Level of Service of Safety

Conceptual Blueprint and Analytical Framework

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While some initial and significant progress has been made in the development of a highway safety manual, much remains to be done in the areas of conceptual development and the diagnostics of safety problems. The concept of level of service of safety (LOSS) in the framework of safety performance function is introduced, and the problem of diagnostics is addressed. LOSS reflects how the roadway segment is performing in regard to its expected accident frequency and severity at a specific level of annual average daily traffic. It provides a comparison of accident frequency and severity only with the expected norms; it does not, however, provide any information related to the nature of the safety problem itself. If the safety problem is present, LOSS will describe only its magnitude. The nature of the problem is determined through diagnostic analysis by direct diagnostics and pattern recognition techniques, which are also discussed.

Transportation engineers have dealt successfully over the years with the question of highway capacity. The problem was clearly formulated by HRB in 1944, when the Committee on Highway Capacity was first established. The first edition of the *Highway Capacity Manual* (HCM) was published by HRB in 1950 (*1*). It provided initial fundamentals of capacity for uninterrupted-flow facilities, signalized intersections, weaving sections, and ramps. Since then there have been new editions of the HCM, and the understanding of highway capacity is enhanced with each successive publication of the HCM by TRB. The relationship between traffic volumes, capacity, and level of service for different types of highway facilities is thus reasonably well understood at present.

In contrast to highway capacity, the relationship between traffic volume, the physical characteristics of roads, and safety is not well understood or known, at least not with the kind of precision customary in other engineering disciplines. Until 1999 there had not been a concerted effort by TRB to produce a highway safety manual (HSM). Conceptually, such a document should systematically examine the expected accident by-product of roadway segments (freeways, arterials, two-lane roads, etc.) as well as junctions (intersections and interchanges). A special conference session on the subject of predicting the highway safety impacts of design and operations decisions was held at the 1999 TRB Annual Meeting. The session concluded that one reason for a lack of emphasis on safety is the absence of a single authoritative document that can be used to estimate impacts on safety. As a follow-up to the TRB conference session, an HSM workshop was held in December 1999 under the sponsorship of eight TRB committees and FHWA. A group of 25 researchers and practitioners concluded that there is a compelling need for the development of an HSM and recommended that the development work commence as soon as possible. In January 2000 the Joint Subcommittee for the Development of a Highway Safety Manual was formed by TRB to direct the efforts to produce an HSM. Later in the year, NCHRP Project 17-18(4) was funded to develop the scope, organization, and outreach strategies for an HSM. Additionally, NCHRP Project 17-26 (Development of Models for Prediction of Expected Safety Performance for Urban and Suburban Arterials) is in the final phase of consultant selection. The research contractor for NCHRP Project 17-26 is directed to work within the framework that the joint subcommittee established for an HSM. While some initial and significant progress has been made in the development of an HSM, much remains to be done in the areas of conceptual development and the diagnostics of safety problems.

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This paper introduces the concept of level of service of safety (LOSS) in the framework of safety performance function (SPF) and addresses the issue of problem diagnostics. Introduction of the LOSS concept will bring about badly needed consensus in the transportation engineering profession on how to quantify the magnitudes of safety problems for different classes of roads. It will also enable transportation engineers to do the following:

- Qualitatively describe the degree of safety or unsafety of a roadway segment;
- Effectively communicate the magnitude of the safety problem to other professionals or elected officials;
- Bring the perception of roadway safety in line with the reality of safety performance for a specific facility;
- Provide a frame of reference for decision making on non-safety-motivated projects (resurfacing or reconstruction, for instance); and
- Provide a frame of reference from a safety perspective for planning major corridor improvements.

LOSS provides a comparison with the expected frequency and severity norms; it does not, however, provide any information related to the nature of the safety problem itself. If the safety problem is present, LOSS will describe only its magnitude. The nature of the problem is determined through diagnostic analysis by direct diagnostics and pattern recognition techniques, which are also discussed in this paper.

SPFs AS ANALYTICAL FRAMEWORK FOR DEVELOPMENT OF LOSS CONCEPT

An HSM, among other things, should provide a realistic estimate of the expected accident frequency per unit of traffic exposure over a unit of time for various types of transportation facilities. The development of such estimates is a critical component in the explicit consideration of safety in highway planning and design. Indeed, if expectations are not clearly defined or well understood, then the question becomes, how is it possible to identify the deviation from the norm and then do something about it? In medical terms, how can a physician be expected to prescribe medication that reduces blood pressure if the thresholds for diastolic and systolic blood pressure levels have not yet been agreed upon by the medical profession? Fortunately, since 1905 (*2*) there has been a consensus among doctors on this subject. Only over the last decade has there been an established consensus among traffic safety researchers that a nonlinear, non-Gaussian relationship exists between traffic exposure and safety. This relationship is reflected by the SPFs calibrated for various classes of roads and intersections. SPFs, in essence, are accident prediction models that generally relate traffic exposure, measured in annual average daily traffic (AADT), to safety, measured in the number of accidents over a unit of time. In statistical modeling of traffic accidents, the modelers are interested in discovering what can be learned about underlying relationships from empirical data containing a random component. Suppose that some complex phenomenon manifested by accident occurrence (the data-generating mechanism) has produced the observations and the desire is to describe it by some simpler, but still realistic, model that reveals the nature of the underlying relationship. Lindsey (*3*) observed that in a model one can distinguish between systematic variability and random variability, in which the former describes the patterns of the phenomenon in which the investigator is particularly interested. A great deal of substantive and comprehensive work in the area of accident modeling was done by Miaou and Lum (*4*), Hauer and Persaud (*5*), and Hauer (*6*), as well as others. The following is a brief description of the modeling methodology and data collection used in this study.

Choice of Model Form

On the basis of substantial empirical evidence derived from observation of the safety performance of various roads over extended time periods as well as the work of other researchers, the following understanding of the relationship between safety and exposure has emerged: accident rates decline when AADT reaches a certain threshold endemic to a particular facility in a specific environment. This understanding suggests a choice of underlying function that would reflect this phenomenon. Such a function can be represented by a model form that will show some leveling off associated with an approach to some threshold exposure value. Two general model forms are usually used:

$$E\{y\} = X^{\beta_0} e^{\beta_1 x + \beta_2 x^2 \cdots} \rightarrow \text{power} - \text{family}$$

$$E\{y\} = X^{\beta_0}(1 + \beta_1 X + \beta_2 X^2 \ldots) \rightarrow \text{polynomial} - \text{family}$$

where

$E\{y\}$ = annual number of accidents expected to occur on a segment of road;
X = is the independent variable (here, AADT); and
β = the parameters to be estimated.

