MOUNTAIN-PLAINS CONSORTIUM

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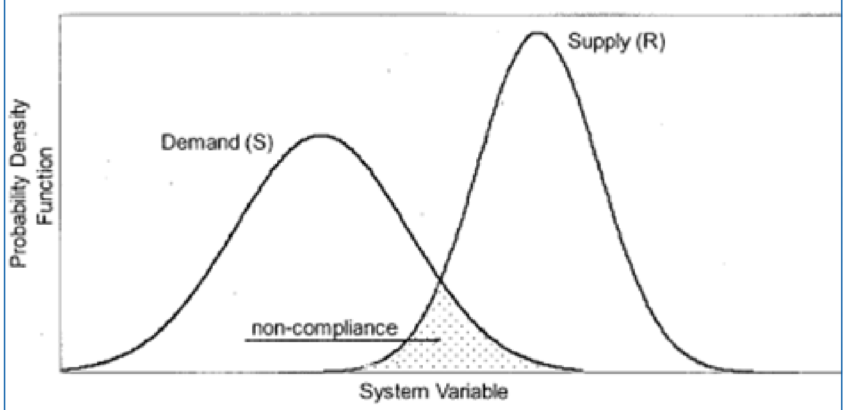
Risk-and-Reliability-Based Approaches to Analyzing Road Geometric Design Criteria



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RISK-AND-RELIABILITY-BASED APPROACHES TO ANALYZING ROAD GEOMETRIC DESIGN CRITERIA

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ABSTRACT

Federal and state transportation agencies set goals related to surface transportation system performance. The variability in factors influencing design criteria (e.g., driver performance, road conditions, and vehicle performance) is often large and is addressed implicitly by using “conservative” values. However, a risk-and-reliability-based analysis in roadway geometric design is proposed in this research to address these gaps. Probabilistic geometric design analysis is well suited to explicitly address the level of variability and randomness associated with design inputs when compared with a more deterministic design approach.

This research critically assesses alternative approaches for incorporating risk and reliability analysis when establishing road geometric design criteria and design decisions. An in-depth investigation of the applicability of reliability analysis was done and a reliability analysis was used to estimate the probability distribution of operational performance that might result from a basic number of lanes decisions made to achieve a design level of service on a freeway. Geometric effects of freeway ramp spacing and auxiliary lane presence on crash frequency and crash severity were also analyzed. Negative binomial and multinomial logit regression models are used to estimate the effects of ramp spacing and auxiliary lane presence on expected crash frequencies and crash severities, respectively.

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1. INTRODUCTION

Federal and state transportation agencies set goals related to surface transportation system performance. The American Association of State Highway and Transportation Officials' (AASHTO's) Strategic Plan, for example, includes goals to cut fatalities in half by 2030, create a congestion-free surface transportation system, and improve system performance (1). Policies and procedures that explicitly consider performance goals at all organizational levels in transportation agencies will maximize the likelihood they are achieved. Performance measures are being used to increase accountability for how highway funds are being spent (2). The Moving Ahead for Progress in the 21st Century Act (MAP-21) establishes a performance-based federal highway program, where investment decisions are made through performance-based planning and programming (2). States are expected to invest resources in projects that achieve performance targets and collectively contribute to achieving national performance goals. Once funds are allocated, road design activities and decisions should be consistent with performance goals set during planning and programming. A performance-based design approach would be a significant contribution to achieving performance objectives and making well-informed design decisions. The Federal Highway Administration (FHWA) has recently formed a task force to explore the transition from a criteria-based road design to a performance-based road design. The Transportation Research Board's (TRB's) Operational Effects of Geometric Committee (AHB65) created a Subcommittee on Performance-Based Analysis to investigate processes and procedures to incorporate safety and operational performance prediction into the project development process.

Current highway geometric design processes require establishment of fundamental design controls (e.g., area type, terrain, functional classification, design vehicle, traffic volume) and selection of design speed. The process then becomes dimensionally based, with minimums, maximums, and ranges in design values directly derived from tables, charts, and equations. Acceptable performance in terms of mobility and safety is presumed to result from proper application of design criteria. The variability in factors influencing design criteria (e.g., driver performance, road conditions, and vehicle performance) is often large and is addressed implicitly by using "conservative" values. This can lead to performance outcomes that are different than intended (6). The relative likelihoods (or probabilities) that design alternatives will meet transportation performance goals throughout their life cycles are not explicitly or quantitatively evaluated. A risk-and-reliability-based highway geometric design approach is a possible solution to address these gaps. This idea has received national interest, evident from an invited TRB podium session at the 2012 annual meeting, "Risk and Reliability Analysis in Geometric Design of Highways and Streets." Design approaches based on levels of risk (the probability of an event occurring and the impact the event will have on the achievement of design, project, or agency objectives) and reliability (the ability of a system to consistently do what it was expected or designed to do) are currently used in several engineering/technical disciplines (e.g., structural design, hydrology and hydraulics, systems engineering, and management). This research provided a strategic step toward development of road design processes that: 1) explicitly consider and quantify the variability and uncertainty in factors that influence design criteria and design decisions; and 2) explicitly incorporate expected performance outcomes and the uncertainty of performance predictions into design decisions.

2. PROJECT AND GEOMETRIC DESIGN PERFORMANCE

Overall project performance may influence and may be influenced by geometric design decisions and their resultant performance. Measuring the effectiveness of overall project performance depends on the goal, intended outcome, nature, or catalyst for the project. Clearly, geometric design choices or geometric design alternatives will influence the outcomes. However, the ultimate measure of project success may not hinge upon the specific geometric element or value of a specific treatment, solution, or mitigation.

Project performance can include other elements that may not be specific to common transportation outcomes of capacity, safety performance, or quality of service for multimodal users. Project performance could include other aspects, such as implementing a highway, street, or design element within a specified project budget or construction timeline. The perceived success of the project may not rely on any specific design element; however, the design elements or choices may, in fact, influence the project performance. Consider two intersection alternative configurations. One option might require right-of-way or result in expensive utility impacts compared with another configuration. Or one alternative could impact sensitive lands (wetlands or park land), requiring additional time to attain local, state, or federal permitting approval. In these two examples, the choice of the geometrics could influence the cost and implementation schedule that was a measure of success for overall project performance. Geometric design performance may be measured by the ability to achieve acceptable (not ideal) traffic operations, geometric design, safety performance, and signing and marking. Performance-based analysis can help guide project decision making.

Geometric performance can greatly influence whether a project achieves intended outcomes. Specific design choices will result in operating speeds, operating environment, driver expectations, and safety performance. Depending on the intended project outcomes, the results of geometric design decisions (geometric design performance) may or may not meet overall project needs. In summary, performance-based analysis of geometric design provides a principles-focused approach that looks at the outcomes of design decisions as the primary measure of design effectiveness. Identifying project intended outcomes (project performance) as the basis for evaluating performance results is the first step in performance-based evaluations. Geometric performance can greatly influence whether a project achieves intended outcomes. Specific design choices greatly influence operating speeds, operating environment, driver expectations, and safety performance. Depending on intended project outcomes, the results of geometric design decisions (geometric design performance) may or may not meet overall project needs. As professionals address transportation needs in various project contexts, performance-based analysis results will support informed decision making.

2.1 Reliability

Reliability is defined as the consistency of performance over a series of time periods (e.g., hour-to-hour, day-to-day, year-to-year). Reliability has become a critical transportation performance measure over the last decade, as evidenced by its role as a theme in the second Strategic Highway Research Program (SHRP 2) and in performance-based decision-making aspects of MAP-21 (2). Reliability of transportation service is commonly linked to travel-time variability, but the basic concept applies to any other travel-time-based metric (e.g., average speed, delay). Reliability is sensitive to geometric design, because the geometric design may affect the ability of a highway or street to "absorb" random, additional traffic demand as well as capacity reductions due to incidents (e.g., crashes, vehicle breakdowns), weather, and maintenance operations, among others. Reliability also is indirectly related to geometry inasmuch as the geometry affects the frequency and severity of random events that impact travel time (e.g., crashes). A more detailed discussion of the expected relationships between reliability and the geometric design of highways and streets is provided in the Supplemental Research Materials Report associated with these guidelines (3).

3. RISK AND RELIABILITY ANALYSIS OF GEOMETRIC DESIGN CRITERIA - A CRITICAL SYNTHESIS [PAPER I]

Federal and state transportation agencies set goals related to surface transportation system performance. The American Association of State Highway and Transportation Officials' (AASHTO's) Strategic Plan, for example, includes goals to cut fatalities in half by 2030, create a congestion-free surface transportation system, and improve system performance (*1*). Policies and procedures that explicitly consider performance goals at all organizational levels in transportation agencies are increasingly common. Performance measures are used to increase accountability for how highway funds are being spent (*2*). Moving Ahead for Progress in the 21st Century Act (MAP-21) established a performance-based federal highway program, where investment decisions are made through performance-based planning and programming. States are expected to invest resources in projects that achieve performance targets and collectively contribute to achieving national performance goals.

Once funds are allocated, road design activities and decisions occur and are also transitioning to performance-based design approaches in order to achieve context-specific performance objectives and make well-informed design decisions. A framework for executing performance-based geometric design analysis was recently published by the U.S. National Cooperative Highway Research Program (NCHRP) (*3*). Reliability assessments were identified as one key aspect of performance-based geometric design analysis within this framework. The U.S. Strategic Highway Research Program 2 (SHRP2) also included a reliability focus, with multiple projects exploring the link between geometric design activities and travel time reliability (*4-5*). This paper focuses on one aspect of reliability assessments: risk and reliability analysis of geometric design parameters and criteria.

Highway and street designers deal with the challenge of designing for a broad range of driver, vehicle, and roadway conditions and capabilities (*6*). Significant variability and uncertainty exist due to inherent randomness and lack of perfect knowledge concerning design inputs and design controls that influence design criteria and design decisions. Generally speaking, uncertainty due to the inherent randomness in the design parameters can never be fully eliminated, as natural uncertainty is associated with the characteristics and performance of drivers, vehicles, traffic, and the environment. These design "inputs" often display variations in both time and space.

Variability in factors that influence design decisions have traditionally been addressed *implicitly* in civil engineering disciplines (*7*). Average values tend to be used if the level of variability in parameters influencing design is insignificant. Conservative values are used if the variability is "large," often the case with highway geometric design (*8*). Probabilistic design approaches have also been used in other civil engineering design disciplines to *explicitly* address variability and uncertainty. Probabilistic design approaches have also been investigated in the road design literature using reliability concepts, but it is yet to be implemented in U.S. design practice. The application of this reliability methodology has demonstrated how to explicitly consider the range of expected design, operational, and/or safety performance to inform design decisions. Given the emerging importance of performance-based design, this paper presents a collective review and assessment of methodological alternatives for quantifying risk and reliability associated with geometric design criteria and decisions.

This first section of this paper provided an introduction and brief description of why risk and reliability analysis is applicable to highway and street design. The second section then concisely presents the paper's objective and scope. Synthesis findings related to different applications of reliability theory to highway geometric design criteria and decisions are then described in the third section. Applications of risk and reliability analysis to stopping sight distance, passing sight distance, horizontal curve design, vertical curve design, basic number of lanes, and acceleration length at entrance ramp terminals are presented. The fourth section describes the general methods used in quantifying limit state functions in reliability theory. Code calibration is briefly discussed in the fifth section. The final sections present a summary discussion, conclusions, and recommendations.

3.1 Objective and Review Scope

The objective of this paper is to identify, review, and critically synthesize published literature on explicitly incorporating uncertainty and reliability analyses into design criteria and decisions that are part of the geometric design of highways and streets. The paper will demonstrate alternative approaches assessing geometric design criteria and decisions that explicitly consider uncertainties in design controls and design "inputs," and their impact on the level of uncertainly in design "outputs" (e.g., performance). National and international research papers were included in the review. As a body of work, these resources attempted to clarify the complex issues of defining and measuring reliability in the highway and street design context. These documents also demonstrated existing differences between deterministic and probabilistic highway and street design approaches.

3.2 Risk and Reliability Assessments of Geometric Design Criteria

The body of published literature related to risk and reliability analysis in highway and street design was significant and diverse. It included empirical studies as well as theoretical and discussion papers. Papers explored the applicability of the reliability concept to various design criteria, including stopping sight distance, passing sight distance, horizontal curve design, vertical curve design, decisions regarding basic number of lanes, and acceleration lane lengths at entrance ramp terminals.

The risk and reliability assessments of geometric design criteria in most of the papers reviewed can be interpreted in the context of a limit state function. This approach is consistent with the "limit state design" concept, taken from structural engineering, which applies the concept of "safety margin" to design in a quantitative way (*9-10*). The next section summarizes the limit state function concept and demonstrates its application to geometric design assessments. Methods to estimate the distribution of the limit state function, explicitly accounting for variability commonly encountered in highway and street design (e.g., user characteristics, vehicle performance) are then described. Major findings from these studies are also critically reviewed and summarized.

3.2.1 Limit State Function in Reliability Analysis

The limit state function is notated in a generic form as:

$$Z = g(X) \tag{1}$$

Where:

Z = limit state function;
X = N-dimensional vector of design inputs and parameters $X = x_1, x_2, x_3, \ldots\ldots x_n$ (e.g., driver eye height, object height, driver comfort thresholds, pavement friction); and
g(X) = probability density function of X.

The limit state function can then be used to quantify the level of reliability associated with some design decisions (or combination of decisions), with reliability defined in this context as the probability that a highway or street will operate as intended in a given situation and on a repeated basis (e.g., user-to-user, hour-to-hour, day-to-day, year-to-year) (*8*). In a case where Z < 0, the system will not meet some specified set of design or operational conditions. One example might include a random combination of traffic volume and capacity-influencing events (e.g., disabled vehicle, poor weather) that lead to a level of service (LOS) lower than the design LOS for some time period. In the case where Z > 0, a system will "meet" some specified set of design or operational conditions. For example, a driver's selected speed combined with tire conditions, roadway conditions, radius of curve, and superelevation leads to a side friction demand less than a skidding and rollover threshold for those conditions. In the case where Z = 0, the system will be at its limit state (*6*); for example, the available sight distance for some specified set of eye height, object height, and roadway geometry equals the minimum required sight distance.

The probability of not meeting some specified set of design or operational conditions (p_f) is the probability of the limit state function being less than or equal to zero. This probability is noted as:

$$p_f = P(g(X) < 0) \tag{2}$$

This condition where the limit state function is less than zero (g(X) < 0) is defined as "failure" or "risk" and, again, can be applicable at various levels of analysis (e.g., user-to-user, hour-to-hour, day-to-day, year-to-year).

Within the context of highway and street design, most studies quantified the limit state function in relation to the "supply" and "demand" of some specific situation (e.g., a driver traversing a horizontal curve), and therefore represented Equation 1 as the difference between "supply" and "demand" as shown in Equation 3:

$$Z = g(X) = S - D \tag{3}$$

where S is the supply for the specific situation and D is the demand for the situation. In highway geometric design, supply refers to the group of design characteristics of a facility (*11*). Demand refers to the driver and vehicle requirements that need to be accommodated (*12*) by the roadway under given conditions. For example, available pavement friction depends on the condition of the pavement, roadway geometry, and weather conditions. It is the amount of friction that is provided or supplied to the drivers; whereas, required tire-pavement friction depends on the type and condition of the tires and vehicle operating characteristics. It is the amount of friction needed for the drivers to successfully complete some maneuver.

Equation 3 can be visually represented as shown in Figure 3.1. The limit state function of a system is negative where the supply is less than the demand (*13*), also shown in Figure 1 as the shaded area. In transportation engineering, the phrase "probability of non-compliance" has been used to represent the probability of supply being less than demand, which is associated with a measure of probability that a specific design would not perform as intended (*14*). This general "limit state" model has been explored in the context of elements of design (i.e., sight distance, horizontal alignment, vertical alignment) as well as in the context of other operational design decisions, including basic number of lanes and acceleration lane length.

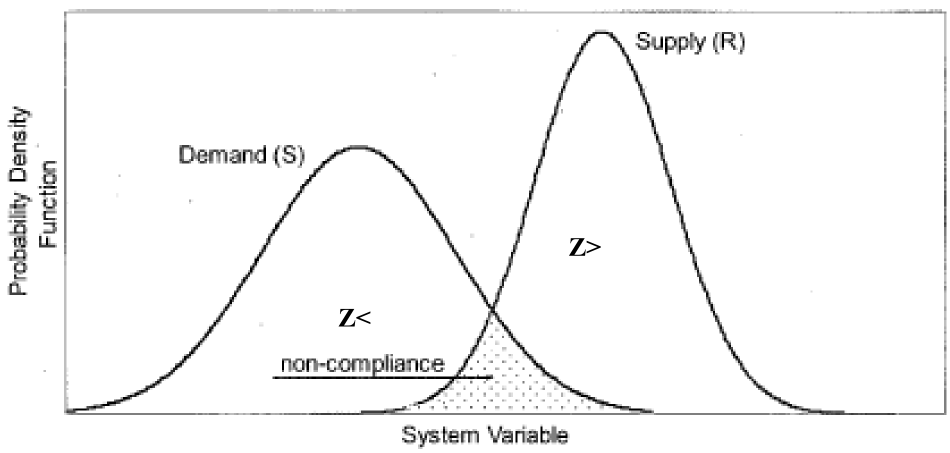


Figure 3.1 Visual Representation of Basic Components of Performance Function (11)

3.2.2 Stopping Sight Distance

The development and applications of probabilistic approaches in highway and street design have been demonstrated in several studies. A significant number of those previous studies have focused specifically on stopping sight distance, probably because it is one of the fundamental criteria for design that is relevant to any location along a roadway. It influences the minimum dimensions of highway features, including vertical curve lengths and offsets to horizontal sightline obstructions (*15*).

