Chapter 3—Fundamentals

3.1. CHAPTER INTRODUCTION

The purpose of this chapter is to introduce the fundamental concepts for understanding the roadway safety management techniques and crash estimation methods presented in subsequent chapters of the *Highway Safety Manual* (HSM).

In the HSM, crash frequency is the fundamental basis for safety analysis, selection of sites for treatment and evaluation of the effects of treatments. The overall aim of the HSM is to reduce crashes and crash severities through the comparison and evaluation of alternative treatments and design of roadways. A commensurate objective is to use limited safety funds in a cost-effective manner.

This chapter presents the following concepts:

- An overview of the basic concepts relating to crash analysis, including definitions of key crash analysis terms, the difference between subjective and objective safety factors that contribute to crashes, and strategies to reduce crashes;
- Data for crash estimation and its limitations;
- A historical perspective of the evolution of crash estimation methods and the limitations their methods;
- An overview of the predictive method (Part C) and Crash Modification Factors (CMFs) (Parts C and D);
- Application of the HSM; and
- The types of evaluation methods for determining the effectiveness of treatment types (Part B).

Users benefit by familiarizing themselves with the material in Chapter 3 in order to apply the HSM and by understanding that engineering judgment is necessary to determine if and when the HSM procedures are appropriate.

3.2. CRASHES AS THE BASIS OF SAFETY ANALYSIS

Crash frequency is used as a fundamental indicator of "safety" in the evaluation and estimation methods presented in the HSM. Where the term "safety" is used in the HSM, it refers to the crash frequency or crash severity, or both, and collision type for a specific time period, a given location, and a given set of geometric and operational conditions.

This section provides an overview of fundamental concepts relating to crashes and their use in the HSM:

- The difference between objective safety and subjective safety;
- The definition of a crash and other crash-related terms;
- The recognition that crashes are rare and random events;

- The recognition that contributing factors influence crashes and can be addressed by a number of strategies;
- The reduction of crashes by changing the roadway/environment.

3.2.1. Objective and Subjective Safety

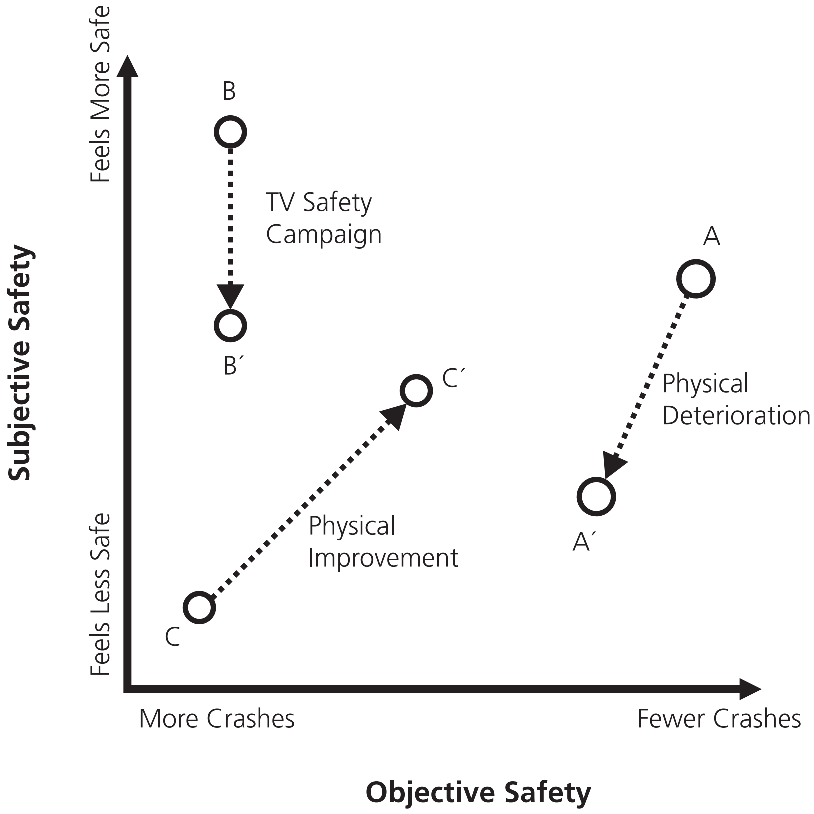
The HSM focuses on how to estimate and evaluate the crash frequency and crash severity for a particular roadway network, facility, or site, in a given period, and hence the focus is on "objective" safety. Objective safety refers to use of a quantitative measure that is independent of the observer. Crash frequency and severity are defined in Section 3.2.2.

In contrast, "subjective" safety concerns the perception of how safe a person feels on the transportation system. Assessment of subjective safety for the same site will vary between observers.

The traveling public, the transportation professional and the statisticians may all have diverse but valid opinions about whether a site is "safe" or "unsafe." Highway agencies draw information from each of these groups in determining policies and procedures to be used to affect a change in crash frequency or severity, or both, among the road or highway system.

Figure 3-1 illustrates the difference between objective and subjective safety. Moving to the right on the horizontal axis of the graph conceptually shows an increase in objective safety (reduction in crashes). Moving up on the vertical axis conceptually shows an increase in subjective safety (i.e., increased perception of safety). In this figure, three examples illustrate the difference:

- The change between Points A to A´ represents a clear-cut deterioration in both objective and subjective safety. For example, removing lighting from an intersection may increase crashes and decrease the driver's perception of safety (at night).
- The change between Points B to B´ represents a reduction in the perception of safety on a transportation network. For example, as a result of a television campaign against aggressive driving, citizens may feel less secure on the roadways because of greater awareness of aggressive drivers. If the campaign is not effective in reducing crashes caused by aggressive driving, the decline in perceived safety occurs with no change in the number of crashes.
- The change from Point C to C´ represents a physical improvement to the roadway (such as the addition of left-turn lanes) that results in both a reduction in crashes and an increase in the subjective safety.



Source: NCHRP 17-27

Figure 3-1. Changes in Objective and Subjective Safety

3.2.2. Fundamental Definitions of Terms in the HSM

Definition of a Crash

In the HSM, a crash is defined as a set of events that result in injury or property damage due to the collision of at least one motorized vehicle and may involve collision with another motorized vehicle, a bicyclist, a pedestrian, or an object. The terms used in the HSM do not include crashes between cyclists and pedestrians, or vehicles on rails (7).

Definition of Crash Frequency

In the HSM, "crash frequency" is defined as the number of crashes occurring at a particular site, facility, or network in a one-year period. Crash frequency is calculated according to Equation 3-1 and is measured in number of crashes per year.

$$\text{Crash Frequency} = \frac{\text{Number of Crashes}}{\text{Period in Years}} \qquad (3\text{-}1)$$

Definition of Crash Estimation

"Crash estimation" refers to any methodology used to forecast or predict the crash frequency of:

- An existing roadway for existing conditions during a past or future period;
- An existing roadway for alternative conditions during a past or future period;
- A new roadway for given conditions for a future period.

The crash estimation method in Part C of the HSM is referred to as the “predictive method” and is used to estimate the “expected average crash frequency”, which is defined below.

Definition of Predictive Method

The term “predictive method“ refers to the methodology in Part C of the HSM that is used to estimate the “expected average crash frequency” of a site, facility, or roadway under given geometric design and traffic volumes for a specific period of time.

Definition of Expected Average Crash Frequency

The term “expected average crash frequency” is used in the HSM to describe the estimate of long-term average crash frequency of a site, facility, or network under a given set of geometric design and traffic volumes in a given time period (in years).

As crashes are random events, the observed crash frequencies at a given site naturally fluctuate over time. Therefore, the observed crash frequency over a short period is not a reliable indicator of what average crash frequency is expected under the same conditions over a longer period of time.

If all conditions on a roadway could be controlled (e.g., fixed traffic volume, unchanged geometric design, etc.), the long-term average crash frequency could be measured. However, because it is rarely possible to achieve these constant conditions, the true long-term average crash frequency is unknown and must be estimated instead.

Definition of Crash Severity

Crashes vary in the level of injury or property damage. The American National Standard ANSI D16.1-1996 defines injury as “bodily harm to a person” (7). The level of injury or property damage due to a crash is referred to in the HSM as “crash severity.” While a crash may cause a number of injuries of varying severity, the term crash severity refers to the most severe injury caused by a crash.

Crash severity is often divided into categories according to the KABCO scale, which provides five levels of injury severity. Even if the KABCO scale is used, the definition of an injury may vary between jurisdictions. The five KABCO crash severity levels are:

- *K*—Fatal injury: an injury that results in death;
- *A*—Incapacitating injury: any injury, other than a fatal injury, that prevents the injured person from walking, driving, or normally continuing the activities the person was capable of performing before the injury occurred;
- *B*—Non-incapacitating evident injury: any injury, other than a fatal injury or an incapacitating injury, that is evident to observers at the scene of the crash in which the injury occurred;
- *C*—Possible injury: any injury reported or claimed that is not a fatal injury, incapacitating injury, or non-incapacitating evident injury and includes claim of injuries not evident;
- *O*—No Injury/Property Damage Only (PDO).

While other scales for ranking crash severity exist, the KABCO scale is used in the HSM.

Definition of Crash Evaluation

In the HSM, “crash evaluation” refers to determining the effectiveness of a particular treatment or a treatment program after its implementation. Where the term effectiveness is used in the HSM, it refers to a change in the expected average crash frequency (or severity) for a site or project. Evaluation is based on comparing results obtained from crash estimation. Examples include:

- Evaluating a single application of a treatment to document its effectiveness;
- Evaluating a group of similar projects to document the effectiveness of those projects;
- Evaluating a group of similar projects for the specific purpose of quantifying the effectiveness of a countermeasure;
- Assessing the overall effectiveness of specific projects or countermeasures in comparison to their costs.

Crash evaluation is introduced in Section 3.7 and described in detail in Chapter 9.

3.2.3. Crashes Are Rare and Random Events

Crashes are rare and random events. By rare, it is implied that crashes represent only a very small proportion of the total number of events that occur on the transportation system. Random means that crashes occur as a function of a set of events influenced by several factors, which are partly deterministic (they can be controlled) and partly stochastic (random and unpredictable). An event refers to the movement of one or more vehicles and or pedestrians and cyclists on the transportation network.

A crash is one possible outcome of a continuum of events on the transportation network during which the probability of a crash occurring may change from low risk to high risk. Crashes represent a very small proportion of the total events that occur on the transportation network. For example, for a crash to occur, two vehicles must arrive at the same point in space at the same time. However, arrival at the same time does not necessarily mean that a crash will occur. The drivers and vehicles have different properties (reaction times, braking efficiencies, visual capabilities, attentiveness, speed choice), that will determine whether or not a crash occurs.

The continuum of events that may lead to crashes and the conceptual proportion of crash events to non-crash events are represented in Figure 3-2. For the vast majority of events (i.e., movement of one or more vehicles and or pedestrians and cyclists) in the transportation system, events occur with low risk of a crash (i.e., the probability of a crash occurring is very low for most events on the transportation network).

In a smaller number of events, the potential risk of a crash occurring increases, such as an unexpected change in traffic flow on a freeway, a person crossing a road, or an unexpected object is observed on the roadway. In the majority of these situations, the potential for a crash is avoided by a driver's advance action, such as slowing down, changing lanes, or sounding a horn.

In even fewer events, the risk of a crash occurring increases even more. For instance, if a driver is momentarily not paying attention, the probability of a crash occurring increases. However, the crash could still be avoided, for example, by coming to an emergency stop. Finally, in only a very few events, a crash occurs. For instance, in the previous example, the driver may not have applied the brakes in time to avoid a collision.

Circumstances that lead to a crash in one event will not necessary lead to a crash in a similar event. This reflects the randomness that is inherent in crashes.

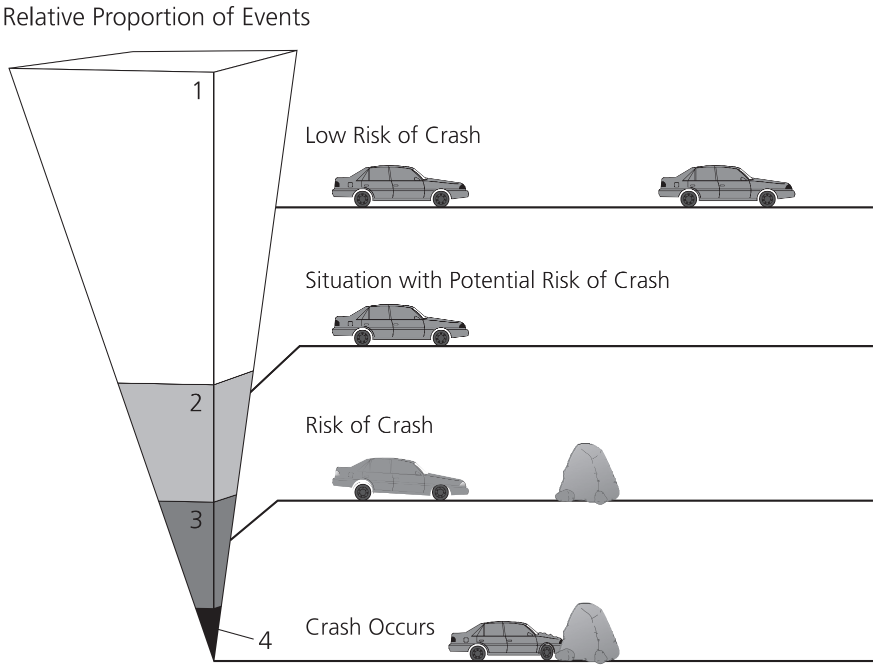


Figure 3-2. Crashes Are Rare and Random Events

3.2.4 Factors Contributing to a Crash

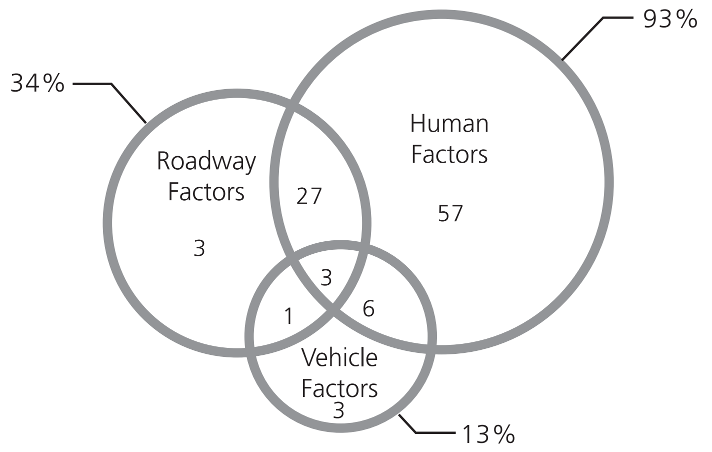
While it is common to refer to the "cause" of a crash, in reality, most crashes cannot be related to a singular causal event. Instead, crashes are the result of a convergence of a series of events that are influenced by a number of contributing factors (time of day, driver attentiveness, speed, vehicle condition, road design, etc.). These contributing factors influence the sequence of events before, during, and after a crash.

- Before-crash events reveal factors that contributed to the risk of a crash occurring, and how the crash may have been prevented. For example, determine whether the brakes of one or both of the vehicles involved were worn;
- During-crash events reveal factors that contributed to the crash severity and how engineering solutions or technological changes could reduce crash severity. For example, determine whether a car has airbags and if the airbag deployed correctly;
- After-crash events reveal factors influencing the outcome of the crash and how damage and injury may have been reduced by improvements in emergency response and medical treatment. For example, determine the time and quality of emergency response to a crash.