E. Hauer, in unpublished working papers, used the Nadaraya–Watson kernel estimator with the Gaussian kernel to obtain the relationship presented in Figure 1. The nonparametric kernel regression used by Hauer is a smoothing technique used to obtain clues about the form of the function underlying the data. Similar functional shapes in Figure 2 were developed and described by Kononov (*7*) by using the neural networks–radial basis function. Neural networks are not constrained by the underlying distributional assumptions and learn by example, inferring a model from training data.

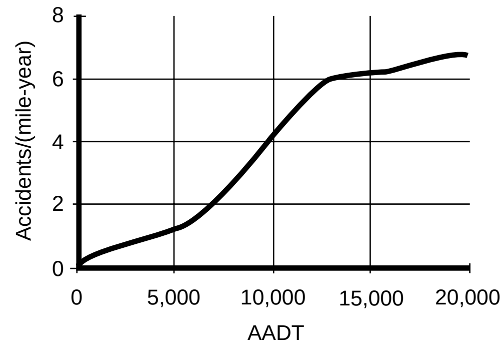

FIGURE 1 Relationship between exposure and safety (from Hauer, unpublished).

Choice of Underlying Distributional Assumptions

In statistical modeling of traffic accidents, it is assumed that the random variation follows certain probability laws and can be characterized by a probability function. Miaou and Lum observed that "The use of a continuous distribution, such as the normal distribution, is at best an approximation to a truly discrete process. The Poisson distribution, on the other hand, is a natural initial candidate distribution for such random discrete and, typically, sporadic events" (*4*). At the same time, if a Poisson assumption is made about the underlying random variability, it will have a restricting effect of always equating the variance to the mean. In the authors' experience with accident data, this assumption is not always true. Similar findings are reported by Dean and Lawless (*8*). In many cases accident data exhibit extra variation or overdispersion relative to the Poisson model. In other words, the variance of the data is often greater than the mean. In this study, Poisson regression was used to fit models in rural areas and negative binomial regression was used to fit models of urban freeways, which generally exhibit overdispersion.

Data Collection and Data Set Preparation

The data set was prepared by using the Colorado Department of Transportation accident database. The accident history for each facility over a period of 14 years was prepared. The AADT for each roadway segment for each of the 14 years was entered into the same data set. For rural freeways, all of the interchange-related accidents were isolated from the accident database before fitting of the model. The reason for isolation of interchange-related accidents in rural areas was to remove the influence of accidents resulting from merge–diverge turbulence at an interchange. For two-lane rural roads, the data set was prepared in a similar fashion, with the exception that intersection-related accidents and 0.1-mi roadway segments containing intersections were removed before fitting of the model. Isolation of a distance of approximately 250 ft on both sides of rural intersections is a conservative measure, but it will ensure that intersection-related conflicts will not pollute the data set that comprises non-intersection-related accidents and road segments. In the urban environment it is virtually impossible to remove the influence of interchanges on safety and operations. Considering this reality, all of the accidents that occurred on ramps and crossroads were removed before fitting of the model, which left only accidents occurring on the urban freeway itself. The data set for urban freeways was prepared by emphasizing that each segment should include only one interchange. Figure 3 illustrates how the data sets were prepared for three different facilities.

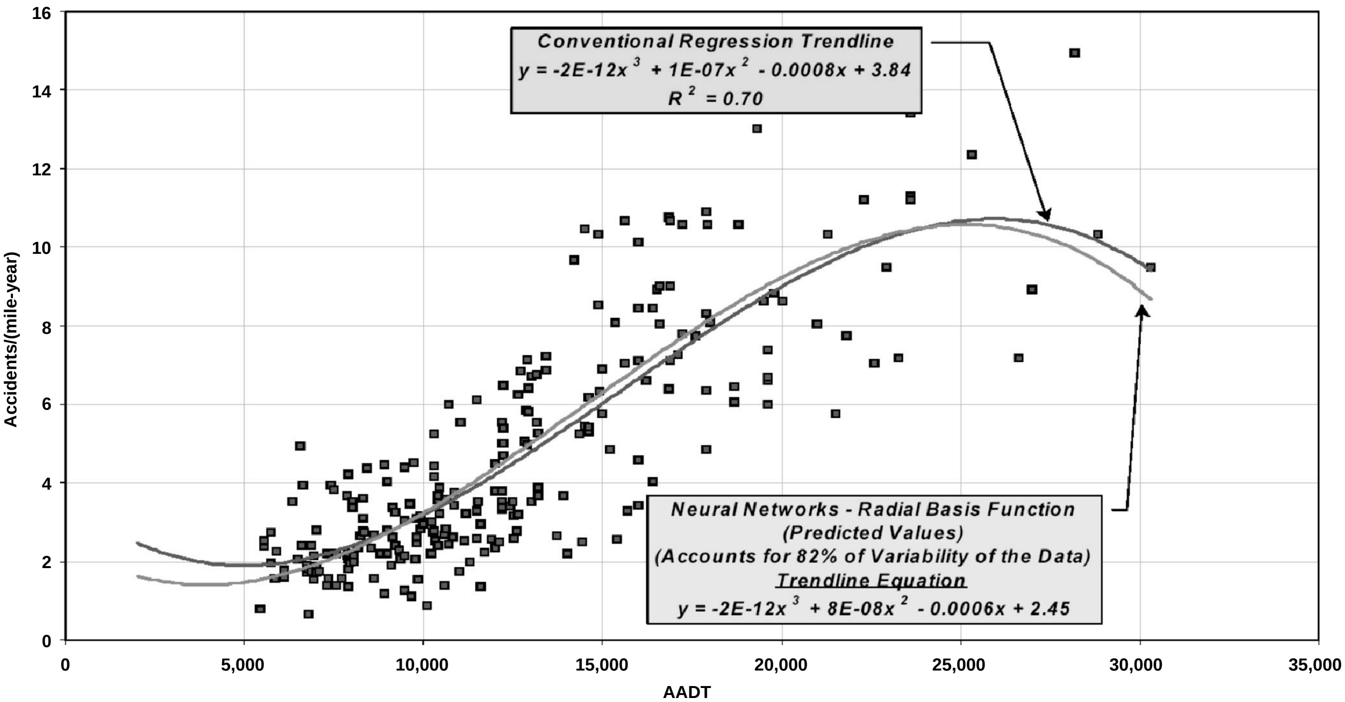

FIGURE 2 SPF developed by using neural networks for a rural mountainous four-lane Interstate.