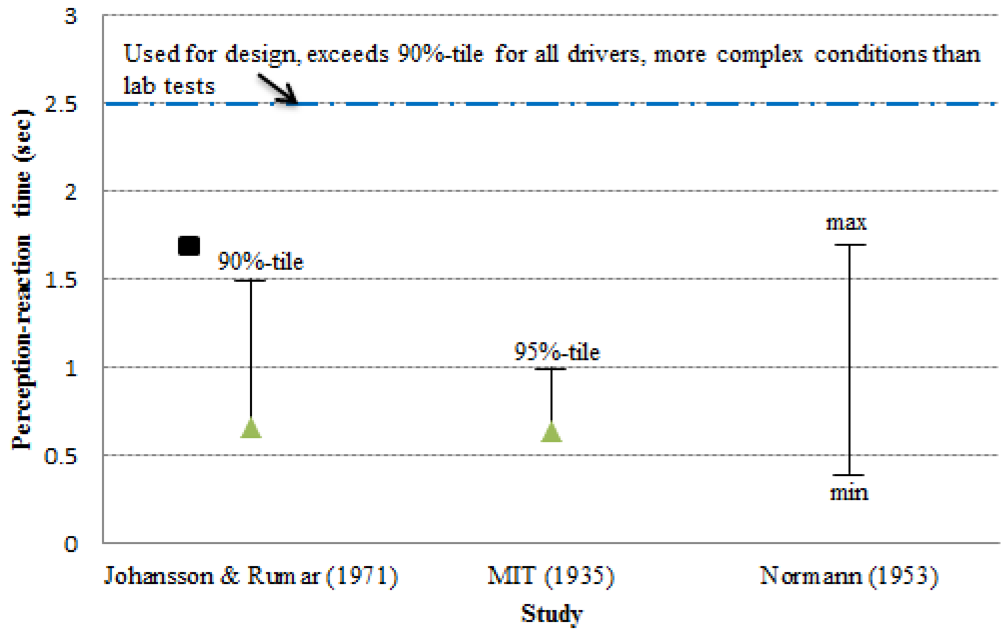
The published reliability assessments recognize the two types of stopping sight distance: required stopping sight distance (R_SSD) and available stopping sight distance (A_SSD) (*12, 15*). R_SSD is the sum of two distances: (1) the distance traversed by a vehicle from the instant a driver sees an object in the roadway necessitating a stop to the instant brakes are applied, and (2) the distance needed to stop a vehicle from the instant that the brakes are applied (*16*). Hence, R_SSD is a function of the design speed, driver, and vehicle factors, as shown in Equation 4.

$$R\_SSD = 1.47Vt + 1.075\frac{V^2}{a} \quad (4)$$

where:

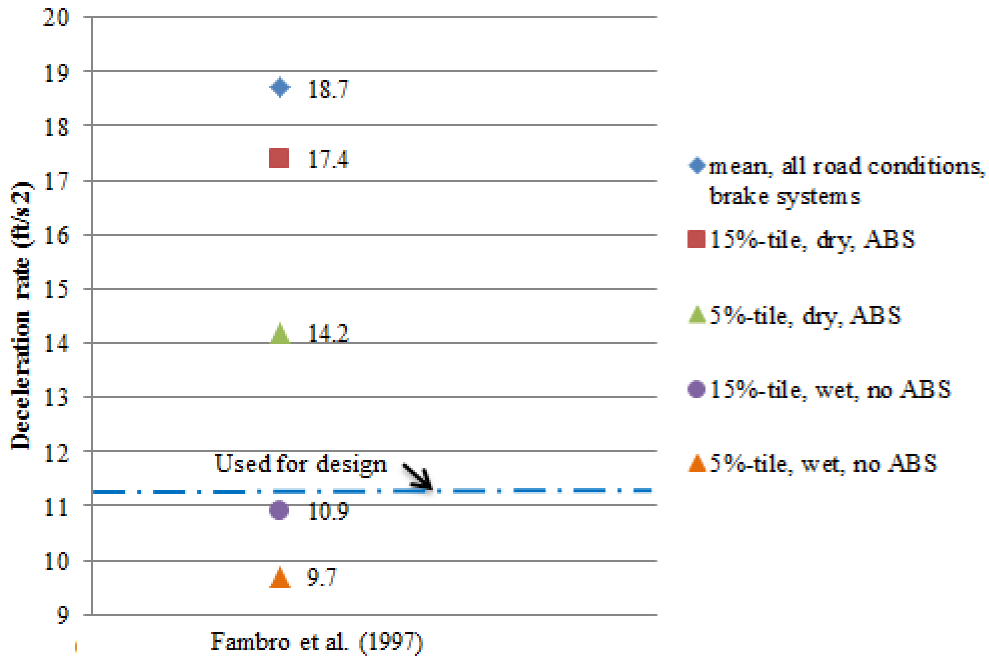
R_SSD = required stopping sight distance [feet (ft)];
V = design speed [miles per hour (mph)];
t = perception-reaction time [seconds (s)]; and
a = deceleration rate (ft/s^2).

Figures 3.2 and 3.3 show the drivers' perception-reaction times and deceleration rate values obtained from different studies (*17-20*) compared with values used for design, as summarized in AASHTO's *A Policy on Geometric Design of Highways and Streets* (Green Book) (*16*).



▲ drivers expected to react
■ drivers do not expect to react (approximated)

Figure 3.2 Perception-Reaction Study Results and Design Values as Summarized in AASHTO's *A Policy on Geometric Design of Highways and Streets*



ABS - Antilock Braking System

Figure 3.3 Deceleration Rate Study Results and Design Values as Summarized in AASHTO's *A Policy on Geometric Design of Highways and Streets*

The studies summarized in the Green Book indicate that the perception-reaction time varies from 0.64s to 3.5s for alerted drivers. There is wide variation in driver reaction times, and with the conditions on the roadway generally more complex than that of the conducted studies, a perception-reaction time of 2.5s is recommended for design, which accommodates the capabilities of most drivers (*16*). Around 90% of the driving population has a faster perception-reaction time than 2.5s (*21*). Similarly, "approximately 90% of all drivers decelerate at rates greater than 11.2 ft/s^2" (*16*). It should also be noted that in Equation 4, the driver is assumed to be traveling at the design speed. Actual speeds vary greatly, as do relative relationships between operating speeds and design speeds (*22*).

A_SSD is the distance along the roadway throughout which an object of specified height is continuously visible to the driver. A_SSD depends on characteristics of the road geometry, vehicle, driver, and object, including cross section elements, roadside conditions, horizontal alignments, vertical alignments, driver eye-height, and object height. Studies (*23-24*) employed statistical approaches for calculating the distance from a reference point to the driver eye for a group of drivers, and a follow-on study measured eye heights, taillights, and headlights for 1,318 vehicles and reported the results (*25*). These and other findings were used by AASHTO in recommending stopping sight distance design values for driver eye-heights (3.5 ft) and object heights (2 ft).

The parameters just reviewed, perception-reaction time, speed, deceleration rates, eye heights, and object heights, are random. Drivers, vehicles, roadways, and objects that appear on the roadway vary greatly. Existing geometric design policies (*16, 21*) *implicitly* consider the randomness in variables formulated for R_SSD (Equation 4) and A_SSD by selecting conservative and practical values, and treating them as deterministic. Figures 2 and 3, as well as other related studies (*8, 26*), show significant variation involved within these design inputs used to make design decisions and assessments related to required and available stopping sight distance. Reliability analysis techniques have been explored as a way to explicitly address and quantify the variability in design situations. Within the context of stopping sight distance, an associated limit state function can be defined in terms of A_SSD and R_SSD, as shown in equation 5:

$$Z_{SSD} = (A\_SSD) - (R\_SSD) \tag{5}$$

where:

Z_{SSD} = limit state function for stopping sight distance;
A_SSD = available stopping sight distance; and
R_SSD = required stopping sight distance.

The limit state function in terms of design speed and driver and vehicle factors can then be written as

$$Z_{SSD} = (A\_SSD) - (1.47Vt + 1.075\frac{V^2}{a}) \tag{6}$$

with all terms defined previously.

Navin (*9*) introduced the concept of reliability analysis in highway geometric design using the limit state design concept to achieve a more consistent road design. In one such study, Navin (*9*) demonstrated the reliability concept using limit state design in the context of stopping sight distance evaluations. To explicitly account for randomness in the design parameters, the mean, standard deviation, and correlation coefficient of the variables used in the stopping sight distance calculations were obtained from various studies (*23-25*). Richl (*27*) investigated the concept of variable stopping sight distance for two vehicle types, two weather conditions (dry and wet), and two alignment conditions (on downgrades and on horizontal curves). The results from the study showed that, at a design speed of 50 mph and at any available stopping sight distance, the probability of non-compliance for trucks is higher than the probability of non-compliance for cars on wet and dry pavements. On wet pavements, for a design speed of 50 mph, at an available stopping sight distance value of 328 ft, the probability of non-compliance values for trucks and cars were 0.85 and 0.54, respectively. Richl and Sayed (*14*) studied the effect of median width and associated median barrier offset along horizontal curves in order to understand the level of potential risk associated with horizontal sightline obstructions. The results showed that the probability of non-compliance values were greater for roadside barriers when compared with small and large rock-ditches.

A study by Ismail and Sayed (*28*) presented two case studies in British Columbia that included horizontal curves with restricted sight distance. The sight distance limitations caused by median barriers, roadside concrete barriers, and associated non-compliance risk were presented in this work. Ibrahim and Sayed (*29*) extended the work and established a link between reliability measures and safety, measured by the expected number of crashes. In the context of stopping sight distance, Ismail and Sayed (*12*) also determined that the effect of crest vertical curves designed at higher design speeds possess a disproportionately high design "factors of safety" compared with curves designed at lower design speeds. For example, the average probability of non-compliance of curves designed at 45 mph is approximately 5.9 times greater than curves designed at 55 mph.

3.2.3 Passing Sight Distance

Design criteria for passing sight distance (PSD) are intended to provide a passing driver enough of a view ahead to determine there are no potentially conflicting vehicles before beginning and completing a passing maneuver (*30*). The LOS on a two-lane, two-way highway is influenced by the percent time spent following (PTSF). Passing zones are designed and implemented to improve overall quality of service (*30*). Similar to stopping sight distance, previous work on reliability assessments of PSD criteria recognize two types of passing sight distance: required passing sight distance (R_PSD) and available passing sight distance (A_PSD).

The R_PSD model in the 2011 Green Book incorporates the interactions of three vehicles: the passing, passed, and the opposing vehicle. The R_PSD model and criteria changed significantly between the 2004 and 2011 versions of the Green Book as a result of research published in NCHRP Report 605 (*31*). Reliability-based approaches to-date have only been applied to the older R_PSD model and are discussed below.

R_PSD formulation can be divided into four quantifiable portions, as illustrated in Figure 3.4 (*32*). The contributing factors needed for the calculation of minimum R_PSD are: driver- and vehicle-related parameters, such as perception-reaction time, acceleration, and deceleration rates when beginning or aborting the passing maneuver; travel speeds; and vehicle lengths, as shown in Equation 7 (*31*):

$$R\_PSD = d_1 + d_2 + d_3 + d_4 \tag{7}$$

where:

d_1 = distance traveled during perception and reaction time and during initial acceleration to the point of encroachment on the left lane;
d_2 = distance traveled while the passing vehicle occupies the left lane;
d_3 = distance between passing vehicle and opposing vehicle at the end of the passing maneuver (such as clearance distance); and
d_4 = distance traveled by an opposing vehicle for two-thirds of the time the passing vehicle occupies the left lane, or 2/3 of d_2.

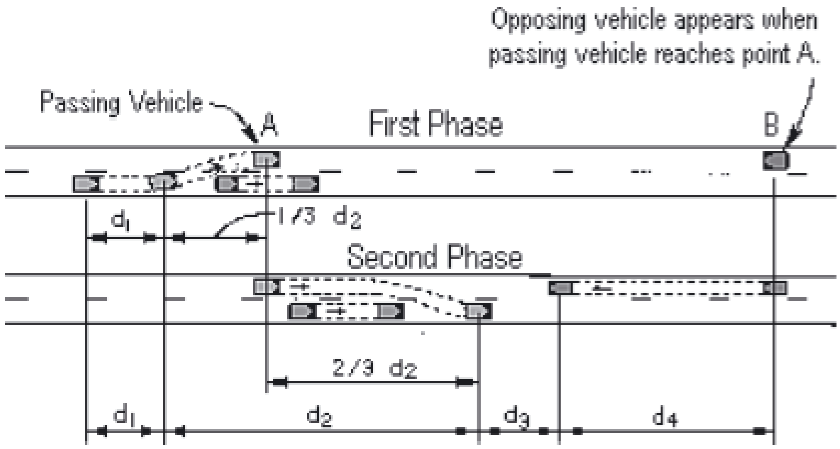


Figure 3.4 Diagram of PSD Components (32)

The design (or minimum) values for the four distances described in Equation 7 were developed using field data and some assumptions stated in the previous versions of the Green Book (*33*). Some studies (*30, 32*) noted that the driver- and vehicle-related parameters used in calculation of minimum R_PSD represent a wide range of driver and vehicle characteristics. This variation was addressed *implicitly* by using conservative values for the distances.

A_PSD is the length of the roadway ahead over which an object (opposing vehicle) would be visible to the driver. As with A_SSD, A_PSD depends on characteristics of the road geometry, vehicle, driver, and object, including cross section elements, roadside conditions, horizontal alignments, vertical alignments, driver eye-height, as well as on the characteristics of the objects to be seen; in this case it would be a certain portion of an opposing vehicle in order for a driver to recognize it as such. To calculate A_PSD provided in the geometric design, the driver eye height is assumed to be 3.5 ft from the road surface, and the opposing object height is also assumed to be 3.5 ft.

The literature on the application of reliability analysis to the study of passing maneuvers have proposed methods that account for the randomness of each of the parameters in the development of the R_PSD requirement (*30*). Within the context of passing sight distance, the limit state function that relates A_PSD to R_PSD, in general form, is written as

$$Z_{PSD} = (A\_PSD) - (R\_PSD) \tag{8}$$

where:

Z_{PSD} = limit state function for passing sight distance;
A_PSD = available passing sight distance; and
R_PSD = required passing sight distance.

The limit state function in terms of the distances making up R_PSD is then written as:

$$Z_{PSD} = (A\_PSD) - (d_1 + d_2 + d_3 + d_4) \tag{9}$$

with all terms previously defined.

In studies by El Khuory (*30*) and Llorca (*13*), a unique microscopic simulation, video recordings, and an instrumented vehicle driven along the road segments were used to replicate and identify passing maneuvers on road segments. These studies developed a risk-based approach for R_PSD criteria. El Khuory and Hobeika (*30*) analyzed the risk indices involved in passing sight distance calculations on two-lane, two-way roads. The study found that at a design speed of 50 mph and available passing sight distance of 650 ft, the probability of non-compliance was around 20%. Llorca (*13*) evaluated the risk levels of passing sight distance design criteria based on the experimental data. The results showed that at a design speed of 50 mph and 60 mph, the probability of non-compliance was 0.08 and 0.17, respectively. Similarly, at an available passing sight distance of 980 ft and 1300 ft, the probability of non-compliance was 0.95 and 0.7, respectively.

3.2.4 Horizontal Curve Design

The elements related to the design of horizontal curves include design speed, side friction, rate of superelevation, and horizontal curve radius. Given a design speed, maximum rate of superelevation, and maximum side friction, the minimum horizontal curve radius is determined using equation 10:

$$R_{min} = \frac{V^2{}_D}{15(0.01e_{max}+f_{max})} \tag{10}$$

where:

V_D = design speed (mph);
e_{max} = maximum rate of superelevation (%);
f_{max} = maximum side friction factor; and
R_{min} = minimum horizontal curve radius (ft)

The maximum superelevation rate is usually constant for a state, region, and/or area type. The maximum side friction values are based on various studies (*34-35*), and are limited primarily by driver comfort in current design policies. Drivers tend to become less tolerable of side friction demand as speed increases. Figure 3.5 shows a summary of the side friction values from previous research as presented in the Green Book (*16*).

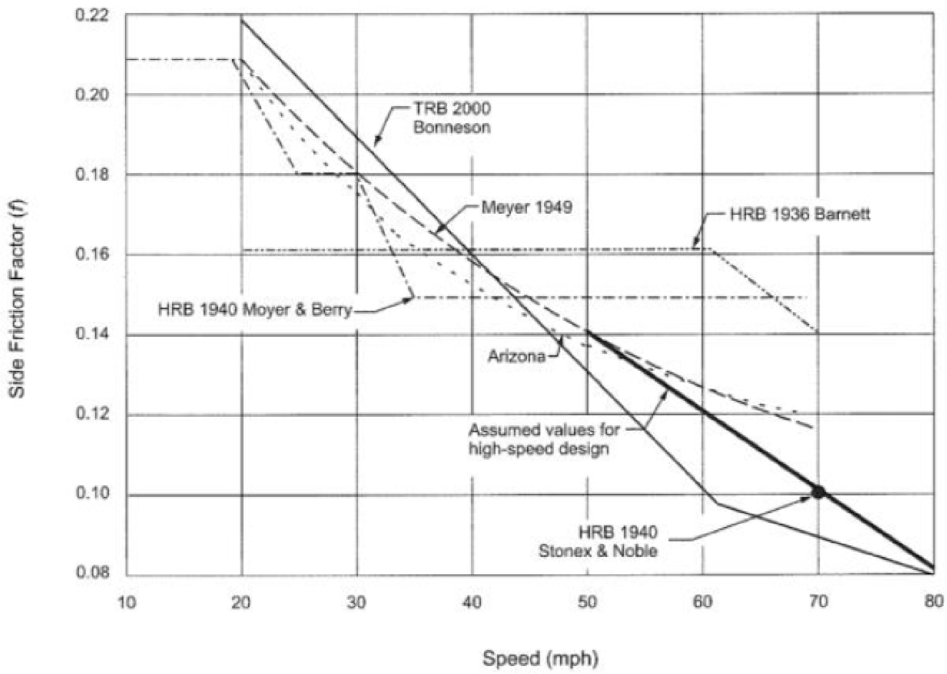


Figure 3.5 Summary of side friction studies (16)

Side friction factors limited by driver comfort have generally not been explored using reliability analysis. Instead, more physical limiting conditions of side friction based on vehicle skidding without rollover (S) and with rollover (S_{RO}) have been analyzed from a reliability perspective. Required side-friction (R_SF) is the necessary side-friction to provide for enough centripetal acceleration for a vehicle to traverse a horizontal curve (*36*). R_SF depends on the curve radius, speed, and design superelevation rate.

Available side-friction (A_SF) is the actual tire-pavement friction available (supplied) for vehicles to traverse a horizontal curve. A_SF depends on the condition of pavement, roadway geometry, weather, and weather-related roadway conditions. The limit state function for side friction and horizontal curve design is shown in equation 11:

$$Z_{SF} = (A\_SF) - (R\_SF) \tag{11}$$

where:

Z_{SF} = limit state function for side-friction;
A_SF = available side-friction; and
R_SF = required side-friction.

On the condition that the appropriate analysis point is the midpoint of the horizontal curve where full superelevation has been reached, a limit state function based on radius of curve, shown in Equation 12, can be used:

$$Z_S = R_S - R_D \tag{12}$$

The limit state function in terms of design speed, maximum available side friction (for skidding without rollover), and superelevation can then be written as:

$$Z_S = R_S - \frac{V^2}{15(0.01e + A_{SF_{max}}(S))} \tag{13}$$

where:

R_S = radius supplied, i.e., the existing horizontal curve radius (ft);
V = vehicle speed (mph);
e = design superelevation rate for the horizontal curve (%);
$A_{SF_{max}}(S)$ = maximum available side-friction (for skidding without rollover).

If the vehicle roll motion effect is included for the failure mode of vehicle skidding, the supplied radius will be the same, but the demand radius is described as:

$$R_{D_{RO}} = \frac{V^2}{g[\left(1-\frac{h_r}{h}\right)e + A_{SF_{max}}(\text{SRO})]}\left[1 + R_\theta\left(1 - \frac{h_r}{h}\right)\right] \tag{14}$$

where:

h = height of center of gravity above the ground;
h_r = height of the roll center above the ground at the longitudinal center of gravity location;
$A_{SF_{max}}(SRO)$ = maximum available side-friction (for skidding with rollover); and
R_θ = roll rate (rad/gravity), expressed by:

$$R_\theta = \frac{\theta}{a_y}$$

where:

a_y = lateral acceleration; and
θ = roll angle.

