in general, the severity of accidents gradually decreases and distribution of accidents by type changes with AADT.

Consequently, to build upon this body of research this paper demonstrates the value of predicting crashes by crash type by comparing results for SPFs developed for the total number of crashes and crash specific models for three- and four-legged unsignalized intersections on rural multilane roadways. The paper presents two comparisons.

The objective of the first comparison was to evaluate two approaches to estimating the total number of crashes. The first approach was to use a single model for all crash types; for the second approach, predictions from models for four crash types were summed type by type to represent the total number of crashes.

The objective of the second comparison was to assess two approaches for estimating the number of crashes for each specific crash type. The predictions from the crash type models were compared to predictions obtained by applying the proportion of each crash type of interest to the predictions from a model for total crash count. This latter approach has been proposed for inclusion in the predictive methodology of the forthcoming HSM (15).

The four crash types used for the crash type models were single-vehicle crashes (SV), opposite direction crashes (OD), same direction crashes (SD) and intersecting direction crashes (ID), as designated by Jonsson et al. (9) The models used for the comparisons have been developed for three- and four-legged stop controlled intersections on multilane rural highways in California. Only the minor road in the intersection was stop controlled, the major road had the right of way.

**COMPARISON METHOD**

How well a model fits the data can be assessed using a variety of goodness of fit (GOF) measures. For this exercise, primarily the Cumulative Residual (CURE) plots (16) were used, in which the cumulative residuals (the difference between the observed and predicted crash frequencies for each site) are plotted in increasing order for a key covariate. The plot shows how well the model fits the data with respect to each individual covariate, in this case only AADT, and has been used by Persaud et al. (3) to assess model transferability. The indication is that the fit is very good for the covariate if the cumulative residuals oscillate around the value of zero. An additional measure used is the Maximum CURE Plot Deviation which is defined as the maximum absolute value that the CURE plot deviates from 0. The other GOF measures used were the mean prediction bias, mean absolute deviation and mean squared prediction error. These measures are defined below.
**Mean Prediction Bias (MPB)**

The mean prediction bias (MPB) is the sum of observed crash frequencies minus predicted crash frequencies divided by the number of data points. This statistic provides a measure of the magnitude and direction of the average prediction error. The smaller the average prediction error, the better the model is at predicting observed data. The MPB can be positive or negative, and is given by:

\[
MPB = \frac{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)}{n}
\]

where \(n\) = data sample size, \(Y_i\) = the observed value, \(\hat{Y}_i\) = the fitted value,

A positive MPB suggests that on average the model underpredicts. Conversely, a negative value suggests systematic overprediction. The magnitude of MPB provides the magnitude of the average error.

**Mean Absolute Deviation (MAD)**

The mean absolute deviation (MAD) is the sum of the observed crash frequencies minus predicted crash frequencies, divided by the number of observations. It differs from mean prediction bias in that positive and negative prediction errors will not cancel each other out. Unlike MPB, MAD can only be positive. The MAD gives a measure of the average magnitude of variability of prediction. Smaller values are preferred to larger values.

\[
MAD = \frac{\sum_{i=1}^{n} \text{abs}(Y_i - \hat{Y}_i)}{n}
\]

**Mean Squared Prediction Error (MSPE) and Mean Squared Error (MSE)**

The mean squared prediction error (MSPE) is the sum of squared differences between observed and predicted crash frequencies, divided by sample size. A lower value of MSPE indicates a better model fit to the data.

\[
MSPE = \frac{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2}{n}
\]
DATA AND MODELS

The data used were acquired from the Highway Safety Information Service (www.hsisinfo.org) for rural multilane intersections in the State of California. These data included crash data, traffic flow data, and geometric data from 1993 to 2002.

Models with only traffic flow in Average Annual Daily Traffic (AADT) as well as with limited additional geometric variables were developed; but for purpose of the comparison in this paper the AADT-only models were used. As discussed above, these models are very popular despite their problems associated with omitted variables bias as well as the possibility of being subjected to a structured variance. The crash data used for the modeling included crashes of all severities.

