A RELIABILITY-BASED GEOMETRIC DESIGN APPROACH TO FREEWAY NUMBER OF LANES DECISIONS

by

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STATEMENT OF THESIS APPROVAL

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ABSTRACT

For more than twenty years, the introduction of reliability-based analysis into roadway geometric design has been investigated. This type of probabilistic geometric design analysis is well suited to explicitly address the level of variability and randomness associated with design inputs when compared to a more deterministic design approach. In this study, reliability analysis was used to estimate the probability distribution of operational performance that might result from basic number of lanes decisions made to achieve a design level of service on a freeway. The concept is demonstrated using data from Interstate 15 and Interstate 80 in Utah. The basic traffic count data used for analysis were obtained from Utah Department of Transportation (UDOT). To account for the uncertainty in the design inputs, statistical distributions were developed and reliability analysis was carried out using Monte Carlo simulation. A statistical software Minitab was used to develop statistical distributions of design inputs involving variability from the traffic count data. Minitab was also used to run Monte Carlo simulation by generating random samples of the design inputs. The outcome of this probabilistic analysis is a distribution of vehicle density for a given number of lanes during the design hour. The main benefit of reliability analysis is that it enables designers to explicitly consider uncertainties in their decision-making and to illustrate specific values of the distributions that correspond their target level of service (e.g., the 65^{th} through 85^{th} percentile density corresponds to the design level of service). The results demonstrate how uncertainty in estimates of K (i.e., the percent of daily traffic in the design hour), directional

distribution, percent heavy-vehicles, and free-flow speed significantly contribute to the variation in the vehicle density on a freeway.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACRONYMS

LOS	Level of Service
30 HV	Thirtieth Highest Hourly Volume
FORM	First Order Reliability Method
PSD	Passing Sight Distance
UDOT	Utah Department of Transportation
POH	Probability of Hazard
HCM	Highway Capacity Manual
AADT	Annual Average Daily Traffic
DHV	Design Hourly Volume
DDHV	Directional Design Hourly Volume
PHF	Peak Hour Factor
RV	Recreational Vehicle
PCE	Passenger Car Equivalent
FFS	Free Flow Speed
AD	Anderson Darling Test
ATR	Automatic Traffic Recorder
LRT	Likelihood Ratio Test

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CHAPTER 1

INTRODUCTION

Road geometric designers must deal with the challenge of designing for a broad range of driver, vehicle and roadway conditions and capabilities (*1*). In other words, there is variability in design inputs and design controls that influence design criteria and design decisions. As noted in Porter (*1*), variability in factors that influence design decisions have traditionally been addressed implicitly in civil engineering disciplines. 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). Currently, the method used in roadway geometric design is deterministic. The design requirements are based on American Association of State Highway and Transportation Officials (AASHTO) Green Book, a geometric design policy which provides deterministic standards (e.g., minimum stopping sight distance required by vehicle travelling at design speed to stop without colliding with an object in the roadway). Road designers sometimes assume that roads meeting current roadway design standards are appropriately safe. This is referred to as nominal safety (*2*). Experienced designers know there is likely some level of uncertainty in the estimates of the design criteria, but it is not quantified. 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 that 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). There have been several previous studies that 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 (*3-4*). 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 the drivers' perceptions of quality of service and acceptable levels of congestion (*5*). 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 thirtieth (30^{th}) highest hourly volume in the design year. The 30^{th} highest hourly volume in the design year tends to reflect the higher end of recurring morning and afternoon peak hour volumes. The one-hundredth (100^{th}) 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" (*5, 6*). It is the constant number of lanes assigned to a route, exclusive of auxiliary lanes (*5, 6*). 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. Figure 1 illustrates the reliability approach applied in this work.

This work presents an alternative approach to road geometric design. This approach is fully sensitive to the broad range of drivers, vehicles, and roadway conditions by utilizing the stochastic nature of these factors in the design process.

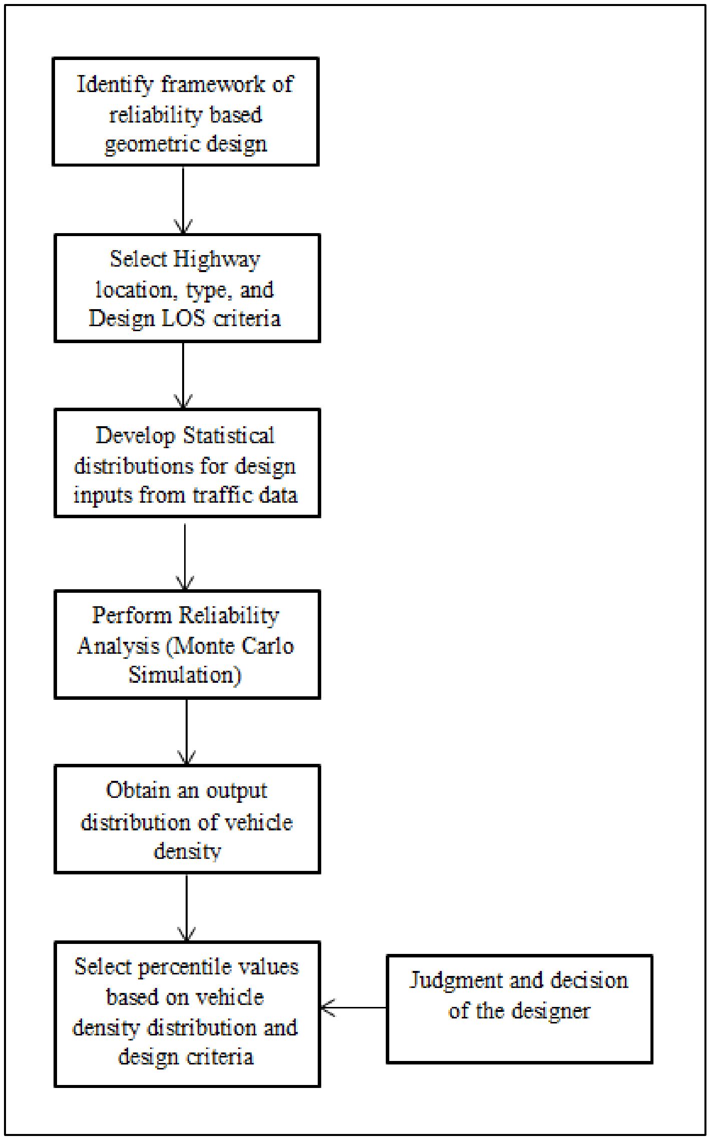


Figure 1 Reliability Based Highway Design Framework

There are five chapters which summarize the content and work of this thesis; together they provide a full view on how reliability analysis can be applied in road geometric design. Chapter 1 provides the introduction of why a probabilistic approach is applicable to roadway design. Chapter 2 summarizes the literature review of probabilistic analysis and the related studies on reliability theory. Chapter 3 discusses 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 level of service on a freeway. It also describes the software that is used to implement the framework. Data collection is also described in Chapter 3. Chapter 4 presents the results obtained from Monte Carlo simulation that is a part of the probabilistic analysis, as well as interpretation of the results. It also includes the results from deterministic analysis approach to provide a basis for comparison between two approaches. The thesis comes to a conclusion with Chapter 5, which summarizes the thesis outcomes, presents discussion and provides recommendations from this research.

CHAPTER 2

LITERATURE

This chapter presents a review of the several studies related to the development and application of probabilistic analysis to highway geometric design. The first section presents background information that involves a theoretical discussion of some issues related to reliability theory in highway design. The second section provides a review of relevant research materials in the literature.

2.1 Background

2.1.1 *Geometric Design Process*

The term "geometric design" pertains to the dimensions and arrangements of the physical features of a highway (*7*). These include horizontal alignment, vertical alignment, cross-section, grades, interchanges, and other physical features that significantly affect highway operation, capacity, drainage and safety. The conventional approach to roadway design was from the design methods that were first codified in the 1930s with the publication of *A Policy on Highway Classification* (*8*). So, in the late 1930s, national design policies and were introduced into highway geometric design. AASHTO's *A Policy on Geometric Design of Highways and Streets (5)* is at the core of this conventional approach. Its design criteria are based on a lot of research and empirical data relating driver, vehicle, and roadway characteristics. In other words, an effective highway or street design should be able to satisfy the purpose for which it is designed, for a wide variety of users under a wide variety of operating conditions.

2.1.2 *Current Design Practice*

The current geometric design process requires establishment of fundamental design controls (e.g., area type, terrain, functional classification, traffic volume, design vehicle) and selection of design speed. Design parameters are dependent upon many variables such as vehicles' speeds, deceleration rate, driver perception reaction time, and acceleration capabilities. They represent wide ranges of driver and vehicle characteristics as well as variable operating conditions. For the current geometric design of roads and highways, engineers calculate the minimum values of these design parameters using "conservative values" for the variables. For example, AASHTO's Green Book (*5*) criteria may incorporate a "safe" percentile value for a parameter (e.g., 15th percentile deceleration rate, 95th percentile reaction time), and that percentile value may be inconsistent across criteria and does not represent the entire range of circumstances.

2.2 Reliability Theory

2.2.1 *Stochastic Components in Highway Design*

Highway geometric design is a multiphased process, with each phase requiring a specific body of knowledge, expertise, and analysis in order to create a solid foundation of engineering decisions (*9*). Similar to other civil engineering disciplines, each design phase entails some assumptions and predictions that contribute to uncertainty in the design process. Highway operation from a motorized vehicle perspective consists of four important components: the driver, the vehicle, the road, and the environment. Driver-related factors such as driver behavior, expectations, perception, visual reception, and control on the vehicle involve variability. Similarly, vehicular factors such as weight, size, and type of vehicle, acceleration, deceleration, and rolling resistance of the vehicle involve variability. Thus, transportation engineers must design facilities to accommodate drivers who possess a wide range of skill levels and characteristics, as well as vehicles with different static, kinematic, and dynamic characteristics. It is therefore necessary to have a method that addresses the randomness of each of the variables in the development of design parameters.

2.2.2 *Probability Theory in Geometric Design*

A probabilistic approach to design includes considering all uncertainties in a problem as well as examining all possible conditions, outcomes, and consequences. Mayer (*10*) was the first to propose the shift from deterministic to probabilistic approach in engineering design. Ang and Cornell (*11*) developed the use of probabilistic tools in structural design in the 1970s. Reliability analysis is an application of probabilistic analysis.

