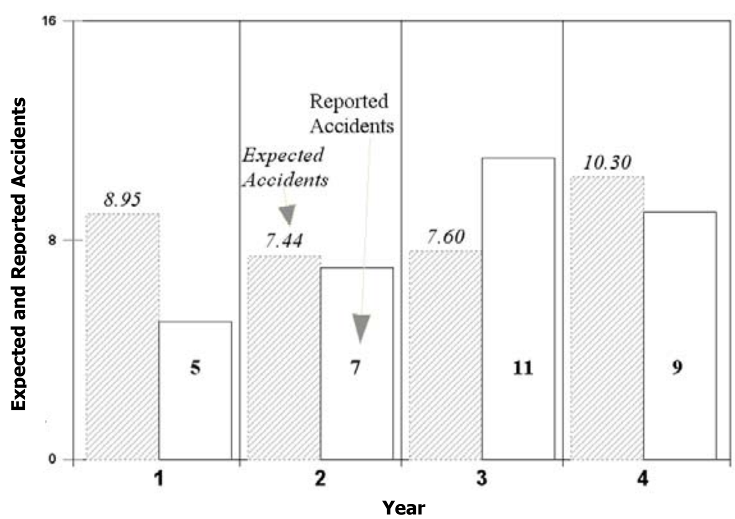
APPENDIX A—AVERAGE CRASH FREQUENCY ESTIMATION METHODS WITH AND WITHOUT HISTORIC CRASH DATA

This appendix provides a summary of additional methods for estimating crash frequency with and without crash data. These methods are a summary of findings from research conducted for NCHRP 17-27 and presented here for reference. The variables and terminology presented in this appendix are not always consistent with the material in Chapter 3.

The additional methods are presented through examples based on the hypothetical situation summarized in Exhibit A-1. This exhibit summarizes an intersection's expected and reported accidents over a four-year period. The expected average crash frequency is shown in the shaded columns. The reported accident count for each year is shown in the un-shaded columns.

Exhibit A-1: Intersection Expected and Reported Accidents for Four Years



A.1 Statistical Notation and Poisson Process

The following notation is defined:

Reported accident count:

X = 'Accident count';

$X = x$ means that the 'Accident count' is some integer x ;

X_i = the subscript 'i' denotes a specific period, for example, in Exhibit A-1 $X_1=5$ for Year 1 and $X_2=7$ for Year 2;

Expected average crash frequency:

E{ } = 'Expected value', for example, in Exhibit A-1 $E\{X_1\}$ is the expected average crash frequency in Year 1;

$E\{X_i\} \equiv \mu_i$, that is, the Greek letter μ has the same meaning as E{ };

Variance :

$V\{X_i\} \equiv$ $E\{(X_i-\mu_i)^2\}$ = the variance of X_i ;

$V\{X_i\}$ $\equiv \sigma_i^{2}$;

'Estimate of':

$\hat{\mu}_i =$ the estimate of μ_i ;

$\hat{\sigma}_i =$ the estimate of σ_i = the standard error of $\hat{\mu}_i$.

In statistics, the common assumption is that several observations are drawn from a distribution in which the expected value remains constant. Using the several observed values, the standard error of the estimate is computed.

In road safety, the expected average crash frequency from one period cannot be assumed to be and is not the same as that of another time period. Therefore, for a specific time period, only one observation is available to estimate μ. For the example in Exhibit A-1, the change from Year 1 to Year 2 is based on only one accident count to estimate μ_1 and one other accident count to estimate μ_2.

Using one accident count per estimate seems to make the determination of a standard error impossible. However, this issue is resolved by the reasonable assumption that the manner of accident generation follows the Poisson process. The Poisson process is the most important example of a type of random process known as a 'renewal' process. For such processes the renewal property must only be satisfied at the arrival times; thus, the interarrival times are independent and identically distributed, as is the case for the occurrence of accidents.

The Poisson probability mass or distribution function is shown in Equation A-1.

$$P(X_i = x) = \frac{\mu_i^{(x)} \times e^{(-\mu_i)}}{x!} \qquad \text{(A-1)}$$

Where,

μi = the expected number of accidents for a facility for period i;

$P(Xi = x)$ = the probability that the reported number of accidents X_i for this facility and period 'i' is x;

It is the property of the Poisson distribution that its variance is the same as its expected value, as shown in Equation A-2.

$$V\{X\} \equiv \sigma^2 = \mu \equiv E\{X\} \qquad \text{(A-2)}$$

Where,

$V(X)$ = variance of X = σ^2;

$\mu \equiv E\{X\}$ = expected average crash frequency .

A.2 Reliability and Standard Error

As all estimates are subject to uncertainty, the reliability of an estimate is required in order to know the relationship between the expected and reported values. This is why, as a rule, estimates are often accompanied by a description of their standard error, variance or some manner of statistical reliability.

The “standard error” is a common measure of reliability. Exhibit A-2 describes the use of the standard error in terms of confidence levels, i.e. ranges of closeness to the true value, expressed in numeric and verbal equivalents.

Exhibit A-2: Values for Determining Confidence Intervals using Standard Error

Desired Level of Confidence	Confidence Interval (probability that the true value is within the confidence interval)	Multiples of Standard Error (MSE) to using in Equation 3-8
Low	65-70%	1
Medium	95%	2
High	99.9%	3

The estimates of the mean and the standard error if X is Poisson distributed are shown in Equation A-3.

$$\hat{\mu}_i = x \quad and \quad \hat{\sigma}_i = \sqrt{x} \qquad (A\text{-}3)$$

Where,

$\hat{\mu}_i$ = the estimate of μ_i;

x = accident count;

$\hat{\sigma}_i$ = the estimate of σ_i or the estimate of the standard error.

For example, the change between two time periods for the intersection in Exhibit A-1 can be estimated as follows:

$$\hat{\mu}_{year\ 1} = 5\ accidents \quad and \quad \hat{\sigma}_{year\ 1} = \pm 2.2\ accidents$$

The change between Year 1 to Year 2 is estimated by the difference between μ_{year2} and μ_{year1}. Using the first part of Equation A-3:

$$\hat{\mu}_{year\ 2} - \hat{\mu}_{year\ 1} = X_2 - X_1 = 7 - 5 = 2\ accidents$$

Since X_1 and X_2 are statistically independent, the variance of the change is as shown in Equation A-4.

$$V\{X_2 - X_1\} = \sigma_1^2 + \sigma_2^2 \qquad (A\text{-}4)$$

Where,

X_i = accident count for specific period;

$\hat{\sigma}_i$ = the estimate of σ_i or the estimate of the standard error.

Using Equation A-3 and Equation A-4 in the example shown in Exhibit A-1, the standard error of the difference between Year 1 and Year 2 is:

$$\hat{\sigma}_{year\ 2} - \hat{\sigma}_{year\ 1} = \sqrt{5+7} = \pm\ 3.5\ accidents$$

In summary, the change between Year 1 and Year 2 is 2 accidents ± 3.5 accidents. As indicated in Exhibit A-2, the standard error means we are:

- 65-70% confident that the change is in the range between -1.5 and +5.5 accidents (2 - 3.5 = -1.5, and 2 + 3.5 = +5.5);
- 95% confident that the change is between is in the range between -5 and +9 accidents (2 - 2×3.5 = -5, and 2 + 2×3.5 = +9);
- 99.9% confident that the change is in the range between -8.5 to 12.5 accidents.

If any one of these ranges was completely on one side of the value zero with zero meaning no change, then an increase or decrease could be estimated with some level of confidence. However, because the ranges are wide and encompass zero, the expected increase of 2 accidents provides very little information about how changes from year 1 to year 2. This is an informal way of telling whether an observed difference between reported accidents counts reflects a real change in expected average crash frequency.

The formal approach requires a statistical hypothesis which postulates that the two expected values were not different.(9) The observed data are investigated and if it is concluded that the hypothesis of 'no difference' can be rejected at a customary level of significance[1] 'α' (α=0.05, 0.01, …) then it may be reasonable to conclude that the two expected values were different.

It is important to understand the results of statistical tests of significance. A common error to be avoided occurs when the hypothesis of 'no difference' is not rejected and an assumption is made that the two expected values are likely to be the same, or at least similar. This conclusion is seldom appropriate. When the hypothesis of no difference is 'not rejected' it may means that the accident counts are too small to say anything meaningful about the change in expected values. The potential harm to road safety management of misinterpreting statistical tests of significance is discussed at length in other publications.(10)

A.3 Estimating Average Crash Frequency Based on Historic Data of One Roadway or One Facility

It is common practice to estimate the expected crash frequency of a roadway or facility using a few, typically three, recent years of accident counts. This practice is based on two assumptions:

- Reliability of the estimation improves with more accident counts;
- Accident counts from the most recent years represent present conditions better than older accident counts.

These assumptions do not account for the change in conditions which occur on this roadway or facility from period-to-period or year-to-year. There are always period-to-period differences in traffic, weather, accident reporting, transit schedule changes, special events, road improvements, land use changes, etc. When the expected average crash frequency of a roadway or facility is estimated using the

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[1] 'α' or the level of statistical significance is the probability of reaching an incorrect conclusion, that is, of rejecting the hypothesis 'no difference' when the two expected values were actually the same

average of the last 'n' periods of accident counts, the estimate is of the average over these 'n' periods; it is not the estimate of the last period or some recent period. If the period-to-period differences are negligible, then the average over 'n' periods will be similar in each of the 'n' periods. However, if the period-to-period differences are not negligible, then the average over 'n' periods is not a good estimate of any specific period.