Therefore, the limit state function for the failure mode of vehicle skidding involving roll motion effect is given by:

$$Z_{S_{RO}} = R_S - \frac{V^2}{g[\left(1-\frac{h_r}{h}\right)e + A_{SF_{max}}(\text{SRO})]}\left[1 + R_\theta\left(1 - \frac{h_r}{h}\right)\right] \tag{15}$$

Current design policy utilizes a "point-mass" model for horizontal curve design, ignoring rollover and treating demand and available side friction as deterministic, even though speed, pavement conditions, tire condition, weather, and vehicle dimensions vary greatly among users. These stochastic characteristics of horizontal curve related design variables have been investigated in multiple studies through experiments and field evaluations (*12, 37-39*), and have been incorporated into a reliability analysis of horizontal alignment design. Zheng (*39*) evaluated the "margin of safety" for a particular horizontal alignment design by incorporating vehicle dynamics, pavement performance, and driver and vehicle interactions, all of which involved uncertainty. The results showed that at a design speed of 75 mph, the probability of non-compliance for an available side friction of 0.30 and 0.20 were 0.02 and 0.86, respectively. You et al. (*37*) calculated the risks associated with the horizontal curve design based on the failure modes of vehicle skidding and rollover. The analysis explicitly incorporated variability in driver operating speeds. The results showed that, at a mean design speed of 45 mph with a standard deviation of 4 mph, the probability of non-compliance for cars, for a side friction of 0.30 and 0.20, were 0.50 and 0.80, respectively. Shin and Lee (*40*) analyzed minimum radii of roadway horizontal curves based on vehicle dynamics on interchange exit ramps. The work investigated the probabilities of rollover and skidding for the minimum radii as determined using the 2011 Green Book (*16*). Himes (*36*) investigated the design of horizontal curves over the possible ranges of vertical grades based on skidding and rollover failures for passenger cars and heavy trucks. Results demonstrated that that required radii for heavy truck skid failure were much larger than the passenger car radii for the same mean speed value. At a design speed of 65 mph, the probability of failure was 0.8 at 1200-ft radius and 0.2 at 1800-ft radius for cars. The work (*36*) also concluded that the difference in operating speeds between heavy trucks and passenger cars is nearly 10 mph when the posted speed is 70 mph.

3.2.5 Vertical Curve Design

Crest vertical curves are designed as transition between two different vertical grades when the value of the ongoing grade is less than the value of the incoming grade. Available stopping sight distance on crest vertical curves is limited by the curve itself. In order to provide adequate, available stopping sight distance, the appropriate length of the curve for a given grade needs to be determined. The general equations relating the length of the crest vertical curve, grade break, driver eye height, object height, and available sight distance are given as:

When S < L
$$L = \frac{AS^2}{100(\sqrt{2h_1}+\sqrt{2h_2})^2} \tag{16}$$

When S > L
$$L = 2S - \frac{200(\sqrt{h_1}+\sqrt{h_2})^2}{A} \tag{17}$$

where:

L = length of vertical curve (ft);
S = minimum available stopping sight distance (ft);
A = algebraic difference in grades (%);
h_1 = height of eye above roadway surface (ft); and
h_2 = height of object above roadway surface (ft).

Assuming vertical curve length and the algebraic difference in grades have been determined, the required stopping sight distance (R_SSD) varies with perception-reaction time, deceleration rate, and vehicle speed. Available stopping sight distance depends on the driver eye height and object height. Thus there is variability associated with the parameters in the available and required stopping sight distance calculations, and the limit state function mentioned in equation 5 is calculated by equations 18 and 19 in the context of vertical curve design:

$$\text{When S < L, } Z_{V-SSD} = (R\_SSD) - \left(\sqrt{\frac{L*100(\sqrt{2h_1}+\sqrt{2h_2})^2}{A}}\right) \quad (18)$$

$$\text{When S >L, } Z_{V-SSD} = (R\_SSD) - \left(\frac{L+\frac{200(\sqrt{h_1}+\sqrt{h_2})^2}{A}}{2}\right) \quad (19)$$

where:

Z_{V_SSD} = limit state function for stopping sight distance along a crest vertical curve; and all other parameters as previously defined.

Reliability analysis of crest vertical curve design explicitly incorporates variability in speed, perception-reaction times, deceleration rates, driver eye heights, and object heights. Zheng (*39*) applied reliability theory to crest vertical curve design. Results showed that as the rate of vertical curvature (K) increased, the probability of non-compliance decreased. For example, for vertical curves with S<L, the probability of non-compliance for K-values of 90 and 95 were 0.065 and 0.01, respectively. The most influential parameter according to the reliability analysis of crest vertical curve design is the deceleration rate of the vehicle (*11*). Ismail (*11*) applied a calibration framework to the standard sight distance design model for crest vertical curves. A new sight distance model was formulated for the combination of horizontal and vertical curves that represented uncertainty in driver and vehicle characteristics and vehicle speed, with the crest curve length and the algebraic difference of grades being deterministic. The work by Ismail (*11*) concluded that the results obtained from code-calibration suggested there is a degree of overdesign in the current standard sight distance model for crest vertical curves. The study also found that the effect of reducing the available sight distance on a crest vertical curve due to superimposing a horizontal curve with sight obstructions on the inside of the curve is eliminated by the corresponding reduction in the operating speed of the vehicle.

3.2.6 Basic Number of Lanes on Freeways

Basic number of lanes on a freeway is "a minimum number of lanes designated and maintained over a significant length of a route, irrespective of the changes in traffic volume and lane balance needs" (*16, 41*). It is the constant number of lanes assigned to a route, exclusive of auxiliary lanes (*16, 41*). Basic number of lanes decisions are often driven by design LOS criteria, which can vary by agency and across area type.

The traffic density per lane directly determines actual LOS for basic freeway segments. For a design year analysis, the traffic density of a facility directly depends on the design year daily traffic, percent of daily traffic in the design hour, directional distribution, percent heavy vehicles, and free-flow speed. The demand volume and the estimated average speed are used to determine the density of traffic stream, as shown in equation 20:

$$Density = \frac{V}{S} = \frac{(K_{30} \times AADT \times D)}{(S \times PHF \times N \times f_{HV})}\ pc/mi \tag{20}$$

where:

V = demand volume (veh/hr);
S = average speed (mph);
K_{30} = proportion of the design year daily traffic in the 30th highest hour of the design year (whether the 30th highest hourly volume is used often depends on area type);
AADT = annual average daily traffic (veh/day);
D = directional distribution;
PHF = peak hour factor;
N = number of lanes in analysis direction; and
f_{HV} = adjustment factor for presence of heavy vehicles.

Estimates of these traffic-related design input parameters that influence number of lanes decisions have uncertainty due to uncertainty in traffic growth estimates, road and vehicle characteristics, and driver characteristics. The predicted density during the design hour (PD) is used to determine an LOS, which is compared to the design LOS criterion for a specific area type (urban/rural) where the basic freeway segment is located.

After determining a maximum design density (DD) to still achieve a selected design LOS, the limit state function can be written in terms of density, as shown in equation 21:

$$Z_D = DD - PD \tag{21}$$

where:

Z_D= limit state function for density;
DD = maximum design density to still achieve a selected design LOS (veh/mi/ln); and
PD = predicted density in the design hour (veh/mi/ln).

This limit state function can also be expressed as shown in equation 22:

$$Z_D = DD - \frac{(K_{30} \times AADT \times D)}{(S \times PHF \times N \times f_{HV})} \tag{22}$$

The study described in (*8*) developed a comprehensive framework for evaluating the effect of variation and uncertainty in design inputs (e.g., percent of daily traffic in design hour, directional distribution, percent heavy vehicles, free-flow speed) on the resulting variation in vehicle density and LOS of a freeway under alternatives for basic number of lanes. Traffic count data were obtained from the automatic traffic recorder stations operated and maintained by Utah Department of Transportation. Estimates of density (DD) and LOS resulting from application of *Highway Capacity Manual* methodologies were determined. Probability density functions (or distributions) that quantify the uncertainty of design inputs were identified and predicted density was determined. The work concluded that the proportion of daily traffic in design hour ranged from 0.09 – 0.11 in urban areas and 0.08-0.15 in rural areas. The probabilities of operating at or above different design LOS criteria were demonstrated for different case studies with multiple numbers of lanes alternatives.

3.2.7 Acceleration Length for Entrance Ramp Terminals

Access to and from a freeway is permitted only by the use of grade-separated interchanges. These areas have the inherent potential for increased driver workload, driver error, and traffic collisions because of the intensity, complexity, and number of maneuvers to be performed by the drivers at interchanges (*42*). Speed change lanes (SCLs) are auxiliary lanes used when a speed change is required for entering or exiting traffic to/from a highway or freeway.

For entrance ramps, the required SCL length (RL) is calculated using basic kinematics and information about initial ramp or entrance speed (usually considered the speed at the PT of the controlling curve), the final merging speed, and the acceleration rate (*43*), as illustrated in equation 23:

$$RL = \frac{(1.47V_2)^2 - (1.47V_1)^2}{2a} \tag{23}$$

where:

RL = required SCL length (ft);
V_2 = desired merging speed of the vehicle (usually close to the operating speed of the mainline), (mph);
V_1 = operating speed at the PT of the controlling curve of the entrance ramp (mph); and
a = acceleration rate (ft/s^2)

In current design policies and guides, such as the Green Book and the TAC design guide, required SCL lengths are calculated based on a deterministic approach. In this approach, a single value for each design parameter in equation 23 is used to conservatively represent the population of drivers, such as a higher percentile vehicle speed and lower percentile acceleration rate. The accumulation of these conservative assumptions may create design scenarios that correspond to cases that do not exist in real life and can lead to overdesign (*28, 42-43*). This could be particularly important given ramp spacing issues as public transportation agencies deal regularly with requests for new freeway access or modifications to existing access (*44*).

The available SCL length (AL) depends on the actual design of the ramp as measured from the PT of the controlling curve of the ramp to some assumed merge point (*41*).

The limit state function for the available and required acceleration lane length is shown in equation 24:

$$Z_{SCL} = AL - RL \tag{24}$$

where:

Z_{SCL} = limit state function for SCL length;
AL = available speed change lane length (ft); and
RL = required speed change lane length (ft).

The limit state function considers acceleration lane length in terms of operating speed at the PT of the controlling curve of the entrance ramp, merging speed, and acceleration rate, and is given in equation 25 as:

$$Z_{SCL} = AL - \frac{(1.47V_2)^2-(1.47V_1)^2}{2a} \quad (25)$$

Fatema and Hassan (*42*) introduced a probabilistic approach for the design of SCL length considering both acceleration and gap acceptance behavior of drivers during the merging process. The study used a simulation model to account for the needs of vehicles to accelerate to a target merge speed as well as the needs of drivers to search for and find an acceptable gap in the freeway through traffic. The results showed that at a controlling ramp curve design speed of 50 mph and SCL length of 800 ft, the probability of non-compliance for freeway mainline volumes of 500 veh/h/ln and 1200 veh/h/ln was 0.22 and 0.38, respectively. This study also uncovered a trend that exists between the reliability measures and safety performance using five-year collision frequencies at the study sites. As the five-year collision frequency increased from three to eight crashes, the probability of non-compliance changed from 0.22 to 0.31. However, more sites were recommended to quantify the accurate relationship between reliability and safety performance.

In summary, reliability analysis has been successfully utilized in geometric design research to assess design criteria and quantify the probability that design decisions will perform as intended on a consistent basis (e.g., user-to-user, hour-to-hour, day-to-day, year-to-year). The random input variables have been assumed to follow selected probability density distributions, yet no empirical data were used to generate these distributions in a majority of the reviewed studies. To validate the usefulness of the reliability approach, real-world data should be used. Table 3.1 provides a summary of design criteria that have been included in the previous reliability research reviewed in this section.

Table 3.1 Summary of Design Criteria Included in Previous Reliability Research

Design Parameter (s), Criteria or Decisions	Previous Research
Stopping Sight Distance	Navin (1992), Richl (2003), Richl and Sayed (2006), Ismail (2006), Ismail and Sayed (2009), Ismail and Sayed (2010), Ibrahim and Sayed (2011), Sarhan and Hassan (2011), Ismail and Sayed (2012), Ibrahim et. al (2012)
Passing Sight Distance	Khoury and Hobeika (2007), Llorca et. al. (2014)
Horizontal Curve Design	Felipe (1996), Zheng (1997), You et al., (2012), You and Sun (2013), Himes (2013)
Vertical Curve Design	Zheng (1997), Ismail (2006), Ismail and Sayed (2009)
Basic Number of Lanes	Musunuru (2014)
Acceleration Length for Entrance Ramp Terminals	Hassan et. al., (2012), Fatema and Hassan (2013)

3.3 Methods to Estimate the Distribution of the Limit State Function

This section provides details on the mathematical procedures used to combine design "inputs" and their associated variability in order to quantify the distribution in some type of defined design output, such as a performance measure or comparison of required versus actual values (i.e., the limit state function). These methods lead to the quantification of performance reliability and unreliability. Both analytical and numerical methods have been used. Numerical methods are typically more robust in the sense that they can be applied to a wide range of problems without restrictive assumptions regarding symmetry for probability distributions (*45*). The methods introduced in this section can be implemented using spreadsheet modeling or any software to perform parametric design studies and first-order estimations.

3.3.1 Monte Carlo Simulation

Stanislaw Ulam and John von Neumann developed the Monte Carlo approach in 1946 to simulate probabilistic events for military purposes (*46*). Monte Carlo simulation is a numerical method that consists of drawing samples of the input variables according to their probabilistic characteristics and then feeding them into a performance function. The results of a Monte Carlo simulation are distributions of possible outcomes that could occur and the likelihood of any outcome occurring (*47*).

The probability of non-compliance (e.g., actual LOS worse than design LOS) can be directly determined using output distributions from this method. The results obtained by Monte Carlo simulation inevitably involve sampling errors, which decrease as sample size increases. One way of avoiding sampling errors is by increasing the sample size. Additional data cannot be obtained to increase the sample size in all cases. A procedure known as variance reduction can be used in these cases to increase the precision of estimates obtained for a given number of iterations (*47*). Reliability is then determined using equation 26:

$$R = 1 - P(u) \tag{26}$$

where:

$P(u) = N_{pu} / N$;
N_{pu} = number of unsatisfactory performances at limit state < 1.0; and
N = number of iterations.

First/Second-Order Reliability Method (FORM/SORM)

First/second order reliability method (FORM/SORM) is considered one of the most desirable computational methods for reliability analysis. This method is used for a direct evaluation of reliability without the need to define the probability density function (pdf) of the design parameters involved in making the design decisions. The performance function of a stochastic approach (M) is given by

M = performance limit – response indicator.

The performance function can be defined such that the limit state or failure surface is given by M = 0. The non-compliance event is defined as the space where M < 0 and the success event is defined as the space where M > 0. Probability of failure is evaluated by the following integral (*47*):

$$P_f = \iiint f_x(x_1, \ldots \ldots, x_n) dx_1 \ldots .. dx_n$$

Where f_x is the joint density function of $x_1 x_2, \ldots \ldots \ldots x_n$, and the integration is performed over the region where M < 0. The integral cannot be easily evaluated because each of the basic random parameters has a unique distribution that interacts with others. The estimation of probability of failure for this method consists of three steps:

1. The transformation of the space of the basic random parameters into a space of standard normal parameters
2. The search in this transformed space of the point of minimum distance from the origin on the limit state surface (this point is called the design point)
3. An approximation of the failure surface near the design point

FORM consists of approaching the surface of failure by a hyper plane tangent to the failure surface at the design point (*47*). The reliability index is the distance or number of standard deviations from the mean to the limit state that has been set. The reliability index utilizes a limit state, which relates capacity (C) and demand (D) through a safety margin that can be estimated assuming either a normal or lognormal distribution.

Normal Distribution. If *C* and *D* are normally distributed, then reliability index is estimated in terms of the safety margin (SM) or *C* – *D*, as shown in Equation 27-28:

$$\beta = \frac{E[SM]}{\sigma[SM]} \tag{27}$$

$$\beta = \frac{E[C-D]}{(\sigma_C{}^2 + \sigma_D{}^2)^{\frac{1}{2}}} \tag{28}$$

Then, an estimate of the failure probability is obtained by Equation 29:

$$P_f = \emptyset(-\beta) \tag{29}$$

Where $\emptyset$ is the cumulative Gaussian distribution of the standard normal law and β is the reliability index. If the linear approximation is not satisfactory, more precise evaluations can be obtained from approximations to higher orders of the failure surface at the design point.

Lognormal Distribution. If *C* and *D* are lognormal distributions, and given their statistical parameters for the expected value of capacity *E*[*C*], expected value of demand *E*[*D*], standard deviation of capacity σ_C, and standard deviation of demand, σ_D that describe the jointly distributed lognormal random variables, there is an equivalent joint normal distribution on the logarithms of *C* and *D* having mean values:

$$\text{E[C]} = \ln\text{[C]} - \sigma_C{}^2/2 \tag{30}$$

$$\text{E[D]} = \ln\text{[D]} - \sigma_D{}^2/2 \tag{31}$$

Where:
σ_C = [ln $(1 + V_C{}^2)]^{1/2}$;
σ_D = [ln $(1 + V_D{}^2)]^{1/2}$;
and where V_C and V_D are the coefficients of variation (ratio of the standard deviation to the expected value).

If the means are approximated as ln [C] and ln [D], and the standard deviations are approximated as $V_C{}^2$ and $V_D{}^2$, then the reliability index β becomes:

$$\beta = \frac{\ln\left(E[C]/E[D]\right)}{(V_C{}^2 + V_D{}^2)^{1/2}} \tag{32}$$

The above expression is for lognormal distribution of C and D and the probability of failure is given by Equation 33:

$$P_f = P(\ln C - \ln D) \leq 0 \tag{33}$$

Second-order reliability method (SORM) is an approximation by a quadratic surface at the design point. This is accomplished by performing second-order Taylor expansion. However, SORM was not used in any of the reliability approximation methods in the reviewed published literature applicable to highway geometric design.

3.3.2 Mean Value First Order Second Moment (M FOSM) Method

The M FOSM method, also known as first order second moment (FOSM) method, is used in a situation when the only information known is the statistical properties of stochastic input variables. The basic idea is to approximate a model by the first-order Taylor series expansion and linear approximation of second moment. The mean and standard deviation of the performance function is then estimated and reliability index is computed. This reliability index is used as a surrogate for the probability of non-compliance.

It has been found there are invariance problems when using FOSM when determining the reliability index or the probability of non-compliance, as two equivalent limit state functions can yield different outcomes. The main issue with this method is that the linearization of the limit state function is made at the mean of the random variables rather than around the point where the limit state function is equal to zero (*28*). Table 3.2 provides a listing of reliability methods used by the studies.