Intersection and Crash Data

Separate models were developed for three-legged and four-legged intersections. For each of the two types of intersections five models were developed; four models for crashes by crash type and one for total number of crashes.

The selection criteria for the intersections were that the major road (with the right-of-way) should be a four-lane rural highway and the minor road should be stop controlled. Only straight angle intersections were used, i.e. Y-intersections were excluded. A total of 378 three-legged intersections and 264 four-legged intersections were used for the modeling.

The major roads had a range of AADT varying from 2,000 to 80,000 vehicles per day, with an average of 16,000. The minor roads had a range of AADT from 10 to 11,000 vehicles per day, with an average of 400. A total of 3,915 crashes occurred during 1993-2002. They are divided on the different crash types according to TABLE 1.

<table>
<thead>
<tr>
<th>Crash Type</th>
<th>Three-legged</th>
<th>Four-legged</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Frequency</td>
<td>Percentage</td>
</tr>
<tr>
<td>Same Direction (SD)</td>
<td>1641</td>
<td>42%</td>
</tr>
<tr>
<td>Opposite Direction (OD)</td>
<td>530</td>
<td>14%</td>
</tr>
<tr>
<td>Intersecting Direction (ID)</td>
<td>875</td>
<td>22%</td>
</tr>
<tr>
<td>Single-vehicle (SV)</td>
<td>869</td>
<td>22%</td>
</tr>
<tr>
<td>TOTAL</td>
<td>3915</td>
<td>100%</td>
</tr>
</tbody>
</table>

Safety Performance Functions

The detailed characteristics about how the SPFs were estimated are omitted here for brevity (complete details available in (14)). All the included variables are significant at the 5%-level. The SPFs are:

\[
\text{ACC}_{3,SV} = 9.56 \times 10^{-6} \times \left( \text{AADT}_{\text{Major}} + \text{AADT}_{\text{Minor}} \right)^{0.035}
\]

\[
\text{ACC}_{3,ID} = 21.3 \times 10^{-6} \times \text{AADT}_{\text{Major}}^{0.671} \times \text{AADT}_{\text{Minor}}^{0.529}
\]

\[
\text{ACC}_{3,OD} = 0.569 \times 10^{-6} \times \text{AADT}_{\text{Major}}^{0.043} \times \text{AADT}_{\text{Minor}}^{0.0425}
\]
\[
\text{ACC}_{3,\text{SD}} = 0.109 \times 10^{-6} \times \text{AADT}_{\text{Major}}^{1.381} \times \text{AADT}_{\text{Minor}}^{0.306}
\]
\[
\text{ACC}_{3,\text{Tot}} = 7.60 \times 10^{-6} \times \text{AADT}_{\text{Major}}^{1.046} \times \text{AADT}_{\text{Minor}}^{0.315}
\]
\[
\text{ACC}_{4,\text{SV}} = 22.4 \times 10^{-6} \times (\text{AADT}_{\text{Major}}^{0.458} + \text{AADT}_{\text{Minor}}^{0.462})^{0.950}
\]
\[
\text{ACC}_{4,\text{ID}} = 409 \times 10^{-6} \times \text{AADT}_{\text{Major}}^{0.436} \times \text{AADT}_{\text{Minor}}^{0.570}
\]
\[
\text{ACC}_{4,\text{OD}} = 96.6 \times 10^{-6} \times \text{AADT}_{\text{Major}}^{0.971} \times \text{AADT}_{\text{Minor}}^{0.291}
\]
\[
\text{ACC}_{4,\text{Tot}} = 240 \times 10^{-6} \times \text{AADT}_{\text{Major}}^{0.670} \times \text{AADT}_{\text{Minor}}^{0.366}
\]

Where ACC - Number of expected crashes per year, number of intersection legs (three or four) and type of crash or Total, SV - Single-vehicle crashes, ID - Intersecting Direction crashes, OD - Opposite Direction crashes, SD - Same Direction crashes, AADT - Average Annual Daily Traffic on major and minor intersecting routes

The form of AADT varies between single- and multi-vehicle crashes. Both forms were tested for the different models and the form with the best fit was chosen. Single-vehicle crashes are dependent on the total sum of incoming vehicles into the intersection rather than any interaction between traffic flows. This is logical as for single-vehicle crashes, there is only one vehicle involved in the crash, while the multi-vehicle crashes depend on an interaction of different vehicles.