Estimating average crash frequency assuming similar crash frequency in all periods

Using the example in Exhibit A-1, the estimate for Year 4 is sought. Using only the accident count for Year 4:

- The estimate is $\hat{\mu}_{year4}$ = 9 accidents, and
- The standard error of the estimate is $\hat{\sigma}$ = √9=±3 accidents.

Alternatively, using the average of all four accident counts:

- The estimate is $\hat{\mu}_{year4}$ = (5+7+11+9)/4 = 8.0 accidents, and
- The standard error of the estimate is $\hat{\sigma} = \sqrt{32/4^{(2)}}$ = ±1.4 accidents.

These results show that using the average of accident counts from all four years reduces the standard error of the estimate. However, the quality of the estimate was, in this case, not improved because the expected frequency is 10.3 accidents in Year 4, and the estimate of 9 accidents is closer than the estimate of 8.0 accidents. In this specific case, using more accident counts did not result in a better estimate of the expected crash frequency in the fourth year because the accident counts during the last year are not similar to the crash frequency in the three preceding years.

Estimating average crash frequency without assuming similar crash frequency in all periods

This estimation of the average crash frequency of a specific roadway or facility in a certain period is conducted using accident counts from other periods without assuming that the expected average crash frequency of a specific roadway or facility's expected average crash frequency is similar in all periods. Equation A-5 presents the relationship that estimates a specific unit for the last period of a sequence.

$$\hat{\mu}_Y = \sum_{y=1}^{Y} X_y \Bigg/ \sum_{y=1}^{Y} d_y \qquad \text{(A-5)}$$

Where,

$\hat{\mu}_Y$ = most likely estimate of μ_Y (last period or year);

$\mu_y \equiv \mu_Y \times d_y$ where y denotes a period or a year (y=1, 2,…., Y; while Y denotes the last period or last year); e.g., for first period d_1=relationship of μ_1/μ_Y;

X_y = the counts of accidents for each period or year y.

Equation A-6 presents the estimate of the variance of $\hat{\mu}_Y$.

$$\hat{V}(\hat{\mu}_Y) = \sum_{y=1}^{Y} X_y \Bigg/ \left(\sum_{y=1}^{Y} d_y\right)^{(2)} \tag{A-6}$$

Where,

$\hat{\mu}_Y$ = most likely estimate of μ_Y (last period or year);

d_y = the μ_1/μ_Y

X_y = the counts of accidents for each period or year y.

For this estimate, it is necessary to add all accident counts reported during this year for all intersections that are similar to the intersection, under evaluation, throughout the network. Using the example given in Exhibit A-1 to illustrate this estimate, the proportion of the accidents counts per year in relation to the annual total accident counts for all similar intersections was calculated. The results are shown in Exhibit A-3, e.g. 27% of annual accidents occur in the first year, 22% in the second year, etc.

Each yearly proportion is modified in relation to the last year, e.g. $d_1 = \mu_1/\mu_4$ = 0.27/0.31=0.87, as shown in Exhibit A-3.

Exhibit A-3: Illustration of Yearly Proportions and Relative Last Year Rates

	Year 1	Year 2	Year 3	Year 4=Y
Proportion of Accidents	0.27	0.22	0.20	0.31
d_y (relative to the last year)	0.87	0.71	0.64	1

For each year, the accidents counts are 5, 7, 11, and 9, see Exhibit A-1. Using Equation A-5 and Equation A-6:

$\hat{\mu}_{year\ 4}$ = (5+7+11+9) / (0.87+0.71+0.64+1) = 32/3.22 = 9.94 estimate of accidents for the last year:

$\hat{\sigma} = \sqrt{32/3.22^2}$ = ± 1.8 accidents as the standard error of the last year's estimate

This method eliminates the need to restrict the data to recent counts and results in increased reliability by using all relevant accident counts. This method also results in a more defensible estimate because the use of d_y allows for change over the period from which accident counts are used.

Estimating average crash frequency using the longer accident record history

The estimate shown below uses historical traffic volumes (Annual Average Daily Traffic or AADT) and historical accident counts. The reliability of the estimate is expected to increase with the number of years used.

This example is shown in Exhibit A-4 where nine years (Row 1) of accident counts (Row 4) and AADT volumes (Row 3) for a one-mile of road are presented. The estimate of the expected annual crash frequency is needed for this road segment in 1997, the most recent year of data entry.

For this road type, the safety performance function (SPFs are discussed in Section 3.5.1.) showed that the expected average crash frequency changes in proportion to AADT as shown in Equation A-7

$$d_y = (AADT_y \ / AADT_n)^{(0.8)} \quad \text{(A-7)}$$

Where,

$AADT_y$ = average daily traffic volume for each year y;

$AADT_n$ = average daily traffic volume for last year y

For example, the corresponding value of $d_{5=1993} = (5600/5400)^{0.8} = 1.030$.

The $\mu_{Y=1997}$ estimate of expected accidents would be 6.00±2.45 accidents when using Equation A-5 and Equation A-6 and the accident count for 1997 only. The $\mu_{Y=1997}$ estimate of expected accidents would be 6.09±1.44 accidents when using Equation A-5 and Equation A-6 and the accident counts for 1995, 1996 and 1997.

Exhibit A-4: Estimates of Expected Average Crash Frequency Using the Longer Accident History

		Data								
1	Year	1989	1990	1991	1992	1993	1994	1995	1996	1997
2	Y	1	2	3	4	5	6	7	8	Y=9
3	AADT	4500	4700	5100	5200	5600	5400	5300	5200	5400
4	Accidents, X_y	12	5	9	8	14	8	5	7	6
		Computations								
5	$d_y = (AADT_y/AADT_{1997})^{0.8}$	0.864	0.895	0.955	0.970	1.030	1.000	0.985	0.970	1.000
6	Cumulative Accidents	74	62	57	48	40	26	18	13	6
7	Cumulative d_y	8.670	7.805	6.910	5.955	4.985	3.955	2.955	1.970	1.000
8	Estimates of μ_{1997}	**8.54**	**7.94**	**8.25**	**8.06**	**8.02**	**6.57**	**6.09**	**6.60**	**6.00**
9	Standard errors	**0.99**	**1.01**	**1.09**	**1.16**	**1.27**	**1.29**	**1.44**	**1.83**	**2.45**
10	No. of years used	9	8	7	6	5	4	3	2	1

This example shows that when the estimate μ_Y is based on one single accident count X_Y, no assumptions need to be made, but the estimate is inaccurate (the standard error is 2.45). When accident counts of other years are used to increase estimation reliability (the standard error decreases with the additional years of data to a value of 0.99 when adding all nine years), some assumption always needs to be made. It is assumed that the additional years from which the accident counts are used have the same estimate μ as year Y (last year).

A.4 Estimating Average Crash Frequency Based on Historic Data of Similar Roadways or Facilities

This section shows how the crash frequency of a specific roadway, facility or unit can be estimated using information from a group of similar roadways or facilities. This approach is especially necessary when accidents are very rare, such as at rail-highway grade crossings where accidents occur on average once in 50 years and when the accident counts of a roadway or facility cannot lead to useful estimates. The two key ideas are that:

1. Roadways or facilities similar in some, but not all, attributes will have a different expected number of accidents (μ's) and this can be described by a statistical function called the 'probability density function.' The E{μ} and V{μ} are the mean and the variance of the group (represented by the function), and Ê{μ} and $\hat{\sigma}_i^2\{\mu\}$ are the estimates of the expected average crash frequency and the variance.

2. The specific roadway or facility for which the estimate forms part of the group (the population of similar roadways or facilities) in a formal way. The best estimate of its estimate μ, the expected number of accidents, is Ê{μ} and the standard error of this estimate is $\hat{V}\{\mu\}$, both of which are derived from the estimates of the group's function.

In practice, as groupings of similar roadways or facilities are only samples of the population of such roadways or facilities, the estimates of the mean and variances of the probability density function will be based on the sample of similar roadways or facilities. The estimates use Equation A-8 and Equation A-9.

$$\bar{x} = \sum_{1}^{n} \left(\frac{x_i}{n} \right) \qquad \text{(A-8)}$$

Where,

$\bar{x}$ = mean of accident counts for the group or sample of similar roadways or facilities;

x_i (i=1,2,...n) = accident counts for n roadways or facilities similar to the roadway or facility of which crash frequency is estimated.

$$s^2 = \sum_{1}^{n} \frac{(x_i - \bar{x})^{(2)}}{(n-1)} \qquad \text{(A-9)}$$

Where,

s^2 = variance of accident counts for the group or sample of similar roadways or facilities;

x_i (i=1,2,...n) = accident counts for n roadways or facilities similar to the roadway or facility of which crash frequency is estimated.

The estimate of the crash frequency of a specific roadway, facility or unit is calculated by using Equation A-10.

$$\hat{E}\{\mu\} = \bar{x} \text{ and } \hat{V}\{\mu\} = s^2 - \bar{x} \qquad \text{(A-10)}$$

Where,

$\hat{E}\{\mu\}$ = expected number of accidents for a roadway or facility based on the group of similar roadways or facilities;

$\overline{x}$ = mean of accident counts for the group or sample of similar roadways or facilities;

$\hat{V}\{\mu\}$ = variance for the expected number of accidents for a roadway or facility based on the group of similar roadways or facilities;

s^2 = variance of accident counts for the group or sample of similar roadways or facilities.

Exhibit A-5 provides an example that illustrates the application of historic data from similar facilities. This example estimates the expected average crash frequency of a rail-highway at-grade crossing in Chicago for 2004. The crossing in Chicago has one rail track, 2 trains per day, and 500 vehicles per day. The crossing is equipped with crossbucks.