2.2.3 *Limit State Design*

The procedure of applying reliability methods in structural engineering is summarized below. In structural design, probabilistic design is done by explicitly considering the uncertainties in different variables and ensuring that a reasonable margin of safety is achieved. Structural reliability depends on the resistance and the load. For a properly designed structure, the probability of having applied loads greater than or equal to the resistance of structure is very small. The condition where the applied load is greater than or equal to the resistance of structure is called the “limit state” of the structure. The variable names have been changed from load and resistance to demand and supply to reflect a more general limit states design rather than an application for structural engineering. This is computed with the help of two random variables, supply (S) and demand (D) in the performance function G (*12*):

$$G = S - D \tag{2.1}$$

2.2.4 *Probability of Failure*

In highway geometric design, supply refers to the group of input variables that are related to the design characteristics of a facility. Demand refers to the driver and vehicle requirements that need to be accommodated (*13*). In the design, when the demand exceeds the supply, the system is said to have failed or been not in compliance with the design parameters. This is termed as probability of failure (P_f), which is the probability that the demand will exceed the supply or that a specific design would not meet requirements (e.g., the required sight distance is greater than available sight distance) (*14*).

Figure 2 is a graphical representation of the system of Equation 2.1 with the corresponding probability of failure and the safety margin. The probability of failure corresponds to the region where the function is negative. Then, the reliability equals one minus the probability of failure.

The true meaning of reliability is “the concept of dependability, successful operation or performance, and the absence of failures” (*15*). Reliability of a highway or street can be defined as the probability that 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).

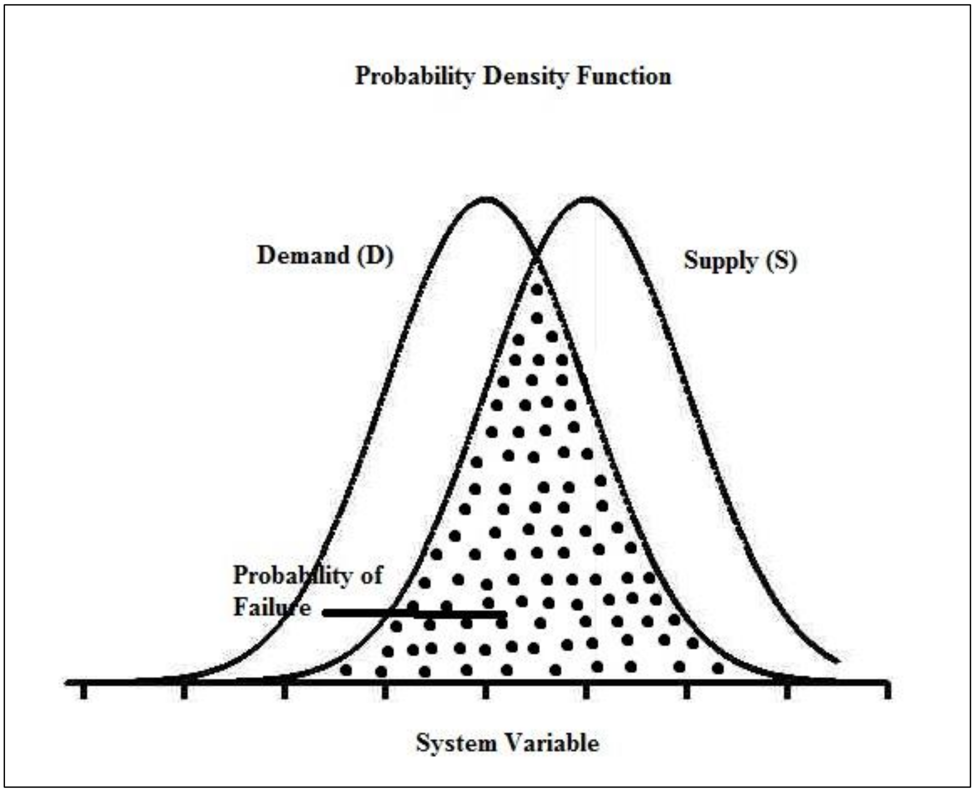


Figure 2 Basic Components of Performance Function

2.3 Previous Studies Related to Reliability Design

Faghri and Demetsky (*16*) applied the principles of reliability and risk assessment in a model for the evaluation of at-grade road-railway crossings. The model predicts the frequency of crash occurrence by taking into account all the variables that have some influence on the crash event. Variables such as driver skill, perception time, environmental conditions, and random crash causes are considered to be stochastic. The mathematical principles of reliability and risk assessment were used to establish a hazard index for a crossing on the basis of the probability that an accident would occur at the crossing. The probabilistic nature of the model is seen as a valuable tool in measuring hazard indices for road-railway crossings, explicitly considering uncertainty.

Navin (*3*) 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, is done by considering the whole of the highway as a unit. In other words, the reliability of the whole structure is a function of reliability of the individual elements that compose the structure. Another work of Felipe (*12*) also stated that a good knowledge of the reliability of the individual elements is essential to design a "consistent" highway. Navin (*4*) adapted the structural terminology to the highway design domain by designating the probability of failure as the probability of noncompliance (P_{nc}).

Easa (*17*) applied probabilistic analysis in computing the intergreen interval (yellow plus red clearance) at signalized intersections. In this analysis, the approach speed, reaction time, deceleration rate, and the vehicle length are considered to be random variables. Similarly, Easa (*18*) also developed a probabilistic model for the intersection sight distance, where design speed, perception-reaction time, and friction coefficient are the random variables. Instead of the common use of percentile values of design variables, the proposed method uses the moments of probability distributions i.e., mean and variance, of all these random variables. First-order probabilistic analysis is used to measure the randomness associated with these design variables in analyzing the design of intergreen interval and sight distances at the intersections (*18-19*). The method also accounted for the correlations among the component random variables.

Researchers have applied principles that follow the limit states design approach used by structural and geotechnical engineers in the transportation safety context. Felipe (*12*) performed controlled experiment and field observations to develop the "limit state design" concept for highway horizontal curves. These measurements allowed one to collect actual information on the basic variables involved in the driving process of horizontal curves. A computer program Reliability Analysis (RELAN) was used to perform First Order Reliability Method (FORM) analysis for passenger cars subjected to skidding by comparing the expected lateral acceleration supplied by the road to the expected lateral acceleration demanded by the vehicle-driver. Probability of noncompliance was also computed by comparing the expected radius supplied by the highway to the expected radius demanded by the car-driver system. Thus reliability analysis was used to measure margin of safety and P_{nc} on horizontal curves. Zheng (*7*) demonstrated that reliability theory is not only useful in road design stage but can also be used to assess possible safety issues related to a highway location. The methodology in his research involved evaluating margin of safety for a particular roadway geometric design by incorporating the variables such as vehicle dynamics, human factor consideration, operational experience, road-vehicle interaction, and pavement performance, all of which involved uncertainty.

Richl and Sayed (*14*) applied reliability analysis techniques on a series of horizontal curves. They studied the effect of median width along curved highway segments in order to understand the risk of sight distance restrictions. The probability distributions of input variables were obtained from previous, relevant studies. Monte Carlo simulation was used to develop "supply" and "demand" distributions. The probability of being unable to stop within the available sight distance was calculated with varying horizontal sight distance restrictions for two highway alignments.

El Khoury and Hobeika (*20*) applied reliability theory in analyzing the risk indices involved in Passing Sight Distance (PSD) calculations on two-lane, two-way roads. Microscopic simulation was used to replicate the passing maneuvers on these roads. The probability distribution of PSD was determined by accounting for variations of all the contributing parameters in PSD formulation and implementing a Monte Carlo simulation. The levels of risk were identified for the various available values of the PSD distribution and also the current PSD standards.

Sarhan and Hassan (*21*) used a reliability-based design approach to calculate the probability of three-dimensional (3D) sight distance limitations. This approach was applied to horizontal curves overlapping with flat grades, crest curves, and sag curves. A Sight Distance Evaluation System (SDES) was used to calculate the available sight distance and it was checked against the required stopping sight distance on a road segment. Probability of Hazard (POH) was also estimated as the probability that available sight distance was less than required stopping sight distance.

Ismail and Sayed (*22*) presented a general framework for developing probabilistic highway design criteria, which deals with the uncertainty associated in the design inputs. This study focused on modifying typically used design models by adding calibration factors that would yield consistent P_{nc} values to crest vertical curve design. A calibrated design model would then have all the reliability analysis results codified in terms of calibration factors. The mathematical form of the calibration factors was constructed so that it compensates for the precalibration distribution of design safety levels. Ismail and Sayed (*23*) also used reliability analysis to predict the safety impacts of sight distance restrictions on horizontal curves. It was done by analyzing two sites, on road segments with constrained roadside environment in British Columbia. FORM is used to calculate P_{nc} that might result when the supply term and demand term are available sight distance and required stopping sight distance, respectively.

Ismail and Sayed (*24*) presented a probabilistic analysis methodology that enables the re-dimensioning of different geometric elements located on highway segments with restricted sight distance. It also provides a decision mechanism for efficient use of available right-of-way for new highway construction. Previous work by the authors Ismail and Sayed (*23*) presented a methodology for risk assessment. But, this work presents a methodology for risk-optimization for highway segments constructed in restricted right-of-way. You et al. (*2*) applied reliability analysis in the design of horizontal curves. In the literature, the performance function is usually formulated on the basis of failure mode of vehicle skidding only (*2*). In this study, the risks associated with the design are based on failure modes of vehicle skidding and rollover in the performance functions of cars and trucks, respectively. The study considered vehicle speed, friction coefficient, and radius to be random variables, and super elevation and vehicle parameters to be deterministic. They took into account all the possible combinations of the design variables and calculated the probability of vehicle skidding or rollover.

Shin and Lee (*25*) 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 and interchanges. The work investigated the probabilities of rollover and sideslip for the minimum radius guided by AASHTO Green Book, using FORM and limit state functions, respectively.

2.4 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.

CHAPTER 3

METHODOLOGY

This chapter describes the general methodology for estimating a probability distribution of operational performance. The first section presents the proposed methodology, software used, and data collection details. The second section presents a detailed discussion of developing distributions of input parameters to fit observed data.

3.1 Proposed Approach

In the design of roads and highways, decisions regarding the basic number of lanes on a freeway are one of the major design decisions. Traditionally, highway design policies, manuals, and guidelines have specified "one" value for each of the design inputs involved in making these decisions. There is, however, an inherent uncertainty involved in these design inputs that influence basic number of lanes design decisions as well as in the operational outcomes. Probabilistic analysis is well suited to address the uncertainties. The first stage in the proposed reliability approach is determination of the reasonable distribution shape for the relevant design inputs. While current deterministic approaches rely on a single deterministic value for each parameter, the proposed reliability approach utilizes the full distribution shape for the parameter values.

Hence, to implement the reliability analysis in a freeway basic 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, and 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 parameters do not take either one value or the other (like accident occurrence, which is referred to as epistemic uncertainty), they have a range of values. Hence they are said to have aleatory variability. Epistemic uncertainty is the scientific uncertainty in the model of a process and is due to limited data and knowledge. This type of uncertainty was not considered in the present study. A single probabilistic representation describes the aleatory uncertainty. Thus, the aleatory 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, the basic freeway segment methodologies described in the Highway Capacity Manual (HCM) (*26*) were used.