Crashes have the following three general categories of contributing factors:

- *Human*—including age, judgment, driver skill, attention, fatigue, experience and sobriety;
- *Vehicle*—including design, manufacture, and maintenance;
- *Roadway/Environment*—including geometric alignment, cross-section, traffic control devices, surface friction, grade, signage, weather, visibility.

By understanding these factors and how they might influence the sequence of events, crashes and crash severities can be reduced by implementing specific measures to target specific contributing factors. The relative contribution of these factors to crashes can assist with determining how to best allocate resources to reduce crashes. Research by Treat into the relative proportion of contributing factors is summarized in Figure 3-3 (10). The research was conducted in 1980 and therefore, the relative proportions are more informative than the actual values shown.



Source: Treat 1979

Figure 3-3. Contributing Factors to Vehicle Crashes

A framework for relating the series of events in a crash to the categories of crash-contributing factors is the Haddon Matrix. Table 3-1 (2) provides an example of this matrix. The Haddon Matrix helps create order when determining which contributing factors influence a crash and which period of the crash the factors influence. The factors listed are not intended to be comprehensive; they are examples only.

Table 3-1. Example Haddon Matrix for Identifying Contributing Factors

Period	Human Factors	Vehicle Factors	Roadway/Environment Factors
Before Crash Factors contributing to increased risk of crash	distraction, fatigue, inattention, poor judgment, age, cell phone use, deficient driving habits	worn tires, worn brakes	wet pavement, polished aggregate, steep downgrade, poorly coordinated signal system
During Crash Factors contributing to crash severity	vulnerability to injury, age, failure to wear a seat belt, driving speed, sobriety	bumper heights and energy adsorption, headrest design, airbag operations	pavement friction, grade, roadside environment
After Crash Factors contributing to crash outcome	age, gender	ease of removal of injured passengers	the time and quality of the emergency response, subsequent medical treatment

Considering the crash contributing factors and what period of a crash event they relate to supports the process of identifying appropriate crash reduction strategies. A reduction in crashes and crash severity may be achieved through changes in:

- The behavior of humans;
- The condition of the roadway/environment;
- The design and maintenance of technology, including vehicles, roadway, and the environment technology;
- The provision of emergency medical treatment, medical treatment technology, and post-crash rehabilitation;
- The exposure to travel, or level of transportation demand.

Strategies to influence the above and reduce crash and crash severity may include:

- Design, Planning, and Maintenance may reduce or eliminate crashes by improving and maintaining the transportation system, such as modifying signal phasing. Crash severity may also be reduced by selection of appropriate treatments, such as the use of median barriers to prevent head-on collisions.
- Education may reduce crashes by influencing the behavior of humans including public awareness campaigns, driver training programs, and training of engineers and doctors.
- Policy/Legislation may reduce crashes by influencing human behavior and design of roadway and vehicle technology. For example, laws may prohibit cell phone use while driving, require minimum design standards, and mandate use of helmets or seatbelts.
- Enforcement may reduce crashes by penalizing illegal behavior, such as excessive speeding and drunken driving.
- Technology Advances may reduce crashes and crash severity by minimizing the outcomes of a crash or preempting crashes from occurring altogether. For example, electronic stability control systems in vehicles improve the driver's ability to maintain control of a vehicle. The introduction of "Jaws of Life" tools (for removing injured persons from a vehicle) has reduced the time taken to provide emergency medical services.
- Demand Management/Exposure reduction may reduce crashes by reducing the number of "events" on the transportation system for which the risk of a crash may arise. For example, increasing the availability of mass transit reduces the number of passenger vehicles on the road and therefore a potential reduction in crash frequency may occur because of less exposure.

A direct relationship between individual contributing factors and particular strategies to reduce crashes does not exist. For example, in a head-on crash on a rural two-lane road in dry, well-illuminated conditions, the roadway may not be considered as a contributing factor. However, the crash may have been prevented if the roadway was a divided road. Therefore, while the roadway may not be listed as a contributing factor, changing the roadway design is one potential strategy to prevent similar crashes in the future.

While all of the above strategies play an important role in reducing crashes and crash severity, the majority of these strategies are beyond the scope of the HSM. The HSM focuses on the reduction of crashes and crash severity where it is believed that the roadway/environment is a contributing factor, either exclusively or through interactions with the vehicle or the driver, or both.

3.3. DATA FOR CRASH ESTIMATION

This section describes the data that is typically collected and used for the purposes of crash analysis, and the limitations of observed crash data in the estimation of crashes and evaluation of crash reduction programs.

3.3.1. Data Needed for Crash Analysis

Accurate, detailed crash data, roadway or intersection inventory data, and traffic volume data are essential to undertake meaningful and statistically sound analyses. This data may include:

- *Crash Data*—The data elements in a crash report describe the overall characteristics of the crash. While the specifics and level of detail of this data vary from state to state, in general, the most basic crash data consist of crash location; date and time; crash severity; collision type; and basic information about the roadway, vehicles, and people involved.
- *Facility Data*—The roadway or intersection inventory data provide information about the physical characteristics of the crash site. The most basic roadway inventory data typically include roadway classification, number of lanes, length, and presence of medians, and shoulder width. Intersection inventories typically include road names, area type, and traffic control and lane configurations.

- *Traffic Volume Data*—In most cases, the traffic volume data required for the methods in the HSM are annual average daily traffic (AADT). Some organizations may use ADT (average daily traffic) as precise data may not be available to determine AADT. If AADT data are unavailable, ADT can be used to estimate AADT. Other data that may be used for crash analysis includes intersection total entering vehicles (TEV), and vehicle-miles traveled (VMT) on a roadway segment, which is a measure of segment length and traffic volume. In some cases, additional volume data, such as pedestrian crossing counts or turning movement volumes, may be necessary.

The HSM Data Needs Guide (9) provides additional data information. In addition, in an effort to standardize databases related to crash analyses there are two guidelines published by FHWA: The Model Minimum Uniform Crash Criteria (MMUCC) and the Model Minimum Inventory of Roadway Elements (MMIRE). MMUCC (http://www.mmucc.us) is a set of voluntary guidelines to assist states in collecting consistent crash data. The goal of the MMUCC is that with standardized integrated databases, there can be consistent crash data analysis and transferability. MMIRE (http://www.mireinfo.org) provides guidance on what roadway inventory and traffic elements can be included in crash analysis, and proposes standardized coding for those elements. As with MMUCC, the goal of MMIRE is to provide transferability by standardizing database information.

3.3.2. Limitations of Observed Crash Data Accuracy

This section discusses the limitations of recording, reporting, and measuring crash data with accuracy and consistency. These issues can introduce bias and affect crash estimation reliability in ways that are not easily addressed. These limitations are not specific to a particular crash analysis methodology and their implications require consideration regardless of the particular crash analysis methodology used.

Limitations of observed crash data include:

- Data quality and accuracy
- Crash reporting thresholds and the frequency-severity indeterminacy
- Differences in data collection methods and definitions used by jurisdictions

Data Quality and Accuracy

Crash data are typically collected on standardized forms by trained police personnel and, in some states, by integrating information provided by citizens self-reporting PDO crashes. Not all crashes are reported, and not all reported crashes are recorded accurately. Errors may occur at any stage of the collection and recording of crash data and may be due to:

- *Data entry*—typographic errors;
- *Imprecise entry*—the use of general terms to describe a location;
- *Incorrect entry*—entry of road names, road surface, level of crash severity, vehicle types, impact description, etc.;
- *Incorrect training*—lack of training in use of collision codes;
- *Subjectivity*—Where data collection relies on the subjective opinion of an individual, inconsistency is likely. For example, estimation of property damage thresholds or excessive speed for conditions may vary.

Crash Reporting Thresholds

Reported and recorded crashes are referred to as observed crash data in the HSM. One limitation on the accuracy of observed crash data is that all crashes are not reported. While a number of reasons for this may exist, a common reason is the use of minimum crash reporting thresholds.

Transportation agencies and jurisdictions typically use police crash reports as a source of observed crash records. In most states, crashes must be reported to police when damage is above a minimum dollar value threshold. This threshold varies between states. When thresholds change, the change in observed crash frequency does not necessarily represent a change in long-term average crash frequency but rather creates a condition where comparisons between previous years cannot be made.

To compensate for inflation, the minimum dollar value for crash reporting is periodically increased through legislation. Typically, the increase is followed by a drop in the number of reported crashes. This decrease in reported crashes does not represent an increase in safety. It is important to be aware of crash reporting thresholds and to ensure that a change to reporting thresholds did not occur during the period of study under consideration.

Crash Reporting and the Frequency-Severity Indeterminacy

Not all reportable crashes are actually reported to police and, therefore, not all crashes are included in a crash database. In addition, studies indicate that crashes with greater severity are reported more reliably than crashes of lower severity. This situation creates an issue called frequency-severity indeterminacy, which represents the difficulty in determining if a change in the number of reported crashes is caused by an actual change in crashes, a shift in severity proportions, or a mixture of the two. It is important to recognize frequency-severity indeterminacy in measuring effectiveness of and selecting countermeasures. No quantitative tools currently exist to measure frequency-severity indeterminacy.

Differences between Crash Reporting Criteria of Jurisdictions

Differences exist between jurisdictions regarding how crashes are reported and classified. This especially affects the development of statistical models for different facility types using crash data from different jurisdictions, and the comparison or use of models across jurisdictions. Different definitions, criteria, and methods of determining and measuring crash data may include:

- Crash reporting thresholds
- Definition of terms and criteria relating to crashes, traffic, and geometric data
- Crash severity categories

As previously discussed, crash reporting thresholds vary from one jurisdiction to the next. Different definitions and terms relating to the three types of data (i.e., traffic volume, geometric design, and crash data) can create difficulties as it may be unclear whether the difference is limited to the terminology or whether the definitions and criteria for measuring a particular type of data is different. For example, most jurisdictions use annual average daily traffic (AADT) as an indicator of yearly traffic volume, others use average daily traffic (ADT).

Variation in crash severity terms can lead to difficulties in comparing data between states and development of models which are applicable to multiple states. For example, a fatal injury is defined by some agencies as "any injury that results in death within a specified period after the road vehicle crash in which the injury occurred. Typically the specified period is 30 days (7). In contrast, World Health Organization procedures, adopted for vital statistics reporting in the United States, use a 12-month limit. Similarly, jurisdictions may use differing injury scales or have different severity classifications or groupings of classifications. These differences may lead to inconsistencies in reported crash severity and the proportion of severe injury to fatalities across jurisdictions.

In summary, the count of reported crashes in a database is partial, may contain inaccurate or incomplete information, may not be uniform for all collision types and crash severities, may vary over time, and may differ from jurisdiction to jurisdiction.

3.3.3. Limitations Due to Randomness and Change

This section discusses the limitations associated with natural variations in crash data and the changes in site conditions. These are limitations due to inherent characteristics of the data itself, not limitations due to the method by which the data is collected or reported. If not considered and accounted for as possible, the limitations can introduce bias and affect crash data reliability in ways that are not easily accounted for.

These limitations are not specific to a particular crash analysis methodology, and their implications require consideration regardless of the particular crash analysis methodology being used.

Limitations due to randomness and changes include:

- Natural variability in crash frequency
- Regression-to-the-mean and regression-to-the-mean bias
- Variations in roadway characteristics
- Conflict between Crash Frequency Variability and Changing Site Conditions

Natural Variability in Crash Frequency

Because crashes are random events, crash frequencies naturally fluctuate over time at any given site. The randomness of crash occurrence indicates that short-term crash frequencies alone are not a reliable estimator of long-term crash frequency. If a three-year period of crashes were used as the sample to estimate crash frequency, it would be difficult to know if this three-year period represents a typically high, average, or low crash frequency at the site.

This year-to-year variability in crash frequencies adversely affects crash estimation based on crash data collected over short periods. The short-term average crash frequency may vary significantly from the long-term average crash frequency. This effect is magnified at study locations with low crash frequencies where changes due to variability in crash frequencies represent an even larger fluctuation relative to the expected average crash frequency.

Figure 3-4 demonstrates the randomness of observed crash frequency and the limitation of estimating crash frequency based on short-term observations.

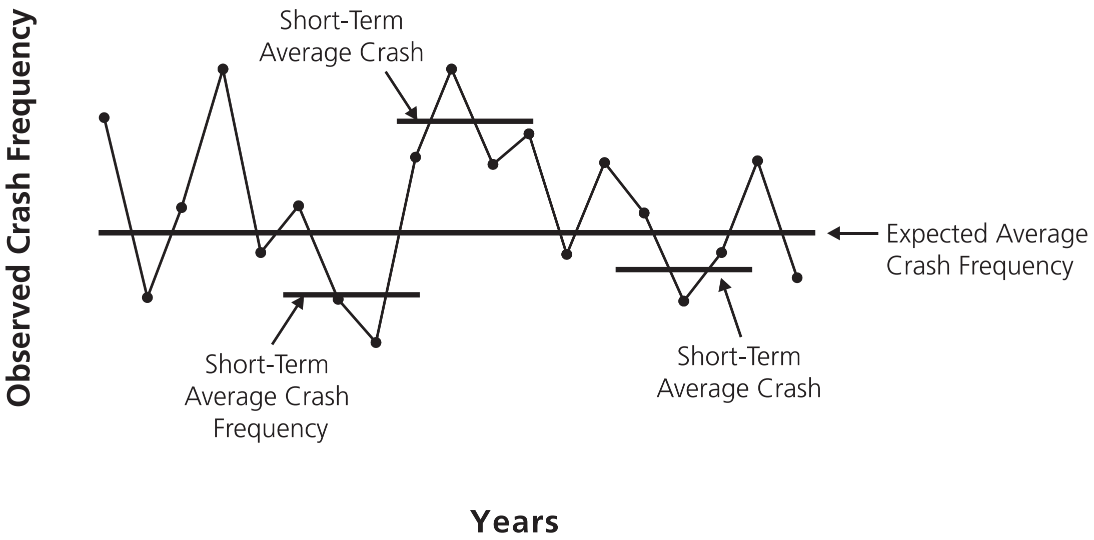


Figure 3-4. Variation in Short-Term Observed Crash Frequency

Regression-to-the-Mean and Regression-to-the-Mean Bias

The crash fluctuation over time makes it difficult to determine whether changes in the observed crash frequency are due to changes in site conditions or are due to natural fluctuations. When a period with a comparatively high crash frequency is observed, it is statistically probable that the following period will be followed by a comparatively low crash frequency (8). This tendency is known as regression-to-the-mean (RTM) and also applies to the high probability that a low crash frequency period will be followed by a high crash frequency period.

Failure to account for the effects of RTM introduces the potential for “RTM bias”, also known as “selection bias”. Selection bias occurs when sites are selected for treatment based on short-term trends in observed crash frequency. For example, a site is selected for treatment based on a high observed crash frequency during a very short period of time (e.g., two years). However, the site’s long-term crash frequency may actually be substantially lower and therefore the treatment may have been more cost-effective at an alternate site. RTM bias can also result in the overestimation or underestimation of the effectiveness of a treatment (i.e., the change in expected average crash frequency). Without accounting for RTM bias, it is not possible to know if an observed reduction in crashes is due to the treatment or if it would have occurred without the modification.

The effect of RTM and RTM bias in evaluation of treatment effectiveness is shown on Figure 3-5. In this example, a site is selected for treatment based on its short term crash frequency trend over three years (which is trending upwards). Due to regression-to-the-mean, it is probable that the observed crash frequency will actually decrease (towards the expected average crash frequency) without any treatment. A treatment is applied, which has a beneficial effect (i.e., there is a reduction in crashes due to the treatment). However, if the reduction in crash frequency that would have occurred (due to RTM) without the treatment is ignored, the effectiveness of the treatment is perceived to be greater than its actual effectiveness.