In summary, these reliability estimation methodologies used to quantify the limit state function, as well as the "risk" in reliability theory, enables the designer to reach a higher level of knowledge regarding the expected design performance. This is because the presented methodologies explicitly take into account the realistic variabilities of design inputs in the analysis process. A software program could be developed for designers to assess the probability of non-compliance for highway geometric design criteria and decisions for any given scenario. The design process would be performance-based, resulting in likely benefits in cost through more informed decision-making.

Table 3.2 Summary of Reliability Methods Used in the Previous Research

Method Type	Previous Research
Monte Carlo simulation	Navin (1992), Richl and Sayed (2006), El Khoury and Hobeika (2007), Sarhan and Hassan (2008), Ismail and Sayed (2010), Hassan et al., (2012), Fatema and Hassan (2012), Musunuru (2014), Llorca et al., (2014)
First/Second Order Reliability Method (FORM/SORM)	Felipe (1996), Zheng (1997), Ismail and Sayed (2009), Ismail and Sayed (2010), Ibrahim and Sayed (2011), Ibrahim and Sayed (2012), Ismail and Sayed (2012), You et al., (2012), Hussein et al., (2014)

3.4 Criteria Calibration Efforts

The concept of code-calibration is modifying standard design models that determine design criteria by means of adding calibration factors to the current design form to yield consistent probability of non-compliance values (*12*). By doing this, a calibrated design model will have all reliability analysis results codified in terms of calibration factors (*12*). The goal of the calibration process then is to find a value of a design parameter, such that the probability of non-compliance of the limit state function equals the pre-specified probability of non-compliance (*48*).

The main steps of the calibration process are outlined by Gayton et al., (*48*) and are summarized below:

1. Define the validity domain of the code, which is the range of design inputs that will be considered in the calibration process. Design inputs beyond this range are not necessarily expected to yield a consistent probability of non-compliance.
2. Select sample design cases from the specified range of the design inputs.
3. Select a target reliability index.
4. Conduct reliability analysis for the design cases to find the corresponding design safety levels.
5. Select calibration factors that will minimize the scatter of the reliability indices around the target value.

The studies (*12, 48*) also mention that to satisfy the proposition that the probability of non-compliance for design outputs should be consistent and close to some acceptable level, a penalty function can be used. This penalty function is the difference between the probability of non-compliance values associated with each design output and target values. However, if the design concept discussed is not very complex, a penalty function may not be included and the design problem is solved for the exact target probability of non-compliance (*48*).

4. A RELIABILITY-BASED GEOMETRIC DESIGN APPROACH TO FREEWAY NUMBER OF LANES DECISIONS [PAPER II]

Road geometric designers must deal with the challenge of designing for a broad range of driver, vehicle, and roadway conditions and capabilities. In other words, there is variability in design inputs and design controls that influence design criteria and design decisions. As noted in (6), variability in factors that influence design decisions have traditionally been addressed implicitly in civil engineering disciplines (7). Average values are used if the variability in certain parameters influencing design is insignificant. Conservative values are used if the variability is "large," the case with road geometric design. The level of variability in road design input parameters is expected to be large because of their aleatory variability (i.e., natural randomness). Probabilistic design approaches have been successfully incorporated into other design disciplines (e.g., probabilistic damage control approach for seismic design of bridges subjected to earthquakes) to explicitly address this variability and uncertainty. The idea has also been explored in the road design literature using reliability concepts, but it is yet to be implemented in U.S. design practice.

The reliability of a highway or street can be defined as the probability it will perform as intended in a given situation and on a repeated basis (e.g., hour-to-hour, day-to-day, year-to-year). Several previous studies have incorporated reliability analysis into highway geometric design issues. These studies followed a "limit state design" concept, taken from structural engineering, which applies the concept of a "safety margin" to highway design in a quantitative way (9-*10*). A research program that focused on incorporating travel time reliability into highway design, construction, and management was also executed as part of the Strategic Highway Research Program 2 (SHRP 2). Although the application of reliability analysis to road design issues appears to be promising, published work on introducing probabilistic concepts to current design policies, criteria, and practice is relatively limited at this time.

Design level of service (LOS) criteria vary by location and highway type and are based on assessments of acceptable levels of congestion (16). Designers generally assess the design LOS for volumes in the design hour, which may have a definition that varies by area type. For example, it is typical for the design hour volume in rural areas to correspond with the 30th highest hourly volume in the design year. The 30th highest hourly volume in the design year tends to reflect the higher end of recurring morning and afternoon peak hour volumes. The 100th highest hourly volume is more common in urban areas. Design year traffic volumes may be based on 20- to 25-year projections stemming from either base traffic counts (more common to rural areas) or calibrated travel demand models (more common to urban areas). The uncertainty involved in design year projections of the traffic-related characteristics that will ultimately influence whether or not a design will maintain the design LOS over a design period is significant. Therefore, design decisions that incorporate these traffic-related projections are a logical application of a probabilistic framework. Basic number of lanes on a freeway is one such decision. Basic number of lanes is "a minimum number of lanes designated and maintained over a significant length of a route, irrespective of the changes in traffic volume and lane balance needs" (16*, 41*). It is the constant number of lanes assigned to a route, exclusive of auxiliary lanes (*16, 41*). This study develops a comprehensive framework for evaluating the effect of variation and uncertainty in design inputs (e.g., percent of daily traffic in design hour, directional distribution, percent heavy vehicles, free-flow speed) on the resulting variation in vehicle density and LOS of a freeway under different basic number of lanes alternatives. The variation in the design inputs is explicitly addressed using statistical distributions derived from observed freeway data collected from urban and rural sections of Interstate 15 and Interstate 80 in Utah.

This first section of the paper provides the introduction and brief description of why a probabilistic design approach is applicable to roadway design. The second section is a literature review of different applications of reliability theory to roadway geometric design decisions and criteria. The research objective and scope is described in the third section. The fourth section describes the general methodology for estimating a probability distribution of operational performance that might result from basic number of lanes decisions made to achieve a design LOS on a freeway and the software used to implement the framework. Data collection is then described in the fifth section, followed by a detailed discussion of developing distributions of input parameters to fit the observed data. The sixth section presents the results obtained from Monte Carlo simulation that is part of the probabilistic approach, as well as interpretation of those results. Results of the current deterministic analysis approach to support number of lanes decisions are also provided as a basis for comparison. The final sections present a summary discussion, conclusions, and recommendations from this research.

4.1 Literature Review

The development and application of probabilistic analysis to highway geometric design is reported in several studies in the literature. Faghri and Demetsky (*49*) conducted a reliability-based assessment of the probability of collisions at highway-rail grade crossings. Navin (10) introduced the concept of reliability analysis in highway geometric design using the limit state design concept to achieve a more "consistent" road design. A consistent design of a highway, as when designing a structural system, was achieved by considering the whole highway as a unit. In other words, the reliability of the whole structure is a function of the reliability of each element in the structure. Similarly, knowledge of the reliability of each highway element is essential to design a consistent highway (*38*). Navin (9) adapted the structural terminology to the highway design domain by designating the probability of failure as the probability of non-compliance (P_{nc}). Easa (*50-52*) applied first-order reliability techniques to analyze the design of the intergreen interval and sight distances at intersections.

Felipe (*38*) investigated the use of reliability analysis to measure the margin of safety and the P_{nc} on horizontal curves. Zheng (39) demonstrated that reliability theory is not only useful in the road design stage, but can also be used to assess possible safety issues related to a highway location. Richl and Sayed (*14*) applied first-order reliability analysis for studying available sight distance at locations with median barriers on horizontal curves. El Khoury and Hobeika (30) applied Monte-Carlo simulation techniques to assess the risk of various available passing sight distances on straight highway segments. Sarhan and Hassan (*15*) applied a Monte Carlo simulation to calculate the probability of three dimensional (3-D) sight distance limitations. This approach was applied to horizontal curves on flat grades, crest curves, and sag curves. Sarhan and Hassan (*15*) also estimated the probability of hazard (POH) that might result from the available sight distance being less than the required sight distance.

Ismail and Sayed (*12*) presented a general framework for developing probabilistic highway design criteria and included an application of their framework to crest vertical curve design.

Ismail and Sayed (*28*) used reliability analysis in two case studies in British Columbia to calculate the safety implication of deviating from sight distance requirements. Ismail and Sayed (26) also presented a methodology for re-dimensioning cross-sections located on highway segments with restricted sight distance. You et al. (*37*) studied the risk associated with a horizontal curve design by formulating performance functions for cars and trucks. They took into account the possible failure modes of vehicle skidding and rollover and their likelihood of occurrence. Shin and Lee (*53*) presented first-order reliability techniques to analyze and optimize minimum radii of roadway horizontal curves. It was based on vehicle dynamics, and their applications mainly focused on exit ramps at interchanges.

4.2 Research Objective

The objective of this study is to demonstrate a reliability-based geometric design approach to making decisions regarding the basic number of lanes on freeways. The uncertainty involved in design year projections of traffic-related characteristics that influence number of lanes decisions provides a logical application of a probabilistic framework. This study adds to the existing knowledge base by developing and executing reliability analysis of geometric design in an operational context. Previous studies focused mainly on safety-related concerns (e.g., available versus required sight distance, probability of vehicle skidding and rollover). The framework and results will allow designers to explicitly consider the probability distribution of operational performance that might result from different basic number of lanes decisions. The proposed approach is demonstrated using data from urban and rural segments of Interstate 15 and Interstate 80 in Utah.

4.3 Methodology

To implement reliability analysis in a freeway number of lanes context, stochastic variables that affect vehicle density and LOS were identified (e.g., design year daily traffic, percent of daily traffic in design hour, directional distribution, percent heavy vehicles, free-flow speed). The method used to quantify the inherent uncertainty in these "input variables" is described in this section. The form of uncertainty relevant to roadway geometric design variables is aleatory uncertainty, which involves natural randomness in a process. The randomness is parameterized by a probability density function. Thus, the uncertainty is evaluated for each input variable using a set of statistical distributions. This study utilized observed data to select appropriate statistical distributions for each input variable. To estimate vehicle density of a facility in the design hour, basic freeway segment methodologies described in the Highway Capacity Manual 2010 (*53*) were used.

Estimated traffic growth rates used to project a base year average annual daily traffic to the design year have a significant amount of uncertainty, but the level of uncertainty is difficult to quantify. Growth rate uncertainty will not be addressed in this paper, but will be the focus of future work. This paper assumes a reasonable estimate of the average annual daily traffic in the design year ($AADT_{Design\ Year}$) as a starting point. The design hourly volume (DHV) is important for highway planning and design purposes because it represents the volume of traffic occurring at peak hours. To get the design hourly volume, $AADT_{Design\ Year}$ is often multiplied by the proportion of daily traffic expected to occur in the design hour (K). Through years of experience, engineers have seen that the 30th highest hourly volume in the design year represents the higher end of recurring morning and afternoon peak hour volumes (*54*). Specific practices vary. The 30th highest hourly volume in the design year may be more common to rural areas, while the 100th highest hourly volume may be more common in urban areas. This detail does not have an impact on the objective of this paper, which is to demonstrate a reliability-based geometric design approach. The concept of 30th highest hourly volume is therefore incorporated into the calculations for both rural and urban areas. K is therefore selected to be the ratio between the 30th highest hourly volume of the year and the average annual daily traffic. The design hour volume is then calculated using Equation 1:

$$DHV = \mathrm{K}_{30} \times AADT_{Design\ Year} \tag{1}$$

where K_{30} = proportion of the daily traffic in the 30th highest hour of the design year.

A roadway with a high percentage of traffic in one direction during the peak hours may require more directional lanes than a roadway having the same AADT, but with a directional split closer to 50%. This percentage of traffic in the peak direction during the design hour is referred to as the directional distribution (D). When DHV is multiplied by D, the result is the directional design hour volume (DDHV), as shown in Equation 2:

$$DDHV = DHV \times \mathrm{D} \tag{2}$$

The DDHV is expressed in units of vehicles per hour and represents the demand volume in the analysis direction. The basis for freeway segment analysis using HCM 2010 methodologies is the peak 15-minute rate of flow, expressed in the equivalent number of passenger cars per hour per lane. This is estimated using equation 3:

$$V = \frac{DDHV}{PHF \times N \times f_{HV}} \tag{3}$$

where V = demand volume under equivalent base conditions (pc/hr/ln);

PHF = peak-hour factor; and
f_{HV} = adjustment factor for presence of heavy vehicles.

The number of heavy vehicles on a highway impacts highway planning, traffic operations, safety, and pavement performance (*54*). The factor that represents the effect of heavy vehicles present in the traffic stream is the heavy vehicle adjustment factor (f_{HV}). Since the 1965 version of the HCM, the impact of heavy vehicles has been described in terms of passenger-car equivalencies (PCEs). PCEs indicate the number of passenger cars displaced by a single heavy vehicle of a particular type under prevailing roadway, traffic, and control conditions (*56*). The heavy vehicle adjustment factor is given by

$$f_{HV} = \frac{1}{1+P_T(E_T-1)+P_R(E_R-1)} \tag{4}$$

where P_T and P_R are the proportions of trucks and RVs during the analysis period, and E_T and E_R are the PCEs for trucks and RVs, respectively. In the present research, the impacts of RVs will be ignored; the focus will be on P_T and E_T.

Free-flow speed (FFS) is defined in Chapter 10 of the HCM to be the average speed (S) at which through automobile drivers travel under low-volume conditions. It is intended to represent travel speeds that drivers choose when not impeded by other traffic along any facility. FFS is influenced by the alignment and the cross section of the roadway as well as by roadside features (*57*). It plays a major role in the estimation of the density and LOS by influencing the selection of the appropriate speed-flow curve, and therefore influencing the average speed estimate for a given demand volume. In other words, S is a function of free-flow speed as shown below:

$$S \sim f\ (FFS) \tag{5}$$

The demand volume and the estimated average speed are used to determine the density of the traffic stream. It is given as by equation 6:

$$Density = \frac{V}{S} = \frac{(K_{30} \times AADT \times D)}{(S \times PHF \times N \times f_{HV})}\ pc/mi/\text{ln} \tag{6}$$

Density then directly determines LOS for a given number of lanes.

In a more traditional, deterministic analysis, K_{30}, AADT, D, S, PHF, and f_{HV} are each treated as "one number" known with certainty. This results in an estimate of density that is also one number and tends to misrepresent the level of precision in the density estimate. Experienced designers know there is likely some level of error or uncertainty in the density estimate, but it is not quantified. Therefore, the uncertainty cannot be explicitly considered in the design decision for basic number of lanes.

To address this limitation, the natural uncertainty and variability is represented in this study using a set of statistical distributions for selected variables. This particular paper focuses on the uncertainty in K_{30}, D, S, and f_{HV} estimates and the effects on the uncertainty in the density and LOS estimates. Observed data, combined with the MINITAB software, were used to select appropriate statistical distributions for each of these input variables. MINITAB, developed at Pennsylvania State University, is user-friendly statistical software that can assist a user in developing distributions of the design inputs involving variability. Goodness-of-fit statistics in MINITAB help identify the "best-fitting" distributions. This software provides two goodness-of-fit statistics: Anderson-Darling (AD) for the maximum likelihood and least squares estimation methods and Pearson (P) correlation coefficient for the least squares estimation method. These statistics help users compare the fit of competing distributions. The AD statistic is a measure of how far the plot points fall from the fitted line in a probability plot. A smaller AD statistic indicates that the distribution fits the data better. The software calculates a P correlation coefficient for least squares estimation. The correlation will range between 0 and 1, and higher values indicate a better fitting distribution.

MINITAB was also used to run Monte Carlo simulations as part of the analysis. This simulation gives a distribution of the output quantity (density in this case) as the result of repeatedly drawing random values from the distributions of the "input variables."

4.4 Data Collection and Analysis

The proposed methodology was tested using data from urban and rural sections of Interstate 15 and Interstate 80 in Utah. The basic traffic count data used for analysis were obtained from the Utah Department of Transportation (UDOT). UDOT provided an Excel file containing traffic data from 14 automated traffic recorder (ATR) sites on Interstate 15 and Interstate 80 in Utah from 2002 through 2012. I-15 runs north-south through the southwestern and central portions of Utah, passing through many of the population centers of the state, including Provo, Salt Lake City, and Ogden. I-80 runs east-west through the northern part of the state, passing through the Salt Lake City metropolitan area and Wasatch Mountains. Of the 14 total sites, seven were located inside the urban boundary and seven were located outside the urban boundary (i.e., in rural areas). For UDOT's 14 ATR sites, data were available on an hourly basis, and area type was associated with each site. This study relies on data from all 14 locations. There were some instances of incomplete traffic data from some ATRs for a variety of reasons (e.g., ATR is turned off, out of service, etc.), but the missing data did not impact the ability to conduct the reliability analysis as described below.

4.4.1 Distributions of Input Variables Involving Uncertainty

The values of the input variables were calculated using the data from Interstate 15 and Interstate 80 in Utah. The uncertainty of these parameters was addressed by developing distributions to fit the observed data. As noted above, this particular paper focuses on the uncertainty in K_{30}, D, S, and f_{HV} estimates. The Utah data contained hourly volumes for every day for each ATR site. The 30th highest hourly volume for every year was identified for each ATR site. Then the value of K_{30} was calculated as the ratio of 30th highest hourly volume to the AADT of each year. The calculated values of K_{30} for the ATR sites in urban and rural area are shown in Table 4.1.

It is currently widely recognized that despite design hour procedures and guidelines, roadways perform better or worse than the operational criteria for which they were designed. This is because there are uncertainties or variation in the estimated design hourly volumes due to uncertainty in the estimate of K. Thus, K was treated as a random variable having a mean μ_k and standard deviation σ_k. Collecting data across multiple sites in similar areas provided insights into what random variation in K, due to both measurable and unmeasurable factors, might look like. The statistical distributions for K obtained from the analysis in MINITAB for the ATR stations in urban and rural area are shown in Figure 4.1-a and 4.1-b. The final recommended distribution was selected based on the AD and P goodness-of-fit test statistics previously described. The natural variation in K_{30} was best represented by a lognormal distribution in urban locations and by a normal distribution in rural locations.

Table 4.1 Values of K30

URBAN AREA											
ATR	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
306	0.097	0.097	0.095	0.092	0.098	0.098	0.101	0.097	0.095	0.087	0.095
315	0.095	0.096	0.095	0.095	0.092	0.089	0.095	0.091	0.093	0.094	0.094
340	-	-	0.108	0.104	0.102	0.101	0.101	0.105	0.102	0.101	0.098
348	-	-	-	-	-	-	0.095	0.097	0.097	0.097	0.097
611	0.095	0.095	0.098	0.097	0.096	0.098	0.099	0.099	0.097	0.091	0.098
612	-	0.090	0.091	0.093	0.091	0.089	0.098	0.091	0.087	0.094	0.095
621	-	-	-	-	0.095	0.095	0.092	0.092	0.095	0.095	0.096
RURAL AREA											
ATR	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
309	0.124	0.125	0.124	0.122	0.116	0.113	0.116	0.100	0.123	0.123	0.084
310	0.131	0.134	0.132	0.131	0.130	0.125	0.130	0.138	0.137	0.133	0.131
313	0.146	0.149	0.139	0.139	0.138	0.137	0.145	0.147	0.146	0.150	0.148
318	0.120	0.124	0.124	0.123	0.113	0.116	0.120	0.126	0.126	0.125	0.104
401	0.127	0.124	0.115	0.116	0.115	0.111	0.119	0.117	0.118	0.122	0.123
403	0.139	0.144	0.135	0.133	0.134	0.132	0.137	0.142	0.143	0.146	0.141
513	0.125	0.134	0.128	0.128	0.127	0.125	0.133	0.134	0.135	0.140	0.130

4.4.1.1 Directional Distribution (D)

The Utah data had directional volumes for every hour for each ATR site. For the 30th highest hour identified, the higher percentage of traffic in a direction was calculated to represent the directional distribution. The values of D for the ATR sites in urban and rural area are provided in Table 4.2.