3.1.1 *Average Annual Daily Traffic*

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 work, but will be the focus of future work. This work assumes a reasonable estimate of the Average Annual Daily Traffic in the design year ($AADT_{Design\ Year}$) as a starting point.

3.1.2 *Design Hourly Volume*

The Design Hourly Volume (DHV) is important for highway planning and design purposes because it generally represents the volume of recurring traffic during peak hours. To get the design hourly volume, $AADT_{Design\ Year}$ is multiplied by the proportion of daily traffic expected to occur in the design hour (K). When looking at a graph of the highest hourly volumes at a counting station, those at the highest end tend to be outliers with a steep slope. However, at some point the slope starts to flatten out. This is shown in Figure 3.

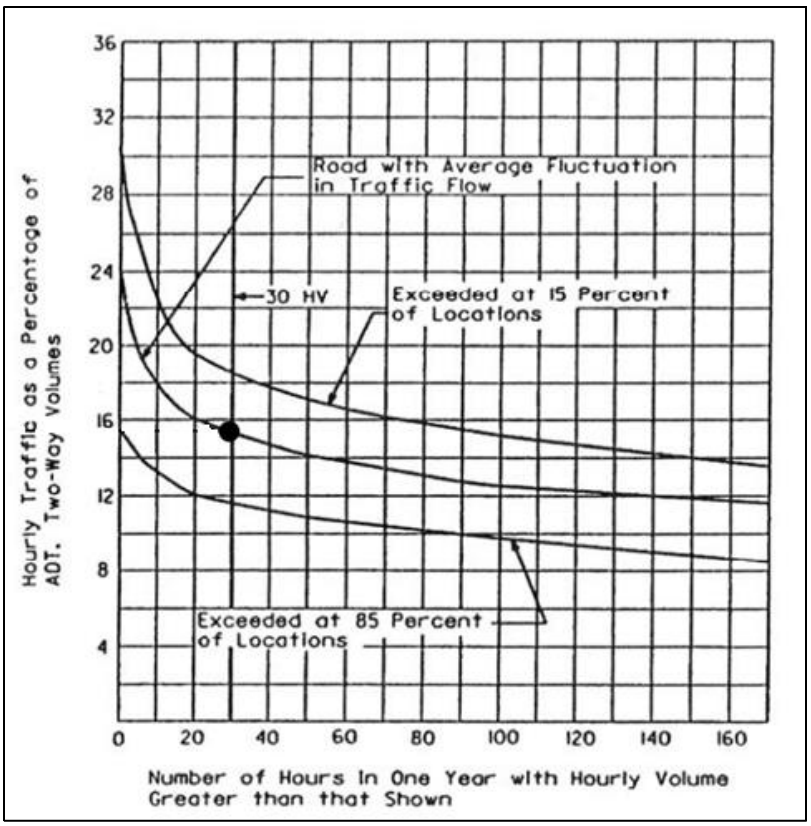


Figure 3 Relation between Peak Hour and Average Daily Traffic Volumes on Rural Arterials: From *A Policy on Geometric Design of Highways and Streets*, 2004, by the American Association of State Highway and Transportation Officials, Washington, D.C. Used by permission

Through years of experience, engineers have seen that the thirtieth highest hourly volume (30 HV) often occurs near that point where the slope flattens and represents the higher end of recurring morning and afternoon peak hour volumes (*27*). Specific practices vary. The 30th highest hourly volume in the design year may be more common to rural areas, while the one-hundredth (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 annual average daily traffic. The design hour volume is then calculated using Equation 3.2:

$$DHV = K_{30} \times AADT_{Design\ Year} \tag{3.2}$$

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

3.1.3 *Directional Design Hourly Volume*

Highway traffic volume varies with respect to location of the facility and direction of traffic flow (*28*). 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 percent. This percentage of traffic in the peak direction during the design hour is referred to as the directional distribution (*D*). Hence, the directional distribution is simply the proportional split of the total traffic volume in two opposite directions during any particular time period. Directional distribution, when multiplied with design-hour volume, results in Directional Design Hour Volume (*DDHV*), and is shown in Equation 3.3:

$$DDHV = DHV \times D \tag{3.3}$$

3.1.4 *Demand Flow Rate*

The *DDHV* for the design year should be the basis of the geometric design and is expressed in units of vehicles per hour. It is the traffic volume that is expected to use a highway segment during the design hour (30th highest hour, in this case) of the design year in the peak 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 3.4:

$$V = \frac{DDHV}{PHF \times N \times f_{HV}} \tag{3.4}$$

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

PHF = peak-hour factor; and

f_{HV} = adjustment factor for presence of heavy vehicles

N = number of lanes in each direction

The peak hour factor represents the variation in traffic flow within an hour. It represents the most critical period for operations and has the highest capacity requirements. Observations of the traffic flow indicate that the flow rates found in the peak 15-minute period within an hour are often not sustained throughout the whole one-hour period (*26*).

3.1.5 *Heavy Vehicle Factor*

Heavy vehicles are generally categorized as trucks, buses, or recreational vehicles (RVs). The number of heavy vehicles on a highway impacts highway planning, roadway capacity, traffic operations, safety, and pavement performance (*29*). 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). They are used in the analysis procedures to convert mixed traffic stream volumes into equivalent passenger car volumes. PCE was defined as "the number of passenger cars displaced in the traffic flow by a truck or bus, under the prevailing roadway and traffic conditions" (*30*). The current definition of PCE in the HCM 2010 is similar, "the number of passenger cars that will result in the same operational conditions as a single heavy vehicle of a particular type under specified roadway, traffic, and control conditions" (*31*). According to HCM 2010, the heavy vehicle adjustment factor is shown in Equation 3.5:

$$f_{HV} = \frac{1}{1+P_T(E_T-1)+P_R(E_R-1)} \tag{3.5}$$

where f_{HV} = heavy vehicle adjustment factor

P_T = truck proportion

P_R = recreational vehicles (RVs) proportion

E_T = truck PCE

E_R = recreational vehicles (RVs) PCE

RVs were excluded from the present analysis due to the lack of adequate RV data. RVs do not represent a significant portion of traffic on Utah highways, so their exclusion is not expected to have any practical impact on the findings. Hence, in the present research, the impact of RVs will be ignored; the focus will be on P_T and E_T.

3.1.6 *Free-flow Speed*

Free-flow Speed (FFS) is defined in Chapter 10 of the HCM as the theoretical speed when the density and flow rate on the study segment are both zero. It is 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 impended 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 (*32*). 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 in Equation 3.6:

$$S \sim f\ (FFS) \tag{3.6}$$

3.1.7 *Density*

Given the input values described in the previous sections, the next stages of an operational analysis include the determination of density and LOS estimates in the design hour. The uncertainty associated with design-year projections of traffic-related characteristics will ultimately result in uncertainty in density and LOS estimates. The demand flow rate and the estimated average speed are used to determine the density of traffic stream. It is given by Equation 3.7:

$$Density = \frac{V}{S} = \frac{(K_{30} \times AADT \times D)}{(S \times PHF \times N \times f_{HV})} pc/mi/ln \tag{3.7}$$

Density then directly determines level of service for a given number of lanes. The right hand side variables of the various relationships will be referred to here as the input parameters. Thus, the purpose of the first stage in the proposed reliability-based approach is to determine the distributions of the input parameters. Once the input parameters are available, we can incorporate these distributions into the design relationships to get an output distribution for the left hand side parameter. In a deterministic approach, the estimate for the left hand parameter (density, in this case) is “one number.” However, in the proposed reliability approach, we get a full distribution of possible density values. Thus, the left hand side parameter is referred to in the proposed approach as the output value distribution, or the intermediate value. The analytical determination of the output value distribution is made by means of Monte Carlo simulation.

To demonstrate the ideas presented so far, consider the relationship that is presented in Equation 3.7 that results in an estimate of density. In this equation, the input parameters that are likely to have some level of error or uncertainty are K_{30}, AADT, D, S, PHF, and f_{HV}. The natural uncertainty and variability is represented in this study using a set of statistical distributions for selected variables. This thesis focuses on the uncertainty in K_{30}, D, S, and f_{HV} estimates and the effects on the uncertainty in the density and level of service estimates. Observed data, combined with the Minitab software, were used to select appropriate statistical distributions for each of these input variables.

3.2 Minitab

Minitab is a statistics package developed at Pennsylvania State University in 1972. It 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 to identify the “best-fitting” distributions. This software provides two goodness-of-fit tests: Anderson-Darling for the maximum likelihood and least squares estimation methods and Pearson correlation coefficient for the least squares estimation method. These goodness of fit measures help users in comparing the fit of alternative distributions.

3.2.1 Anderson-Darling Test

The Anderson-Darling (*AD*) statistic is a measure of how far the plot points fall from the fitted line in a probability plot. The statistic is a weighted squared distance from the plot points to the fitted line with larger weights in the tails of the distribution. A smaller Anderson-Darling statistic indicates that the distribution fits the data better. AD is one among the best distance tests for small samples (*33*).

This test is implemented using a well-defined series of steps. First, assume a prespecified distribution (e.g., Lognormal). Then, estimate the distribution parameters (e.g., mean and variance) from the data. Such a process yields a null hypothesis (H_0) that the data for a variable fits the assumed distribution with the estimated distribution parameters. The negation of the assumed distribution (or its parameters) is the alternative hypothesis (H_a). Using the dataset, test the hypothesized (assumed) distribution. Finally, H_0 is rejected whenever any one of the elements composing H_0 is not supported by the data with a defined level of confidence.

3.2.2 Pearson Correlation Coefficient

The software calculates a Pearson (*P*) correlation coefficient for least squares estimation. If the plot points on a probability plot fall on a straight line, then the distribution will fit the data well. The correlation measures the strength of the linear relationship between X and Y variables on a probability plot. The X variables are the observed data and the Y variables are the data generated according to the distribution that is prespecified and the observed data is being checked against. The correlation will range between 0 and 1, and higher values indicate a better fitting distribution (*34*). Minitab statistical software is used to run Monte Carlo simulations as part of the analysis. This simulation uses repeated random sampling to simulate the data (input variables in this case) and gives a distribution of the output quantity (density in this case).