The effect of RTM bias is accounted for when treatment effectiveness (i.e., reduction in crash frequency or severity) and site selection is based on a long-term average crash frequency. Because of the short-term year-to-year variability in observed crash frequency and the consequences of not accounting for RTM bias, the HSM focuses on estimating of the “expected average crash frequency” as defined in Section 3.2.4.

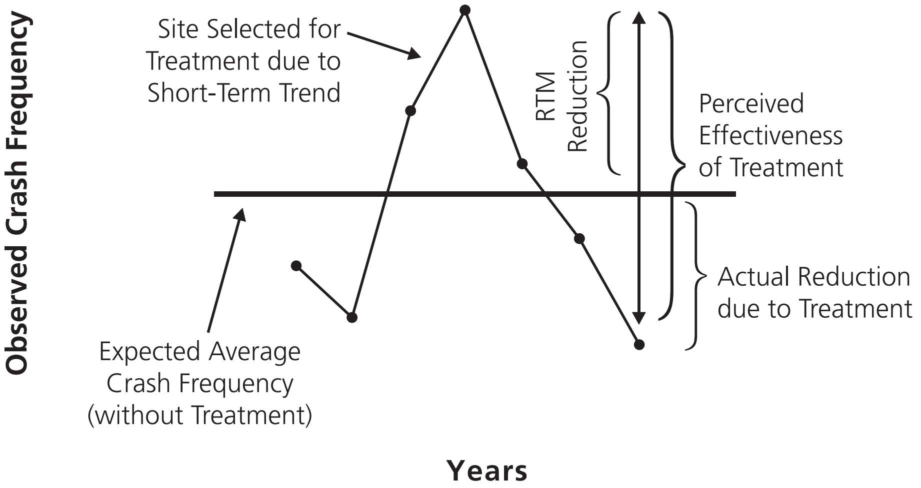


Figure 3-5. Regression-to-the-Mean (RTM) and RTM Bias

Variations in Roadway Characteristics and Environment

A site’s characteristics, such as traffic volume, weather, traffic control, land use, and geometric design, are subject to change over time. Some conditions, such as traffic control or geometry changes at an intersection, are discrete events. Other characteristics, like traffic volume and weather, change on a continual basis.

The variation of site conditions over time makes it difficult to attribute changes in the expected average crash frequency to specific conditions. It also limits the number of years that can be included in a study. If longer time periods are studied (to improve the estimation of crash frequency and account for natural variability and RTM), it becomes likely that changes in conditions at the site occurred during the study period. One way to address this limitation is to estimate the expected average crash frequency for the specific conditions for each year in a study period. This is the predictive method applied in Part C.

Variation in conditions also plays a role in evaluation of the effectiveness of a treatment. Changes in conditions between a "before" period and an "after" period may make it difficult to determine the actual effectiveness of a particular treatment. This may mean that a treatment's effect may be over- or underestimated, or unable to be determined. More information about this is included in Chapter 9.

Conflict between Crash Frequency Variability and Changing Site Conditions
The implications of crash frequency fluctuation and variation of site conditions are often in conflict. On one hand, the year-to-year fluctuation in crash frequencies tends toward acquiring more years of data to determine the expected average crash frequency. On the other hand, changes in site conditions can shorten the length of time for which crash frequencies are valid for considering averages. This push/pull relationship requires considerable judgment when undertaking large-scale analyses and using crash estimation procedures based on observed crash frequency. This limitation can be addressed by estimating the expected average crash frequency for the specific conditions for each year in a study period, which is the predictive method applied in Part C.

3.4. EVOLUTION OF CRASH ESTIMATION METHODS

This section provides a brief overview of the evolution of crash estimation methods and their strengths and limitations. The development of new crash estimation methods is associated not only with increasing sophistication of the statistical techniques, but is also due to changes in the thinking about road safety. Additional information is included in Appendix 3A. The following crash estimation methods are discussed:

- Crash estimation using observed crash frequency and crash rates over a short-term period and a long-term period (e.g., more than 10 years).
- Indirect safety measures for identifying high crash locations. Indirect safety measures are also known as "surrogate safety measures".
- Statistical analysis techniques (specifically the development of statistical regression models for estimation of crash frequency), and statistical methodologies to incorporate observed crash data to improve the reliability of crash estimation models.

3.4.1. Observed Crash Frequency and Crash Rate Methods

Crash frequency and crash rates are often used for crash estimation and evaluation of treatment effectiveness. In the HSM, the historic crash data on any facility (i.e., the number of recorded crashes in a given period) is referred to as the "observed crash frequency".

"Crash rate" is the number of crashes that occur at a given site during a certain time period in relation to a particular measure of exposure (e.g., per million vehicle miles of travel for a roadway segment or per million entering vehicles for an intersection). Crash rates may be interpreted as the probability (based on past events) of being involved in a crash per instance of the exposure measure. For example, if the crash rate on a roadway segment is one crash per one million vehicle miles per year, then a vehicle has a one-in-a-million chance of being in a crash for every mile traveled on that roadway segment. Crash rates are calculated according to Equation 3-2.

$$\text{Crash Rate} = \frac{\text{Average Crash Frequency in a Period}}{\text{Exposure in Same Period}} \tag{3-2}$$

Observed crash frequency and crash rates are often used as a tool to identify and prioritize sites in need of modifications and for evaluation of the effectiveness of treatments. Typically, those sites with the highest crash rate or perhaps with rates higher than a certain threshold are analyzed in detail to identify potential modifications to reduce crashes. In addition, crash frequency and crash rate are often used in conjunction with other analysis techniques, such as reviewing crash records by one or more of the following: year, collision type, crash severity, or environmental conditions to identify other apparent trends or patterns over time. Appendix 3A.3 provides examples of crash estimation using historic crash data.

Advantages in the use of observed crash frequency and crash rates include:

- *Understandability*—observed crash frequency and rates are intuitive to most members of the public;
- *Acceptance*—it is intuitive for members of the public to assume that observed trends will continue to occur;
- *Limited alternatives*—in the absence of any other available methodology, observed crash frequency is the only available method of estimation.

Crash estimation methods based solely on historical crash data are subject to a number of limitations. These include the limitations associated with the collection of data described in Sections 3.3.2 and 3.3.3.

Also, the use of crash rate incorrectly assumes a linear relationship between crash frequency and the measure of exposure. Research has confirmed that while there are often strong relationships between crashes and many measures of exposure, these relationships are usually non-linear (1,5,11).

A (theoretical) example which illustrates how crash rates can be misleading is to consider a rural two-lane two-way road with low traffic volumes with a very low observed crash frequency. Additional development may substantially increase the traffic volumes and consequently the number of crashes. However, it is likely that the crash rate may decline because the increased traffic volumes. For example, the traffic volumes may increase threefold, but the observed crash frequency may only double, leading to a one third reduction in crash rate. If this change isn't accounted for, one might assume that the new development made the roadway safer.

Not accounting for the limitations described above may result in ineffective use of limited safety funding. Further, estimating crash conditions based solely on observed crash data limits crash estimation to the expected average crash frequency of an existing site where conditions (and traffic volumes) are likely to remain constant for a long-term period, which is rarely the case. This precludes the ability to estimate the expected average crash frequency for:

- The existing system under different geometric design or traffic volumes in the past (considering if a treatment had not been implemented) or in the future (in considering alternative treatment designs);
- Design alternatives of roadways that have not been constructed.

As the number of years of available crash data increases, the risk of issues associated with regression-to-the-mean bias decrease. Therefore, in situations where crashes are extremely rare (e.g., at rail-grade crossings), observed crash frequency or crash rates may reliably estimate expected average crash frequency and therefore can be used as a comparative value for ranking (see Appendix 3A.4 for further discussion on estimating average crash frequency based on historic data of similar roadways).

Even when there have been limited changes at a site (e.g., traffic volume, land use, weather, driver demographics have remained constant) other limitations relating to changing contributing factors remain. For example, the use of motorcycles may have increased across the network during the study period. An increase in observed motorcycle crashes at the site may be associated with the overall change in levels of motorcycle use across the network rather than in increase in motorcycle crashes at the specific site.

Agencies may be subject to reporting requirements which require provision of crash rate information. The evolution of crash estimation methods introduces new concepts with greater reliability than crash rates, and therefore the HSM does not focus on the use of crash rates. The techniques and methodologies presented in this First Edition of the HSM are relatively new to the field of transportation and will take time to become "best" practice. Therefore, it is likely that agencies may continue to be subject to requirements to report crash rates in the near term.

3.4.2. Indirect Safety Measures

Indirect safety measures have also been applied to measure and monitor a site or a number of sites. Also known as surrogate safety measures, indirect safety measures provide a surrogate methodology when crash frequencies are not available because the roadway or facility is not yet in service or has only been in service for a short time, when crash frequencies are low 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 crashes to materialize before a problem is recognized and a remedy applied.

Past practices have mostly used two basic types of surrogate measures to use in place of observed crash frequency. These are:

- Surrogates based on events which are proximate to and usually precede the crash event. For example, at an intersection encroachment time, the time during which a turning vehicle infringes on the right-of-way of another vehicle may be used as a surrogate estimate.
- Surrogates that presume existence of a causal link to expected crash frequency. For example, proportion of occupants wearing seatbelts may be used as a surrogate for estimation of crash severities.

Conflict studies are another indirect measurement of safety. In these studies, direct observation of a site is conducted in order to examine "near-crashes" as an indirect measure of potential crash problems at a site. Because the HSM is focused on quantitative crash information, conflict studies are not included in the HSM.

The strength of indirect safety measures is that the data for analysis is more readily available. There is no need to wait for crashes to occur. The limitations of indirect safety measures include the often unproven relationship between the surrogate events and crash estimation. Appendix 3D provides more detailed information about indirect safety measures.

3.4.3. Crash Estimation Using Statistical Methods

Statistical models using regression analysis have been developed which address some of the limitations of other methods identified above. These models address RTM bias and also provide the ability to reliably estimate expected average crash frequency for not only existing roadway conditions, but also changes to existing conditions or a new roadway design prior to its construction and use.

As with all statistical methods used to make estimation, the reliability of the model is partially a function of how well the model fits the original data and partially a function of how well the model has been calibrated to local data. In addition to statistical models based on crash data from a range of similar sites, the reliability of crash estimation is improved when historic crash data for a specific site can be incorporated into the results of the model estimation.

A number of statistical methods exist for combining estimates of crashes from a statistical model with the estimate using observed crash frequency at a site or facility. These include:

- Empirical Bayes method (EB Method)
- Hierarchical Bayes method
- Full Bayes method

Jurisdictions may have the data and expertise to develop their own models and to implement these statistical methods. In the HSM, the EB Method is used as part of the predictive method described in Part C. A distinct advantage of the EB Method is that, once a calibrated model is developed for a particular site type, the method can be readily applied. The Hierarchical Bayes and Full Bayes method are not used in the HSM, and are not discussed within this manual.

3.4.4. Development and Content of the HSM Methods

Section 3.3 through 3.4.3 discussed the limitations related to the use of observed crash data in crash analysis and some of the various methods for crash estimation that have evolved as the field of crash estimation has matured. The HSM has been developed due to recognition amongst transportation professionals of the need to develop standardized quantitative methods for crash estimation and crash evaluation that address the limitations described in Section 3.3.

The HSM provides quantitative methods to reliably estimate crash frequencies and severities for a range of situations, and to provide related decision-making tools to use within the road safety management process. Part A provides an overview of Human Factors (in Chapter 2) and an introduction to the fundamental concepts used in the HSM (Chapter 3). Part B focuses on methods to establish a comprehensive and continuous roadway safety management process. Chapter 4 provides numerous performance measures for identifying sites which may respond to improvements. Some of these performance measures use concepts presented in the overview of the Part C predictive method presented below. Chapters 5 through 8 present information about site crash diagnosis, selecting countermeasures, and prioritizing sites. Chapter 9 presents methods for evaluating the effectiveness of improvements. Fundamentals of the Chapter 9 concepts are presented in Section 3.7.

Part C, overviewed in Section 3.5, presents the predictive method for estimating the expected average crash frequency for various roadway conditions. The material in this part of the HSM will be valuable in preliminary and final design processes.

Finally, Part D contains a variety of roadway treatments with crash modification factors (CMFs). The fundamentals of CMFs are described in Section 3.6, with more details provided in the Part D—Introduction and Applications Guidance.

3.5. PREDICTIVE METHOD IN PART C OF THE HSM

3.5.1. Overview of the Part C Predictive Method

This section is intended to provide the user with a basic understanding of the predictive method found in Part C. A complete overview of the method is provided in the Part C Introduction and Application Guidance. The detail method for specific facility types is described in Chapters 10, 11, and 12 and the EB Method is explained fully in Part C, Appendix A.

The predictive method presented in Part C provides a structured methodology to estimate the expected average crash frequency (by total crashes, crash severity, or collision type) of a site, facility or roadway network for a given time period, geometric design and traffic control features, and traffic volumes (AADT). The predictive method also allows for crash estimation in situations where no observed crash data is available or no predictive model is available.

The expected average crash frequency, $N_{expected}$, is estimated using a predictive model estimate of crash frequency, $N_{predicted}$ (referred to as the predicted average crash frequency) and, where available, observed crash frequency, $N_{observed}$. The basic elements of the predictive method are:

- Predictive model estimate of the average crash frequency for a specific site type. This is done using a statistical model developed from data for a number of similar sites. The model is adjusted to account for specific site conditions and local conditions;
- The use of the EB Method to combine the estimation from the statistical model with observed crash frequency at the specific site. A weighting factor is applied to the two estimates to reflect the model's statistical reliability. When observed crash data is not available or applicable, the EB Method does not apply.

Basic Elements of the Predictive Models in Part C

The predictive models in Part C vary by facility and site type, but all have the same basic elements:

- *Safety Performance Functions (SPFs)*—Statistical "base" models are used to estimate the average crash frequency for a facility type with specified base conditions.
- *Crash Modification Factors (CMFs)*—CMFs are the ratio of the effectiveness of one condition in comparison to another condition. CMFs are multiplied with the crash frequency predicted by the SPF to account for the difference between site conditions and specified base conditions;
- *Calibration Factor (C)*—multiplied with the crash frequency predicted by the SPF to account for differences between the jurisdiction and time period for which the predictive models were developed and the jurisdiction and time period to which they are applied by HSM users.

While the functional form of the SPFs varies in the HSM, the predictive model to estimate the expected average crash frequency Npredicted, is generally calculated using Equation 3-3.

$$N_{\text{predicted}} = N_{SPF\,x} \times (CMF_{1x} \times CMF_{2x} \times \ldots CMF_{yx}) \times C_x \tag{3-3}$$

Where:

$N_{\text{predicted}}$ = predictive model estimate of crash frequency for a specific year on site type x (crashes/year);

$N_{SPF\,x}$ = predicted average crash frequency determined for base conditions with the Safety Performance Function representing site type x (crashes/year);

CMF_{yx} = Crash Modification Factors specific to site type x;

C_x = Calibration Factor to adjust for local conditions for site type x.

The HSM provides a detailed predictive method for the following three facility types:

- *Chapter 10*—Rural Two-Lane Two-Way Roads;
- *Chapter 11*—Rural Multilane Highways;
- *Chapter 12*—Urban and Suburban Arterials.

Advantages of the Predictive Method

Advantages of the predictive method are that:

- Regression-to-the-mean bias is addressed as the method concentrates on long-term expected average crash frequency rather than short-term observed crash frequency.
- Reliance on availability of limited crash data for any one site is reduced by incorporating predictive relationships based on data from many similar sites.
- The method accounts for the fundamentally nonlinear relationship between crash frequency and traffic volume.
- The SPFs in the HSM are based on the negative binomial distribution, which are better suited to modeling the high natural variability of crash data than traditional modeling techniques based on the normal distribution.