The directional distribution varies during the hour, day, and month of the daily peak volume hours and also with the road type (*58*). Land use, travel patterns, and capacity are some of the factors that are uncertain and affect the directional distribution of traffic. Hence, D was also treated as a random variable with mean μ_D and standard deviation σ_D. Statistical distributions for D obtained from the analysis in MINITAB for the ATR stations in urban and rural area are shown in Figure 4.1-c and 4.1-d. The natural variation in D is best represented by a two-parameter exponential distribution in urban locations and by a normal distribution in rural locations.

Table 4.2 Values of D

URBAN AREA											
ATR	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
306	0.506	0.510	0.523	0.521	0.534	0.528	0.523	0.538	0.580	0.566	0.543
315	0.600	0.576	0.595	0.592	0.587	0.567	0.611	0.518	0.555	0.579	0.506
340	-	-	0.631	0.522	0.616	0.502	0.587	0.502	0.587	0.539	0.519
348	-	-	-	-	-	-	0.513	0.500	0.509	0.522	0.504
611	0.604	0.535	0.613	0.602	0.595	0.607	0.543	0.561	0.583	0.640	0.583
612	-	0.511	0.505	0.539	0.562	0.541	0.576	0.545	0.558	0.557	0.568
621	-	-	-	-	0.516	0.511	0.500	0.516	0.503	0.562	0.507
RURAL AREA											
ATR	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
309	0.588	0.649	0.677	0.704	0.694	0.524	0.679	0.503	0.676	0.510	0.524
310	0.696	0.689	0.564	0.658	0.626	0.573	0.633	0.669	0.606	0.548	0.725
313	0.617	0.692	0.622	0.687	0.522	0.722	0.687	0.633	0.702	0.613	0.745
318	0.639	0.579	0.554	0.602	0.617	0.690	0.539	0.542	0.548	0.571	0.611
401	0.511	0.684	0.545	0.555	0.666	0.562	0.619	0.730	0.636	0.548	0.629
403	0.579	0.659	0.603	0.578	0.642	0.560	0.587	0.678	0.552	0.714	0.632
513	0.609	0.559	0.536	0.623	0.595	0.622	0.600	0.631	0.526	0.692	0.664

4.4.1.2 Average Speed (S) as a Function of Free-Flow Speed (FFS)

As noted above, free-flow speed plays a major role in the estimation of the density and LOS by influencing the selection of the appropriate speed-flow curve, and therefore influencing the average speed estimate for a given demand volume. Even under similar roadway conditions, drivers select a range of speeds based on the road characteristics. Some driver-specific differences are present in the perception of speed and control of the vehicle as well, which causes additional variation in free-flow speeds (*59*). This kind of variation in speeds is generally approximated by the normal distribution. The Utah ATR data did not include information on speeds. The mean and the standard deviation of the speeds were approximated to a value as 65-70 mph and 7-10 mph for urban and rural areas, respectively. Hence free-flow speed was considered to be random variable with mean μ_{FFS} and standard deviation σ_{FFS}. The distributions for free-flow speeds are shown in Figure 4.1-e and 4.1-f. The standard deviation of mean speeds was assumed to be equal to σ_{FFS}.

4.4.1.3 Heavy-Vehicle Adjustment Factor (f_{HV})

The heavy vehicle adjustment factor has inherent uncertainty because of 1) uncertainty in the heavy vehicle volume estimates (i.e., P_T) and 2) uncertainty in passenger-car equivalencies (i.e., E_T). This study only considered the uncertainty in the heavy vehicle volumes, which are due to the difficulty of quantifying effects of region and area populations and demand (*60*). The PCE value of trucks was assumed to be a constant value of 1.5 for this analysis and was taken from the HCM for level terrain. The values of f_{HV} were calculated based on equation 4 using the ranges of heavy vehicle percentages observed at the ATR sites. Hence, f_{HV} was considered to be a random variable with mean μ_{fHV} and standard deviation σ_{fHV}. The values of f_{HV} for the ATR sites in urban and rural area are shown in the Table 4.3, and the distributions are shown in Figure

1-g and 1-h. A Weibull distribution was selected to represent the variability in f_{HV} for both urban and rural locations.

Table 4.3 Values of f_{HV}

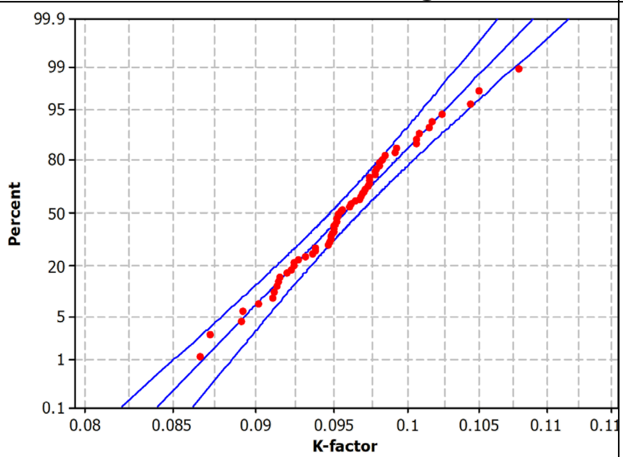
URBAN AREA										
ATR	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
306	-	0.791	0.971	0.909	0.939	0.866	0.905	0.913	0.885	0.930	-
315	-	0.901	0.962	0.966	0.962	0.962	0.957	0.957	0.943	0.877	-
340	-	-	0.966	0.957	0.957	0.935	0.935	0.935	0.935	0.935	-
348	-	-	-	-	-	-	0.922	0.873	0.930	0.885	-
611	-	0.858	0.952	0.909	0.948	0.866	0.893	0.901	0.851	0.901	-
612	-	0.901	0.943	0.943	0.939	0.943	0.939	0.909	0.877	0.851	-
621	-	-	-	-	0.917	0.922	0.922	0.922	0.881	0.881	-
RURAL AREA											
ATR	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
309	-	0.803	0.787	0.775	0.813	0.806	0.803	0.810	0.813	0.810	-
310	-	0.897	0.885	0.877	0.870	0.873	0.873	0.877	0.909	0.862	-
313	-	0.847	0.943	0.935	0.930	0.922	0.873	0.897	0.901	0.830	-
318	-	0.816	0.851	0.893	0.844	0.840	0.781	0.781	0.781	0.855	-
401	-	0.897	0.897	0.866	0.897	0.901	0.905	0.913	0.922	0.922	-
403	-	0.881	0.885	0.877	0.866	0.870	0.866	0.870	0.889	0.885	-
513	-	0.877	0.877	0.870	0.862	0.866	0.866	0.877	0.889	0.889	-

The selected distribution and statistics for all design inputs discussed in this section are shown in Table 4.4.

Table 4.4 Statistics of Input Variables

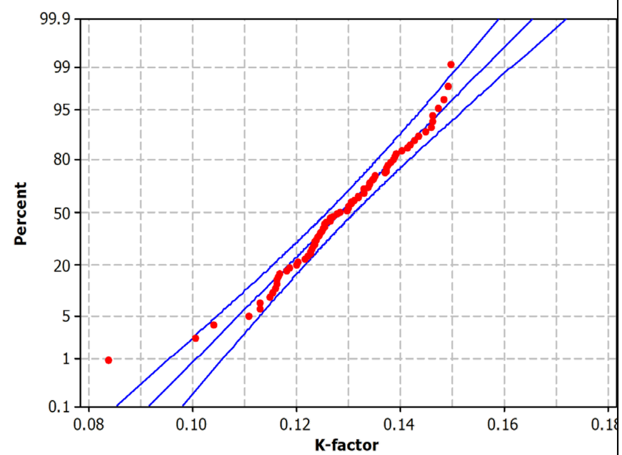
DESIGN INPUT	DISTRIBUTION AND DESCRIPTIVE STATISTICS	URBAN AREA	RURAL AREA
K_{30}	Distribution	Lognormal	Normal
	Mean	0.095	0.128
	Stdev	0.004	0.012
D	Distribution	2-parameter Exponential	Normal
	Mean	0.551	0.617
	Stdev	0.038	0.062
FFS	Distribution	Normal	Normal
	Mean	69.33	66.71
	Stdev	7.633	9.094
f_{HV}	Distribution	Weibull	Weibull
	Mean	0.917	0.865
	Stdev	0.037	0.041

[1-a] K 30 for Urban - Lognormal



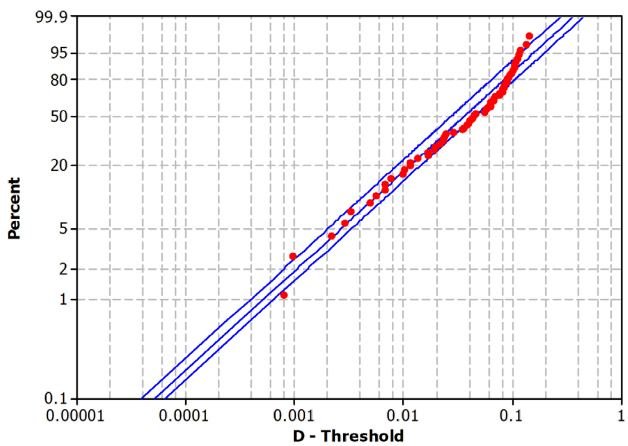
AD = 0.437, P-Value = 0.289

[1-b] K 30 for Rural - Normal



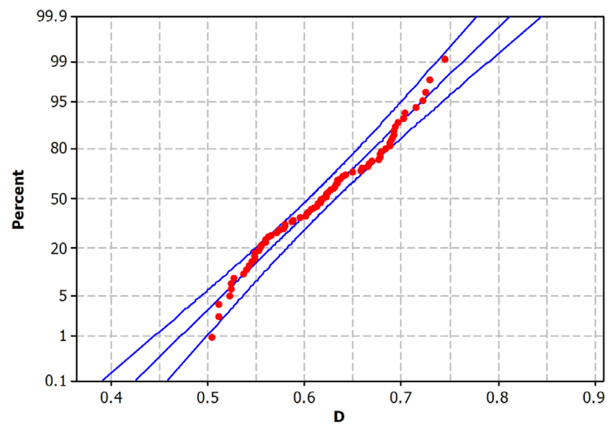
AD = 0.359, P-Value = 0.442

[1-c] D for Urban – 2 P Exponential



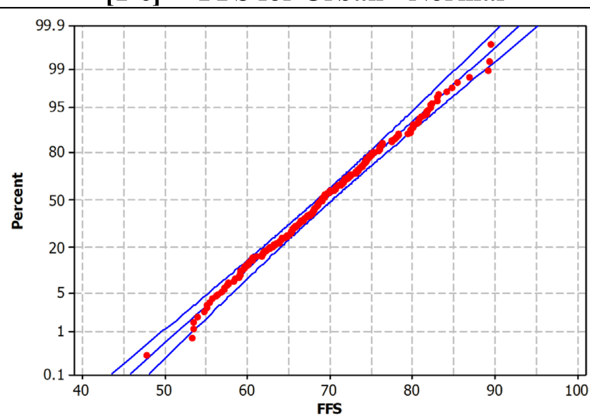
AD = 1.197, P-Value = 0.055

[1-d] D for Rural - Normal



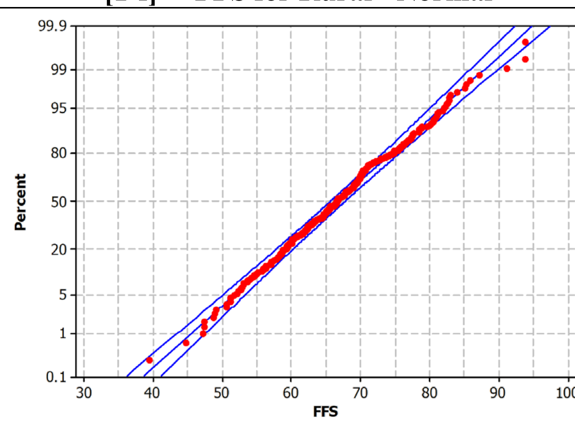
AD = 0.660, P-Value = 0.082

[1-e] FFS for Urban - Normal



AD = 0.256, P-Value = 0.724

[1-f] FFS for Rural - Normal



AD = 0.355, P-Value = 0.458

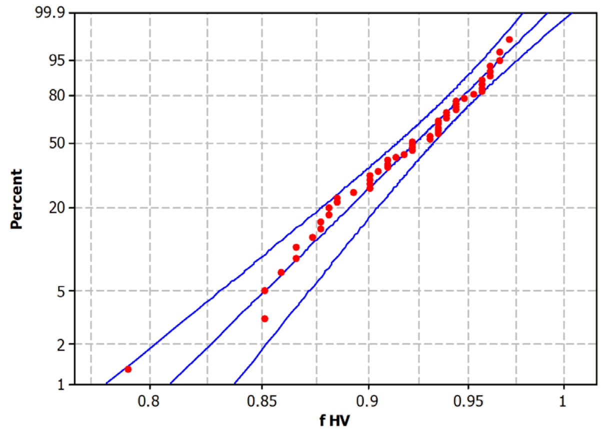
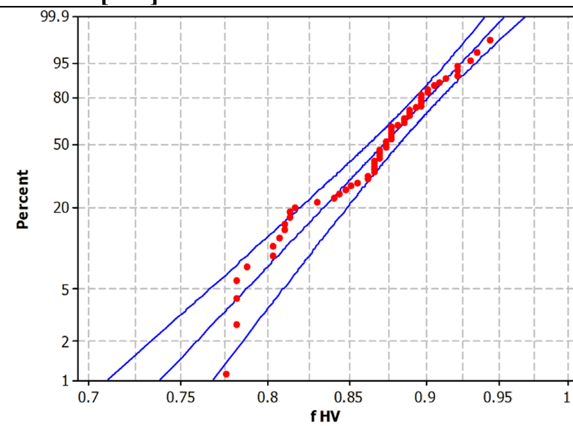
[1-g] f HV for Urban - Weibull	[1-h] f HV for Rural - Weibull
	
AD = 0.406, P-Value > 0.250	**AD = 0.616, P-Value = 0.105**

Figure 4.1 Statistical Distributions of K_{30}, D, FFS, f_{HV} for Urban and Rural Areas

4.5 Example Results (Density Estimation)

As previously discussed, the LOS for a freeway segment is determined from estimates of traffic density. Designers and transportation agencies face decisions on whether design alternatives with a certain basic number of lanes will result in "acceptable" operations. Comparisons of estimated LOS to a design LOS provide critical insights to these decisions. Estimates for density and LOS resulting from the application of HCM methodologies are "one number" and "one letter." However, the uncertainty involved in design year projections of traffic-related characteristics will ultimately result in uncertainty in density and LOS estimates in the design hour. This uncertainty could influence whether or not a design alternative maintains the design LOS over the design period. In this study, the variability of the vehicle density and LOS resulting from uncertainty in the traffic-related variables is obtained by means of Monte Carlo simulation. This provides designers with an explicit, quantitative understanding of what the range in operational performance resulting from design decisions is likely to be. Vehicle density was also determined by the current deterministic approaches so the meaning of results obtained from the two approaches could be compared.

4.5.1 Method I: Reliability-Based Method (Monte Carlo Simulation)

Monte Carlo simulation requires the knowledge of the distributions of the input variables and a performance function to correlate this distribution with vehicle density. As applied in this case, the Monte Carlo simulation generated 100,000 sets of random input values based on the selected statistical distributions developed to obtain a distribution of the vehicle density. Design year AADT values of 75,000 and 14,000 and PHF values of 0.92 and 0.88 were assumed for an urban and rural segment, respectively. These represented average AADT values for the Interstate 15 and Interstate 80 segments used to develop the statistical distributions of input variables. For a given number of lanes, vehicle density was then computed using Monte Carlo simulation as part of the proposed reliability-based framework. The results are presented in Table 4.5, which includes descriptive statistics of density distributions and selected percentile values for densities. Figure 4.2 shows example density distributions for three directional travel lanes on the urban segment with 75,000 vehicles per day and for two travel lanes on the rural segment with 14,000 vehicles per day. Similar figures were developed for each area type and number of lanes combination.

4.5.1.1 Discussion of Results: Urban Segment

The top half of Table 4.5 provides information on the probability distribution of operational performance that might result from basic number of lanes decisions made to achieve a design LOS on an urban freeway in flat terrain with a design year AADT of 75,000 vehicles per day. The results account for uncertainty in estimates of K_{30}, D, FFS, f_{HV}. The design LOS for this urban freeway segment is C. The segment would be expected (i.e., on average) to operate at LOS D with a density of 34 pc/mi/ln if two lanes per direction were provided. There is a 3% chance that the segment would operate at or better than the design LOS of C; a little more than a 25% chance that the segment would operate at LOS E; and a 5% chance that the segment would operate at LOS F with two lanes per direction.

The segment would be expected to operate at LOS C with a density of 23 pc/mi/ln with three lanes per direction. There is an approximately 84% chance that the segment would operate at or better than the design LOS of C; a little more than a 16% chance that the segment would operate at LOS D. There is a very minimal chance (i.e., less than 1%) that the segment would operate at LOS E. There is a 99% chance that the segment would operate at LOS C or better with four directional lanes. This includes a 75% chance that the segment would operate at LOS B or better.

Table 4.5 Statistics and Percentile Values of Vehicle Density for Different Number of Lanes Alternatives

URBAN AREA							
Number of Lanes	**Avg. density (pc/mi/ln)**	**Standard deviation**	**50th percentile**	**75th percentile**	**95th percentile**	**99th percentile**	**Probability that design LOS C is not met**
2	34.105	5.447	33.348	37.038	44.067	50.850	96.95%
3	22.737	3.631	22.232	24.692	29.378	33.895	16.46%
4	17.053	2.723	16.674	18.519	22.030	25.424	0.77%
RURAL AREA							
Number of Lanes	**Avg. density (pc/mi/ln)**	**Standard deviation**	**50th percentile**	**75th percentile**	**95th percentile**	**99th percentile**	**Probability that design LOS B is not met**
2	11.098	2.308	10.825	12.431	15.264	17.807	0.88%
3	7.399	1.540	7.217	8.287	10.176	11.871	0%

4.5.1.2 Discussion of Results: Rural Segment

The bottom half of Table 4.5 provides information on the probability distribution of operational performance that might result from basic number of lanes decisions made to achieve a design LOS on a rural freeway in flat terrain with a design year AADT of 14,000 vehicles per day. As with the urban area analysis, the results account for uncertainty in estimates of K_{30}, D, FFS, f_{HV}. The design LOS for this rural freeway segment is B. The segment would be expected (i.e., on average) to operate at a high LOS B with a density of 11 pc/mi/ln with two lanes per direction. There is a 50% chance that the rural segment would operate at LOS A and a very minimal (i.e., less than 1% chance) that the rural segment would operate worse than LOS B with two lanes per direction. Given the low design year AADT, an LOS A is expected with three lanes per direction with only a 1% chance of operating at LOS B.