3.3 Data Collection, Description and Analysis

The proposed methodology was tested using data from urban and rural sections of Interstate 15 and Interstate 80 in Utah. In this section, data sources are described. Generally, traffic data are collected at permanent Automatic Traffic Recorder (ATR) stations. ATRs continuously record the distribution and variation of the traffic flow by hours of the day, days of the week, and months of the year from year to year. The traffic information collected is used to estimate *K*-factor, *D*-factor for each permanent ATR location. The basic traffic count data used for analysis here were obtained from the Utah Department of Transportation (UDOT). UDOT provided an Excel file containing traffic data of 14 ATR sites on Interstate 15 and Interstate 80 in Utah for the years 2002 through 2012. Of the 14 total sites, seven sites were located inside the urban boundary and seven sites 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 for some ATR's 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. The potential data sources for different input variables are shown in Figure 4.

3.4 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

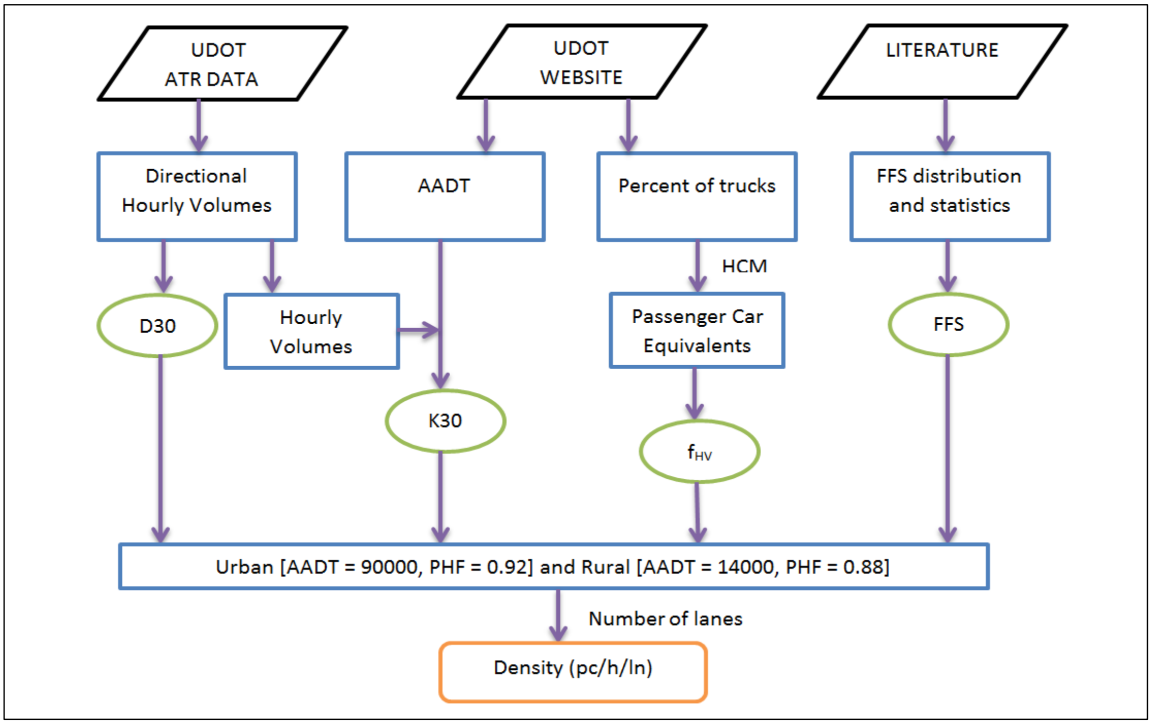


Figure 4 Potential Data Sources

developing distributions to fit the observed data. As noted above, this particular work focuses on the uncertainty in K_{30}, D, S, and f_{HV} estimates.

3.4.1 *K-factor*

The Utah data contained directional hourly volumes for every day for each ATR site. The directional hourly volumes are summed together to get the hourly volumes of each site. The thirtieth highest hourly volume for every year was identified for each ATR site. Then the value of K_{30} was calculated as the ratio of thirtieth 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 1.

Table 1 Values of *K*30 for ATR Sites in Urban and Rural Areas

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

The K-factors are considered to represent typical traffic demand on similar roadways (*35*). 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 of the fact that there are uncertainties or variation in the estimated design hourly volumes because there is uncertainty in the estimate of *K*. Thus, *K* was treated as a random variable having a mean μ_k and standard deviation σ_k. When performing reliability analysis, a distribution must be chosen to model the data. The more closely the distribution fits the data, the more likely the reliability statistics will accurately describe the variable. In addition, a well-fitting model can be used to make reasonable projections when extrapolating beyond the range of data.

There is no strong theoretical support behind the distribution selection for *K*, *D*, and f_{HV}; the distribution selections were instead guided by empirical testing as well as the practicality of implementing the distributions in the Monte Carlo method. The empirical tests done for the distribution selection included the Anderson-Darling test and the Pearson Correlation coefficient test. The data were input into Minitab and *AD* and *P*-values were determined for all the distributions. A distribution with a relatively lower *AD* value and a higher *P* value indicated a better fitting distribution, given that the *P* value is greater than 0.05. The goodness of fit test (i.e., *AD* and *P* test) and the probability plot for different distribution alternatives for *K* are shown in Table 2 and Figure 5, respectively.

A distribution is considered to be the best fit if the data points exactly follow the straight line in Figure 5. It is seen that there are a few outliers and no distribution exactly fits the data. Hence, the distribution in which the data points roughly follow a straight line and have relatively better *AD* and *P* values is selected as the recommended distribution, given the threshold *P* value is met. The selection of the distribution itself for each variable did not impact the research objective of demonstrating a reliability-based approach in making highway geometric design decisions.

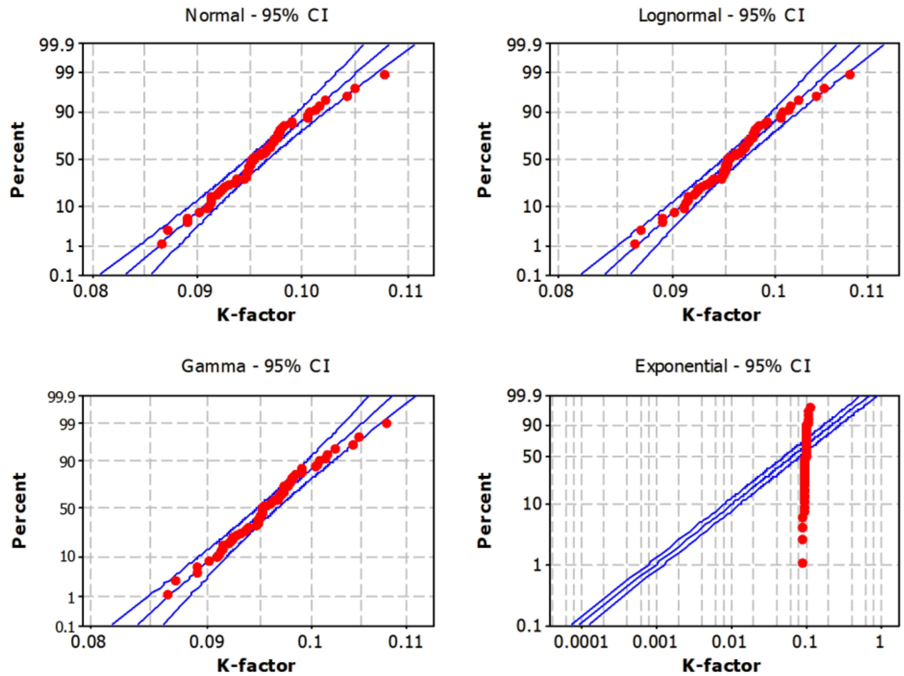
The finalized statistical distributions for *K* obtained from the analysis in Minitab for the ATR stations in urban and rural areas are shown in Figure 6.

Table 2 Goodness-of-fit Test Statistics for Different Distributions for *K*

URBAN AREA			
DISTRIBUTION	**AD**	**P**	**LRT P**
Normal	0.483	0.222	
Lognormal	0.437	0.289	
Gamma	0.437	>0.250	
Exponential	27.085	<0.003	
RURAL AREA			
DISTRIBUTION	**AD**	**P**	**LRT P**
Normal	0.359	0.442	
Lognormal	0.656	0.084	
3-parameter Lognormal	0.350	*	0.0009
Box-Cox Transformation ($\lambda = 3$; Normal)	0.383	0.390	

- Asterisk (*) : p-value cannot be calculated for the distribution; LRT P - Likelihood Ratio Test

(A) URBAN AREA



(B) RURAL AREA

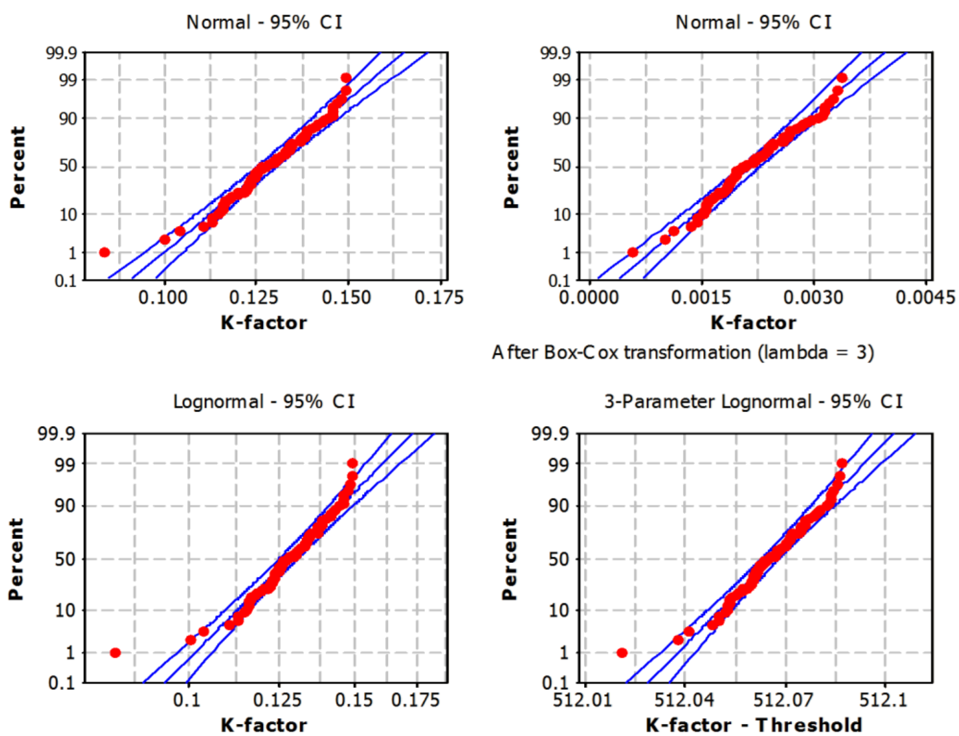
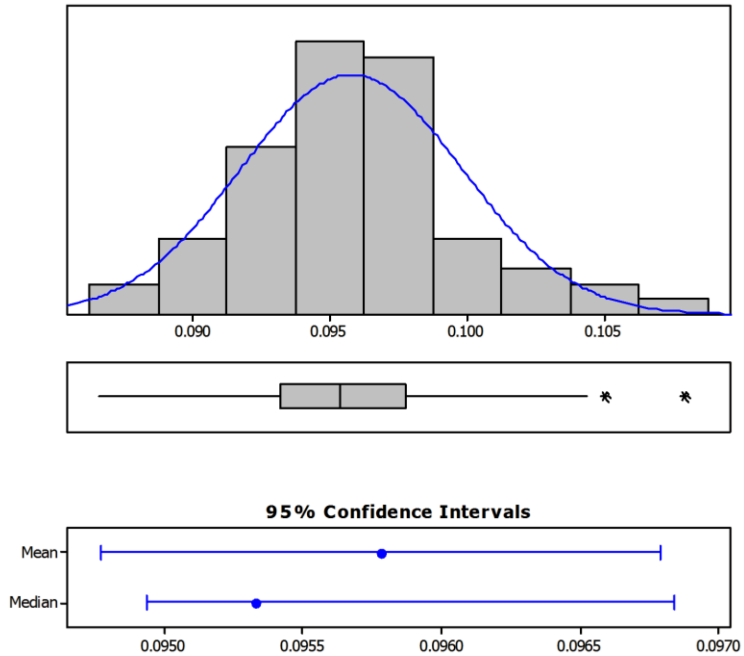


