1238

TRANSPORTATION RESEARCH RECORD

Application and Management of Accident Data

TRANSPORTATION RESEARCH BOARD
NATIONAL RESEARCH COUNCIL
WASHINGTON, D.C. 1989

Transportation Research Record 1238
Price: $12.00

mode
1 highway transportation

subject area
51 transportation safety

Printed in the United States of America

Library of Congress Cataloging-in-Publication Data
National Research Council. Transportation Research Board.

Application and management of accident data.
p. cm.—(Transportation research record, ISSN 0361-1981 : 1238)
Papers presented at the 68th Annual Meeting of the Transportation Research Board, held Jan. 1989 in Washington, D.C.
ISBN 0-309-04974-1
1. Traffic accidents. 2. Traffic accidents—Research. 3. Traffic safety. I. National Research Council (U.S.). Transportation Research Board. II. National Research Council (U.S.). Transportation Research Board. Meeting (68th : 1989 : Washington, D.C.) III. Series.
TE7.H5 no. 1238
[HE5614]
388 s—dc20
[363. 12′5] 90-6128
CIP

Sponsorship is indicated by a footnote at the end of each paper. The organizational units, officers, and members are as of December 31, 1988.

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Contents

Foreword

In the highway system, crash data are a primary measure of system effectiveness. Discussed in this Record are projects that developed crash forecasting and prediction methods, a technique for identifying hazardous locations, comparisons between states based on crash data, crash data management systems, and an estimate of the change in safety as motorization increases in a foreign country.

Even though crash data are expensive and time consuming to collect and accumulate enough for analysis, they still appear to be the only readily accepted indicator of highway system safety. The research described in this Record suggests ways to improve management of the data and new methods for using crash data to provide useful information to policy and decision makers as well as to system operators. It is encouraging that these kinds of development are taking place successfully despite the many acknowledged deficiencies of existing crash data.

Combined with continuing efforts to improve data quality and consistency, the type of research reported here indicates that the potential insights from and usefulness of crash data will eventually be realized.

Accidents on Rural Two-Lane Roads: Differences Between Seven States

JERRY C. N. NG AND EZRA HAUER

Data on accidents, road characteristics, and traffic for rural, two-lane roads in seven states have been assembled. It was found that, for the same amount of traffic, different states record widely discrepant numbers of accidents. The discrepancy does not disappear even when roads with the same lane width, shoulder type, and terrain are examined. It is concluded that (a) data from different states should not be pooled, (b) warrants and standards based on accidents should be tailored to each state, and (c) the cause of the noted differences should be investigated.

To examine how accident occurrence is affected by lane width, shoulder width, shoulder type, curvature, and other characteristics of the road and how it depends on the amount of traffic flow, a large amount of data must be used, and they must be subjected to sophisticated statistical analysis. To secure a sufficient amount of data covering a wide range of conditions, it is common practice to pool data from several states. In this paper, the issue of whether data from different states can be combined is examined.

THE DATA

The data base used was assembled by Zegeer et al. and by Hummer (*1,2*). The data have been thoroughly checked and documented. They include information about the road, roadside, accident history, and traffic volume for almost 5,000 miles of two-lane roads collected from seven American states (Alabama, Michigan, Montana, North Carolina, Utah, Washington, and West Virginia). These states were selected to secure consistency in both accident reporting and coding policies. These 5,000 miles consist of 1,944 road sections. A road section is a stretch of road that is homogeneous with respect to lane width, shoulder width and type, and so forth. The roadway sections are ½ to 10 miles long. Of the 1,944 road sections, 1,801 are located in rural areas.

The majority of the road sections have a 5-yr history (1980–1984) of police-recorded accidents. Only the total number of accidents per road section (by type and severity) is available. Estimates of the average daily traffic (ADT) are for the sum of flows in both directions.

DIFFERENCES IN "ACCIDENTS PER MILE-YEAR" BETWEEN STATES

In Table 1 the pooled data from all seven states are used to examine how the "average number of single-vehicle accidents per mile-year" varies with ADT on rural two-lane roads. The somewhat irregular ADT ranges were selected so that each range has approximately one-fifth of all accidents. These averages are plotted in Figure 1.

The smooth curve in Figure 1 is the best fit to the disaggregate data when the model

$$\text{accidents/mile-year} = b_0\,(\text{ADT})^{b_1} \qquad (1)$$

is used. It appears that the change in single-vehicle accidents is nonlinear; the increase is sharp initially but tapers off as ADT becomes larger. This relationship agrees with the findings of previous research work as summarized by Satterthwaite (*3*).

The pooled road sections were separated by state to check whether the same accidents-versus-ADT relationship holds in all seven states, and the results are plotted in Figure 2. Although the points show considerable scatter, it is clear that there are major differences between the states. Thus, for the same ADT, for example, there seem to be three to four times as many single-vehicle accidents in West Virginia (filled triangles) as in Alabama (filled squares).

Similar accidents-versus-ADT plots are provided for head-on and sideswipe (opposite and same direction) accidents for each state in Figures 3, 4, and 5. The results are similar to that in Figure 2.

It appears that for the same ADT, different states record a markedly different number of accidents per mile-year. Unless this discrepancy can be attributed to other independent variables (lane width, shoulder type, terrain, etc.), it would have to be concluded that the pooling of state data is not advisable. The danger of pooling is that the relationship in Figure 1 could be an artifact of the composition of the sample and not a reflection of a real regularity in the relationship between accidents and traffic flow. Similar confounding in other variables could invalidate the results of statistical modeling.

It is therefore mandatory to go a step further to establish whether the differences in Figures 2 through 5 can be explained

TABLE 1 TABULATION OF SINGLE-VEHICLE ACCIDENTS VERSUS ADT

ADT Range	Mean ADT	Total No. of Accid.	Total Mile-Years	Ave. No. of Accid./M-Y	No. of Road Sections
0 - 1600	858	3629	10138	0.3580	644
1601 - 3010	2300	3444	5170	0.6662	400
3011 - 4550	3762	3546	3622	0.9791	309
4551 - 7000	5557	3554	2472	1.4377	235
7000 - 30000	10432	3507	1830	1.9169	193

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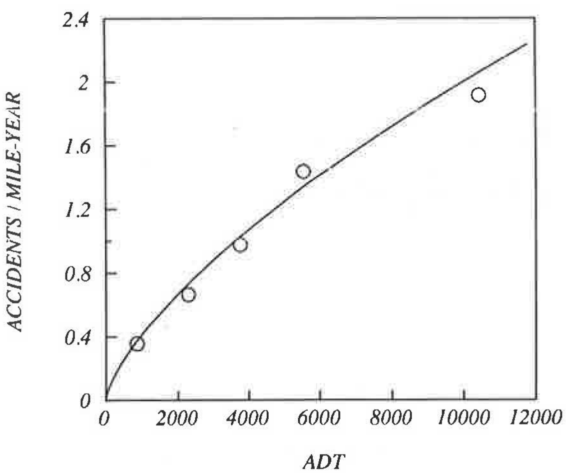

FIGURE 1 Accidents versus ADT, single-vehicle accidents, rural two-lane roads.

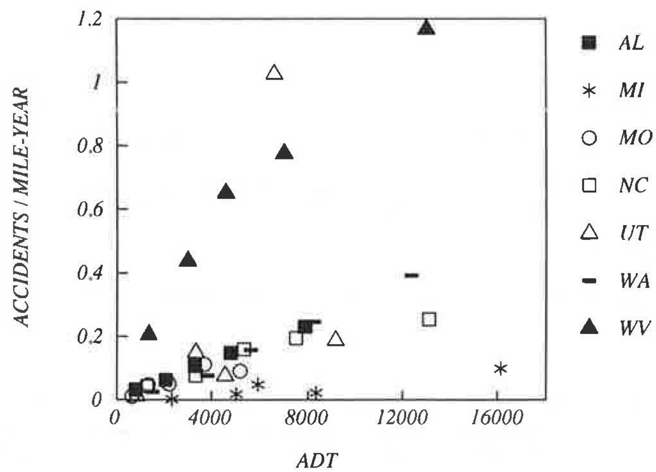

FIGURE 4 Accidents versus ADT, sideswipe (opposite direction) accidents, rural two-lane roads, by states.

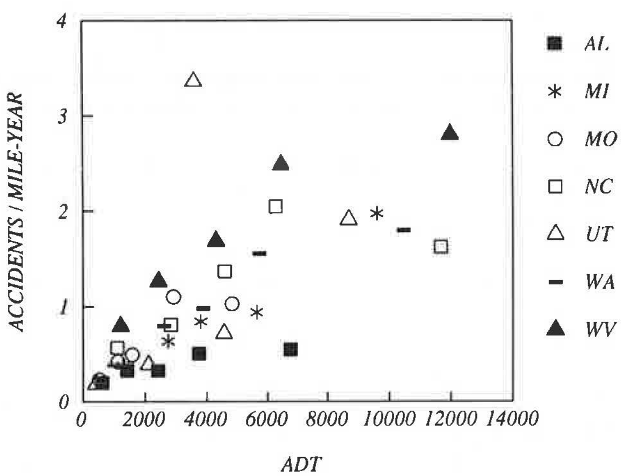

FIGURE 2 Accidents versus ADT, single-vehicle accidents, rural two-lane roads, by states.

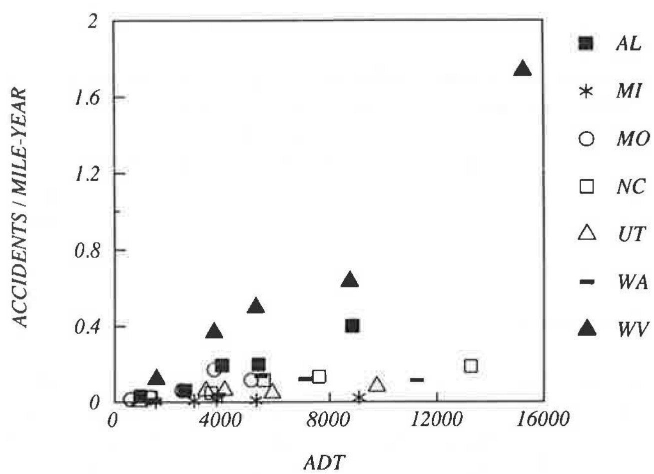

FIGURE 5 Accidents versus ADT, sideswipe (same direction) accidents, rural two-lane roads, by states.

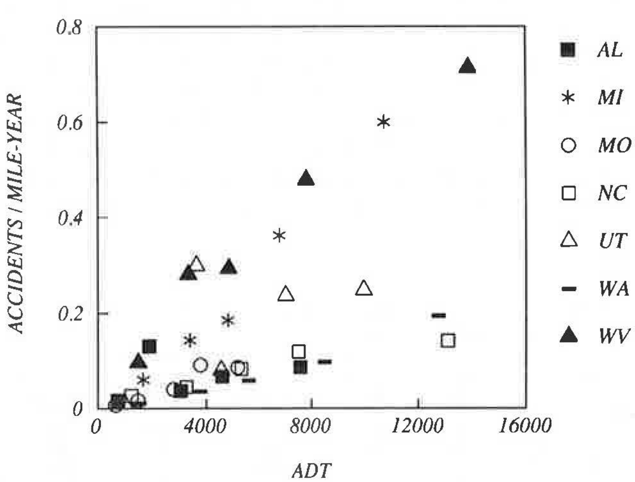

FIGURE 3 Accidents versus ADT, head-on accidents, rural two-lane roads, by states.

by the differences among states in lane width, shoulder width, terrain type, and so on.

ELIMINATION OF SOME INDEPENDENT VARIABLES

To determine whether the differences between Alabama and West Virginia are due to road conditions that we know about or to other, unknown factors, accidents-versus-ADT plots for road sections are compared with similar features. For a reliable comparison, an effort has been made to find that set of conditions that is found frequently enough in both states.

Only in the "rolling terrain" category are there enough road sections in both states. For this terrain, roads with 10- and 11-ft lanes are studied separately. Because the majority of the roads in both states do not have paved shoulders, only roads with unpaved shoulders are used. All road sections with a total unpaved shoulder width between 0 and 5 ft are used.

Thus, in Tables 2a and 2b, how the number of single-vehicle accidents varies with ADT for Alabama and West Virginia is examined using only rural two-lane roads in rolling terrain, with unpaved shoulders of 0 to 5 ft, and for lane widths of 10 and 11 ft. Because of the small samples, the road sections are grouped into four ADT ranges and the results plotted in Figures 6a and 6b. The bars in the diagrams are placed at two standard errors, corresponding statistically to a 95 percent confidence interval, above and below the estimated means. The smooth curves are the best fits to the disaggregated data when Equation 1 is used. It is clear from Figures 6a and 6b that West Virginia has consistently more single-vehicle accidents than Alabama for the same ADT, even after equalizing for road conditions.

Similar accident-versus-ADT tabulations and plots are provided for head-on and sideswipe accidents in Tables 3, 4, and 5 and in Figures 7, 8, and 9, respectively. In these, the lane width of 11 ft is studied because only for this condition are there enough road sections and accidents in both states for a

TABLE 2 TABULATION OF SINGLE-VEHICLE ACCIDENTS VERSUS ADT, RURAL, ROLLING TERRAIN, UNPAVED SHOULDER 0–5 FT

(a) LANE WIDTH - 10 FT.

ALABAMA			WEST VIRGINIA		
Mean ADT	Ave. No. of Accidents/Mile-Year	Std. Error	Mean ADT	Ave. No. of Accidents/Mile-Year	Std. Error
535	45/145.28 = 0.31	0.05	1467	137/144.65 = 0.95	0.08
964	36/122.16 = 0.29	0.05	2250	129/106.60 = 1.21	0.11
1636	52/ 81.57 = 0.64	0.09	4857	142/ 61.95 = 2.29	0.19
5002	33/ 31.98 = 1.03	0.18	11040	148/ 49.05 = 3.02	0.25

(b) LANE WIDTH - 11 FT.

ALABAMA			WEST VIRGINIA		
Mean ADT	Ave. No. of Accidents/Mile-Year	Std. Error	Mean ADT	Ave. No. of Accidents/Mile-Year	Std. Error
1338	59/177.12 = 0.33	0.04	1750	60/ 35.45 = 1.69	0.22
2101	65/121.21 = 0.54	0.07	3633	53/ 41.05 = 1.29	0.18
3394	56/ 95.75 = 0.58	0.08	4450	60/ 19.55 = 3.07	0.40
7046	64/ 84.21 = 0.76	0.10	8300	66/ 25.10 = 2.63	0.32

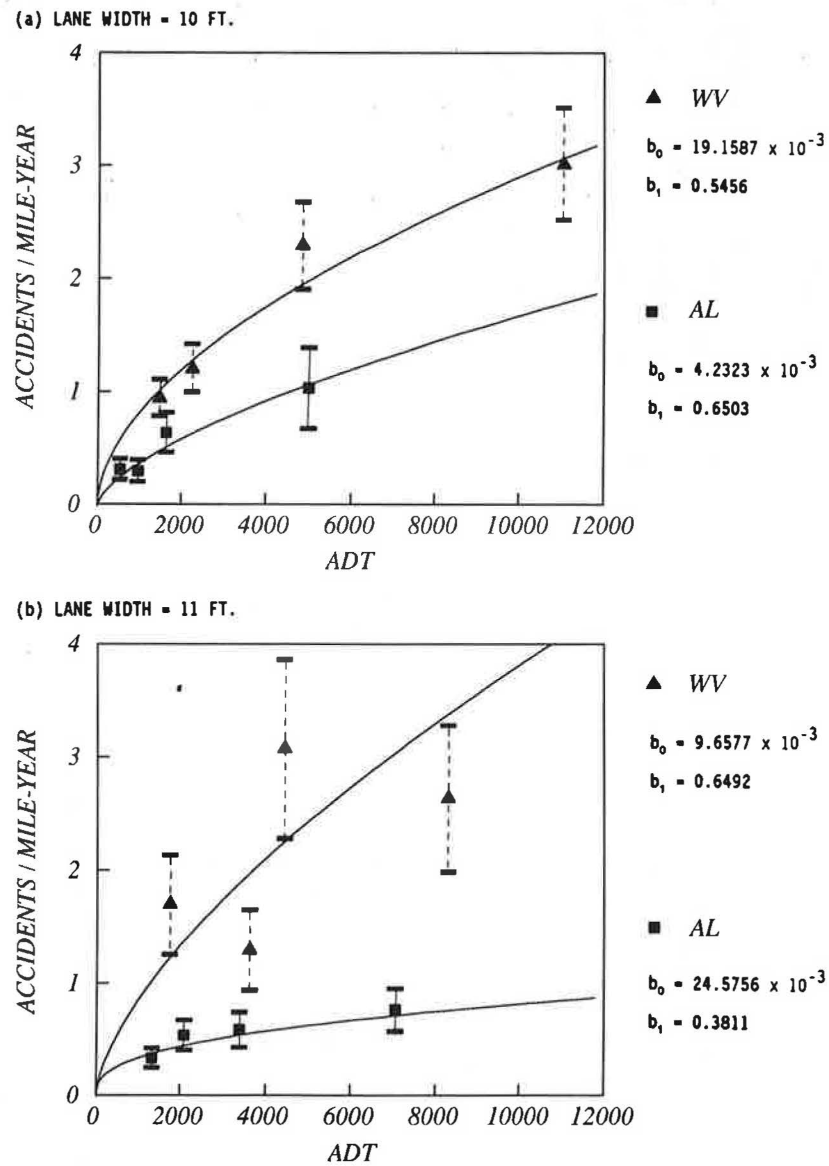

FIGURE 6 Alabama and West Virginia, single-vehicle accidents, rural two-lane roads, rolling terrain, unpaved shoulders 0–5 ft.

TABLE 3 TABULATION OF HEAD-ON ACCIDENTS VERSUS ADT, RURAL, ROLLING TERRAIN, UNPAVED SHOULDERS 0–5 FT, LANE WIDTH 11 FT

ALABAMA			WEST VIRGINIA		
Mean ADT	Ave. No. of Accidents/Mile-Year	Std. Error	Mean ADT	Ave. No. of Accidents/Mile-Year	Std. Error
1577	6/267.33 = 0.02	0.01	1750	7/ 35.45 = 0.20	0.07
3281	9/126.75 = 0.07	0.02	3633	5/ 41.05 = 0.12	0.05
4942	8/ 46.68 = 0.17	0.06	4633	9/ 29.02 = 0.31	0.10
8550	8/ 37.54 = 0.21	0.08	9400	6/ 15.45 = 0.39	0.16

TABLE 4 TABULATION OF OPPOSITE DIRECTION SIDESWIPE ACCIDENTS VERSUS ADT, RURAL, ROLLING TERRAIN, UNPAVED SHOULDERS 0–5 FT, LANE WIDTH 11 FT

ALABAMA			WEST VIRGINIA		
Mean ADT	Ave. No. of Accidents/Mile-Year	Std. Error	Mean ADT	Ave. No. of Accidents/Mile-Year	Std. Error
1482	15/216.93 = 0.07	0.01	1750	13/ 35.34 = 0.37	0.10
2938	18/159.46 = 0.11	0.03	3633	9/ 41.05 = 0.22	0.07
4687	20/ 60.67 = 0.33	0.07	4633	14/ 29.20 = 0.48	0.13
8121	13/ 41.23 = 0.32	0.09	9400	23/ 15.45 = 1.49	0.31

TABLE 5 TABULATION OF SAME DIRECTION SIDESWIPE ACCIDENTS VERSUS ADT, RURAL, ROLLING TERRAIN, UNPAVED SHOULDERS 0–5 FT, LANE WIDTH 11 FT

ALABAMA			WEST VIRGINIA		
Mean ADT	Ave. No. of Accidents/Mile-Year	Std. Error	Mean ADT	Ave. No. of Accidents/Mile-Year	Std. Error
1577	18/267.33 = 0.07	0.02	2060	12/ 46.40 = 0.26	0.07
2964	15/ 88.04 = 0.17	0.04	4125	16/ 49.65 = 0.32	0.08
4382	23/ 85.38 = 0.27	0.06	5200	8/ 12.90 = 0.62	0.22
8550	18/ 37.54 = 0.48	0.11	11400	24/ 12.20 = 1.97	0.40

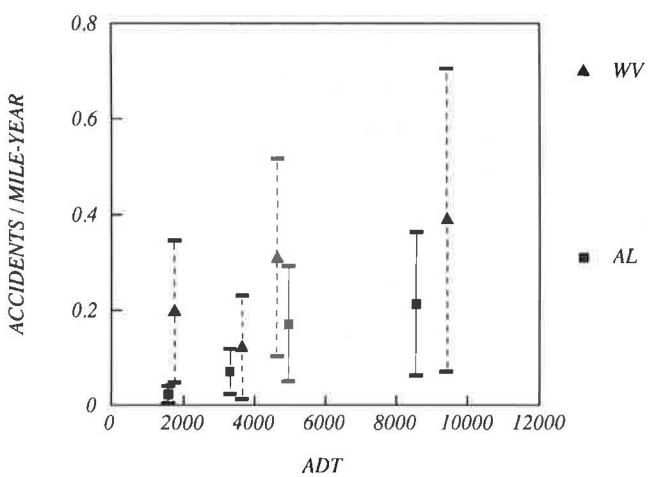

FIGURE 7 Alabama and West Virginia: Head-on accidents, rural two-lane roads, rolling terrain, unpaved shoulder 0–5 ft, lane width 11 ft.

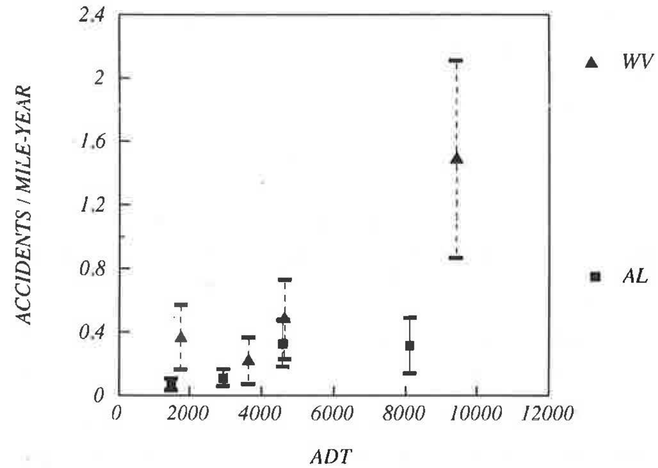

FIGURE 8 Alabama and West Virginia: Opposite sideswipe accidents, rural two-lane roads, rolling terrain, unpaved shoulder 0–5 ft, lane width 11 ft.

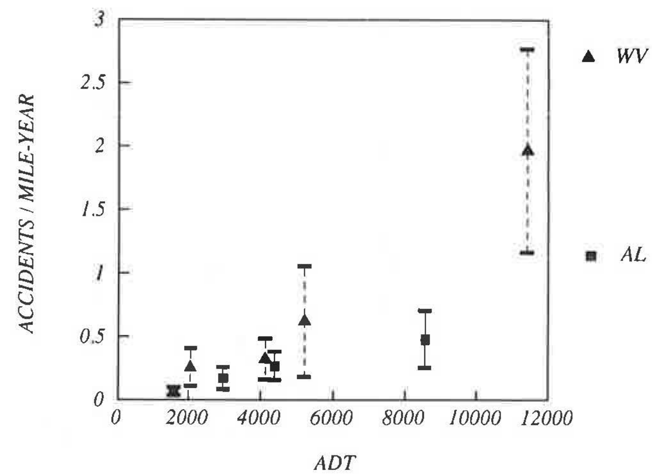

FIGURE 9 Alabama and West Virginia: Sideswipe accidents, rural two-lane roads, rolling terrain, unpaved shoulder 0–5 ft, lane width 11 ft.

reliable comparison. For these accidents no model has been fitted to the data. The relationship between traffic and multivehicle accidents will be a subject matter of a subsequent report. The results of Figures 7, 8 and 9 are as before, under similar conditions (ADT, terrain, lane width, shoulder width and type); West Virginia records more accidents per mile-year than does Alabama.

CONCLUSIONS

Under similar conditions different states have different average numbers of accidents per mile-year. Because we cannot account for these differences, and they are large, we conclude that data from different states should not be pooled for use in multivariate analyses.

More important, the existence of large, unexplained differences invites investigation. Are they a reflection of differences in accident reporting criteria or variable degrees of accident reporting (*4*), or do they contain hints to important differences in highway design or traffic management from which we could learn? It is the kingpin of epidemiology to identify the differences and search for their cause. The cause of the important differences noted should be found.

As a corollary, because of the large differences that are not currently explained, safety standards, warrants, and procedures that are based on accident frequency or rate should be tailored to each state individually. A nationwide accident warrant seems to make little sense when, under seemingly identical conditions, one state has on the average three to four times as many accidents as another.

ACKNOWLEDGMENTS

Work on this subject has been made possible by the support of the Federal Highway Administration, U.S. Department of Transportation. Their continued support and help are gratefully acknowledged.

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Publication of this paper sponsored by Committee on Traffic Records and Accident Analysis.

DISCUSSION

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The paper by Ng and Hauer, "Accidents on Rural Two-Lane Roads: Differences Between Seven States," addresses an important issue relative to whether state data should ever be "pooled" for use in large-scale accident analyses. Accident experience by accident type is shown for all seven states (i.e., Alabama, Michigan, Montana, North Carolina, Utah, Washington, and West Virginia) before consideration of differing roadway features by state. Then the report focuses on a comparison of the single-vehicle accident experience between only two of the seven states, Alabama and West Virginia, for specific data subsets. The authors found unexplained differences and concluded that "data from different states should not be pooled for use in multivariate analyses." On the basis of our independent analysis of that same data base, however, we would offer some further analysis results and conclusions.

Before selecting these seven states for use in the initial research study (*1*), it was recognized that the 50 American states have varying degrees of accident reporting thresholds, reporting jurisdictions, accuracy for reporting the accident locations, and other accident data characteristics. For example, states that comply with a low accident reporting threshold (e.g., \$100 to \$200 per accident) may have considerably more property damage only (PDO) accidents reported (all else being equal) than states with a higher reporting threshold (e.g., those that report only towaway accidents and injury and fatal accidents). These and other factors were carefully considered when these seven states originally were selected for data collection. Accident and other data from the states determined the seven to be among the best states in terms of relatively good data quality and consistency. The large differences in geography, climate, terrain, and other factors among the seven states were recognized and considered desirable, so that the study results would represent a wide range of roadway, traffic, and other conditions found in the United States.

One of the first steps to test for differences between state data bases could be to explore overall average accident experiences (e.g., rates, severities, and types) in each of the seven states. Differences in accident reporting levels, as well as differing geometric and roadway conditions, could account for differences in overall accident statistics between states. The same basic data base was analyzed as that used by Ng and Hauer except for some minor adjustments made in the data base in recent years (e.g., 1,940 sections instead of 1,944 were used because of the omission of four high-volume sites with widely varying ADT throughout the section). The mean total accident rates in accidents/MVM ranged from 1.82 in Washington to 4.01 in West Virginia, as shown in Table 6. Overall average rates for the other five states ranged from 1.99 (Montana) to 2.82 (Michigan). Fatal accident rates ranged between .026 and .044 for five of the states, with higher values (.060 and .064) for West Virginia and Montana. The rate of injury accidents ranged from 0.66 to 1.00 for six of the states, with West Virginia again high at 1.63 (injury accidents per million vehicle miles). The rate of single-vehicle accidents was considerably lower for the Alabama sample sections (0.54) compared with the other states, highest in West Virginia (1.43), and relatively similar in the other five states (0.83 to 1.16).

To understand these accident trends better, it is useful to review the roadway and traffic characteristics of the data samples in the individual states. For purposes of this discussion, we have summarized average values for some key traffic and roadway features in Table 7. The averages of AADTs in the state samples range from 1,720 for Montana sites to 4,765 in North Carolina for these state-maintained roadway sections. West Virginia sites can be seen to have among the most restrictive geometrics, particularly in terms of narrow lanes (average of 10.4 ft), hazardous roadside conditions (4.6, where 7.0 is the most hazardous and 1.0 is the least hazardous), and the largest amount of sharp curves (i.e., 39.9 percent of the West Virginia sample has horizontal curvature of 2.5 degrees or greater). Thus, the combination of sharp curves, dangerous roadside, and narrow lanes would lead one to expect a higher experience of accidents than state samples with less severe roadway designs.

TABLE 6 SUMMARY OF ACCIDENT STATISTICS FOR SAMPLE SECTIONS IN SEVEN STATES

Accident Statistics	Alabama	Michigan	Montana	North Carolina	Utah	Washington	West Virginia
Sample Size (Number of Sections)	437	282	168	273	203	231	346
Rate of Single Vehicle Accidents (Acc/MVM)	0.54	0.83	1.16	0.95	1.11	0.86	1.43
Rate of Non-Run-Off-Road Accidents (Acc/MVM)	1.92	1.99	0.83	1.53	1.20	0.96	2.58
Rate of Fatal Accidents (Acc/MVM)	0.037	0.026	0.064	0.044	0.044	0.032	0.060
Rate of Injury Accidents (Acc/MVM)	0.66	0.78	0.86	1.00	0.78	0.80	1.63
Rate of Total Accidents	2.46	2.82	1.99	2.48	2.31	1.82	4.01

TABLE 7 SUMMARY OF ROADWAY CHARACTERISTICS FOR SAMPLE SECTIONS IN SEVEN STATES

Roadway Characteristics	Alabama	Michigan	Montana	North Carolina	Utah	Washington	West Virginia
Average Annual Daily Traffic (AADT)	2,978	3,182	1,720	4,765	2,380	3,713	4,619
Lane Width (feet)	10.5	11.3	11.5	10.6	12.3	11.1	10.4
Shoulder Width (feet)	5.9	8.2	1.9	6.6	3.0	5.8	4.1
Roadside Hazard Rating	3.7	3.6	3.5	4.1	3.8	4.1	4.6
Horizontal Curvature: Percent of section with 2.5 degree of curve or greater (percent)	10.9%	4.8%	8.8%	18.0%	25.0%	16.2%	39.9%

Ng and Hauer found differences in specific accident types between state data samples when accidents were plotted against ADT. However, this is not surprising, at least partly because of the differences in roadway conditions between the state samples. For example, as might be expected, the single-vehicle, head-on, and opposite direction sideswipe accidents were quite high in West Virginia compared with the other states. This may be expected as a result of the generally curvy, narrow roadways with more hazardous roadside conditions for the West Virginia sample compared with the other states. The incidence of opposite direction sideswipe accidents was quite low in Michigan, as might be expected; the Michigan sample sites have the widest combined width of lanes (11.3 ft) plus shoulders (8.2 ft), as well as only 4.8 percent of horizontal curves (which was the mildest horizontal curvature of the seven states). Thus, wide, relatively straight roadways would be expected to result in a relatively low incidence of opposite direction sideswipe accidents, as the data showed.

Although some of such variation in accident types can be explained by roadway and traffic differences, there are some differences in accident reporting, driver behavior, and so on that can also cause differences in accident types. One example is the low rate of reported single-vehicle accidents in Alabama. Although the total accident rate in the Alabama sample sections was right about in the middle of the seven states, the rate of single-vehicle accidents was the lowest of the seven states. One likely reason is the fact that accident types used for the seven-state data base had to be developed into a common definition based on the different accident report forms in each state. The Alabama accident report form does not have a specific code for run-off-road accidents, so a combination of several accident variables had to be used to classify each accident. By selecting data subsets and further dividing the data by specific accident type, state, roadway geometrics, and ADT category (as done by Ng and Hauer), there is also the likelihood of creating some cells with relatively small sample sizes of specific accident types where unreliable accident rates may result.

We would like to point out that on the basis of past research, accident relationships with roadway geometrics generally differ considerably between urban and rural areas. In fact, all of the computer modeling conducted in the initial research study by Zegeer et al. (*1*) was based on analysis of rural samples only. The analysis by Ng and Hauer apparently combined the high-volume urban sections with rural sections in developing their accident rate figures by state and ADT. Much of the spread in their accident rates for the seven states is in the highest ADT groups (i.e., above 10,000), where sample sections are mostly urban and where very small sample sizes exist (only 166 miles or 3.3 percent of the data base is urban).

In particular, for ADTs of 8,000 or less (which are nearly all rural roadways), accident levels for most accident types are much more consistent between the seven states.

It is also questioned why a measure of roadside hazard (i.e., either roadside hazard rating or roadside recovery area distance as contained in the data base for each section) was not used as a control variable by Ng and Hauer when comparing single-vehicle accidents between states. Roadside hazard rating (or recovery distance) was found in the original research study (*1*) to be the most important roadway factor (except for ADT) in explaining single-vehicle and other related accident types. By ignoring the roadside condition, unexplainable differences in single-vehicle accidents would surely occur when comparing state data samples that have differing levels of roadside hazard.

It should also be mentioned that the distribution of accidents by type can vary considerably depending on many roadway features. For example, if the data sample in State A has more intersections and driveways than the sample in State B, then one would expect a higher percent of right-angle, rear-end, and turning accidents for the data sample in State A than in State B. Such a condition would not necessarily require separating the data sets for analysis. Instead, one may use a measure of intersection or driveway frequency as part of the analysis.

Ng and Hauer conclude that because they found large differences between state data that they could not explain, they recommend setting standards, warrants, and procedures on the basis of accident frequency and rate to be "tailored to each state individually." This recommendation would appear to assume that accident data within a given state will be stable and consistent. Unfortunately, many differences exist within some states in terms of their reporting criteria (e.g., the city of Detroit investigates and reports a much smaller percentage of noninjury accidents than are reported in many other Michigan areas).

Further, some states have greatly differing terrain (mountainous areas and flatlands) and amounts of rain and snow, and even greatly differing driver characteristics (e.g., tourists versus mostly local drivers), depending on the area of the state. Thus, differences in accident experience may occur on roads in a state that may not be explainable by traffic and roadway variables alone. Such intrastate differences could cause equal or larger variations in accident experience than reported by Ng and Hauer between states. Does this mean that we must split each state's data into many data subsets before conducting accident analyses? We believe that it is reasonable to pool data for some states or jurisdictions but not for others on the basis of the characteristics of the data sets in question and the purposes of the analyses.

The point of Ng and Hauer that substantial differences may exist in data obtained from different states is well taken and, certainly, state differences should be investigated. When variables and relationships seem comparable across states, however, then analyses of combined data sets should yield estimates of relationships that are, in a sense, smoothed over a broader range of conditions and, hence, may be more widely applicable than those obtained from data within a single state. As Ng and Hauer pointed out, when major differences between states are found, they may suggest certain other factors that should be considered or potential problems with certain variables or data systems. Even when differences do exist, it still may be possible to smooth certain relationships across states while allowing others to differ from state to state.

For example, weighted log linear regression models were fit to subsets of the seven-state base to investigate relationships between ran-off-road accidents and roadway/roadside factors, such as ADT, lane width, shoulder width, recovery distance, roadside hazard rating, and terrain. Initial analyses indicated that the distributions of the relevant variables were similar and that it was reasonable to pool the data for the states of Michigan, Montana, North Carolina, Utah, and Washington. Alabama had much lower ran-off-road accident rates than did the five-state group, and West Virginia had much higher ran-off-road accident rates.

To investigate further the nature of these differences, the data from West Virginia were combined with the five-state data and analyses carried out; a significant state effect was found for West Virginia but no significant interactions. This suggests that although the magnitude of ran-off-road accidents is higher in West Virginia than in the other five states, relationships between accident rate and the roadway/roadside characteristics are similar. With Alabama data, on the other hand, significant interactions indicate that rates of single-vehicle accidents not only differ in magnitude from those of the other states but also that the nature of the relationships with the roadway/roadside factors is quite different. This could well be the result of problems in classifying ran-off-road accidents in Alabama, as discussed earlier, though not a particular problem in data for the other six states. One might reasonably conclude that pooling data from six of the seven sites may be quite reasonable for analysis of single-vehicle accidents. Further testing may well show that Alabama data may appropriately be combined with that of the other six states for analysis of total accidents and/or certain other accident types (particularly as the average total accident rate for Alabama was near the middle of the range of accident rates for the seven states).

In conclusion, we would again compliment Ng and Hauer on their addressing a very timely issue, that is, whether to combine data from several states. We do not agree, however, that state data bases should never be combined for analysis purposes. Instead, we believe that certain criteria should be used to determine whether two or more data sets should or should not be combined for a particular analysis. For example, such criteria may be expressed in the following questions.

1. Are the data variables defined consistently?
2. Are accident reporting thresholds reasonably similar? If not, it may still be reasonable to pool data from two states with differing reporting of property damage accidents and analyze only the injury and fatal accidents (if all other criteria are met).
3. How detailed does the analysis need to be? Do available data variables provide for sufficient accuracy for the intended analysis?
4. Is there a need to combine data from various geographic areas, regions, climates, and so on for a global accident analysis; or is analysis of a single state, city, or county sufficient?

We appreciate the opportunity to provide these comments and welcome other thoughts and further research on this timely subject.

AUTHORS' CLOSURE

In the first part of their discussion Zegeer and Stewart provide important further detail about the data that served as a basis of this paper and also of an earlier work (*1*). Eventually they conclude that the differences in accidents/mile-year that we show to exist are "due at least in part to the differences in roadway conditions between the state samples." They state, "Although some such variation in accident types can be explained by roadway and traffic differences, there are some differences in accident reporting, driver behavior, and so on that can also cause differences in accident types."