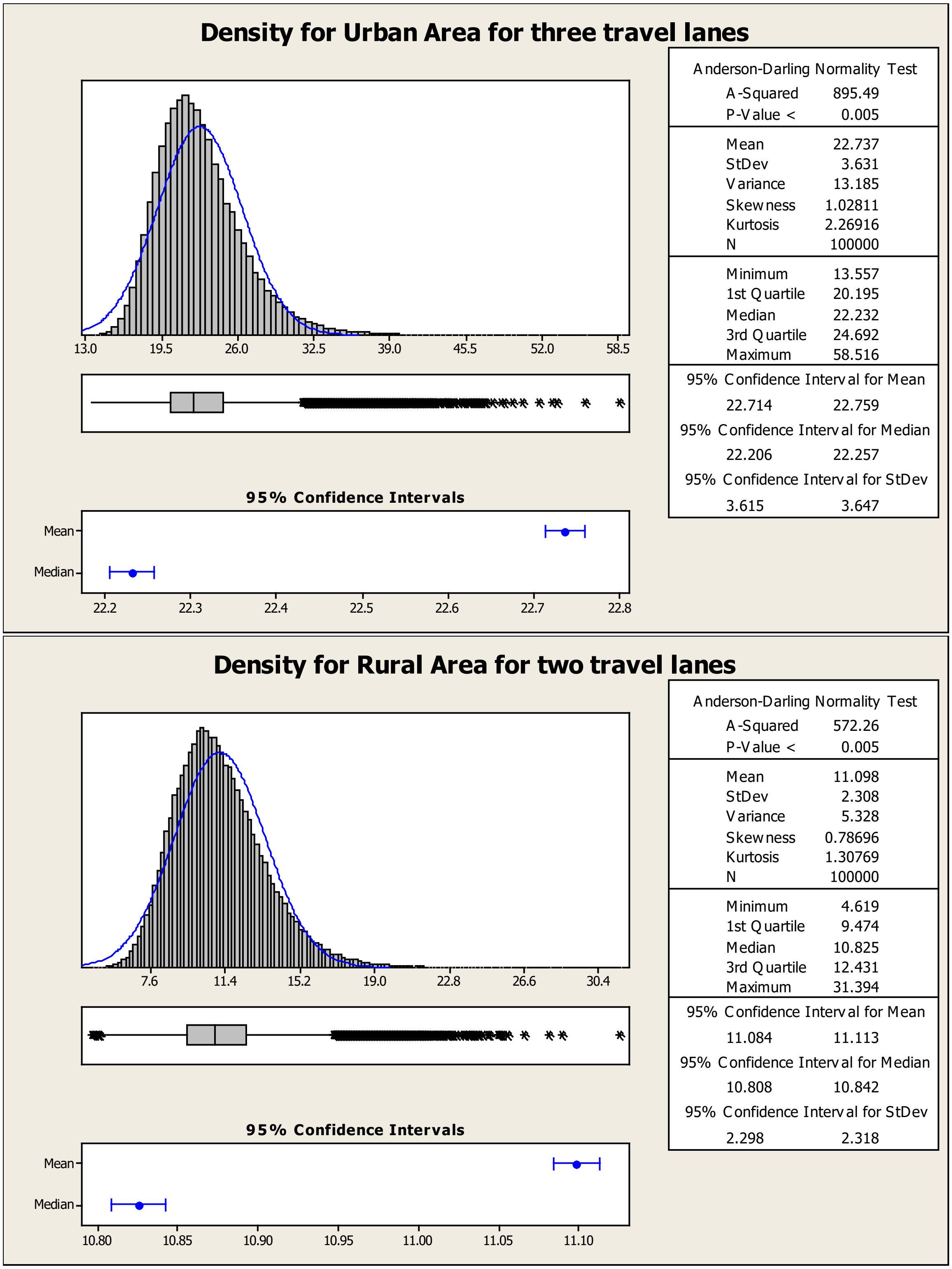


Figure 4.2 Vehicle Density Distributions for a Given Number of Lanes in Urban and Rural Areas

4.5.2 Method II: Current Deterministic Approach

Deterministic analysis does not explicitly consider uncertainties in input variable values. As mentioned earlier, in a deterministic sense, there exists only "one number/value" for density from a deterministic approach. The vehicle density is calculated using equation 6, by inserting one value for each of the input parameters. The values of AADT and PHF were assumed to be the same as above (i.e., 75,000 vehicles per day and 0.92 for the urban segment and 14,000 vehicles per day and 0.88 for the rural segment). Values for K_{30}, D, FFS, and f_{HV} were taken to be the means of the variable distributions used in the reliability-based approach. The density values estimated for different number of lanes alternatives, and the resulting LOS, are presented in Table 4.6. Example density calculations for three directional travel lanes in an urban area and two directional travel lanes in a rural area are shown below:

For an urban area:

$$Density = \frac{(K \times D \times AADT)}{(S \times f_{HV} \times N \times PHF)} = \frac{(0.095 \times 0.551 \times 75000)}{(69.33 \times 0.917 \times 3 \times 0.92)} = 22.37 pc/mi/ln$$

For a rural area:

$$Density = \frac{(K \times D \times AADT)}{(S \times f_{HV} \times N \times PHF)} = \frac{(0.128 \times 0.617 \times 14000)}{(66.71 \times 0.865 \times 2 \times 0.88)} = 10.89 pc/mi/ln$$

As noted, one number and one letter represent estimates for density and LOS in a deterministic analysis. For example, the deterministic analysis indicates a design LOS C, with a density of approximately 23 pc/mi/ln on the urban segment in flat terrain with three lanes per direction. Recall from the probabilistic approach that the segment would be expected (i.e., on average) to operate at LOS C with a density of 23 pc/mi/ln with three lanes per direction. However, the probabilistic approach provides the following additional details:

- There is an approximately 84% chance that the segment would operate at or better than the design LOS C.
- There is little more than a 16% chance that the segment would operate at LOS D.
- There is a very minimal chance (i.e., less than 1%) that the segment would operate at LOS E.

In other words, there would be about a 17% chance that three directional lanes would not be sufficient in the design year to maintain the design LOS. The designer would have this possibility to weigh against other performance information, trade-offs, impacts, and costs when making the ultimate number of lanes decisions.

It is important to note that this paper did not explore uncertainty in traffic growth rate used to project a design year AADT, which is expected to be quite significant and complex to estimate. Instead, uncertainties in only K_{30}, D, FFS, and f_{HV} were considered to demonstrate the basic concept. Traffic growth rate estimates will be addressed by future research.

Table 4.6 Values of Vehicle Density and LOS for Different Number of Lanes Alternatives

URBAN AREA		
Number of lanes	**Density (pc/mi/ln)**	**LOS**
2	33.914	D
3	22.609	C
4	16.956	B
RURAL AREA		
Number of lanes	**Density (pc/mi/ln)**	**LOS**
2	10.886	A
3	7.257	A

5. A COMBINED CRASH FREQUENCY – CRASH SEVERITY EVALUATION OF GEOMETRIC DESIGN DECISIONS: ENTRANCE-EXIT RAMP SPACING AND AUXILIARY LANE PRESENCE [PAPER III]

5.1 Introduction

Requests for new access or modifications to existing access on freeways are frequently evaluated by U.S. state departments of transportation (DOTs). Interchange improvements are often intended to increase access to and improve operations on the surrounding network surface streets as well as improve the efficiency and safety of movements to and from the freeway mainline. The Federal Highway Administration (FHWA), part of the U.S. DOT, must approve all new or modified points of access on interstate routes. When adding or improving freeway access points, the FHWA and state DOTs must sometimes balance concerns regarding closely spaced interchange ramps on the freeway mainline and its impact on freeway mainline operations and safety. Significant amounts of documented knowledge and practical experience exist on geometric considerations (*16, 61*), traffic operations (*61*, 69), and signing (*61*, 62) in the context of interchange ramp spacing. Until recently, very little information existed on the safety impacts of ramp spacing. The first edition of the *Highway Safety Manual* concluded that "decreasing interchange spacing appears to increase crashes…the magnitude of the crash effect is not certain at this time" (63).

Access management activities and geometric design decisions related to interchange and ramp spacing have traditionally taken a nominal approach to safety. Additional background on this issue is summarized in (44) and is briefly discussed here. With a nominal approach to safety, acceptable safety performance in the context of interchange ramp spacing is presumed to result from attaining some desired minimum ramp spacing value. New access point requests or modifications to existing access may be denied if the result is ramp spacing smaller than established minimums. A frequently referenced document for minimum ramp spacing values is AASHTO's *A Policy on Geometric Design of Highways and Streets* (Green Book) (16). *NCHRP Web Only Document 169* included a historical look at the origins of current interchange and ramp spacing guidance in the Green Book (64). This web only document noted that Jack E. Leisch presented a paper to the Region 2 AASHTO Operating Committee on Design in Mobile, Alabama. Leisch's paper contained a table with "Recommended Minimum Ramp Terminal Spacing" for various combinations of ramps (65). The values recommended by Leisch have influenced all succeeding versions of AASHTO's design policies (*16, 33, 66-69*). The values are a function of ramp sequence (e.g., entrance followed by exit, two consecutive entrance ramps) and interchange types (system or service). The focus of this paper is the ramp sequence of an entrance ramp followed by a downstream exit ramp (EN-EX).

Ramp braids or collector-distributor roads are sometimes explored as alternatives to EN-EX ramp sequences with shorter spacing values to remove intense weaving movements from the freeway mainline. The Green Book also notes that an auxiliary lane to connect the speed change lanes of the entrance and exit ramps should be provided when the ramp spacing is less than 1,500 feet. Meeting minimum criteria values satisfies the nominal approach to safety, and the geometric condition is presumed "reasonably safe."

The nominal approach to safety oversimplifies driver behavior and complex interactions between roadway geometrics, traffic operations, and safety (*64*). It also oversimplifies the decision-making framework of managing freeway access and promotes a "one size fits all" approach to evaluating interchange design alternatives. Benefits, costs, and impacts should be quantified and evaluated on a case-by-case basis. Tools are becoming increasing available to take more of a performance-based safety approach to interchange design and freeway access management. Most relevant to this topic, recent research developed crash modification factors for EN-EX ramp spacing and auxiliary lane presence (*44*). It quantified how and by how much expected crash frequency increases as ramp spacing decreases. Multiple-vehicle crashes were most sensitive to the changes in ramp spacing compared with other crash types. Single-vehicle crashes were also modeled but showed no relationship to ramp spacing. The sensitivity between expected crash frequency and ramp spacing was highest at shorter spacing values. At longer values for ramp spacing, there was a point beyond which the spacing effect "disappeared" and the safety performance approached that of a basic freeway segment. Similarly, an auxiliary lane connecting the speed change lanes of the entrance and exit ramps had greater safety benefits (in terms of a percent reduction in expected crash frequency) as ramp spacing decreased.

Safety is defined not only by expected crash frequency, but also by the severity of crashes. The previous work reported in (*44*) started to uncover some potentially useful findings regarding the effects of ramp spacing on crash severity. Separate crash frequency models for different levels of severity suggested an increase in the frequency of severe (fatal-plus-injury) crashes with decreasing ramp spacing; however, the expected proportion of crashes resulting in a fatality or injury appeared to decrease as ramp spacing decreased. This finding was derived from a set of separate crash frequency models for different levels of severity [i.e., one model for the frequency of total crashes (all severities), another separate model for fatal-plus-injury crashes]. Previous severity modeling research has noted that a series of crash frequency models, developed in this way for each level of severity, "can introduce significant estimation errors in that it implicitly assumes that the factors generating the occurrence of an accident are independent across severity outcomes" (*70*). Severity may be more appropriately handled by a "severity distribution function," which predicts proportions of different crash severity levels as a function of traffic and roadway features, including geometrics.

This paper extends previous work in (*44*), which focused on the relationships between expected crash frequency and interchange ramp spacing (with or without auxiliary lanes) by exploring the effects of freeway ramp spacing and auxiliary lane presence on both crash frequency and crash severity. Crash severity effects are predicted from a "severity distribution function," developed using a multinomial logit modeling approach. The paper then demonstrates how to combine quantitative knowledge related to the effects of ramp spacing and auxiliary lane presence on both crash frequency and severity into a framework for assessing the overall crash cost for different ramp configurations. Ideas for this research were based on a critical assessment of published research to date, which is summarized in the next section.

5.2 Literature Review

Only four studies the authors know of have taken a direct look at the relationship between interchange or ramp spacing and safety (*44; 71-73*). Other research has explored the issue somewhat indirectly, either by estimating the effect of ramp and interchange presence on safety without considering a spacing effect (74-*79*) or by reporting the safety effects of a ramp or interchange count or density on a freeway segment through a multivariate regression model (80-*81*). Of those papers directly exploring the ramp spacing safety effect, the research reported in (*44*), which developed crash modification factors for EN-EX ramp spacing and auxiliary lane presence, is most relevant to this paper. Results in (44) were discussed at length in the introduction section of this paper, with particular attention to potential weaknesses in how crash severity was addressed. It was noted that crash severity may be more appropriately handled by a "severity distribution function," which predicts proportions of different crash severity levels as a function of traffic and roadway features, including geometrics.

Severity distributions are likely to change significantly with traffic volume. Design decisions may also influence severity distributions through a resulting increase or decrease in operating speeds (e.g., an increase or decrease in lane and shoulder widths, increase or decrease in ramp spacing). Severity distributions are likely to vary with traffic volumes and design decisions depending on the crash type of interest. Research in modeling crash severity as a function of these types of roadway features and others has been extensive. A comprehensive summary is provided by (*80*). The multinomial logit (*83*), nested logit (*84*), and ordered outcome models (*85*) are frequently explored modeling alternatives for developing severity distribution functions that were considered for this paper.

Results of crash frequency models can be combined with the results of crash severity models to estimate the number of crashes of different severity levels (*86, 87*). A similar approach was recently implemented as part of NCHRP 17-45, *Enhanced Safety Prediction Methodology and Analysis Tool for Freeways and Interchanges (88).* In summary, the published literature and ongoing research work have shown promise in creating severity distributions functions using different types of discrete choice modeling approaches and then combining information on both crash frequency and severity to gain a more comprehensive view of the safety effects of design decisions.

5.3 Research Objective

The objective of this paper is to quantify the effects of interchange ramp spacing and auxiliary lane presence on both expected crash frequency and crash severity. Crash frequencies are predicted using a safety performance function, and crash severity distributions are estimated from a "severity distribution function," developed using a multinomial logit modeling approach. The quantitative knowledge related to the effects of ramp spacing and auxiliary lane presence on both crash frequency and severity are then combined into a framework for assessing the overall crash cost for different ramp configurations. A case study is provided to demonstrate this application.

5.4 Data Collection

Developing both crash frequency and crash severity models requires two different datasets. The two following sections provide descriptions of the crash frequency dataset and crash severity dataset. More detail is provided on the frequency dataset because the crash severity dataset includes the same data and variables, but structured in a different form than is necessary for estimating crash severity models.

5.4.1 Crash Frequency Dataset

The crash frequency dataset was essentially the same as that described in (*44*), with some key differences in the crash counts used for analysis required for the combined frequency-severity assessment in this paper. Data included freeway geometric features, traffic characteristics, and crash counts collected in California and Washington State. These two states were selected because both have comprehensive and accessible freeway, ramp, and crash databases. Data were collected using a combination of various tools and resources:

- Digital mapping and satellite imaging applications, primarily Google Earth and Google Maps
- Online interchange database available through Washington State Department of Transportation's (WSDOT) Interchange Viewer
- Online video logs available through WSDOT's SRweb and the California Department of Transportation's (Caltrans) Performance Measurement System-PeMS
- FHWA's Highway Safety Information System (HSIS) database

More than 1,600 directional miles of freeways in Washington State and more than 2,000 directional miles of freeways in California were scanned using Google Maps and Google Earth to identify candidate freeway segments to study. The analysis described in this paper was focused only on segments with diamond interchanges, including basic diamonds as well as tight urban diamonds, half diamonds, and single point urban interchanges (SPUIs). For the frequency modeling, a study segment (i.e., one row in the database) was defined from cross street to cross street. Ramp spacing was defined from painted gore to painted gore. These definitions are illustrated in Figure 5.1.

Segments were excluded from the dataset if construction activity was identified on or near the segment from 2006 through 2008 (the observation period for each segment). Temporary traffic control devices on the video logs or construction areas present on current and archived Google Earth photographs were used to identify these segments. Segments with missing volume counts were also excluded, as well as segments that included rest-area ramps between entrance and exit ramps associated with two consecutive cross streets. The final datasets used to estimate the crash frequency models consisted of 404 segments, 154 from Washington State and 250 from California.

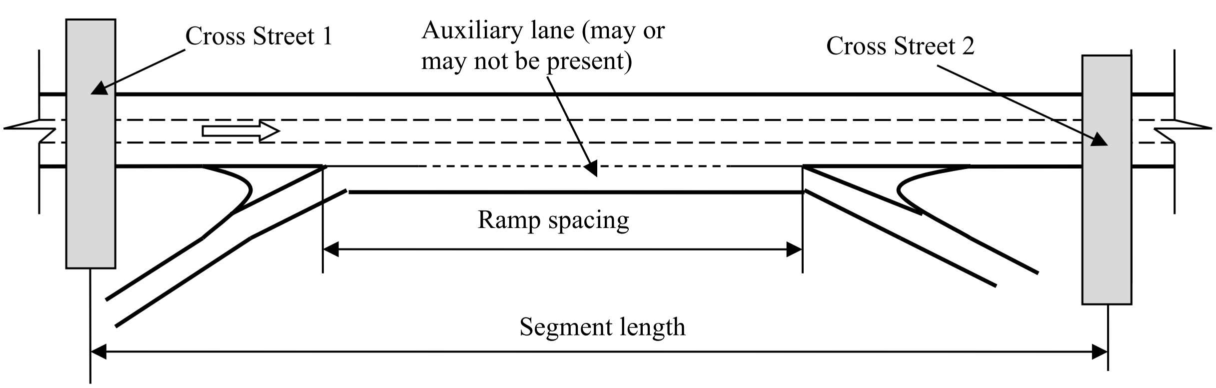


Figure 5.1 Freeway Segment and Ramp Spacing Definition (6)

5.4.1.1 Traffic and Geometric Data for Defined Freeway Segments

Traffic and geometric data were collected for each defined freeway segment. Freeway mainline traffic volumes were collected from HSIS roadway files using route number and mainline milepost variables to identify the correct volume measurement. The mainline traffic volume assigned to each defined freeway segment represented the average daily traffic just upstream of the segment. The HSIS files included bi-directional traffic volumes. Directional traffic for all segments would have been ideal since the segments were direction specific. The authors of (*44*) completed an exploratory analysis on a smaller scale using directional daily traffic for Washington segments, estimated using WSDOT's Permanent Traffic Recorder (PTR) stations. Data collected at PTR stations are summarized in WSDOT's annual traffic reports and include directional mainline traffic volumes. The directional volume information was used to estimate a directional traffic volume ratio (D). The research team then assumed that the directional traffic volume ratio for each defined freeway segment was the same or very close to the volume ratio at the nearest PTR station. All defined freeway segments had an estimated directional traffic volume ratio falling between 0.49 and 0.51 using this approach. The assumption that directional volume equals approximately one-half of the bidirectional volume was made based on these findings. Entering and exiting traffic volumes were determined using ramp identification numbers and ramp milepost variables and represented the average daily traffic on the entrance and exit ramp-freeway terminals, respectively. The number of through lanes was determined using HSIS roadway files and confirmed with video logs, Google Earth's aerial photography, and Google Maps' Street View. The presence of an auxiliary lane between an entrance and exit ramp was determined from the interchange diagrams and also confirmed with video logs and Google Earth. The relative vertical positions between the freeway mainline and cross streets, as well as the number of lanes at the entrance ramp-freeway terminal, were determined from video logs and Google Earth. Data on the presence of high occupancy vehicle (HOV) lanes on the mainline or entrance ramp, as well as the presence of ramp meters, were collected using satellite photography, video logs, and interchange diagrams. The measurement tool in Google Earth was also used in some cases to verify segment length and ramp spacing determined from the video logs and interchange diagrams.