Figure 5 Probability Plot for *K*-factor in A) Urban and B) Rural Areas for Different Probability Distributions

(A) URBAN AREA – LOGNORMAL DISTRIBUTION



(B) RURAL AREA – NORMAL DISTRIBUTION

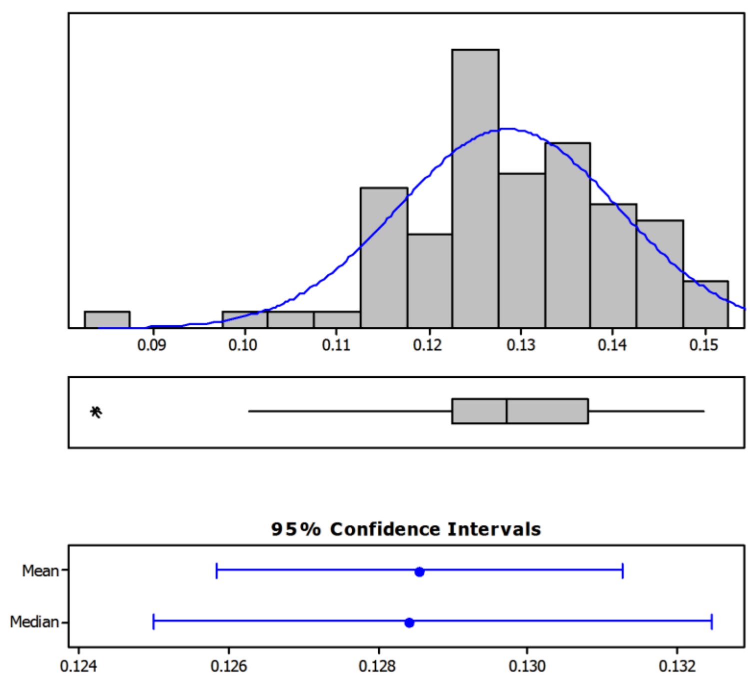


Figure 6 Finalized Statistical Distributions for *K* in A) Urban and B) Rural Areas

The natural variation in K_{30} was best represented by a lognormal distribution in urban locations and by a normal distribution in rural locations. The descriptive statistics for K_{30} for urban and rural locations are shown in Table 3.

In urban areas, distribution of the data appears to be roughly symmetric and is modeled with a Lognormal distribution. *K30* is influenced by the timing of trips during the day. *K30* will be lower on roads which serve many trip making purposes distributed throughout the day (*35*). As the roads in an urban area provide an opportunity to serve many types of trips, the *K* values are lower in urban area (while the AADT values are generally higher).

In rural areas, distribution of the data appears to be symmetric and is modeled with a Normal distribution. Roads which serve few purposes during defined times of the day will normally exhibit high *K* values (*35*). This could be the reason for higher values of *K* in rural areas than urban areas.

After selecting the distribution based on the above mentioned steps, no further tests were conducted. For example, in the above case, a normal distribution was selected as a good fit for K-values in rural areas. The reason for the values of skewness and kurtosis not being zero for normal distribution might be because of outliers in the data.

3.4.2 *Directional Distribution*

The Utah data had directional volumes for every hour for each ATR site. For the thirtieth highest hour identified, the higher percentage of traffic in a direction was calculated to represent the directional distribution. The values of directional distribution for the ATR sites in urban and rural area are provided in Table 4.

Table 3 Descriptive Statistics for *K* in Urban and Rural Areas

URBAN AREA								
MEAN	**St DEV**	**SKEWNESS**	**KURTOSIS**	**MINIMUM**	**1st QUARTILE**	**MEDIAN**	**3rd QUARTILE**	**MAXIMUM**
0.096	0.004	0.3655	0.8544	0.086	0.093	0.095	0.097	0.1079
95% CI for Mean			0.0947	0.0967				
95% CI for Median			0.0949	0.0968				
95% CI for StDev			0.0034	0.0048				
RURAL AREA								
MEAN	**St DEV**	**SKEWNESS**	**KURTOSIS**	**MINIMUM**	**1st QUARTILE**	**MEDIAN**	**3rd QUARTILE**	**MAXIMUM**
0.128	0.012	-0.6705	1.5861	0.083	0.122	0.128	0.137	0.1497
95% CI for Mean			0.1258	0.1312				
95% CI for Median			0.1249	0.1324				
95% CI for StDev			0.0103	0.0142				

CI – Confidence Interval

Table 4 Values of *D* for ATR Sites

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

The directional distribution varies during the hour, day and month of the daily peak volume hours and also with the road type (*36*). Land use impacts, travel patterns, capacity, and queuing are some of the factors that are uncertain and affect the directional distribution of traffic. Hence directional distribution (*D*) was also treated as a random variable with mean μ_D and standard deviation σ_D. The final, recommended distribution was selected based on the *AD* and *P* goodness-of-fit test statistics previously described. The goodness of fit test (i.e., *AD* and *P* test) and the probability plot for different distribution alternatives for *D* are shown in Table 5 and Figure 7, respectively.

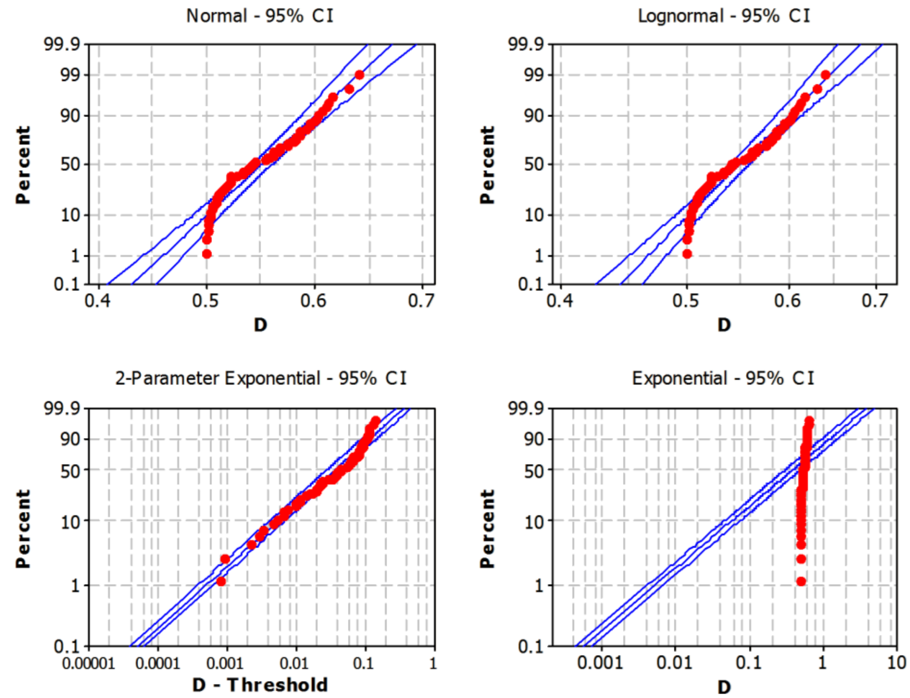
The finalized statistical distributions for *D* obtained from the analysis in Minitab for the ATR stations in urban and rural areas are shown in Figure 8. The natural variation in *D* is best represented by a two-parameter Exponential distribution in urban locations and by a Normal distribution in rural locations. The descriptive statistics for *D* for urban and rural locations are shown in Table 6.

Table 5 Goodness-of-fit Test Statistics for Different Distributions for *D*

URBAN AREA			
DISTRIBUTION	**AD**	**P**	**LRT P**
Normal	1.301	<0.005	
Lognormal	1.242	<0.005	
2-parameter Exponential	1.197	0.055	0.000
Exponential	25.503	<0.003	
RURAL AREA			
Normal	0.660	0.082	
Lognormal	0.690	0.069	
3-parameter Lognormal	0.689	*	0.638
Box-Cox Transformation (λ = 0.5; Normal)	0.663	0.080	

- Asterisk (*) indicates that p-value cannot be calculated for the distribution
- LRT P - Likelihood Ratio Test