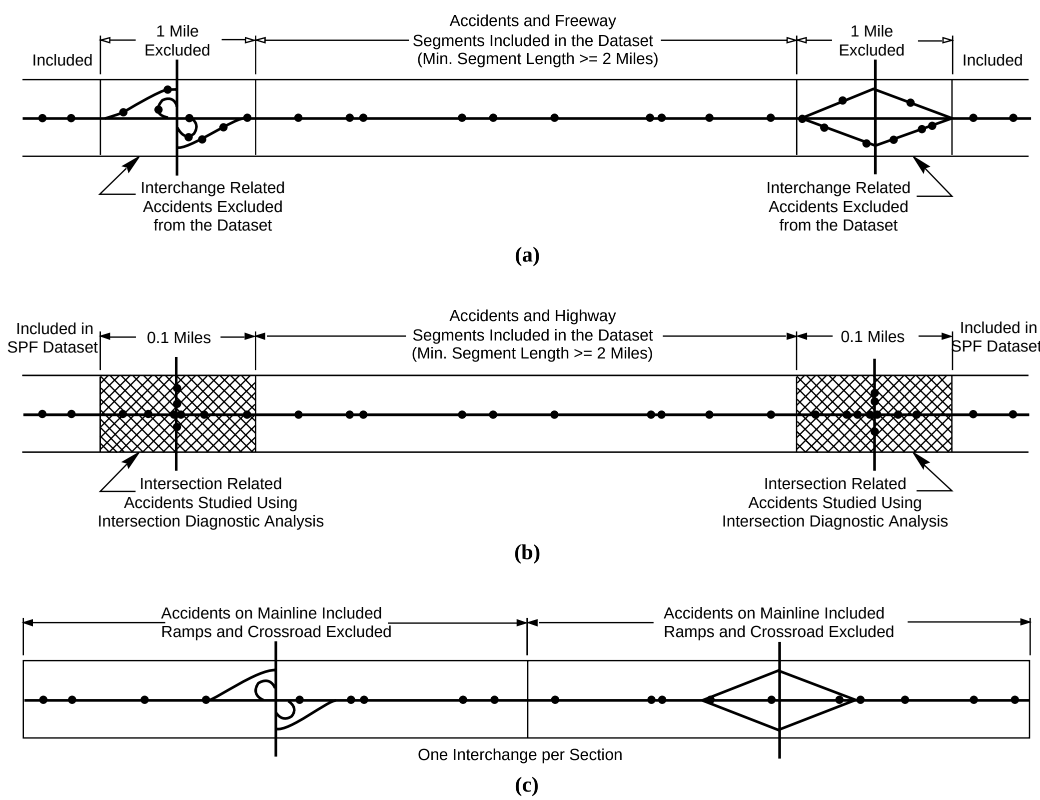

FIGURE 3 Details of data set preparation: (*a*) four-lane rural freeway, (*b*) two-lane rural arterial, and (*c*) six-lane urban freeway.

MODEL FITTING

The model parameters were estimated by the maximum-likelihood method with the Generalized Linear Model spreadsheet of STATISTICA (*9*). For rural freeways and arterials, which typically do not exhibit overdispersion, the regression parameters are estimated by maximizing the Poisson log-likelihood function. Maximization of the log-likelihood function has computational advantages over maximization of the ordinary likelihood function L, which represents the product of the individual Poisson probability density functions.

$$\mu = \text{AADT}^{\beta_0}\left(1 + \text{AADT}^{\beta_1} + \text{AADT}^{\beta_2} + \cdots + \text{AADT}^{\beta_n}\right)$$

$$\mu \in \text{Poisson} \therefore \text{Var}(y) = \mu \therefore \sigma = \sqrt{\mu}$$

$$P(x = y_i) = \frac{\mu_i^{y_i}}{y_i!} e^{-\mu_i} \therefore L(\mu_p) = \prod_{i=1}^{n}\left(\frac{\mu_i^{y_i} e^{-\mu_i}}{y_i!}\right)$$

$$\ln(L) = \sum_{i=1}^{n}(y_i \ln \mu_i - \mu_i - \ln y_i!)$$

where

AADT = annual average daily traffic,
μ = estimated number of accidents on roadway segment i over a period of a year,
Var(y) = variance of y,
σ = standard deviation for population,
y_i = observed number of accidents on roadway segment i over a period of a year,
$L(\mu_p)$ = Poisson likelihood function, and
β = estimated regression parameters.

Urban freeway data sets generally exhibit overdispersion. Although the geometric characteristics of the freeways themselves are fairly uniform because they are designed to Interstate standards, the overdispersion was consistently present. This can possibly be explained by the influence of ramp flows and spacing on safety performance. The influence of ramps was not introduced as an independent variable but was reflected by the number of accidents on the main line. To minimize the influence, each urban freeway segment in the data set contained only one interchange. The β parameters for the urban freeways were estimated by maximizing the log-likelihood function of the negative binomial distribution.

$$\mu \in \text{negative} - \text{binomial} \therefore \text{Var} > \mu$$

$$\text{Var}(y) = \mu(1 + \alpha\mu) = \mu + \alpha\mu^2 \therefore \sigma = \sqrt{\mu + \alpha\mu^2}$$

$$L(\alpha, \mu) = \prod_{i=1}^{n} \frac{\Gamma(\alpha^{-1} + y_i)}{\Gamma(\alpha^{-1}) y_i!}\left(\frac{\alpha\mu_i}{1 + \mu_i}\right)^{y_i}\left(\frac{1}{1 + \alpha\mu_i}\right)^{\alpha^{-1}}$$

$$\ln[L(\alpha, \mu)] = \sum_{i=1}^{n}\left\{\ln\left[\frac{\Gamma(\alpha^{-1} + y_i)}{\Gamma(\alpha^{-1}) y_i!}\right] + y_i \ln\left(\frac{\alpha\mu_i}{1 + \alpha\mu_i}\right) + \alpha^{-1}\ln\left(\frac{1}{1 + \alpha\mu_i}\right)\right\}$$

where α is the overdispersion parameter, also estimated by maximizing the negative binomial log-likelihood function.