5.4.1.2 Crash Frequencies

The number of crashes occurring on each freeway segment (i.e., between the cross streets) in the years 2006, 2007, and 2008 were counted using route number and milepost variables. Previous work found that multiple-vehicle crashes were most sensitive to the changes in ramp spacing and single-vehicle crashes showed no relationship to ramp spacing (*44*). Therefore, this paper focuses only on multiple-vehicle crashes. The following crash counts were made:

- Number of reported multiple-vehicle crashes resulting in at least one fatality or injury of any level (MV-KABC)
- Number of reported multiple-vehicle crashes resulting in property damage only (MV-O)

Crashes were counted if they were coded as occurring anywhere in the roadway or roadside of the freeway mainline and in the same direction of travel served by the interchange ramps. These included, for example, crashes that occurred in the outside lanes adjacent to the entrance and exit ramp terminals and crashes that occurred on the inside lanes, possibly a result of lane changing associated with drivers attempting to avoid the traffic disturbance caused by the weaving movements or any other general reason for lane changing.

5.4.1.3 Variable Definitions and Data Summary

Notations and definitions of the key variables for this study are defined in Table 5.1. Descriptive statistics for the crash frequency dataset are provided in Table 5.2.

5.4.2 Crash Severity Dataset

The frequency model database was used to estimate crash frequency models for both the expected number of multiple-vehicle crashes resulting in at least one fatality or injury of any level (MV-KABC) and the number of reported multiple-vehicle crashes resulting in property damage only (MV-O). The purpose of the crash severity models is to further disaggregate the MV-KABC into estimated proportions of multiple-vehicle fatal crashes (MV-K), multi-vehicle incapacitating injury crashes (MV-A), multi-vehicle non-incapacitating injury crashes (MV-B), and multi-vehicle possible injury crashes (MV-C), with the severity of the crash defined by the most severe injury sustained by any driver or occupant involved in the crash. A severity model is not needed to predict property damage only (PDO) crashes, as they are estimated separately during the frequency modeling (i.e., the MV-O crash frequency model predicts only PDO crashes, so there is no need to further disaggregate them by severity level).

The database used to estimate the MV-KABC severity model consisted of the same crashes and road segments as those in the MV-KABC frequency model database, but restructured so that the basic observation unit (i.e., database row) is a crash instead of a road segment. There were 4,262 multi-vehicle fatal plus injury (MV-KABC) crashes across all 404 freeway segments. Therefore, the crash severity dataset had 4,262 observations. Each crash had associated with it an overall crash severity [1 = fatality (K); 2 = incapacitating injury (A); 3 = non-incapacitating injury (B); and 4 = possible injury (C)] as well as the traffic and roadway characteristics at the location and time of the crash. Descriptive statistics for the geometric, traffic, and crash severity outcomes associated with the 4,262 MV-KABC crashes are provided in Table 5.3.

Table 5.1 Crash Frequency and Severity Key Variables and Definitions

Name	Definition
L (miles)	Segment length, defined from the cross street associated with the entrance ramp to the cross street associated with the next downstream exit ramp
Ln(DADT)	Estimated one-way (directional) average daily traffic volume upstream of the entrance ramp (vehicles/day)
Ln(ADTEn)	Average daily traffic volume on the entrance ramp (vehicles/day)
Ln(ADTEx)	Average daily traffic volume on the exit ramp (vehicles/day)
DADT/1000	Estimated one-way (directional) average daily traffic volume upstream of the entrance ramp (thousands of vehicles/day)
ADT_{en}/1000	Average daily traffic volume on the entrance ramp (thousands of vehicles/day)
ADT_{ex}/1000	Average daily traffic volume on the exit ramp (thousands of vehicles/day)
S	Ramp spacing, defined from painted gore of the entrance ramp to painted gore of the exit ramp (feet)
Invspa	Inverse of ramp spacing, 1/S ($feet^{-1}$)
Auxln	Indicator variable for the presence of an auxiliary lane connecting the entrance and exit ramps (1= auxiliary lane present, 0 otherwise)
Invspa_aux	Interaction variable for inverse spacing and the presence of an auxiliary lane (Invspa*Auxln = Auxln/S)
Upstream_2	Indicator variable of study segments with 2 travel way lanes upstream of the entrance ramp gore (1 = freeway mainline has 2 lanes upstream of segment, and 0 otherwise)
Upstream_3	Indicator variable of study segments with 3 travel way lanes upstream of the entrance ramp gore (1 = freeway mainline has 3 lanes upstream of segment, and 0 otherwise)
Mainline1	Indicator variable for the relative vertical position between the freeway mainline and the cross street associated with the entrance ramp (1=mainline over cross street, 0 otherwise)
Mainline2	Indicator variable for the relative vertical position between the freeway mainline and the cross street associated with the exit ramp (1=mainline over cross street, 0 otherwise)
Rmpmet	Indicator variable for the presence of a ramp meter on the entrance ramp (1= ramp meter present, 0 otherwise)
HOV_{en}	Indicator variable for the presence of an HOV lane on the entrance ramp (1=presence of an HOV lane, 0 otherwise)
HOV_{main}	Indicator variable for the presence of an HOV lane on the freeway mainline (1=presence of an HOV lane, 0 otherwise)
CA_5	Indicator variable for study segments located on Interstate 5 in California (1= I-5 in California, 0 otherwise)
CA_10	indicator variable for study segments located on Interstate 10 in California (1= I-10 in California, 0 otherwise)
WA_5	Indicator variable for study segments located on Interstate 5 in Washington (1= I-5 in Washington, 0 otherwise)
MV-KABC	Number of reported multiple-vehicle crashes resulting in at least one fatality or injury of any level
MV-O	Number of reported multiple-vehicle crashes resulting in property damage only

Table 5.2 Descriptive Statistics for Geometric, Traffic and Crash Data for 404 Segments used for the Crash Frequency Modeling

Variable	Mean	Std. Dev.	Min	Max
L (miles)	2.35	1.80	0.50	10.41
Ln(DADT) (vehicles/day)	10.672	0.823	8.544	11.9415
Ln(ADT_{En}) (vehicles/day)	8.345	1.346	2.833	9.864
Ln(ADT_{Ex}) (vehicles/day)	8.349	1.307	3.219	9.873
S (feet)	9677.19	9508.98	316.80	52219.20
HOVMain	0.07	0.25	0	1
HOVEn	0.06	0.23	0	1
RampMet	0.12	0.32	0	1
AuxLane	0.12	0.32	0.00	1.00
Upstream_2	0.48	0.50	0	1
Upstream_3	0.27	0.44	0	1
Mainline1	0.43	0.50	0	1
Mainline2	0.43	0.50	0.00	1.00
CA_5	0.42	0.49	0	1
CA_10	0.20	0.40	0	1
WA_5	0.20	0.40	0	1
MV-O	22.04	31.42	0	359
MV-KABC	10.55	13.58	0	96

Table 5.3 Descriptive Statistics for Geometric, Traffic, and Crash Severity Outcomes for the 4,262 MV-KABC Crashes used for the Crash Severity Modeling

Variable	Mean	Std. Dev.	Min	Max
SEVERITY[a]	3.63	0.65	1	4
MV-K	0.02	0.13	0	1
MV-A	0.05	0.21	0	1
MV-B	0.23	0.42	0	1
MV-C	0.71	0.46	0	1
L (miles)	1.76	1.45	0.50	10.41
DADT/1000 (thousands of vehicles/day)	76.55	37.90	5.13	154
ADT_{En}/1000 (thousands of vehicles/day)	7.21	4.26	0.04	19.23
ADT_{Ex}/1000 (thousands of vehicles/day)	7.34	4.50	0.03	19
S (feet)	6671.08	7568.18	317	52219
InvSpai	3.23E-04	3.34E-04	1.92E-05	3.16E-03
AuxLn	0.17	0.38	0	1
Upstream_2	0.17	0.38	0	1
Upstream_3	0.24	0.43	0	1
Mainline1	0.47	0.50	0	1
Mainline2	0.47	0.50	0	1
RampMet	0.36	0.48	0	1
HOVMain	0.20	0.40	0	1
HOVEn	0.15	0.36	0	1
CA_5	0.34	0.47	0	1
CA_10	0.42	0.49	0	1
WA_5	0.12	0.32	0	1

[a]1 = fatality (K); 2 = incapacitating injury (A); 3 = non-incapacitating injury (B); and 4 = possible injury (C)

5.5 Analysis Methodology

This section describes the development of safety performance functions and severity distribution functions used to predict expected crash frequencies and severity distributions, respectively.

5.5.1 Crash Frequency Modeling

The relationships between ramp spacing and the expected frequencies of multi-vehicle crashes were explored in this study using a negative binomial regression modeling approach. In these negative binomial models, the expected number of multi-vehicle crashes of severity group i on freeway segment j was expressed as:

$$\mu_{ij} = E(Y_{ij}) = e^{\left(X_j\beta + ln(L_j)\right)} \tag{1}$$

where:

$\mu_{ij} = E(Y_{ij})$ = the expected number of crashes of severity group *i* on freeway segment *j*;
X_j = a set of traffic and geometric variables characterizing freeway segment *j* (including ramp spacing and auxiliary lane presence);
β = regression coefficients estimated with maximum likelihood that quantify the relationship between $E(Y_{ij})$ and variables in X;
L_j = length of freeway segment *j*; and,
$L_n(L_j)$ = the natural logarithm of segment length.

Specifications of the crash frequency models followed the same general approach as that laid out in (44). Ramp spacing and auxiliary lane presence were the primary variables of interest in the matrix of explanatory variables, X_j. However, a number of other traffic and geometric variables were included to decrease unexplained variation in expected crash frequency and to try and minimize omitted variable bias. Indicator variables for the specific California and Washington interstates were also included to capture the effects of variables common to these corridors, but not captured in the models (e.g., terrain type, weather). This resulted in a form of a fixed effects model. A number of model estimations with and without these indicator variables showed that including them appeared to be effective in reducing omitted variable bias and providing a more accurate estimate of the ramp spacing effects.

Segment length, L, was included in the models as an offset variable (i.e., the regression coefficient for the natural logarithm of segment length was constrained to 1.0) and captures the linear increase in expected crash frequency with an increase in segment length due to increased exposure.

5.5.2 Crash Severity Modeling

The severity distribution functions were estimated using a multinomial logit regression modeling approach. The estimated multinomial logit model can be used to predict the probability (i.e., proportion) of crashes with a specific injury severity outcome, conditioned on a crash having occurred at a location with a defined set of traffic and roadway characteristics. Crash severity was defined by the most severe injury sustained by any driver or occupant involved in a crash. There were four crash severity categories included in the MV-KABC data: 1 = fatality (K); 2 =

incapacitating injury (A); 3 = non-incapacitating injury (B); and 4 = possible injury (C). In the multinomial logit model, the probability that accident *n* will have severity *i* is given by:

$$p_n(i) = \exp(\beta_i X_n) / \sum_I \exp(\beta_I X_n) \quad (2)$$

where:

$p_n(i)$ = the probability that crash n will have overall crash severity level *i*;

X_n = a set of variables (e.g., traffic, geometrics) that influence the crash severity; and

β_i = a vector of parameters to be estimated.

When estimating the multinomial logit model parameters, one severity category is set as the base outcome and the parameters (i.e., β's) for that severity in equation 2 are set to zero. The parameters associated with specific variables and other severity levels then provide an idea how a particular variable (e.g., ramp spacing) either increases or decreases the chance of that particular crash severity outcome compared with the base outcome. Possible injury (C) crashes were set as the base outcome for this analysis. Therefore, the estimated β's for the fatality (K), incapacitating injury (A), and non-incapacitating injury (B) crashes show how a specific feature either increases (positive) or decreases (negative) the likelihood of that injury outcome compared with a possible injury (C) outcome.

5.6 Model Estimation Results and Discussion

The negative binomial and multinomial logit models were estimated using the STATA software package. Model estimation results are provided in "equation form" in the following sections, along with discussion and interpretation of key variables in the models.

5.6.1 Crash Frequency Model Estimation Results

The negative binomial regression model estimation results for the expected number of multiple-vehicle crashes resulting in at least one fatality or injury of any level (MV-KABC) and the expected number of multiple-vehicle crashes resulting in property damage only (MV-O) are represented in equations 3 and 4, respectively:

$$\text{MV-KABC} = L * e^{X_{F\&I}} \quad (3)$$

With

$$\begin{aligned} X_{F\&I} = {} & -18.313 + 1.723 * ln(DADT) + 0.210 * ln(ADT_{en}) + 0.0009 * ln(ADT_{ex}) \\ & + 545.282 * Invspa - 385.564 * Invspa_{Aux} + 0.35 * Upstream\_2 \\ & + 0.031 * Upstream\_3 + 0.143 * Mainline1 - 0.041 * Mainline2 \\ & + 0.087 * Rmpmet - 0.122 * HOV_{en} - 0.066 * HOV_{main} \\ & - 0.417 * CA_{I5} - 0.282 * CA_{I10} - 0.540 * WA\_I5 \end{aligned}$$

$$\text{MV-O}= L * e^{X_{PDO}} \tag{4}$$

With

$$X_{PDO} = -16.373 + 1.622 * ln(DADT) + 0.118 * ln(ADT_{en}) + 0.058 * ln(ADT_{ex}) + 577.065 * Invspa - 332.986 * Invspa_{Aux} + 0.313 * Upstream\_2 + 0.053 * Upstream\_3 - 0.019 * Mainline1 + 0.022 * Mainline2 + 0.021 * Rmpmet - 0.132 * HOV_{en} + 0.162 * HOV_{main} - 0.202 * CA_{I5} + 0.014 * CA_{I10} - 0.499 * WA\_I5$$

Both models contain multiple variables that influence freeway mainline safety, as measured by expected multi-vehicle crash frequencies. The coefficient magnitudes and signs generally conform to engineering intuition. The discussion in this paper will focus on ramp spacing and auxiliary lane presence as the main variables of interest. The inverse ramp spacing parameters for multi-vehicle crash frequencies are positive and statistically significant at the 95% confidence level for both models. The positive parameter indicates an increase in expected multi-vehicle crash frequency as ramp spacing decreases. Figure 5.2 displays the expected annual frequency of MV-KABC and MV-O crashes on a per-mile basis as a function of ramp spacing. It shows that expected crash frequencies increase at a faster and faster rate as spacing gets shorter and shorter. The safety benefit of providing an auxiliary lane (in terms of reductions in expected multi-vehicle crash frequencies) also gets larger as ramp spacing becomes shorter.

All modeling results are consistent with the findings previously presented in (*44*). This paper now extends the findings even further by estimating a severity distribution function, which will take the MV-KABC frequencies, and disaggregate them into estimated proportions of multi-vehicle fatal crashes (MV-K), multi-vehicle incapacitating injury crashes (MV-A), multi-vehicle non-incapacitating injury crashes (MV-B), and multi-vehicle possible injury crashes (MV-C), as a function of traffic and freeway geometrics, including ramp spacing and auxiliary lane presence.