As the accident history of this crossing is not sufficient (small sample size) for the estimation of its expected average crash frequency, the estimate uses national accident historical data for rail-highway crossings. Exhibit A-5 sets out accident data for urban rail-highway at-grade crossings in the United States for crossings that have similar attributes to the crossing in Chicago[(4)].

Exhibit A-5: National Accident Data for Railroad-Highway Grade Crossings (with 0-1,000 vehicles/day, 1-2 trains/day, single track, urban area) 2004

Number of Accident Counts/Year(2004) (x_i)	Number of Crossings (n_i)	$A_j=(x_i)\times(n_i)/N$	$S_j=[(x_i)-\overline{X}]^2\times(n_i)/(N-1)$
0	10234	0.0000	0.0003
1	160	0.0154	0.0148
2	11	0.0021	0.0042
3	3	0.0009	0.0026
	$\sum n$ = N =10408 total similar crossings	$\overline{x}=\sum_{1}^{j} A_j$ = = 0.0184 expected accidents /year per crossing in this group	$s^2=\sum_{1}^{j} S_j$ = 0.0219

Using Equation A-10 and the data shown for similar crossings in Exhibit A-5, a reasonable estimate of the crash frequency of the crossing in Chicago for 2004 is 0.0184 accidents/year, i.e., the same as the sample mean ($\overline{x}$). The standard error is estimated as $\sqrt{0.0219-0.0184}$ = ± 0.059 accidents/year.

It was possible to calculate this estimate because rail-highway at-grade crossings are numerous and official statistics about the crossings are available.

For roadways or facilities such as road segments, intersections, and interchanges, it is not possible to obtain data from a sufficient number of roadways or facilities with similar attributes. In these circumstances, SPFs and other multivariable regression models (Part III) are used to estimate the mean of the probability distribution and its standard error. Section A.5 describes the use of SPFs to improve the estimation of the expected average crash frequency of a facility.

A.5 Estimating Average Crash Frequency Based on Historic Data of the Roadway or Facilities and Similar Roadways and Facilities

The estimation of expected average crash frequency of a certain roadway or facility can be improved, i.e., the reliability of the estimate can be increased, by combining the roadway or facility's count of past accidents (Section A.3) with the accident record of similar roadways or facilities (Section A.4).

The "best" estimate combined with the minimum variance or standard error is given by Equation A-11.

$$\hat{\mu} = \omega \times \hat{\mu}_s + (1-\omega) \times \hat{\mu}_a \qquad \text{(A-11)}$$

where

$$\omega = \frac{1}{\left(1 + \frac{V\{\mu_s\}}{E\{\mu_s\}}\right)}$$

Where,

$\hat{\mu}$ = the "best" estimate of a given roadway or facility;

$\hat{\mu}_s$ = the estimate based on data of a group of similar roadways or facilities;

$\hat{\mu}_a$ = the estimate based on accident counts of the given roadway or facility;

$V\{\mu_s\}$ = variance of the estimate based on data for similar roadways or facilities;

$E\{\mu_s\}$ = the estimate of expected average crash frequency based on the group of similar roadways or facilities;

ω = the weight based on the estimate and the degree of its variance resulting from the grouping of similar roadways or facilities.

When $\hat{\mu}$ is estimated by Equation A-11, its variance is given by Equation A-12.

$$V(\hat{\mu}) = \omega \times V\{\mu_s\} = (1-\omega) \times E\{\mu_s\} \qquad \text{(A-12)}$$

Where,

$V(\hat{\mu})$ = variance of the "best" estimate;

$V\{\mu_s\}$ = variance of the estimate based on data from similar units or a group of similar roadways or facilities;

$E\{\mu_s\}$ = the estimate of expected number of accidents based on the group of similar roadways or facilities;

ω = weight generated by the variance of the estimate of expected average crash frequency.

As an example, the expected average crash frequency of a 1.23 mile section of a six-lane urban freeway in Colorado is estimated below. The estimate is based on 76 accidents reported during a 3-year period, and accident data for similar sections of urban freeways.

There are 3 steps in the estimation:

Step 1: As expressed by Equation A-3, using the accidents reported for the specific roadway or facility:

$$\hat{\mu}_i = x = 76 \text{ accidents} \quad \text{and} \quad \hat{\sigma}_i = \sqrt{x} = \pm 8.7 \text{ accidents} \qquad \text{(A-3)}$$

Where,

$\hat{\mu}_i$ = the expected number of accidents for a roadway or facility for period i ;

x = the reported number of accidents for this roadway or facility and period i;

$\hat{\sigma}_i$ = standard error for the expected number of accidents for this roadway or facility and period i.

Step 2: Based on AADT volumes, the percentage of trucks, and accident counts on similar urban freeways in Colorado, a multivariable regression model was calibrated (Section B.1). When the model was applied to a 1.23 mile section for a 3-year period, the following estimates (Equation A-10) result:

$$\hat{E}\{\mu_s\} = \hat{E}\{\mu\} = \bar{x} = 61.3 \text{ accidents}$$

$$\hat{V}\{\mu_s\} = \hat{V}\{\mu\} = s^2 - \bar{x} = 266.7 \text{ accidents}^2$$

$$\hat{\sigma}_i = \sqrt{s^2 - \bar{x}} = \pm 16.3 \text{ accidents}$$

Where,

$\hat{E}\{\mu_s\}$ = the estimate of expected number of accidents based on the group of similar roadways or facilities;

$\hat{V}\{\mu_s\}$ = the estimate of the variance of $\hat{E}\{\mu_s\}$;

$\bar{x}$ = mean of accident counts for the group of similar roadways or facilities for the AADT volume and truck percentage for the specific roadway or facility;

$\hat{V}\{\mu\}$ = variance for the expected number of accidents for the specific roadway or facility based on the group's model;

s^2 = variance of accident counts for the group or sample of similar roadways or facilities ;

$\hat{\sigma}_i$ = standard error for the expected number of accidents for the specific roadway or facility based on the group's model.

Step 3: using the statistical relative weight of the two estimates obtained from Step 1 and Step 2, the 'best' estimate of the expected number of accidents on this 1.23 mile of urban freeway is:

The 'weight' ω (Equation A-11) is:

$$\omega = \frac{1}{\left(1 + \frac{V\{\mu_s\}}{E\{\mu_s\}}\right)} \tag{A-11}$$

Where,

$V\{\mu_s\}$ = variance of the estimate based on data about similar units or groups;

$E\{\mu_s\}$ = the estimate of expected number of accidents based on the group of similar roadways or facilities;

Thus:

ω = 1 / (1 + 266.7 /61.3) = 0.187

The "best" estimate of a given unit, roadway or facility is estimated as:

$$\hat{\mu} = \omega \times \hat{\mu}_s + (1-\omega) \times \hat{\mu}_a \tag{A-11}$$

with the variance as:

$$V(\hat{\mu}) = \omega \times V\{\mu_s\} = (1-\omega) \times E\{\mu_s\} \tag{A-12}$$

Where,

$\hat{\mu}$ = the "best" estimate of a certain roadway or facility;

$\hat{\mu}_s$ = the estimate based on data about similar units or group of similar roadways or facilities;

$\hat{\mu}_a$ = the estimate based on accident counts;

ω = the weight indicative of the estimate and the degree of its variance resulting from the grouping of similar roadways or facilities;

$\hat{V}\{\mu\}$ = variance for the expected average crash frequency for a certain roadway or facility based on the group's model;

$\hat{E}\{\mu_s\}$ = the estimate of expected average crash frequency based on the group of similar roadways or facilities;

$\hat{V}\{\mu_s\}$ = the estimate of the variance of $\hat{E}\{\mu_s\}$

Thus:

$$V\{\hat{\mu}\} = (1-0.187) \times 61.3 = 49.83 \text{ accidents}^2$$

$$\hat{\sigma}_i = \pm 7.1 \text{ accidents}$$

Exhibit A-6 shows the results of the three steps, and that the estimate that combines the estimation of a certain roadway or facility with the estimation of similar roadways or facilities results in an estimation with the smallest standard of error.

Exhibit A-6: Comparison of Three Estimates (an example using accident counts, groups of similar roadways or facilities, and combination of both)

	Expected Number of Accidents (3 years)	Standard Error
Estimate based only on accident counts	76.0	± 8.7
Estimate based only on data about similar roadways or facilities	61.3	± 16.3
Estimate based on both accident counts and data about similar roadways or facilities	73.3	± 7.1

Another example that illustrates the use of a SPF in the estimation of the expected average crash frequency of a facility is shown below. SPFs were derived for stop-controlled and signalized four-leg intersections.(15,17) The chosen function for both types of intersection control is shown in Equation A-13.

$$\hat{E}\{\mu\} = \alpha \times F_{Major}^{(\beta_1)} \times F_{Minor}^{(\beta_2)} \times e^{(\beta_3 F_{Minor})} \quad \text{(A-13)}$$

Where,

$\hat{E}\{\mu\}$ = the estimate of the average expected frequency of injury accidents;

F = the entering AADT on the major and minor approaches;

α, β_1, β_2 and β_3 = the estimated constants shown in Exhibit A-7;

e = base of natural logarithm function.