We of course concur with this conclusion. What we have tried to show is that even after one does account for differences in road conditions, large differences in accidents/mile-year still remain. That there are differences between the states is evident from Figures 2 to 5. That only a small part of the difference is due to "roadway and traffic differences" we show in Figures 6 to 9. In these we have compared road sections that are all in the same terrain, have the same lane width, same type of shoulder and shoulder width. The comparison is always between sections which serve the same ADT.

As the discussants note, roadside hazard and curvature have been accounted for only indirectly by comparing road sections that all are in a "rolling terrain." This is certainly a deficiency. We could not account for curvature directly because for more than half of the road sections in the data base this piece of information is missing. This is also why Zegeer et al. (*1*) did not use curvature as an independent variable. To examine further the effect of roadside hazard, we repeated the analysis for Figure 6, this time ensuring that the average road hazard rating and curvature for the Alabama and West Virginia road sections are very similar. The results are shown in Figure 10. Comparing it with Figure 6, the difference for 10-ft lanes is diminished but for 11-ft lanes it remains virtually as before.

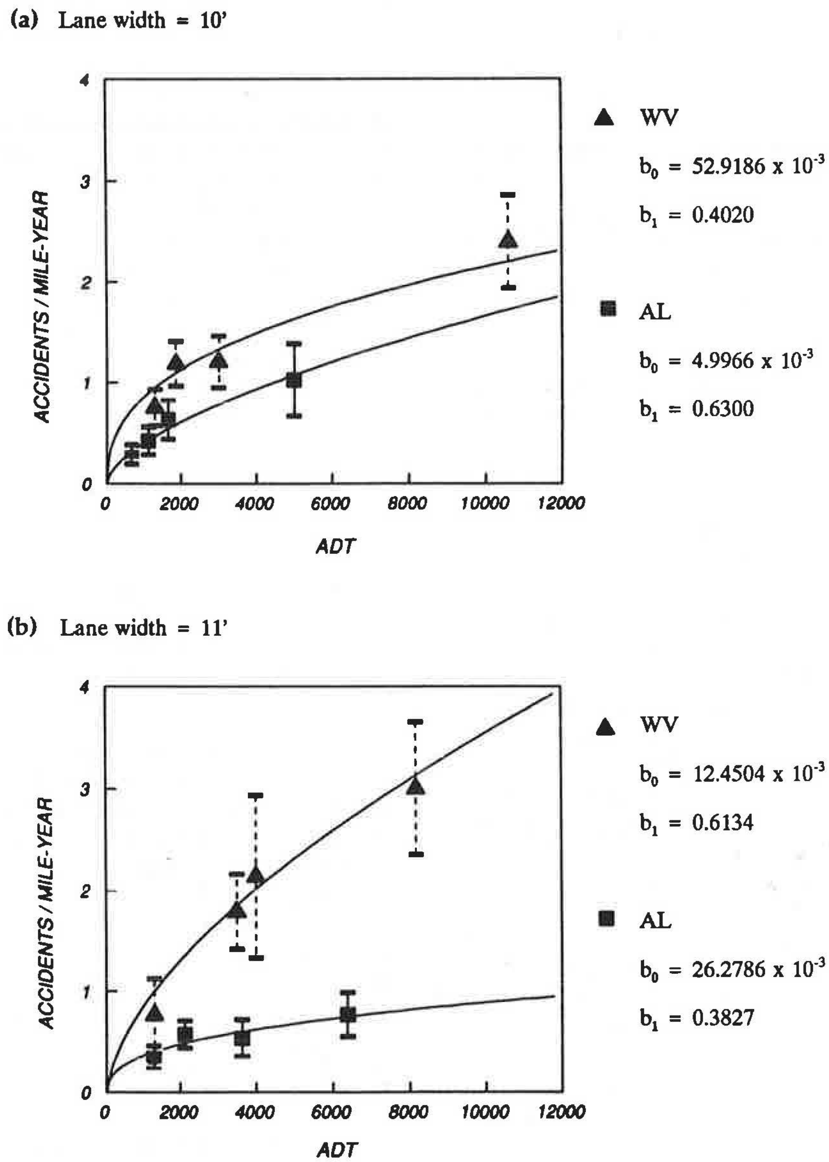

FIGURE 10 Alabama and West Virginia: Single-vehicle accidents, rural two-lane roads, rolling terrain, unpaved shoulders 0–5 ft.

Thus, the difference between the two states remains large, and neither the road geometrics nor the traffic flow about which we have data suffice to explain the differences in accidents/mile-year. Zegeer and Stewart seem to come to the same conclusions when they eventually say that in a multivariate model "Alabama had much lower ran-off-road accident rates than did the five-state group, and West Virginia had much higher ran-off-road accident rates." In addition, they find that "a significant state effect was found for West Virginia" and that for Alabama, "rates of single-vehicle accidents not only differ in magnitude from those of other states, but also that the nature of the relationship with the roadway/roadside factors is quite different." It appears that, reluctantly, the discussants agree with the observation that different states seem to have a different number of accidents per mile-year even when the road and traffic conditions appear to be similar.

We state in the paper: "Under similar conditions different states have different average numbers of accidents per mile-year. Because we cannot account for these differences, and they are large, we conclude that data from different states should not be pooled for use in multivariate analyses." Zegeer and Stewart seem to take issue with this conclusion when they say: "We believe that it is reasonable to pool data for some states or jurisdictions but not for others on the basis of the characteristics of the data sets in question and the purposes of the analyses."

Of course, it always true that data can be pooled for "some states or jurisdictions." To be specific, data can be pooled for those states and jurisdictions to which the same multivariate model can be fitted. However, when "there is a significant state effect" or "when the nature of the relationship with roadway/roadside factors is quite different," to pool data is perilous.

To illustrate, consider State *X* in which roads have an average roadside hazard rating of 3.7 and 40 percent of reportable accidents are reported, whereas in State *Y* the average roadside hazard rating is 4.6 and 80 percent of the reportable accidents are reported. In all other respects the roads and traffic in *X* and *Y* are very similar. The difference in the extent of accident reporting alone will cause State *Y* to have twice as many reported accidents/mile-year as State *X*. However, in a multivariate analysis in which data for *X* and *Y* are simply pooled, this will be seen as caused by the difference of 0.9 in the average roadside hazard rating. Thus the importance of roadside hazard will be exaggerated and money may be misspent.

The West Virginia road sections in the data set used here and elsewhere (*1*) have an average roadside hazard rating of 4.6 but for Alabama it is 3.6. (see Table 7). At the same time a West Virginia road section will have up to four times as many accidents as an Alabama road section with the same traffic and geometrics (see Figure 6 and Figure 10). If now data for West Virginia and Alabama are pooled, is there not a danger that in the ensuing multivariate model the real and the fictitious are inextricably mixed?

In no way do we intend to imply that the results of Zegeer et al. (*1*) are incorrect. This is impossible to say without a reanalysis of the data, which is now in progress. Our intent was only to point to the large differences between the seven states and to show that information about traffic and geometrics is not sufficient to explain it.

A Comparison of Techniques for the Identification of Hazardous Locations

JULIA L. HIGLE AND MARI B. HECHT

Techniques for the identification of hazardous locations, based on both classical and Bayesian statistical analyses, are evaluated and compared in terms of their ability to identify hazardous locations correctly. A simulation experiment, which is described in detail, is used. One classically based technique exhibits a tendency to err in the direction of false negatives. Another classically based technique yields relatively few false negative errors and produces results that are virtually indistinguishable from the results obtained from the Bayesian techniques. A variation of the Bayesian method proposed by Higle and Witkowski exhibits a tendency to perform well, producing low numbers of both false negative and false positive errors. Observed sensitivities of the various procedures are discussed.

The identification of hazardous locations is an important first step in any highway safety plan. The technique used to identify these locations should be sufficiently accurate to instill a high degree of confidence in the reported results. Hauer and Persaud compare the identification process to a sieve that should "catch" the hazardous sites while allowing the nonhazardous sites to "pass through" (*1*). A technique that tends to catch hazardous sites while allowing nonhazardous sites to pass through works well. Similarly, a technique that tends to allow a large fraction of hazardous sites to pass through while catching a number of nonhazardous sites is probably flawed. In this paper, the results of an experiment designed to evaluate empirically the relative performance of various techniques for the identification of hazardous locations are reported.

From the Hauer and Persaud analogy, it can be seen that an identification procedure partitions the sites under consideration into four categories, depending on whether or not they are truly hazardous (labeled H and NH, respectively) and whether or not they are identified, or flagged, by the identification technique (labeled F and NF, respectively). If a technique works perfectly, all sites that are hazardous are flagged and all sites that are not hazardous are not flagged. That is, in the absence of error, $F = H$ and $NF = NH$. Unfortunately, sites are flagged on the basis of data that are subject to random variation. It follows that some sites that are not hazardous are flagged and some sites that are hazardous are not flagged. The former event is a "false positive" identification, and the latter is a "false negative" identification. If the number of false negative identifications tends to be low, one can be reasonably assured that the set of sites that is flagged contains most of the truly hazardous sites. Similarly, if the number of false positive identifications tends to be high, then one suspects that many of the sites that are flagged are not truly hazardous. In evaluating the effectiveness of an identification technique, the relative severity of these two types of errors must be considered. It is generally agreed that a false negative error is far more serious than a false positive error. Thus, one might conclude that a technique that tends to yield a low number of false negatives is a good technique, as long as the low number of false negatives is not accompanied by an excessively large number of false positives.

Higle and Witkowski propose an empirical Bayesian method for the identification of hazardous locations (*2*). In comparing the output of their procedure to that of procedures based on classical statistical techniques, they speculate that at least one of the classically based techniques may be prone to err in the direction of false negatives. This observation is based on the authors' interpretation of the empirical results presented in the paper. On the basis of their study, it is impossible to know which sites are actually hazardous (H); thus their observations cannot be considered conclusive. In an effort to compare the ability of various identification techniques to distinguish correctly between hazardous and nonhazardous locations, the performance of the various techniques discussed by Higle and Witkowski (*2*) are investigated. In particular, the performance of identification techniques that are derived from classical statistical procedures is compared with those that are derived from the Bayesian procedure defined by Higle and Witkowski.

This paper is organized as follows. The next section contains a detailed explanation of the experimental method used. Salient points regarding the experimental method are discussed next. The results of the experiment are tabulated and presented, and the following section contains a discussion of the sensitivities of the various techniques observed during the course of the experiment. Conclusions are presented last.

EXPERIMENTAL METHOD

The experiment is based on a simple design. It is assumed that we are given a collection of accident rates (i.e., the number of accidents per million vehicles entering an intersection) for m locations, $\{\Lambda_i\}_{i=1}^{m}$, which represents a state of "perfect knowledge." That is, it is assumed that Λ_i represents the long-term expected accident rate at location i under its current configuration. With these accident rates, three years' worth of accidents are randomly generated, thereby simulating the accident data that might be available to a safety analyst. The simulated data are then analyzed using the various techniques. The set of sites identified as hazardous by each technique is compared with a set of sites that is known to be hazardous based on the true rates, $\{\Lambda_i\}_{i=1}^{m}$. Because the output of the

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experiment can be expected to vary with the simulated data, 30 independent repetitions of the experiment are performed to allow for the observation of general trends that might emerge.

In its most basic form, the experiment consists of the following phases:

1. The selection of the "true" accident rates, $\{\Lambda_i\}_{i=1}^m$,
2. The identification of the set of sites that is "truly" hazardous,
3. The generation of the simulated accident data,
4. The analysis of the simulated data and the identification of hazardous sites, and
5. The comparison of the sites identified as hazardous with those that are truly hazardous.

Each of these phases is discussed in turn.

True Accident Rates

The goal of this experiment is to glean an understanding of the performance characteristics of the various techniques as they are commonly implemented. Thus a hypothetical collection of "true accident rates" that can capture some of the idiosyncrasies associated with true rate distributions with a reasonable degree of accuracy is required. To do this, observed accident data were used as a hypothetical collection of true rates. Four data sets, containing accident and traffic volume data for signalized intersections from communities under various jurisdictions within the state of Arizona, are used. By using data sets that differ in size and underlying characteristics, a variety of test scenarios is achieved. Consistent results across all scenarios considered should provide evidence for and against the various techniques.

The two data sets included by Higle and Witkowski (*2*) are used in this study and are labeled DS1 and DS2. In addition, two remaining data sets, DS3 and DS4, are also used. DS3 corresponds to the set of accident rates associated with signalized intersections under the jurisdiction of the City of Tempe Traffic Engineering Division, Tempe Arizona, during 1982 and 1984, whereas DS4 corresponds to accident histories associated with signalized intersections under the jurisdiction of the City of Tucson Department of Transportation, Tucson Arizona, during 1983–1986. Within each data set, each location's accident data are combined to represent a single annual accident rate (i.e., average number of accidents per million vehicles entering the intersection). The cumulative distributions for these preliminary sets of rates are depicted in Figure 1.

DS1 consists of 33 intersections and yields an approximately s-shaped curve. DS2 consists of 35 intersections and is characterized by an approximately linear curve with three rates that are significantly higher than all other rates. In Figure 1b, these outliers can be seen to affect the tail of the distribution. DS3 consists of 28 sites and exhibits the most nearly linear curve, with no obvious outliers. DS4 consists of 96 intersections and is characterized by a gently shaped s-curve. For the purposes of this experiment, the accident rates taken from the data sets DS1–DS4 are thought of as representing perfect information, subject to no randomness whatsoever, and thus are considered to be the true accident rates (i.e., those that the identification procedures attempt to estimate).

Truly Hazardous Locations

To assess the performance of the various techniques, it is necessary to identify a set of locations that are truly hazardous. This identification is based on the collection of true rates, $\{\Lambda_i\}_{i=1}^m$, as it represents a state of perfect knowledge. To be consistent with current practice, a location is considered hazardous if the true accident rate is sufficiently higher than the population mean. That is, if

$$\Lambda_i > \mu + k\sigma \tag{1}$$

where μ and σ are the mean and standard deviation associated with the true distribution of rates (as depicted in Figure 1), then location i is identified as truly hazardous. The symbol H is used to represent those sites that are truly hazardous.

For the purpose of this experiment, three values of k are considered: 1.282, 1.645, and 2.327. These values are arbitrarily selected to correspond to the critical values associated with a classical statistical test of hypothesis at the 0.90, 0.95, and 0.99 confidence levels, respectively. These values are obtained from the normal distribution function and thus have no particular meaning in terms of the distribution of true rates associated with the four preliminary data sets DS1–DS4. Note that they are used simply because they coincide with the commonly used classical statistical procedures discussed elsewhere (*2, 3*) and thus provide for a convenient comparison of the set of truly hazardous sites and the sets of sites that are flagged by the various techniques.

Recognizing that Equation 1 may be an unsatisfactory method for determining those locations that are truly hazardous, a second method in which a threshold value is used is also considered. That is, one may alternatively state that if

$$\Lambda_i > \Lambda_T, \tag{2}$$

where Λ_T represents an upper limit on the acceptable accident rates, then location i is identified as truly hazardous (H). Note that Equations 1 and 2 are equivalent when

$$k = \frac{\Lambda_T - \mu}{\sigma} \tag{3}$$

Thus one may equivalently think of Λ_T as implying a critical value for the multiplier k.

It should be noted that because $\{\Lambda_i\}_{i=1}^m$ represents the true accident rates, locations are identified as truly hazardous (H) independent of both the simulated data and the technique being tested. Thus, all techniques attempt to identify the same set of locations for all simulated data sets. Naturally, the set of truly hazardous locations will vary with the four preliminary data sets, DS1–DS4.

Simulation of Data

Given a collection of true rates, accident data comparable with what would be available to a safety analyst are randomly generated using a computer simulation. The number of accidents at intersection i is generated according to a Poisson distribution with a mean of $\Lambda_i V_i$, where V_i represents the traffic volume at the intersection. The Poisson is a logical

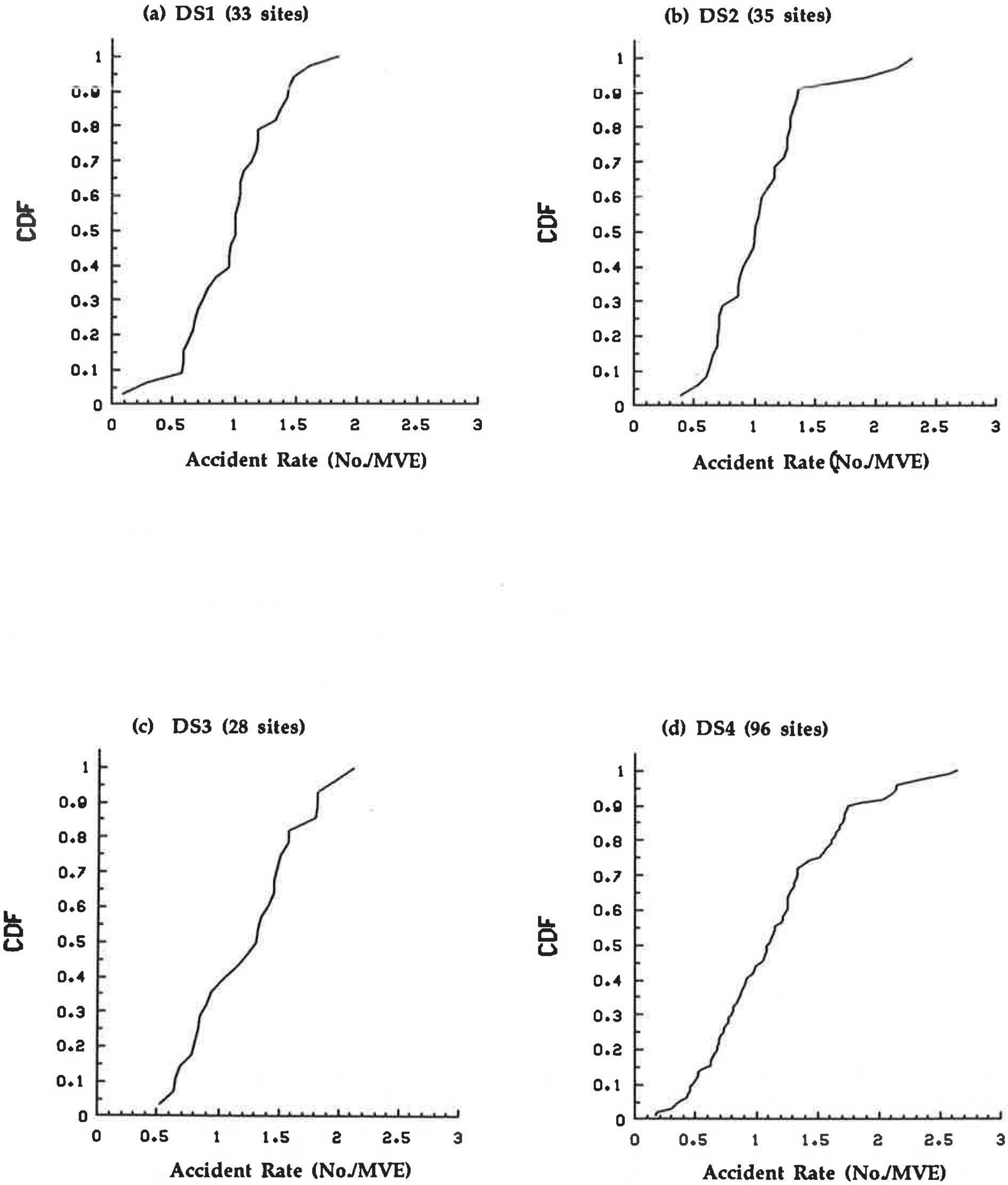

FIGURE 1 Cumulative distributions.

choice for a probabilistic model for numerous reasons, such as those presented by Ross (*4*). In general, if the numbers of events (e.g., accidents) occurring in disjoint time intervals are independent random variables with distributions varying with the length of the interval and the probability of multiple events occurring in a small interval of time is low, the Poisson distribution is an appropriate model for the random process. Similarly, if one envisions the relationship between traffic volume and accidents at a particular intersection in such a fashion that each vehicle entering the intersection has some probability of being involved in an accident, then again the Poisson distribution is an appropriate choice for modeling the number of accidents at the intersection (*5*, p. 66).

Analysis of Simulated Data

The simulated data are analyzed using the techniques discussed by Higle and Witkowski (*2*). The term "flag" and the symbol *F* are used to distinguish between those sites that are identified as hazardous by the techniques being tested (i.e., using the simulated data) and those sites that are truly hazardous (i.e., "H," those based on the true rates).

The techniques being tested vary somewhat, depending on whether Equation 1 or 2 is used to determine the set of truly hazardous locations. In what follows, $\hat{\lambda}_i$ represents the accident rate observed at location i, based on the traffic volume at the intersection and the simulated number of accidents, $\bar{x}$ and s represent the sample mean and standard deviation of the observed (simulated) data, and x_R is the observed system rate. The symbol $\tilde{\lambda}_i$ is used to represent the true accident rate at location i, which some techniques explicitly treat as a random variable. When truly hazardous locations are determined by Equation 1, the identifcation techniques are defined as follows:

C1 Site i is flagged as hazardous if

$$\hat{\lambda}_i > \bar{x} + k_\delta s \tag{4}$$

C2 Site i is flagged as hazardous if

$$\hat{\lambda}_i > x_R + k_\delta \left(\frac{x_R}{V_i}\right)^{\frac{1}{2}} + \frac{1}{2V_i} \tag{5}$$

B1 Site i is flagged as hazardous if

$$P(\tilde{\lambda}_i > \bar{x}) > \delta \tag{6}$$

B2 Site i is flagged as hazardous if

$$P(\tilde{\lambda}_i > x_R) > \delta. \tag{7}$$

The values of $\bar{x}$ and x_R are computed as described by Higle and Witkowski (*2*), and s is computed as described by Quaye (*2*, p. 33). The probabilities presented in Equations 6 and 7 are computed as done by Higle and Witkowski (*2*), with the modification for the estimation of the parameters of the regional distribution of the accident rates provided in the discussion by Morris (*2*). Note that in each of the preceding techniques, the values of δ used to determine whether or not a site is flagged are allowed to vary freely and are generally supplied by the safety analyst. In making comparisons between the various techniques, δ is held constant so that the four inequalities have analogous interpretations. That is, with δ fixed, C1 and C2 are interpreted as indicating that a flagged site has a true rate that exceeds $\bar{x}$ and x_R, respectively, with a confidence of $\delta \times 100$ percent, whereas B1 and B2 are interpreted as indicating that a flagged site has a true rate that exceeds $\bar{x}$ and x_R, respectively, with a probability of δ. The values of δ tested are 0.90, 0.95, and 0.99. Correspondingly, k_δ takes on the values 1.282, 1.645, and 2.327, respectively. These values are intentionally selected to agree with the values used when identifying the truly hazardous locations, thereby facilitating the comparison of H and F.

C1 is based on the concept of confidence intervals associated with classical statistical tests of hypothesis. C2 is the rate-quality technique defined by Norden, Orlansky, and Jacobs (*6*) and Morin (*7*) and can be thought of as a refinement of C1. B1 and B2 differ only in their respective use of $\bar{x}$ and x_R and are simply two variations of the Bayesian technique defined by Higle and Witkowski (*2*). Both C1 and C2 are computationally straightforward, whereas B1 and B2 require the numerical integration of a gamma probability density function and are thus computationally intensive.

When truly hazardous locations are identified via a threshold value, as in Equation 2, the values of δ used in the Bayesian techniques will vary. As B1 is intended to be analogous to C1 (in a Bayesian fashion), the appropriate value of δ is taken to depend on $\bar{x}$, s, and Λ_T. That is, building from the observation leading to Equation 3, let

$$k_T = \frac{\Lambda_T - \bar{x}}{s} \tag{8}$$

and δ_T represent the confidence level whose critical value corresponds to k_T. For example, if $\frac{\Lambda_T - \bar{x}}{s} = 1.58$ the value of δ_T used in Equation 7 is 0.9429 [see Ross (*4*, p. 73)]. On the other hand, B2 is intended to be analogous to C2, which differs from C1; thus the value of δ used will differ from the value associated with Equation 8. Using logic similar to that which yields Equation 3, let

$$k_{Ti} = \frac{\Lambda_T - (x_R + 1/2V_i)}{\left(\frac{x_R}{V_i}\right)^{1/2}} \tag{9}$$

and let δ_{Ti} represent the confidence level whose critical value corresponds to k_{Ti}. Note that because k_{Ti} depends on V_i, δ_{Ti} will vary with the location. This is not the case for B1 when Equation 2 is used to define the truly hazardous locations. When truly hazardous locations are identified using Equation 2, the techniques being tested are defined as follows:

B1T Site i is flagged as hazardous if

$$P(\tilde{\lambda}_i > \bar{x}) > \delta_T \tag{10}$$

B2T Site i is flagged as hazardous if

$$P(\tilde{\lambda}_i > x_R) > \delta_{Ti} \tag{11}$$

where the threshold probabilities δ_T and δ_{Ti} are computed in accordance with Equations 8 and 9, respectively. The letter T is appended to the names given to the techniques to indicate that a threshold rate has been used to determine the set of truly hazardous locations.

Comparison of Techniques

As previously mentioned, a procedure that works perfectly will flag every site that is truly hazardous and no others, yielding $F = H$. It is reasonable, however, to expect that none of the techniques being tested work perfectly. Thus, errors will be made, and the challenge lies in determining how to describe these errors quantitatively.

As discussed in earlier work (*2*), a simple accounting of the two types of mistakes, false negative and false positive identifications, yields an inadequate summary of the accuracy of the procedures. For example, consider a site that is deemed truly hazardous based on Equation 1 with k corresponding to $\delta = 0.95$. If the probability computed in Equation 6 (criterion B1) is at least 0.95, the site is correctly flagged as hazardous. Otherwise, B1 yields a false negative identification for this location. A false negative identification based on a computed probability of 0.949 (representing a "near miss") might be judged less harshly than one based on a computed probability of 0.70. Hence, there is some value in knowing the magnitude of the error associated with a misidentification.

Consider a hazardous site i that is not flagged (NF) by the technique under consideration (i.e., a false negative). Let δ represent the value corresponding to k for which the site is hazardous according to Equation 1 (i.e. $\delta = 0.90$, 0.95, or 0.99). Under C1 and C2, one can easily determine $\bar{\delta}_i$, the maximum level for which the site would be flagged. For example, using C1 (Equation 4), set $\bar{k}_i = \hat{\lambda}_i - \bar{x}/s$. Then $\bar{\delta}_i$ can easily be determined. The values of $\bar{k}_i$ and $\bar{\delta}_i$ are analogously defined using C2 (Equation 5). In this case, because i is a false negative identification, $\bar{\delta}_i < \delta$, and thus,

$$\rho_i = \delta - \bar{\delta}_i \quad (12)$$

represents the magnitude of the error associated with the misidentification. With the Bayesian methods B1 and B2, $\bar{\delta}_i$ is equal to the probabilities computed via Equations 6 and 7, respectively. The magnitude of the error associated with a false positive identification is similarly obtained. In this case, a site that is not hazardous is flagged at some value of δ. Using logic similar to that above, let Δ_i represent the value corresponding to $\Lambda_i - \mu/\sigma$ (from Equation 1). Then Δ_i can be interpreted as representing the appropriate level at which the site would be identified as truly hazardous. In this case, because i is a false positive, $\Delta_i < \delta$, and thus

$$\tau_i = \delta - \Delta_i \quad (13)$$

represents the magnitude of the error. Because a site that is flagged when $\delta = 0.95$ will also be flagged when $\delta = 0.90$, a site need not be uniquely flagged (or identified as hazardous) at one level. In cases where a site is misidentified for multiple values of δ, the maximum value of the error is used for comparative purposes.

Finally, the consequences of false negative and false positive identifications are distinct. As such, the magnitudes of the two types of errors are considered separately. That is, letting $NF \cap H$ represent the set of sites receiving false negative identifications and n represent the number of sites in this category, then

$$\frac{1}{n} \sum_{i \in NF \cap H} \rho_i \quad (14)$$

represents the average error per false negative identification. Similar values can be computed using τ_i for the false positive identifications. To summarize, two statistics—(I) number of false identifications and (II) average error per misidentification—can be computed for each of the techniques identified by Equations 4 to 6, for each type of error. Statistic I is averaged over the 30 repetitions of the experiment, whereas statistic II is averaged only over those repetitions in which a misidentification occurs. In addition, two other statistics are of interest: (III) maximum number of misidentifications (over the 30 repetitions) and (IV) number of repetitions on which there are no misidentifications.

When Equation 2, the threshold technique, is used to determine the set of truly hazardous sites, comparisons are made between B1T and B2T (Equations 10 and 11, respectively). Because B1T and B2T involve the direct computation of a probability, the same four statistics can be computed for these methods (i.e., by comparing the computed probabilities to δ_T for B1T and δ_{Ti} for B2T). One might be interested in knowing which observed rates exceed Λ_T. Unfortunately, this simple "hit or miss" decision precludes an opportunity for comparison with other methods. As such, when Equation 2 is used, comparisons are made only between the Bayesian techniques B1T and B2T, affording an opportunity to investigate the relative value of allowing the threshold probability to vary with the site.

DISCUSSION

As discussed earlier, four distinct data sets are used to provide four sets of "true" accident rates. The reasons for this are twofold. First, to be able to make useful conclusions regarding the various techniques, it is necessary to use data that somehow capture some of the idiosyncrasies of a collection of real accident rates (such as accident rate/traffic volume pairings, central or outlying tendencies, etc.). Although the literature suggests a tendency toward using a gamma distribution to represent the true rates (e.g. *1,2,8,9*) it is possible that, within this experiment, such a choice might bias the results toward the Bayesian techniques, as the gamma distribution figures heavily in its development. Second, it is possible that a given set of rates might, on average, favor a particular technique. Note that the variance of this hypothetical collection of true rates is (on average) higher than the variance of those rates from which they have been generated. To overcome these potential shortcomings, multiple data sets with differing characteristics are used in an effort to establish sensitivities to the characteristics of the preliminary data set. Consistent results across all data sets would suggest that any such sensitivities that might exist are probably negligible.

The second phase of the experiment, the identification of truly hazardous locations, proves to be by far the most elusive part of the experimental design. To complete this task, it is necessary to decide how to interpret perfect information. The method corresponding to Equation 1 is used simply because it provides a convenient comparison of H and F (i.e., via δ). Thus, the reader is urged to interpret Statistic II, the average deviation per misidentification, as nothing more than a "ballpark estimate." Note that the use of Equation 1 is likely to bias the experiment in favor of C1. To allow for other interpretations of perfect information, Equation 2 is also used as a second method for determining a set of truly hazardous intersections. As an added benefit, Equation 2 allows for an assessment of the relative value of allowing the critical probabilities used in the Bayesian techniques to vary from one site to another.

The multiple statistics presented earlier are necessary to gain a full appreciation of the differences between the various techniques. For example, a large value of Statistic I (number of errors, averaged over the 30 repetitions) combined with low values of Statistic II (average deviation per error) suggests that a large number of "near misses" are observed. Because an increase in the statistics associated with the false positives may be tolerable if a substantial decrease in the statistics associated with the false negatives ensues, the statistics are computed separately for false negative and false positive identifications.

RESULTS

The results of the study are separated on the basis of the method used to determine the set of truly hazardous locations. Presented first are the results of those repetitions associated with the method identified by Equation 1.

In Table 1 the distribution of the sites among the four categories determined by the combinations of *H*, *NH*, *F*, and *NF* are summarized. The values reported represent average values over the 30 repetitions of the experiment. As throughout this paper, within these figures, *H* corresponds to those sites that are truly hazardous, and *F* corresponds to those sites that are flagged as hazardous by the technique under consideration. The prefix *N* is used to represent the complement of the set. For the purposes of consistent comparison, the δ levels at which a site is deemed truly hazardous and flagged by the technique under consideration must agree to obtain a correct identification.

In reading Table 1, note that when $\delta = 0.90$, C1 correctly identifies (on average) 2.17 of the truly hazardous sites (*H-F*) and 28.67 of the truly nonhazardous sites (*NH-NF*) for DS1, while incorrectly identifying 0.83 of the truly hazardous sites (*H-NF*, false negatives) and 1.33 of the truly nonhazardous sites (*NH-F*, false positives). The corresponding values for B1, on the other hand, are 2.50 and 24.93 for the correct identification of hazardous and nonhazardous sites, respectively, and 0.50 and 5.07 for the incorrect identifications. Note that for DS1, when $\delta = 0.90$, 3 sites (2.17 + 0.83) are truly hazardous but 30 are not.

A number of trends are immediately visible in Table 1. First, note that in nearly every instance, C2, B1, and B2 correctly identify a significantly higher fraction of the truly hazardous sites than does C1. Consequently, it follows that, of the four techniques tested, C1 consistently yields the highest number of false negative identifications. The obvious exception to this trend is found in DS3 when $\delta = 0.99$. In this case, there is no site that is truly hazardous, and none of the techniques flag any sites. Further, for all techniques, the false positive identifications appear to be lowest for DS2. This is the data set that contains the outliers, true rates that are

TABLE 1 DISTRIBUTION SUMMARY

		Technique							
		C1		C2		B1		B2	
		F	NF	F	NF	F	NF	F	NF
DS1 (33 Sites)									
δ=0.90	H	2.17	0.83	2.43	0.57	2.50	0.50	2.43	0.57
	NH	1.33	28.67	4.63	25.37	5.07	24.93	4.60	25.40
δ=0.95	H	1.13	0.87	1.30	0.70	1.33	0.67	1.23	0.77
	NH	0.73	30.27	4.47	26.53	4.93	26.07	4.20	26.80
δ=0.99	H	0.20	0.80	0.63	0.37	0.57	0.43	0.57	0.43
	NH	0.17	31.83	2.90	29.10	2.93	29.07	2.73	29.27
DS2 (35 Sites)									
δ=0.90	H	2.70	0.30	3.00	0.00	3.00	0.00	3.00	0.00
	NH	0.40	31.60	4.50	27.50	4.60	27.40	4.33	27.67
δ=0.95	H	2.50	0.50	2.97	0.03	2.97	0.03	2.97	0.03
	NH	0.23	31.77	3.07	28.93	3.10	28.90	2.83	29.17
δ=0.99	H	1.27	0.73	2.00	0.00	2.00	0.00	2.00	0.00
	NH	0.27	32.73	2.23	30.77	2.20	30.80	2.03	30.97
DS3 (28 Sites)									
δ=0.90	H	3.07	1.93	4.60	0.40	4.67	0.33	4.60	0.40
	NH	0.33	22.67	3.20	19.80	3.63	19.37	3.13	19.87
δ=0.95	H	0.70	0.30	1.00	0.00	1.00	0.00	1.00	0.00
	NH	1.03	25.97	5.83	21.17	6.13	20.87	5.70	21.30
δ=0.99	H	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	NH	0.17	27.83	5.00	23.00	5.13	22.87	4.83	23.17
DS4 (96 Sites)									
δ=0.90	H	8.83	1.17	9.93	0.07	9.97	0.03	9.93	0.07
	NH	2.10	83.90	18.87	67.13	20.63	65.37	18.77	67.23
δ=0.95	H	6.40	2.60	8.97	0.03	8.97	0.03	8.97	0.03
	NH	0.40	86.60	16.70	70.30	18.50	68.50	16.33	70.67
δ=0.99	H	1.37	0.63	2.00	0.00	2.00	0.00	2.00	0.00
	NH	1.03	92.97	18.70	75.30	20.13	73.87	17.77	76.23

substantially higher than all other rates within the set. One should expect that, in general, the observed rates associated with these outliers will be correspondingly higher, and it follows that any reasonable identification technique should perform well in such a situation. Of course, note also that for a fixed value of δ, C1 tends to flag fewer sites than the remaining techniques. Consequently, it yields a larger number of false negative errors and a smaller of false positive errors than the other techniques.

To appreciate the magnitudes of the errors associated with the various techniques, the four summary statistics are presented in Tables 2 and 3.

Statistic I, the average number of false identifications, is related to the data presented in Table 1. In deriving the statistics presented in these tables, a site that is incorrectly identified for two or more values of δ is counted only once when computing Statistic I. As previously stated, the maximum magnitude of the error associated with the misidentification is used when computing Statistic II.

Again, a number of trends are immediately visible in these tables. Note again that C1 consistently yields a significantly higher number of false negative identifications (Statistic I, Table 2) than the other techniques. Moreover, its corresponding error per false negative identification (Statistic II, Table 2) tends to be comparable with that of the other techniques, although in most situations it is somewhat lower than the others. Note that for all but DS1, a substantial majority of the 30 repetitions of the experiment yield no false negative identifications for C2, B1, and B2. By looking at Statistics III and IV, note that only one false negative identification is ever made by C2, B1, and B2 over the 30 iterations with DS2 (Table 2). Similar comments hold for DS4 and, to a lesser extent, for DS3. As previously mentioned, this trend among the false negative identifications is reversed when the false positive identifications (Table 3) are considered, where all four statistics are generally better for C1 than for C2, B1, and B2.