The quality of fit was examined by the cumulative residuals method described by Hauer and Bamfo (*10*). This method consists of plotting the cumulative residuals for each independent variable. The goal is to graphically observe how well the function fits the data set. To generate a cumulative residuals plot, sites are sorted by their average AADT. Then, for each site, the residual (which is the predicted number of accidents minus the observed number of accidents) is computed. The residuals are then added up, and a cumulative residual value is plotted for each value of the independent variable. Because of the random nature of accident counts, the cumulative residual line represents a so-called random walk. For a model that fits well in all ranges of AADT, the cumulative residual plot should oscillate around 0. If the cumulative residual value steadily increases within an AADT range, this means that within that AADT range the model predicts more accidents than the number that have been observed. Conversely, a decreasing cumulative residual line in an AADT range indicates that in that range more accidents than the number predicted by the model have been observed. A frequent departure of the cumulative residual line beyond 2 standard deviations of a random walk indicates the presence of outliers or signifies an ill-fitting model. All of the models in the study produced a very satisfactory fit, in which the random walk stayed well within 2 standard deviations while oscillating around 0. Figure 4 illustrates a cumulative residual plot reflecting the model fit for the SPF calibrated for two-lane rural mountainous highways.

LEVEL OF SERVICE OF SAFETY

The development of SPF lends itself well to the conceptual formulation of LOSS. The concept of level of service uses qualitative measures that characterize the safety of a roadway segment in reference to its expected performance. If the level of safety predicted by SPF represents the normal or expected number of accidents at a specific level of AADT, then the degree of deviation from the norm can be stratified to represent specific levels of safety. Road safety should be described from the frequency and severity standpoints. Toward this goal, two kinds of SPFs were calibrated: one for the total number of accidents and the other for injury and fatal accidents only. Therefore, when the magnitude of the safety problem is assessed, it is described from the frequency and severity standpoints. Figures 5 and 6 illustrate the concept by using the SPFs calibrated for the total accidents and injury and fatality-only accidents expected on six-lane urban freeways, respectively. The delineated boundary line is located 1.5 standard deviations from the mean. Four LOSSs can be proposed:

- LOSS-I indicates a low potential for accident reduction,
- LOSS-II indicates better than expected safety performance,
- LOSS-III indicates less than expected safety performance, and
- LOSS-IV indicates a high potential for accident reduction.

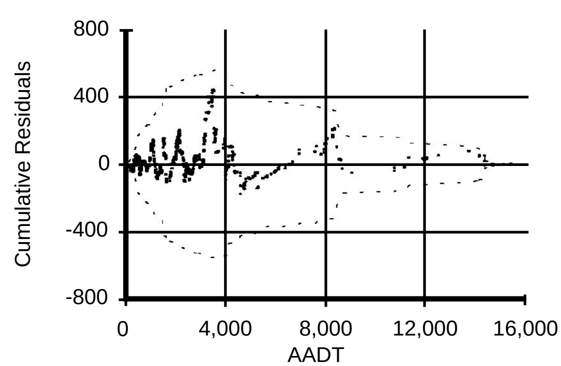

FIGURE 4 Cumulative residual plot for two-lane mountainous highways.

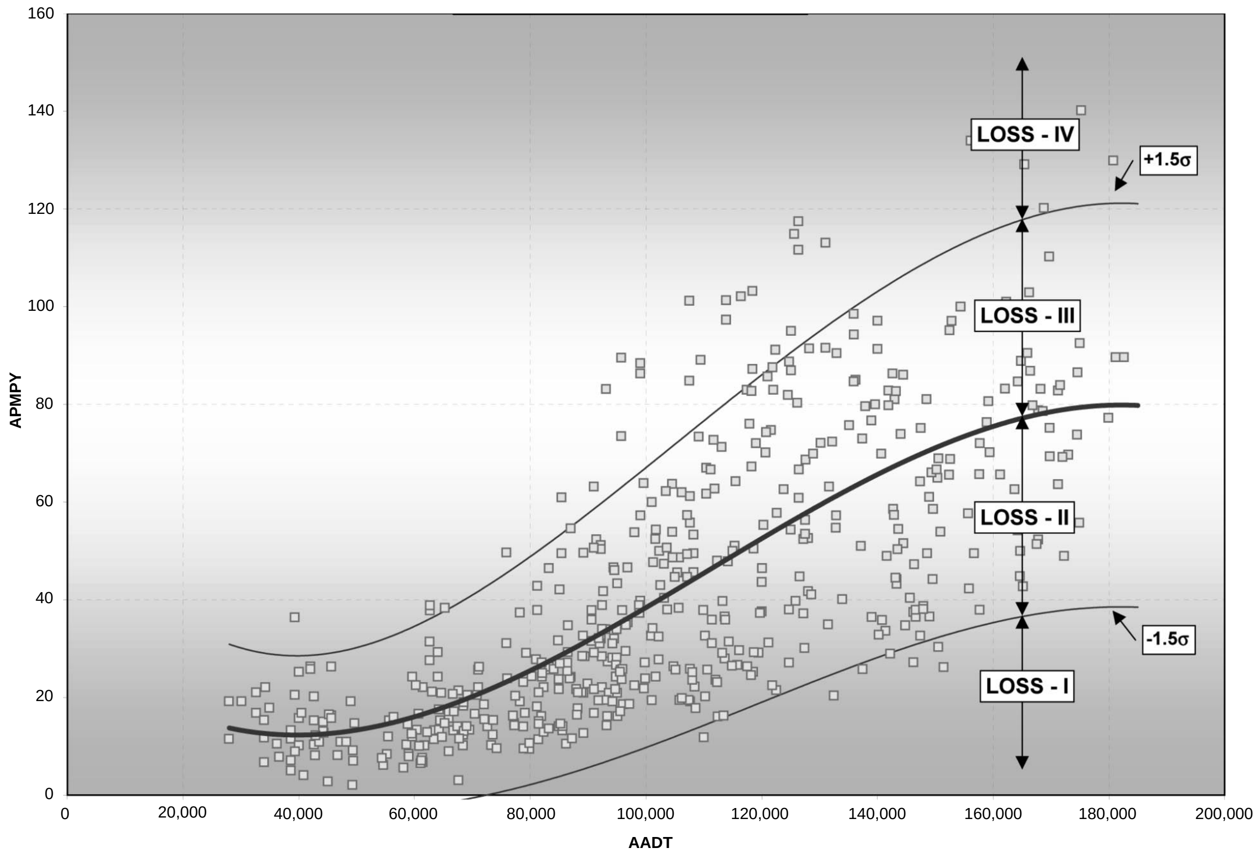

FIGURE 5 Urban six-lane freeway LOSS-SPF graph (total accidents) (APMPY = accidents per mile per year).