First-time users of the HSM who wish to apply the predictive method are advised to read Section 3.5 (this section), read the Part C—Introduction and Applications Guidance, and then select an appropriate facility type from Chapters 10, 11, or 12 for the roadway network, facility, or site under consideration.

3.5.2. Safety Performance Functions

Safety Performance Functions (SPFs) are regression equations that estimate the average crash frequency for a specific site type (with specified base conditions) as a function of annual average daily traffic (AADT) and, in the case of roadway segments, the segment length (L). Base conditions are specified for each SPF and may include conditions such as lane width, presence or absence of lighting, presence of turn lanes, etc. An example of an SPF (for roadway segments on rural two-lane highways) is shown in Equation 3-4.

$$N_{SPF\,rs} = (AADT) \times (L) \times (365) \times 10^{(-6)} \times e^{(-0.4865)} \tag{3-4}$$

Where:

$N_{SPF\,rs}$ = estimate of predicted average crash frequency for SPF base conditions for a rural two-lane two-way roadway segment (described in Section 10.6) (crashes/year);

$AADT$ = average annual daily traffic volume (vehicles per day) on roadway segment;

L = length of roadway segment (miles).

While the SPFs estimate the average crash frequency for all crashes, the predictive method provides procedures to separate the estimated crash frequency into components by crash severity levels and collision types (such as run-off-the-road or rear-end crashes). In most instances, this is accomplished with default distributions of crash severity level or collision type, or both. As these distributions will vary between jurisdictions, the estimations will benefit from updates based on local crash severity and collision type data. This process is explained in Part C, Appendix A. If sufficient experience exists within an agency, some agencies have chosen to use advanced statistical approaches that allow for prediction of changes by severity levels (6).

The SPFs in the HSM have been developed for three facility types (rural two-lane two-way roads, rural multilane highways, and urban and suburban arterials), and for specific site types of each facility type (e.g., signalized intersections, unsignalized intersections, divided roadway segments, and undivided roadway segments). The different facility types and site types for which SPFs are included in the HSM are summarized in Table 3-2.

Table 3-2. Facility Types and Site Types Included in Part C

HSM Chapter	Undivided Roadway Segments	Divided Roadway Segments	Intersections			
			Stop Control on Minor Leg(s)		Signalized	
			3-Leg	4-Leg	3-Leg	4-Leg
10—Rural Two-Lane Roads	✓	—	✓	✓	—	✓
11—Rural Multilane Highways	✓	✓	✓	✓	—	✓
12—Urban and Suburban Arterial Highways	✓	✓	✓	✓	✓	✓

In order to apply an SPF, the following information about the site under consideration is necessary:

- Basic geometric and geographic information of the site to determine the facility type and to determine whether a SPF is available for that facility and site type.
- Detailed geometric design and traffic control features conditions of the site to determine whether and how the site conditions vary from the SPF baseline conditions (the specific information required for each SPF is included in Part C.
- AADT information for estimation of past periods or forecast estimates of AADT for estimation of future periods.

SPFs are developed through statistical multiple regression techniques using observed crash data collected over a number of years at sites with similar characteristics and covering a wide range of AADTs. The regression parameters of the SPFs are determined by assuming that crash frequencies follow a negative binomial distribution. The negative binomial distribution is an extension of the Poisson distribution, and is better suited than the Poisson distribution to modeling of crash data. The Poisson distribution is appropriate when the mean and the variance of the data are equal. For crash data, the variance typically exceeds the mean. Data for which the variance exceeds the mean are said to be overdispersed, and the negative binomial distribution is very well suited to modeling overdispersed data. The degree of overdispersion in a negative binomial model is represented by a statistical parameter, known as the overdispersion parameter that is estimated along with the coefficients of the regression equation. The larger the value of the overdispersion parameter, the more the crash data vary as compared to a Poisson distribution with the same mean. The overdispersion parameter is used to determine the value of a weight factor for use in the EB Method described in Section 3.5.5.

The SPFs in the HSM must be calibrated to local conditions as described in Section 3.5.4 below and in detail in Part C, Appendix A. The derivation of SPFs through regression analysis is described in Appendix 3B.

3.5.3. Crash Modification Factors

Crash Modification Factors (CMFs) represent the relative change in crash frequency due to a change in one specific condition (when all other conditions and site characteristics remain constant). CMFs are the ratio of the crash frequency of a site under two different conditions. Therefore, a CMF may serve as an estimate of the effect of a particular geometric design or traffic control feature or the effectiveness of a particular treatment or condition.

CMFs are generally presented for the implementation of a particular treatment, also known as a countermeasure, intervention, action, or alternative design. Examples include illuminating an unlighted road segment, paving gravel shoulders, signalizing a stop-controlled intersection, or choosing a signal cycle time of 70 seconds instead of 80 seconds. CMFs have also been developed for conditions that are not associated with the roadway, but represent geographic or demographic conditions surrounding the site or with users of the site (e.g., the number of liquor outlets in proximity to the site).

Equation 3-5 shows the calculation of a CMF for the change in expected average crash frequency from site condition ‘a’ to site condition ‘b’ (3).

$$CMF = \frac{\text{Expected Average Crash Frequency with Site Condition } b}{\text{Expected Average Crash Frequency with Site Condition } a} \tag{3-5}$$

CMFs defined in this way for expected crashes can also be applied to comparison of predicted crashes between site condition ‘a’ and site condition ‘b’.

The values of CMFs in the HSM are determined for a specified set of base conditions. These base conditions serve the role of site condition ‘a’ in Equation 3-5. This allows comparison of treatment options against a specified reference condition. Under the base conditions (i.e., with no change in the conditions), the value of a CMF is 1.00. CMF values less than 1.00 indicate the alternative treatment reduces the estimated average crash frequency in comparison to the base condition. CMF values greater than 1.00 indicate the alternative treatment increases the estimated average crash frequency in comparison to the base condition. The relationship between a CMF and the expected percent change in crash frequency is shown in Equation 3-6.

$$\text{Percent in Reduction in Crash} = 100 \times (1.00 - CMF) \tag{3-6}$$

For example,

- If a $CMF = 0.90$, then the expected percent change is $100\% \times (1.00 - 0.90) = 10\%$, indicating a reduction in expected average crash frequency.
- If a $CMF = 1.20$, then the expected percent change is $100\% \times (1.00 - 1.20) = -20\%$, indicating an increase in expected average crash frequency.

The SPFs and CMFs used in the Part C predictive method for a given facility type use the same base conditions so that they are compatible.

Crash Modification Factor Examples

Example 1

Using an SPF for rural two-lane roadway segments, the expected average crash frequency for existing conditions is 10 injury crashes/year (assume observed data is not available). The base condition is the absence of automated speed enforcement. If automated speed enforcement were installed, the CMF for injury crashes is 0.83. Therefore, if there is no change to the site conditions other than implementation of automated speed enforcement, the estimate of expected average injury crash frequency is 0.83 × 10 = 8.3 crashes/year.

Example 2

The expected average crashes for an existing signalized intersection is estimated through application of the EB Method (using an SPF and observed crash frequency) to be 20 crashes/year. It is planned to replace the signalized intersection with a modern roundabout. The CMF for conversion of the base condition of an existing signalized intersection to a modern roundabout is 0.52. As no SPF is available for roundabouts, the project CMF is applied to the estimate for existing conditions. Therefore, after installation of a roundabout, the expected average crash frequency is estimated to be 0.52 × 20 = 10.4 crashes/year.

Application of CMFs

Applications for CMFs include:

- Multiplying a CMF with a crash frequency for base conditions determined with an SPF to estimate predicted average crash frequency for an individual site, which may consist of existing conditions, alternative conditions, or new site conditions. The CMFs are used to account for the difference between the base conditions and actual site conditions;
- Multiplying a CMF with the expected average crash frequency of an existing site that is being considered for treatment, when a site-specific SPF applicable to the treated site is not available. This estimates expected average crash frequency of the treated site. For example, a CMF for a change in site type or conditions such as the change from an unsignalized intersection to a roundabout can be used if no SPF is available for the proposed site type or conditions;
- Multiplying a CMF with the observed crash frequency of an existing site that is being considered for treatment to estimate the change in expected average crash frequency due to application of a treatment, when a site-specific SPF applicable to the treated site is not available.

Application of a CMF will provide an estimate of the change in crashes due to a treatment. There will be variance in results at any particular location.

Applying Multiple CMFs

The predictive method assumes that CMFs can be multiplied together to estimate the combined effects of the respective elements or treatments. This approach assumes that the individual elements or treatments considered in the analysis are independent of one another. Limited research exists regarding the independence of individual treatments from one another.

CMFs are multiplicative even when a treatment can be implemented to various degrees such that a treatment is applied several times over. For example, a 4 percent grade can be decreased to 3 percent, 2 percent, and so on, or a 6-ft shoulder can be widened by 1-ft, 2- ft, and so on. When consecutive increments have the same degree of effect, Equation 3-7 can be applied to determine the treatment's cumulative effect.

$$CMF \text{ (for } n \text{ increments)} = [CMF \text{ (for 1 increment)}]^{(n)} \qquad (3\text{-}7)$$

This relationship is also valid for non-integer values of n.

Applying Multiplicative Crash Modification Factors

Example 1

Treatment '*x*' consists of providing a left-turn lane on both major-road approaches to an urban four-leg signalized intersection, and treatment '*y*' is permitting right-turn-on-red maneuvers. These treatments are to be implemented, and it is assumed that their effects are independent of each other. An urban four-leg signalized intersection is expected to have 7.9 crashes/year. For treatment t_x, CMF_x = 0.81; for treatment t_y, CMF_y = 1.07.

What crash frequency is to be expected if treatment *x* and *y* are both implemented?

Answer to Example 1

Using Equation 3-7, expected crashes = 7.9 × 0.81 × 1.07 = 6.8 crashes/year.

Example 2

The CMF for single-vehicle run-off-the-road crashes for a 1 percent increase in grade is 1.04 regardless of whether the increase is from 1 percent to 2 percent or from 5 percent to 6 percent. What is the effect of increasing the grade from 2 percent to 4 percent?

Answer to Example 2

Using Equation 3-8, expected single-vehicle run-off-the-road crashes will increase by a factor of $1.04^{(4-2)} = 1.04^2 = 1.08$ = 8 percent increase.

Multiplication of CMFs in Part C

In the Part C predictive method, an SPF estimate is multiplied by a series of CMFs to adjust the estimate of crash frequency from the base condition to the specific conditions present at a site. The CMFs are multiplicative because the effects of the features they represent are presumed to be independent. However, little research exists regarding the independence of these effects, but this is a reasonable assumption based on current knowledge. The use of observed crash frequency data in the EB Method can help to compensate for bias caused by lack of independence of the CMFs. As new research is completed, future HSM editions may be able to address the independence (or lack of independence) of these effects more fully.

Multiplication of CMFs in Part D

CMFs are also used in estimating the anticipated effects of proposed future treatments or countermeasures (e.g., in some of the methods discussed in Section C.8). The limited understanding of interrelationships between the various treatments presented in Part D requires consideration, especially when more than three CMFs are proposed. If CMFs are multiplied together, it is possible to overestimate the combined effect of multiple treatments when it is expected that more than one of the treatments may affect the same type of crash. The implementation of wider lanes and wider shoulders along a corridor is an example of a combined treatment where the independence of the individual treatments is unclear, because both treatments are expected to reduce the same crash types. When CMFs are multiplied, the practitioner accepts the assumption that the effects represented by the CMFs are independent of one another. Users should exercise engineering judgment to assess the interrelationship or independence, or both, of individual elements or treatments being considered for implementation.

Compatibility of Multiple CMFs

Engineering judgment is also necessary in the use of combined CMFs where multiple treatments change the overall nature or character of the site; in this case, certain CMFs used in the analysis of the existing site conditions and the proposed treatment may not be compatible. An example of this concern is the installation of a roundabout at an urban two-way stop-controlled or signalized intersection. The procedure for estimating the crash frequency after installation of a roundabout (see Chapter 12) is to estimate the average crash frequency for the existing site conditions (as an SPF for roundabouts in currently unavailable), and then apply a CMF for a conventional intersection to roundabout conversion. Installing a roundabout changes the nature of the site so that other CMFs applicable to existing urban two-way stop-controlled or signalized intersections may no longer be relevant.

CMFs and Standard Error

The standard error of an estimated value serves as a measure of the reliability of that estimate. The smaller the standard error, the more reliable (less error) the estimate becomes. All CMF values are estimates of the change in expected average crash frequency due to a change in one specific condition. Some CMFs in the HSM include a standard error, indicating the variability of the CMF estimation in relation to sample data values.

Standard error can also be used to calculate a confidence interval for the estimated change in expected average crash frequency. Confidence intervals can be calculated using Equation 3-8 and values from Table 3-3.

$$CI(y\%) = CMF_x \pm SE_x \times MSE \tag{3-8}$$

Where:

$CI(y\%)$ = the confidence interval for which it is y percent probable that the true value of the CMF is within the interval;

CMF_x = Crash Modification Factor for condition x;

SE_x = Standard Error of the CMF_x;

MSE = Multiple of Standard Error (see Table 3-3 for values).

Table 3-3. 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 use in Equation 3-8
Low	65–70%	1
Medium	95%	2
High	99.9%	3

Appendix 3C provides information of how a CMF and its standard error affect the probability that the CMF will achieve the estimated results.

CMF Confidence Intervals Using Standard Error

Situation

Roundabouts have been identified as a potential treatment to reduce the estimated average crash frequency for all crashes at a two-way stop-controlled intersection. Research has shown that the CMF for this treatment is 0.22 with a standard error of 0.07.

Confidence Intervals

The CMF estimates that installing a roundabout will reduce expected average crash frequency by 100 × (1 – 0.22) = 78 percent.

Using a Low Level of Confidence (65–70 percent probability) the estimated reduction at the site will be 78 percent ± 1 × 100 × 0.07 percent, or between 71 percent and 85 percent.

Using a High Level of Confidence (i.e., 99.9 percent probability) the estimated reduction at the site will be 78 percent ± 3 × 100 × 0.07 percent, or between 57 percent and 99 percent.

As can be seen in these confidence interval estimates, the higher the level of confidence desired, the greater the range of estimated values.

CMFs in the HSM

CMF values in the HSM are either presented in text (typically where there are a limited range of options for a particular treatment), in formula (typically where treatment options are continuous variables), or in tabular form (where the CMF values vary by facility type or are in discrete categories). Where CMFs are presented as a discrete value, they are shown rounded to two decimal places. Where a CMF is determined using an equation or graph, it must also be rounded to two decimal places. A standard error is provided for some CMFs.

All CMFs in the HSM were selected by an inclusion process or from the results of an expert panel review. Part D contains all CMFs in the HSM, and the Part D—Introduction and Applications Guidance chapter provides an overview of the CMF inclusion process and expert panel review process. All CMFs in Part D are presented with some combination of the following information:

- Base conditions, or when the CMF = 1.00;
- Setting and road type for which the CMF is applicable;
- AADT range in which the CMF is applicable;
- Crash type and severity addressed by the CMF;
- Quantitative value of the CMF;
- Standard error of the CMF;
- The source and studies on which the CMF value is based;
- The attributes of the original studies, if known.

This information presented for each CMF in Part D is important for proper application of the CMFs. CMFs in Part C are a subset of the Part D CMFs. The Part C CMFs have the same base conditions (i.e., CMF is 1.00 for base conditions) as their corresponding SPFs in Part C.

3.5.4. Calibration

Crash frequencies, even for nominally similar roadway segments or intersections, can vary widely from one jurisdiction to another. Calibration is the process of adjusting the SPFs to reflect the differing crash frequencies between different jurisdictions. Calibration can be undertaken for a single state, or where appropriate, for a specific geographic region within a state.