TABLE 3 FALSE POSITIVE SUMMARY STATISTICS

		Criterion			
Data Set	Statistic	C1	C2	B1	B2
DS1 (33 Sites)	I	1.70	5.97	6.37	5.90
	II	0.111	0.183	0.192	0.182
	III	3	8	8	8
	IV	6	0	0	0
DS2 (35 Sites)	I	0.63	5.40	5.50	5.20
	II	0.154	0.234	0.235	0.231
	III	2	9	9	9
	IV	15	0	0	0
DS3 (28 Sites)	I	1.47	7.57	8.10	7.50
	II	0.068	0.141	0.149	0.139
	III	3	10	11	10
	IV	2	0	0	0
DS4 (96 Sites)	I	3.30	26.70	28.50	26.53
	II	0.069	0.167	0.179	0.167
	III	6	30	32	30
	IV	1	0	0	0

A final trend emerging from these tables warrants observation. There is virtually no difference between the performances of C2, B1, and B2. Close agreement between B1 and B2 is to be expected, as there is generally little difference between $\bar{x}$ and x_R in Equations 6 and 7. However, that C2 so closely agrees with the Bayesian techniques may follow from the fact that the Poisson distribution plays so heavily in the derivations of Equations 5, 6, and 7.

We now turn to the presentation of the results of the experiment when Equation 2, the threshold criterion, is used to define the set of truly hazardous intersections. In Table 4 the distribution of the sites among the four categories determined by the combinations of *H*, *NH*, *F*, and *NF* is summarized.

TABLE 2 FALSE NEGATIVE SUMMARY STATISTICS

		Criterion			
Data Set	Statistic	C1	C2	B1	B2
DS1 (33 Sites)	I	1.70	0.90	0.97	1.00
	II	0.101	0.186	0.165	0.184
	III	3	2	2	2
	IV	0	11	9	8
DS2 (35 Sites)	I	1.13	0.03	0.03	0.03
	II	0.063	0.059	0.061	0.063
	III	3	1	1	1
	IV	6	29	29	29
DS3 (28 Sites)	I	2.17	0.40	0.33	0.40
	II	0.115	0.149	0.155	0.170
	III	4	1	1	1
	IV	0	18	20	18
DS4 (96 Sites)	I	3.70	0.07	0.03	0.07
	II	0.049	0.081	0.087	0.083
	III	6	1	1	1
	IV	1	28	29	28

TABLE 4 DISTRIBUTION SUMMARY, THRESHOLD VALUES

	Technique			
	B1T		B2T	
	F	NF	F	NF
DS1 (33 Sites) Λ_T=1.5/*MVE*				
H	1.57	0.43	1.27	0.73
NH	6.40	24.60	1.97	29.03
DS2 (35 Sites) Λ_T=1.5/*MVE*				
H	3.00	0.00	2.93	0.07
NH	6.30	25.70	1.47	30.53
DS3 (28 Sites) Λ_T=2.0/*MVE*				
H	1.00	0.00	0.73	0.27
NH	6.17	20.83	0.93	26.07
DS4 (96 Sites) Λ_T=2.0/*MVE*				
H	8.97	0.03	8.17	0.83
NH	19.63	67.37	3.37	83.63

Again, the values reported represent average values over the 30 iterations. The threshold values, Λ_T were arbitrarily chosen in the range of the 90th to 95th percentile of the true distributions presented in Figure 1 and are comparable with, but not identical to, the critical values identified in Equation 1.

As with the results presented in Table 1, B1T and B2T appear to identify successfully most sites that are truly hazardous (i.e., $H \cap NF$ tends to be small, relative to H). Although B2T results in a slightly higher number of false negative identifications than does B1T, it is generally accompanied by a substantial decrease in the number of false positive identifications.

In Table 5, the average fractions of truly hazardous sites that are not flagged by the various techniques, the false negative identifications, are presented. Similar information regarding the false positive identifications is contained in Table 6. Note that this information is directly obtained from Tables 1 and 4. It is included here to facilitate qualitative comparisons between the various techniques.

In evaluating the false negative identifications as a fraction of the number of sites that are truly hazardous, Table 5 indicates that in 8 of the 11 cases in which there are truly hazardous locations, C2, B1, and B2 yield fractions that are, at most, 0.08 (in 7 cases, this fraction is, at most, 0.01). The corresponding fractions for C1 are much higher, with values above 0.25 in 7 of the 11 cases and one fraction as high as 0.8 (although this corresponds to a situation in which only one site in the data set is hazardous). This can be taken to be encouraging evidence that C2, B1, and B2 are generally successful in flagging sites that are truly hazardous. Unfortunately, this success comes at a cost of a substantial increase in the number of false positive identifications over the number associated with C1. In reviewing Table 6, note that of the sites flagged, C1 yields a consistently lower fraction of false positive identifications than the other three. This false positive trend, which opposes the false negative trend, is to be expected because false positive and false negative errors are inversely related.

As one might expect, B1T exhibits both false negative and false positive profiles that are roughly comparable to those exhibited by B1 (and hence, by C2 and B2 as well). Of course, differences between B1T and B1 are to be expected because the true rates do not follow a normal distribution; thus, for example, the 95th percentile of the true distribution does not necessarily correspond to $\mu + 1.645\sigma$. B2T, on the other hand, appears to exhibit false negative profiles that are comparable with those exhibited by B2 (and hence, by B1 and C2) while exhibiting false positive profiles that are comparable with those exhibited by C1. The most notable difference occurs with DS3, where an average of 27 percent of the truly hazardous sites receive a false negative identification under B2T (note that there is only one such site).

Tables 7 and 8 contain the summary statistics associated with the portion of the experiment pertaining to the threshold values. In reviewing Tables 7 and 8, note again that B2T suffers from a higher number of false negative identifications than does B1T. In looking at Statistic II, however, it appears that with the exception of DS1, the false negative identifications associated with B2T are "near misses." This is true even for DS3, for which the large fraction of false negative identifications was previously reported. This "near miss" phenomenon is observed to an even greater extent with the false positives. Thus, it seems that in general, B2T yields more false negatives than B1T, although it tends to come very close to identifying all hazardous sites correctly. In addition, B2T identifies fewer false positives than B1T and tends to come closer to identifying them correctly than does B1T, as indi-

TABLE 5 FALSE NEGATIVE FRACTIONS, $NF \cap H/H$

	δ	C1	C2	B1	B2	B1T	B2T
DS1							
	0.90	0.28	0.19	0.17	0.19		
	0.95	0.43	0.35	0.34	0.39	0.215	0.365
	0.99	0.80	0.37	0.43	0.43		
DS2							
	0.90	0.10	0.	0.	0.		
	0.95	0.17	0.01	0.01	0.01	0.	0.023
	0.99	0.37	0.	0.	0.		
DS3							
	0.90	0.39	0.08	0.07	0.08		
	0.95	0.30	0.	0.	0.	0.	0.27
	0.99	n/a	n/a	n/a	n/a		
DS4							
	0.90	0.12	0.007	0.007	0.007		
	0.95	0.29	0.003	0.003	0.003	0.033	0.092
	0.99	0.32	0.	0.	0.		

TABLE 6 FALSE POSITIVE FRACTIONS, $F \cap NH/NH$

	δ	C1	C2	B1	B2	B1T	B2T
DS1							
	0.90	0.044	0.154	0.169	0.153		
	0.95	0.024	0.144	0.159	0.135	0.206	0.063
	0.99	0.005	0.091	0.092	0.085		
DS2							
	0.90	0.012	0.141	0.144	0.135		
	0.95	0.007	0.096	0.097	0.088	0.197	0.046
	0.99	0.008	0.067	0.067	0.062		
DS3							
	0.90	0.014	0.139	0.158	0.136		
	0.95	0.038	0.216	0.227	0.211	0.228	0.034
	0.99	0.006	0.178	0.183	0.173		
DS4							
	0.90	0.024	0.219	0.240	0.218		
	0.95	0.005	0.192	0.213	0.188	0.226	0.039
	0.99	0.011	0.199	0.214	0.189		

TABLE 7 FALSE NEGATIVE SUMMARY STATISTICS, THRESHOLD VALUES

Data Set	Criterion Statistic	B1T	B2T
DS1 (33 Sites)	I	0.43	0.73
	II	0.2533	0.2352
	III	2	2
	IV	19	13
DS2 (35 Sites)	I	0.00	0.07
	II	n/a	0.0306
	III	0	1
	IV	30	28
DS3 (28 Sites)	I	0.00	0.27
	II	n/a	0.0027
	III	0	1
	IV	30	22
DS4 (96 Sites)	I	0.03	0.83
	II	0.0627	0.0119
	III	1	2
	IV	29	9

TABLE 8 FALSE POSITIVE SUMMARY STATISTICS, THRESHOLD VALUES

Data Set	Criterion Statistic	B1T	B2T
DS1 (33 Sites)	I	6.40	1.97
	II	0.0823	0.0113
	III	12	4
	IV	0	3
DS2 (35 Sites)	I	6.30	1.47
	II	0.1082	0.0133
	III	11	5
	IV	0	10
DS3 (28 Sites)	I	6.17	0.93
	II	0.0449	0.0001
	III	9	3
	IV	0	8
DS4 (96 Sites)	I	19.63	3.37
	II	0.0539	0.0001
	III	22	7
	IV	0	0

cated by Statistic II. Thus, with the Bayesian technique, it seems that there is some merit in allowing the probability that must be exceeded before a site is flagged to vary with the site.

DISCUSSION OF SENSITIVITY

Given that the procedures being tested represent statistical analyses of data that are subject to random variations, one must expect that some sites will be incorrectly categorized. One should expect sites with true accident rates that are close to the critical rate, $\mu + k\sigma$ or Λ_T, to be prone to misidentification. In fact, *all* of the false negative errors associated with DS1 for $\delta = 0.99$ are attributed to this phenomenon. There is one site with a true rate only slightly higher than the critical rate suggested by Equation 1. Similarly, in DS3 there is one rate that is slightly higher than the critical rate for $\delta = 0.90$. This particular site accounts for nearly 60 percent of the C2, B1, and B2 false negative errors and for nearly 30 percent of the C1 false negative errors. This phenomenon, which is largely unavoidable, accounts for approximately one-half of all misidentifications. Several other phenomena cause false negative and false positive identifications among locations that do not have this characteristic. These phenomena, which might not be expected, are discussed next.

Many of the false negatives produced by C1 can be directly attributed to the dependence of the C1 critical rates (defined by Equation 4) on the sample mean and variance of the simulated data. A high sample mean and/or a high sample variance yields a high critical value that must be exceeded before C1 flags a site as hazardous. When these sample statistics are high, the generated accident rate at a given location must be high enough to exceed the critical rate. Such an occurrence will naturally result in a lower number of sites flagged as hazardous and a correspondingly higher number of false negative identifications. Additionally, cases were observed in which a single site having the same observed accident rate in two different repetitions of the experiment was flagged for only one of the repetitions, because of differences in the sample statistics.

The false positive identifications are much more dramatic for C2, B1, and B2 than for C1, as indicated by Tables 3 and 6. This appears to result from a sensitivity of these criteria to large variations in the traffic volume at the locations involved, as alluded to in the discussion by Morris (*2*). Recall that in the Bayesian procedure, the parameters associated with the gamma distributions from which the desired probabilities are computed are updated using the number of accidents observed at the site and the traffic volume at the site [see Higle and Witkowski (*2*)]. In general, a low traffic volume will result in a distribution with a high variance, a distribution that is fairly "spread out." For a site with a low traffic volume, the computed probabilities tend to be lower than for a site with a high traffic volume, whose accident rate distribution has a lower variance and is more "peaked." Thus, when using B1 and B2, a site with a low rate and a high volume will be sensitive to the observation of a "higher than expected" number of accidents. Such an occurrence leads to a false positive identification. Most of the false positive identifications associated with B1, B2, and C2 are due to this sensitivity to the traffic volumes. Because traffic volumes tend to be high, relative to the number of accidents, C2 and the Bayesian criteria used in the first phase of the experiment, indicated by Equations 6 and 7, can be expected to be plagued by a high number of false positive identifications.

Although C2, B1, and B2 tend to perform well in terms of the number of false negative identifications, Tables 2 and 5 indicate that they yield the largest number of false negative identifications for preliminary data set DS1. This increase over the remaining preliminary data sets appears to be directly attributed to a single site that is truly hazardous for $\delta = 0.95$ and, consequently, for $\delta = 0.90$ as well. This particular site has a low volume, and the updated distribution used in the Bayesian procedure has a correspondingly high variance. As a result it is prone to false negative identification, particularly when the observed accident rate is lower than the true accident rate.

The second phase of the experiment allows for the comparison of two variations of the Bayesian technique presented elsewhere (*2*). With B1T, a single "critical value" is applied to all sites, whereas with B2T, the critical value varies among the sites as a function of the traffic volume at the site. Based on Table 4, the difference between these two variations is dramatic. B1T is essentially the same as the procedures B1 and B2 and thus exhibits the previously discussed sensitivity to the traffic volume, resulting in a number of false positive identifications. With B2T, a large traffic volume results in a correspondingly large value that the computed probability must exceed to be flagged as hazardous. In addition, these values are generally higher than the value used in B1T, and it follows that fewer sites are flagged by B2T than by B1T. The dramatic reduction in the number of false positive identifications follows. As might be expected, this reduction is accompanied by an increase in the number of false negative identifications made by B2T. With the exception of preliminary data set DS1 (See Tables 4 and 5), however, B2T still exhibits a tendency to identify the truly hazardous locations correctly. As with C2, B1, and B2, B2T is plagued by the truly hazardous site in DS1 that is subject to low traffic volumes. This site still receives false negative identifications when the observed accident rate is low.

CONCLUSIONS

In evaluating the performance of the various criteria, one must weigh the relative severity of false negative and false positive errors. A false negative error is likely to result in a failure to improve a truly hazardous location, and may lead to various forms of catastrophic loss. False positive errors may or may not result in the unnecessary improvement of a location that is not truly hazardous, depending on the judgment of the safety analyst and budgetary constraints. Thus, false negative errors are considered far more serious than false positive errors.

Because all techniques tested within the confines of this experiment behave consistently across all data sets, it does not appear that the underlying characteristics of the set of true accident rates influence the performance of a technique. Thus, these techniques can be expected to perform in a manner similar to that observed within this experiment, independent of regional data characteristics that might exist for a given jurisdiction. In reviewing cases in which the various techniques tested yield incorrect identifications (either false negatives or false positives), a number of trends become clear. Many of the errors are associated with locations whose true accident rates are close to the critical rates used to define the set of sites that are truly hazardous. This phenomenon, which accounts for a large fraction of the errors, is observed among all techniques tested; it is to be expected and is probably unavoidable.

C1, the classically based statistical technique, flags a smaller number of sites and consequently yields a greater number of false negative identifications and larger magnitudes of false negative error than the other techniques. Surprisingly, many of the false negative identifications associated with C1 result from its apparent sensitivity to the sample mean and standard deviation of the observed accident rates. It is disconcerting to note that even when two sets of data yield the same observed accident rate at a given location, differing sample statistics can result in differing identifications. This sensitivity, which is not observed among the other techniques, casts doubt on the reliability of C1 as an appropriate technique for the identification of hazardous locations.

The Bayesian techniques B1 and B2 and the classically based rate-quality technique C2 perform in a similar fashion. Each yields low numbers of false negative identifications and correspondingly low false negative errors. This comes at the expense of an increase in the number of false positive identifications, which may be the result of a sensitivity to the volume of traffic at the sites. The relatively large number of false positive errors is disconcerting but may not be serious, given that false negative identifications are to be avoided. It appears that B1, B2, and C2 exhibit a sensitivity to the volume of traffic at the sites that can result in a large number of false positive identifications. This may present difficulties in that many of the sites identified as hazardous are often not truly hazardous. Nonetheless, the rate-quality technique, C2, yields results that are virtually indistinguishable from those of the Bayesian techniques and is computationally straightforward.

In an effort to counteract the apparent sensitivity of C2, B1, and B2 to large variations in traffic volume, one can use a variation of the Bayesian method in which the value the computed probability must exceed before a site is identified as hazardous is allowed to vary as a function of the traffic volume at the site. B2T is an example of such a technique. With this technique, a small (but noticeable) increase in the number of false negative identifications is accompanied by a dramatic decrease in the number of false positive identifications. Thus, B2T tends to identify correctly sites that are truly hazardous without additionally identifying as hazardous a large number that are not truly hazardous. On the basis of the results obtained when Equation 2 is used in the identification of truly hazardous locations, it appears that there is some merit in allowing the probability used to flag locations in the Bayesian technique to vary among the sites, as suggested by Equations 8–11. Continued investigation into the potential advantage of this observation is encouraged. In particular, in using the observation leading to Equation 3, it will be interesting to note whether or not such a refinement of the Bayesian technique will yield sufficient improvement over the rate-quality technique to justify the computational burden associated with the technique.

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Publication of this paper sponsored by Committee on Methodology for Evaluating Highway Improvements.

Applications of Accident Prediction Models

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One of the current methods used to overcome "regression-to-mean" problems in safety studies is to employ a combination of accident histories and accident prediction model estimates for estimating future safety. Besides applications in before-and-after studies, there is also a wide range of applications of accident prediction models (e.g., accident surveillance, network simulation and optimization studies); and they are the focus of this paper. The prediction model used in this paper is a three-level prediction procedure being planned for implementation by the California Department of Transportation (CALTRANS). This staged procedure also allows different applications to be made for a wide variety of projects with different input and output requirements. It is shown that the three-level prediction procedure provides a very detailed, comprehensive, and yet flexible framework for safety evaluations of highway intersections. Meanwhile, one can also appreciate from the discussion that great care should be taken in using those estimates for different purposes. It is also apparent that as accident prediction models are becoming more sophisicated and important to safety studies, a close link should be developed between people who are developing those models and those who are applying them in practice, so that maximum benefits can be obtained.

This paper is based on a 2-yr project sponsored by the California Department of Transportation (CALTRANS) and Federal Highway Administration (FHWA) as shown in Figure 1. Some applications of accident prediction models with numerical illustrations are described. A paper covering the development of the injury accident prediction models used in this paper was presented at the 67th Annual Meeting of the Transportation Research Board (*1*) (see Figure 1). A summary of the development of the injury, property-damage-only (PDO), and fatal accident models used is included later in this paper for easy and quick reading. This paper concentrates on applications of accident prediction models, an adjustment procedure for underreporting level of PDO accidents, and highlights of the PDO and fatal accident models that were not discussed in the earlier work (*1*). Further details of the development of the models can be found elsewhere (*1,2*).

In the past, accident studies have concentrated mainly on before-and-after studies, which are aimed at finding the "treatment effect" of improvement measures, and have placed relatively little emphasis on accident prediction models. One of the causes of such a trend may have been the belief that accidents are accidents—they are difficult to predict. Unfortunately, most of the results of before-and-after studies have been found to be too optimistic as a result of the way the entities are selected for improvement studies. Specifically, the entities are selected on the basis of their recent poor accident performances, and it is very likely that those entities will revert to the "mean" even though no treatment is applied to them. One of the current methods used to overcome "regression-to-mean" problems is to use a combination of accident history and group estimate for estimating future safety (*3*). The group estimates here refer to accident prediction model estimates, and they turn out to be essential elements of this new approach. A similar concern can also be found in a paper by Elvik (*4*). Besides before-and-after studies, there is also a wide range of applications of accident prediction models (e.g., accident surveillance, network simulation, and optimization studies), and they are the focus of this paper.

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THE ACCIDENT PREDICTION MODELS USED

The accident prediction models used are derived through an intuitive methodology based on the Traffic Accident Surveillance and Analysis System (TASAS) in California. A fairly new grouping and classifying technique called Classification and Regression Trees (CART) (*5*) was used as a building block for developing accident prediction models. The proposed methodology includes a three-level prediction procedure with a "tree" structure for easy interpretation and applications and an adjustment procedure for different reporting levels of PDO accidents in different police jurisdictions. This staged procedure also allows different applications to be made for a wide variety of projects with different input and output requirements.

Classification of Accidents and Selection of Response Variable

Accidents may be classified by type of collision, turning movement conflicts, severity, or a wide variety of other measures. Classification of accidents for this study was confined to injury, fatal, and PDO-type accidents. Advantages of the severity classification include its easy comprehension and simple translation into monetary terms, required by most economic and feasibility analyses. The disadvantages of this classification scheme include inadequacy in reflecting the actual process of collisions and the concept of traffic conflicts.

The selection of a response variable for injury, PDO, and fatal accidents is a very important step in the process because the response variable largely determines the final model. The

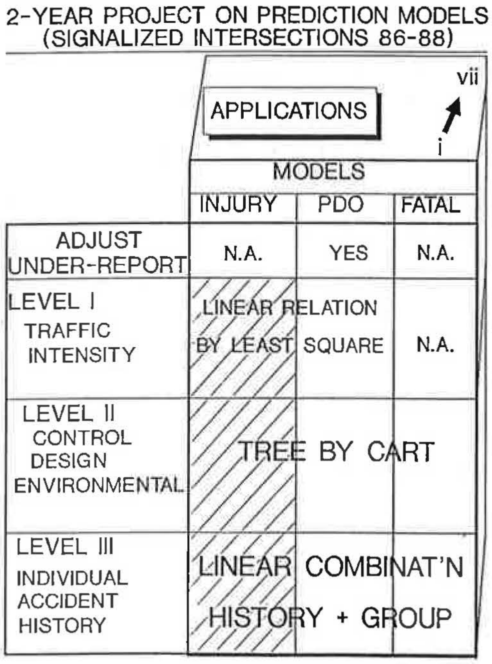

FIGURE 1 Two-year project on accident prediction models.

selection of the preferred model may hinge on the choice of the response variable. The response variable, also known as the dependent variable, is a measure of the performance of the system (e.g., the risk level of an intersection). In this study, injury, PDO, and fatal accidents are studied and addressed, so an immediate task is to find an interesting derivative of injury, PDO, or fatal accidents for comparison and evaluation because common sense indicates that it is not preferable to compare an intersection with one accident in 1 yr with another intersection with one accident in 10 yr. Normalization by time seems to be a logical step. A further normalization by traffic intensity is performed in many accident rate analyses; however, traffic intensity is used as a predictor variable, as shown later in this paper.

Adjustment for Different Reporting Levels

Underreporting of accidents (especially of PDO accidents) is a very common problem. It was found in Smith's study (*6*) that the overall reporting level of PDO accidents was about 38 percent. There was also a difference in underreporting levels in different police jurisdictions. An attempt was made to derive a factor for adjusting the number of reported PDO accidents without the need for collecting additional information from police jurisdictions by interviews or surveys. A proposed procedure is shown in Figure 2. An example of the application of the procedure can be found in the section called "Level II Applications." No attempts have been made to adjust the number of reported injury and fatal accidents because of the constraints of the study and the high reporting levels of injury (about 90 percent) and fatal (about 100 percent) accidents (*6*).

Generation of Base Model—Level I

Instead of putting some forms of the traffic intensity variable in the denominator of the response variable, a base model was built with injury or PDO accidents per year as the response variable and traffic intensity, expressed in millions of vehicles entering the intersection per year from all approaches, as a predictor variable. One of the advantages of this approach is that it allows researchers to see the relationship between the two variables in an undistorted manner, as in a scatter plot. Based on the untransformed information on a graph, one can try different functional forms to model the relationship between the two variables. Estimates of the parameters can be obtained using such techniques as least square, maximum likelihood, and so forth. The base model so obtained is referred to as Level I prediction. A slightly different approach was adopted for fatal accidents and is described briefly in the section headed "Fatal Accidents" because a reasonable relationship cannot be established between the number of fatal accidents and traffic intensity.

Grouping Intersections by CART—Level II

Further information, such as design, control, proportion of cross street traffic, and environmental features of the intersections, is also considered as other major factors affecting the safety of intersections. The importance of these factors can sometimes be reflected in the large variations found in most scatter plots between the number of accidents and traffic intensity. One possible approach is to analyze the residuals of the base model on the basis of other intersection characteristics. In other words, those intersections with similar characteristics that have higher or lower accident records than other intersections in general can be grouped together. The residual is defined as the difference between the observed value and predicted value by the base model. As for the fatal accident model, the number of fatal accidents, but not the residual, can be used as the response variable for grouping by CART. An immediate question arises as to how many groups should be selected to represent high/low accident risk intersections. Extreme solutions include 1 and *n* groups, where *n* is the number of intersections in the data base. With a single group, it is equivalent to the base model and, therefore, is not interesting, because some understanding of the design factors that tend to affect the safety of intersections is desirable. When there are *n* groups, it may indicate that the given characteristics of the intersections cannot be used to produce a grouping that can reflect similar patterns. Also, with *n* groups there is no way to identify those intersections that are "out of line" for purposes of accident surveillance. So engineering judgment and a technique to group intersections with error measures would be very important to the process. The rule of determining whether a node is a terminal node in the CART procedure is quite complex and related to the issue of tree pruning. The process of pruning limbs from a full-grown tree makes CART different from all other tree-structured techniques, such as THAID (*7*). The other techniques keep splitting a node until there is no further improvement. The advantage of the CART approach is that it allows an average split to occur, so that it can set up for some good splits further down the tree. An average split is a split that does not provide

Legend:

I_{fj} : Total number of Injury accidents that occurred in jurisdiction j under 'full' reporting condition.

I_{rj} : Total number of Injury accidents that are reported in jurisdiction j.

PDO_{rj} : Total number of reported PDO accidents in jurisdiction j.

PDO_{fj} : Total number of PDO accidents that occurred in jurisdiction j under 'full' reporting condition.

PDO_{ri} : Number of reported PDO accidents at intersection i per year.

PDO_{fi} : Number of PDO accidents estimated at intersection i per year under 'full' reporting condition.

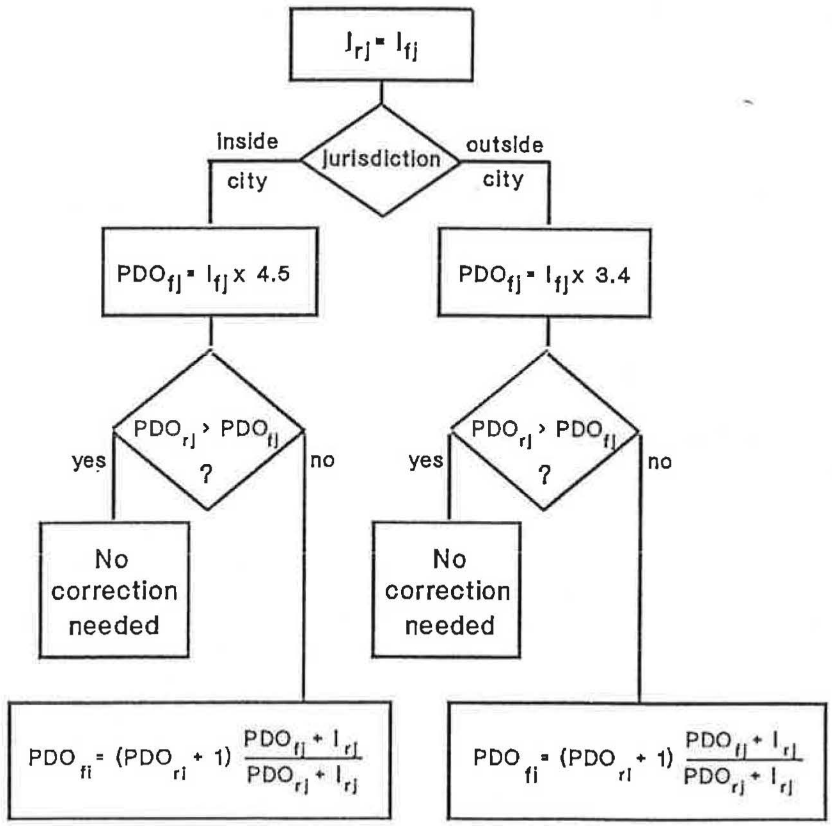

FIGURE 2 Proposed adjustment procedure for PDO accidents.

a large improvement in prediction error measures. The CART program has demonstrated potential in many medical and military fields. At the University of San Diego Medical Center, CART is used to assist doctors in developing the diagnosis and prognosis of heart attack patients. In the military field, it is used to classify ship types (e.g., oil tankers versus warships) from radar range profiles.

The CART program is used to analyze the residuals of the base model of injury and PDO accidents and to group intersections with similar accident patterns. The refinement of estimates by grouping intersections based on other intersection characteristics is referred to as Level II prediction. In the case of fatal accidents, the response variable would be the number of fatal accidents per year because, unlike injury or PDO accidents, a base model could not be established for fatal accidents. The predictor variables used in this level of analysis of fatal accidents also include main and side street ADTs as they have not been used in Level I analysis. The prediction trees obtained are shown in Figures 3, 4, and 5 for injury, PDO, and fatal accidents, respectively. Details of the development of the trees can be found elsewhere (*2*). However, applications of these models or trees with numerical illustrations can be found later in this paper.

Another unique feature of CART is the concept of prediction errors. For example, in regression context, one would usually view the coefficient of determination (R^2) as a yardstick of prediction accuracy. One obvious disadvantage of this approach is that one could artificially increase this value simply by increasing the number of predictor variables or parameters in a model; the same data set is used to estimate model parameters and the same data set is used to calculate error measures. Although there are many ad hoc solutions to mitigate this problem, it is obvious that a basic approach is to adopt a concept of prediction accuracy by independent samples, such as test set or cross-validation techniques. Independent data sets are used to estimate model parameters and to calculate prediction errors in both of these methods. An example of a cross-validated relative prediction error ($r(d)$) of 0.90 was found in Figure 3. A relative prediction error of 0.90 implies that CART was able to reduce the prediction error further by about 10 percent. It may look like a marginal improvement; however, remember that it is a "honest" esti-

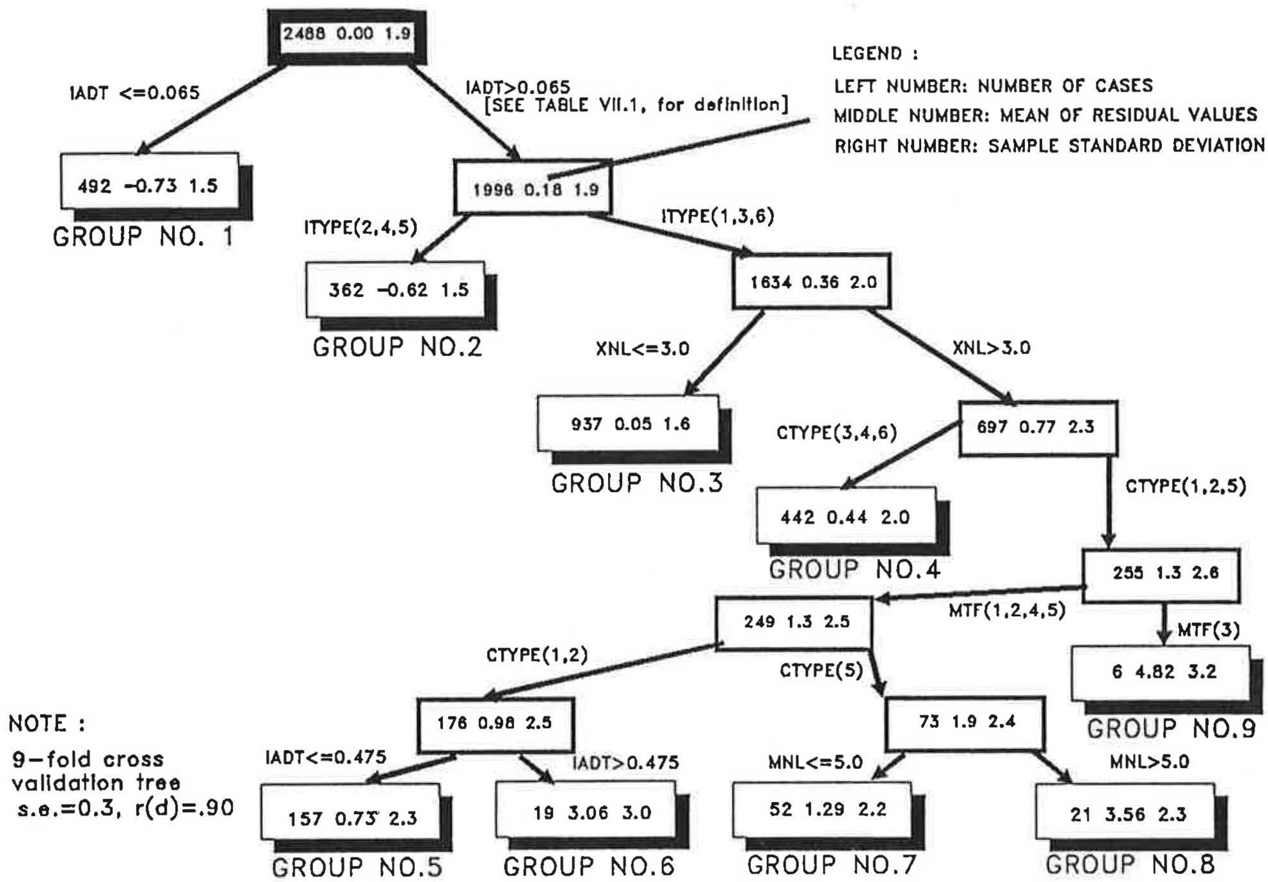

FIGURE 3 Regression tree for injury accidents by CART.

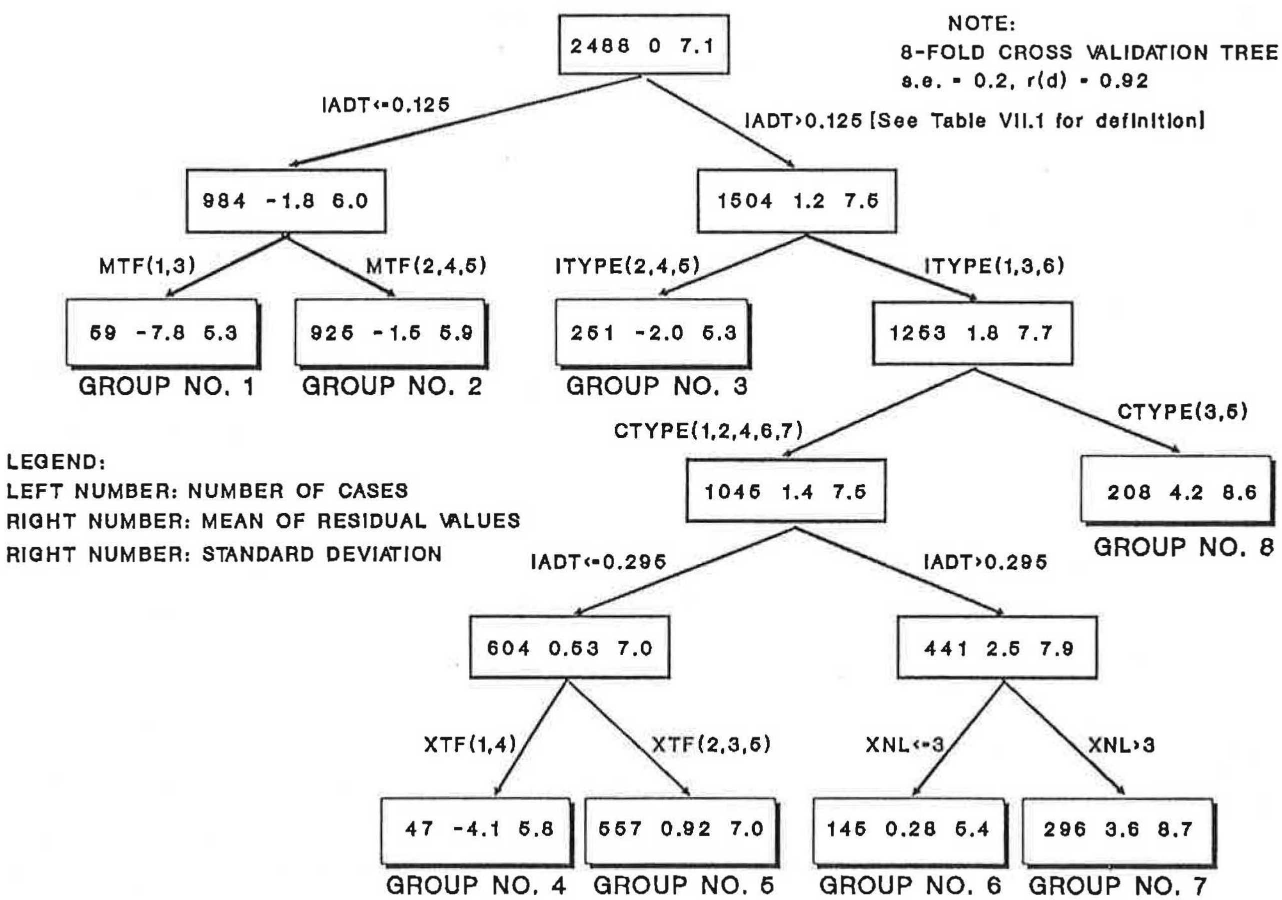

FIGURE 4 Regression tree for PDO accidents by CART.