Exhibit A-7: Estimated Constants for Stop-Controlled and Signalized Four-Leg Intersections SPF Shown in Equation A-13 Including the Statistical Parameter of Overdispersion φ (an example)

	Stop-controlled (17)	Signalized (15)
α	3.22×10^{-4}	8.2×10^{-5}
β_1	0.50	0.57
β_2	0.43	0.55
β_3	0 (not in model)	6.04×10^{-6}
φ	2.3	4.6

The surfaces of the two SPFs (one for stop-controlled intersections and one for signalized four-leg intersections) are shown in Exhibit A-8 and Exhibit A-9.

Exhibit A-8: Estimated Injury Accidents at Stop-Controlled Four-Leg Intersections

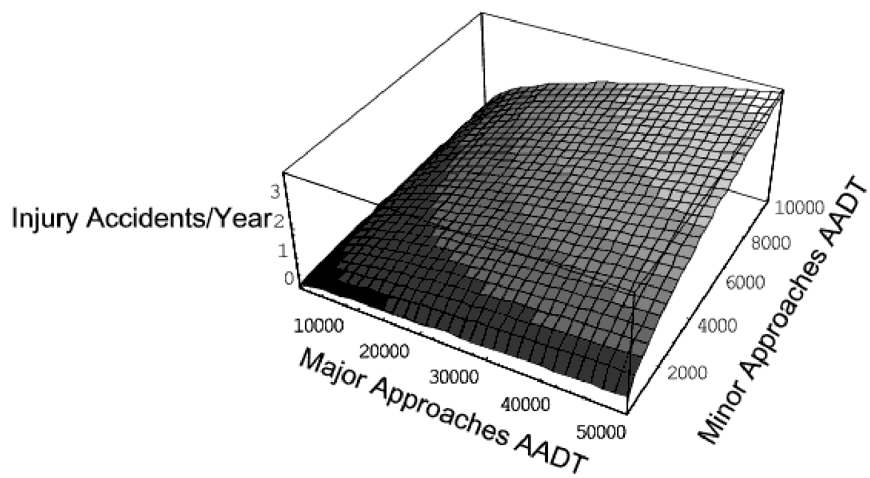
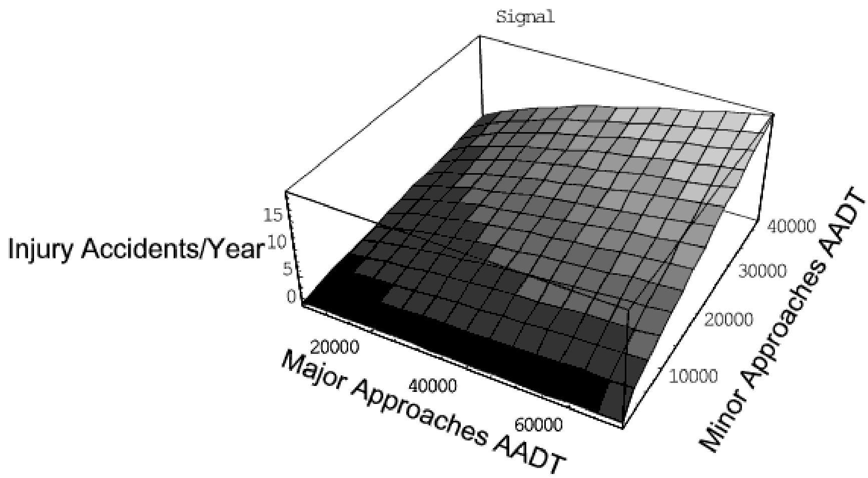


Exhibit A-9: Predicted Injury Accidents at Signalized Four-Leg Intersections



AADT is a major attribute when considering crash frequency, but there are many other attributes which, although not explicitly shown in the SPF, influence the estimate for a given facility or roadway. In the example above, many attributes of the two groups of intersections, besides AADT, contribute to the values for E{μ} computed Equation A-17 for major and minor approach AADTs. Inevitably, the difference between any two values is an approximation of the change expected if, for example, a stop-controlled intersection is signalized, because it does not separate the many attributes other than traffic control device.

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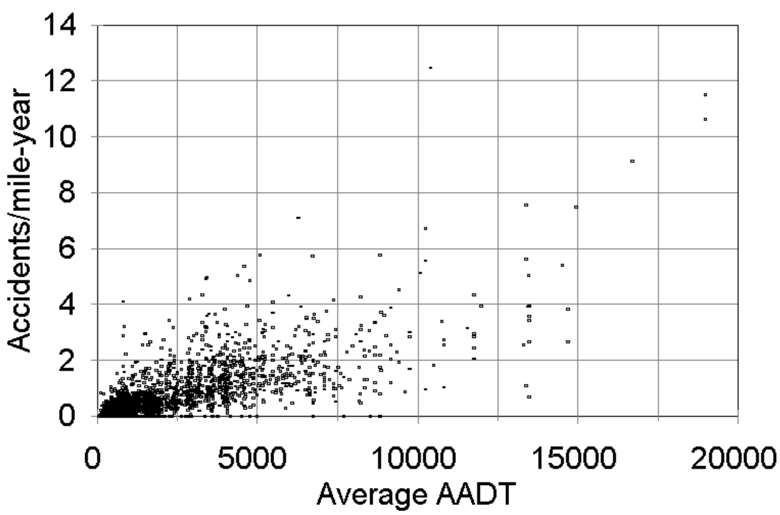
APPENDIX B—DERIVATION OF SPFS

The variables and terminology presented in this appendix are not always consistent with the material in Chapter 3.

B.1 Safety Performance as a Regression Function

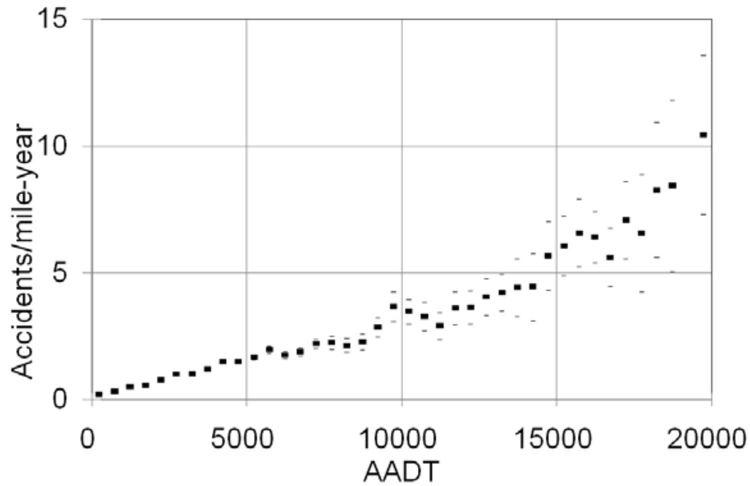
SPFs are developed through statistical regression modeling using historic accident data collected over a number of years at sites with similar roadway characteristics. The validity of this process is illustrated conceptually though the following example using Colorado data for rural two-lane road segments (excluding intersections). Segment length, terrain type (mountainous or rolling), crash frequency and traffic volumes were collected for each year from 1986 to 1998. Crashes per mile-year for each site were plotted against traffic volume, based on average AADT over the 13-year period. The data points were then separated by terrain type to account for the different environmental factors of each type. The crash frequency plot for rural two-lane roads with rolling terrain is shown in Exhibit B-1.

Exhibit B-1: Crashes per Mile-Year by AADT for Colorado Rural Two-Lane Roads in Rolling Terrain (1986-1998)



The variability in the points in the plot reflects the randomness in crash frequency, the uncertainty of AADT estimates, and characteristics that would affect expected average crash frequency but were not fully accounted for in this analysis, such as grade, alignment, percent trucks, and number of driveways. Despite the variability of the points, it is still possible to develop a relationship between expected average crash frequency and AADT by averaging the number of crashes. Exhibit B-2 shows the results of grouping the crashes into AADT bins of 500 vehicles/day, that is, averaging the number of crashes for all points within a 500 vehicles/day increment.

Exhibit B-2: Grouped Crashes per Mile-Year by AADT for Colorado Rural Two-Lane Roads in Rolling Terrain (1986-1998)



NOTE: The black squares are the ratio of the number of accidents for all road sections in a bin divided by the sum of the corresponding road segment lengths. The bars around the black squares are ± two standard errors of this ratio.

Exhibit B-2 illustrates that in this case, there is a relationship between accidents and AADT, when using average bins. These associations can be captured by continuous functions which are fitted to the original data. The advantage of fitting a continuous function is to smooth out the randomness where data are sparse, such as for AADTs greater than 15,000 vehicles/day in this example. Based on the regression analysis, the "best fit" SPF for rural two-lane roads with rolling terrain from this example is shown in Equation B-1. ***Note that this is not the SPF for rural two-lane two-way roads presented in Chapter 10 of the HSM. As the base conditions of the SPF model shown below are not provided, its use is not recommended for application with the Part C predictive method.***

$$\hat{E}\{\mu\} = 1.95 \times \left(\frac{AADT}{1000}\right)^{(0.71)} \times e^{\left(0.53 \times \left(\frac{AADT}{1000}\right)\right)} \qquad (B\text{-}1)$$

Where,

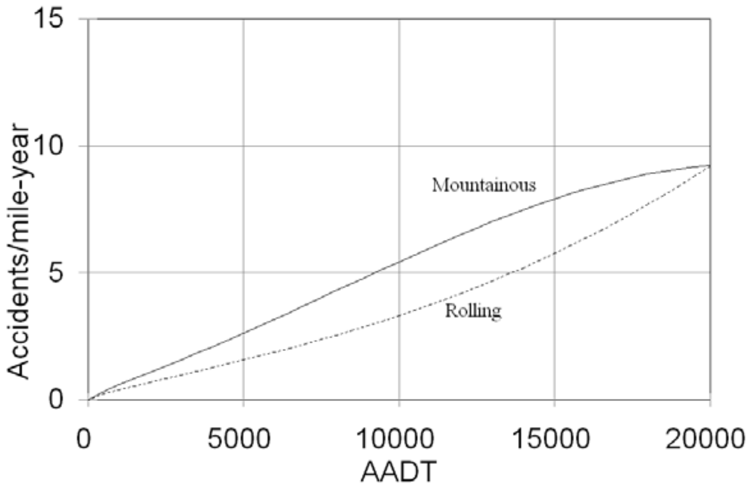
$\hat{E}\{\mu\}$ = the estimate of the average crash frequency per mile;

AADT = the average annual daily traffic.