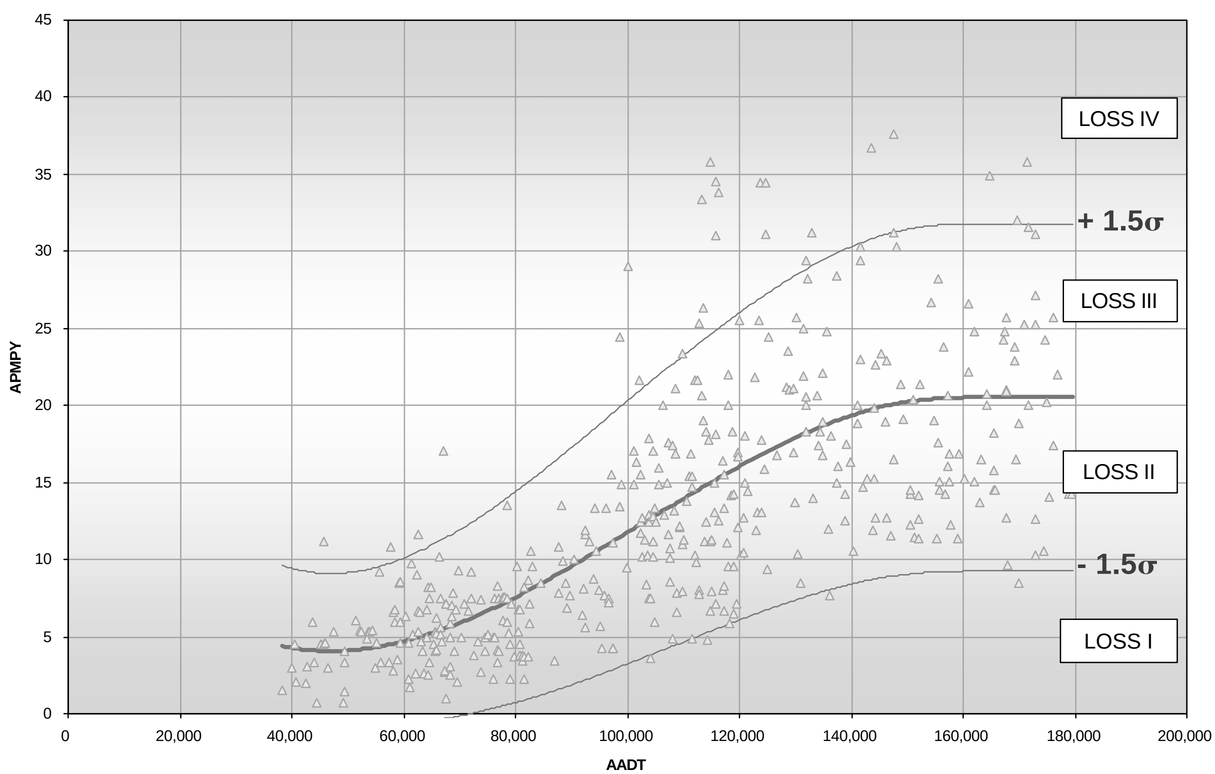

FIGURE 6 Urban six-lane freeway LOSS-SPF graph (1989–2001, injuries plus fatalities only, sections ≥ 0.9 mi) (APMPY = accidents per mile per year).

For instance, a segment can have LOSS-II on the total accidents SPF and LOSS-III on the injuries plus fatalities SPF. Therefore, from the safety perspective the same segment can be described as having a LOSS-II frequency and a LOSS-III severity. In the authors' experience, however, most segments generally exhibit the same LOSS from the frequency and severity perspectives. A gradual change in the degree of deviation of the LOSS boundary line from the fitted model mean reflects the observed increase of variability in the number of accidents per mile as AADT increases. This increase is consistent with the Poisson error structure for rural freeways and arterials. For urban freeways the negative binomial error structure reflects the overdispersion typical of this environment. A possible explanation for the overdispersion in the urban freeway data set may be the influence of different ramp volumes on the freeway safety performance. LOSS reflects how the roadway segment is performing in regard to its expected accident frequency and severity at a specific level of AADT. It provides a comparison of accident frequency and severity only with the expected norms; it does not, however, provide any information related to the nature of the safety problem itself. If the safety problem is present, LOSS will describe only its magnitude. The nature of the problem is determined through diagnostic analysis by direct diagnostics and pattern recognition techniques.

DIAGNOSTICS OF SAFETY PROBLEMS

In the course of in-depth project-level safety studies of hundreds of locations, a comprehensive methodology was developed to conduct diagnostic analysis of safety problems for different classes of roads in various environments. Direct diagnostics methods and a pattern recognition algorithm are described by Kononov (*11*) and Kononov and Janson (*12*). A framework of 84 normative parameters was developed to provide a knowledge base for diagnostic analysis of different classes of roads in rural and urban environments. Because traffic accidents can be viewed as random Bernoulli trials, it is possible to detect deviation from the random statistical process by computing the observed cumulative probability for each of the 84 normative parameters. The 84 parameters can be grouped into 11 general categories: accident type, severity, accident location, road condition, direction of travel, lighting condition, vehicle type, human factors, driver condition, weather condition, and time of day. It is important to note that some, but not all, normative parameters within the same SPF change with AADT. For instance, in general, the severity of accidents gradually decreases and the distribution of accidents by accident type changes with AADT. With this in mind, 84 normative parameters were stratified for three ranges of AADT: low, medium, and high. In the process of assessing the nature and magnitude of safety problems at specific locations, SPF analysis should be used in conjunction with an appropriate diagnostic investigation by using the pattern recognition algorithm. The stratification of the diagnostic parameters by AADT improves the ability to identify accident patterns more accurately. For instance, for the low range of AADT on two-lane mountainous roads, the average proportion of head-on collisions is 2%, while it is 8% for the high range of AADT. Not accounting for this change would lead to misdiagnosis of the problem. Figure 7 presents LOSS in the framework of SPF with normative diagnostic categories for three ranges of AADT. While LOSS provides a means of assessment of the magnitude of the safety problem, it is important to understand that accident patterns susceptible to correction may exist with or without overrepresentation in total frequency, as detected by SPF.

APPLICATION OF LOSS ANALYSIS AND DIAGNOSTIC INVESTIGATION

To illustrate the application of the concept, a roadway segment in a rural mountainous area was selected and LOSS analysis was conducted, followed by a diagnostic examination of accident causality. The site selected was located on a two-lane mountainous road in southwestern Colorado. The site selected is approximately 3 mi long and is located between mileposts 196.00 and 199.00 on State Highway 50. This roadway segment carries approximately 2,200 cars per day and experienced approximately 5.5 accidents per mile per year over the last 3 years. The frequency and severity of accidents observed at the site exhibit LOSS-IV (only the frequency graph is shown in Figure 8 because of format limitations), which suggests a high potential for accident reduction.