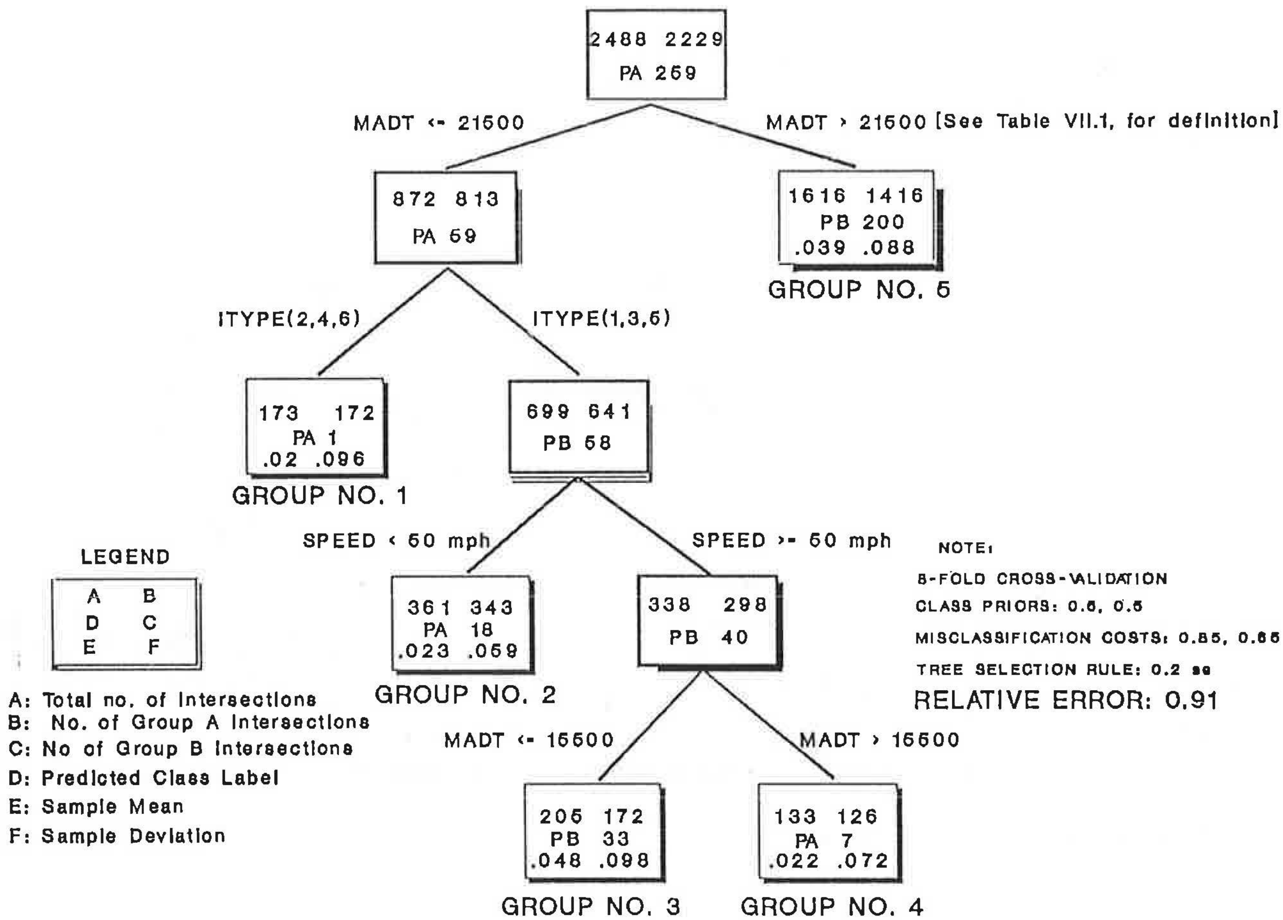

FIGURE 5 Classification tree for fatal accidents by CART.

mate by independent samples. For details of the interpretation of other results, see work by Lau and May (*2*).

Adjustment by Accident History—Level III

The preceding discussions refer to estimates of accident prediction for groups of intersections. In other words, all intersections within a certain group will have an equal estimate. It can be argued that the grouping made was based only on information that was available in the list of predictor variables and that they may not contain all of the factors that affect accident occurrences. As a result, the accident history of individual intersections becomes a very valuable source of information reflecting the safety level of individual intersections. The idea of a linear combination of group estimate and individual accident history, as proposed by Hauer et al. (*3*), is referred to as Level III in this study; and its applications in evaluating the benefits of safety improvements are discussed in the section on Level III applications and in Figure 6. As a whole, it is believed that this staged procedure (Levels I, II, and III) is more flexible than some other existing methods in that it allows users to have different input requirements for a wide variety of projects while it gives them an opportunity to appreciate the evolvement of their estimates.

TYPES OF APPLICATION OF ACCIDENT PREDICTION MODELS

Applications of accident prediction models can be grouped into the following categories:

1. Large-scale regional transportation planning studies—Level I;
2. Estimate of safety performance of new intersections—Level II;
3. Estimate of safety performance of redesigned intersections—Level II;
4. Network simulation and optimization studies—Level I;
5. Accident surveillance—Level II;
6. Estimate of safety of an existing intersection with accident history—Level III; and
7. Before-and-after studies—Level III.

Although the sections that follow are structured according to Levels I, II, and III, as described earlier, one can see from Figure 7 that this structure also falls into two large subgroups. The first group concerns new or modified intersections, and the second group concerns existing intersections. Before the discussion on applications, there is a numerical illustration of the mechanics of predicting injury, PDO, and fatal accidents.

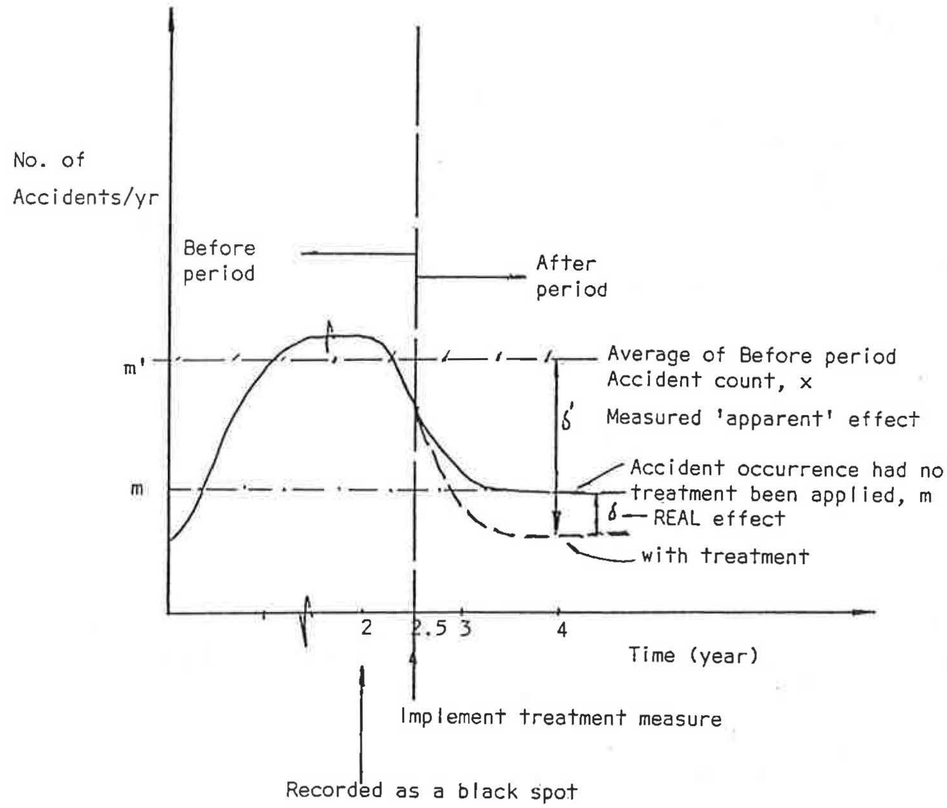

FIGURE 6 Random fluctuation of accidents.

Numerical Illustration by Sample Intersection

The sample intersection has mainline and cross street ADTs of 49,000 and 10,000, respectively. It is a four-legged intersection with two lanes on each main and cross street approach. It has a multiphase, pretimed signal controller with left turns permitted. A sketch of this intersection and other relevant information is shown in Figure 8. A summary of the predictions made by the models and accident experience from 1979 through 1985 at this intersection is shown in the following table. Detailed calculations for injury, PDO, and fatal accidents can be found elsewhere (*2*, Tables VII.2, VIII.4, and IX.2, respectively). A brief rundown can also be found in the next section.

	Predictions			
Level	*I*	*II*	*III*	*Observed Values (1979–1985)*
Injury	4.26[a]	4.99	5.74	5.86
PDO	15.68	16.60	17.94	17.97[b]
Fatal	0.018	0.057	0.141	0.29

[a]Unit in number of accidents/year.
[b]Adjusted value (reported = 5.56).

ILLUSTRATIONS OF APPLICATIONS OF ACCIDENT PREDICTION MODELS

The illustrations, in three groups, are described in the sections that follow.

Level I Applications

For this level of analysis, only the traffic intensity, expressed in millions of vehicles entering an intersection from all approaches (MVYR), is required for injury and PDO accident models. As expected, the results provide only a crude estimate of the safety of intersections. As for fatal accidents, a bedrock value or constant is used in this level of analysis, as described in the section headed "Fatal Accidents."

Large-Scale Regional Transportation Planning Studies

There are many cases in regional transportation studies in which only information on traffic intensity is available, but crude estimates of the safety of proposed strategies are also required for overall assessments and economical evaluations. For example, in large-scale regional transportation planning studies, in addition to the conventional system measures, such as speed, vehicle-miles of travel, and so forth, such safety measures as number of injury accidents, PDO accidents, and fatal accidents can provide valuable information for cost-effectiveness evaluations.

Injury Accidents The following equation, which was derived in earlier work (*1*) for estimating the forecasted number of injury accidents per year (FIACCYR) at an intersection with

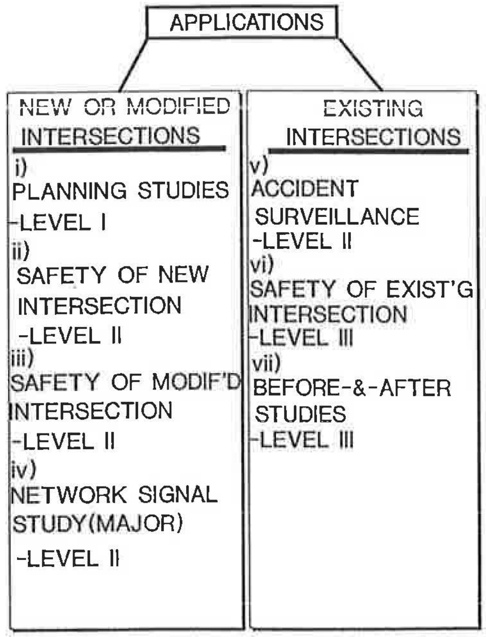

FIGURE 7 Types of application of accident prediction models.

the number of vehicles entering the intersection from all approaches (MVYR), could be used:

$$FIACCYR = 0.61856 + 0.16911 * MVYR$$

To illustrate, the values of main and side street ADTs of an intersection are 49000 and 10000, respectively, making 21.53 million vehicles (MVYR) entering the intersection (=(49000 + 10000) * 365/1000000). When 21.53 is put into the preceding equation, one finds that FIACCYR is about 4.26 forecasted injury accidents per year. So without further information, 4.26 could be used as the expected number of injury accidents per year at this new intersection for large-scale transportation planning studies.

PDO Accidents Because of different reporting levels of PDO accidents in different jurisdictions, the number of reported PDO accidents must be adjusted, as described earlier, to find the true number of PDO accidents per year. The following equation, from an earlier work (*2*), for PDO accidents has been constructed by the adjusted number of PDO accidents, so the forecast number of PDO accidents per year (FPDOYR) represents adjusted values:

<u>Intersection Characteristics</u>:

MADT=49000 veh/day (2-way)
XADT=10000
ITYPE=1 (four legged).
CTYPE=2 (multiphase pretime signal).
MTF=2 (left turn permitted).
XTF=2 (left turn permitted).
MNL=4 (2 lanes per approach).
XNL=4 (2 lanes per approach).
SPEED=6 (design speed 50-54 mph).

RORU=2 (urban).
IORO=1 (inside city).
PDO_{rj}=656
(total number of reported PDO accidents per year in jurisdiction j).
I_{rj}=651
(total number of injury accidents per year reported in jurisdiction j under 'full' reporting condition.

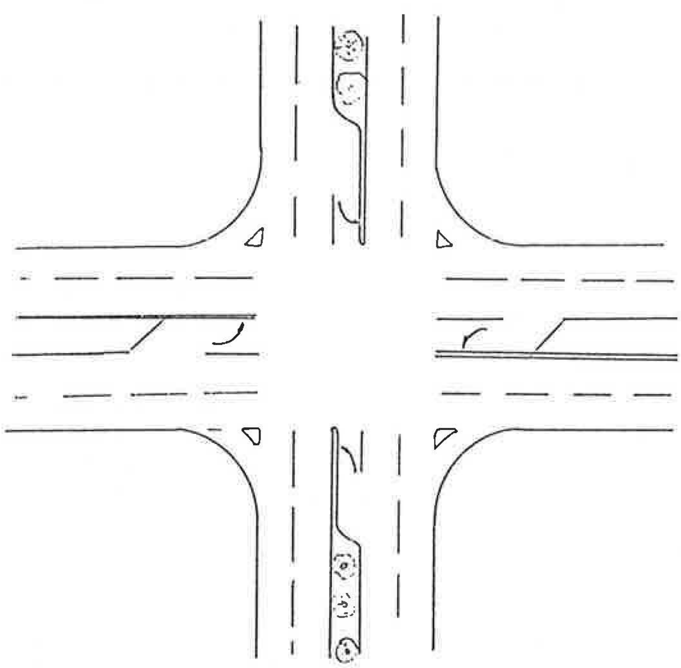

FIGURE 8 Characteristics of sample intersection.

$$FPDOYR = 4.6029 + 0.5142 * MVYR$$

Because MVYR equals 21.53, it is found, on the basis of this equation, that FPDOYR is 15.68. This is the same value found in the preceding table; consequently, this value could be used as the expected number of PDO accidents per year at this new intersection in large-scale transportation planning studies.

Fatal Accidents Because the number of fatal accidents per year does not have a strong relationship with the MVYR, an equation like the preceding formula was not constructed. Instead a concept of system risk was formulated, and a bedrock value of 0.018 fatal accidents per year was used as a Level I estimate to reflect the proportion of fatal accidents that are related to sobriety, drug, or physical impairment (S/D/P) of the people involved in the accident. No such amendment was made to injury and PDO models because the S/D/P problem was found to be applicable only to fatal accidents. Unlike injury and PDO accidents, this Level I estimate should not be used alone because it is just a constant term to be added to the Level II estimate. Of course, the Level II estimate for fatal accidents could be used alone as described in the following sections.

Level II Applications

Detailed information, such as design, control, demand, and environmental features of the intersection, is usually required for this level of analysis. Level II estimates are basically refinements of Level I estimates using such information as design, control, and so on. Applications of Level II estimates can include the following categories:

1. Estimate of safety performance of a new intersection;
2. Estimate of safety performance of a redesigned intersection;
3. Network simulation and optimization studies; and
4. Accident surveillance studies.

Estimate of Safety Performance of New Intersections

New intersections include intersections that have not been built. Hence, accident histories of these intersections are not available. For example, suppose an intersection is planned and designed to have the same characteristics as the sample intersection shown in Figure 8.

Injury Accidents From Level I analysis, the forecast number of injury accidents per year can be calculated, with a result of about 4.26 accidents. On the basis of Level II analysis and the classification tree for injury accidents as shown in Figure 3, one can see that this intersection belongs to Group 5 of the tree, with an expected mean of positive 0.73. This is the mean of the 492 residuals, as defined in the earlier section on grouping intersections with CART, of the 492 intersections with characteristics under Group 5 of the tree in Figure 3. The characteristics of the intersection are shown in Figure 8. As a result, one should add 0.73 injury accident per year to the Level I estimate of 4.26. In other words, with more information on design, control, and so forth, the Level I estimate could now be refined to 4.99 (= 4.26 + 0.73), which is a more accurate estimate of the expected number of injury accidents per year at an intersection with the characteristics under discussion.

PDO Accidents From Level I analysis, one can get an estimate of 15.68 PDO accidents per year. On the basis of Level II analysis and the tree for PDO accidents as shown in Figure 4, one can see that this intersection falls into Group 5 with a sample mean of positive 0.92. Adding 0.92 and 15.68 results in a Level II estimate of 16.60, and this value could be used as the expected number of PDO accidents per year occurring at an intersection with the characteristics under discussion. Because the reported number of accidents at this intersection in TASAS is 5.56, as appeared in the preceding table, one might wish to "undo" the adjusted 16.60 to the likely reported 5.06 for purposes of comparison. The value 5.06 can be obtained by the equations in Figure 2 and shown again here for illustration.

$$PDO_{fj} = I_{fj} * 4.5 = 651 * 4.5 = 2929.5$$

(inside city)

$$\begin{aligned}(PDO_{ri} + 1) &= PDO_{fi}/((PDO_{fi} + I_{rj})/(PDO_{rj} + I_{rj}))\\ &= 16.60/((2929.5 + 651)/(656 + 651))\\ &= 6.06\\ PDO_{ri} &= 6.06 - 1 = 5.06\end{aligned}$$

Fatal Accidents For Level II analysis and the tree as shown in Figure 5, one can see that this intersection falls into Group 5 (predicted class B, PB) of that tree with a sample mean of 0.039. So the Level II estimate is equal to the summation of 0.018 from Level I and 0.039 from Group 5 of the tree, and this becomes 0.057 fatal accident per year. The same interpretation used for injury and PDO accidents can be applied here as well.

Estimate of Safety Performance of Redesigned Intersection

On the basis of the earlier procedure and the trees shown in Figures 3, 4, and 5, one could get some ideas about how an intersection should be redesigned so that the expected number of accidents could be reduced. To put this decision process into proper perspective, let us look at the injury accident tree in Figure 3. It is obvious that if this intersection were changed to a multiphase, fully vehicle actuated signal intersection, there could be a reduction in injury accidents. The new value would be 4.70 (= 4.26 + 0.44) instead of 4.99, as found earlier, because this redesigned intersection would belong to Group 4 of the tree. Of course, this is just a thought exercise because there are other considerations besides safety (e.g., efficiency) that an engineer must take into account when redesigning an intersection. One can also view this as a classic example of a trade-off between safety and efficiency in an engineering design (more phases implies less efficiency versus a lower number of accidents). Furthermore, any changes in other parts of the network that result from such an improvement should also be considered carefully. Furthermore, there is another issue that should be approached very cautiously when redesigning intersections on the basis of any accident prediction models. Nearly all prediction models are built with a view to derive some associations between some design, control, demand, or other factors and some kind of accident experience. They could not establish a cause-and-effect relationship because a cause-and-effect relationship can be established only if the intersections are selected randomly to receive a cause (treatment) and are observed for its effects (subsequent performance). Unfortunately, this kind of experiment can be very expensive and sometimes politically unacceptable because, in this type of experiment, an engineer needs to implement some potentially good measures at intersections chosen at random and not on the basis of their poor accident records. The base line here is that, when redesigning an intersection on the basis of accident prediction models, it is important to realize that one's judgment is being placed on some associational relationships and not on real cause-and-effect relationships. A discussion of some ideas about conducting improvement studies using knowledge-based expert systems can be found elsewhere (*8*).

Network Simulation and Optimization Studies

For most network simulation and optimization studies, there are at least two situations one might want to distinguish as far as a safety estimation is concerned. If the study is concerned with intersections that have not been built, or if major changes are likely to occur to these intersections so that their individual accident histories no longer represent their future safety characteristics, then Level II estimates (similar to the procedure in the preceding section) could be used. The Level II estimates could be calculated at all the intersections to form an overall system safety index (e.g., total number of accidents) that could then be combined with the other system efficiency index (e.g., total delay) for overall system optimization. On the other hand, if the study is aimed at optimization of signal timing intervals and not at changes in phase arrangements and the like, one might want to consider the individual accident histories of the intersections to reflect their unique characteristics. Minor changes in signal timing intervals are not likely to change intersection safety characteristics to a large extent. In this case, then, one might want to go to Level III estimates, which are discussed later.

Accident Surveillance Studies

The purpose of most accident surveillance studies is to provide an early indication or warning to highway agencies of the past performance of their road elements, such as intersections. With this information, the agencies might want to investigate further those intersections that have been identified as "out of line" with other intersections in their group. The criteria for identifying outliers can be very controversial because one can identify outliers by total accidents or by deviations from the group, a controversy that is not the subject of this study. However, one element that is very important to the process, regardless of what criteria may be adopted in the selection process, is estimation of the safety of the group of intersections to which a particular intersection belongs. A Level II estimate can be used as the group estimate for this purpose because it represents the expected number of injury (or PDO or fatal) accidents per year for the group of intersections to which the intersection belongs.

Level III Applications

For this level of analysis, the individual accident history of an intersection is required in addition to the information required in Levels I and II. Level III results represent future safety estimates of existing intersections. These estimates are based on a concept of linear combination of two estimates—individual accident history and group estimate. Hauer and Persaud (*3*) derived an estimate, Z, based on a linear combination of the two results to predict the safety of an individual intersection using the following equation:

$$Z = aE\{m\} + (1 - a)x \tag{1}$$

where

$a = (1 + \mathrm{Var}\{m\}/E\{m\})^{-1}$,
m = expected accident statistics, and
x = accident count.

They also suggested that the sample mean $\bar{x}$ could be used to estimate $E\{m\}$ and sample standard deviations(s) could be used to estimate $\mathrm{Var}\{m\}$ using the following equations:

$$E\{m\} = E\{x\} \tag{2}$$

$$\mathrm{Var}\{m\} = (s^2 - \bar{x}) \tag{3}$$

Further illustration of this approach and some numerical examples can be found in the section on before-and-after studies and in Figure 6. Main applications of this level of analysis can include the following:

1. To estimate the future safety of an existing intersection when no changes to the intersection are made with an accident history, and
2. To allow before-and-after studies to be conducted when the "regression-to-mean" effect cannot be avoided.

Estimate of Future Safety of an Existing Intersection with Accident History

The individual accident history of an intersection can give a picture of the unique characteristics of the intersection that could not be captured by the group or model estimate. The Level III estimate can be used for this purpose, and numerical examples can be found in the sections that follow.

Injury Accidents This particular intersection has a history of 5.86 injury accidents per year, and the group estimate for this type of intersection, as obtained in Level II analysis, is about 4.99 injury accidents per year. Using Equations 1 through 3, one would obtain an estimate of 5.74, which is a linear combination of 4.99 and 5.86 injury accidents per year. For detailed calculation, see Lau and May (*2*, Sections VII.3 and VII.4). As far as the estimation of future safety of this intersection is concerned, it is believed that 5.74 is a better estimate than 4.99 because the group estimate of 4.99 cannot reflect the unique characteristics of this intersection. On the other hand, the accident history of 5.86 is not an optimal estimator because it is likely that the safety of this intersection would somehow revert to the mean value (4.99) in the future. Thus the Level III estimate is usually regarded as the best estimate for this purpose.

PDO Accidents From the earlier table, the Level III estimate for this intersection is 17.94. This value could be used as an estimate of the future safety (PDO accidents) of this intersection under such conditions.

Fatal Accidents Also from the table, the Level III estimate for this intersection is 0.141. By a similar token, the value 0.141 could be used as the estimate of future safety (fatal accidents) for this intersection.

Signal Timing Changes in Network Simulation Studies

Using similar reasoning, one could use the same method (the Level III estimate) to estimate the safety of intersections that are subject only to changes in minor signal timing intervals in network simulation and optimization studies. It is not implied that signal timing settings and phases are not important to the safety of intersections; it means only that the current prediction models could not be used for such purposes.

Before-and-After Studies

The aim of most before-and-after studies is to estimate the treatment effects of some improvement schemes. Because of the selection process and the "regression-to-mean" effect, however, one should look at the following comparison:

> "COMPARING what the safety would have been 'after' had treatment not been applied WITH what safety was 'after' with treatment in place."

The intersections selected for the study are usually those with poor recent accident records; the time of implementing some measure can be as short as 6 months or so. The problem is quite clear in Figure 6 with the horizontal axis representing time in years and the vertical axis representing number of accidents per year. As a result of random fluctuation of accident occurrence, one might find curves like the solid line in Figure 6. For example, at time = 2 yr, let's say the intersection was detected as a black spot intersection and 6 months later an improvement measure is applied to it. The dotted line represents accident occurrences after an improvement measure with a treatment of δ is applied to it at time = 2.5 yr. In a conventional before-and-after study, the measured treatment effect would have been δ' in Figure 6, as opposed to the real treatment effect of δ. To estimate the real treatment δ, one needs to find an estimate of m as shown in the same figure. It is suggested that Level III estimates would be a good candidate. On the other hand, the period between identification and implementation is in the range of 2 to 3 yr; then the problem would not be very serious at all because of the extra long buffer period allowed. This could easily be seen in Figure 6 as well. Specifically, one would like to know the meaning of the following three estimates, why they are different, and how they are related to before-and-after studies:

1. 4.99—Level II,
2. 5.86—accident history; and
3. 5.74—Level III.

The Level III estimate (= 5.74) represents the future safety measure of the intersection if the conditions of the intersection remain unchanged, and the "would have been" safety measure of the intersection in the "after" period if no treatment had been applied. One of the reasons that the accident history (5.86) is not the same as the Level III estimate is because of the random fluctuation of accident occurrences. It also is expected that the future safety measure of this intersection is likely to move closer to that of the expected group characteristics, which is 4.99 in this particular case. The argument for not using the accident history to estimate the future safety of this intersection, even though no changes are anticipated in the future, is because of the regression-to-mean effect found in many accident studies. Another element that could have caused the difference between 5.86 and 4.99 is the unique characteristics of the intersection that could not be captured by the model (Level II). As a compromise measure, a linear combination estimator, such as a Level III estimate, could be used. This is called m in Figure 6. Futhermore, the measure m' as shown in Figure 6 will not represent the safety of the intersection of the "after" period if an improvement measure is not applied. However, another measure of safety such as m (and not m') is exactly what is required for a meaningful before-and-after study because one would like to compare this measure with the after-period count. Furthermore, the difference or ratio of these two quantities represents the real improvement or the treatment effect. Finally, it can be said that the Level III estimate (= 5.74), and not 4.99 or 5.86, is the safety measure that should be used in any before-and-after study as the safety measure for the "after" period had treatment not been applied; then it should be compared with the safety measure with treatment in place. The interpretation for PDO and fatal accidents would be the same, and no numerical illustration is needed for these two models.

It is believed that a Level III prediction estimate should be used when applicable, and it could be quite different from the recent accident history of an intersection. A comparison of the observed values and Level III estimates in Figure 7 would reveal that they are very similar. This similarity is due mainly to the fact that the intersection was chosen at random for illustration purposes. If the intersections had been chosen on the basis of their recent poor accident records, however, as in most before-and-after studies, there could have been a big difference between them. Consequently, one would then appreciate the importance of Level III estimates in improvement studies to avoid an inflated treatment effect.

CONCLUSIONS

One can see that the three-level prediction procedure provides a very detailed, comprehensive, yet flexible framework for safety evaluations of highway segments. Meanwhile, it is also evident from the preceding discussion that great care should be taken in using those estimates for different purposes. It is apparent that, as accident prediction models are becoming more sophisticated and important in safety studies, a close link should be developed between people who are developing those models and those who are applying them in practice, so that maximum benefits can be obtained. Finally, it should be recognized that accident prediction models are only association relationships and do not represent cause-and-effect relationships. That fact might present some problems in improvement studies; however, the association relationships could be used for accident surveillance studies.

ACKNOWLEDGMENTS

The authors acknowledge with thanks the sponsorship of this research by the California Department of Transportation and the Federal Highway Administration. The permission of those agencies to publish this paper is also acknowledged. They wish to thank L. Seamons of CALTRANS for reviewing this paper and for his suggestions during the course of research. The authors also thank Professors Scott and Breiman of the Statistics Department of the University of California, Berkeley, for their valuable suggestions and advice during the course of the study.

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Publication of this paper sponsored by Committee on Traffic Records and Accident Analysis.

A Method for Comparing and Forecasting Annual Traffic Death Totals

FRANK A. HAIGHT

Total traffic fatalities are considered to result from a combination of two factors: safety of travel (per vehicle mile or per vehicle) and exposure to travel (distance traveled or number of vehicles). The method proposed models these factors separately and then combines them to estimate fatalities.

A time series representing the number of traffic deaths (in a given jurisdiction) invariably shows considerable irregularity. When small populations are involved (a city or small state, for example), the fluctuations may be so great as to obscure entirely any long-range trends. With a large population, such as that of the entire United States, it should be possible to overcome this difficulty and search for long-range trends that may be present and that characterize the cost in human life associated with the development of a motorized society. In this paper, a method for such an analysis is proposed, extracting basic developmental trends from short-term influences, such as economic conditions, safety programs, and so forth.

The method is based on the assumption that the long-range trend (shown in Figure 1) actually represents a combination of two distinct, and fundamentally antithetical, trends: safety and exposure. To disaggregate total fatalities in this way is not a novel idea; several authors have observed that total road transportation ("vehicle miles of travel") has in the past increased as safety ("fatalities per vehicle miles of travel") has also increased. In an earlier paper (*1*) the metaphor of two racing horses (travel and safety) was used, sometimes with one ahead and sometimes the other. The idea of competing forces could account for the irregularity in Figure 1 and, in turn, suggests the type of analysis in this paper.

It is important to bear in mind that safety and transportation are not necessarily measured by the parameters just given. These parameters are used in this preliminary investigation mainly because the data are easily accessible and reasonably reliable. It might be better to use "passenger miles of travel" and "injury." However, an analysis of these—and other—more complex variables must be deferred for the present.

Another problem relates to the comparison of fatality trends in different countries. In some jurisdictions, vehicle miles of travel are not compiled or, if they are, the measurements are inaccurate or in series that are too short for present purposes. In such cases the "number of registered vehicles" seems to be the best surrogate available. To facilitate future studies comparing different countries, it is proposed that both "vehicle miles of travel" (vmt) and "number of registered vehicles" (nrv) be used as indicators of transportation quantity, with the corresponding measures of safety measured in fatalities, per vmt or per nrv.

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UNITED STATES 1947–1987: VEHICLE MILES OF TRAVEL

The annual number of traffic deaths (National Safety Council data) is shown in Figure 1. Decomposing the series into two constituent parts—safety and transportation—gives Figure 2 (deaths per vmt) and Figure 3 (total vmt).

The trend in Figure 2 illustrates the change in traffic safety in the United States in the postwar years. In mathematical terms, a simple model would be to assume a theoretical curve called the "negative exponential." This curve is always decreasing but at an ever lower rate, so that the greatest declines are observed in the earliest period. Certainly the "death per vmt" rate seems to have some of these characteristics: the drop between 1947 and 1957 is much greater, for example, than between 1977 and 1987. On the other hand, there has been one period (1960–1967) when the rate was

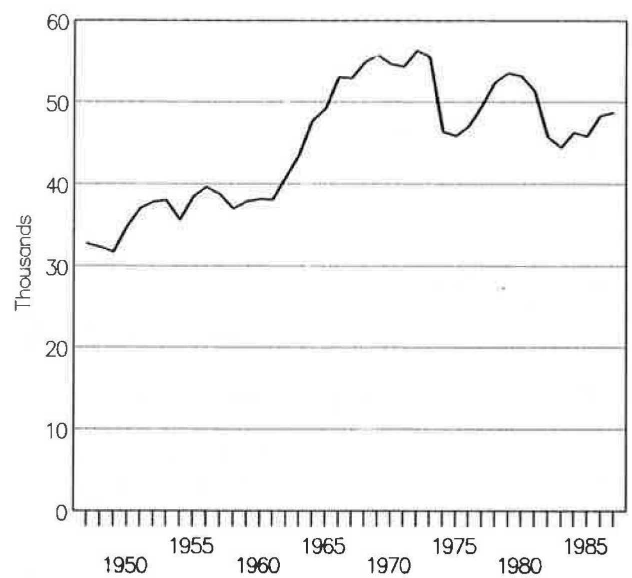


FIGURE 1 Total traffic fatalities, United States: 1947 to 1987.

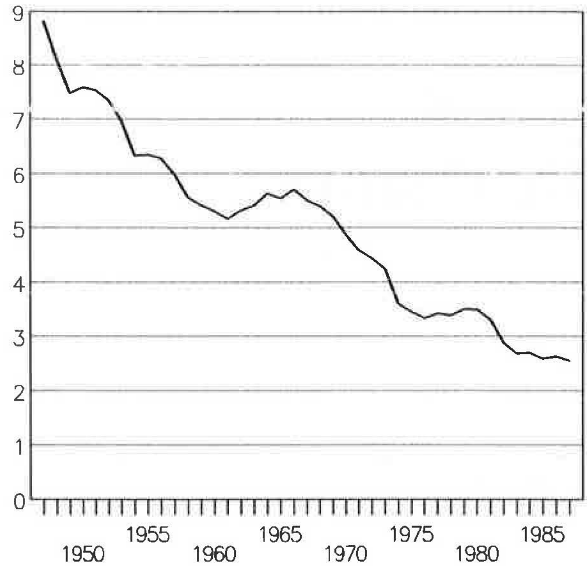


FIGURE 2 Traffic fatality rate per 10^8 vehicle miles of travel, United States: 1947 to 1987.

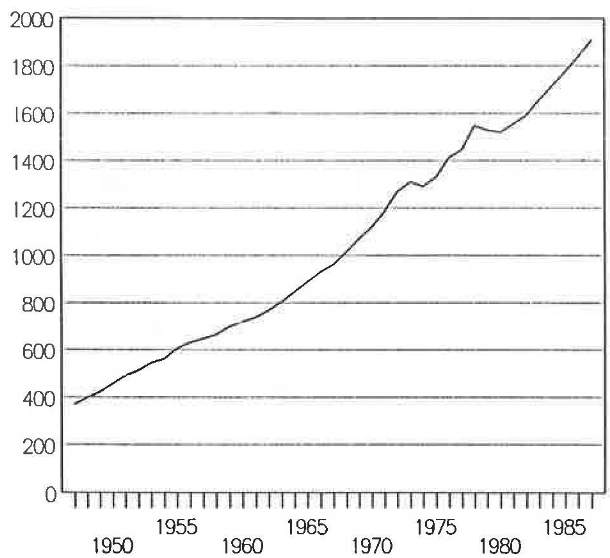


FIGURE 3 Vehicle miles of travel (× 10^9), United States: 1947 to 1987.

actually rising and another (1975–1980) when it was more or less unchanged. These "bumps" appear to be superimposed on the general trend; there may be some evidence that they correspond to periods of increased economic activity (*2*).

If the basic conjecture (negative exponential curve) is correct, then a straight line should be obtained if each data point is replaced by its natural logarithm. Figure 4 shows the result of this transformation and, again with allowance for (economic?) bumps, appears to support the conjecture.

Before proceeding to test the hypothesis of linearity, consider the model for vmt as shown in Figure 3. Certain parts of Figure 3 seem to be remarkably linear in present form, specifically 1947–1967 and perhaps in the 1970s and 1980s.

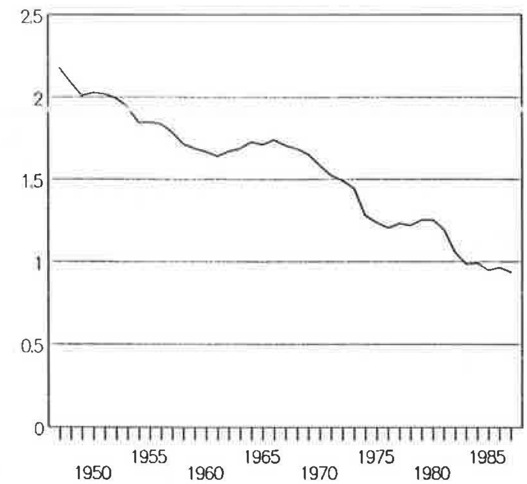


FIGURE 4 Log_e deaths per vehicle miles of travel, United States: 1947 to 1987.

Perhaps the most remarkable aspect of Figure 3 is the indication that the graph, to the extent that it is not entirely linear, is concave upward. This indicates that not only is travel demand increasing year by year but also that the rate of increase itself may be increasing slightly. The other interesting feature of Figure 3 is that both oil panics (in 1974 and in 1979) show up as distinct deviations from the trend.

As a simple and tentative hypothesis, Figure 3 is modeled as a straight line for purposes of the present analysis. No doubt a model based on several broken segments would give better fits but at the cost of additional parameters.