The overdispersion parameter for rural two-lane roads with rolling terrain in Colorado from this example was found to be 4.81 per mile.

The SPF for rural two-lane roadways on rolling terrain shown in Equation B-1 is depicted in Exhibit B-3 alongside a similar SPF derived for mountainous terrain.

Exhibit B-3: Safety Performance Functions for Rural Two-Lane Roads by Terrain Type



B.2 Using a Safety Performance Function to Predict and Estimate Average Crash Frequency

Using the SPFs shown in Exhibit B-3, an average two-lane rural road in Colorado with AADT=10,000 vehicles/day is expected to have 3.3 accidents/mile-year if in rolling terrain and 5.4 accidents/mile-year if in mountainous terrain.

When an equation is fitted to data, it is also possible to estimate the variance of the expected number of accidents around the average number of accidents. This relationship is shown in Equation B-2.

$$V\{\mu\} = \frac{(E\{\mu\})^{(2)}}{k} \quad \text{(B-2)}$$

Where,

k = the overdispersion parameter

E{μ} = the average crash frequency per mile

V{μ} = the variance of the average crash frequency per mile

As an example to illustrate its use, Exhibit B-3 shows that an *average* two-lane rural road in a rolling terrain in Colorado with AADT=10,000 vehicles/day is expected to have 3.3 accidents/mile-year. Thus, for a road segment with 0.27mile length, it is expected that there will be on average 0.27×3.3=0.89 accidents/year.

When the SPF for two-lane roads in Colorado was developed, the overdispersion parameter (k) for rolling terrain was found to be 4.81/mile.

Thus:

$\hat{V}\{\mu\}$= variance = $(E\{\mu\})^{(2)}/\varphi$) = $0.89^{(2)}$ / (0.27×4.81)

= 0.55 $(\text{accidents/year})^2$ or

$\hat{\sigma}\{\mu\}$ = standard error = $\sqrt{0.55} = \pm 0.74$ accidents/year

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APPENDIX C—AMF AND STANDARD ERROR

The variables and terminology presented in this appendix are not always consistent with the material in Chapter 3.

The more precise an AMF estimate, the smaller its standard error. The reliability level of AMFs is illustrated by means of probability density functions. A probability density function is any function f(x) that describes the probability density in terms of the input variable x in the manner described below:

- f(x) is greater than or equal to zero for all values of x
- The total area under the graph is 1:

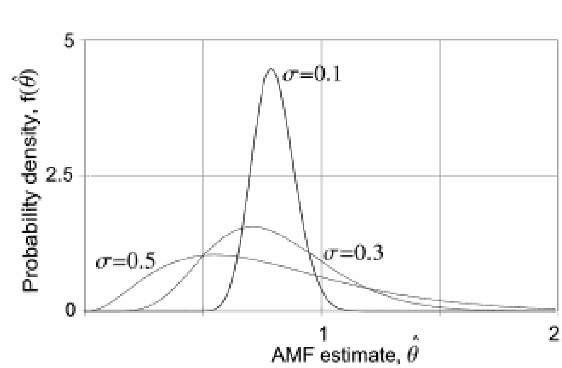
$$\int_{-\infty}^{\infty} f(x)dx = 1 \qquad (C\text{-}1)$$

In other words, a probability density function can be seen as a "smoothed out" version of the histogram that one would obtain if one could empirically sample enough values of a continuous random variable.

Different studies have different probability density functions, depending on such factors as the size of the sample used in the study and the quality of the study design. Exhibit C-1 shows three alternative probability density functions of an AMF estimate. These functions have different shapes with different estimates of AMFs at the peak point, i.e. at the mode (the most frequent value) of the function. The mean value of all three probability density functions is 0.8. The value of the standard error indicates three key pieces of information:

1. The compact probability density function with standard error σ = 0.1 represents the results of an evaluation research study using a fairly large data set and good method
2. The probability density function with standard error σ = 0.3 represents the results of a study that is intermediate between a good and a weak study
3. The wide probability density function with standard error σ=0.5 represents the results of a study that is weak in data and/or method

Exhibit C-1: Three Alternative Probability Density Functions of AMF Estimates

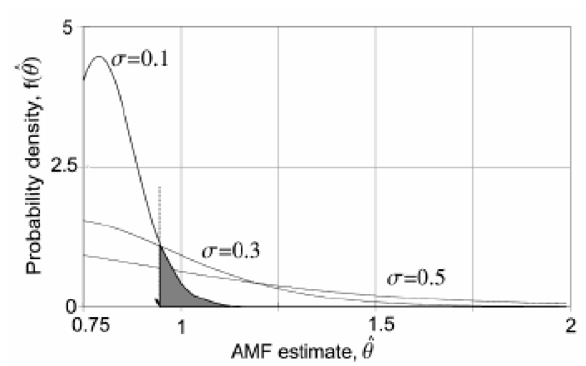


As an example of the use of AMFs and standard errors, consider a non-expensive and easy to install treatment that might or might not be implemented. The cost of this installation can be justified if the expected reduction in accidents is at least 5% (i.e., if θ < 0.95). Using the AMF estimates in Exhibit C-1 for this particular case, if the AMF estimate is 0.80 (true and mean value of θ, as shown in Exhibit C-1), the reduction in expected accidents is clearly greater than 5% (θ = 0.8 < 0.95).

However, the key question is: 'what is the chance that installing this treatment is the wrong decision?' Whether the AMF estimate comes from the good, intermediate, or weak study, will define the confidence in the decision to implement.

The probability of making the wrong decision by accepting an AMF estimate from the good study (σ = 0.1 in Exhibit C-1) is 6%, as shown by the shaded area in Exhibit C-2 (the area under the graph to the right of the 0.95 estimate point). If the AMF estimate came from the intermediate study (σ = 0.3 in Exhibit C-1), the probability of making an incorrect decision is about 27%. If the AMF estimate came from the weak study (σ = 0.5 in Exhibit C-1) the probability of making an incorrect decision is more than 31%.

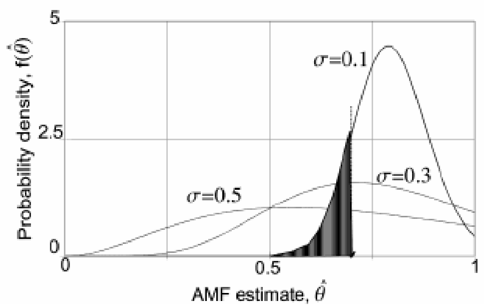
Exhibit C-2: The Right Portion of Exhibit C-1; Implement if AMF < 0.95



Likewise, what is the chance of making the wrong decision about installing a treatment that is expensive and not easy to implement, and that can be justified only if the expected reduction in accidents is at least 30% (i.e., if θ < 0.70). Using the AMF estimates in Exhibit C-1 for this particular case, implementing this intervention would be an incorrect decision because θ = 0.80 (Exhibit C-1) is larger than the θ = 0.70 which is required to justify the installation cost.

The probability of making the wrong decision by accepting an AMF estimate from the good study (σ = 0.1 in Exhibit C-1) is 12%, as shown by the shaded area in Exhibit C-3 (the area under the graph to the left of the 0.70 estimate point). If the AMF estimate came from the intermediate study (σ = 0.3 in Exhibit C-1), the probability of making an incorrect decision is about 38%. If the AMF estimate came from the weak study (σ = 0.5 in Exhibit C-1) the probability of making an incorrect decision is about 48%.

Exhibit C-3: The Left Portion of Exhibit C-1; Implement if AMF < 0.70



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APPENDIX D—INDIRECT SAFETY MEASUREMENT

The variables and terminology presented in this appendix are not always consistent with the material in Chapter 3.

Indirect safety measurements, also known as safety surrogate measures, were introduced in Section 3.4 and are described in further detail here. They provide the opportunity to assess safety when accident counts are not available because the roadway or facility is not yet in service or has only been in service for a short time, or when crash counts are few or have not been collected, or when a roadway or facility has significant unique features. The important added attraction of indirect safety measurements is that they may save having to wait for sufficient accidents to materialize before a problem is recognized and the remedy applied. In addition, knowledge of the pattern of events that precedes accidents might provide an indication of appropriate preventative measures. The relationships between potential surrogate measures and expected crashes have been studied and are discussed below.