(A) URBAN AREA



(B) RURAL AREA

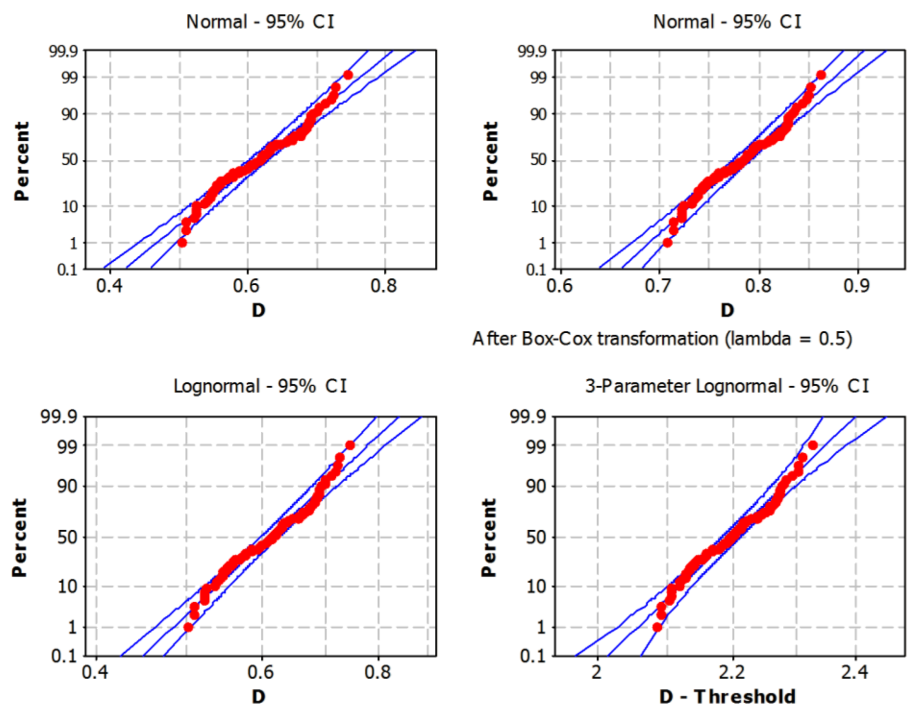
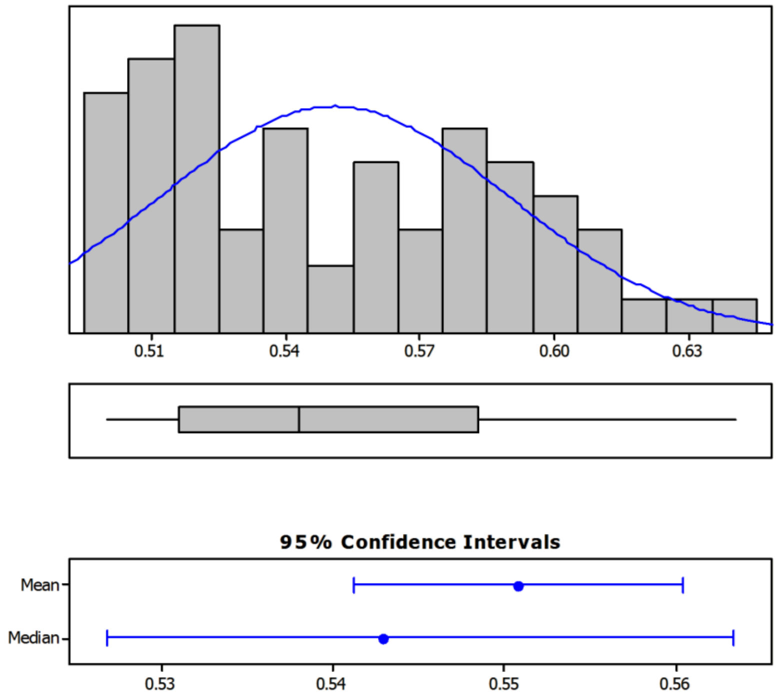


Figure 7 Probability Plot for Directional Distribution in A) Urban and B) Rural Areas

(A) URBAN AREA – 2-PARAMETER EXPONENTIAL DISTRIBUTION



(B) RURAL AREA – NORMAL DISTRIBUTION

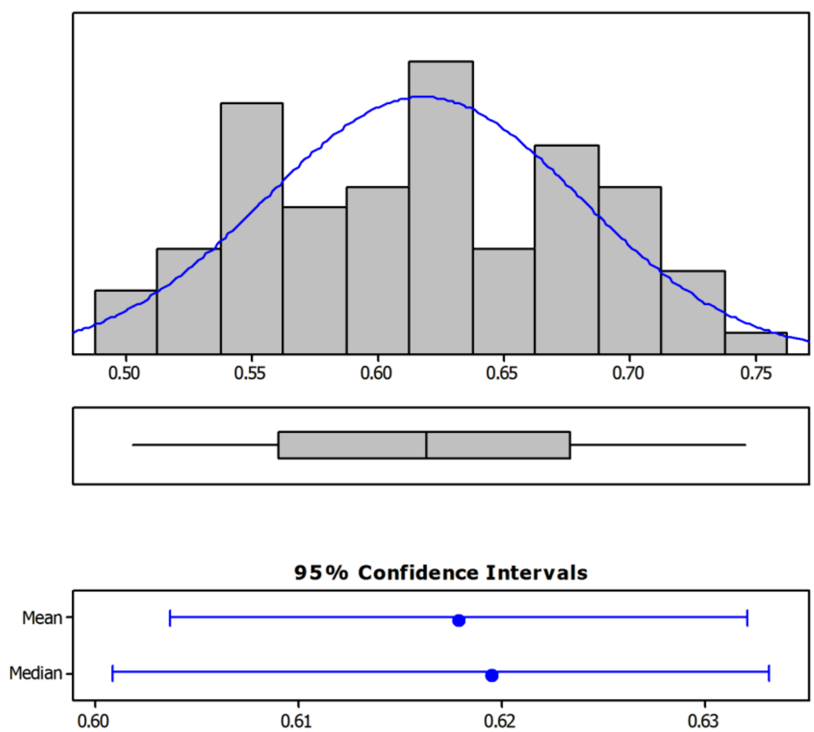


Figure 8 Finalized Statistical Distributions for *D* in A) Urban and B) Rural Areas

Table 6 Descriptive Statistics for *D* in Urban and Rural Areas

URBAN AREA								
MEAN	**St DEV**	**SKEWNESS**	**KURTOSIS**	**MINIMUM**	**1st QUARTILE**	**MEDIAN**	**3rd QUARTILE**	**MAXIMUM**
0.551	0.038	0.3997	-0.9788	0.500	0.516	0.543	0.583	0.6402
95% CI for Mean			0.5412	0.5604				
95% CI for Median			0.5268	0.5633				
95% CI for StDev			0.0328	0.0467				

RURAL AREA								
MEAN	**St DEV**	**SKEWNESS**	**KURTOSIS**	**MINIMUM**	**1st QUARTILE**	**MEDIAN**	**3rd QUARTILE**	**MAXIMUM**
0.618	0.062	0.032	-1.0218	0.503	0.561	0.619	0.676	0.745
95% CI for Mean			0.6036	0.6320				
95% CI for Median			0.6008	0.6332				
95% CI for StDev			0.0540	0.0744				

CI – Confidence Interval

3.4.3 *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).

The values of f_{HV} for the ATR sites in urban and rural area are shown in Table 7. Uncertainty in heavy vehicle volumes is due to the difficulty of quantifying effects of region and area populations and demand (*37*). Uncertainty in PCEs is due to roadway conditions, such as terrain type, and traffic conditions, such as flow rate and heavy vehicle percentage (*38*). This study considered the uncertainty in heavy vehicle volumes in this phase. 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. In the extended analysis shown in the later phase, the uncertainty in PCE values was also considered. These two types of uncertainties would completely address the randomness of heavy vehicle adjustment factor, which is shown in the extended analysis section.

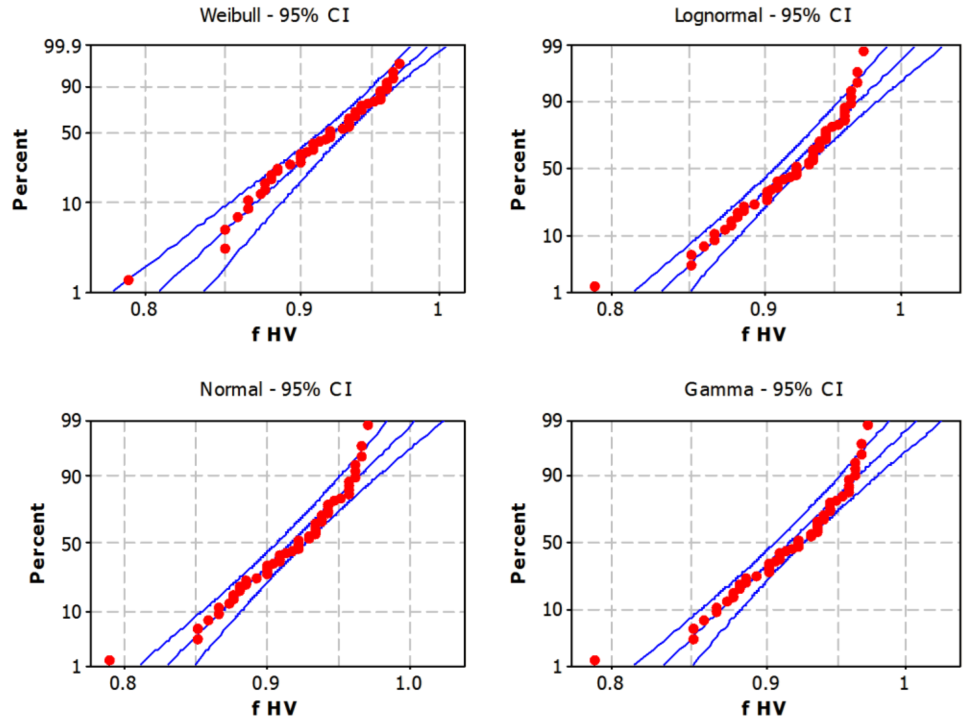
Table 7 Values of f_{HV} for ATR Sites

ATR	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
URBAN AREA											
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 values of f_{HV} were calculated based on Equation 3.5, 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 final, recommended distribution was selected based on the *AD* and *P* goodness-of-fit test statistics previously described. The probability plot for different distribution alternatives (i.e., normal, lognormal, Weibull, gamma, and exponential distributions) for f_{HV} is shown in Figure 9. The goodness of fit test (i.e., *AD* and *P* test) for f_{HV} is shown in Table 8. These distributions only apply for the uncertainty in heavy vehicle volumes which are based on the data from the ATR stations. It was clearly seen in Figure 9 that Weibull distribution follows the straight line in the graph. The graphs, combined with *AD* and *P* test were used to make a selection of f_{HV} distribution in urban and rural areas.