Geographic regions may differ markedly in factors such as climate, animal population, driver populations, crash reporting threshold, and crash reporting practices. These variations may result in some jurisdictions experiencing different reported crashes on a particular facility type than in other jurisdictions. In addition, some jurisdictions may have substantial variations in conditions between areas within the jurisdiction (e.g., snowy winter driving conditions in one part of the state and only wet winter driving conditions in another). Methods for calculating calibration factors for roadway segments C_r and intersections C_i are included in Part C, Appendix A to allow highway agencies to adjust the SPF to match local conditions.

The calibration factors will have values greater than 1.0 for roadways that, on average, experience more crashes than the roadways used in developing the SPFs. The calibration factors for roadways that, on average, experience fewer crashes than the roadways used in the development of the SPF, will have values less than 1.0. The calibration procedures are presented in Part C, Appendix A.

Calibration factors provide one method of incorporating local data to improve estimated crash frequencies for individual agencies or locations. Several other default values used in the methodology, such as collision type distributions, can also be replaced with locally derived values. The derivation of values for these parameters is also addressed in the calibration procedure shown in Part C, Appendix A.1.

3.5.5. Weighting Using the Empirical Bayes Method

Estimation of expected average crash frequency using only observed crash frequency or only estimation using a statistical model (such as the SPFs in Part C) may result in a reasonable estimate of crash frequency. However, as discussed in Section 3.4.3, the statistical reliability (the probability that the estimate is correct) is improved by combining observed crash frequency and the estimate of the average crash frequency from a predictive model. While a number of statistical methods exist that can compensate for the potential bias resulting from regression-to-the mean, the predictive method in Part C uses the Empirical Bayes method, herein referred to as the EB Method.

The EB Method uses a weight factor, which is a function of the SPF overdispersion parameter, to combine the two estimates into a weighted average.

The weighted adjustment is therefore dependent only on the variance of the SPF and is not dependent on the validity of the observed crash data.

The EB Method is only applicable when both predicted and observed crash frequencies are available for the specific roadway network conditions for which the estimate is being made. It can be used to estimate expected average crash frequency for both past and future periods. The EB Method is applicable at either the site-specific level (where crashes can be assigned to a particular location) or the project specific level (where observed data may be known for a particular facility, but cannot be assigned to the site specific level). Where only a predicted or only observed crash data are available, the EB Method is not applicable (however, the predictive method provides alternative estimation methods in these cases).

For an individual site, the EB Method combines the observed crash frequency with the statistical model estimate using Equation 3-9:

$$N_{expected} = w \times N_{predicted} + (1 - w) \times N_{observed} \tag{3-9}$$

Where:

$N_{expected}$ = expected average crashes frequency for the study period;

w = weighted adjustment to be placed on the SPF prediction;

$N_{predicted}$ = predicted average crash frequency predicted using an SPF for the study period under the given conditions;

$N_{observed}$ = observed crash frequency at the site over the study period.

The weighted adjustment factor, w, is a function of the SPF's overdispersion parameter, k, and is calculated using Equation 3-10. The overdispersion parameter is of each SPF is stated in Part C.

$$w = \frac{1}{1 + k \times \left(\sum_{\substack{\text{all study}\\ \text{years}}} N_{predicted} \right)} \tag{3-10}$$

Where:

k = overdispersion parameter from the associated SPF

As the value of the overdispersion parameter increases, the value of the weighted adjustment factor decreases. Thus, more emphasis is placed on the observed rather than the predicted crash frequency. When the data used to develop a model are greatly dispersed, the reliability of the resulting predicted crash frequency is likely to be lower. In this case, it is reasonable to place less weight on the predicted crash frequency and more weight on the observed crash frequency. On the other hand, when the data used to develop a model have little overdispersion, the reliability of the resulting SPF is likely to be higher. In this case, it is reasonable to place more weight on the predicted crash frequency and less weight on the observed crash frequency. A more detailed discussion of the EB Methods is presented in Part C, Appendix A.

3.5.6. Limitations of Part C Predictive Method

Limitations of the Part C predictive method are similar to all methodologies which include regression models: the estimations obtained are only as good as the quality of the model. Regression models do not necessarily always represent cause-and-effect relationships between crash frequency and the variables in the model. For this reason, the variables in the SPFs used in the HSM have been limited to AADT and roadway segment length, because the rationale for these variables having a cause-and-effect relationship to crash frequency is strong. SPFs are developed with observed crash data which, as previously described, has its own set of limitations. SPFs vary in their ability to predict crash frequency; the SPFs used in the HSM are considered to be among the best available. SPFs are, by their nature, only directly representative of the sites that are used to develop them. Nevertheless, models developed in one jurisdiction are often applied in other jurisdictions. The calibration process provided in the Part C predictive method provides a method that agencies can use to adapt the SPFs to their own jurisdiction and to the time period for which they will be applied. Agencies with sufficient expertise may develop SPFs with data for their own jurisdiction for application in the Part C predictive method. Development of SPFs with local data is not a necessity for using the HSM. Guidance on development of SPFs using an agency's own data is presented in the Part C—Introduction and Applications Guidance.

CMFs are used to adjust the crash frequencies predicted for base conditions to the actual site conditions. While multiple CMFs can be used in the predictive method, the interdependence of the effect of different treatment types on one another is not fully understood and engineering judgment is needed to assess when it is appropriate to use multiple CMFs (see Section 3.5.3).

3.6. APPLICATION OF THE HSM

The HSM provides methods for crash estimation for the purposes of making decisions relating to the design, planning, operation, and maintenance of roadway networks.

These methods focus on the use of statistical methods in order to address the inherent randomness in crashes. The use of the HSM requires an understanding of the following general principles:

- Observed crash frequency is an inherently random variable, and it is not possible to predict the value for a specific period. The HSM estimates refer to the expected average crash frequency that would be observed if a site could be maintained under consistent conditions for a long-term period, which is rarely possible.
- Calibration of SPFs to local state conditions is an important step in the predictive method. Local and recent calibration factors may provide improved calibration.
- Engineering judgment is required in the use of all HSM procedures and methods, particularly selection and application of SPFs and CMFs to a given site condition.
- Errors and limitations exist in all crash data that affect both the observed crash data for a specific site and the models developed.
- Development of SPFs and CMFs requires understanding of statistical regression modeling and crash analysis techniques. The HSM does not provide sufficient detail and methodologies for users to develop their own SPFs or CMFs.

3.7. EFFECTIVENESS EVALUATION

3.7.1. Overview of Effectiveness Evaluation

Effectiveness evaluation is the process of developing quantitative estimates of the effect a treatment, project, or a group of projects has on expected average crash frequency. The effectiveness estimate for a project or treatment is a valuable piece of information for future decision making and policy development. For instance, if a new type of treatment was installed at several pilot locations, the treatment's effectiveness evaluation can be used to determine if the treatment warrants application at additional locations.

Effectiveness evaluation may include:

- Evaluating a single project at a specific site to document the effectiveness of that specific project;
- Evaluating a group of similar projects to document the effectiveness of those projects;
- Evaluating a group of similar projects for the specific purpose of quantifying a CMF for a countermeasure;
- Assessing the overall effectiveness of specific types of projects or countermeasures in comparison to their costs.

Effectiveness evaluations may use several different types of performance measures, such as a percentage reduction in crash frequency, a shift in the proportions of crashes by collision type or severity level, a CMF for a treatment, or a comparison of the benefits achieved to the cost of a project or treatment.

As described in Section 3.3, various factors can limit the change in expected average crash frequency at a site or across a cross-section of sites that can be attributed to an implemented treatment. Regression-to-the-mean bias, as described in Section 3.3.3, can affect the perceived effectiveness (i.e., over- or underestimate effectiveness) of a particular treatment if the study does not adequately account for the variability of observed crash data. This variability also necessitates acquiring a statistically valid sample size to validate the calculated effectiveness of the studied treatment.

Effectiveness evaluation techniques are presented in Chapter 9. The chapter presents statistical methods which provide improved estimates of the crash reduction benefits as compared to simple before-after studies. Simple before-after studies compare the count of crashes at a site before a modification to the count of crashes at a site after the modification to estimate the benefits of an improvement. This method relies on the (usually incorrect) assumption that site conditions have remained constant (e.g., weather, surrounding land use, driver demographics) and does not account for regression-to-the-mean bias. Discussion of the strengths and weaknesses of these methods are presented in Chapter 9.

3.7.2. Effectiveness Evaluation Study Types

There are three basic study designs that can be used for effectiveness evaluations:

- Observational before/after studies
- Observational cross-sectional studies
- Experimental before/after studies

In observational studies, inferences are made from data observations for treatments that have been implemented in the normal course of the efforts to improve the road system. Treatments are not implemented specifically for evaluation. By contrast, experimental studies consider treatments that have been implemented specifically for evaluation of effectiveness. In experimental studies, sites that are potential candidates for improvement are randomly assigned to either a treatment group, at which the treatment of interest is implemented, or a comparison group, at which the treatment of interest is not implemented. Subsequent differences in crash frequency between the treatment and comparison groups can then be directly attributed to the treatment. Observational studies are much more common in road safety than experimental studies, because highway agencies operate with limited budgets and typically prioritize their projects based on benefits return. In this sense, random selection does not optimize investment selection and, therefore, agencies will typically not use this method unless they are making systemwide application of a countermeasure, such as rumble strips. For this reason, the focus of the HSM is on observational studies. The two types of observational studies are explained in further detail below.

Observational Before/After Studies

The scope of an observational before/after study is the evaluation of a treatment when the roadways or facilities are unchanged except for the implementation of the treatment. For example, the resurfacing of a roadway segment generally does not include changes to roadway geometry or other conditions. Similarly, the introduction of a seat belt law does not modify driver demography, travel patterns, vehicle performance, or the road network. To conduct a before/after study, data are generally gathered from a group of roadways or facilities comparable in site characteristics where a treatment was implemented. Data are collected for specific time periods before and after the treatment was implemented. Crash data can often be gathered for the "before" period after the treatment has been implemented. However, other data, such as traffic volumes, must be collected during both the "before" and the "after" periods if necessary.

The crash estimation is based on the "before" period. The estimated expected average crash frequency based on the "before" period crashes is then adjusted for changes in the various conditions of the "after" period to predict what expected average crash frequency would have been had the treatment not been installed.

Observational Cross-Sectional Studies

The scope of an observational cross-sectional study is the evaluation of a treatment where there are few roadways or facilities where a treatment was implemented, and there are many roadways or facilities that are similar except they do not have the treatment of interest. For example, it is unlikely that an agency has many rural two-lane road segments where horizontal curvature was rebuilt to increase the horizontal curve radius. However, it is likely that an agency has many rural two-lane road segments with horizontal curvature in a certain range, such as 1,500- to 2,000-ft range, and another group of segments with curvature in another range, such as 3,000 to 5,000 ft. These two groups of rural two-lane road segments could be used in a cross-sectional study. Data are collected for a specific time period for both groups. The crash estimation based on the crash frequencies for one group is compared with the crash estimation of the other group. It is, however, very difficult to adjust for differences in the various relevant conditions between the two groups.

3.8. CONCLUSIONS

Chapter 3 summarizes the key concepts, definitions, and methods presented in the HSM. The HSM focuses on crashes as an indicator of safety, and in particular is focused on methods to estimate the crash frequency and severity of a given site type for given conditions during a specific period of time.

Crashes are rare and randomly occurring events which result in injury or property damage. These events are influenced by a number of interdependent contributing factors that affect the events before, during, and after a crash.

Crash estimation methods are reliant on accurate and consistent collection of observed crash data. The limitations and potential for inaccuracy inherent in the collection of data apply to all crash estimation methods and need consideration.

As crashes are rare and random events, the observed crash frequency will fluctuate from year to year due to both natural random variation and changes in site conditions that affect the number of crashes. The assumption that the observed crash frequency over a short period represents a reliable estimate of the long-term average crash frequency fails to account for the non-linear relationships between crashes and exposure. The assumption also does not account for regression-to-the-mean (RTM) bias (also known as selection bias), resulting in ineffective expenditure of limited safety funds and over- (or under-) estimation of the effectiveness of a particular treatment type.

In order to account for the effects of RTM bias and the limitations of other crash estimations methods (discussed in Section 3.4), the HSM provides a predictive method for the estimation of the expected average crash frequency of a site, for given geometric and geographic conditions, in a specific period for a particular AADT.

Expected average crash frequency is the crash frequency expected to occur if the long-term average crash frequency of a site could be determined for a particular type of roadway segment or intersection with no change in the sites conditions. The predictive method (presented in Part C) uses statistical models, known as SPFs, and crash modification factors, CMFs, to estimate predicted average crash frequency. These models must be calibrated to local conditions to account for differing crash frequencies between different states and jurisdictions. When appropriate, the statistical estimate is combined with the observed crash frequency of a specific site using the EB Method, to improve the reliability of the estimation. The predictive method also allows for estimation using only SPFs, or only observed data in cases where either a model or observed data in not available.

Effectiveness evaluations are conducted using observational before/after and cross-sectional studies. The evaluation of a treatment's effectiveness involves comparing the expected average crash frequency of a roadway or site with the implemented treatment to the expected average crash frequency of the roadway element or site had the treatment not been installed.

3.9. REFERENCES

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APPENDIX 3A—AVERAGE CRASH FREQUENCY ESTIMATION METHODS WITH AND WITHOUT HISTORIC CRASH DATA

Appendix 3A 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 Figure 3A-1. This Figure summarizes an intersection's expected and reported crashes over a four-year period. The expected average crash frequency is shown in the shaded columns. The reported crash count for each year is shown in the un-shaded columns.

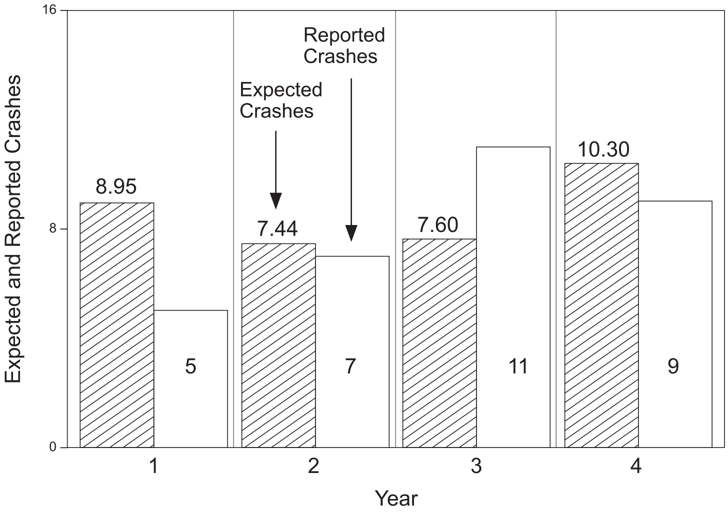


Figure 3A-1. Intersection Expected and Reported Crashes for Four Years

3A.1. STATISTICAL NOTATION AND POISSON PROCESS

The following notation is defined:

Reported crash count:

X = 'crash count';

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

X_i = the subscript 'i' denotes a specific period, for example, in Figure 3A-1, $X_1 = 5$ for Year 1 and $X_2 = 7$ for Year 2.

Expected average crash frequency:

$E\{\ \}$ = 'Expected value', for example, in Figure 3A-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 Figure 3A-1, the change from Year 1 to Year 2 is based on only one crash count to estimate μ_1 and one other crash count to estimate μ_2.

Using one crash 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 crash 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 crashes.