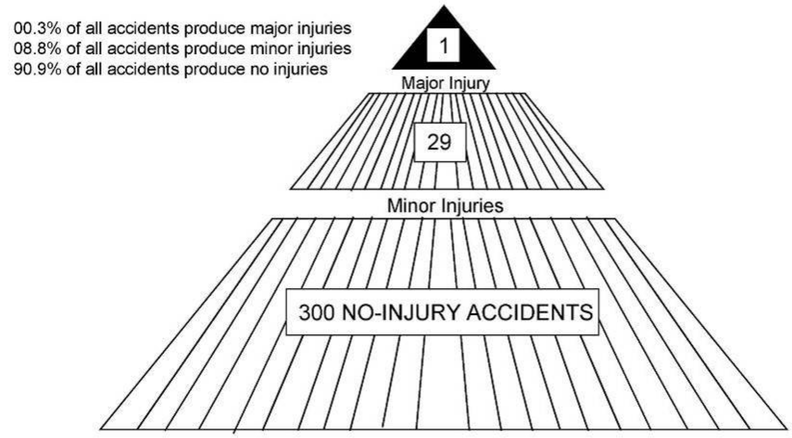
The Heinrich Triangle and Two Basic Types of Surrogates

Past practices have mostly used two basic types of surrogate measures. These are:

- Surrogates based on events which are proximate to and usually precede the accident event
- Surrogates that presume existence of a causal link to expected average crash accident frequency. These surrogates assume knowledge of the degree to which safety is expected to change when the surrogate measure changes by a given amount

The difference between these two types of surrogates is best explained with reference to Exhibit D-1 which shows the 'Heinrich Triangle.' The 'Heinrich Triangle' has set the agenda for Industrial and Occupational Safety ever since it was first published in 1932.[13] The original Heinrich Triangle is founded on the precedence relationship that 'No Injury Accidents' precedes 'Minor Injuries.'

Exhibit D-1: The Heinrich Triangle



Source: H. W. Heinrich, Industrial Accident Prevention, 1950, p. 24.

There are two basic ideas:

- Events of lesser severity are more numerous than more severe events, and events closer to the base of the triangle precede events nearer the top
- Events near the base of the triangle occur more frequently than events near the triangle's top, and their rate of occurrence can be more reliably estimated

Events Closer to the Base of the Triangle Precede Events Nearer the Top

The shortest Time to Collision (TTC) illustrates the idea that events closer to the base of the triangle precede events nearer the top. The shortest TTC was proposed as a safety surrogate by Hayward in 1972[(21)] and applied by van der Horst.[(22)] The approach involves collecting the number of events in which the TTC ≤ 1s: events that were never less than, and are usually larger than the number of events in which TTC ≤ 0.5s which are never less than, and usually larger than the number of crashes (equivalent to TTC = 0). Thus, for all events TTC > 0, the event did not result in a collision. The importance of this idea for prevention is that preventing less severe events (with greater values of TTC) is likely to reduce more severe events (with lower values of TTC).

Events Near the Base Occur More Frequently and can Be More Reliably Estimated

The second basic idea of the Heinrich Triangle is that because events near the base occur more frequently than events near its top, their rate of occurrence can be more reliably estimated. Therefore, one is able to learn about changes or differences in the rate of occurrence of the rare events by observing the changes or differences in the rate of occurrence of the less severe and more frequent events.

This relationship, in its simplest form, is shown in Equation D-1.

$$\begin{bmatrix}\text{Number of accidents expected}\\ \text{to occur on an entity in a certain}\\ \text{period of time}\end{bmatrix} = \begin{bmatrix}\text{Number of surrogate events}\\ \text{occurring on the entity in}\\ \text{that period of time}\end{bmatrix} \times \begin{bmatrix}\text{Accidents per}\\ \text{surrogate event}\\ \text{for that entity}\end{bmatrix} \quad \text{(D-1)}$$

Equation D-1 is always developed separately for each accident type. Equation D-1 can be rewritten as shown in Equation D-2.

$$\hat{\mu} = \sum_i \left(\hat{C}_i \times \hat{p}_i\right) \quad \text{(D-2)}$$

Where,

$\hat{\mu}$ = the expected average crash frequency of a roadway or facility estimated by means of surrogate events;

$\hat{C}_i$ = estimate of the rate of surrogate event occurrence for the roadway or facility for each severity class i. The estimate is obtained by field observation, by simulation, or by analysis;

$\hat{p}_i$ = estimate of the accident/surrogate-event ratios for the roadway or facility for each severity class i. The estimate is the product of research that uses data about the occurrence of surrogate events and of accidents on a set of roadways or facilities.

The success or failure of a surrogate measure is determined by how reliably it can estimate expected accidents. This is expressed by Equation D-3.(12)

$$V\{\hat{\mu}\} \cong \sum\left(\hat{C}_i^{(2)} \times V\{\hat{p}_i\} + \hat{p}_i^{(2)} \times V\{\hat{C}_i\}\right) \quad \text{(D-3)}$$

Where,

$\hat{C}_i$ = estimate of the rate of surrogate event occurrence for the roadway or facility for each severity class i. The estimate is obtained by field observation, by simulation, or by analysis;

$\hat{p}_i$ = estimate of the accident/surrogate-event ratios for the roadway or facility for each severity class i. The estimate is the product of research that uses data about the occurrence of surrogate events and of accidents on a set of roadways or facilities;

$V\{\hat{C}_i\}$ = the variance of $\hat{C}_i$. This depends on the method by which $\hat{C}_i$ was obtained, the duration of observations, etc;

$V\{\hat{p}_i\}$ = the variance of $\hat{p}_i$. This depends mainly on the similarity of $\hat{p}_i$ from roadway or facility to roadway and facility.

The choice of surrogate events will determine the size of the variance $V\{\hat{p}_i\}$. A good choice will be associated with a small $V\{\hat{p}_i\}$.

Some surrogate measures at intersections

Exhibit D-2 list several events at intersections which have been used as safety surrogates in the past.[6]

Exhibit D-2: Surrogate Measures at Intersections

Surrogate Measure	Description
Encroachment Time (ET)	Time duration during which the turning vehicle infringes upon the right-of-way of through vehicle.
Gap Time (GT)	Time lapse between completion of encroachment by turning vehicle and the arrival time of crossing vehicle if they continue with same speed and path.
Deceleration Rate (DR)	Rate at which through vehicle needs to decelerate to avoid accident.
Proportion of Stopping Distance (PSD)	Ratio of distance available to maneuver to the distance remaining to the projected location of accident.
Post-Encroachment Time (PET)	Time lapse between end of encroachment of turning vehicle and the time that the through vehicle actually arrives at the potential point of accident.
Initially Attempted Post-Encroachment Time (IAPT)	Time lapse between commencement of encroachment by turning vehicle plus the expected time for the through vehicle to reach the point of accident and the completion time of encroachment by turning vehicle.
Time to Collision (TTC)	Expected time for two vehicles to collide if they remain at their present speed and on the same path.

The reliability of the events listed in Exhibit D-2 in predicting expected accidents has not been fully proven.

Other types of surrogate measures are those construed more broadly to mean anything "that can be used to estimate average crash frequency and resulting injuries and deaths."[1] Such surrogate measures include driver workload, mean speed, speed variance, proportion of belted occupants, and number of intoxicated drivers.

From research conducted since the 'Heinrich Triangle' (Exhibit D-1) was developed, it is now known that for many circumstances, such as pedestrian accidents to seniors, almost every accident leads to injury. For these circumstances, the 'No Injury Accidents' layer is much narrower than the one shown in Exhibit D-1.

Furthermore, it is also known that, for many circumstances, preventing events of lesser severity may not translate into a reduction of events of larger severity. An example is the installation of a median barrier where the barrier increases the number of injury accidents due to hits of the barrier, but reduces fatalities by largely eliminating cross-median crashes. In the case of median barriers, the logic of Heinrich Triangle' (Exhibit D-1) does not apply because the events that lead to fatalities (median crossings) are not the same events as those that lead to injuries and property-damage (barrier hits).

In 2006, a new approach to the use of surrogates was under investigation.[23] This approach observes and records the magnitude of surrogates such as Time-To-Collision (TTC) or Post-Encroachment-Time (PET). The observed values of the surrogate event are shown as a histogram for which values near 0 are missing. An accident occurs when TTC or PET are 0. The study is using Extreme Value Theory to estimate the missing values, thus the number of accident events implied by the observed data.

APPENDIX E—SPEED AND SAFETY

The variables and terminology presented in this appendix are not always consistent with the material in Chapter 3.

Driving is a self-paced task: the driver controls the speed of travel and does so according to perceived and actual conditions. The driver adapts to roadway conditions and adjacent land use and environment, and one of these adaptations is operating speed. The relationship between speed and safety depends on human behavior, and driver adaptation to roadway design, traffic control, and other roadway conditions.

Recent studies have shown that certain roadway conditions, such as a newly resurfaced roadway, result in changes to operating speeds. [14]

The relationship between speed and safety can be examined during the 'pre-event' and the 'event' phases of an accident. The 'pre-event' phase considers the probability that an accident will occur, specifically how this probability depends on speed. The 'event' phase considers the severity of an accident, specifically the relationship between speed and severity. Identifying the errors that contribute to the cause of crashes helps to better identify potential countermeasures.