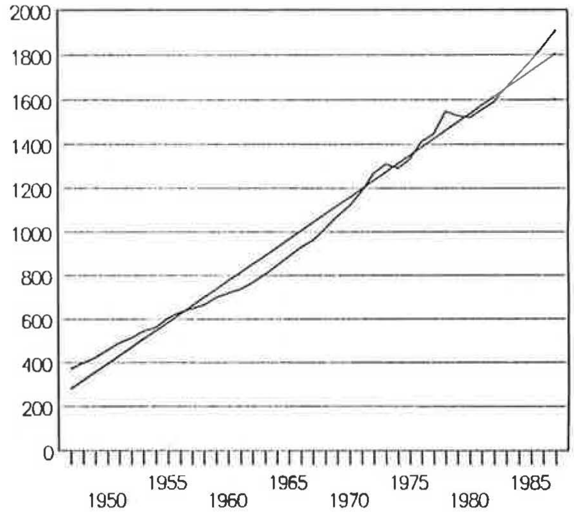
As a test for the acceptability of the hypotheses of linearity in Figures 3 and 4, linear regressions were performed using a program contained in *Quattro: The Professional Spreadsheet*. The results of these linear fittings are shown in Figure 5 (for vehicle miles of travel, from Figure 3) and Figure 6 (for the logarithm of deaths per distance traveled, from Figure 4). Note that the R^2 values indicate an acceptable linear fit for both graphs; this tends to support the initial conjectures. (In fact the R^2 is greater for vmt in Figure 5 than it is in Figure 6.)

The model shown in Figure 6 can now be transferred back to vmt death rates (corresponding to Figure 2) by exponentiating. The resulting fit is shown in Figure 7.

Finally, the models of Figures 5 and 7 can be multiplied to give an estimate of total deaths corresponding to Figure 1; this result is shown in Figure 8.

It is clear that this procedure, although it models the gross trend (which was its purpose), does not replicate the large bumps in Figure 1. These bumps may indeed represent the effects of economic conditions, as several authors have suggested (*2–4*), and deserve to be studied in more detail.

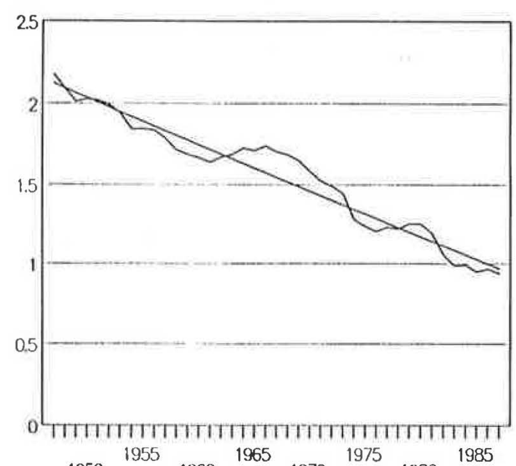
The model—and the data—show the major trend of vehicular mortality with the development of motorization, namely, a sharp rise followed by an apparent declining tendency. It is noteworthy that the model used implies a future eventual decline in fatalities whenever the slope of the line in Figure 6 is negative. This suggests that an important distinction between the road safety future of various countries may be implied by the value of this slope.



REGRESSION OUTPUT:

CONSTANT	-73987.5
STD ERR OF Y EST	55.9442
R SQUARED	0.985596
NO. OF OBSERVATIONS	41
DEGREES OF FREEDOM	39
X COEFFICIENT(S)	38.1446
STD ERR OF COEF.	0.738413

FIGURE 5 Vehicle miles of travel fitted by linear regression, United States: 1947 to 1987.



REGRESSION OUTPUT:

CONSTANT	58.29338
STD ERR OF Y EST	0.082387
R SQUARED	0.947486
NO. OF OBSERVATIONS	41
DEGREES OF FREEDOM	39
X COEFFICIENT(S)	-0.02885
STD ERR OF COEF.	0.001087

FIGURE 6 Log_e deaths per vehicle miles of travel fitted by linear regression, United States: 1947 to 1987.

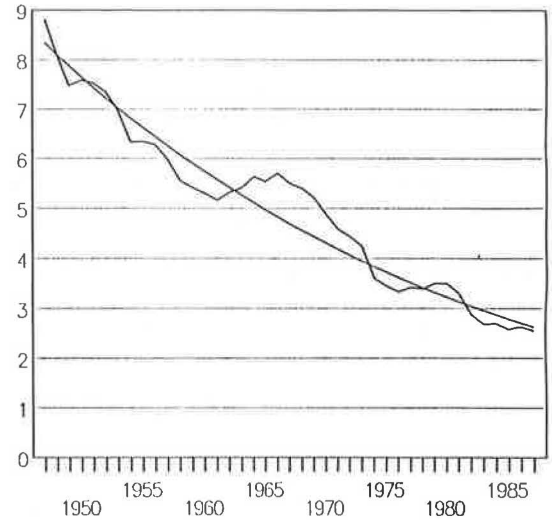


FIGURE 7 Traffic death rate per 10^8 vehicle miles of travel, fitted from Regressions 5 and 6, United States: 1947 to 1987.

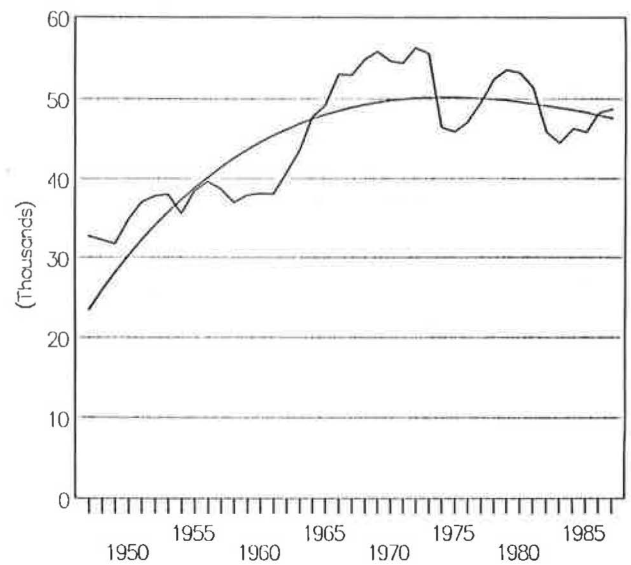


FIGURE 8 Total traffic deaths fitted from Regressions 5 and 6, United States: 1947 to 1987.

UNITED STATES 1947–1987: NUMBER OF VEHICLES

The exercises of the preceding section are now replicated using number of registered vehicles in place of number of vehicle miles of travel. There are reasons for this short detour. First, there is considerable uncertainty in estimating vehicle miles of travel, whether the method is through vehicle counts, fuel consumption, or surveys. Figures given in highly motorized countries for recent years may be fairly accurate; but those of 30 or 40 years ago are probably less so, and even earlier data are sometimes considered little better than an educated guess. If a relationship can be found between the results based on vmt and those based on number of vehicles (which is measured with greater accuracy) we will be in a better position to use vehicles as a surrogate for vehicle miles of travel.

Such knowledge will be helpful not only in going further back in U.S. historical series but also in making international comparisons. Few if any departments of transportation have records on distance traveled that go back as far as those of the U.S. Department of Transportation, and in developing countries—which are of great importance in studying traffic safety—such records often are entirely missing. For this reason, many jurisdictions compute fatality rates per registered vehicle, or per capita. The latter, although useful as an indication of road transportation as a hazard to public health, is unsatisfactory for present purposes in that it takes not even the slightest account of transportation, and so gives a misleading comparison between highly motorized and less motorized societies.

Per vehicle calculations, on the other hand, do take mobility into account to some extent, although they are biased by variations in distance traveled per vehicle, which seems to fall in the range of 10,000–20,000 km per vehicle per year for most countries providing reliable data.

For these reasons, the calculations given in the first section of this paper are now repeated, using "vehicles" rather than "vehicle miles of travel" as the intermediate variable. Display of the various steps that would correspond to Figures 2 through 7 is omitted, and only the curve modeling the total number of deaths (Figure 9) is shown. (The R^2 for number of vehicles was 0.987286 and, for the logarithm of number of deaths per vehicle, was 0.9555337, again indicating quite good fits for the linear assumptions.) In comparison with Figure 8, the method based on vehicles substantially overestimates the true numbers before 1965 but gives a reasonable fit after that year. The conclusion must be that number of registered vehicles is a somewhat less valid indicator of total transportation than is vehicle miles of travel and should be used with caution.

UNITED STATES 1947–1969: VEHICLE MILES OF TRAVEL

The model that forms the basis for this investigation has the advantage of simplicity but a number of flaws that have been mentioned and then glossed over. Before using the results for comparing countries or for forecasting future trends, it is only prudent to test the method by attempting to forecast the present from the past.

For this purpose the foregoing calculations are now repeated using data from the period 1947–1969. The year 1969 was chosen somewhat arbitrarily but partly because total fatalities had not yet peaked (that happened in 1972), so there could be no suggestion that the falling numbers forecast for the remainder of the millennium were a consequence of an already falling tendency rather than of the intrinsic merit of the model.

Figure 10 shows a forecast to 1987 based on 1947–1969 data, as well as the actual figures. The difference between Figures 8 and 10 can be regarded as supportive of the model (the curves are fairly similar) or as evidence against the model (they are not exactly the same).

With a little imagination, Figure 10 may also be used to provide "evidence" of the efficacy of traffic safety measures—or some other long-range trend—in the past 30 yr. Certainly a forecast to 1987 made on the basis of data to 1969 would have predicted more fatalities than were actually observed, except for a 3-yr period in the early 1980s.

EXTRAPOLATION TO 2045

Figure 11 extrapolates Figure 8 (based on vmt) to the year 2045, and Figure 12 extrapolates Figure 9 (based on registered vehicles). The difference between Figures 11 and 12, while noticeable, is remarkably slight considering the important difference in mediating variables. According to one method,

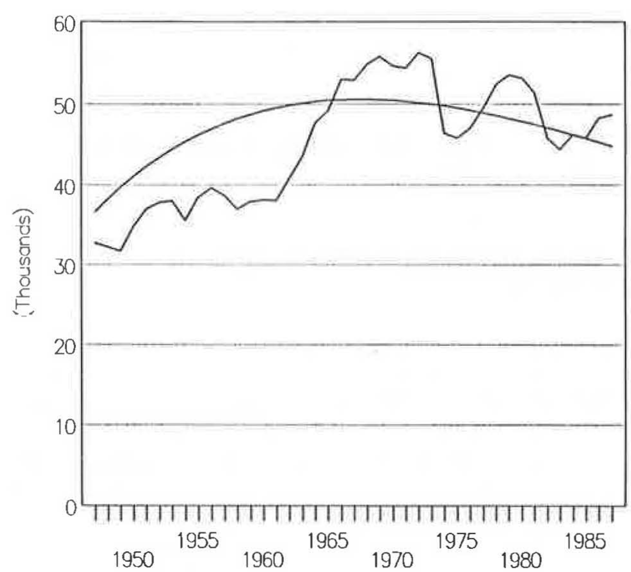


FIGURE 9 Total traffic deaths fitted by using vehicles as intermediate variable, United States: 1947 to 1987.

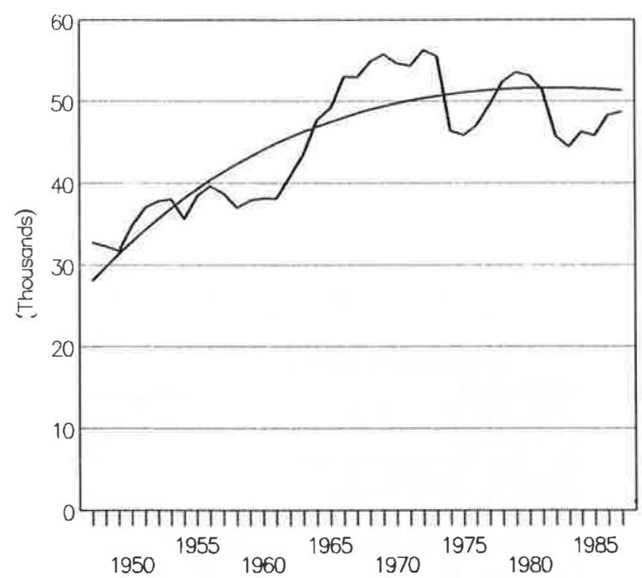


FIGURE 10 Total traffic deaths forecast based on 1947 to 1969 projection (VMT method), United States.

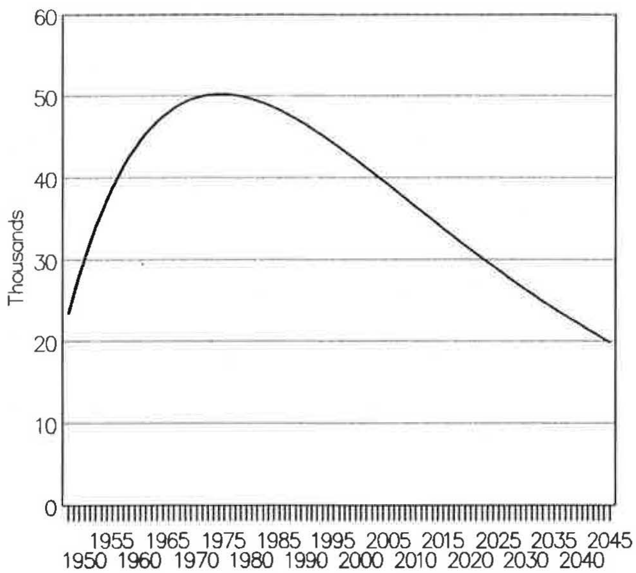


FIGURE 11 Forecast to 2045 using Figure 8 (VMT method, 1947 to 1987 data), United States.

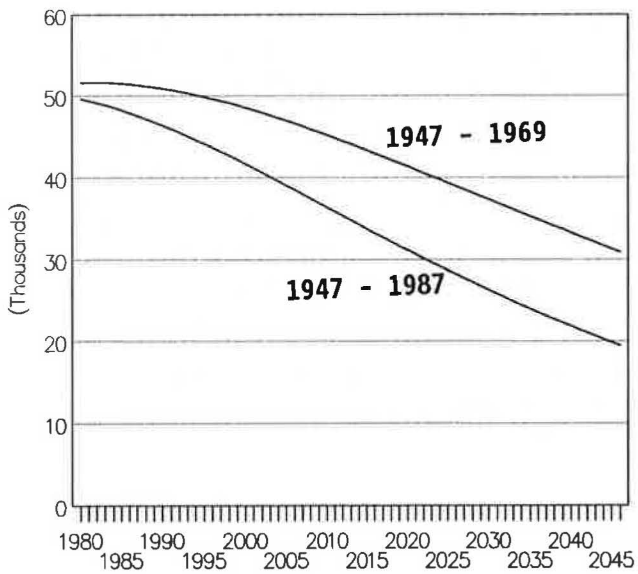


FIGURE 13 Forecast to 2045 based on 1947 to 1987 data, in comparison with forecast to 2045 based on 1947 to 1969 data.

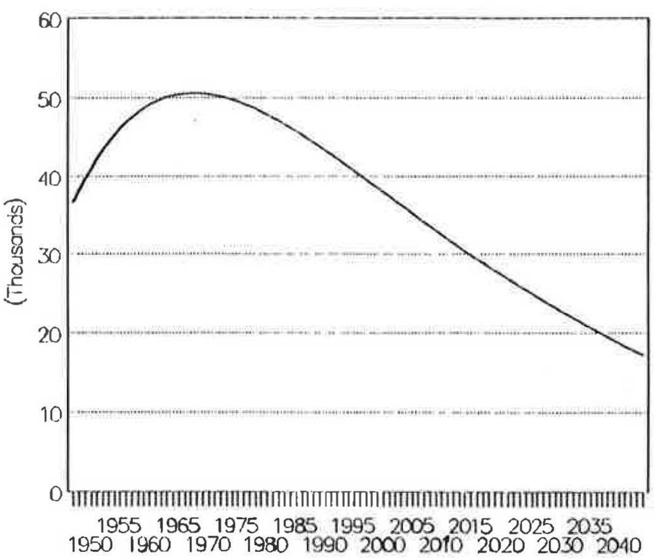


FIGURE 12 Forecast to 2045 using Figure 9 (vehicles, 1947 to 1987 data).

20,000 fatalities are expected in 2045 and, according to the other, 18,000. Using vmt gives a more conservative forecast and using vehicles, a more optimistic one. This does provide some assurance that the second method can be used, within the framework of the various assumptions, nearly as well as the first, opening the door for many international comparisons.

A more interesting comparison is between deaths to 2045 based on 1947–1987 data and those that would have been forecast in 1969, as shown in Figure 10. In Figure 13, the upper line is based on the regressions leading to Figure 10 and the lower, on those leading to Figure 8.

DISCUSSION

It is important to emphasize that the model used in this paper says nothing about the cause of the rise and decline in number of deaths. It must also be pointed out that the extrapolations given depend critically on a continuation of the trends established in 1947–1987 and do not, of course, provide any evidence that such will indeed be the case. There is, in fact, considerable reason to suppose that neither of the trends on which this analysis is based will continue as indicated by Figures 5 and 7, respectively.

First, consider Figure 7. The improvement in safety, from whatever cause, does not obviously have the horizontal axis as asymptote, as the negative exponential model would imply. As we enter the next century, it may become clear that the asymptote is at a higher level, perhaps one death per 100 million vmt. If this—or some other result—proves true, the exponential model would need to be modified to take into account this newly discovered parameter. Such an increase in the minimum irreducible level of risk would, of course, imply that the estimates shown in Figure 10 are too optimistic.

Second, the assumption of linearly increasing travel is open to serious question. The curve that an experienced probabilist would choose would be "s-shaped," beginning at a low level with the development of motorized travel in the period 1900–1920 and tapering off substantially with travel saturation. In the present analysis, the horizontal left tail of this curve is invisible because the data begin in 1947, when the United States was already a highly motorized society. Also, it is unreasonable to expect a continuation of the nearly 4 percent per year increase in travel in a population that is itself growing by about 1 percent. The breaks in Figure 3 may constitute the first signs of travel saturation. This small evidence of reduction in linearly increasing travel would suggest that the forecasts shown in Figures 11 and 12 are pessimistic; that is, they predict more traffic fatalities than would actually occur if and when travel saturation begins to take effect.

Thus, there is reason to believe that the two ingredients of the model, previously described as "antithetical," may, even if modified, continue to exert opposing influences on the future number of traffic fatalities. We must simply wait until well into the 21st century for the story to continue.

In the meanwhile, it will be interesting, and perhaps instructive, to perform the foregoing analyses on data from other countries. Very similar work has been done by Oppe (*5*), and the idea for the "rising-and-then-falling-to-an-asymptote" curve was suggested to the author by Jørgensen (unpublished personal communication, 1985).

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Publication of this paper sponsored by Committee on Traffic Records and Accident Analysis.

HISAM: An Accident Data Base Manager

DAVID L. HARKEY AND RAFAEL RUIZ

The Highway Safety Analysis and Monitoring software was developed under a Federal Highway Administration research contract and is designed to aid local agencies with data base development and accident analysis. The package of programs is designed to enter, retrieve, process, and analyze traffic accident report data, link description data, and node description data. The city of Charlotte, North Carolina, with a population of 350,000, was chosen as the test site for the developed softwware. The average 20,000 accidents per year provided an excellent data base with which the software could be tested. By the end of the test phase the city was able to identify high-accident locations based on accident frequencies, accident rates, or EPDO indexes and rates. This paper describes both the data input and the report output of HISAM, as well as the city's experience with the software.

The extent and sophistication of efforts associated with improving highway safety vary considerably with the resources (i.e., equipment, manpower, budget, computer facilities) available to an agency. Computer facilities are particularly important in the process because most agencies deal with thousands of accidents, extensive roadway networks with varying features, and widely differing traffic conditions. This means a considerable amount of information must be processed as part of highway safety improvement efforts.

The ultimate effectiveness of a safety program depends on the availability of comprehensive and integrated data bases encompassing accident, traffic, and highway data elements. The capability to merge this information is critical to effective safety analysis. For example, the merging of accident data and volume counts permits the ranking of sites on the basis of accident rates. The review of highway features data provides a means to compare similar locations such as right-turn-on-red intersections, high-speed roadways, and narrow bridges. Traffic and highway data are also valuable to the detailed investigation of safety deficiencies at specific locations.

The Highway Safety Analysis and Monitoring (HISAM) software is designed to aid local agencies with data base development and accident analysis. The package of programs is designed to enter, retrieve, process, and analyze traffic accident report data, link data, and node data (*1*, *2*).

The development of the HISAM software is oriented toward the following users:

- City or county engineers who may have little or no formal highway safety background yet require a data management tool to conduct accident analyses, and
- City police officers who are familiar with traffic enforcement but may have little knowledge about highway safety analysis.

Therefore, the package

- Requires minimum field data,
- Involves very little human decision,
- Involves simple input and output,
- Does not require a mainframe computer,
- Does not require the user to have a computer programming background, and
- Is a user-friendly system.

HISAM is designed to run on the IBM PC, PC-XT, PC-AT, and 100 percent IBM-compatible microcomputers. The system must have the following:

- DOS, version 2.0 or higher;
- 640K of main memory;
- A 5.25-in. floppy disk drive;
- A hard-disk drive with a minimum of 10MB;
- A monochrome or color monitor; and
- A printer that is compatible with the computer and operating system just listed.

FUNCTIONAL DESIGN

Some of the features that allow the software to be used by many agencies follow.

- The system is modular in design to allow additional future routines to increase program capabilities,
- Programs are menu driven to facilitate their use,
- Programs allow for the integration of accident and inventory data bases,
- Data entry programs have standardized formatted screens to facilitate the data input process,
- Data entry programs have internal validity checks for alphanumerical characters of all data fields,
- Programs provide error messages and interpretation information to facilitate use of the system, and
- Complete documentation provides the user with instructions to facilitate system use.

It is particularly important to provide linkages between files for the integration of data. For example, the length of a link and the average annual daily traffic volume from the link data base can be combined with the number of accidents on the

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link from the accident data base to determine the accident rate for the link. This feature is currently limited or nonexistent in available microcomputer software.

HISAM is made up of five modules (the main program module, data base module, analysis module, system utilities module, and system information module), as shown in Figure 1. The main module serves as the primary operating system for HISAM and links the other modules together. It is entered each time the system is initiated and provides a means for the user to interact with the various subsystems included in HISAM. This is done through use of the main menu, which provides the user with options, each corresponding to the four system modules. The data base module of HISAM is used to store, view, modify, and remove data from the data bases. Three files are incorporated into the data base module: an accident report file, a link description file, and a node description file.

The analysis module contains several programs to perform a number of analyses and produce reports that are useful in highway safety management. Among the reports generated are high-accident location reports, accident rate reports, and equivalent property damage only (EPDO) reports.

The system utilities module contains programs to merge data base files that may have been entered on separate computers. This module also allows the user to reindex files that may have been damaged as a result of operating errors, such as turning off the computer during data entry.

The system information module of HISAM is accessed to determine the amount of space available on the hard disk and the number of records stored in the HISAM program.

DATA BASE CAPABILITIES

The HISAM data bases are structured to allow for the effective management and monitoring of collected data as well as integration between data files. The three HISAM data bases—accident report, link description, and node description—are menu driven for easy access by the user. The menu for the link description data base is shown in Figure 2. The functional capabilities of each data base (add, view, modify, and remove) allow for the efficient storage and retrieval of data while they minimize the chance of operation errors.

The accident report file is used to maintain the accident record system. Each accident that occurs within the specified system of links and nodes is recorded under a separate report number. Figure 3 shows the HISAM accident data entry screen with the variables that can be entered for each accident.

The format for the link and node description data bases is similar to that shown in Figure 3. Contained in these link and node description files is information describing the physical and operational characteristics of the system. Some of these variables include

- Link and node location codes;
- Street name;
- Length of link;
- Highway type (divided, undivided, etc.);
- Administrative class (state, federal, etc.);
- Number of lanes;
- Speed limit;
- Pavement type;
- Parking;
- Roadway width;
- Curb, median, and shoulder characteristics; and
- Traffic volumes (used for accident rate calculations).

ANALYSIS CAPABILITIES

The analysis module contains programs that generate reports used in highway safety analysis. They are as follows:

- Link Accident Location Report,
- Node Accident Location Report,
- Total Accident Frequency Report,
- Accident Frequency by Accident Type Report,

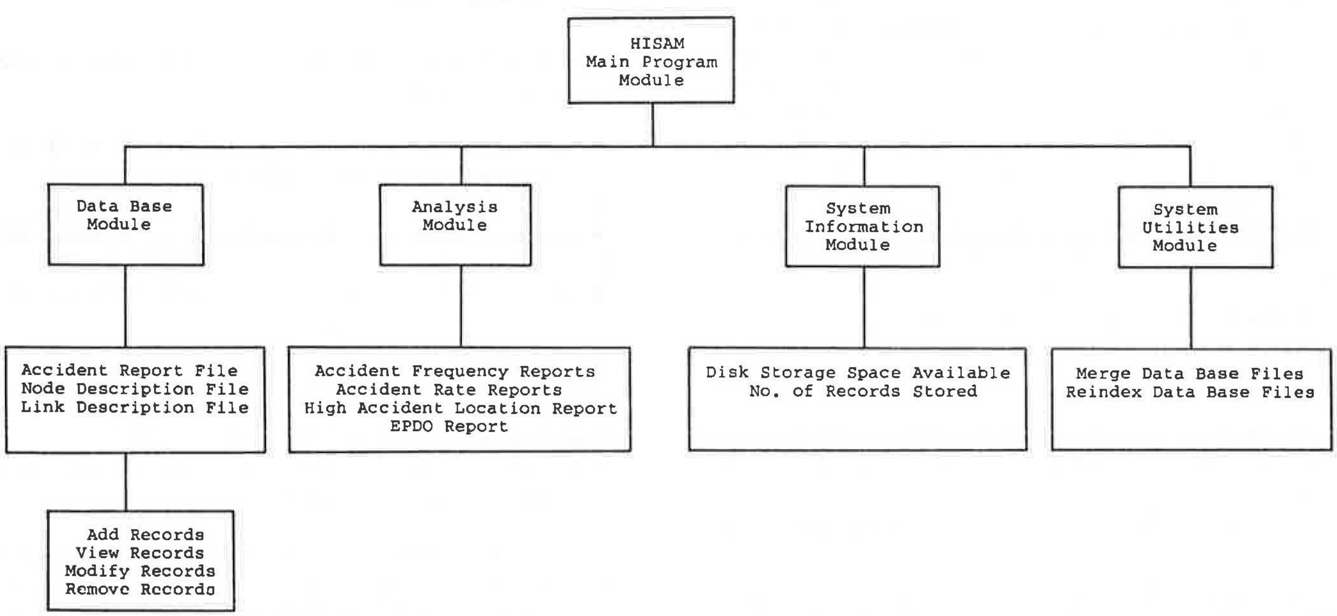

FIGURE 1 HISAM fundamental structure.

```
L I N K   D E S C R I P T I O N   D A T A B A S E
            DATA BASE MAINTENANCE MENU

   F1: Add Link Description Reports to Data Base
   F2: View an Existing Link Description Report
   F3: Modify an Existing Link Description Report
   F4: Remove an Existing Link Description Report
   F5: Link Data Base Information
   F9: Return to Master Menu

               Press Desired Key:
```

FIGURE 2 Link description data base menu.

```
Move Forward: Tab     | Move Backward: Ctrl-E      | Save: Ctrl-Z Aftr Rsp Rq Fs
Clear Field: Ctrl-Y   | Clear to left: BackSpace   | Clear to right: Ctrl-G
=========A C C I D E N T   D A T A   E N T R Y====Report No.: ______
 Accident Location:      Location Code:         Reference Code:
 Accident Date:          Day of Week:           Time of Accident:
 Distance:               Accident Type:         Total Prsns Invl:
 No. Injured:            No. Killed:            Accident Severity:

             Vehicle No. 1         Vehicle No. 2        Vehicle No. 3
           Driver  Passenger     Driver  Passenger    Driver  Passenger

 Inj. Class |
 Belt Use   |

            | Dr   Dr   Veh   Veh/Ped  Drink  Travel  Veh  Driv   Vio
            | Age  Sex  Type  Manvr    Cond   Speed   Dir  Fault  Ind

 Vehicle #1 |
 Vehicle #2 |
 Vehicle #3 |

 Rd.Char. :      Surface Cond:      Light Cond:      Weather Cond:

 Enter a number with leading zeros if any.
```

FIGURE 3 Accident data entry screen.

- Missing Location Codes Report,
- Link Accident Rate Report,
- Node Accident Rate Report,
- Equivalent Property Damage Only (EPDO) Report, and
- Accident Report List.

The Link Accident Location Report is used to determine the distances (in feet) at which accidents occurred along a given highway segment during a specified time period. The Node Accident Location Report is used to determine the distances at which accidents occurred within varying radii from a particular intersection during a specified time period. The Total Accident Frequency Report is used to rank the links and/or nodes in descending order of number of accidents occurring at each location during the specified time period. The Accident Frequency by Accident Type Report ranks accidents in the same manner as the Accident Frequency Report but also lists the accidents by type for up to four user codes. A typical report of this type is shown in Figure 4.

The Missing Location Codes Report is used to determine which links and nodes have not been entered in their respective data bases but have been entered on at least one accident report. This aids the user in maintaining a complete data base at all times.

The Link and Node Accident Rate Reports rank locations in descending order of accident rates. The accident rate for links is calculated as follows:

$$R = \frac{N \times 1{,}000{,}000}{L \times \text{AADT} \times 365 \times n}$$

where

R = accident rate per million-vehicle miles (mvm),
N = number of accidents on the link during the year,
L = length of the link (miles),
AADT = annual average daily traffic on the link, and
n = number of years of accident data being considered.

The calculation for the node accident rate is as follows:

$$R = \frac{N \times 1{,}000{,}000}{\text{AAEDT} \times 365 \times n}$$

where

R = accident rate per million entering vehicles,
N = number of accidents at the node during the year,
AAEDT = total annual average daily entering volume at the node, and
n = number of years or accident data being considered.

A typical Link Accident Rate Report is shown in Figure 5. It is important to note that the accident rates for nodes and links cannot be directly compared because the calculations do not use the same variables; thus the rates do not have the same units.

In addition to the accident rate listing, the reports also list all links or nodes for which no volume is found in the data base. This helps the user to identify which links and nodes need volume counts.

The Equivalent Property Damage Only (EPDO) Report calculates the EPDO index and the EPDO rate for accidents and ranks accident locations (links and nodes) on the basis of the index. A sample report is shown in Figure 6. The EPDO index for a given location is calculated as follows:

$$\text{EPDO index} = F(\text{C1}) + A(\text{C2}) + B(\text{C3}) + C(\text{C4})$$
$$= \text{PDO}$$

where

F = number of fatality accidents,
A = number of Class A accidents
B = number of Class B accidents,
C = number of Class C accidents,
PDO = number of property-damage-only accidents, and
C1, C2, C3, C4 = constants by which the accident totals are multiplied (input by the user).

The EPDO rate is calculated as follows:

$$R = \frac{\text{EPDO index} \times 1{,}000{,}000}{\text{ADT} \times 365 \times n}$$

where

R = EPDO accident rate per million vehicles (links) or per million entering vehicles (nodes),

Accident Frequencies by Acc. Type From 010182 To 010187

Location Code	Frequency	22 Type	08 Type	11 Type	06 Type	Other Type
36D09	10	2	4	2	0	2
47A04	23	2	8	4	3	6
36D19	5	0	0	0	5	0
36D16	26	1	0	15	10	0
36D15	24	10	4	6	0	4

FIGURE 4 Accident frequency by accident type report.

Accident Frequencies and Rates From 010182 To 010187

Link Code	Frequency	AADT	Rate
29A0809	14	2500	4.824
36D0910	10	9000	3.754
28B0315	22	12000	2.890
286CA3370	16	100000	2.870
28D1112	11	20000	2.24
28C0237	9	32110	1.68

FIGURE 5 Link accident rate report.

Accident Equivalent Property Damage Only (EPDO) From 010182 To 010187

Fatality	Type A Injury	Type B Injury	Type C Injury	PDO Co.
9.50	3.50	3.50	3.50	1.00

Location Code	Fatal Accident	A-type Accident	B-type Accident	C-type Accident	PDO Accident	EPDO Index	EPDO Rate
36D09	0	0	3	14	29	88.50	4.82
36D09	0	0	3	14	29	88.50	3.68
47A04	0	0	2	9	20	58.50	6.42
47A04	0	0	2	9	20	58.50	7.89
46B09	0	0	5	8	10	55.50	2.60
46B09	0	0	5	8	10	55.50	3.20

FIGURE 6 Equivalent property damage only report.

ADT = annual average daily traffic (links) or annual average total entering volume (nodes), and
n = number of years of accident data being considered.

The final report, the Accident Report List, lists all accidents at a given link or node along with selected data on each accident (e.g., time and date of accident, severity, distance of the accident from the point of reference).

CHARLOTTE TESTING AND ENHANCEMENTS

Once the software was developed, a thorough test of its capabilities was conducted by the Charlotte Department of Transportation (CDOT). The city of Charlotte currently averages 20,000 accidents per year and, until this test of the HISAM software, manually handled all of the accident data and safety analyses. The system consisted of keeping three years' worth of accident data (approximately 60,000 accident reports) on file by intersection. This limited any analyses to a specific location. To monitor accident data or conduct safety analyses for an artery, thoroughfare section, planning area, or the whole city was impossible. The HISAM software not only allowed the city to create an interactive microcomputer accident data base but also increased city capabilities in accident analyses.

The 1985 accident data base, consisting of 23,522 accidents reported by the Charlotte Police Department, was used for testing the software. A total of 15,306 accidents were entered in the HISAM accident file, requiring a total storage of 1.98 megabytes. In addition, a street network was developed requiring data to be input for 4,800 nodes and 7,500 links.

CDOT was very satisfied with the data entry process and the amount of information that could be stored in the HISAM data base. However, the reports produced by HISAM were limited and actually used only 5 of the 28 variables entered in the accident report. Although these 5 variables (accident frequency, accident type, injury class, total entering volume, and average daily traffic volume) are used to produce the reports most commonly used in accident analysis, it was felt that output could be greatly enhanced by

- Expanding the data analysis and report capabilities using a proprietary data base manager,
- Creating a computerized accident location file interactive with the HISAM link and node files, and
- Generating computerized collision diagrams with a CAD software package using information from the HISAM accident file.

DATA BASE MANAGEMENT

Concerned citizens and communities are often interested in accidents and roadway safety and continuously contact the CDOT with questions about safe speeds, drunk driving, seat belt effectiveness, and more. Answering these questions requires a complete data base and the ability to analyze many variables. The first part, a complete data base, already existed within the HISAM accident file; however, the ability to analyze the data was limited.

The reports produced by HISAM are adequate for most accident analyses, but there are some limitations as a result of the Federal Highway Administration policy that does not allow the use of proprietary software in the development of any computer programs. Therefore, an "off-the-shelf" data base manager could not be incorporated into the HISAM software package by the contractor, Analysis Group, Inc. Thus the ability to search, sort, and analyze any variable or combination of variables was not achievable.

The CDOT, as part of its expansion of the HISAM software, incorporated a data base manager, dBASE-III Plus, with the HISAM accident files. This particular data base management package was chosen because the city already used this package; note, however, that any data base manager would work. To incorporate the two packages, a program was written by the CDOT in Turbo-Pascal (the language in which HISAM was developed) to convert the HISAM accident file to an ASCII text file. dBASE III-Plus was then used to read the ASCII file and convert it to a dBASE file. Because of the size of this file, it was split into two smaller files to speed the data analysis process. One file contained the driver and passenger data (seat belt usage, driver at fault, etc.) on each accident report, and the other contained the rest of the information on the report. As a result of the dBASE programming, detailed analyses using the accident data were obtained; these analyses included the generation of tables and charts describing the 1985 accident figures and trends.

Today, the CDOT intensively monitors on a regular basis its dBASE-generated accident files. Concepts for improvement of defined network sections or planning areas and benefit-cost analyses are periodically developed on the basis of their accident experience. Besides being interactive with community interest, the file has also been used to provide data analyses reports to other local departments, including the police department.

LOCATION DIAGRAM FILE

In the HISAM accident data entry, the location of an accident is defined by a location (link or node) and a reference code (nearest node). The city did not have a network coding system that would meet the HISAM requirements. Thus a new coding system was developed. The new system codes each pair of nodes with an alphanumeric five-digit code and codes each link with an alphanumeric nine-digit code using part of the code from each end-node. To ensure that the node codes were unique, a Lotus-123 file that included the node code and the crossing street names was developed.

A location diagram form was designed, and a manually kept accident location file was generated to aid in the coding process. The location diagram (Figure 7) describes an intersection by its code, the incident link codes, the adjacent intersection codes, and all corresponding street names. The node code is obtained by the concatenation of map area number, the alpha subarea reference, and the intersection number. The link code is obtained by the combination of the two end-node codes.

Although location listings were obtained from the Lotus-123 file sorted either by location codes or by street names, the entry of the location and reference codes in the HISAM accident data screen became slower as the location diagram file grew.

The CDOT designed and wrote a Turbo-Pascal program named NALDD to generate the location diagrams in a microcomputerized file. The screen generated by the program is the same as the location diagram in the designed form.

Initially, this new program required the entry of data already available in three different existing files: the Lotus-123 file described earlier, the HISAM node file that includes the node code and the codes of the incident links, and the HISAM link file that includes the link code, the street name, and the codes of the end-nodes.