The parameters in the separate crash type models differ significantly both from each other and the SPFs for total number of crashes. Same direction crashes increase the most rapidly with an increase in AADT. FIGURE 1 demonstrates how the proportion of same direction crashes increases at larger values of AADT for the three-legged intersections. This is not as evident for the four-legged intersections, see FIGURE 2.

TABLE 1 illustrates the proportions of each crash type for the two intersection types. The numbers only provide an overall estimate, regardless of AADT level. These proportions were used together with the predicted total number of crashes to estimate the number of crashes by type from the total predicted count.
Three-legged intersections - Distribution of crashes by collision type as a function of major road AADT

FIGURE 1 Distribution of Crashes by Crash Type for Three-legged Stop-controlled Intersections Plotted v. AADT Major, AADT Minor is set to 400 veh/day

Four-legged intersections - Distribution of crashes by collision type as a function of major road AADT

FIGURE 2 Distribution of Crashes by Crash Type for Four-legged Stop-controlled Intersections Plotted v. AADT Major, AADT Minor is set to 400 veh/day
RESULTS

Prediction of Total Crashes

TABLE 2 summarizes the GOF results for the two approaches to predict total crash frequency at three-legged stop-controlled intersections. The results for the two approaches are similar and both performed quite well. The maximum deviation of the CURE plots is quite good for both major and minor road AADT considering that the sum of crashes is equal to 3,915. The CURE plot in FIGURE 3 shows that the two approaches provide similar estimates of total crashes for the range of major road AADT.

<table>
<thead>
<tr>
<th>Measure</th>
<th>three-legged Intersections</th>
<th>four-legged Intersections</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sum of Crash Type SPF</td>
<td>0.07</td>
<td>0.32</td>
</tr>
<tr>
<td>Total Crash SPF</td>
<td>0.03</td>
<td>0.29</td>
</tr>
<tr>
<td>MAD</td>
<td>6.28</td>
<td>6.05</td>
</tr>
<tr>
<td>MSPE</td>
<td>146.77</td>
<td>89.93</td>
</tr>
<tr>
<td>Maximum CURE Plot Deviation v. Major AADT</td>
<td>154.76</td>
<td>145.73</td>
</tr>
<tr>
<td>Maximum CURE Plot Deviation v. Minor AADT</td>
<td>190.68</td>
<td>132.59</td>
</tr>
<tr>
<td>Total Observed Crashes</td>
<td>3,915</td>
<td>2,838</td>
</tr>
</tbody>
</table>

FIGURE 3 Major AADT CURE Plot for Total Crashes at three-legged Stop-Controlled

TABLE 2 gives the GOF results for the prediction of total crashes at four-legged stop-controlled intersections. As was the case for three-legged intersections, the results for the two approaches are similar and satisfactory. The maximum deviation of the CURE plots is quite good for both major and minor road AADT considering that the sum of crashes is equal to 2,838. The CURE plot in FIGURE 4 shows that the two approaches provide similar estimates of total crashes for the range of major road AADT.
TABLE 3 gives the GOF results for the prediction of specific crash types at three-legged stop-controlled intersections. The results are somewhat mixed. The MPB, MAD and MSPE measures are similar for the two approaches although generally slightly better for the models directly calibrated to each crash type. However, the maximum deviations of the CURE plots (FIGURE 5 through FIGURE 8) indicate that the directly calibrated models perform significantly better for the SD, ID, and SV crash types. This indicates that for certain AADT ranges the crash type models perform significantly better than applying the crash type proportion to a total crash prediction model. This is not surprising given that one would expect the proportion of different crash types to vary with AADT (e.g., single-vehicle crashes would likely decline as a proportion of total crashes as AADT increases). For OD crashes, the two approaches perform just as well reflecting the fact that the proportion of OD crashes varies little across AADT as can be seen in Figure 1.