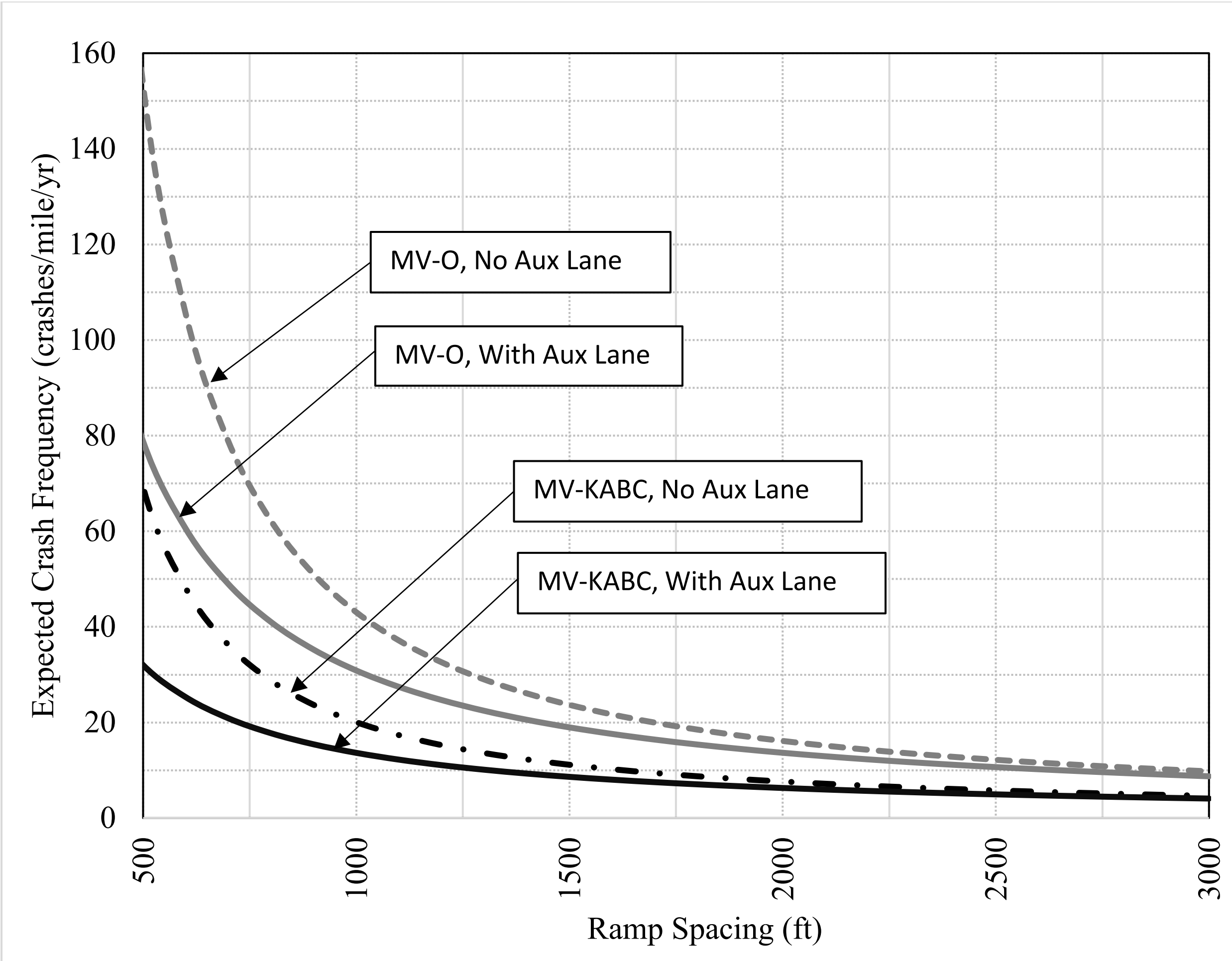


Figure 5.2 The Predicted Number of MV-KABC and MV-O as a Function of Ramp Spacing

5.6.2 Severity Model Estimation Results

The multinomial logit model estimation results can be used to predict the proportion of each crash severity as a function of traffic and road characteristics, including ramp spacing and auxiliary lane presence. Expressions to predict the proportions of crashes that have the classifications of MV-K, MV-A, MV-B, and MV-C severities are provided in equations 5 through 8 below:

$$P_n(\text{MV-K}) = \frac{e^{\beta_K X_K}}{1+e^{\beta_K X_K}+e^{\beta_A X_A}+e^{\beta_B X_B}} \tag{5}$$

$$P_n(\text{MV-A}) = \frac{e^{\beta_A X_A}}{1+e^{\beta_K X_K}+e^{\beta_A X_A}+e^{\beta_B X_B}} \tag{6}$$

$$P_n(\text{MV-B}) = \frac{e^{\beta_B X_B}}{1+e^{\beta_K X_K}+e^{\beta_A X_A}+e^{\beta_B X_B}} \tag{7}$$

$$P_n(\text{MV-C}) = 1 - P_n(\text{MV-K}) - P_n(\text{MV-A}) - P_n(\text{MV-B}) \tag{8}$$

Where:

P_n(MV-K), P_n(MV-A), P_n(MV-B), and P_n(MV-C) represent the proportions of the MV-KABC crashes that are MV-K, MV-A, MV-B, and MV-C, respectively. The estimated beta coefficients associated with each variable are provided in the equations for $\beta_K X_K$, $\beta_A X_A$, and $\beta_B X_B$ below:

$$\beta_K X_K = 2.864 - 0.0258 * ADT/1000 - 0.0261 * ADTEn/1000 + 0.0314 * ADTEx/1000 - 512.43 * InvSpai + 727.95 * InvSpaAux + 0.057 * Upstream\_2 - 0.654 * Upstream\_3 - 0.376 * Mainline1 + 0.0155 * Mainline2 + 0.7509 * RampMet - 0.5106 * HOVEn + 0.00655 * HOVMain + 0.767 * CA\_5 + 1.658 * CA\_10 + 0.551 * WA\_5 \quad (9)$$

$$\beta_A X_A = -2.861 - 0.000752 * ADT/1000 - 0.0231 * ADTEn/1000 - 0.00161 * ADTEx/1000 - 774.98 * InvSpai + 279.28 * InvSpaAux + 0.533 * Upstream\_2 - 0.058 * Upstream\_3 - 0.0602 * Mainline1 + 0.0522 * Mainline2 - 0.294 * RampMet + 0.0256 * HOVEn + 0.0446 * HOVMain + 0.759 * CA\_5 + 0.493 * CA\_10 + 0.517 * WA\_5 \quad (10)$$

$$\beta_B X_B = -1.035 - 0.00151 * ADT/1000 - 0.0344 * ADTEn/1000 + 0.0201 * ADTEx/1000 - 959.25 * InvSpai + 900.70 * InvSpaAux + 0.386 * Upstream\_2 - 0.155 * Upstream\_3 + 0.0536 * Mainline1 + 0.0182 * Mainline2 - 0.0589 * RampMet + 0.0228 * HOVEn - 0.280 * HOVMain + 0.471 * CA\_5 + 0.545 * CA\_10 + 0.402 * WA\_5 \quad (11)$$

The inverse ramp spacing parameter for crash severity is negative in the MV-K, MV-A, and MV-B severity equations, but it is only statistically significant in the non-incapacitating injury (B) equation. The negative inverse ramp spacing parameters for the MV-K, MV-A, and MV-B severity equations indicate a decrease in the proportions of MV-KABC crashes that are MV-K, MV-A, and MV-B as ramp spacing decreases, creating an increase in the proportion of crashes that are MV-C. This indicates that crash severity is decreasing (as measured by the proportions of severe crash outcomes) as ramp spacing decreases. The finding is somewhat intuitive, as speeds are expected to decrease as lane changing intensity increases at shorter ramp spacing values. Adding an auxiliary lane, which is expected to improve operations, increases speeds and decreases expected crash frequency, but does increase overall crash severity, as measured by the proportions of severe crash outcomes. Again, this finding is not surprising given the high levels of sensitivity between operating speeds and crash severity. Figure 5.3 provides an illustration of crash severity proportions as a function of ramp spacing with and without auxiliary lanes.

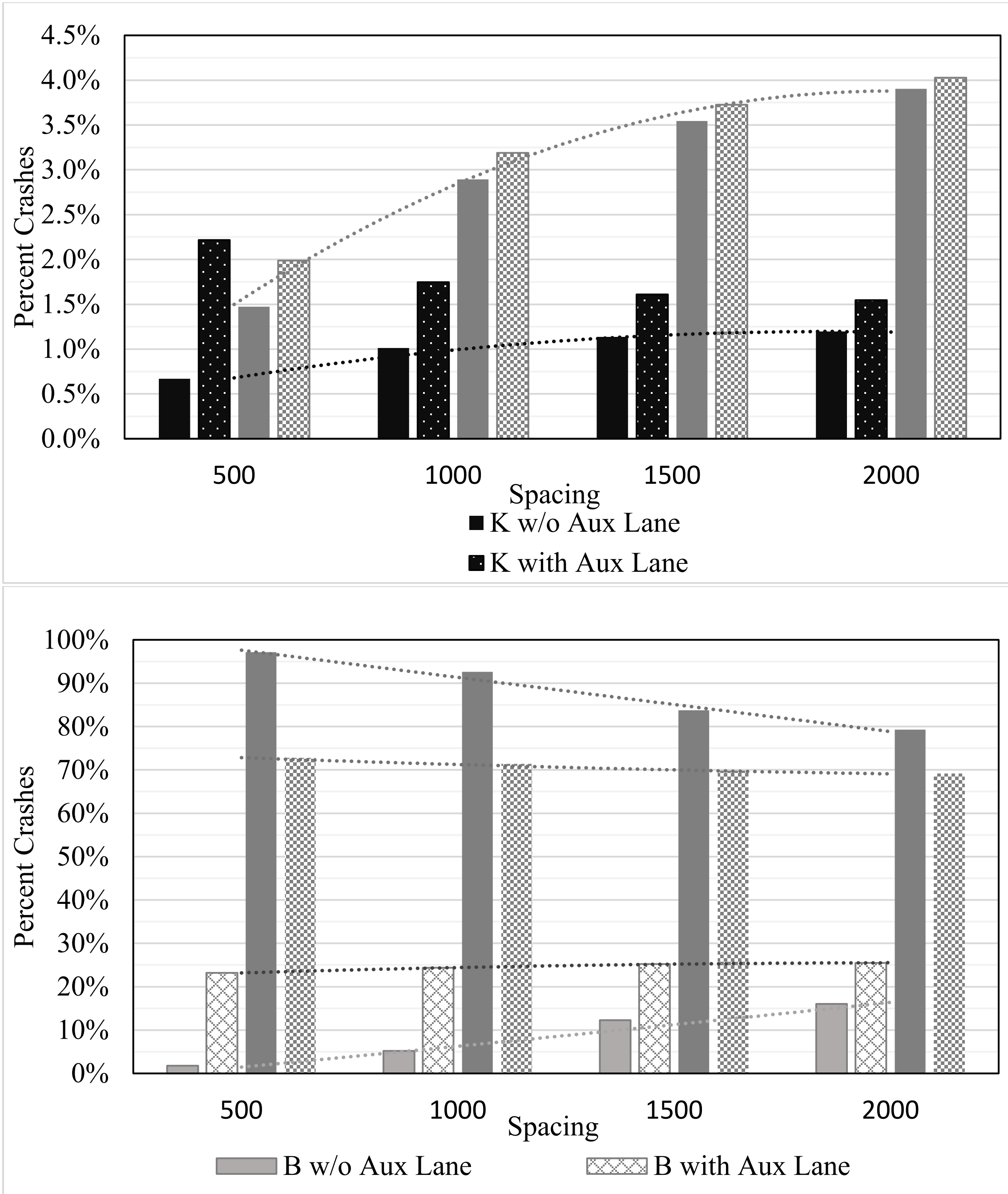


Figure 5.3 Crash Severity Proportions as a Function of Ramp Spacing With and Without Auxiliary Lanes

5.7 Case Study Demonstrating the Frequency-Severity Model Application

A case study comparison was developed to aid in the conceptual understanding of the influence of ramp spacing and auxiliary lane presence on the combination of crash frequency and severity. The case study depicted a 1.3-mile segment with five lanes in each direction (DADT 131,500, ADTEn 5,100, ADTEx 19,400), ramp metering, an HOV onramp lane, and an HOV mainline lane. The mainline crossed over the upstream cross street and under the downstream cross street. Table 5.4 provides the calculated crash frequencies for the case study under three different freeway and interchange design alternatives: one resulting in a 2,200-feet EN-EX ramp spacing without an auxiliary lane; the second resulting in an 1,800-feet EN-EX ramp spacing without an auxiliary lane; and the third a modification of the second, an 1,800-feet EN-EX ramp spacing with an auxiliary lane. Total predicted crash frequency decreases by approximately three crashes per year when increasing the ramp spacing by 400 feet (from 1,800 feet to 2,200 feet without an auxiliary lane). Adding an auxiliary lane to the 1,800-feet spacing alternative decreases predicted crash frequency by approximately 10 crashes per year when compared with the 1,800-feet spacing without the auxiliary lane, with a majority of the reduction focused on the possible injury and property damage only crashes.

The National Safety Council (NSC) calculates costs of motor vehicle injuries as the combined wage and productivity loss, medical expense, administrative expense, motor vehicle damage, and employers' uninsured costs (*89*). The NSC identifies the economic costs for the following crash severities: Fatal (K), \$1,410,000; Incapacitating (A), \$72,700; Non-incapacitating (B), \$23,400; Possible injury (C), \$13,200; and Property damage only (O), \$8,900. Extending the EN-EX ramp spacing by 400 feet, from 1,800 feet to 2,200 feet, without an auxiliary lane, reduces the annual crash cost by \$32,000/year. Providing an auxiliary lane for the 1,800-feet spacing reduces the annual crash cost by \$103,000/year compared with the 1,800-feet spacing without the auxiliary lane and also results in a crash cost that is \$71,000/year less than the 2,200-feet spacing without an auxiliary lane.

Table 5.4 Case Study of Crash Frequency With and Without an Auxiliary Lane

Spacing	Auxiliary Lane	Annual Predicted Crash Frequency						Annual Crash Cost
		K	A	B	C	PDO	Total	
2200	No	0.1	0.7	2.8	13.8	35.8	53.2	\$ 708,000
1800	No	0.1	0.7	2.7	14.8	38.0	56.3	\$ 740,000
1800	Yes	0.1	0.6	3.2	10.6	31.6	46.0	\$ 637,000

6. CONCLUSIONS

6.1 Paper I

It is clear from the discussion in Chapter 3 that the design inputs and design controls, which influence design criteria and decisions in highway geometric design, have variability and uncertainty in both time and space. Currently, geometric design policies *implicitly* address the variation in design inputs using a single value of the design parameter that conservatively represents the population of drivers and/or vehicle operating characteristics (for example, higher percentile vehicle speed and perception-reaction time, and lower percentile acceleration rate). To *explicitly* address the variability and uncertainty, reliability concepts associated with highway geometric design criteria and decisions have been investigated in the highway design literature. The applications of these reliability methodologies have demonstrated how to explicitly consider the range of expected design, operational, and/or safety performance to inform design decisions. The resulting performance-based process for establishing design criteria would allow designers to consider and balance the accommodation of driver and vehicle operating characteristics, safety, design, and construction costs in any given context.

This paper synthesizes the research on different applications of reliability theory to highway geometric design criteria and decisions. Probability of non-compliance was assessed for selected design criteria with variabilities in their design input parameters, including stopping sight distance, passing sight distance, horizontal curvature, vertical curvature, basic number of lanes, and acceleration lane length. The methodologies outlined in this paper equip the designer with more information to reach a higher level of confidence in knowing the reliability of design performance in the presence of realistic and context-specific variabilities. The inherent risk associated with design criteria have commonly been linked to a probability of non-compliance. While at least two studies successfully linked this measure to safety, measured by expected crash frequency, additional related work is needed. Additional research is also needed to demonstrate how a designer could more efficiently develop the distributions for random input parameters when establishing a project's applicable design criteria and to validate the usefulness of reliability approach in terms of more cost-effective designs.

6.2 Paper II

The proposed reliability-based approach in this paper incorporates the uncertainty associated with traffic-related characteristics to determine the probability distribution of operational performance that might result from basic number of lanes decisions made to achieve a design level of service (LOS). Example analyses and results were provided for urban and rural freeway segments. The contributions of uncertainty in the traffic-related variables to the variation of vehicle density were evaluated using Monte Carlo simulation. Distributions for the input variables were developed using data from urban and rural sections of Interstate 15 and Interstate 80 in Utah.

Monte Carlo simulation was an effective method for implementing the probabilistic analysis approach. As applied in this case, the Monte Carlo simulation generated 100,000 sets of random input values based on the selected statistical distributions of traffic characteristics developed to obtain a distribution of the vehicle density. The results indicated that uncertainty in input variables has important effects on the probability distribution of the operational performance on a freeway. The uncertainty was attributed to the aleatory variability (i.e., natural randomness) in the input variables. Designers can use this method to explicitly consider uncertainty in vehicle density and LOS (i.e., operational performance). Instead of just "one number" for density and "one letter" for LOS, the designer would instead have estimates of the chance (i.e., probability) that the design LOS will or will not be met in the design year. This information could then be weighed against other considerations (e.g., trade-offs, impacts, costs, right-of-way constraints) when making basic number of lanes decisions.

This study adds to the existing knowledge base by developing and executing reliability analysis of geometric design in an operational context. Previous studies focused mainly on safety-related concerns (e.g., available versus required sight distance, vehicle skidding and rollover). The framework allows designers to explicitly consider the probability distribution of operational performance that might result from different basic number of lanes decisions. The analysis in this paper can further be improved by the following:

- Incorporating uncertainty involved in the projection of AADT by considering annual growth rate as a random variable.
- Incorporating uncertainty into the passenger-car equivalencies (PCEs) of trucks, because PCE values in HCM were calculated using steady-state flow conditions, independent of LOS, and are also likely to vary based on specific truck characteristics.
- Accommodating the likely variation in PHF, which is affected by land-use change, traveler behavior changes, and other known and unknown factors.
- Incorporating actual free-flow speed data as well as speed-flow relationships.
- Testing the methodology for a broader range of area type, traffic volume combinations in different operational settings (e.g., providing auxiliary lanes, selecting maximum vertical grade, selection of intersection control type and lane arrangement).

6.3 Paper III

The objective of the third paper, Chapter 5, was to quantify the effects of interchange ramp spacing and auxiliary lane presence on both crash frequency and crash severity. Multi-vehicle crash frequencies were predicted using a safety performance function, estimated using negative binomial regression modeling. Results show that expected multi-vehicle crash frequency increases as ramp spacing decreases. The sensitivity between expected multi-vehicle crash frequency and ramp spacing was highest at shorter spacing values. At longer values for ramp spacing, there was a point beyond which the spacing effect "disappeared" and the safety performance approached that of a basic freeway segment. Providing an auxiliary lane is expected to decrease expected multi-vehicle crash frequency for a given ramp spacing; the safety benefits in terms of expected crash frequency reductions become larger as ramp spacing decreases. These findings are consistent with the findings previously presented in (*44*).

Safety is defined not only by expected crash frequency, but also by the severity of crashes. This paper advanced previous work on the safety effects of ramp spacing and auxiliary lane presence by also exploring the relationship between ramp spacing and crash severities using "severity distribution functions," which were estimated using a multinomial logit regression modeling approach. The severity distribution function can be used to predict the probability (i.e., proportion) of crashes with a specific injury severity outcome, conditioned on a crash having occurred at a location with a defined set of traffic and roadway characteristics. Results showed that crash severity decreases (as measured by the proportions of severe crash outcomes) as ramp spacing decreases. The finding is somewhat intuitive, as speeds are expected to decrease as lane-changing intensity increases at shorter ramp spacing values. Adding an auxiliary lane, which is expected to improve operations, increase speeds, and decrease expected crash frequency, does increase overall crash severity as measured by the proportions of severe crash outcomes. In other words, providing an auxiliary lane is expected to decrease crash frequency, but the reduction appears to be primarily in less severe crashes (possible injury and property damage only). It is important to note that the segment definitions used for this paper and the accompanying models are not likely capturing the severe back-of-queue crashes that sometimes occur in congested conditions.

The methodology proposed in this paper appears to effectively capture the complex relationships between geometric design and operations and the high sensitivity between speed and crash severity. The paper provides quantitative tools for making informed freeway and interchange design decisions where ramp spacing is a consideration. A case study demonstrates how to combine quantitative knowledge related to the effects of ramp spacing and auxiliary lane presence on both crash frequency and severity into a framework for assessing the overall crash cost for different ramp configurations.

Future work should extend the methodology into a more disaggregated analysis, where variations in traffic volumes throughout the day are considered (as opposed to average daily volumes). This includes research to quantify the safety effects of variable operating conditions throughout the day and explore the prevalence of severe back-of-queue collisions that may occur when higher traffic volumes and closely spaced ramps contribute to excessive mainline queuing. While a variety of number of lanes variables were tested during data analysis, the research was not able to quantify a safety effect of lane balance. Future data collection and analysis should seek to include enough sites with and without lane balance to capture this effect. Additional costs resulting from crash occurrence in the form of non-recurrent congestion should also be considered in the framework to estimate overall safety effects. There are inherent inaccuracies in the police reporting of crash severities on the “KABCO” scale, even at the more severely coded injury levels. Severity predictions will improve as the ability to link crashes to injury outcomes as determined by medical professionals becomes more readily available.

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