To avoid the reentry of available data, the design of the program included the merging of these three files. Once these files were merged, the resulting location diagram file was integrated with the HISAM software. An option was added to the HISAM main menu to update the location diagram

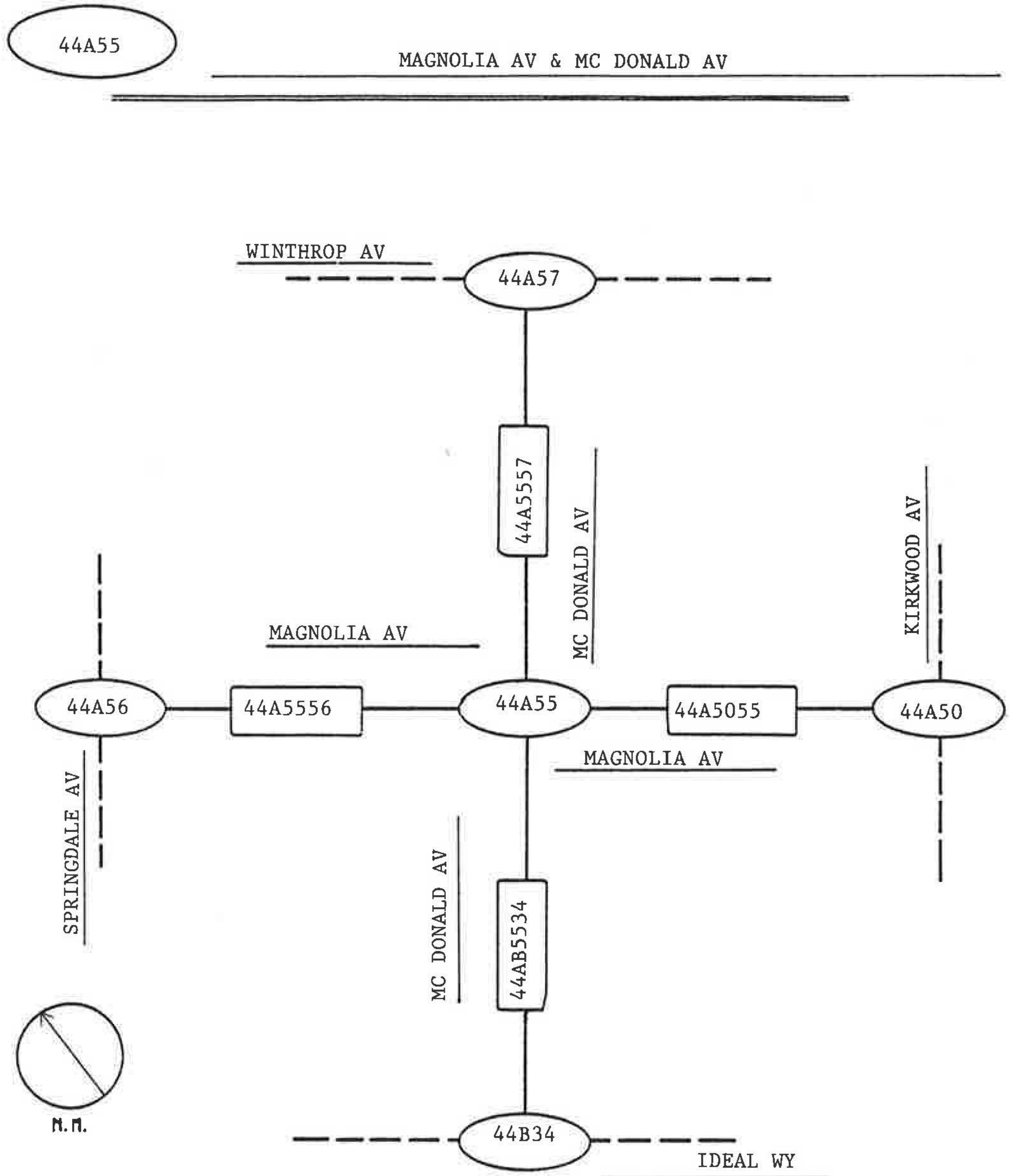

FIGURE 7 Link and node location diagram.

file. From this option, a submenu, including the options to add, modify, view, and delete a location diagram, can be displayed on the monitor system.

The design also incorporated the feature of viewing the location diagram when the "add an accident report" option is selected from the HISAM accident data menu. If the user wants to view the diagram on the monitor screen, this location can be retrieved by the node code or by the names of the crossing streets at the closest intersection. The accident number, location code, and reference codes are displayed on the screen with the location diagram. These data, once entered, are transferred to the HISAM accident data screen where the user can continue and complete the accident data entry.

The creation of the location diagram file and its integration in the HISAM software package have obviously increased the speed of accident data entry and technically improved the system. The location diagram file is also used for planning by other divisions of the CDOT.

COMPUTERIZED COLLISION DIAGRAM

Manually drawn collision diagrams have added a lengthy step to the data analysis processes. The CDOT is currently working to computerize the collision diagram process.

Because the HISAM accident file includes the direction of the vehicles prior to the accident and the vehicle maneuvers, and the location diagram file shows the geographic orientation, an accident collision diagram could be drawn from the available data using a basic CAD software package.

After considering available software packages, the CDOT purchased Prodesign II. A base map form was designed for all collision diagrams and includes a description of the graphic representation for the accident types, travel speed, weather conditions, driver at fault, and the date. All these data can be retrieved from the HISAM accident file and the location diagram files.

With the development of the base map, the CDOT is now working to create a memory bank or template defining the different accident types in all possible directions and maneuvers.

CONCLUSION

Overall, the HISAM software package enables a local municipality to develop and maintain an accident data base and to conduct accident analyses. Detailed information about accidents, links, and nodes can be entered, stored, viewed, and modified. From this information, high-accident locations may be determined based on accident rates, accident frequencies, or EPDO indexes and rates.

The software is complete as packaged and does not require any other software for its operation. It is now available through McTrans Center at the University of Florida. For those cities, counties, and regions interested in conducting more detailed analyses than can be provided by HISAM, the software provides an excellent starting point for an advanced data base and analysis system, as was demonstrated by the city of Charlotte. For more information on these packages, see the references that follow.

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2. D. L. Harkey, K. Colpitts, and H. D. Robertson. *Computer Programs for Safety Analysis: Techshare Report*. FHWA/TS-87-211. FHWA, U.S. Department of Transportation, Washington, D.C., Jan. 1987.

Publication of this paper sponsored by Committee on Traffic Records and Accident Analysis.

An Overview of New Jersey's Accident Processing Costs Based on a National Survey

THOMAS M. BATZ

New Jersey historically has processed all reported accidents within the state. Because of the increased number of accidents and their accompanying increase in processing costs, however, the state decided in summer 1987 to conduct a survey of the states. The purpose of the survey was to determine what time- or labor-saving methods had been implemented or investigated by other states to reduce their accident processing costs. From the survey it was concluded that New Jersey's accident processing unit was one of the most efficient in the country on the basis of the per accident rate. As a result of the large number of accidents, however, the state also had one of the highest total costs. The four most significant cost-saving techniques mentioned by the other states were to (a) Implement a data base file to replace the tape-disk system; thus the user would pick up the cost of computer runs for which the processor now pays; (b) Raise "property damage only" accidents' threshold or eliminate these accidents from processing completely; this could create savings from the present budget up to 60 percent; (c) Reduce the number of items per accident that are processed; the savings would depend on the items deleted; and (d) Have local municipalities or state police input the data from accident forms. Substantial savings could be made in the future; however, there would be start-up and training costs.

New Jersey historically has processed all reported accidents within the state. Escalation of the number of accidents and the cost of processing them, however, has increased substantially over time. As a result, it has become necessary to consider time- and labor-saving methods that could reduce this processing burden. Therefore, in early August, the questionnaire shown in Figure 1 was sent to the persons responsible for accident record processing in the other 49 states to obtain ideas on any such methods. Thirty-five states, including New Jersey, have responded, and the following are general observations about the responses to the specific questions in each of the questionnaire's four sections. This is followed by conclusions and an options section based on these responses. The figures included are also based on these responses and represent the agencies that have primary responsibility for processing their state's accident records.

GENERAL INFORMATION

- In most states accident reports are processed by either the Department of Transportation (15 states), the state police (10), or the Department of Public Safety (8). New Jersey's accidents are processed by the Department of Transportation (Figure 2).
- Of the 35 states responding, 23 used all state money to process their accidents. Of the other 12, the federal share ranged from 4 to 100 percent. New Jersey had a 50 percent share (Figure 3).
- Of the 35 states, 11 did not include accident processing costs on their forms. The 24 that did so had processing costs that ranged from $80,000 to $2,500,000. New Jersey's accident processing costs were $750,000 (Figure 4). No breakdown of these cost data, such as salary, overhead, fringe cost, computer cost, and so on, was requested or received.
- Accident processing staff size ranged from 4 to 121 persons. New Jersey's staff numbered 38 persons (Figure 5).
- Accident processing costs per staff member ranged from $12,400 to $37,500 a year. New Jersey's cost per person was $19,700 per year (Figure 6).
- Of the 35 states, only 2 had not finished processing their 1986 accidents by the end of August 1987. Unfortunately, New Jersey was one of them.
- Twenty-three states noted that they would meet their desired completion date for 1987 accident processing, and 12 noted that they would not. Again, New Jersey was one of the worst in the latter group (Figure 7). For those states that will not meet their expected date, processing completion is desired in either March or April.
- The number of items processed per accident ranges from 45 to 250. New Jersey processed 145 items (Figure 8).
- The cost per processed accident item [total cost/(total accidents × items processed)] ranged from 2 to 17 cents. New Jersey's cost was 2.1 cents per processed item (Figure 9).
- The number of accident report items processed per staff member [(total accidents × items processed)/staff size] ranged from 142,000 to 1,621,000 items. New Jersey processed 932,000 items per staff member (Figure 10).
- Thirty states did not process a narrative for each accident, and three states entered a narrative for some accidents; two states entered a narrative for all accidents. New Jersey did not process a narrative.

SPECIFIC ACCIDENT DATA

- The total number of accidents processed ranged from 12,250 to 674,600. New Jersey processed 244,000 accidents (Figure 11).

Division of Research and Demonstration, New Jersey Department of Transportation, 1035 Parkway Avenue, Trenton 08625.

GENERAL INFORMATION

State of ______________________________

Please list below the agencies that are responsible for any part of the accident record processing procedure, from the handling of hard copy police reports to the final yearly summaries. Also, list the specific function(s) performed by the agency, funding, funding source and staff size.

Agency Name and Address	Processing Functions Performed	Costs	Funding Source(%)	Staff Size
			Federal ___ State ___ Local ___	
			Federal ___ State ___ Local ___	
			Federal ___ State ___ Local ___	
			Federal ___ State ___ Local ___	

What is the last full year for which you have completed your accident processing procedure?________

What is your expected completion date for processing of 1987 acccidents?________

Is this date the desired completion date?_______

If not, what is the desired completion date?_______

How may items on each accident report are coded in your processing procedure?________

Do you code a narrative about the accident?________

SPECIFIC ACCIDENT DATA

Please record below the number of accidents for each category shown. Please use the last full year of processed accidents.

	Fatal	Injury	Property Damage Only	
			Police Reported	Driver Only Reported
Interstate and State Highways				
County Roads				
Local Streets				
Other (explain)				

For the property damage only accidents listed above, what was your state's monetary threshold?_______

Has it changed since then?_______

FIGURE 1 Accident questionnaire.

USER INFORMATION

Please check (X) below those agencies which use the processed accident information. Give a short explanation of how the accident information is used and note any federal, state or local laws or regulations which require this function to be performed.

USERS	USE	LAWS OR REGULATIONS
_____ Traffic Bureau		
_____ Research Bureau		
_____ Planning Bureau		
_____ Design Bureau		
_____ Safety Bureau		
_____ State Police		
_____ County Agencies		
_____ Municipal Agencies		
_____ Other (list)		

PROCESSING PROCEDURE

Please briefly comment on those techniques which you now use or plan to use in the near future to improve the timeliness of the accident processing procedure.

Technique	Presently Use	Planned for Future Use
Optical Scanners		
Automated Field Coding by Police		
Electronic Maps		
Computer Printouts		
Other (please explain) For example, processing less items, increasing PDO monetary threshold, not processing PDO accidents, processing only state road jurisdiction accidents, increase staff, etc.		

Are there any general or specific comments about your accident processing procedure which should be noted?

Name and address of person completing this questionnaire:

Do you want a copy of the results of this questionnaire?_______

FIGURE 1 (*continued*)

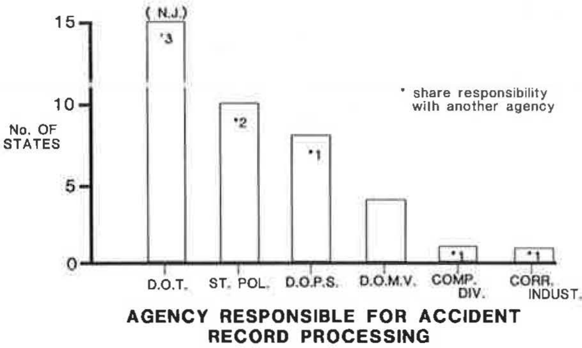

FIGURE 2 Accident record processing responsibility by agency.

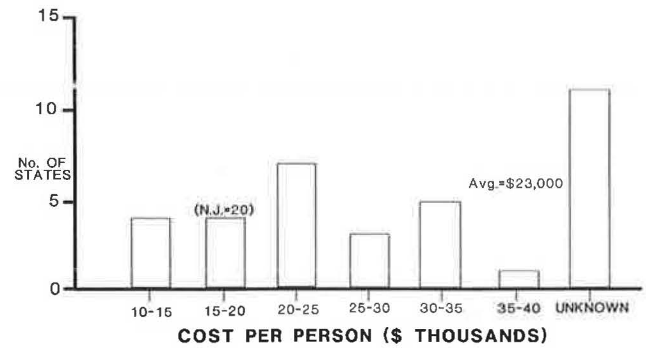

FIGURE 6 Accident processing cost per staff member.

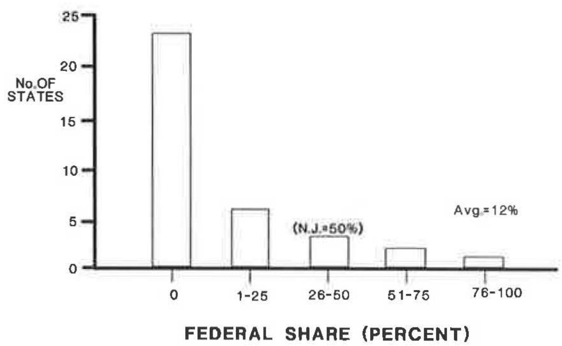

FIGURE 3 Federal share of expenditure for accident record processing.

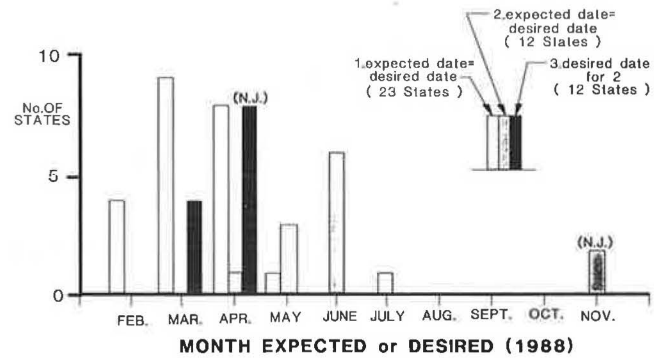

FIGURE 7 Completion date for processing of 1987 accidents.

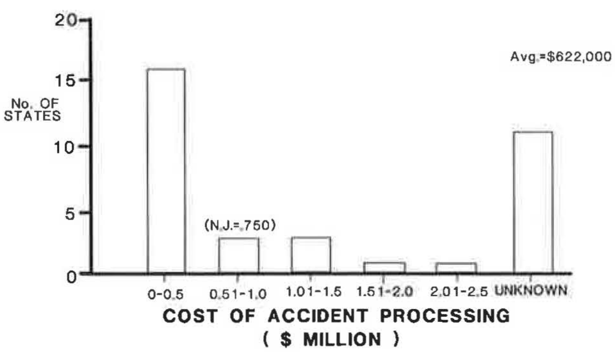

FIGURE 4 Cost of accident record processing by states.

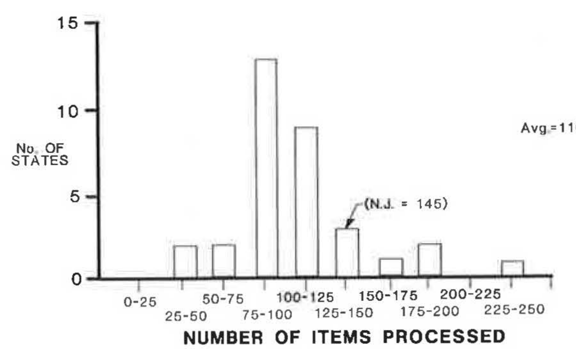

FIGURE 8 Number of items processed per accident.

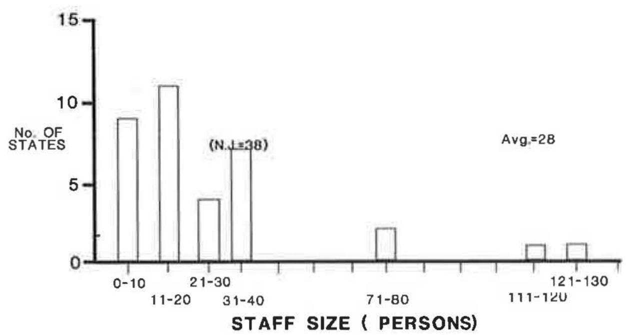

FIGURE 5 Accident record processing staff size.

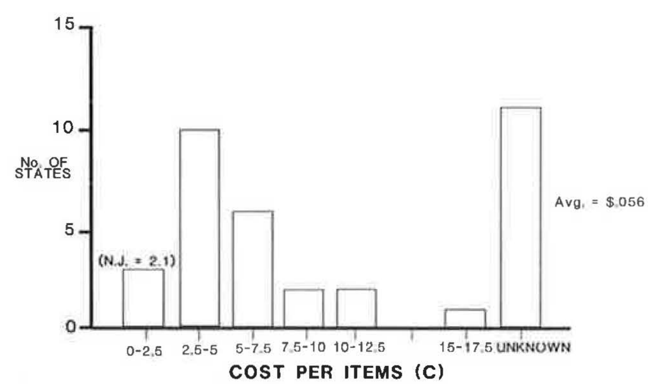

FIGURE 9 Cost per item processed.

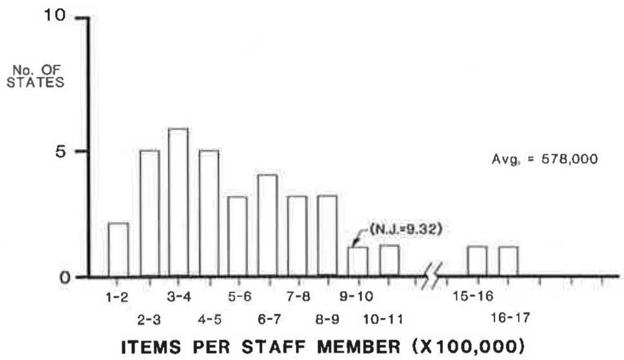

FIGURE 10 **Items processed per staff member.**

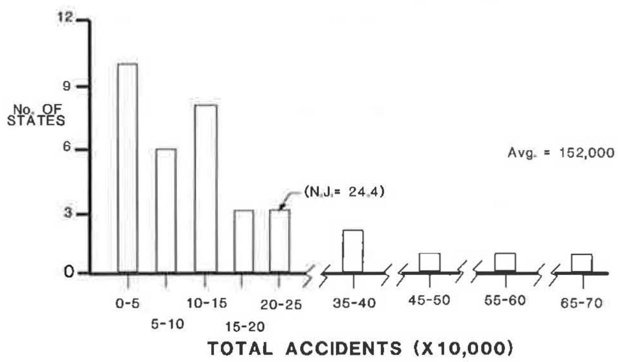

FIGURE 11 **Total accidents processed by states.**

- Processing cost per accident ranged from \$2.30 to \$19.60. New Jersey's cost per accident was \$3.10 (Figure 12).
- Twenty-seven states did not process private property accidents. Of the eight that did, five did not know the percentage of their total made up by private property accidents; these percentages for the remaining three were 1, 11, and 14, respectively. New Jersey did not process private property accidents.
- Twenty-four states did not have or process driver-only reported accidents. Of the 11 that did, 3 did not know the percentage of the total made up by driver only reported accidents; these percentages for the remaining 8 states were 3, 5, 7, 8, 19, 21, 25, and 25, respectively. New Jersey did not process driver only reported accidents.
- The property damage only (PDO) accident threshold ranged from as little as \$150 total accident damage to a nonexistent threshold for one state that did not process property damage accidents at all, no matter what the property damage was. New Jersey's threshold was \$500 for an individual's property (Figures 13a and 13b).
- Six states changed or will change their threshold for PDO accidents. One increased it from \$600 to \$1,000; another from \$250 to \$400; and another from \$150 to \$400. A fourth state was going to drop driver only reported PDO accidents completely, which would cause a 6–8 percent decrease in the accidents processed. The fifth state increased the threshold from \$400 for total accident damage to \$500 for one individual's property. This was predicted to decrease the accidents reported by 9–14 percent. The sixth state increased it from \$300 to \$500. An 8 percent reduction was predicted.

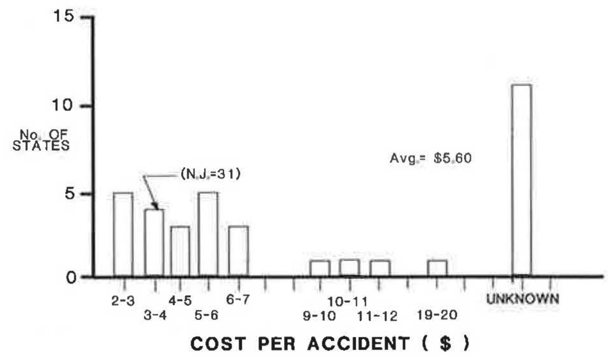

FIGURE 12 **Processing cost per accident.**

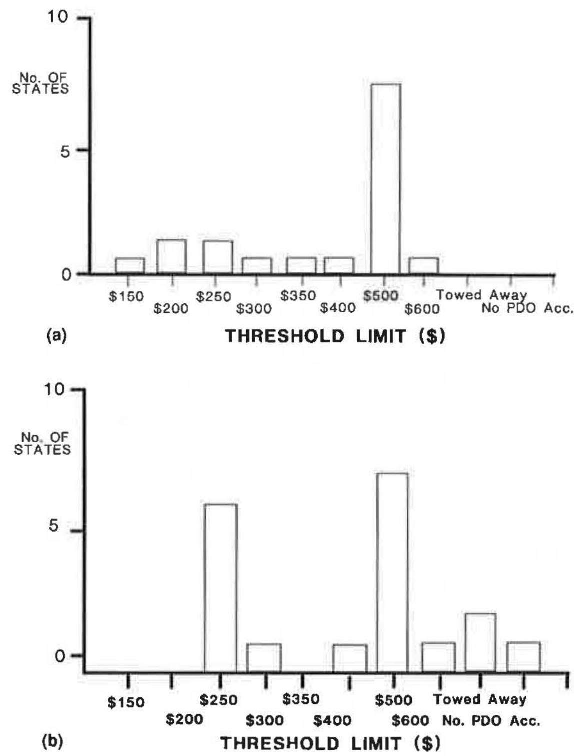

FIGURE 13 **Threshold limits for (a) total property damage only accidents (b) individual property damage only accidents.**

USER INFORMATION

Data on the use of the final processed accidents show many users, for many uses, and a few rules or regulations that required that the data be analyzed or collected (Figures 14 through 16).

PROCESSING PROCEDURE

- All thirty-five states produced computer outputs once the data had been coded and keypunched.
- There were 14 specific techniques mentioned to improve timeliness or reduce the costs of accident processing (Figure 17). The first nine are possibilities to reduce costs that New Jersey has not tried. The next four are techniques to reduce

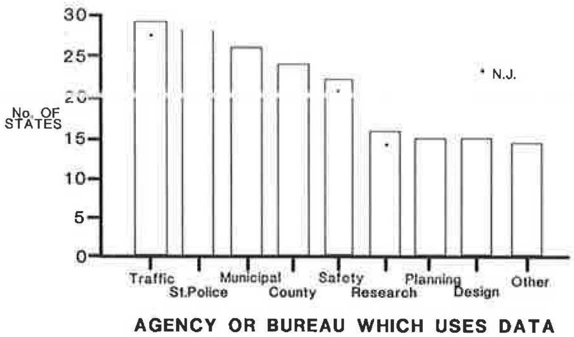

FIGURE 14 Users of processed accident data.

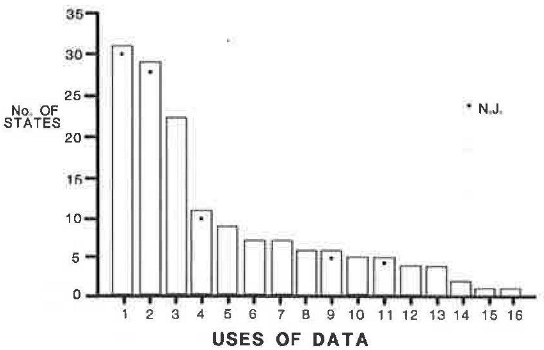

FIGURE 15 Uses of processed accident data.

1 = Engineering justification, 2 = Identify hazardous locations, 3 = State police patrol, 4 = Before/after evaluations, 5 = Statistical safety analysis, 6 = Public education, 7 = Request for funding, 8 = HPMS-maintenance, 9 = Design exceptions, 10 = Design improvements, 11 = Benefit/cost analysis, 12 = News stories, 13 = Planning, 14 = Construction program, 15 = State police budget, and 16 = Pupil transportation safety.

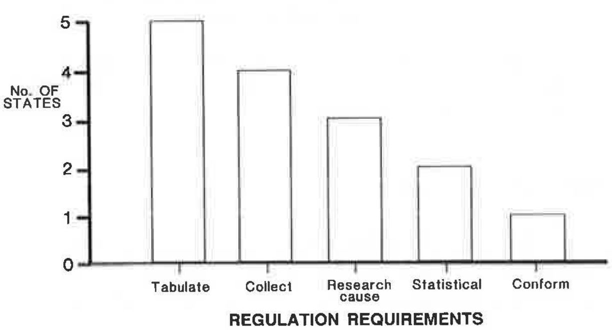

FIGURE 16 State regulations regarding use of processed accident data.

costs that New Jersey has already implemented. The final one would actually increase costs. New Jersey is planning to add staff in the future to improve the timeliness of its accident processing.

• Besides New Jersey, the following states responded and would like to receive a copy of the findings: Alabama, Arizona, Arkansas, California, Georgia, Idaho, Illinois, Indiana,

1. Implement data base file rather than tape-disk system: investigated by eight states, implemented by three of them.
2. Use of optical scanners: investigated by four states with one state predicting a 30 percent reduction in staff needs.
3. Accident form data input by municipalities or State Police: investigated by six states, partially implemented by three of them.
4. Raise property damage only accident threshold: investigated by five states, reduction of 8–14 percent of total accidents.
5. CAD mapping system for location of accidents: investigated by three states.
6. Drop property damage only accidents completely: investigated by one state, has been implemented.
7. Use of floppy disk for pulled-out, specific accident data: investigated by one state.
8. Reduce amount of data entered for property damage only accidents: investigated by two states.
9. Use of credit card type registration and driver license for automated field entry: investigated by one state.
10. Drop driver only reported accidents: investigated by one state, predicting a reduction of 7 percent of total accidents.
11. Drop accidents on private property: investigated by one state.
12. Input data directly from accident form rather than using code sheets: investigated by one state.
13. Change accident form to use numeric codes: investigated by one state.
14. Add staff: investigated by two states.

FIGURE 17 Techniques mentioned by other states to improve timeliness or reduce costs of accident processing.

Iowa, Kansas, Kentucky, Louisiana, Maine, Maryland, Minnesota, Missouri, Montana, Nebraska, Nevada, New Mexico, New York, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, South Carolina, South Dakota, Texas, Virginia, Washington, Wisconsin, and Wyoming.

CONCLUSIONS

From these data it can definitely be concluded that New Jersey is one of the states lagging the most when it comes to timeliness of processing accidents. Its November 1988 expected completion date for processing 1987 accidents is matched by only one other state. All the other responding states expected to have their processing completed at least by June 1988.

As for cost, New Jersey had the sixth highest budget for processing accidents of the 24 budget-responding states. It was also among those with the greatest use of federal funds. However, the state had the sixth highest number of accidents to process and the fifth highest number of items to code. When these figures are combined, New Jersey's cost per accident was the sixth lowest of the 24 states. If the number of specific items to be processed is included, New Jersey becomes the second most efficient state of the 24 in processing accident reports.

When staff size is added to these calculations, the same point is evident. New Jersey's staff size is the sixth largest of the 35 states. Its cost per staff member, however, is the seventh lowest among the 24 budget responding states. When the number of items to be processed for the year is divided by the number of staff members, New Jersey has the fourth highest ratio of the 35 states.

Figures 18 and 19 were attempts at trying to find a relationship between the expected completion date of processing the 1987 accidents and two of these combinations—cost per processed item and processed items per staff member. As can be seen, the points are quite spread out and, although no statistical relationship was calculated, the data for processed items per staff member do seem to increase as the expected completion date is extended.

From these numbers it is certainly evident that although New Jersey is lagging behind in processing accidents, that is not the fault of the processors themselves. The state is one of the top two or three states in terms of efficiency, getting more work completed for less money per unit. Therefore, how can New Jersey improve its overall processing standing while keeping costs down? The next section attempts to answer this question.

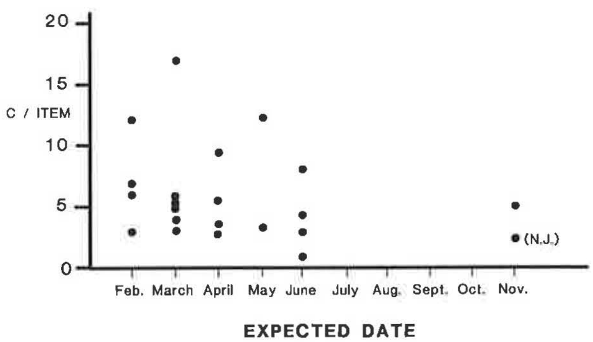

FIGURE 18 Cost/item vs. expected completion date of processing 1987 accidents.

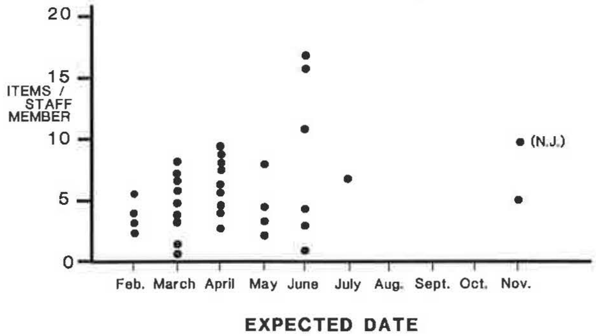

FIGURE 19 Items/staff member vs. expected completion date of processing 1987 accidents.

OPTIONS

Figure 1 lists 14 possibilities, which at least one state has investigated, for reaching the goals of improved timeliness and continued low costs. The first option to be discussed that could improve timeliness is to increase staff. Although this option conflicts with the other goal of keeping costs down, the cost per processed item for New Jersey is currently so low that this increase still would not push it near the national average.

If reduction of costs is the major concern, the first nine possible remedies shown in Figure 17 might be investigated. One of the four best of these possibilities is to implement a data base file to replace the tape system used today. Eight states mentioned this option, and three had already implemented it. This implementation would allow the accident record section to drop part of its data processing costs by permitting users direct access to the data while charging the costs directly to them.

The second option is either to raise the monetary threshold for "property damage only" accidents or to eliminate them entirely. One state has already eliminated PDO accidents. The costs saved by eliminating PDO accidents would be dramatic because approximately 60 percent of all New Jersey accidents are in that category. An increase in the threshold would not, of course, yield the same reduction. However, two states have set their threshold for a PDO accident at a vehicle being towed away, which again reduced the number substantially.

A less drastic technique would be a reduction in the number of items that are input for a "property damage only" accident. Two states mentioned this option. The amount of costs saved from this option would depend on the amount of data eliminated from the processing procedure. These data could still be obtained by reviewing the hard copy microfiche.

The final possible solution would be for municipalities and/or the state police to input the accident data. Three states have partially implemented this option, and three others are planning it in the future. This option would probably have a high implementation cost because the municipality would have to be supplied with the computer hardware and software and the operator's costs paid for the first year or two to help the municipality cope with these increased costs. In the long run, however, the state's costs would be reduced tremendously.

Other possible options, which were not investigated by other states but should be considered, include charging a fee to users of the processed accident data, so that total processing costs would be provided by these users and not by the processors. Another option, reducing the number of items processed for all accidents, could reduce the processing costs substantially, depending on how much data was eliminated. Processing only those accidents that occur on state-operated roads is another option. This would reduce the processing procedure by 70 to 90 percent, depending on whether the PDO accidents were also eliminated. The final two options are, first, to stop editing or correcting accident reports and, second, to stop processing all accidents entirely on the state level.

It must be noted that a few of the options just discussed are quite drastic and the decision concerning which, if any, to implement will be difficult. Therefore, the next step must be an open discussion with the users of processed accident data to determine how each of these options would affect them and whether they could fulfill their responsibilities if the options were implemented. From this discussion, a better decision could be made about which options are realistic alternatives. Also, a few of the options deal with local municipalities picking up part of the workload. A discussion with representatives of some of these municipalities would be helpful in again determining if these options are realistic.

Finally, it must be pointed out that these solutions may eliminate the existing need for a large staff at the state level. Reduction of this staff is a delicate and troublesome aspect that must be handled appropriately if any of these options is to be implemented.

Publication of this paper sponsored by Committee on Traffic Records and Accident Analysis.

Accidents, Convictions, and Demerit Points: An Ontario Driver Records Study

A. SMILEY, B. PERSAUD, E. HAUER, AND D. DUNCAN

A sample of 827,955 records of Ontario drivers containing information about age, gender, convictions, accidents, demerit points, and suspensions for 1981–1984 has been examined. On this basis 16 alternate models to estimate a driver's accident potential have been formulated. It appears that the currently used demerit point system, wherein the number of points associated with an offense reflects the perceived seriousness of the offense, is not a good predictor of accident potential. One can predict better by relying on the driver's record of accidents and convictions and still better by making use of a model for which the "regression weights" have been rigorously estimated. The performance of alternative models for the estimation of drivers' accident potential is described in terms of "hits" and "false alarms." It is shown, for example, that if the top 10,000 drivers are selected by the best model, 3,757 of these are expected to have an accident potential in excess of four times the population average; these are the "hits." Of the same 10,000, one should expect 792 to have an accident potential that is below the population average. These are the "false alarms." The best model uses age, gender, total accidents, and 14 conviction categories. This model identifies approximately twice as many high accident potential drivers as the current demerit point system. Even the simplest model, which uses total convictions as the only variable, predicts 50 percent more high accident potential drivers than the current system.

The current demerit point system in use in Ontario allocates points to offenses on the basis of the perceived seriousness of the offense. An offense is considered serious if it is thought to be associated with a relatively large chance of precipitating an accident. This is why a nonmoving violation, such as not having a trailer permit, receives no points but running a red light receives several points. The goal of the work described in this paper was to allocate points to offenses with a different purpose in mind. The purpose here was to use a driver's record of convictions and accidents to predict, as well as possible, which drivers, based on their past record, are most likely to have an accident in the near future. This is determined by estimating "accident potential" for each driver, namely, how many accidents per year a driver is likely to have, on the average.

Because a person's "accident potential" can be only indirectly estimated (not directly measured) and because, mercifully, it is rare for any one driver to be involved in an accident, the accuracy with which a driver's accident potential can be estimated is bound to be severely circumscribed. Thus, the aim of this work is not only to produce for each driver an estimate of his or her accident potential but also to say how accurate that estimate is.

Such estimates are the kind of knowledge that might then be used in the determination of post-licensing-control action. Thus although a nonmoving violation may not be a threat to traffic safety, such a conviction on a driver's record may be an important clue about that person's likelihood of future accidents.

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DRIVER RECORD SAMPLE

The analysis examined driver records over a recent 4-yr period. Of the 5.5 million Ontario drivers, 827,995 qualified for inclusion in the sample. Driver record data included the following information: age and gender; for each conviction: type, date, and demerit points assigned; for each accident: degree of severity and date; and for each suspension: type and time period.

PREPARATION FOR ANALYSIS

Making sense of large data sets requires careful preparation. First, it was established that the sample statistics correspond to what is known about the population of Ontario drivers. Next, several consistency checks were performed on a sample of the data. Inconsistencies could not be removed in all cases. For example, of 45 drivers convicted for "failing to remain" at the scene of an accident, only 28 show an associated accident. Also, the count of a certain conviction changed from 0 in 1981 to 68 in 1984. This must reflect a change in law or enforcement practices. Following these preliminaries the main preparatory task—grouping the multitude of offenses into a smaller number of categories—was begun.