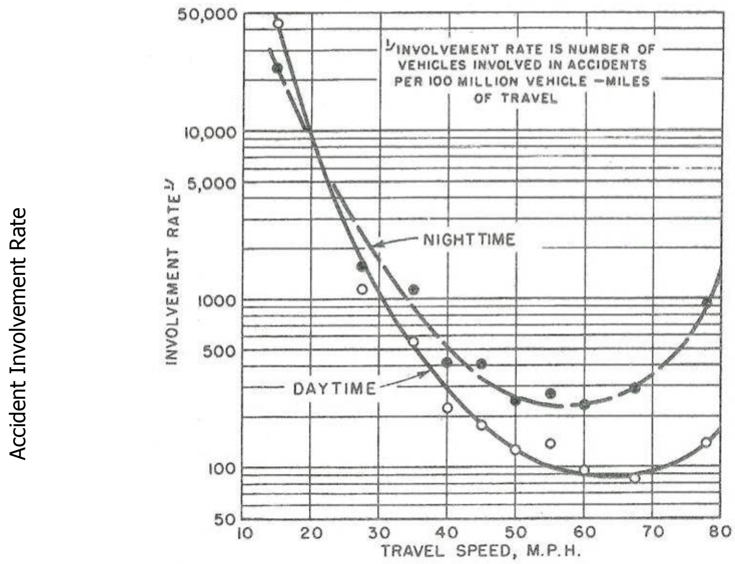
The following sections describe the pre-event phase and the relationship between speed and the probability of an accident (Section E.1), the event phase and the relationship between the severity of an accident and change in speed at impact (Section E.2), and the relationship between average operating speed and crash frequency (Section E.3). In the following discussion, terms such as running speed and travel speed are used interchangeably.

E.1 Pre-Event or Pre-Crash Phase: Accident Probability and Running Speed

It is known that with higher running speeds, a longer stopping distance is required. It is therefore assumed that the probability of an accident increases with higher running speeds. However, while opinions on the probability of an accident and speed are strongly held, empirical findings are less clear.[21]

For example, Exhibit E-1 shows that vehicles traveling at speeds approaching 50 mph , are less involved in accidents than vehicles traveling at lower speeds. This is the opposite of the assumed relationship between speed and accident probability in terms of accident involvement rate.

Exhibit E-1: Accident Involvement Rate by Travel Speed (22)

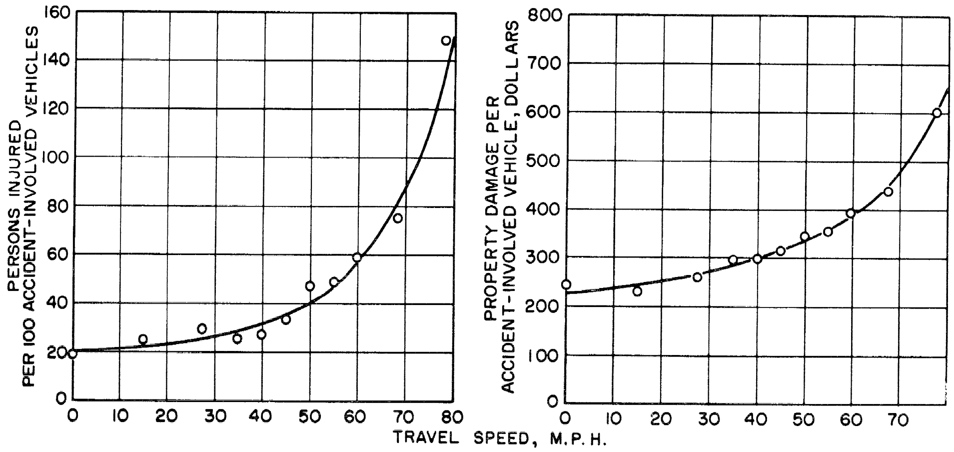


(Reproduced from Solomon's Figure 2)(22)

The data used to create Exhibit E-1 included turning vehicles.(21) Therefore accidents that appear to be related to low speeds may in fact be related to a maneuver that required a reduced speed. In addition, the shape of the curve in exhibit E-1 is also explained by the statistical representation of the data, that is, the kind of data assembled leads to a U-shaped curve.(8)

Exhibit E-1 also shows that for speeds greater than 60 mph, the probability of involvement increases with speed. At travel speeds greater than 60 mph, there is also likely to be a mixture of crash frequency and severity. Accidents of greater severity are more likely to be reported and recorded. Exhibit E-2 shows that the number of accidents by severity increases with travel speed.(22) It is not known what contributes to this trend: the increase in reported accidents with increasing running speed and the increase in accident occurrence at higher speeds, the more severe outcomes of accidents that occur at higher speeds, or a mixture of both causes. Section 3.3 provides discussion of the frequency-severity indeterminacy. Speed and accident severity are discussed in more detail in Section E.2.

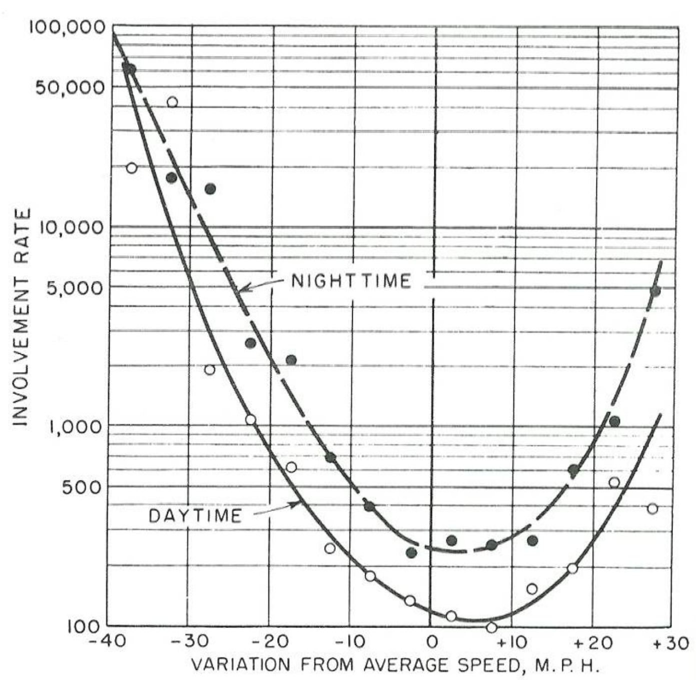
Exhibit E-2: Persons Injured and Property Damage per Accident Involvement by Travel Speed [22]



(Reproduced from Solomon's Figure 3)[22]

The data can be also presented by showing the deviation from mean operating speed on the horizontal axis (Exhibit E-3) instead of running speed (Exhibit E-1). The curve shown in Exhibit E-3 suggests that "the greater the variation in speed of any vehicle from the average speed of all traffic, the greater its chance of being involved in an accident."[22] However, attempts by other researchers to replicate the relationship between variation from mean operating speed and probability of involvement by other researchers have not been successful.[5,24,25]

Exhibit E-3: Accident Involvement Rate by Variation from Average Speed[22]



(From Solomon's Figure 7) [22]

Another consideration in the discussion of speed and probability of involvement is the possibility that some drivers habitually choose to travel at less or more than the average speed. The reasons for speed choice may be related to other driver characteristics and may include the reasons that make some drivers cautious and others aggressive. These factors, as well as the resulting running speed, may affect the probability of accident involvement.

Although observed data do not clearly support the theory that the probability of involvement in an accident increases with increasing speed, it is still reasonable to believe that higher speeds and longer stopping distances increase the probability of accident involvement and severity (Section E.2).

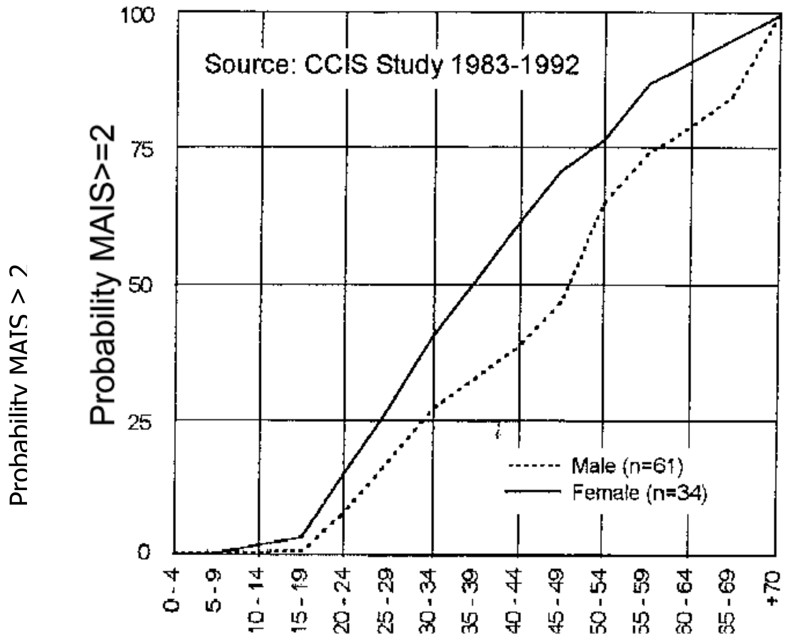
E.2 Event Phase: Accident Severity and Speed Change at Impact

The relationship between the change in speed at impact and accident severity is clearer than the relationship between running speed and the probability of accident involvement. A greater change of speed at impact leads to a more severe outcome. Damage to vehicles and to occupants depends on pressure, deceleration, change in velocity and the amount of kinetic energy dissipated by deformation. All these elements are increasing functions of velocity. Although vehicle speed and speed distribution are commonly used, in the context of accident severity it is more appropriate to use the vector 'velocity' instead of the scalar 'speed.'