At this point of the diagnostic investigation, all that is known is that the site has experienced significantly more accidents than expected, but nothing is yet known as to why. The accident type distribution profile observed on the study segment over the last 3 years is then examined. As can be seen from Figure 8, the most frequent accident type is a fixed-object collision. Fixed-object collisions represent 54% of the total. This appears to be somewhat higher than the expected rate of 39% typical of the low AADT range for a two-lane mountainous road in the rural environment. The direct diagnostics test can be applied by considering the observed accident history of 51 total accidents and 28 fixed-object collisions:

$$\begin{aligned} P(X \geq 28) &= 1 - P(X \leq 27) \\ &= 1 - \sum_{i=0}^{27} \frac{51!}{(51-i)!\,i!} 0.39^{i}(1-0.39)^{51-i} \\ &= 0.015 \end{aligned}$$

where P represents the cumulative probability of observing 28 fixed-object collisions or more out of 51 total accidents, and 0.39 is the Bernoulli probability of fixed-object collisions in the low AADT range on two-lane mountainous roads.

The result of the direct diagnostics test for fixed-object collisions suggests that there is something in the roadway environment that triggers a deviation from the random process of accident occurrence in the direction of reduced safety. More specifically, it triggers fixed-object collisions. As yet it is not known what it is.

The study segment was then examined for the concentrations of fixed-object accidents. Figure 9 shows the cumulative fixed-object collisions throughout the study area. The cumulative concentration of fixed-object collisions in Figure 9 reveals two apparent accident clusters, one between mileposts 196 and 196.5 and the other between mileposts 197.5 and 197.8. Application of the pattern recognition algorithm described by Kononov (*11*) confirmed that the observed accident clusters represent patterns of the fixed-object collisions. It is of interest to note that even though this site is located within a mountain pass zone (5 mi from the summit), the percentage of accidents related to weather and road conditions is well within the expected range. It can now be concluded that a significantly higher than expected accident frequency (LOSS-IV) reflected in the SPF analysis can be attributed to the presence of two sizable clusters of fixed-object collisions. These clusters are located between mileposts 196.00 and 196.50 and mileposts 197.50 and 198.00. The accidents within the clusters were then examined more closely and an attempt was made to identify additional common characteristics among them. Filtering of accidents

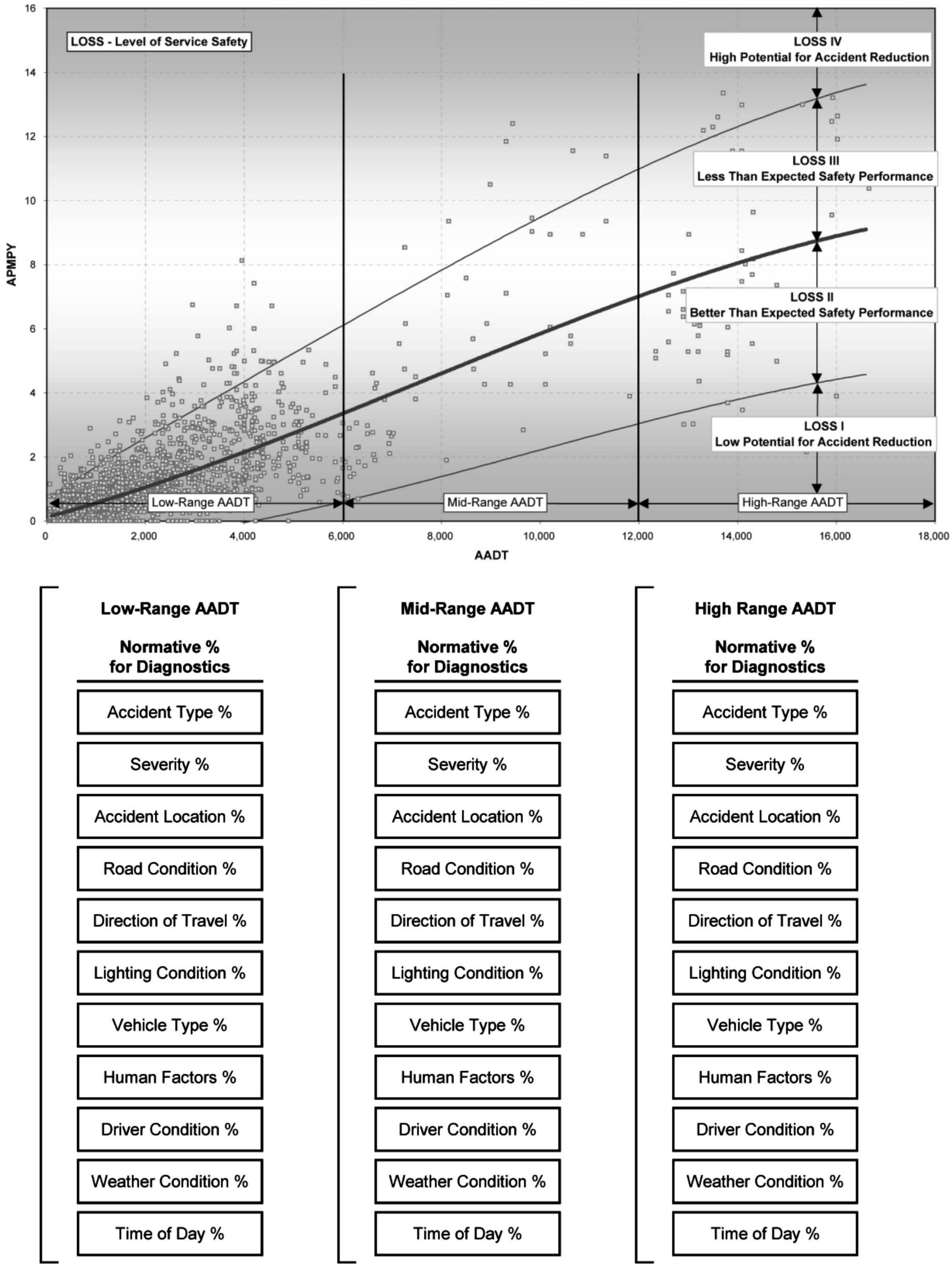

FIGURE 7 LOSS-SPF with stratified diagnostic norms, rural mountainous two-lane highway LOSS-SPF graph (APMPY = accidents per mile per year).