(A) URBAN AREA



(B) RURAL AREA

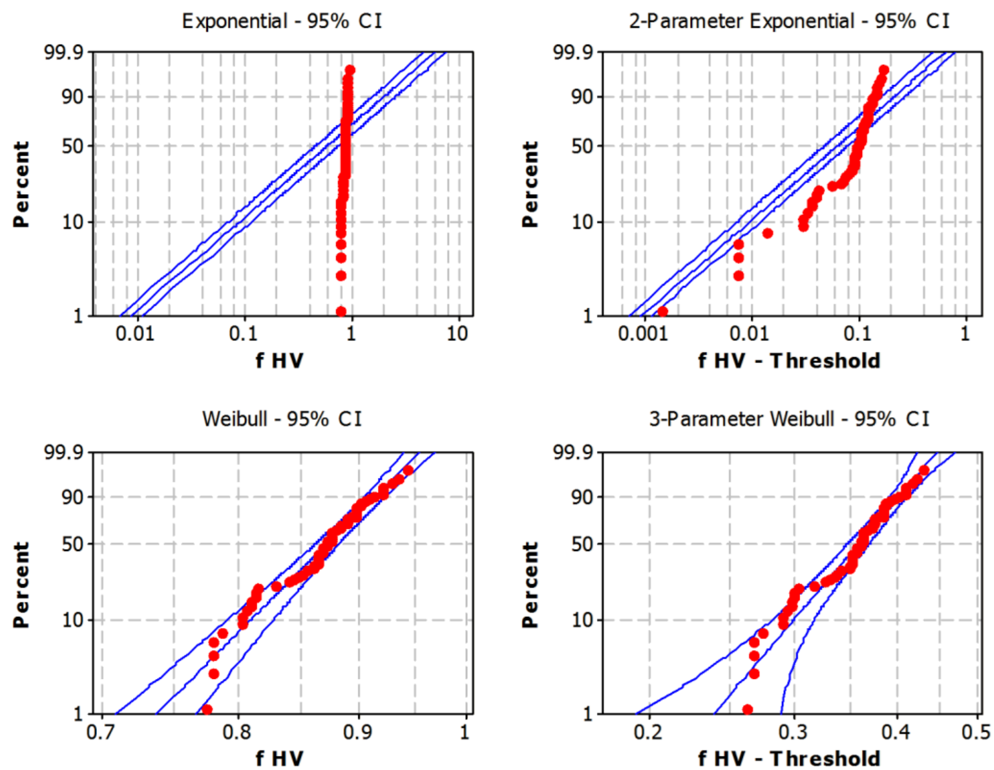


Figure 9 Probability Plot for f_{HV} in A) Urban and B) Rural Areas

Table 8 Goodness-of-fit Test Statistics for Different Distributions for f_{HV}

DISTRIBUTION	AD	P	LRT P
URBAN AREA			
Weibull	0.406	>0.250	
Lognormal	0.901	0.020	
Gamma	0.866	0.026	
Normal	0.790	0.038	
RURAL AREA			
Exponential	26.325	<0.003	
Weibull	0.616	0.105	
2-parameter Exponential	8.492	<0.010	0.000
3-parameter Weibull	0.704	0.031	0.583

- LRT P - Likelihood Ratio Test

A Weibull distribution was selected to represent the variability in f_{HV} for both urban and rural locations. The descriptive statistics for f_{HV} for urban and rural locations are shown in Table 9. In urban areas, distribution of the data is skewed to the left and modeled with a Weibull distribution. The finalized statistical distributions for f_{HV} obtained from the analysis in Minitab for the ATR stations in urban and rural areas are shown in Figure 10.

Table 9 Descriptive Statistics for f_{HV} in Urban and Rural Areas

URBAN AREA

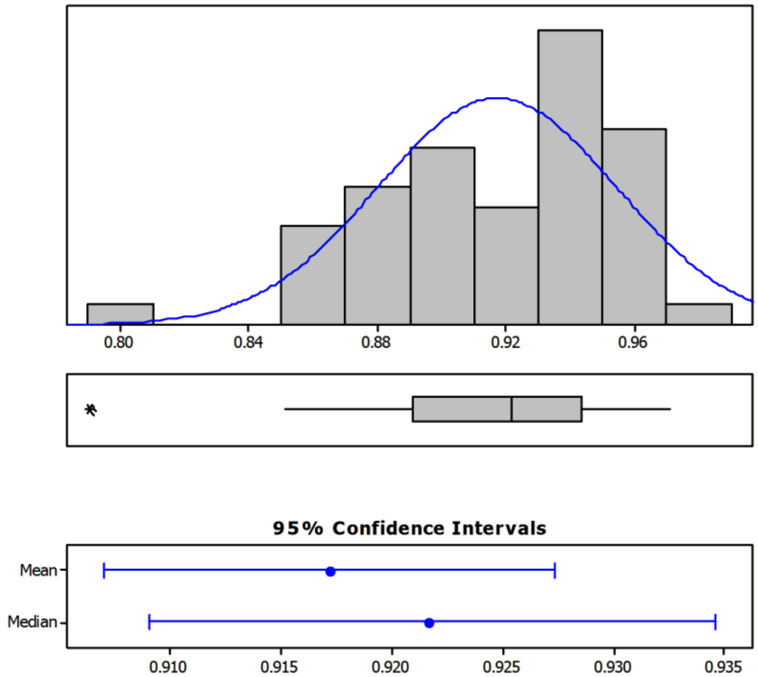
MEAN	St DEV	SKEWNESS	KURTOSIS	MINIMUM	1st QUARTILE	MEDIAN	3rd QUARTILE	MAXIMUM
0.917	0.037	-0.904	1.032	0.790	0.891	0.921	0.943	0.9708
95% CI for Mean			0.9070	0.9273				
95% CI for Median			0.9090	0.9346				
95% CI for StDev			0.0313	0.0459				

RURAL AREA

MEAN	St DEV	SKEWNESS	KURTOSIS	MINIMUM	1st QUARTILE	MEDIAN	3rd QUARTILE	MAXIMUM
0.866	0.041	-0.5686	-0.3134	0.775	0.844	0.873	0.897	0.9434
95% CI for Mean			0.8553	0.8762				
95% CI for Median			0.8658	0.8803				
95% CI for StDev			0.0352	0.0503				

CI – Confidence Interval

(A) URBAN AREA – WEIBULL DISTRIBUTION



(B) RURAL AREA – WEIBULL DISTRIBUTION

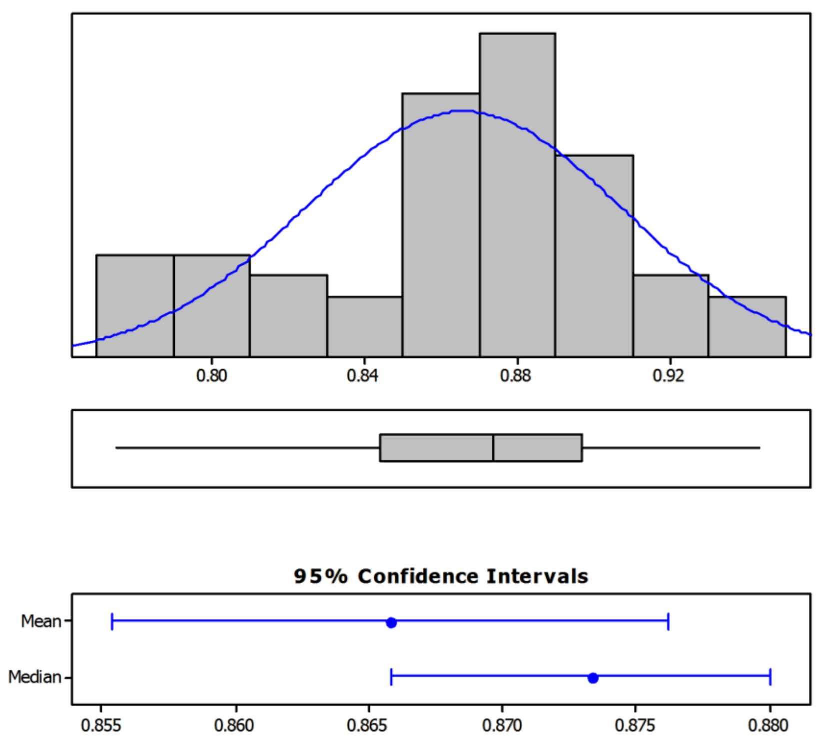


Figure 10 Finalized Statistical Distributions for f_{HV} in A) Urban and B) Rural Areas

Figure 10 shows that f_{HV} values are more concentrated on the right side (i.e., higher values of f_{HV}). Higher values of f_{HV} relate to the lower values of percent of trucks. The lower percent of trucks in the urban area can be justified for the reason that the main truck routes in Utah mostly pass through outside urban boundaries. In rural areas, distribution of the data is skewed to the left, but lesser than the urban area. It is also modeled with a Weibull distribution.

3.4.4 *Average Speed (S) as a Function of Free-flow Speed*

As noted above, Free-flow Speed (FFS) plays a major role in the estimation of the density and level of service 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. All vehicles do not travel at the same speed because of the variation in driver and vehicle characteristics i.e., 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 (*39*). This kind of variation can be approximated by the normal distribution. The Utah ATR data did not include any information on the speeds.

McLean (*40*) has given an overview of FFS studies on two-lane highways. He concluded that the desired speeds of cars can be "reasonably well represented by a normal distribution with mean of about 56 to 62 mph and a coefficient of variation of about 0.11 to 0.14." This results in a standard deviation of around 6 to 9 mph. Accordingly, in this work, the mean and standard deviation of the speeds were approximated to a value of 65 to 70 mph and 7-10 mph for urban and rural areas, respectively. Hence, free-flow speed was considered to be a random variable with mean

μ_{FFS} and standard deviation σ_{FFS}. The random numbers in the normal distribution were generated in Excel using the “norminv” function. The distributions were generated in Minitab software according to the generated random numbers. The descriptive statistics for free-flow speeds for urban and rural areas are shown in Table 10. The distributions for free-flow speeds in urban and rural locations are shown in Figure 11.

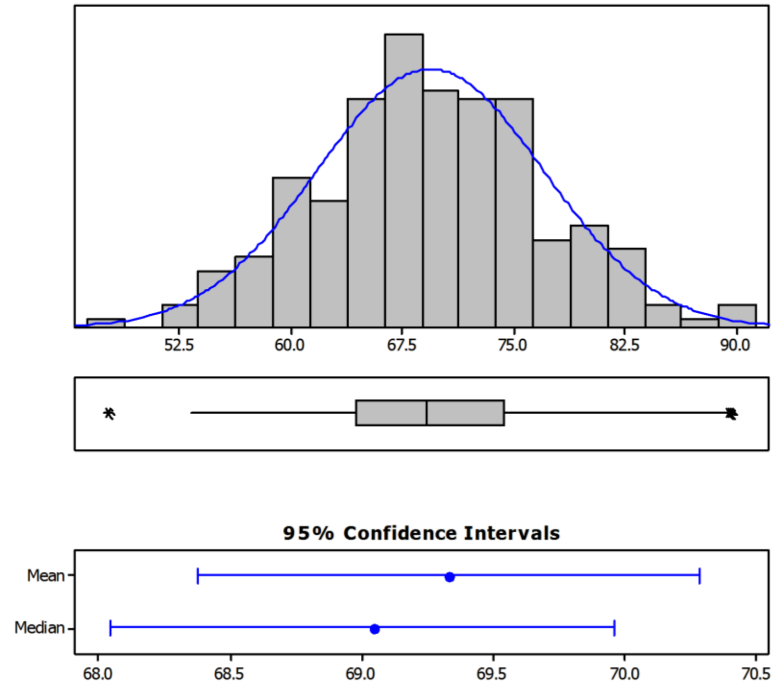
As mentioned earlier, the selection of the distributions of K, D, and f_{HV} was based purely on empirical testing and the feasibility of implementing the distribution in the Monte Carlo method. These distributions were used to demonstrate the intended objective of applying reliability analysis in highway geometric design decisions. The choice of the distributions did not impact the ability to draw conclusions in a broader context. The selected distribution and statistics (mean and standard deviation) for all the design inputs discussed in this section are shown in Table 11.