Selection of Conviction Categories

A preliminary analysis of a sample of about 8,000 drivers indicated that, during the 4-yr period 1981–1984, these drivers were convicted of approximately 200 different traffic offenses. Speeding accounted for some 60 percent of non-accident-related convictions; seat belt offenses accounted for about 10 percent and failure to stop at an intersection, for about 5 percent. Most of the other offense types had very few convictions. It was obviously impractical to assign different weights for each of 200 conviction types. Nor was it feasible to obtain statistically reliable estimates of how much these "leaner" convictions add to a driver's expected number of accidents. It was therefore necessary to place offenses with few convictions into larger groups. It should be noted that the same approach is already present in the current Ontario demerit point system. There are essentially 7 categories of offenses, that is, those assigned 0, 2, 3, 4, 5, 6, and 7 demerit points. For example, all the nonmoving violations as well as some of the moving ones fall into the 0-point category.

The clustering of all possible offense types into a manageable number of categories was accomplished in several steps. The first step was to combine the offense types that are quite similar in nature. In this way the various conviction types were combined into 45 categories. This first step was based on judging which offenses were of a similar nature. In the second step, groups of offenses were identified that were similar in their contribution to a driver's average number of accidents. To obtain results that are unambiguous and free of confounding, the only records used were those for drivers who in any one of the 4 yr had a single conviction. The results are given in Table 1. For example, there were 12,337 drivers who in 1 yr were convicted for not wearing a seat belt (offense *m*1) and had no other conviction in that year. During the

TABLE 1 ACCIDENTS FOR DRIVERS WITH ONE CONVICTION IN 1 YR

Category	Brief Description	No. of Drivers	3 yr. Accs.	Wghtd Mean	95% Upper	Limits Lower
n1	Minor neglect, licenses, permit	6495	2918	0.434	0.445	0.422
n2	Neglect, insurance, permits, etc.	1589	719	0.414	0.438	0.392
n3	License suspended, HTA	874	454	0.424	0.456	0.394
n4	Learners	34	18	0.343	0.502	0.212
v1	Minor veh.; lamps, noise	2954	1498	0.468	0.485	0.451
v2	Brakes, tires, unsafe vehicle	946	451	0.400	0.430	0.371
v3	Comm. veh.; size & weights	503	369	0.542	0.583	0.500
m1	Seat belt	12337	4858	0.376	0.384	0.368
m2	Speeding	173592	55211	0.319	0.321	0.317
m3	Careless driving	902	342	0.327	0.357	0.299
m4	Slow driving	45	11	0.119	0.237	0.055
m8	STOP sign, ROW violations	14024	3935	0.288	0.295	0.281
m9	PXO violations	1237	355	0.296	0.320	0.272
m10	Turn violations; right, left, U	18231	4942	0.283	0.289	0.277
m11	Unsafe move; open door	1649	542	0.334	0.355	0.312
m13	Disobey red light	13731	4270	0.313	0.321	0.306
m14	Amber light	3453	982	0.285	0.299	0.271
m15	Advance green	274	73	0.265	0.317	0.218
m16	Fail to share road	170	62	0.303	0.372	0.242
m17	Passing violations	1305	459	0.327	0.351	0.303
m18	Wrong-way one way street	1582	458	0.284	0.306	0.264
m19	Improper driving divided h'way	2599	900	0.361	0.379	0.344
m20	F.T.C.	934	337	0.344	0.374	0.316
m21	Emerg. veh., school X'ing	48	15	0.159	0.280	0.084
m22	R/R crossing violations	95	35	0.314	0.408	0.233
m24	Headlight beam not lowered	225	71	0.260	0.318	0.209
m25	Improper parking	145	77	0.407	0.484	0.334
m26	Fail to stop for school bus	604	133	0.281	0.317	0.249
m28	Disobey traffic signals	1650	529	0.322	0.344	0.301
m29	Fail to report accident	224	73	0.266	0.324	0.215
m30	Fail to remain at scene	236	75	0.315	0.373	0.261
m32	Dangerous driving C.C.C.	5	2	0.010	0.421	0.000
m33	Fail to remain at accident C.C.C.	66	39	0.377	0.491	0.274
m34	Dangerous driving C.C.C.	89	46	0.281	0.376	0.202
m35	Impaired driving C.C.C.	2381	1040	0.443	0.462	0.424
m36	Fail/refuse breath test C.C.C.	94	37	0.218	0.306	0.149
m37	Fail or ref. breath test C.C.C.	120	50	0.314	0.397	0.241
m38	Driving with >80 mgs. alcohol	3676	1502	0.386	0.401	0.371
m41	Crowding driver seat	120	36	0.280	0.362	0.211
m44	Radar device in vehicle	68	27	0.251	0.359	0.166
m45	No safe helmet, motorcycle	96	47	0.266	0.357	0.191
m46	Fail to signal to stop	18	6	0.080	0.277	0.019
m47	FTC, commercial vehicle	67	35	0.362	0.475	0.262
m48	Fail to stop for police officer	12	6	0.086	0.340	0.016

remaining 3 yr these drivers recorded 4,858 accidents, for an average of 0.394 accident per driver. To eliminate any bias due to differences in the age-gender distribution that might be associated with specific offenses, all averages were recalculated for a "standard population." The "standard population" used had an age-gender composition of those drivers who had exactly one conviction of any kind in the 4 yr. This is why in the "weighted average" column, the average number of accidents in the remaining 3 yr associated with this seat belt offense is listed as 0.376 rather than 0.394. Similarly, the 173,592 drivers who had only a single speeding conviction in some year have an adjusted average of 0.319 accident in 3 yr. The last two columns give 95 percent confidence limits for the weighted average.

Some of the 45 conviction categories were found to be associated with a similar weighted average and could be combined. The resulting 14 conviction groupings, the associated 3-yr average number of accidents, and 95 percent confidence limits are shown in Figure 1. Also shown are estimates of accident potential for conviction-free drivers, those who had no convictions of any type during 1 calendar yr.

In summary, the final 14 conviction categories to be used in analysis were established on the basis of the following considerations:

1. Conviction types within each category were similar in nature,

2. The accident potentials associated with each conviction within a category were similar, and

3. The numbers of drivers with offenses in each category was sufficient to provide a reliable estimate of accident potential for that category.

Inspection of Figure 1 leads to the question of why it is that convictions for, say, minor neglect of vehicular condition (No. 5) are found to be associated with more accidents than those offenses traditionally deemed very dangerous, such as speeding (No. 13) or running a red light (No. 12). Several reasons combine to explain this apparent paradox. First, the convictions associated with most accidents (Nos. 1 and 2 in Figure 1) are those characteristic of truck drivers. These drivers cover 10–20 times the distance of a passenger car driver. Therefore, it is to be expected that they will have, on the average, more accidents. Thus most of those who have a type 1 or 2 conviction are truck drivers who by virtue of exposure have a greater than average number of accidents. This, in turn, results in the average number of accidents associated with these conviction types being greater than those associated with other conviction types, simply because a greater percentage of drivers with this conviction type are truck drivers.

The second reason is easiest to explain through an example. Assume that 1,000 run-the-red offenses lead to 5 accidents and that 1,000 fail-to-signal-turn offenses lead to 1 accident. Thus running a red is a more dangerous offense than failure

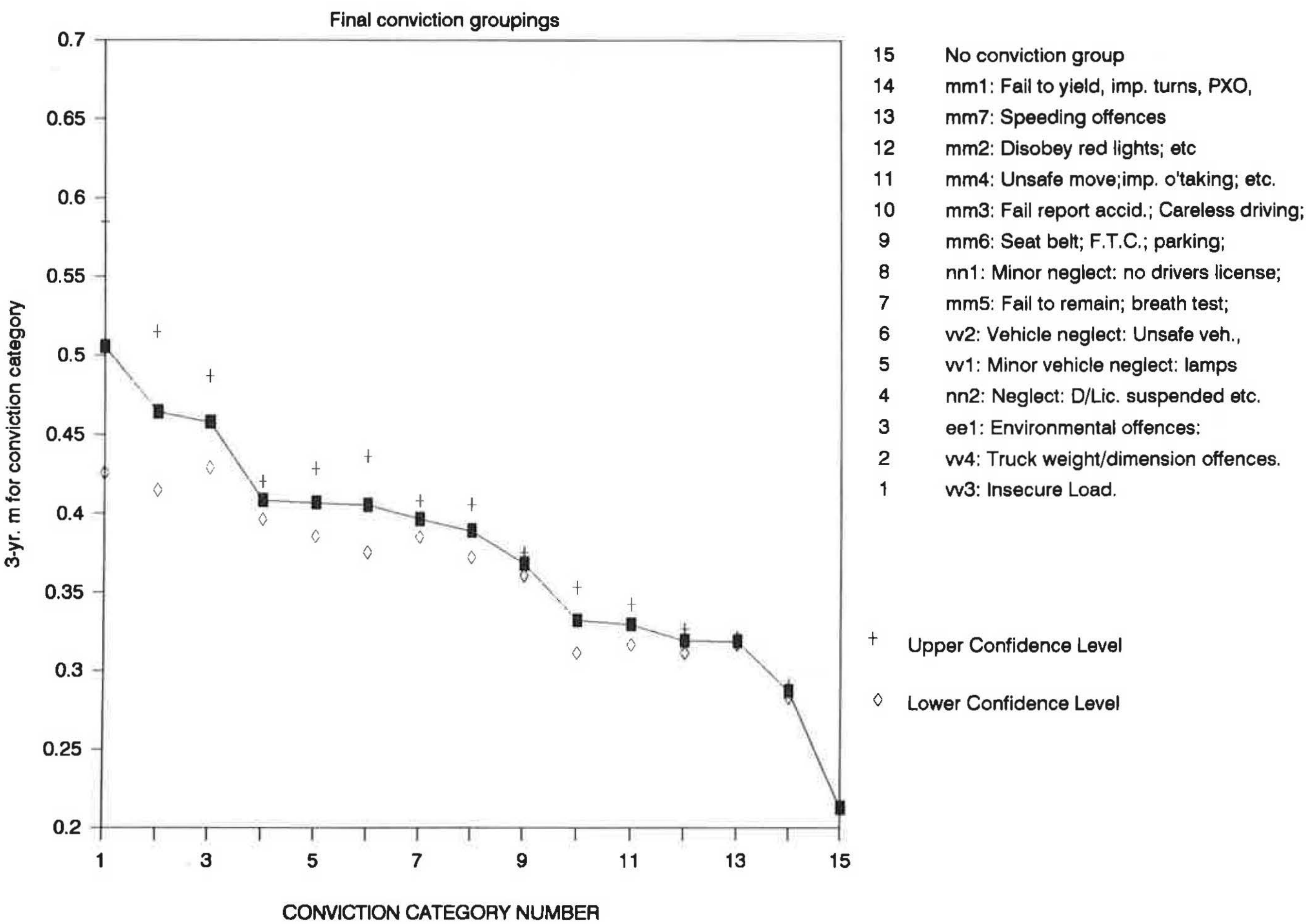

FIGURE 1 Expected numbers of accidents in a subsequent 3-yr period for drivers with one conviction in any year.

to indicate a turn. However, the enforcement for the offenses is unequal (perhaps because one is assumed to be more dangerous than the other). Assume that of the 1,000 run-the-red offenses, 10 lead to a conviction, whereas of the 1,000 fail-to-signal offenses 1 leads to a conviction. Thus, in a figure similar to Figure 1, we would see 5/10 = 0.5 accident per conviction for running the red and 1/1 = 1.0 accident per conviction for failure to indicate a turn. Even though, according to the starting assumption, running the red is five times more dangerous than failing to indicate a turn, because enforcement of the two offenses is unequal, the final result indicates the contrary. The problem is caused by the fact that the driver record contains information about convictions, not about the number of illegal actions committed by a driver.

A third reason might be related to the connection between different types of behavior and convictions. The incidents on a person's driving record, convictions and accidents, are indications of his or her overall driving behavior. As a result, the types of convictions committed by certain types of people may also provide insight into their potential for accidents. If a person engages in certain behaviors that lead to certain convictions, he or she may also engage in certain other behaviors that predispose the participant to accidents. To illustrate, drivers with environmental types of convictions (e.g., a noisy muffler) were found to have a higher weighted mean of accidents than drivers with most other types of convictions. Most drivers quickly have their noisy muffler fixed and are unlikely to receive this type of conviction. The attitude that results in drivers coming to the attention of the police and being charged with this offense may be related to a similar careless attitude toward behavior that results in accidents.

Two conclusions follow. First, one should not interpret the results in Figure 1 as providing information about the danger inherent in this or that offense. Second, one should not be surprised when, in the subsequent analysis, innocuous offenses prove to be strongly related to the driver's accident potential.

Age and Gender Categories

It is well known that the average number of accidents for a driver depends on gender and age. To account for this fact, age and gender will be used in the analysis as "variables." It is relatively simple to account for gender because it comes in two natural categories. The relationship between age and number of accidents, however, is continuous in nature and distinctly nonlinear, as shown in Figure 2. To include age in the analysis, it was necessary to establish a number of age categories. After careful analysis, the boundaries between age groups were chosen so that the average number of accidents within each group remained nearly constant while sufficient numbers of drivers within each age category were still retained to maintain statistical reliability. The eight age categories chosen are indicated on Figure 2.

Exclusion of Drivers with Suspended Licenses

Some drivers in the sample had their licenses suspended during the study period. Many are drivers who had a number of convictions that carried points. The extent to which a suspended driver curtails his or her driving is unknown. This

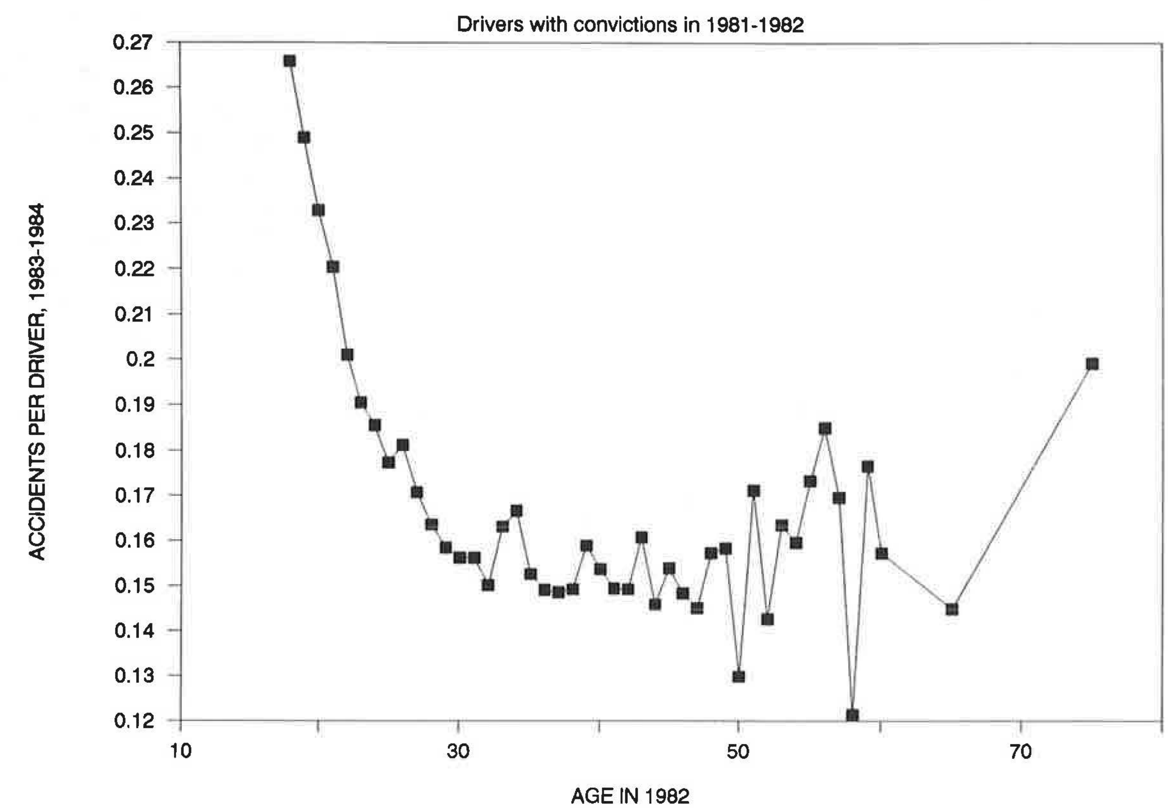

FIGURE 2 Relationship between age and accidents.

leads to serious difficulty in the statistical analysis. Consider a driver who in the first 2-yr period had many convictions and was suspended. That driver can be expected to drive less in the second 2-yr period and therefore to have proportionately fewer accidents. In the statistical analysis this would tend to create a negative correlation. That is, it would lead to the incorrect result that the larger the number of convictions in the first 2 yr, the fewer accidents a person is likely to have in a subsequent period. The net effect of this difficulty is to distort the results of analysis in some unpredictable way. In fact, in the initial statistical analyses, this distortion was so large that negative weights were produced for criminal code offenses for which drivers were likely to be suspended. As a result of this finding, it was necessary to remove from the data set and from subsequent analysis those drivers who were under suspension at any time in the period 1981–1984. The outcome of this decision is that whatever results are obtained in the course of the analysis apply directly only to those drivers whose licenses have not been suspended. The extension to drivers who were suspended under the present demerit point system is therefore an extrapolation.

ANALYSIS AND RESULTS

The various activities described so far (checking for representativeness, conducting consistency checks, selecting conviction categories, determining age groups, and removing suspended drivers) are all preliminary to the main activity, namely, the establishment of a relationship between information contained in a driver's record and his or her expected number of future accidents. The information used was a driver's gender, age, the count of accidents (at-fault, not-at-fault, or total), and the count of convictions in each of the 14 categories. This information from the first 2 yr is used to estimate "regression weights" that best fitted the accident record in the second 2-yr period. These regression weights are the relative number of points each conviction category should be assigned for the best prediction of the likelihood of an accident in the second 2-yr period. Only the records of those drivers who had at least one conviction in the first 2-yr period were used (*n*" 170,000). The tool of analysis was GLIM (*1*), which yields maximum likelihood estimates of the regression weights and facilitates estimation using the negative binomial error structure, which is appropriate in this case.

Schemes and Variants Examined

The Ontario Ministry of Transportation was interested in a number of variants, each using different sets of variables. These fall into three categories:

1. Models that made use of age and gender information and models that did not;
2. Models that assigned points for accidents (with the further distinction between at-fault, not-at-fault, and total) and models that did not assign points for accidents; and
3. Models that assigned different numbers of points for each conviction category and models in which all convictions carried the same weight.

In total, 16 different combinations of variables from the first 2-yr period were used to estimate "weights" to calculate the expected number of accidents in the second 2-yr period. Each of these 16 combinations results in a prediction equation that is termed a "model." Table 2 shows which variables were used in each "model."

Details about the models are given elsewhere (*2*). Here the essential nature of the models is illustrated, using Model A2. Consider a female driver, 24 yr of age, who in the first period had two speeding convictions: one conviction for failing to yield the right of way and one for an at-fault accident. Regression weights for Model A2 are shown in Table 3. The base driver for all models is a 17–20-yr-old male who is conviction and accident free in the first period and who is expected to have 0.176 accident in the second period. From this value one has to subtract 0.061 for being female and 0.039 for being 24 yr old. One has to add 0.027 for each speeding conviction, 0.027 for the right-of-way conviction, and 0.058 for the accident. On the basis of Model A2, this driver is expected to have $0.176 - 0.061 - 0.039 + 2(0.027) + 0.027 + 0.058 = 0.215$ accident in the second 2-yr period.

The Distribution of "Accident Potential"

The models estimate for each driver the number of accidents he or she is expected to have per year in the second 2-yr period. For brevity, this number is called a driver's accident potential. Of course, not all drivers have the same accident potential: some drive more, some drive less; some take risks, others are more cautious. Before examining results for each model, let us examine the diversity of accident potential in the population of Ontario drivers. This will reveal how many drivers there are in the population who have a high accident potential. How many of these "high accident potential" drivers will indeed be identified for postlicensing control under the current demerit point scheme and the new models is examined later.

The number of accidents in the second 2-yr period was used to estimate the mean accident potential (0.055 accident/year) and its standard deviation (0.055 accident/year) in the total driver record sample. Details of the method are given elsewhere (*1*). This information was then used to plot the distribution of accident potential in a population of 5 million Ontario drivers shown in Figure 3. Using Figure 3 it can be established how many drivers in the population have an accident potential between any two chosen levels. Thus, for example, almost 90,000 drivers are estimated to have an accident potential of 0.22 accident/year or higher.

Performance of the Current Demerit Point System and of the New Models

Because the 16 new models were derived using appropriate statistical methods rather than by subjectively weighting each offense according to its perceived seriousness, they should perform better than the current demerit point system. However, all models face the same difficulties as the current demerit point system. Namely, because of the randomness inherent in the process of accident occurrence and the randomness inherent in the process by which drivers acquire convictions,

TABLE 2 VARIABLES USED FOR REGRESSION RUNS (*x* INDICATES VARIABLE USED IN RUN)

Run	Age & Sex Dummy Variables	Variables For Each Conviction Group	Variable for Total Convictions	Accident Variables: Total	Accident Variables: Fault	Accident Variables: At Fault
A1	x	x				
A2	x	x		x		
A3	x	x			x	
A4	x	x			x	x
B1		x				
B2		x		x		
B3		x			x	
B4		x			x	x
C1	x		x			
C2	x		x	x		
C3	x		x		x	
C4	x		x		x	x
D1			x			
D2			x	x		
D3			x		x	
D4			x		x	x

Note: x = indicates variable used in run.

a 2-yr record is just too short for an accurate estimate of a driver's accident potential. As will be seen, the new models are an improvement on the current system but, like the current system, still fail to detect many of the high accident potential drivers. In addition, many drivers identified by the models do not have a high accident potential.

Two measures of performance will be used to judge the quality of a model. The first measure of performance is straightforward. Consider, for example, the 10,000 drivers who in the first 2-yr period had the most demerit points (last row in Table 4). Checking the accident records of the same drivers, we find that during the second 2-yr period they had 1,452 accidents per year (see sum of first three columns in Table 4). Consider now another group of 10,000, this time those who in the first 2-yr period had the most accidents (the second from last row in Table 4). This second group recorded 1,828 accidents per year in the subsequent 2-yr period. Evidently, it is better to identify drivers by their previous accident record than by previous demerit points. Imagine now that a third group of 10,000 drivers is identified, this time those for whom Model A4 estimates the highest accident potential on the basis of their age and gender, as well as of convictions and accidents in the first 2-yr period. This group has 2,084 accidents per year in the second period. Thus, selection by Model A4 gives a richer catch than selection either by previous accidents or by the current demerit point system. In interpreting

TABLE 3 REGRESSION COEFFICIENTS FOR MODEL A2

Description of Variable		Estimated Coefficient	Standard Error
Intercept (Male <21)		0.1763	0.002876
Dummy variable for age 21-25		-0.03856	0.002852
Dummy variable for age 26-30		-0.0565	0.002913
Dummy variable for age 31-35		-0.06006	0.003044
Dummy variable for age 36-40		-0.05202	0.003516
Dummy variable for age 41-50		-0.06013	0.00351
Dummy variable for age 51-60		-0.05774	0.004832
Dummy variable for age > 60		-0.06156	0.007068
Dummy variable for female		-0.06122	0.001735
mm1:	Fail to yield, imp. turns, PXO, amber violations, etc.	0.02696	0.001753
mm2:	Disobey red lights; rail crossing violations	0.042125	0.002916
mm3:	Fail report acc.; careless driving; dang. driving; crim. neg. caus. death	0.023304	0.008613
mm4:	Unsafe move; imp. o'taking; disobey signs	0.06359	0.004959
mm5:	Fail to remain; breath test; alcohol; impairment	0.2444	0.054575
mm6:	Seat belt; F.T.C.; parking; divided h'way offences	0.03221	0.00213
nn1:	Minor neglect; no drivers license; permits; insurance, address change	0.02624	0.010463
nn2:	Neglect: D/Lic. suspended or not produced; plates, insurance	0.03366	0.003708
vv1:	Minor vehicle neglect: lamps windows obstructed, etc.	0.04954	0.006561
vv2:	Vehicle neglect: unsafe veh., brakes, tires	0.08673	0.009296
vv3:	Insecure load	0.159215	0.02721
vv4:	Weights and dimension offences	0.11074	0.011895
ee1:	Environmental offences: noise, fumes	0.08748	0.008334
mm7:	Speeding offences	0.026515	0.000866
Total accidents in period 1		0.05831	0.001580

these results one has to keep in mind that the count of (Period 2) accidents is always subject to random fluctuations.

Several conclusions emerge. First, one can do better than to use the current demerit point weights. Second, it is important to make use of the driver's record of accidents. This is already evident from the comparisons of the last two rows. It also emerges, however, from the poor performance of Models A1, B1, C1, and D1, which do not make use of accident data. In fact, the top 1,000 drivers can be well identified by their previous accident record alone. Third, the more drivers are identified, the lesser the "yield." Thus, the top 1,000 drivers have a Period 2 accident rate of "0.3 accident/year, which is approximately six times the population average; for the first 10,000 drivers, the average accident rate is "0.2, and so on.

The measure of performance examined so far leaves the impression that the drivers who are identified indeed have an accident potential that is substantially larger than that for the population of all drivers. Although this is true for the group "on the average," this group itself may not be a homogeneous one. The second measure of performance by which the quality of the alternative models is to be judged relates to the diversity of accident potential within the group of drivers that these models identify.

A weighting scheme is like a net with which an attempt is made to catch drivers who, based on their 2-yr record, are likely to have an unusually high number of accidents in the next 2 yr. For illustration here, consider "unusually high" to be 3 standard deviations above the mean. Because the mean for an Ontario driver is 0.055 accident/year and the standard deviation happens also to be 0.055 accident/year, it is hoped that drivers whose accident potential is larger than 0.22 accident per year will be identified. If we manage to identify such a driver, we will call this a "hit." Conversely, if based on the 2-yr record we identify, and call in for treatment, a driver

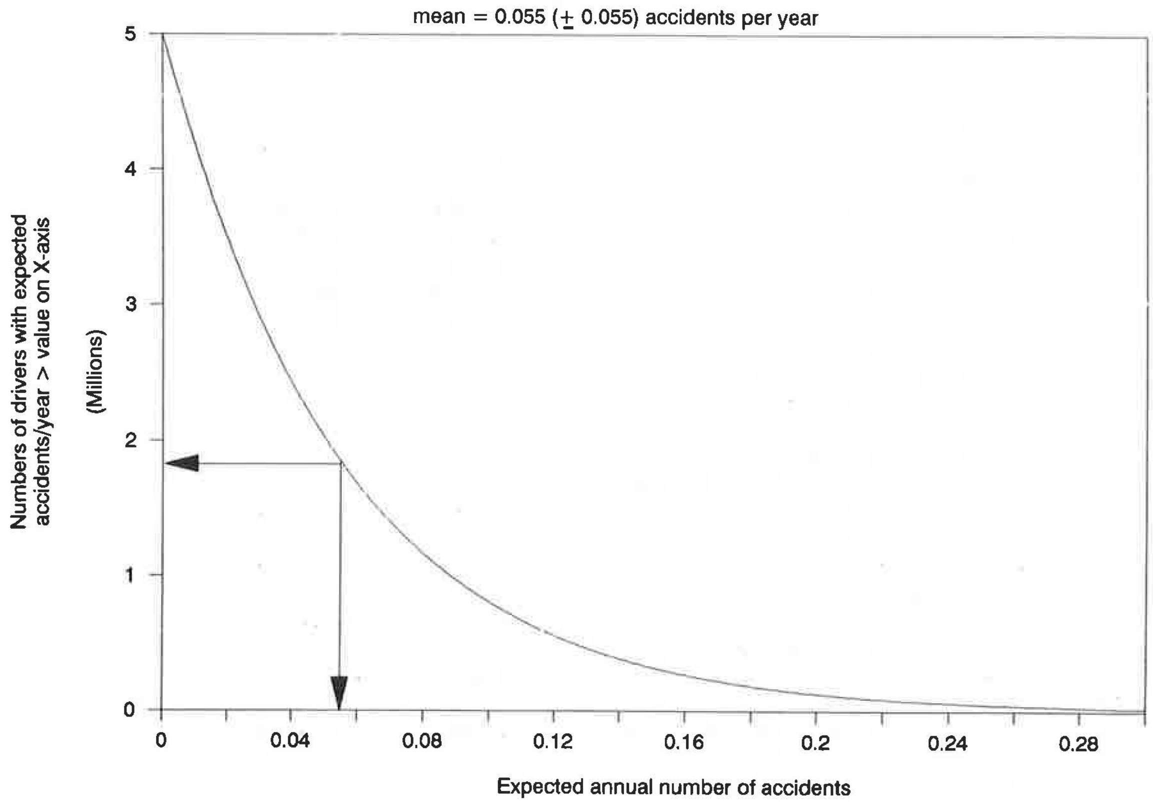

FIGURE 3 Distribution of accident potential in Ontario driver population.

whose accident potential is lower than the average accident potential in the population (that is, 0.05 accident per year), we will call this a "false alarm."

To illustrate, Models A4 and B4 are used. (The variables that these models use to estimate accident potential are shown in Table 2.) Drivers were ranked in terms of accident potential as estimated by each model based on their record during the first 2-yr period. Table 5 shows the hits (drivers correctly determined to have accident potential larger than 0.22 accident/year) and also the false alarms (drivers whose accident potential is below the population average of accidents/year) for consecutive groups of drivers identified by the two models as ranking highest on accident potential from a population of 5 million drivers.

Looking again at Figure 3, it can be seen that out of 5 million drivers, 90,000 drivers are expected to have an accident potential larger than 0.22 accident/year. As Table 5 shows, using Model A4 to select the 10,000 drivers with the worst records will catch 3,697 of the high accident potential drivers; calling in the next 10,000 will identify 2,679 more hits. Calling in the next 100,000 will yield another 15,987 hits. Thus, even after those 120,000 drivers of 5 million who have the highest estimated accident potential according to Model A4 have been selected for treatment, only 22,363 hits can be expected. Of the 90,000 drivers in the population who have an unusually high accident potential (>0.22) 67,637 remain still unidentified. The whole driver population would have to be called in before all the hits would be identified.

Table 6 compares performances among the 16 models, and the current demerit point system, in terms of hits and false alarms for the worst 10,000 drivers identified by each model. It should be noted that, although there always will be considerable overlap between groups of drivers identified by different models, there also will be systematic differences. Thus, for example, the use of Model Series *A* and *B* will lead to groups that contain more truck drivers than the current system, simply because the current system does not assign any points for truck weight or truck dimension offenses, whereas Models A and B weight these heavily.

Although comparison in terms of hits and false alarms is good for purposes of illustration, it depends on a rather arbitrary definition of what is to be considered an "unusually high" accident potential. A more comprehensive way to characterize the performance of different models is by continuous curves, as shown in Figure 4.

In Figure 4, accident potential is measured on the abscissa. The ordinate gives the number of drivers out of 10,000 whose true accident potential exceeds the value on the abscissa. The lowest curve represents the current demerit point scheme. In a group of 10,000 drivers who, in a population of 5 million, have the most demerit points, one can expect to find 2,800 who have an accident potential above 0.2 accident per year. The highest curves represent Models A4 and B4. In a group of 10,000 drivers who, in a population of 5 million, have the highest estimated accident potential by Model A4, one can expect to find some 4,200 drivers who have an accident potential above 0.2 accident per year. Thus, the higher the curve, the better the "net."

TABLE 4 ACCIDENTS PER YEAR RECORDED BY DRIVERS SELECTED BY VARIOUS MODELS

Model	Drivers estimated by model to be in:					
	Top 1,000	Next 4,000	Next 5,000	Next 10,000	Next 100,000	Total
A1	188	712	904	1660	13308	16772
A2	324	856	936	1798	14192	18016
A3	276	736	860	1712	13700	17284
A4	320	868	896	1736	14060	17880
B1	212	704	824	1548	12888	16176
B2	320	832	980	1628	13688	17448
B3	272	748	804	1712	13336	16872
B4	304	876	956	1636	13684	17456
C1	208	744	760	1592	13016	16320
C2	356	808	900	1672	13732	17468
C3	276	780	780	1424	13684	16944
C4	356	804	928	1616	13748	17452
D1	176	748	688	1432	12260	15304
D2	352	824	784	1608	13268	16836
D3	244	756	852	1360	13084	16296
D4	364	840	788	1576	13216	16784
Accs.*	312	756	760	1432	10780	14040
DP**	180	640	632	Not	Available	

* - Drivers with the highest accident counts in period 1 were selected

** - Drivers with the highest demerit points acquired in period 1

TABLE 5 FIGURES FOR MODELS A4 AND B4

Drivers estimated by model to be in:		Number of drivers expected to have: $m > 0.22$		$m > 0.05$	
		Model A4	Model B4	Model A4	Model B4
the top	1,000	528	541	39	45
the next	4,000	1568	1595	246	289
the next	5,000	1601	1620	390	458
the next	10,000	2679	2657	933	1110
the next	100,000	15987	15291	14198	16928
TOTALS:	120,000	22363	21704	15806	18830

TABLE 6 FIGURES OF MERIT FOR 10,000 DRIVERS WITH HIGHEST *ms* (FOR EACH MODEL)

Model	Number of drivers expected to have: $m > 0.22$	$m < 0.05$
A1	3258	908
A2	3691	676
A3	3449	817
A4	3698	674
B1	3331	1062
B2	3750	806
B3	3516	923
B4	3757	792
C1	2911	1024
C2	3411	756
C3	3147	922
C4	3429	752
D1	2978	1211
D2	3441	909
D3	3155	1101
D4	3451	906
CURRENT DP	2231	1251

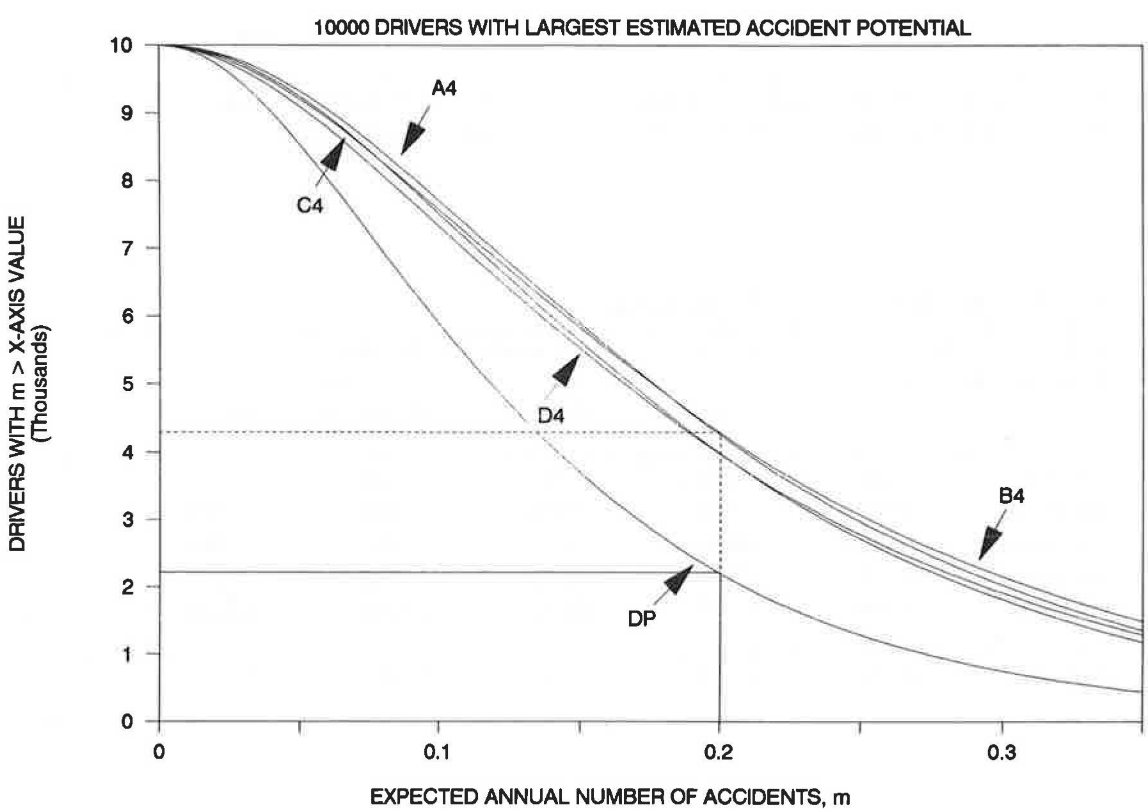

FIGURE 4 Current DP versus Schemes A4, B4, C4, D4.

SUMMARY AND CONCLUSIONS

The purpose of this work was to use a driver's record of convictions and accidents to predict, as well as possible, which drivers, based on their past record, are most likely to have an accident in the near future.

A sample of 827,955 records of drivers licensed to drive in Ontario during 1981–1985 has been examined. Each driver record contained information about the driver's gender, age, and details of accidents, convictions, demerit points, and suspensions.