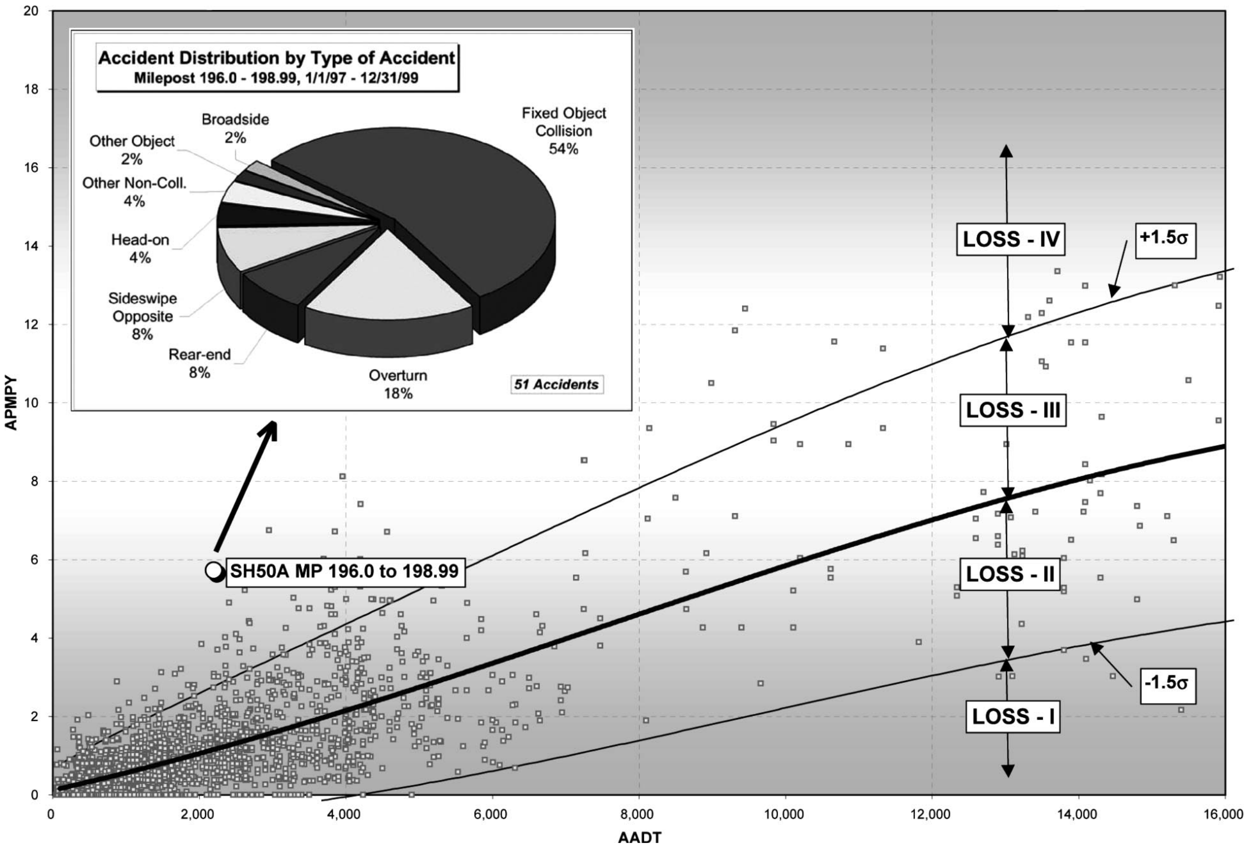

FIGURE 8 LOSS analysis with initial diagnostics, rural mountainous two-lane highway LOSS-SPF graph (Coll. = collision) (APMPY = accidents per mile per year).

by direction revealed that all fixed-object collisions in both clusters occurred while vehicles were traveling in the westbound direction. Both accident clusters are contained within horizontal curves situated on the downgrade in the westbound direction.

Review of the existing plans indicated that the design speeds for the horizontal curves containing accident clusters are only 30 mph. Both curves are preceded by long segments of tangent or mild horizontal curvature situated on the steep vertical grade. This information is presented in Figure 10. A combination of steep grades, a sharp horizontal curvature, and long tangents or segments of mild curvature preceding the curves is known to be associated with loss of control on the curves, which results in accidents. Possible countermeasures may include placement of guardrails around the curves and additional signing, in combination with an automated speed detection system connected to the variable-message signboards.

CONCLUSIONS

Development of the SPF lends itself well to the conceptual formulation of LSOS. The concept of level of service uses qualitative measures that characterize the safety of a roadway segment in reference to its expected performance. Four LOSSs are proposed:

- LOSS-I indicates a low potential for accident reduction,
- LOSS-II indicates better than expected safety performance,
- LOSS-III indicates less than expected safety performance, and
- LOSS-IV indicates a high potential for accident reduction.

Road safety should be described from the frequency and severity perspectives by using SPFs calibrated for total accidents and injury and fatality-only accidents. Although most segments generally exhibit the same LOSS from the frequency and severity perspectives, this is not always the case.

A gradual change in the degree of deviation of the LOSS boundary line from the fitted model mean reflects the observed increase in variability in the number of accidents per mile as AADT increases. This increase is consistent with a Poisson error structure for rural freeways and arterials. For urban freeways the negative binomial error structure reflects the overdispersion typical of this environment. LOSS reflects how the roadway segment is performing in regard to its expected accident frequency at a specific level of AADT. It provides a comparison of accident frequency and severity only with the expected norm; it does not, however, provide any information related to the nature of the safety problem itself. If the safety problem is present, LOSS will describe only its magnitude. The nature of the problem is determined through diagnostic analysis by using direct diagnostics and pattern recognition techniques.

SPFs and diagnostic norms were developed by using Colorado Department of Transportation accident databases. While the methodology presented in this paper can be applied to other states and countries, such an application would require local calibration to reflect the prevalent characteristics of accident reporting, climate, driver behavior, and design practices and other local factors.