**Prediction of Specific Crash Types**

FIGURE 4 Major AADT CURE Plot for Total Crashes at four-legged Stop-Controlled Intersections

![Graph showing comparison of collision type and SPF predictions for total crashes at stop-controlled intersections.](image-url)
TABLE 3 GOF Measures for three-legged Stop-Controlled by Crash Type

<table>
<thead>
<tr>
<th>Model</th>
<th>MPB</th>
<th>MAD</th>
<th>MSPE</th>
<th>Maximum CURE Plot Deviation v. Major AADT</th>
<th>Maximum CURE Plot Deviation v. Minor AADT</th>
<th>Sum of Observed Crashes</th>
</tr>
</thead>
<tbody>
<tr>
<td>SD SPF</td>
<td>0.07</td>
<td>2.92</td>
<td>36.41</td>
<td>84.04</td>
<td>72.41</td>
<td>1,641</td>
</tr>
<tr>
<td>SD by Proportion</td>
<td>0.01</td>
<td>3.10</td>
<td>39.17</td>
<td>253.34</td>
<td>55.01</td>
<td></td>
</tr>
<tr>
<td>OD SPF</td>
<td>0.0004</td>
<td>1.43</td>
<td>8.51</td>
<td>34.62</td>
<td>52.73</td>
<td>530</td>
</tr>
<tr>
<td>OD by Proportion</td>
<td>0.0039</td>
<td>1.43</td>
<td>8.47</td>
<td>33.93</td>
<td>55.04</td>
<td></td>
</tr>
<tr>
<td>ID SPF</td>
<td>-0.03</td>
<td>2.09</td>
<td>14.76</td>
<td>63.27</td>
<td>78.42</td>
<td>875</td>
</tr>
<tr>
<td>ID by Proportion</td>
<td>0.01</td>
<td>2.23</td>
<td>17.19</td>
<td>171.07</td>
<td>141.90</td>
<td></td>
</tr>
<tr>
<td>SV SPF</td>
<td>0.03</td>
<td>1.81</td>
<td>12.25</td>
<td>53.54</td>
<td>42.86</td>
<td>869</td>
</tr>
<tr>
<td>SV by Proportion</td>
<td>0.01</td>
<td>1.93</td>
<td>12.79</td>
<td>53.53</td>
<td>132.36</td>
<td></td>
</tr>
</tbody>
</table>

FIGURE 5. Major AADT CURE Plot for Same Direction Crashes at three-legged intersections
FIGURE 6. Major AADT CURE Plot for Opposite Direction Crashes at three-legged intersections

FIGURE 7. Major AADT CURE Plot for Intersecting Direction Crashes at three-legged Intersections
TABLE 4 summarizes the GOF results for the prediction of specific crash types at four-legged stop-controlled intersections. GOF results are similar to those for three-legged intersections. The MPB, MAD and MSPE measures are similar for the two approaches although estimates are generally slightly better with crash type specific models. However, the maximum deviations of the CURE plots (FIGURE 9 through FIGURE 12) indicate that the directly calibrated models generally perform significantly better and in particular for the SD and ID crash types. As seen for the three-legged intersection models, for OD crashes, the two approaches perform just as well reflecting the fact that the proportion of OD crashes varies little across AADT as can be seen in Figure 2. The results for SV are also close for the two approaches.