The Poisson probability mass or distribution function is shown in Equation 3A-1.

$$P(X_i = x) = \frac{\mu_i^{(x)} \times e^{(-\mu_i)}}{x!} \tag{3A-1}$$

Where:

μ_i = the expected number of crashes for a facility for period i;

$P(X_i = x)$ = the probability that the reported number of crashes 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 3A-2.

$$V\{X\} \equiv \sigma^2 = \mu \equiv E\{X\} \tag{3A-2}$$

Where:

V$\{X\}$ = variance of $X = \sigma^2$;

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

3A.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. Table 3A-1 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.

Table 3A-1. 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 Use 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 3A-3.

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

Where:

$\hat{\mu}_i$ = the estimate of μ_i;

x = crash 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 Figure 3A-1 can be estimated as follows:

$$\hat{\mu}_{\text{Year 1}} = 5 \text{ crashes} \quad \text{and} \quad \hat{\sigma}_{\text{Year 1}} = \pm 2.2 \text{ crashes}$$

The change between Year 1 to Year 2 is estimated by the difference between $\mu_{\text{Year 2}}$ and $\mu_{\text{Year 1}}$. Using the first part of Equation 3A-3:

$$\hat{\mu}_{\text{Year 2}} - \hat{\mu}_{\text{Year 1}} = X_2 - X_1 = 7 - 5 = 2 \text{ crashes}$$

Since X_1 and X_2 are statistically independent, the variance of the change is as shown in Equation 3A-4.

$$V\{X_2 - X_1\} = \sigma_1^2 + \sigma_2^2 \tag{3A-4}$$

Where:

X_i = crash count for specific period;

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

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

$$\hat{\sigma}_{\text{Year 2}} - \hat{\sigma}_{\text{Year 1}} = \sqrt{5+7} = \pm 3.5 \text{ crashes}$$

In summary, the change between Year 1 and Year 2 is 2 crashes ± 3.5 crashes. As indicated in Table 3A-1, the standard error means we are:

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

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 crashes 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 crash 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 (8). 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 ‘α’ ($\alpha = 0.05, 0.01, \ldots$), then it may be reasonable to conclude that the two expected values were different.[1]

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 mean that the crash 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 (9).

3A.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 crash counts. This practice is based on two assumptions:

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

These assumptions do not account for the change in conditions that occur on this roadway or facility from period-to-period or year-to-year. There are always period-to-period differences in traffic, weather, crash 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 average of the last *n* periods of crash 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 Figure 3A-1, the estimate for Year 4 is sought. Using only the crash count for Year 4:

- The estimate is $\hat{\mu}_{\text{Year 4}} = 9$ crashes, and
- The standard error of the estimate is $\hat{\sigma} = \sqrt{9} = \pm 3$ crashes.

Alternatively, using the average of all four crash counts:

- The estimate is $\hat{\mu}_{\text{year 4}} = \dfrac{(5+7+11+9)}{4} = 8.0$ crashes, and
- The standard error of the estimate is $\hat{\sigma} = \sqrt{\dfrac{32}{4^2}} = \pm 1.4$ crashes.

These results show that using the average of crash 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 crashes in Year 4, and the estimate of 9 crashes is closer than the estimate of 8.0 crashes. In this specific case, using more crash counts did not result in a better estimate of the expected crash frequency in the fourth year because the crash counts during the last year are not similar to the crash frequency in the three preceding years.

[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.

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 crash 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 3A-5 presents the relationship that estimates a specific unit for the last period of a sequence.

$$\hat{\mu}_Y = \sum_{y=1}^{Y} X_y \Big/ \sum_{y=1}^{Y} d_y \qquad \text{(3A-5)}$$

Where:

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

μ_y ≡ $\mu_y \times d_y$ 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 crashes for each period or Year y.

Equation 3A-6 presents the estimate of the variance of $\hat{\mu}_Y$.

$$\hat{V}(\hat{\mu}_Y) = \sum_{y=1}^{Y} X_y \Big/ \left(\sum_{y=1}^{Y} d_y\right)^2 \qquad \text{(3A-6)}$$

Where:

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

d_y = the μ_1/μ

X_y = the counts of crashes for each period or Year y.

For this estimate, it is necessary to add all crash counts reported during this year for all intersections that are similar to the intersection, under evaluation, throughout the network. Using the example given in Figure 3A-1 to illustrate this estimate, the proportion of the crashes counts per year in relation to the annual total crash counts for all similar intersections was calculated. The results are shown in Table 3A-2, e.g., 27 percent of annual crashes occur in the first year, 22 percent 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 Table 3A-2.

Table 3A-2. Illustration of Yearly Proportions and Relative Last Year Rates

	Year 1	Year 2	Year 3	Year 4 = *Y*
Proportion of Crashes	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 crashes counts are 5, 7, 11, and 9, see Figure 3A-1. Using Equations 3A-5 and 3A-6:

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

$\hat{\sigma} = \sqrt{32 / 3.22^2} = \pm 1.8$ crashes 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 crash counts. This method also results in a more defensible estimate because the use of d_y allows for change over the period from which crash counts are used.

Estimating Average Crash Frequency Using the Longer Crash Record History

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

This example is shown in Table 3A-3 where nine years (Row 1) of crash counts (Row 4) and AADT volumes (Row 3) for a one-mile segment 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 3A-7:

$$d_y = \left(AADT_y / AADT_n \right)^{(0.8)} \tag{3A-7}$$

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 crashes would be 6.00 ± 2.45 crashes when using Equations 3A-5 and 3A-6 and the crash count for 1997 only. The $\mu_{Y=1997}$ estimate of expected crashes would be 6.09 ± 1.44 crashes when using Equations 3A-5 and 3A-6 and the crash counts for 1995, 1996, and 1997.

Table 3A-3. Estimates of Expected Average Crash Frequency Using the Longer Crash 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	Crashes, 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 Crashes	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 crash count X_Y, no assumptions need to be made, but the estimate is inaccurate (the standard error is 2.45). When crash 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 crash counts are used have the same estimate μ as Year Y (last year).

3A.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 crashes are very rare, such as at rail-highway grade crossings where crashes occur on average once in 50 years and when the crash 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 crashes (μ's), and this can be described by a statistical function called the 'probability density function.' The $E\{\mu\}$ and $V\{\mu\}$ are the mean and the variance of the group (represented by the function), and $\hat{E}\{\mu\}$ 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 crashes, is $\hat{E}\{\mu\}$ 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 Equations 3A-8 and 3A-9.

$$\bar{x} = \sum_{1}^{n}\left(\frac{x_i}{n}\right) \tag{3A-8}$$

Where:

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

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

$$s^2 = \sum_{1}^{n}\frac{\left(x_i - \bar{x}\right)^{(2)}}{n-1} \tag{3A-9}$$

Where:

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

x_i (i=1,2,...n) = crash 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 3A-10.

$$\hat{E}\{\mu\} = \bar{x} \quad \text{and} \quad \hat{V}\{\mu\} = s^2 - \bar{x} \tag{3A-10}$$

Where:

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

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

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

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

Table 3A-4 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 crash history of this crossing is not sufficient (small sample size) for the estimation of its expected average crash frequency, the estimate uses national crash historical data for rail-highway crossings. Table 3A-4 sets out crash data for urban rail-highway at-grade crossings in the United States for crossings that have similar attributes to the crossing in Chicago (4).

Table 3A-4. National Crash Data for Railroad-Highway Grade Crossings (with 0–1,000 vehicles/day, 1–2 trains/day, single track, urban area) (2004)

Number of Crash Counts/ Year(2004) (x_i)	Number of Crossings (n_i)	$A_j = (x_i) \times (n_i)/N$	$S_j = \frac{\left[(x_i) - \bar{X}\right]^2 \times (n_i)}{(N-1)}$
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	$\bar{X} = \sum_{1}^{j} A_j =$ 0.0184 expected crashes/year per crossing in this group	$s^2 = \sum_{1}^{j} S_j = 0.0219$

Using Equation 3A-10 and the data shown for similar crossings in Table 3A-4, a reasonable estimate of the crash frequency of the crossing in Chicago for 2004 is 0.0184 crashes/year, i.e., the same as the sample mean ($\bar{X}$). The standard error is estimated as $\sqrt{0.0219 - 0.0184} = \pm 0.059$ crashes/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 3A.5 describes the use of SPFs to improve the estimation of the expected average crash frequency of a facility.

3A.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's or facility's count of past crashes (Section 3A.3) with the crash record of similar roadways or facilities (Section 3A.4).

The "best" estimate combined with the minimum variance or standard error is given by Equation 3A-11.

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

Where:

$$\omega = \frac{1}{\left(1 + \frac{V\{\mu_s\}}{E\{\mu_s\}}\right)} \quad (3A\text{-}11)$$

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 crash 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 3A-11, its variance is given by Equation 3A-12.

$$V(\hat{\mu}) = \omega \times V\{\mu_s\} = (1-\omega) \times E\{\mu_s\} \quad (3A\text{-}12)$$

Where:

$\hat{V}\{\mu\}$ = 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 crashes 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-mi section of a six-lane urban freeway in Colorado is estimated below. The estimate is based on 76 crashes reported during a three-year period, and crash data for similar sections of urban freeways.

There are 3 steps in the estimation:

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

$\hat{\mu}_i = x = 76$ crashes and $\hat{\sigma}_i = \sqrt{x} = \pm 8.7$ crashes

Where:

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

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

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

Step 2—Based on AADT volumes, the percentage of trucks, and crash 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-mi section for a three-year period, the following estimates (Equation 3A-10) result:

$$E\{\mu_s\} = E\{\mu\} = \bar{x} = 61.3 \text{ crashes}$$
$$V\{\mu_s\} = V\{\mu\} = s^2 - \bar{x} = 266.7 \text{ crashes}^2$$
$$\sigma_i = \sqrt{s^2 - \bar{x}} = \pm 16.3 \text{ crashes}$$

Where:

$\hat{E}\{\mu_s\}$ = the estimate of expected number of crashes 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 crash 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 crashes for the specific roadway or facility based on the group's model;

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

$\hat{\sigma}_i$ = standard error for the expected number of crashes 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 crashes on this 1.23-mi section of urban freeway is:

The 'weight' ω (Equation 3A-11) is:

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

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 crashes based on the group of similar roadways or facilities;

Thus:

$$\omega = \frac{1}{\left(1 + \frac{266.7}{61.3}\right)} = 0.187$$

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

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

with the variance as:

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

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 crash 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:

$$V(\hat{\mu}) = (1 - 0.187) \times 61.3 = 49.83 \text{ crashes}$$
$$\hat{\sigma}_i = \pm 7.1 \text{ crashes}$$

Table 3A-5 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.

Table 3A-5. Comparison of Three Estimates (an example using crash counts, groups of similar roadways or facilities, and combination of both)

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

Another example that illustrates the use of an 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 3A-13.

$$\hat{E}\{\mu\} = \alpha \times F_{\text{Major}}^{(\beta_1)} \times F_{\text{Minor}}^{(\beta_2)} \times e^{(\beta_3 F_{\text{Minor}})} \tag{3A-13}$$

Where:

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

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

α, β_1, β_2 and β_3 = the estimated constants shown in Table 3A-6;

e = base of natural logarithm function.

Table 3A-6. Estimated Constants for Stop-Controlled and Signalized Four-Leg Intersections' SPF Shown in Equation 3A-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 Figures 3A-2 and 3A-3.

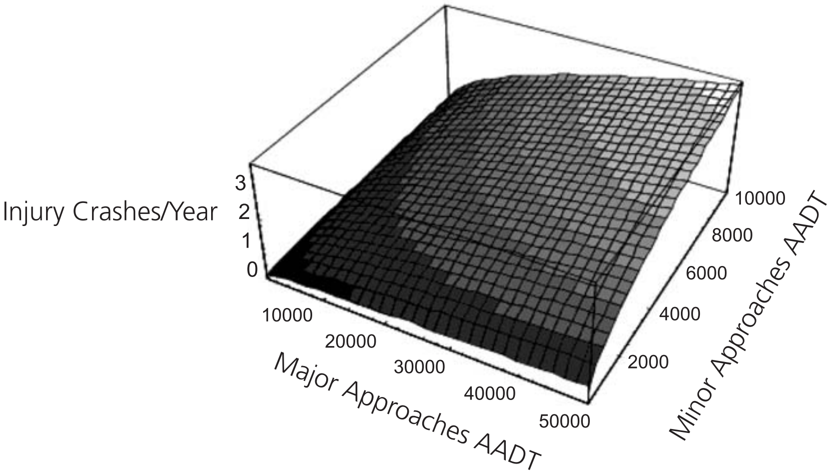


Figure 3A-2. Estimated Injury Crashes at Stop-Controlled Four-Leg Intersections

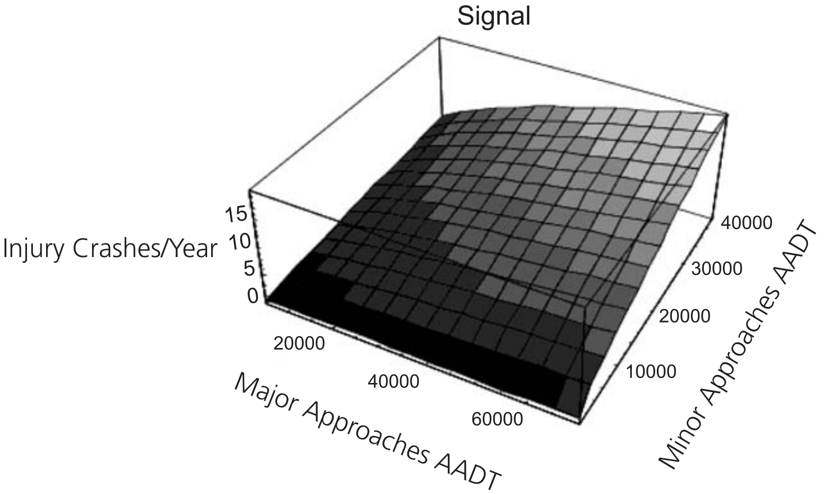


Figure 3A-3. Predicted Injury Crashes at Signalized Four-Leg Intersections

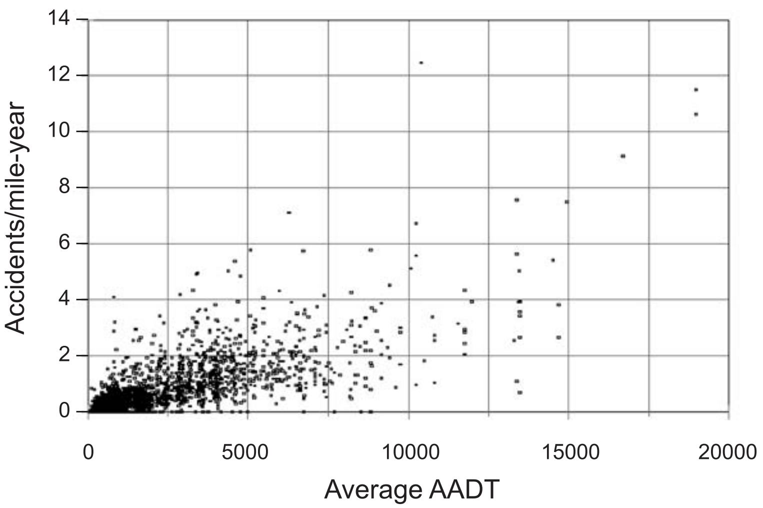
AADT is a major attribute when considering crash frequency, but there are many other attributes which, although not explicitly shown in the SPF, influence the estimate for a given facility or roadway. In the example above, many attributes of the two groups of intersections, besides AADT, contribute to the values for $E\{\mu\}$ computed Equation 3A-13 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.