The relationship between accident severity and change of velocity at impact is strongly supported by observed data. For example, Exhibit E-4 shows the results of a ten-year study of the impact of crashes on restrained front-seat occupants. Injury severity is shown on the vertical axis represented by MAIS, the Maximum 'Abbreviated Injury Scale' (MAIS) score (An alternative way to define injury is the Abbreviated Injury Scale (AIS), an integer scale developed by the Association for the Advancement of Automotive Medicine to rate the severity of individual injuries. The AIS scale is commonly used in detailed accident investigations. Injuries are ranked on a scale of 1 to 6, with 1 being minor, 5 being severe and 6 being an unsurvivable injury. The scale represents the 'threat to life' associated with an injury and is not meant to represent a comprehensive measure of severity.[(10)]) The horizontal axis of is Exhibit E-4 "the change in velocity of a vehicle's occupant compartment during the collision phase of a motor vehicle crash."[(2)]

Exhibit E-Exhibit E-4 shows that the proportion of occupants sustaining a moderate injury (AIS score of 2 or higher) rises with increasing change in velocity at impact. The speed of the vehicle prior to the crash is unknown. For example, in a crash where the change in velocity at impact is 19 mph–21 mph, about 40% of restrained female front-seat occupants will sustain an injury for which MAIS ≥ 2. When the change in velocity at impact is 30-33 mph, about 75% of restrained female front-seat occupants sustain such injury.[(16)]

Exhibit E-4: Probability of Injury to Restrained Front-Seat Occupants by Change in Velocity of a Vehicle's Occupant Compartment at Impact (Adapted from Mackay)*(16)*

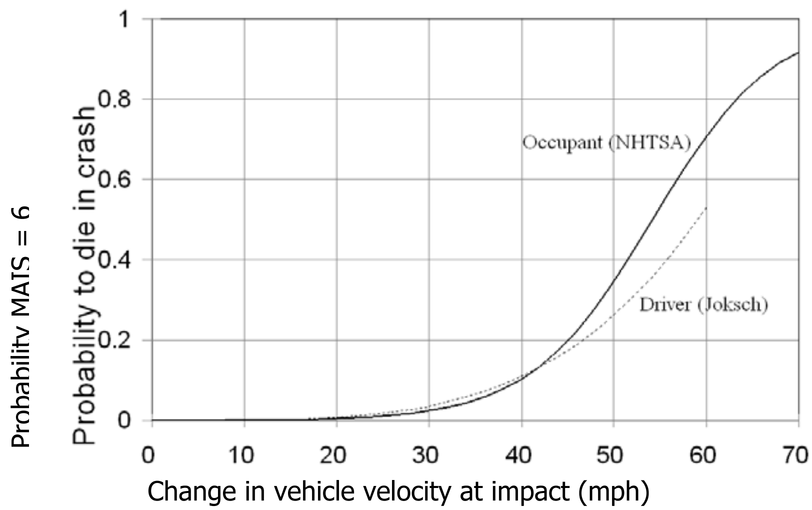


Change in velocity of vehicle occupant compartment at impact (km/h)

Exhibit E-5 illustrates another example of the relationship between the change in velocity at impact and accident severity. This Exhibit illustrates data collected for two studies. The dashed line labeled Driver (Joksch) is based on a seven year study of the proportion of passenger car drivers killed when involved in accidents.*(7)* The solid line labeled Occupant (NHTSA) is based on equations developed to calculate the risk probability of injury severity based on the change in velocity for all MAIS = 6 (the fatal-injury level).*(20)*

Observed data show that accident severity increases with increasing change in velocity at impact.

Exhibit E-5: Probability of Fatal Injury (MAIS = 6) to Drivers or Occupants by Change in Vehicle Velocity at Impact[7,20]



E.3 Crash Frequency and Average Operating Speed

The overall relationship between safety and speed is difficult to state based on observed data, as discussed in the previous sections. The effect of changes in the average speed or the variance of the speed distribution on accident probability is well established. This section discusses the relationship between crash frequency and changes in the average operating speed of a road.

For fatal accidents, the change in safety is the ratio of the change in average operating speed to the power of 4 (Equation D-1). This result is based on several studies of roadways where the average operating speed changed from “before” to “after” time periods.[18,19]

$$\frac{N_1}{N_0} = \left(\frac{\bar{v}_1}{\bar{v}_0}\right)^{\alpha} \qquad (D\text{-}1)$$

Where,

N_0 = crash frequency of the roadway before;

N_1 = crash frequency of the roadway after;

$\bar{v}_0$ = average operating speed of a roadway before;

$\bar{v}_1$ = average operating speed of a roadway after ;

α = 4 for fatal accidents;

α = 3 for fatal & serious injury accidents ;

α = 2 for all injury accidents.

Additional estimated values for the exponent α are shown in Exhibit E-6.

Exhibit E-6: Estimates of α (exponent in Equation D-1)

Severity	Estimate of α	95% Confidence Interval
Fatalities	4.5	4.1-4.9
Seriously Injured Road Users	2.4	1.6-3.2
Slightly Injured Road Users	1.5	1.0-2.0
All Injured Road Users (Including Fatally)	1.9	1.0-2.8
Fatal Accidents	3.6	2.4-4.8
Serious Injury Accidents	2.0	0.7-3.3
Slight Injury Accidents	1.1	0.0-2.4
All Injury Accidents (Including Fatal)	1.5	0.8-2.2
PDO Accidents	1.0	0.0-2.0

Exhibit E-7 illustrates fatal accident data from a study of 97 published studies containing 460 results for changes in average operating speed.(3) For most roads where the average operating speed increased, the number of fatal accidents also increased, and vice versa. As can be seen in Exhibit E-7, there is considerable noise (variation) in the data. This noise (data variation) reflects three issues: the randomness of accident counts, the variety of circumstances under which the data were obtained, and the variety of causes of changes in average operating speed.

Exhibit E-7: Change in Average Operating Speed vs. Relative Change in Fatal Accidents(3)

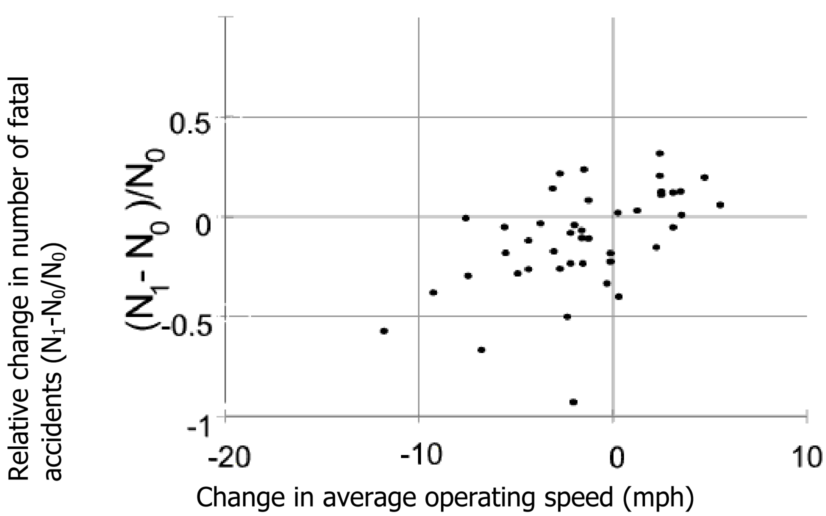


Exhibit E-8 summarizes Accident Modification Factors (AMFs) for injury and fatal accidents due to changes in average operating speed of a roadway.(11) For example, if a road has an average operating speed of 60 mph ($\bar{v}_0$ = 60 mph), and a treatment that is expected to increase the average operating speed by 2 mph ($\bar{v}_1 - \bar{v}_0$ = 2 mph) is implemented, then injury accidents are expected to increase by a factor of 1.10 and fatal accidents by a factor of 1.18. Thus, a small change in average operating speed can have a large impact on crash frequency and severity.

The question of whether these results would apply irrespective of the cause of the change in average speed cannot be well answered at this time. If the change in crash frequency reflects mainly the associated change in severity, then the AMFs in Exhibit E-8 apply

Exhibit E-8: Accident Modification Factors for Changes in Average Operating Speed[(11)]

Injury Accidents	$\bar{V}_0$ [mph]					
$\bar{V}_1 - \bar{V}_0$ [mph]	**30**	**40**	**50**	**60**	**70**	**80**
-5	0.57	0.66	0.71	0.75	0.78	0.81
-4	0.64	0.72	0.77	0.80	0.83	0.85
-3	0.73	0.79	0.83	0.85	0.87	0.88
-2	0.81	0.86	0.88	0.90	0.91	0.92
-1	0.90	0.93	0.94	0.95	0.96	0.96
0	1.00	1.00	1.00	1.00	1.00	1.00
1	1.10	1.07	1.06	1.05	1.04	1.04
2	1.20	1.15	1.12	1.10	1.09	1.08
3	1.31	1.22	1.18	1.15	1.13	1.12
4	1.43	1.30	1.24	1.20	1.18	1.16
5	1.54	1.38	1.30	1.26	1.22	1.20

Fatal Accidents	$\bar{V}_0$ [mph]					
$\bar{V}_1 - \bar{V}_0$ [mph]	**30**	**40**	**50**	**60**	**70**	**80**
-5	0.22	0.36	0.48	0.58	0.67	0.75
-4	0.36	0.48	0.58	0.66	0.73	0.80
-3	0.51	0.61	0.68	0.74	0.80	0.85
-2	0.66	0.73	0.79	0.83	0.86	0.90
-1	0.83	0.86	0.89	0.91	0.93	0.95
0	1.00	1.00	1.00	1.00	1.00	1.00
1	1.18	1.14	1.11	1.09	1.07	1.05
2	1.38	1.28	1.22	1.18	1.14	1.10
3	1.59	1.43	1.34	1.27	1.21	1.16
4	1.81	1.59	1.46	1.36	1.28	1.21
5	2.04	1.75	1.58	1.46	1.36	1.27

NOTE: Although data used to develop these AMFs are international, the results apply to North American conditions.

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