<table>
<thead>
<tr>
<th>Model</th>
<th>MPB</th>
<th>MAD</th>
<th>MSPE</th>
<th>Maximum CURE Plot Deviation v. Major AADT</th>
<th>Maximum CURE Plot Deviation v. Minor AADT</th>
<th>Sum of Observed Crashes</th>
</tr>
</thead>
<tbody>
<tr>
<td>SD SPF</td>
<td>0.19</td>
<td>2.18</td>
<td>16.15</td>
<td>50.14</td>
<td>50.14</td>
<td>796</td>
</tr>
<tr>
<td>SD by Proportion</td>
<td>0.08</td>
<td>2.29</td>
<td>18.39</td>
<td>99.35</td>
<td>36.62</td>
<td></td>
</tr>
<tr>
<td>OD SPF</td>
<td>0.03</td>
<td>1.41</td>
<td>7.40</td>
<td>36.02</td>
<td>23.55</td>
<td>410</td>
</tr>
<tr>
<td>OD by Proportion</td>
<td>0.04</td>
<td>1.47</td>
<td>7.97</td>
<td>48.06</td>
<td>60.14</td>
<td></td>
</tr>
<tr>
<td>ID SPF</td>
<td>0.05</td>
<td>3.26</td>
<td>28.35</td>
<td>89.17</td>
<td>64.12</td>
<td>1,085</td>
</tr>
<tr>
<td>ID by Proportion</td>
<td>0.11</td>
<td>3.42</td>
<td>30.05</td>
<td>149.08</td>
<td>108.71</td>
<td></td>
</tr>
<tr>
<td>SV SPF</td>
<td>0.04</td>
<td>1.53</td>
<td>5.11</td>
<td>34.46</td>
<td>51.35</td>
<td>547</td>
</tr>
<tr>
<td>SV by Proportion</td>
<td>0.06</td>
<td>1.54</td>
<td>4.73</td>
<td>30.08</td>
<td>96.82</td>
<td></td>
</tr>
</tbody>
</table>
FIGURE 9. Major AADT CURE Plot for Same Direction Crashes at four-legged Intersections

FIGURE 10. Major AADT CURE Plot for Opposite Direction Crashes at four-legged Intersections
PRACTICAL IMPLICATIONS
When estimating models separately by crash type, the number of crashes can sometimes be too small to produce good or reliable models (18). In this case several alternative approaches exist. The ideal approach would be twofold: first the development of a predictive model that includes
other variables beyond AADT; and second a model to predict severity proportions (for example (18)). If the analyst prefers to apply the proportional assumption CURE plots should be used to test predictions across all ranges of the independent variables. The latter approach would require the recalibration of the overdispersion parameter using the predicted and observed crash counts.

CONCLUSIONS

Beyond the practical implications discussed earlier, it is apparent that when predicting the number of crashes separately by crash types, then the crash type models have a better fit than using the total estimate together with the overall proportion of each crash type. The reason for this is that the relationship between number of crashes and the traffic flow is not linear and the exponents on flow vary among crash types. For example, the number of same direction crashes increases more rapidly with flow than single-vehicle crashes, which is intuitive as the number of same direction crashes can be assumed to depend on both the number of vehicles which potentially could be running into another vehicle as well as the number of vehicles to run into, while the single-vehicle crashes only depend on one flow.

This is an important finding, since knowing the actual distribution of crash types at a given intersection leads to improved prediction of the severity distribution. It also seems logical that road safety improvements should be made on the basis of reducing fatal and severe injury crashes. On that premise, being able to better predict crashes by crash type is valuable for computing more reliable estimates of crashes by severity level as well.

It needs to be pointed out that the crash type models used in this comparison are based on a very large data set, and are thus of a better quality than could normally be expected.

ACKNOWLEDGMENTS

This work was sponsored by the American Association of State Highway and Transportation Officials (AASHTO), in cooperation with the Federal Highway Administration, and was conducted in the National Cooperative Highway Research Program (NCHRP), which is administered by the Transportation Research Board (TRB) of the National Academies.
REFERENCES