APPENDIX 3B—DERIVATION OF SPFs

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

3B.1. SAFETY PERFORMANCE AS A REGRESSION FUNCTION

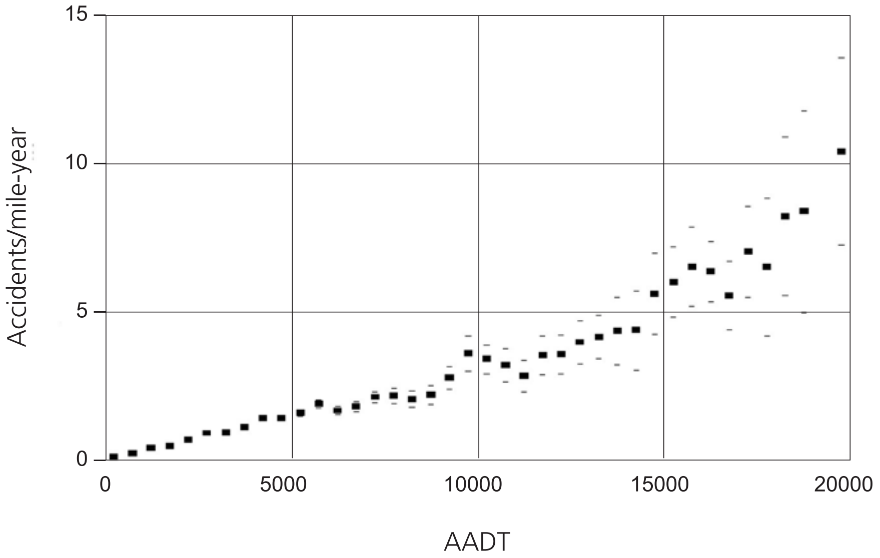
SPFs are developed through statistical regression modeling using historic crash data collected over a number of years at sites with similar roadway characteristics. The validity of this process is illustrated conceptually though the following example using Colorado data for rural two-lane road segments (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 thirteen-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 Figure 3B-1.



Note: The term *accidents* is used in this graphic to remain consistent with the original source. The HSM does not use the term *accidents,* and AASHTO prefers the use of the term *crashes*.

Figure 3B-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. Figure 3B-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.



Notes: (1) The blank squares are the ratio of the number of crashes for all road sections in a bin divided by the sum of the corresponding road segment lengths. The bars around the blank squares are ±2 standard errors of this ratio.

(2) The term *accidents* is used in this graphic to remain consistent with the original source. The HSM does not use the term *accidents*, and AASHTO prefers the use of the term *crashes*.

Figure 3B-2. Grouped Crashes per Mile-Year by AADT for Colorado Rural Two-Lane Roads in Rolling Terrain (1986–1998)

Figure 3B-2 illustrates that in this case, there is a relationship between crashes 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 3B-1.

Note that this is not the SPF for rural two-lane, two-way roads presented in Chapter 10. 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.

$$\hat{E}\{\mu\} = 1.95 \times \left(\frac{AADT}{1000}\right)^{(0.71)} \times e^{\left(0.53 \times \left(\frac{AADT}{1000}\right)\right)} \tag{3B-1}$$

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 3B-1 is depicted in Figure 3B-3 alongside a similar SPF derived for mountainous terrain.

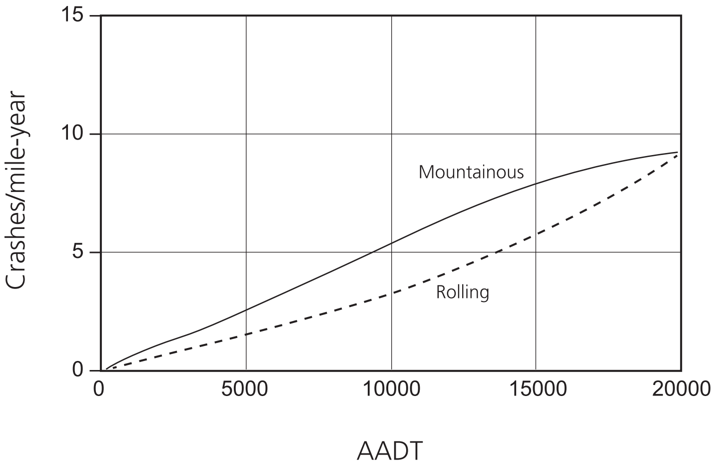


Figure 3B-3. Safety Performance Functions for Rural Two-Lane Roads by Terrain Type

3B.2. USING A SAFETY PERFORMANCE FUNCTION TO PREDICT AND ESTIMATE AVERAGE CRASH FREQUENCY

Using the SPFs shown in Figure 3B-3, an average rural two-lane road in Colorado with AADT = 10,000 vehicles/day is expected to have 3.3 crashes/mile-year if in rolling terrain and 5.4 crashes/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 crashes around the average number of crashes. This relationship is shown in Equation 3B-2.

$$V\{\mu\} = \frac{\left(E\{\mu\}\right)^2}{k} \tag{3B-2}$$

Where:

k = the overdispersion parameter

$E\{\mu\}$ = the average crash frequency per mile

$V\{\mu\}$ = the variance of the average crash frequency per mile

As an example to illustrate its use, Figure 3B-3 shows that an average rural two-lane road in a rolling terrain in Colorado with AADT = 10,000 vehicles/day is expected to have 3.3 crashes/mile-year. Thus, for a road segment with a 0.27-mile length, it is expected that there will be on average 0.27 × 3.3 = 0.89 crashes/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 = $(E\{\mu\})^2/\varphi = 0.89^2/(0.27 \times 4.81)$

= 0.55 (crashes/year)^2 or

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

APPENDIX 3C—CMF AND STANDARD ERROR

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

The more precise a CMF estimate, the smaller its standard error. The reliability level of CMFs 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:

$$\int_{-\infty}^{\infty} f(x)\,dx = 1 \tag{3C-1}$$

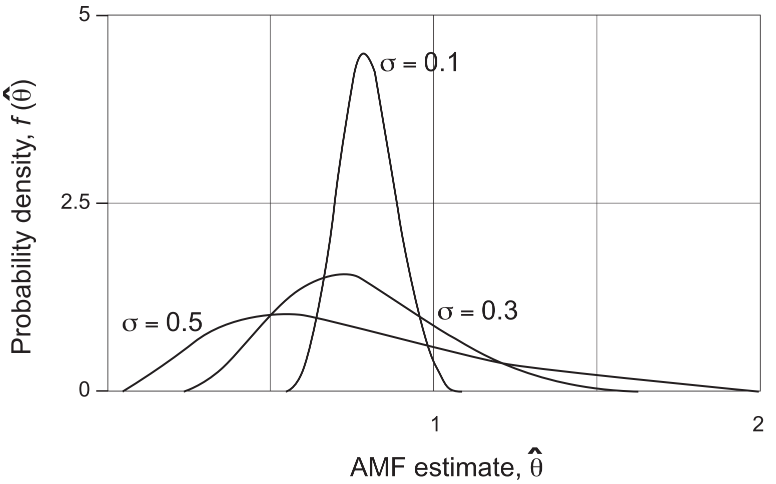
In other words, a probability density function can be seen as a "smoothed out" version of the histogram that one would obtain if one could empirically sample enough values of a continuous random variable.

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. Figure 3C-1 shows three alternative probability density functions of a CMF estimate. These functions have different shapes with different estimates of CMFs 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 $\sigma = 0.1$ 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 $\sigma = 0.3$ 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 $\sigma = 0.5$ represents the results of a study that is weak in data and/or method.



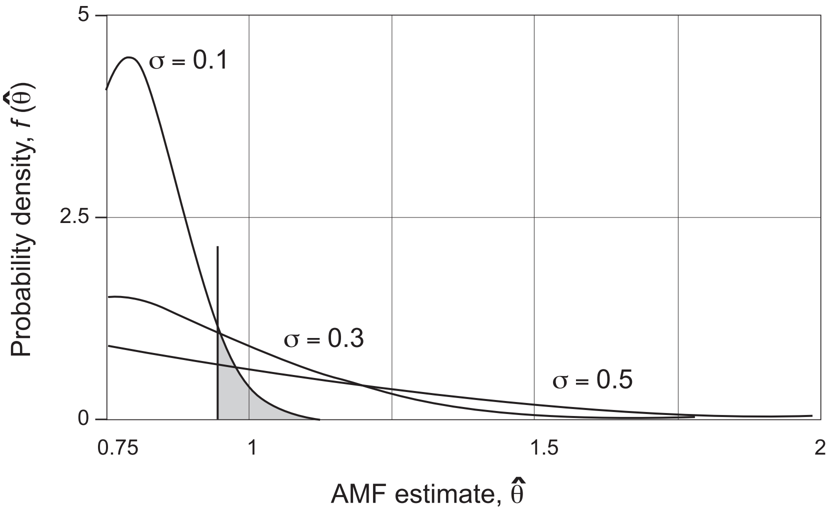
Note: The term AMF (*accident modification factor*) is used in this graphic to remain consistent with the original research. The HSM does not use the term AMF, and AASHTO prefers the use of the term CMF (*crash modification factor*).

Figure 3C-1. Three Alternative Probability Density Functions of CMF Estimates

As an example of the use of CMFs 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 crashes is at least 5 percent (i.e., if $\theta < 0.95$). Using the CMF estimates in Figure 3C-1 for this particular case, if the CMF estimate is 0.80 (true and mean value of θ, as shown in Figure 3C-1), the reduction in expected crashes is clearly greater than 5 percent ($\theta = 0.8 < 0.95$).

However, the key question is: "What is the chance that installing this treatment is the wrong decision?" Whether the CMF 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 a CMF estimate from the good study ($\sigma = 0.1$ in Figure 3C-1) is 6 percent, as shown by the shaded area in Figure 3C-2 (the area under the graph to the right of the 0.95 estimate point). If the CMF estimate came from the intermediate study ($\sigma = 0.3$ in Figure 3C-1), the probability of making an incorrect decision is about 27 percent. If the CMF estimate came from the weak study ($\sigma = 0.5$ in Figure 3C-1) the probability of making an incorrect decision is more than 31 percent.

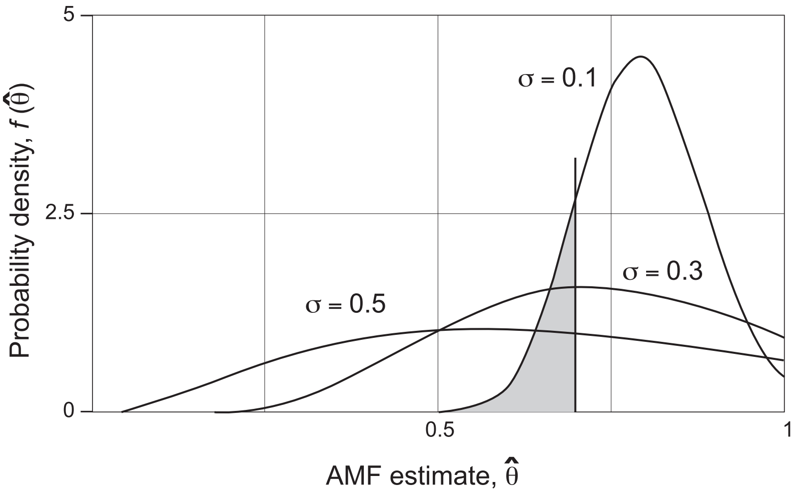


Note: The term AMF (*accident modification factor*) is used in this graphic to remain consistent with the original research. The HSM does not use the term AMF, and AASHTO prefers the use of the term CMF (*crash modification factor*).

Figure 3C-2. The Right Portion of Figure 3C-1; Implement if CMF < 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 crashes is at least 30 percent (i.e., if $\theta < 0.70$). Using the CMF estimates in Figure 3C-1 for this particular case, implementing this intervention would be an incorrect decision because $\theta = 0.80$ (Figure 3C-1) is larger than the $\theta = 0.70$ which is required to justify the installation cost.

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



Note: The term AMF (*accident modification factor*) is used in this graphic to remain consistent with the original research. The HSM does not use the term AMF, and AASHTO prefers the use of the term CMF (*crash modification factor*).

Figure 3C-3. The Left Portion of Figure 3C-1; Implement if CMF < 0.70

APPENDIX 3D—INDIRECT SAFETY MEASUREMENT

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

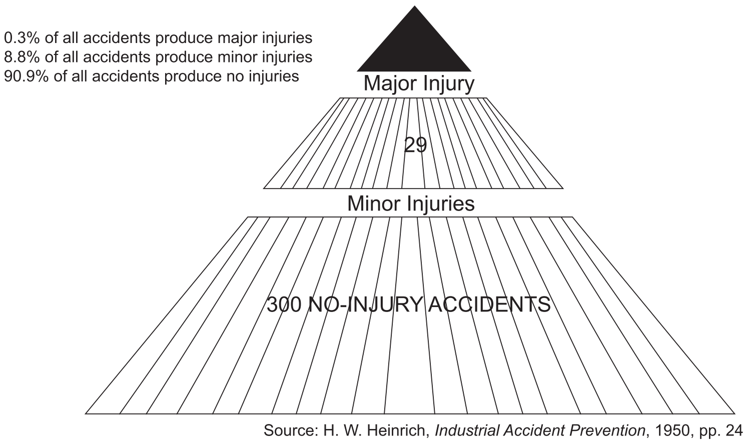
Indirect safety measurements, also known as safety surrogate measures, were introduced in Section 3.4 and are described in further detail here. They provide the opportunity to assess safety when crash counts are not available because the roadway or facility is not yet in service or has only been in service 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 crashes to materialize before a problem is recognized and the remedy applied. In addition, knowledge of the pattern of events that precedes crashes 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 crash event.
- Surrogates that presume existence of a causal link to expected average crash 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 Figure 3D-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 1931 (12). The original Heinrich Triangle is founded on the precedence relationship that 'No Injury Crashes' precedes 'Minor Injuries'.



Note: The term *accident* is used in this graphic to remain consistent with the original source. The HSM does not use the term *accident,* and AASHTO prefers the use of the term *crash.*

Figure 3D-1. The Heinrich Triangle

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 ≤ 1 s; events that were never less than, and are usually larger than the number of events in which TTC ≤ 0.5 s 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 3D-1.

$$\begin{bmatrix}\text{Number of crashes expected to}\\\text{occur on an entity in a certain}\\\text{period of time}\end{bmatrix} = \begin{bmatrix}\text{Number of surrogate events}\\\text{occurring on the entity in}\\\text{that period of time}\end{bmatrix} \times \begin{bmatrix}\text{Crashes per}\\\text{surrogate event}\\\text{for that entity}\end{bmatrix} \qquad \text{(3D-1)}$$

Equation 3D-1 is always developed separately for each crash type. Equation 3D-1 can be rewritten as shown in Equation 3D-2.

$$\hat{\mu} = \sum_i \left(\hat{C}_i \times \hat{p}_i\right) \qquad \text{(3D-2)}$$

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 crash/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 crashes on a set of roadways or facilities.

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

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

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 crash/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 crashes 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 $V\{\hat{p}_i\}$.

Events at intersections that have been used as safety surrogates in the past (6) include the following:

- *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 crash.
- *Proportion of Stopping Distance (PSD)*—Ratio of distance available to maneuver to the distance remaining to the projected location of crash.
- *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 crash.
- *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 crash 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 these events in predicting expected crashes 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 (Figure 3D-1) was developed, it is now known that for many circumstances, such as pedestrian crashes to seniors, almost every crash leads to injury. For these circumstances, the ‘No Injury Crashes’ layer is much narrower than the one shown in Figure 3D-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 crashes due to hits of the barrier, but reduces fatalities by largely eliminating crossmedian crashes. In the case of median barriers, the logic of Heinrich Triangle (Figure 3D-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 crash occurs when TTC or PET are 0. The study is using Extreme Value Theory to estimate the missing values, thus the number of crash events implied by the observed data.