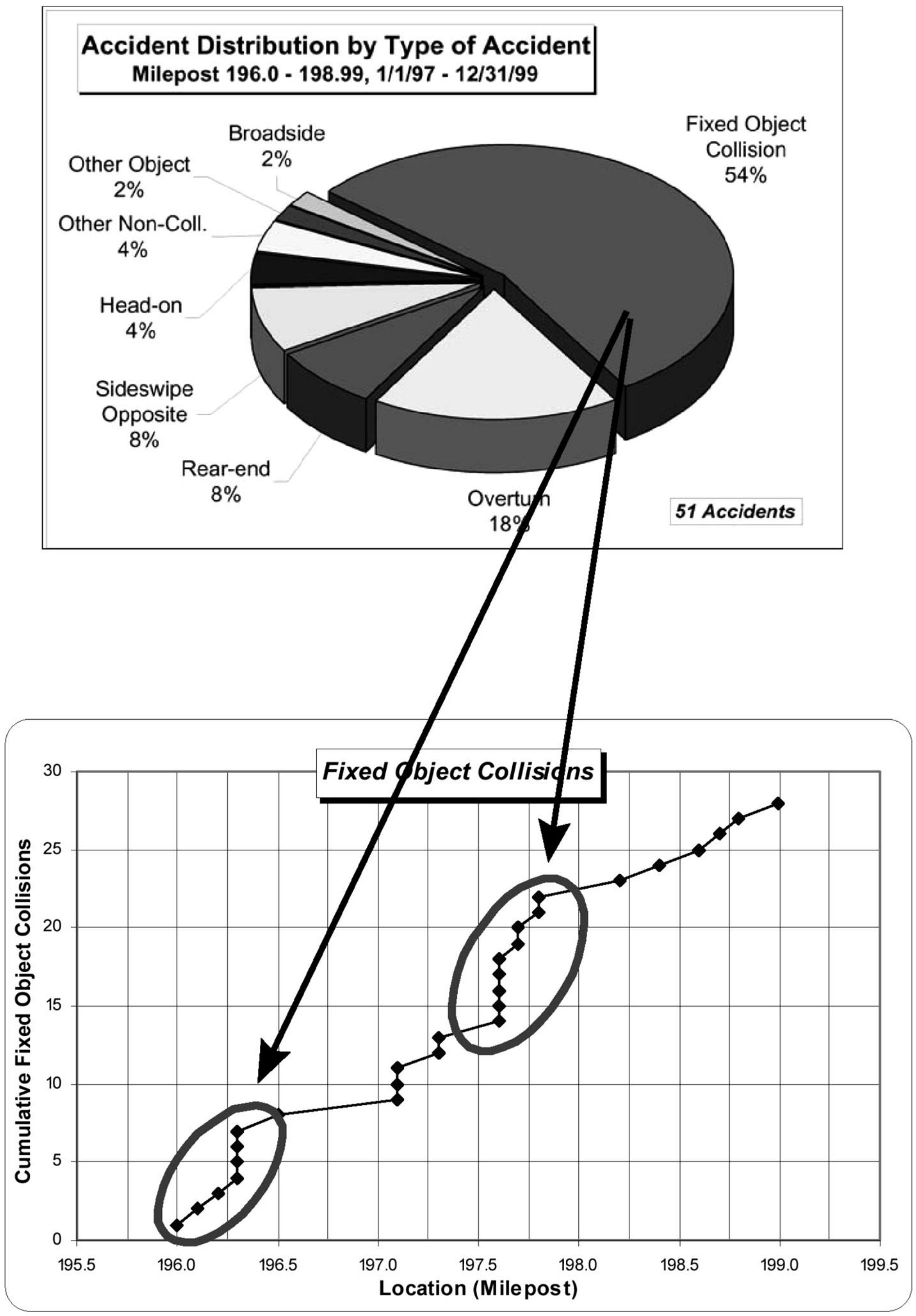

FIGURE 9 Fixed-object collisions cumulative concentration graph (Coll. = collision).

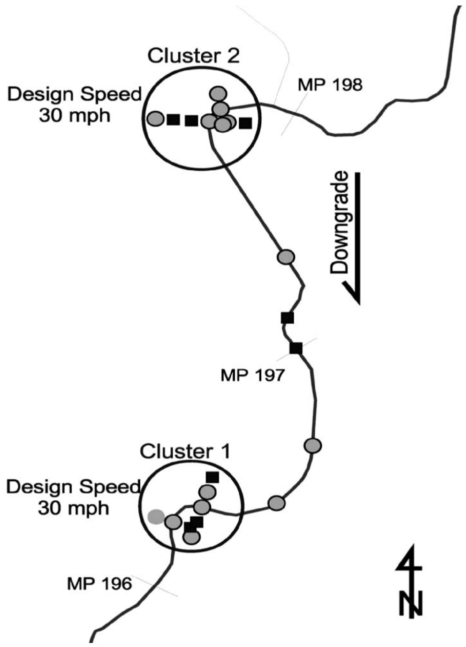

FIGURE 10 Accident concentration geographic information system map (MP = milepost).

REFERENCES

1. *Highway Capacity Manual.* HRB, National Research Council, Washington, D.C., 1950.
2. Dictionary of Medical Equipment. Blood Pressure Measurement, History and Method. http://www.themedweb.co.uk/dictionary/Dictionary.htm. Accessed July 2, 2002.
3. Lindsey, J. K. *Applying Generalized Linear Models.* Springer-Verlag, New York, 1997.
4. Miaou, S., and H. Lum. Modeling Vehicle Accidents and Highway Geometric Design Relationships. *Accident Analysis & Prevention,* Vol. 25, No. 6, 1993, pp. 689–709.
5. Hauer, E., and B. Persaud. *Safety Analysis of Roadway Geometric and Ancillary Features.* Transportation Association of Canada, 1997.
6. Hauer, E. Identification of Sites with Promise. In *Transportation Research Record 1542,* TRB, National Research Council, Washington, D.C., 1996, pp. 54–60.
7. Kononov, J. Relationship Between Traffic Safety and Traffic Volume on Rural Freeways and Conceptual Development of the Level of Service of Safety. *Proc., 10th International Conference, Traffic Safety on Two Continents.* Swedish National Road and Transport Research Institute, Malmo, Sweden, 1999.
8. Dean, C., and J. F. Lawless. Tests for Detecting Overdispersion in Poisson Regression Models. *Journal of the American Statistical Association,* Vol. 84, No. 406, June 1989, pp. 467–472.
9. STATISTICA. Statsoft Software, 1998. http://www.statsoft.com.
10. Hauer, E., and J. Bamfo. Two Tools for Finding What Function Links the Dependent Variable to the Explanatory Variables. *International Cooperation on Theories and Concepts in Traffic Conference Proceedings,* Lund, Sweden, 1997.
11. Kononov, J. Identifying Locations with Potential for Accident Reductions: Use of Direct Diagnostics and Pattern Recognition Methodologies. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1784,* TRB, National Research Council, Washington, D.C., 2002, pp. 153–158.
12. Kononov, J., and B. N. Janson. Diagnostic Methodology for the Detection of Safety Problems at Intersections. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1784,* TRB, National Research Council, Washington, D.C., 2002, pp. 51–56.

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