In preparation for analysis, the many hundreds of offense types had to be grouped into a manageable number of categories. First, offenses that were similar in nature were put in the same group; then those offenses that were associated with a similar average number of accidents were consolidated. It turned out, for example, that drivers who in 1 yr had a single speeding conviction had fewer accidents in the remaining 3 yr than other drivers who had a single conviction in that year for a relatively minor offense, such as a missing lamp. This finding may initially be puzzling but, on reflection, aids the correct interpretation of later results. It arises partly because not all illegal behaviors lead to convictions at the same rate, partly because some offenses are specific to truck drivers who drive 10 to 20 times as much as car drivers and tend to have proportionately more accidents, and partly because behavior that results in a fairly innocuous offense, such as a noisy muffler, may be of the type that also leads to accidents. Therefore neither the ratio of accidents to convictions nor the "weights" that are later attached to particular offenses are an indication of the gravity of those offenses.

Drivers with a suspended license will curtail their driving to some extent. This is why, during the suspension period, one would expect some reduction in the number of accidents in which they are involved. However, the extent to which driving is curtailed is unknown. To assume that suspended drivers stop driving would introduce a bias into the analysis; assuming that they continue to drive would cause another bias. To protect the integrity of the results, drivers who were suspended had to be removed from the analysis. Therefore, the conclusions of this study apply directly only to drivers who have not been suspended. The extension to drivers who were suspended under the present demerit point system is therefore an extrapolation.

Sixteen models have been examined to estimate the expected number of future accidents for a driver based on age, gender, convictions, and accidents. The models differ from one another in the information they use. Some make use of age and gender, others do not. In some, each of 14 types of convictions is given a different weight; in others, all convictions have the same weight. In some, at-fault accidents are counted separately from not-at-fault accidents; in others, they are lumped together. All 16 models have a common structure: a "weighted sum" of convictions and, in some models, of accidents.

Two measures of performance were used to judge the quality of a model. The first measure of performance is the number of second-period accidents in a group of drivers (of fixed size) identified on the basis of their first-period record. Thus, those 10,000 drivers who in the first 2-yr period had the most demerit points recorded 1,452 accidents per year during the second 2-yr period. Those 10,000 drivers who in the first 2-yr period had the most accidents recorded 1,828 accidents per year in the subsequent 2-yr period. A third group of 10,000 drivers, those who by Model A2 have the highest accident potential when calculated on the basis of the first period data, recorded 2,116 accidents per year in the second period. Thus, selection by Model A2 gives a richer catch than selection either by previous accidents or by current demerit points. On this score, Model A2 performs best.

Several conclusions emerge. First, one can do better than to use the current demerit point weights. Second, it is important to make use of the driver's record of accidents. Third, the more drivers are identified, the lesser the "yield." Thus, the top 1,000 drivers have an accident rate of ″0.3 accident/year, which is approximately six times the population average; for the first 10,000 drivers, the average accident rate is ″0.2, and so on.

Not all drivers have the same expected number of accidents per year. Some drive more, some less; many drivers are prudent, some take unwise risks. On the basis of the accident data, it is shown how many drivers in Ontario have what expected number of accidents. Thus, for example, of 5 million drivers, some 90,000 have an expected number of accidents that is 3 standard deviations above the average for the population. It is these "high accident potential" drivers whom a demerit point scheme aims to identify.

A 2-yr record of convictions and accidents is just too short for estimating a driver's expected number of accidents with accuracy. This is why some of those identified by the model as having the highest expected number of accidents turn out, in reality, to be just average drivers. Conversely, this is why most high accident potential drivers may not have, in 2 yr, a record that identifies them as such. It was shown, for example, that of the 10,000 drivers who, by the "richest" model (A4) were estimated to have the highest expected number of accidents, 3,698 have an accident potential in excess of 3 standard deviations above the mean for the population. At the same time, 674 of those 10,000 were average drivers or better.

It may be of interest to note that little is gained by giving different numbers of points to different offenses. Model D1 uses simply 1 point per conviction and no accident data; Model D2 uses 1 point per conviction and 1.88 points per accident. Model D2 is only slightly worse than Model B2, which assigns different numbers of points to each of 14 offense classes. Table 7 compares hits and false alarms among the worst 10,000 drivers for those models. The more drivers selected, however, the more separate weights improve performance (in terms of predicting the number of future accidents). For the 100,000 worst drivers, separate weights help to increase the number of hits and to reduce the number of false alarms by about 10 percent.

In summary, if the purpose of a demerit point system is to identify drivers who are most likely to have an accident, the scheme used now is not as efficient as alternative schemes would be. Even by giving equal weights to all convictions and a weight of ″2 to an accident (D2), one can do much better. It is important to use data about accident involvement, but it does not pay to differentiate between at-fault and not-at-fault accidents.

For the top 5,000 or so drivers, the inclusion of age and gender information appears to be unimportant. For the next 100,000 drivers, consideration of age and gender improves performance (in terms of predicting future accidents) by a few percentage points. Consideration of age and gender does

TABLE 7 COMPARISON OF HITS AND FALSE ALARMS AMONG WORST 10,000 DRIVERS

	Hits >0.22	False Alarms <0.055 acc./yr.
Current Demerit Points	2231	1251
D1	2973	1211
D2	3441	909
B2	3750	806

not seem to increase the number of hits, but it helps in reducing the number of false alarms by some 10 percent.

With all this, one has to keep in mind that if only a few drivers are identified (say about 10,000), 30–40 percent of those will be genuine high accident potential drivers and 6–10 percent will be falsely identified better-than-average drivers. However, only 3 percent of all high accident potential drivers in the population will be in this group of 10,000 drivers. It does not help much to increase the size of the group because performance deteriorates with size. Thus, in a group of 120,000 drivers, only "19 percent genuinely have a high accident potential, whereas 13–16 percent are falsely identified. Even when as many as 120,000 drivers are identified by the richest model, only 22,363 of the 90,000 "high accident potential" drivers are caught in the net.

The performance of models for the estimation of a person's accident potential can be further improved. Consideration should be given to a system that tracks a person's accident potential nearly continuously. If during a certain period of time (measured in weeks) the driver did not acquire a conviction and was not involved in an accident, his or her estimated accident potential would be revised downward. If during that period of time, convictions or accidents were recorded, the estimated accident potential would correspondingly be revised upward. A person's aging, the general accident trend, and seasonal variation would also be reflected in these revisions. In this manner, a person's current estimated accident potential could be made a reflection of his or her entire driving history. In such a scheme, there is no need to specify an arbitrary period of time after which points are forgiven.

In the models developed so far, involvement in an accident adds a fixed amount to a driver's accident potential. Under the newly suggested scheme, an accident by a person with an already high accident potential would be weighed more heavily. In general, a "revision" scheme of this nature relies on solid mathematical logic and is expected to perform better than other possible schemes.

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Publication of this paper sponsored by Committee on Traffic Records and Accident Analysis.

Increased Motorization and Highway Fatalities in the People's Republic of China

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Highway accident, injury, and fatality data for 1985 for the 29 provinces and municipalities of the People's Republic of China were analyzed in terms of population, number of vehicles, and number of licensed drivers. China is clearly at the beginning of the "highway safety transition," as evidenced by high fatality-per-vehicle and low fatality-per-population rates. Although changes in fatality rates over time could not be analyzed, the number of fatalities per vehicle was found to decrease with increasing vehicle ownership in the provinces in accordance with Smeed's law. Growth in the number of vehicles is extremely rapid, and private ownership is being encouraged in the spirit of the new economic reforms. The costs due to traffic fatalities, injuries, and property damage must be included in the total price of developing the highway system that is so badly needed for China's economic development.

A "highway safety transition," similar to the demographic transition, has been described by Haight (*1,2*). In this transition, the total number of highway fatalities increases, the fatalities-per-unit-travel decrease, and the fatalities-per-population remain stable over time as a country moves from "developing" to "industrialized" status (Figure 1). The implication of this transition, convincingly presented by Haight, is that the effects of any one traffic safety measure are nearly impossible to evaluate from aggregate data, such as a falling fatalities-per-vehicle-kilometer curve. In essence, what this natural evolution means is that as a traffic system matures and safety improves, travel also increases, so the burden imposed on the public health system remains the same. This burden can be masked by the use of transportation-based fatality and injury rates.

The objectives of this paper are to demonstrate that the People's Republic of China is at the beginning of this transition and to discuss the implications of this fact for the highway safety, transportation planning, and public health community in China.

The People's Republic of China is experiencing a phenomenal rate of growth and development. Despite setbacks suffered during the "Great Leap Forward" in 1960 and the Cultural Revolution of 1966–1976, the volume of passenger traffic on the roadways per 10^8 person-km has increased 193 times between 1949 and 1985; while passenger-kilometer travel by rail, water, and civil aviation has increased 18, 11, and 65 times, respectively (*3*). The number of highway vehicles has increased almost 170 times from an estimated 51,000 in 1950 to 8.64 million in 1985 (*4*). These figures are somewhat misleading in that the greatest growth rates have occurred since 1979. For example, the number of passenger cars in the city of Guangzhou increased from fewer than 20,000 in 1979 to 114,000 in 1984 (*5*). Road construction has not kept pace with the increase in vehicles and passenger travel, resulting in increased congestion and decreased average travel speeds. However, one of the major goals of development is to remedy this situation, as illustrated in the province of Inner Mongolia, where 160 new roadways, covering 3,000 km, were built in 1985 alone. This construction was approximately equal to the total roadway construction in that province for the previous 38 years (*6*).

As expected, this increase in motorization has resulted in an increase of highway crashes, injuries, and fatalities. Unfortunately, these increases have not been as well documented as has the growth in vehicles and vehicular travel. Despite the paucity of crash data, sufficient information is now available to examine the status of the highway safety transition in China.

METHODS

The total number of motor vehicle crashes, fatalities, and injuries and the total population in 1985 for the 26 provinces and 3 municipalities (29 units) administered by the Central Government of the People's Republic of China were obtained from the Chinese Statistical Bureau (*7*). In addition, the total numbers of registered motor vehicles and licensed drivers for the 29 units were obtained from the Ministry of Public Security. The estimates of passenger and freight volume by year for the country as a whole were obtained from the Chinese Automotive Industry Yearbook (*3*). From these, rates based on population, vehicles, and licensed drivers were calculated. More detailed data for the cities and suburban areas of Beijing and Tianjin were also obtained. Because vehicle and licensed driver data are not reported by city and suburban area, these rates could not be calculated.

To explore the relationship of increasing motorization upon fatalities, the number of vehicles per population was regressed on the number of fatalities per vehicle, according to what is known as "Smeed's law."

LIMITATIONS OF THE DATA

As has been discussed in numerous previous studies of crash rates in developing countries (*1,2,8*), these rates must be viewed

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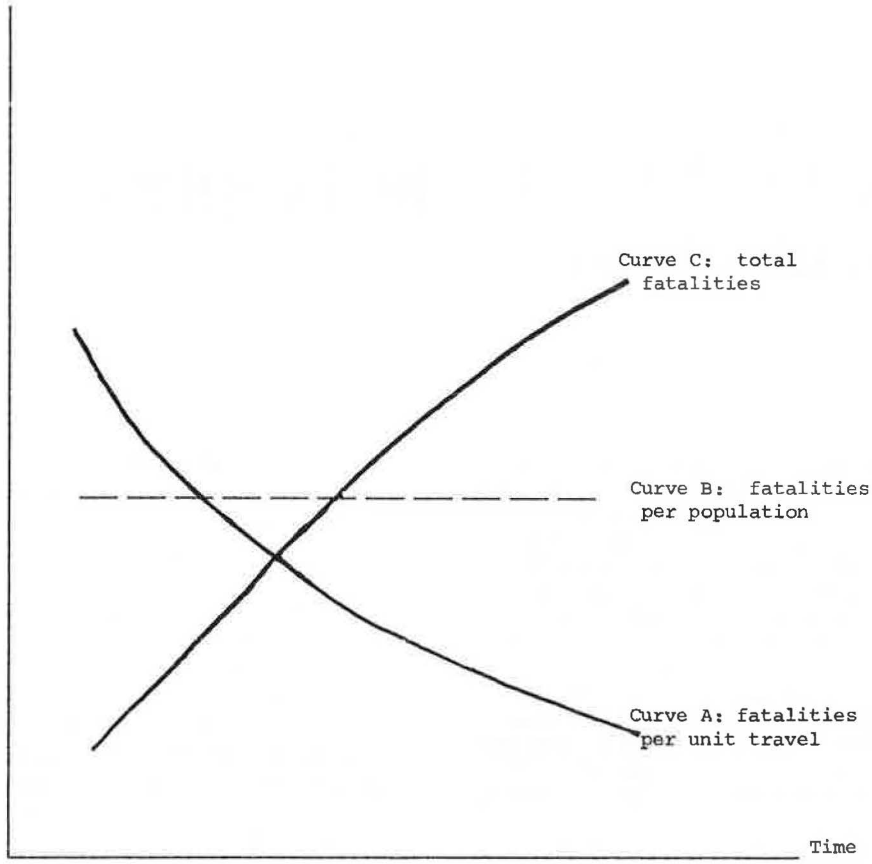

FIGURE 1 Highway safety transition [adapted from work by Haight (*1*)].

as very preliminary. The difficulties of obtaining accurate reports, especially of crashes and injuries, must be kept in mind. Although data were analyzed across provinces and not across time, the more developed and industrialized provinces may have more accurate and uniform data collection systems because they have been reporting crashes for a longer time. Higher numbers of crashes reported from these provinces may thus be influenced by reporting differences.

Although mortality is generally considered to be more accurately reported than morbidity for all diseases and injuries, the fatalities reported here should also be considered underestimates because of the lack of reliability of the reporting system. Further, a motor vehicle fatality in China is defined as one that has occurred within 7 days of the crash. Although this definition will yield an underestimate when compared with those of countries that use a 30-day or longer period (*9*), the magnitude of this underestimate is less for such countries as China in which an emergency medical services system is in its infancy.

A more significant problem with the data is that the number of bicycles registered in each unit could not be obtained, nor are crash data enumerated by type of vehicle involved. The total number of bicycles in China is estimated to be at least 200 million. The exclusive use of bicycles for commuting to work, transporting goods and people, and achieving pleasure and recreation by a large segment of the Chinese population (*10*) and the lack of helmets (*11*) are well known. On the basis of experience in the United States, the majority of the bicycle-related fatalities can be assumed to have involved at least one motor vehicle (*12*). The vehicle-based total crash and injury rates, however, are more severely overestimated as a result of the underenumeration of total vehicles on the road. The rates based on licensed drivers are also overestimates because the number of crashes involving only bicycles is unknown. Again, the fatalities per licensed driver are probably the least affected by this error as a result of the low number of fatal bicycle-only crashes.

In addition to the problems due to lack of bicycle data, the exact definitions of "accident" and "injury" used by the Chinese are unknown. For these reasons, the more detailed analyses were limited to the fatality data. The lack of information regarding the crash reporting system process imposes severe limitations on the conclusions that may be drawn from the data.

RESULTS

The crash, injury, and fatality rates based on population, vehicles, and licensed drivers are presented in Tables 1, 2, and 3. The fatality rate per 100,000 people for the country as a whole was 3.9, compared with the U.S. rate of 18.3 (*13*). The five highest rates ranged from 9.8 to 6.7 in western and northern provinces of Qinghai, Tibet, Mongolia, and Xinjiang and in the municipality of Beijing. The rates for Beijing probably reflect better reporting. Two of the four lowest rates are also found in northern provinces, Inner Mongolia and Heilongjiang. Quick explanations of these rates are thus difficult,

TABLE 1 TOTAL MOTOR VEHICLE ACCIDENTS, INJURIES, AND DEATHS/10,000 POPULATION, 1985

Province and municipality	Acc/10,000 population	Inj/10,000 population	Deaths/10,000 population
Beijing*	8.3271	5.1219	0.7917
Tianjin*	5.2005	3.4022	0.6448
Hebei	1.6581	1.0101	0.3551
Shanxi	2.4937	1.6913	0.6437
Neimeng	1.4141	0.8615	0.2980
Liaoning	4.6408	3.1799	0.5269
Jilin	1.6258	1.0335	0.3407
Heilongjiang	0.6442	0.3818	0.2609
Shanghai*	5.8513	4.7067	0.5629
Jiangsu	1.0765	0.6895	0.2945
Zheiiang	2.3467	1.9395	0.5476
Anhui	1.1676	0.8103	0.2799
Fujian	2.199	1.6922	0.4360
Jiangxi	1.3812	0.8991	0.3474
Shandong	1.6938	0.9771	0.3845
Henan	1.7574	1.0589	0.3327
Hubei	1.6321	1.1452	0.4537
Hunan	2.1789	1.4708	0.3801
Guangdong	2.9859	1.7956	0.3793
Guangxi	1.1407	0.7756	0.3349
Sichuan	1.5165	1.1632	0.3968
Guizhou	1.8747	1.2433	0.3312
Yunnan	2.0085	1.6850	0.4328
Tibet	2.8543	2.2714	0.9347
Shaanxi	2.0247	1.4117	0.4530
Gansu	1.1053	0.8354	0.3484
Qinghai	5.8108	3.6093	0.9828
Ningxia	3.3976	1.8482	0.6699
Xinjiang	3.7869	2.0705	0.6819
Country as a whole	2.0119	1.3551	0.3997

* Municipality

TABLE 2 TOTAL MOTOR VEHICLE ACCIDENTS, INJURIES, AND DEATHS/10,000 VEHICLES, 1985

Province and municipality	Acc/10,000 vehicles	Inj/10,000 vehicles	Deaths/10,000 vehicles
Beijing*	25.6000	15.7190	2.4300
Tianjin*	38.8000	25.3880	4.8120
Hebei	13.3000	8.0850	2.8420
Shanxi	21.8000	14.8060	5.6350
Neimeng	13.4000	8.1510	2.8190
Liaoning	36.6000	25.1110	4.1610
Jilin	18.6000	11.8340	3.9020
Heilongjiang	7.6000	4.5120	3.0840
Shanghai*	68.2000	54.8310	6.5570
Jiangsu	29.0000	18.5770	7.9360
Zheiiang	34.2000	28.2270	7.9710
Anhui	•38.7000	26.8420	9.2710
Fujian	38.0000	29.2380	7.5340
Jiangxi	37.0000	24.1430	9.3280
Shangdong	21.7000	12.5470	4.9380
Henan	20.8000	12.5340	3.9380
Hubei	18.1000	12.7150	5.0370
Hunan	76.6000	51.6800	13.3560
Guangdong	29.9000	18.0000	3.8030
Guangxi	24.8000	16.8880	7.2910
Sichuan	23.7000	18.1680	6.1980
Guizhou	46.7000	31.0020	8.2590
Yunnan	22.0000	18.4180	4.7310
Tibet	22.4000	17.8440	7.3430
Shaanxi	12.7000	8.8550	2.8420
Gansu	5.2000	3.9040	1.6280
Qinghai	20.4000	12.6850	3.4540
Ningxia	18.6000	10.1130	3.6650
Xinjiang	36.5000	19.9780	6.5790
Country as a whole	24.2000	16.300	4.8000

* Municipality

TABLE 3 TOTAL MOTOR VEHICLE ACCIDENTS, INJURIES, AND DEATHS/1,000 LICENSED DRIVERS, 1985

Province and municipality	Acc/100 licensed drivers	Inj/100 licensed drivers	Deaths/100 licensed drivers
Beijing*	3.9349	2.4203	0.3741
Tianjin*	5.7807	3.7818	0.7167
Hebei	3.4848	2.1229	0.7463
Shanxi	4.2951	2.9130	1.1087
Neimeng	2.0681	1.2600	0.4358
Liaoning	6.0168	4.1227	0.6831
Jilin	1.1187	0.7111	0.2345
Heilongjiang	0.9758	0.5783	0.3953
Shanghai*	6.9051	5.5543	0.6642
Jiangsu	3.3915	2.1725	0.9280
Zheiian	11.9598	9.8845	2.7911
Anhui	4.3747	3.0361	1.0486
Fujian	9.2316	7.1040	1.8305
Jiangxi	4.8922	3.1847	1.2305
Shangdong	4.5258	2.6108	1.0274
Henan	4.2284	2.5476	0.8004
Hubei	4.6085	3.2336	1.2810
Hunan	7.5698	5.1098	1.3205
Guangdong	6.6592	4.0046	0.8460
Guangxi	4.2886	2.9160	1.2590
Sichuan	6.0080	4.6085	1.5722
Guizhou	7.8467	5.2039	1.3863
Yunnan	7.1770	6.0208	1.5464
Tibet	2.4447	1.9454	0.8006
Shaanxi	4.2951	2.9130	1.1087
Gansu	2.6925	2.0349	0.8486
Qinghai	5.5051	3.4195	0.9311
Ningxia	6.1839	3.3639	1.2192
Xinjiang	4.6422	2.5382	0.8358
Country as a whole	4.5323	3.0526	0.9004

* Municipality

as both groups of provinces are sparsely settled, mountainous regions.

The high vehicle-based rates are also those expected in the first stages of motorization. The fatality rate per 10,000 vehicles was 48.2 for the country as a whole, compared with 2.5 for the United States (*13*). The four highest rates ranged from 82.5 to 133.5 in a belt of provinces in the south extending from Guizhou to Anhui. The lowest, ranging from 24.3 to 28.4, are seen in the northern provinces of Ningxia, Inner Mongolia, and Hebei and in the municipality of Beijing. Fatalities per 1,000 licensed drivers follow a similiar pattern: 9.0 for the country compared with the U.S. rate of 0.28 in 1985 (*13*). The highest rates were experienced in the southern provinces of Sichuan, Yunnan, Zheiiang, and Fujian (ranging from 15.5 to 27.9) and the lowest, in the northern provinces of Inner Mongolia, Heilongjiang, Jilin, and in the municipality of Beijing (ranging from 2.3 to 4.3). A comparison of these summary rates for China and various other countries is given in Table 4.

Population data for the municipalities of Beijing and Tianjin were available by inner city and suburbs. Population-based crash, fatality, and injury rates are shown in Table 5. In Beijing, the distribution is what would be expected: the rates of total crashes and injuries are higher in the more congested central city than in the suburbs; however, the rate of fatal crashes is much higher in the suburbs than in the city. In Tianjin, however, the pattern is reversed: the crash rates for all categories are much higher in the suburbs than in the inner city. Although this could be due to differences in reporting practices, no conclusive explanations for this reversal are apparent.

Sufficient data for year-to-year comparisons of crash rates could not be obtained. Because of the year-to-year fluctuations in traffic crashes and deaths known to occur in all countries and the inability to separate the effect of any one change in a highway system from the decline in crashes that appears to occur over time as a traffic system matures (*1,2*), time-series analyses should be used to analyze traffic crash data. Even 2- or 3-yr comparisons can yield very misleading conclusions about whether highway mortality and morbidity are getting "better" or "worse."

Although comparisons over time could not be made, the differences in the stages of development within the provinces and cities of China provide an opportunity for a cross-sectional analysis of the effects of motorization on fatality rates. The number of deaths (D) per motor vehicles (V) has been found to be related to the number of motor vehicles per person (V/P) according to Smeed's formula (*9*):

$$D/V = 0.0003\ (V/P)^{-0.667} \qquad (1)$$

In a similar analysis for 32 developing countries using data

TABLE 4 VEHICULAR AND POPULATION-BASED MOTOR VEHICLE ACCIDENT RATES FOR SELECTED COUNTRIES AND YEARS

Motor vehicle accident rates	Country						
	China	USA		Kuwait	Zambia(d)		
	1985	1913(a)	1985(b)	1977(c)	1960	1969	1974
deaths/100,000 population	3.99	4.40	18.34	31.70	6.70	15.30	18.70
deaths/1000 vehicles	48.16	33.38	0.25	10.85	45	62	57
deaths/1000 licensed drivers	9.00	---	0.28	---	---	---	---
Vehicles/1000 population	8.29	13.62	740.00	350	15.00	24.60	33.20

(a) National Safety Council, Accident Facts 1987, Chicago, National Safety Council 1988.

(b) National Highway Traffic Safety Administration, Fatal Accident Reporting System, 1985. DOT/HS/ 807 071, Washington, D.C., U.S. Department of Transportation February, 1987.

(c) Bayowmi, A., The epidemiology of fatal motor vehicle accidents in Kuwait. Accid Anal Prev. 13(4): 339-348, 1981.

(d) Emoenalo, S., et al, Analysis of road traffic accidents data in Zambia. Accid Anal Prev. 9: 81-91, 1977.

TABLE 5 TOTAL MOTOR VEHICLE ACCIDENT, INJURY, AND FATALITY RATES[a] FOR BEIJING AND TIANJIN, BY CITY AND SUBURBAN AREAS, 1985

Beijing	City	Suburbs
Total accident	107	75
Injuries	64	47
Fatalities	4	9
Tianjin	**City**	**Suburbs**
Total accident	26	105
Injuries	20	61
Fatalities	2	15

(a) Per 100,000 population

for 1968, Jacobs and Bardsley (*14*) found the relationship to be expressed by the following equation:

$$D/V = 0.0007(V/P)^{-0.43} \tag{2}$$

The motorization rate (V/P) for all of China in 1985 was 8.29 vehicles per 1,000 population, ranging from 2.84 per 1,000 in the province of Hunan to 32.58 per 1,000 in the municipality of Beijing. Deaths per 1,000 motor vehicles for the entire country in 1985 were 4.80, ranging from 1.63 in the province of Gansu to 13.40 in the province of Hunan. Smeed's formula for China for 1985 is

$$(D/V) = 0.00025(V/P)^{-0.633} \tag{3}$$

which is significant at the p equals 0.0001 level. The adjusted R^2 equals 0.645.

DISCUSSION

As would be expected in a country where the majority of the population still is not exposed to motor vehicle travel as a routine part of daily living, population-based crash, injury, and fatality rates are relatively low (Table 1). The 43.15 reported fatalities per 100,000,000 person-km traveled (*3*) is also the rate expected in the first stages of motorization. The methods by which person-kilometers are estimated in China are unknown, so the figure should be considered a very rough estimate. The use of person-kilometers instead of vehicle-kilometers is much more appropriate because single-occupant trips are the exception in China, as in most developing countries (*2*).

The relationship between motorization and fatalities, commonly known as Smeed's law, was originally developed using 1938 data for 20 countries (16 European countries, the United

States, Canada, Australia, and New Zealand). It has since been applied to these same countries and been found to remain very stable (*14*). In a group of 32 developing countries, however, the fatality rates increased by 24 percent for similar levels of vehicle ownership over the period 1968–1971 (*14*); and in a group of 34 developing countries, the rate "increased markedly" over the period 1965–1978 (*15*). On further investigation (*14*), it was found that the proportion of motorcycles (as a percentage of all vehicles), the proportion of pedestrian fatalities (as a percentage of all fatalities), and the number of fatalities per crash due to increased overloading of vehicles had all increased during the 3-yr period. The usefulness of the formula in the identification of inconsistent changes in fatalities per vehicle was thus demonstrated.

The results reported here indicate that a doubling of vehicle ownership across the provinces yields a 35 percent decrease in fatalities per vehicle, within 2 percent of what was shown earlier for the developed countries (33 percent) and developing countries (37 percent). Smeed's formula can also be expressed as

$$D/P = -0.70(V/P)^{0.37} \quad (4)$$

which directly relates the rate of increase in fatalities per population to the degree of motorization ($R^2 = 0.37$). These results show that for every doubling of vehicle ownership there is a 29 percent increase in fatalities per person. Although Smeed's law is rarely presented this way, but rather is used to indicate the much more positive decrease in fatalities per vehicle, a doubling of vehicle ownership was reported to be accompanied by a 181 percent increase in fatalities per population over the period 1964 to 1974 in Zambia (*16*).

Besides the use of Smeed's law to present only the positive impacts of increased motorization, a second criticism is the inability to separate the various factors influencing each of the aggregate rates within the equation (*8,17*). Haight cautioned against the use of the law as an objective standard by which to judge whether an area is "safe" (*1*). His criticism of the formula as a means to compare developing countries because of its sensitivity to political decisions affecting the import or manufacture of certain vehicles (*2*) is also very appropriate for China. Total vehicle registration and manufacturing quotas by area are being used to control motorization; however, the importance of the differing vehicle safety standards available in vehicles manufactured by different countries does not appear to be recognized by the Chinese.

The fit of the data presented here indicates that the provinces and municipalities within China can be considered separate entities in different stages of motorization. Indeed, the populations of most of the individual provinces and municipalities far exceed the total population of the developing countries analyzed by Jacobs (*14*) and are as diverse as these countries with regard to ethnic heritage, climate, and terrain. One of the greatest challenges facing the Chinese government is developing traffic safety programs that will be effective across the country as a whole.

Despite the problems with Smeed's formula, finding a significant relationship between motorization rates and vehicle fatality rates does provide a basis for examination of some of the differences seen among the 29 units within China.

Some possible explanations for the differences are that those areas in which the vehicles-per-capita rate is higher are also assumed to have greater numbers of more experienced drivers, a more experienced population with regard to sharing motorways with motor vehicles, and decreased use of bicycles and cycle-rickshaws. Not surprisingly, vehicles-per-capita is strongly associated with licensed drivers-per-capita ($r = 0.70$, $p = 0.0001$); however, amount of experience or how long ago the license was obtained cannot be inferred from these data. Again, time-series analyses are needed. For the second assumption, no support can be derived either way from the data presented here. The number of vehicles by type registered per year for each unit for as many years as possible would have to be examined. A second indicator of support for this assumption would be the percent of total fatalities that occur among pedestrians; however, the fatality data are not routinely summarized by type. The third assumption is actually false, at least with regard to bicycles. Although no bicycle registration data were readily available by unit, bicycle ownership-per-100 households has increased from 31 to 74 from 1978 to 1984 for the country as a whole (*18*). Although it could be assumed that the number of cycle-rickshaws would decrease with increased vehicle ownership, this may not necessarily be the case. Ownership of a cycle-rickshaw could also be a possible first step in the entrepreneurship encouraged by the new economic reforms.

Although lack of information regarding driving experience and vehicle type limits the development of explanations for the findings shown here, the decrease in fatalities may represent nothing more than a response to a decrease in vehicle speeds due to the congestion caused by increased vehicle ownership. A primary goal of the Traffic Bureau is to decrease this congestion, which clearly is a major obstacle to the current program of economic development. The implications of this policy need to be examined in light of the role of vehicle speeds in crash and fatality rates. The cost of traffic-related mortality, morbidity, and property damage acceptable to Chinese society will be higher than that acceptable to a fully industrialized society as a justifiable cost of development. In developed countries, however, the costs of traffic safety have all too often been conveniently excluded from the calculation of the "true" costs of the development of a highway system, especially in comparison with other transport systems (*2*). It is hoped that the Chinese will not follow this pattern of economic analysis.

Although sufficient data to examine the effect of speed were not available, the effects of population density and vehicle density on fatality rates were examined. The ratio of fatalities to expected fatalities was found to decrease as population per area increased for states in the United States in 1963 (*9*). This relationship was not found to hold for other countries, however, nor was it found here for China. Clearly, the United States was at a stage of motorization in which the congestion of built-up areas influenced fatalities differently than it did in the other countries examined.

Motorization can roughly be divided into two stages (*2*): a "honeymoon" of maximum fascination for, and growth of, vehicle ownership; and when "the honeymoon is over," a period during which motor vehicle ownership is taken for granted as an often aggravating but necessary part of daily living. The first stage is characterized by high vehicle and vehicle-unit-travel fatality rates, as appreciation of the forces exerted in motor vehicle collisions is so low as to be non-existent. It is during this phase that several interventions have been shown to be effective:

- Standardizing regulations and ordinances with regard to the roadway, vehicle, and driver;
- Maximizing driver skill and performance as opposed to changing attitudes or increasing knowledge of regulations; and
- Increasing the beliefs held by the total population regarding the real dangers due to motor vehicle usage. The use of "horror" stories was found to start this process effectively (*1,2*).

The first of these interventions is taken for granted; but the second two now are believed to be ineffective, to the point of being ridiculed, in those countries well into the second phase of motorization. The danger for developing countries is that they and their advisors may fail to place their current traffic crash patterns in a historical perspective.

The People's Republic of China is experiencing an explosive period of growth and development and, in doing so, is looking to the developed nations for advice and technology. The tables and figures presented here show that China appears to exhibit the same patterns as have been seen in the developed countries in the first stage of motorization: fatalities per vehicle and driver are high, whereas fatalities per population are low. Growth in the number of vehicles is extremely rapid and, more important, private ownership of vehicles is being encouraged in the spirit of the new economic reforms. For example, in 1980, in the city of Beijing there were 4 taxi companies that owned a total of 4,200 vehicles. In 1987, the number of companies had increased to 252 and the total number of cabs to 13,000 (*19*). What is not apparent from the numbers, but is apparent from even a brief visit to China, is that the Chinese clearly have entered the period of infatuation not only with the automobile but with mobility itself.

One of the primary goals of economic and social development is improved movement of goods and people. How to increase such movement to the maximum possible while keeping any resultant loss of life and property to a minimum has been the subject of decades of study costing billions of dollars. Traffic safety, public health, and transportation planning professionals in developing countries need to be able to judge whether or not the lessons learned from these studies can be applied to conditions on their roadways. If relationships between the patterns of increased motorization that result from development and the patterns of subsequent motor vehicle crashes do not exist across nations, then each country will be forced to examine the methods needed to reduce motor vehicle mortality and morbidity among its own individual population (*20*). Work by Wintemute (*20*) and the extensive work by the Overseas Unit of the United Kingdom Transport and Road Research Laboratory [*21–24*, each cited by Jacobs and Sayer (*15*)] have determined that such relationships do exist. However, these relationships "vary greatly among groups of developing nations and between the developing and developed nations as groups" (*20*). The assumption by any country that the interventions that proved successful elsewhere can simply be applied to its own situation could result in a tremendous loss of resources, time, and, of course, productive years of life.

The similarities between the developed countries and China reported here are not meant to imply that such an assumption could or should be made. No conclusions can be drawn from these limited analyses as to whether these patterns of similarity will continue. The continuing debate regarding the usefulness of Smeed's work is also recognized (*1,8,17,25,26*). These results are clearly preliminary and do little more than identify the need for more and better data. Indeed, it is hoped that these results will highlight two important areas that must be addressed by the Chinese before their highway safety transition can occur. First is the need for a well-designed and implemented data collection system. China has an advantage in that one bureau is responsible for registering vehicles, issuing driver's licenses, and recording crashes for the entire country. A consistent set of definitions and practices can thus be used; however, the degree of uniformity with which this system is being implemented across the country is unknown. In addition, there appears to be little communication among the different units within the bureau with regard to crash reporting so that highway safety priorities can be determined or programs evaluated.

The second issue is also related to communication between governmental units. The Chinese have stated that reliance on the functions of one government agency cannot solve all of their traffic-related problems (*27*). The functions listed as necessary by Fang (*27*), however, currently are all performed by one government ministry. Notable in their absence are the Statistical Bureau and the Ministry of Public Health. It appears that the Ministry of Public Health currently has little to no involvement in traffic casualty prevention. Trauma data are not routinely reported by type, and thus the role of traffic deaths in comparison with all deaths, or even injury deaths, cannot easily be ascertained (*28*). In addition, the burden that traffic injury places on the health care delivery system in China is currently very difficult to determine. Information from the Ministry of Public Health could assist the Transportation Bureau in its attempts to balance the pressures for rapid development with the need to minimize the traffic-related deaths and injuries that will accompany that development. In addition, health professionals could provide personnel, expertise, and resources to augment those of the Transportation Bureau.

The effects of the failure of the developed countries, and especially the United States, to come to terms with whether traffic safety is a health or a transportation problem are presented by Haight (*2*). The current emphasis in the United States on highway death as a matter of concern to public health professionals may be the result of the unspoken belief that further decreases in the number of fatalities-per-kilometer traveled will come about only with very costly changes in the vehicle or highway system; it is thus up to the medical community to convince people that prevention of highway deaths is up to them as individuals, that they must "change their life style." Even if this is the case, there still can be tremendous positive results from the incorporation of an entire body of professionals into the highway safety effort. Traffic safety personnel need to consider themselves health professionals, and health professionals need to understand the means of preventing traffic-related injuries and deaths and to incorporate this understanding into their practice. It is hoped that in China, as well as in all developing countries, this need will not be recognized at as late a stage in the motorization process as has occurred in the United States.

SUMMARY

Based on an analysis of very preliminary data, it has been shown that the People's Republic of China is at the beginning of the highway safety transition. Increases in the number of highway fatalities can be expected to coincide with the increased motorization due to economic development. To be able to predict and respond to changes in highway fatality rates, a uniform, accurate, and integrated reporting system is needed for crash, vehicle, and driver data. In addition, traffic crashes need to be recognized as a health problem so that the resources and expertise of the public health community can be enlisted in the prevention of these needless deaths and injuries.

ACKNOWLEDGMENT

Zhao-Sheng Yang co-authored this paper at the University of Illinois while he was a visiting scholar from Jilin University, Changchun, the People's Republic of China.

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Publication of this paper sponsored by Committee on Traffic Records and Accident Analysis.