APPENDIX 3E—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 (13).

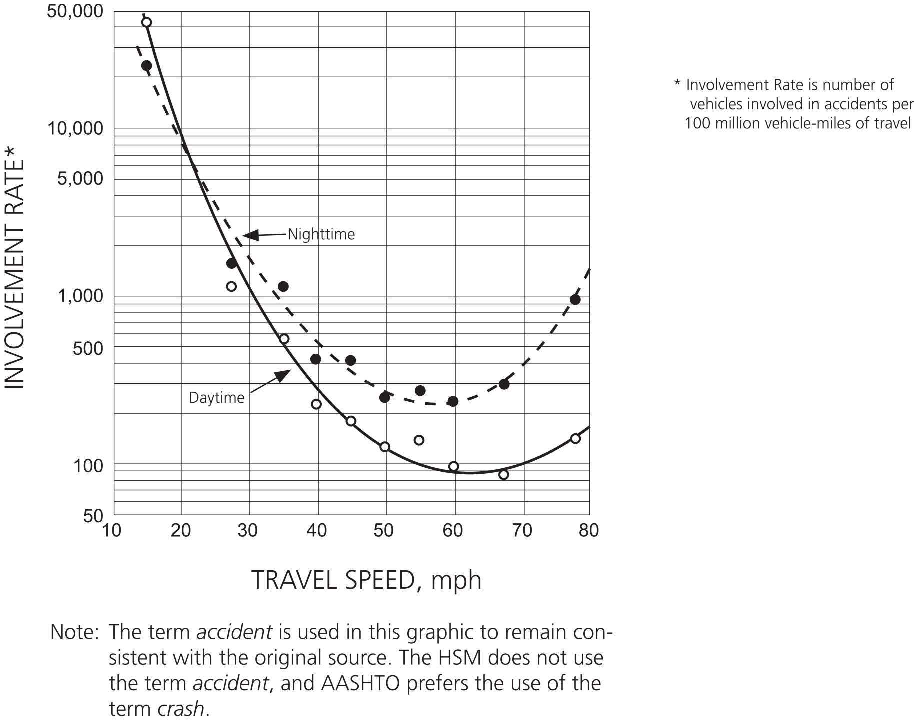
The relationship between speed and safety can be examined during the ‘pre-event’ and the ‘event’ phases of a crash. The ‘pre-event’ phase considers the probability that an crash will occur, specifically how this probability depends on speed. The ‘event’ phase considers the severity of an crash, specifically 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 crash (Section 3E.1), the event phase and the relationship between the severity of an crash and change in speed at impact (Section 3E.2), and the relationship between average operating speed and crash frequency (Section 3E.3). In the following discussion, terms such as running speed and travel speed are used interchangeably.

3E.1. PRE-EVENT OR PRE-CRASH PHASE—CRASH 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 crash increases with higher running speeds. However, while opinions on the probability of an crash and speed are strongly held, empirical findings are less clear (21).

For example, Figure 3E-1 shows that vehicles traveling at speeds approaching 50 mph, are less involved in crashes than vehicles traveling at lower speeds. This is the opposite of the assumed relationship between speed and crash probability in terms of crash involvement rate.

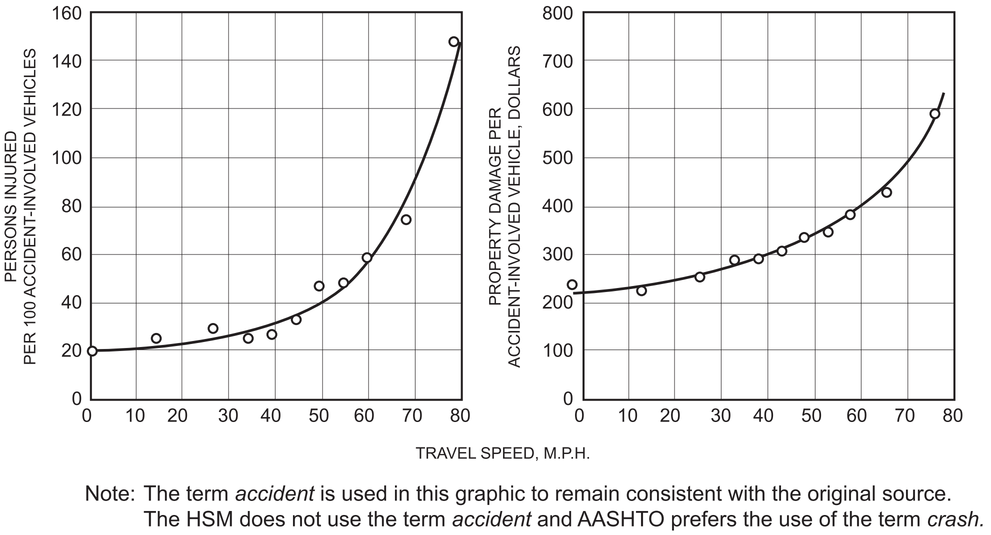


(Reproduced from Solomon's Figure 2) (22)

Figure 3E-1. Crash Involvement Rate by Travel Speed (22)

The data used to create Figure 3E-1 included turning vehicles (21). Therefore, crashes 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 Figure 3E-1 is also explained by the statistical representation of the data, that is, the kind of data assembled leads to a U-shaped curve (7).

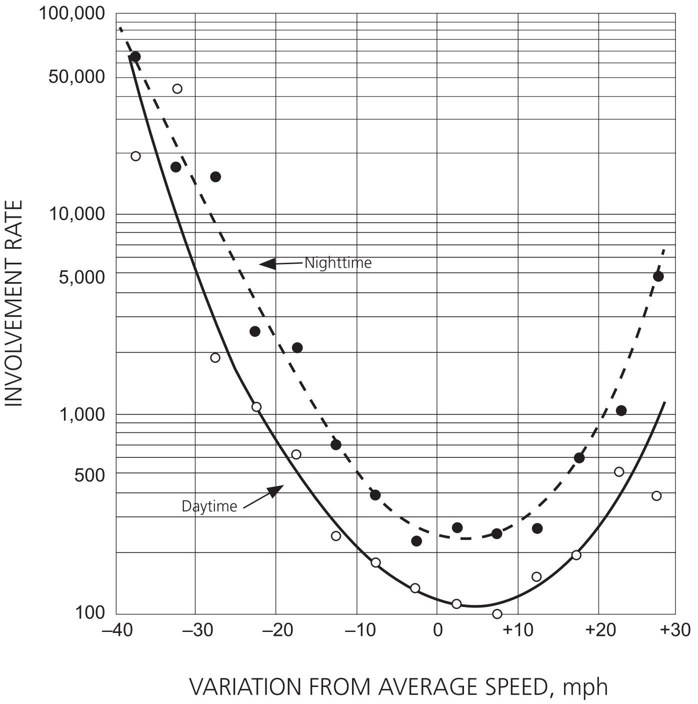
Figure 3E-1 also shows that for speeds greater than 60 mph, the probability of involvement increases with speed. At travel speeds greater than 60 mph, there is also likely to be a mixture of crash frequency and severity. Crashes of greater severity are more likely to be reported and recorded. Figure 3E-2 shows that the number of crashes by severity increases with travel speed (22). It is not known what contributes to this trend—the increase in reported crashes with increasing running speed and the increase in crash occurrence at higher speeds, the more severe outcomes of crashes that occur at higher speeds, or a mixture of both causes. Section 3.3 provides discussion of the frequency-severity indeterminacy. Speed and crash severity are discussed in more detail in Section 3E.2.



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

Figure 3E-2. Persons Injured and Property Damage per Crash Involvement by Travel Speed (22)

The data can be also presented by showing the deviation from mean operating speed on the horizontal axis (Figure 3E-3) instead of running speed (Figure 3E-1). The curve shown in Figure 3E-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 a crash" (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).



(From Solomon's Figure 7) (22)

Figure 3E-3. Crash Involvement Rate by Variation from Average Speed (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 crash involvement.

Although observed data do not clearly support the theory that the probability of involvement in an crash increases with increasing speed, it is still reasonable to believe that higher speeds and longer stopping distances increase the probability of crash involvement and severity (Section 3E.2).

3E.2. EVENT PHASE—CRASH SEVERITY AND SPEED CHANGE AT IMPACT

The relationship between the change in speed at impact and crash severity is clearer than the relationship between running speed and the probability of crash 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 crash severity it is more appropriate to use the vector "velocity" instead of the scalar "speed".

The relationship between crash severity and change of velocity at impact is strongly supported by observed data. For example, Figure 3E-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 crash 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 (9)). The horizontal axis of Figure 3E-4 is "the change in velocity of a vehicle's occupant compartment during the collision phase of a motor vehicle crash" (2).

Figure 3E-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 19–21 mph, about 40 percent 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 percent of restrained female front-seat occupants sustain such injury (16).

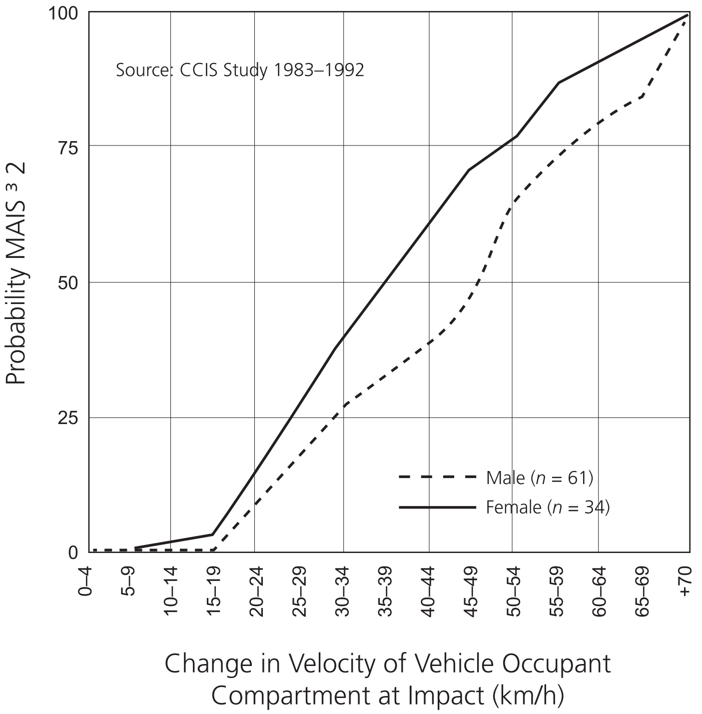


Figure 3E-4. Probability of Injury to Restrained Front-Seat Occupants by Change in Velocity of a Vehicle's Occupant Compartment at Impact (Adapted from Mackay) (16)

Figure 3E-5 illustrates another example of the relationship between the change in velocity at impact and crash severity. Figure 3E-5 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 crashes (14). 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 crash severity increases with increasing change in velocity at impact.

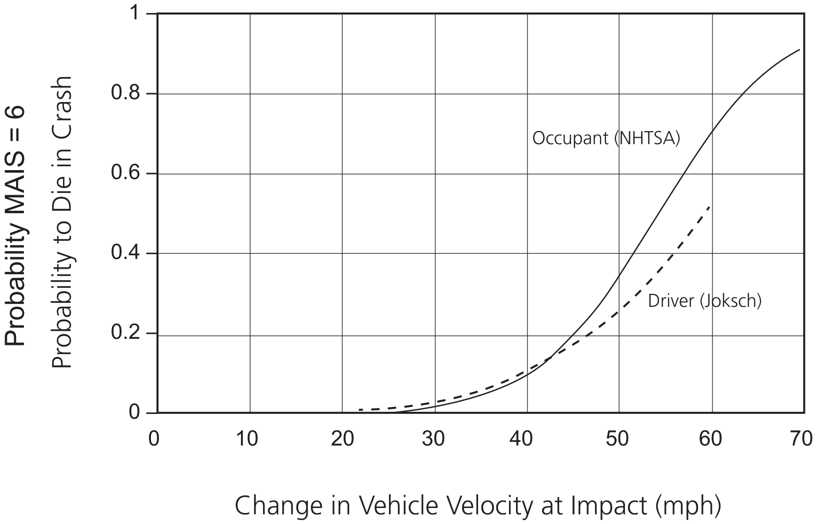


Figure 3E-5. Probability of Fatal Injury (MAIS = 6) to Drivers or Occupants by Change in Vehicle Velocity at Impact (14,20)

3E.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 crash probability is well established. This section discusses the relationship between crash frequency and changes in the average operating speed of a road.

For fatal crashes, the change in safety is the ratio of the change in average operating speed to the power of 4 (Equation 3E-1). This result is based on several studies of roadways where the average operating speed changed from "before" to "after" time periods (18,19).

$$\frac{N_1}{N_0} = \left(\frac{\bar{V}_1}{\bar{V}_0}\right)^{\alpha} \qquad \text{(3E-1)}$$

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 crashes;

α = 3 for fatal-and-serious-injury crashes;

α = 2 for all injury crashes.

Additional estimated values for the exponent α are shown in Table 3E-1.

Table 3E-1. Estimates of α (exponent in Equation 3E-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 crashes	3.6	2.4–4.8
Serious injury crashes	2.0	0.7–3.3
Slight injury crashes	1.1	0.0–2.4
All injury crashes (including fatal)	1.5	0.8–2.2
PDO crashes	1.0	0.0–2.0

Figure 3E-6 illustrates fatal crash 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 crashes also increased, and vice versa. As can be seen in Figure 3E-6, there is considerable noise (variation) in the data. This noise (data variation) reflects three issues: the randomness of crash counts, the variety of circumstances under which the data were obtained, and the variety of causes of changes in average operating speed.

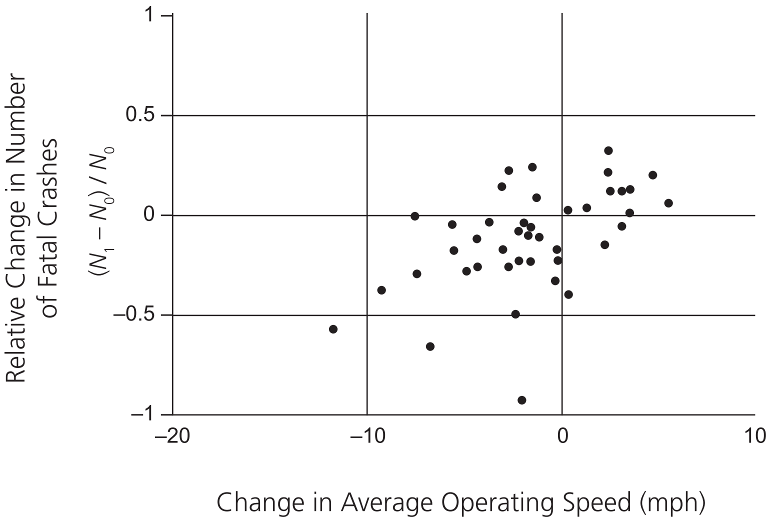


Figure 3E-6. Change in Average Operating Speed vs. Relative Change in Fatal Crashes (3)

Table 3E-2 summarizes Crash Modification Factors (CMFs) for injury and fatal crashes due to changes in average operating speed of a roadway (10). 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 crashes are expected to increase by a factor of 1.10 and fatal crashes 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 answered well at this time. If the change in crash frequency reflects mainly the associated change in severity, then the CMFs in Table 3E-2 apply.

Table 3E-2. Crash Modification Factors for Changes in Average Operating Speed (10)

Injury Crashes			$\bar{V}_0$ **[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

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

Fatal Crashes			$\bar{V}_0$ **[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 CMFs are international, the results apply to North American conditions.

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