Table 10 Descriptive Statistics for Free-flow Speeds in Urban and Rural Areas

URBAN AREA								
MEAN	**St DEV**	**SKEWNESS**	**KURTOSIS**	**MINIMUM**	**1st QUARTILE**	**MEDIAN**	**3rd QUARTILE**	**MAXIMUM**
69.33	7.633	0.086	-0.130	47.67	64.381	69.046	74.284	89.534
95% CI for Mean			68.379	70.280				
95% CI for Median			68.043	69.956				
95% CI for StDev			7.017	8.367				
RURAL AREA								
MEAN	**St DEV**	**SKEWNESS**	**KURTOSIS**	**MINIMUM**	**1st QUARTILE**	**MEDIAN**	**3rd QUARTILE**	**MAXIMUM**
66.71	9.094	0.124	0.093	39.425	60.192	66.599	71.831	93.887
95% CI for Mean			65.659	67.776				
95% CI for Median			65.447	67.840				
95% CI for StDev			8.405	9.908				

CI – Confidence Interval

(A) URBAN AREA – NORMAL DISTRIBUTION



(B) RURAL AREA – NORMAL DISTRIBUTION

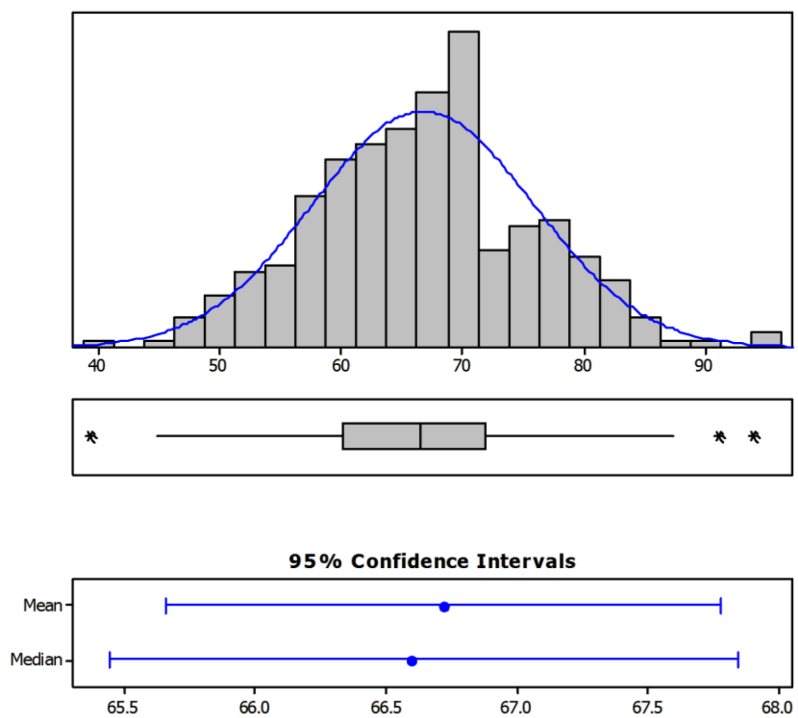


Figure 11 Statistical Distributions for Free-flow Speeds in A) Urban and B) Rural Areas

Table 11 Selected Distributions, Mean, and Standard Deviation of Input Variables

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

CHAPTER 4

RESULTS

This chapter presents the vehicle density results obtained from Monte Carlo simulation, as part of the probabilistic approach to determining basic number of lanes on freeways. It also provides examples of basic number of lanes analysis using the current deterministic approach. This is done to provide a basis for comparison between the two approaches.

4.1 Density Estimation

Density, speed, and flow are the three critical parameters for traffic analysis (*41*). Density is the number of vehicles divided by the length of the road segment. Density estimation provides important information for road planning, and traffic control. Traffic density estimation or prediction is considered to be difficult because density cannot be predicted with certainty as "one number." Contributors to the disturbance term in density estimation include location, weather, land-use type, and vehicle types, and driver characteristics. Further, lane-changing behavior affects lane-wise density significantly. This work considered the disturbances in overall density estimation and not lane-wise density, in particular.

As previously discussed, the LOS for a freeway segment is determined from estimates of traffic density. LOS qualitatively describes the operating conditions of a roadway based on factors such as speed, travel time, maneuverability, delay, and safety (*31*). The level of service of a facility is designated with a letter, A to F, with A representing the best operating conditions and F, the worst.

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 traditional 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.

4.2 Method I: Reliability – Based Method

4.2.1 *Monte Carlo Simulation*

Monte Carlo simulation is widely used to simulate the behavior of various systems, with significant uncertainty in inputs. It is a probabilistic technique that uses a large set of random numbers or samples to measure uncertainty. It requires the knowledge of the distributions of the input variables and a performance function to correlate this distribution with vehicle density. The objective is to generate a sample for each one of these input variables from a distribution that has already been identified. Random sampling may be performed using Minitab's random data functionality. Hence, random samples are generated for the inputs, according to their underlying distributions. 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. The simulations then provide a good representation of the vehicle density under various uncertainties. The example of a Monte Carlo simulation is shown in Figure 12.

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

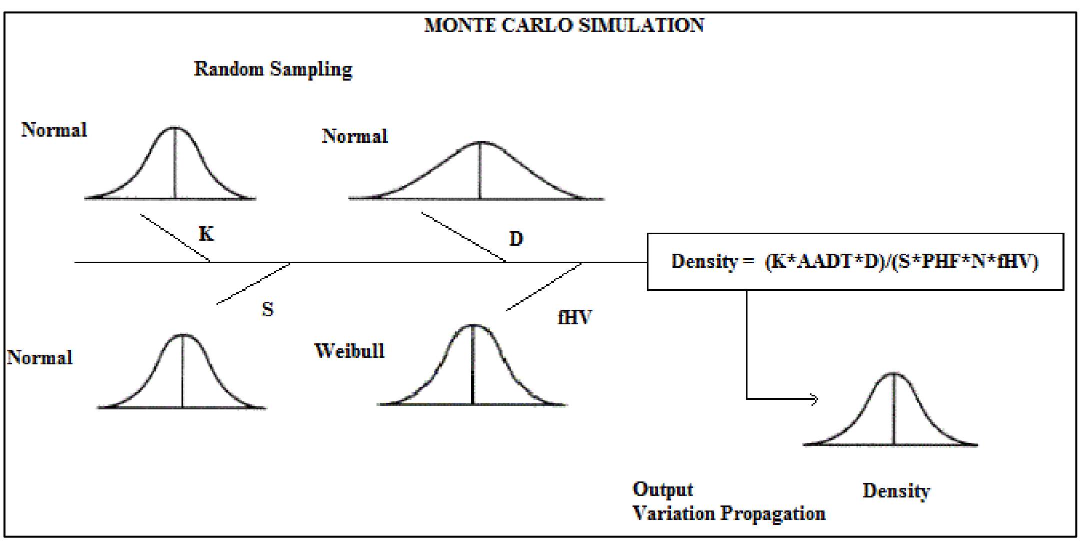


Figure 12 Example of a Monte Carlo Simulation

reliability-based framework. It is now possible to analyze the distribution of the simulated output variable (vehicle density, in this case). The analysis provides a better understanding of how much variability in the output can be expected in normal operating conditions. The results are presented in Table 12, which includes descriptive statistics of density distributions and selected percentile values for densities. Density distributions for two, three, and four directional travel lanes on the urban segment with 75,000 vehicles per day and for two, and three travel lanes on the rural segment with 14,000 vehicles per day are shown in Figure 13 and 14, respectively.

In Figure 13 and Figure 14, the x-axis and y-axis refer to the vehicle density in terms of pc/mi/ln and frequency of vehicle density, respectively. In other words, Figures 13 and 14 are the histograms for vehicle density of the travel lanes. Vehicle density values range from 10-52 pc/mi/ln in urban areas and 2-22 pc/mi/ln in rural areas for different number of lanes alternatives.

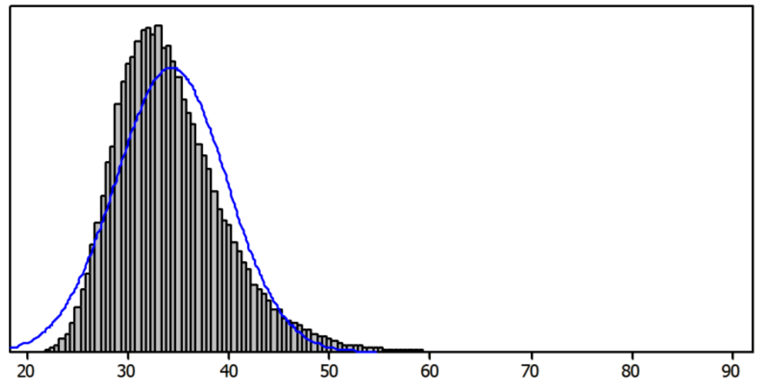
Table 12 Statistics and Percentile Values of Vehicle Density for Different Number of Lanes Alternatives

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	34.285	5.481	33.506	37.268	44.362	50.898	97.24%
3	22.857	3.654	22.337	24.845	29.574	33.932	17.28%
4	17.143	2.740	16.753	18.634	22.181	25.449	0.77%

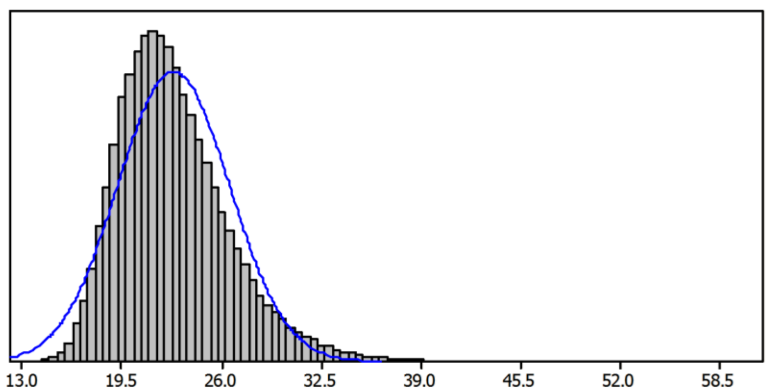
RURAL AREA							
Number of Lanes	**Avg. density (pc/mi/ln)**	**Standard deviation**	**50th percentile**	**75th percentile**	**95th percentile**	**99th percentile**	**Probability that design LOS B is not met**
2	11.130	2.321	10.868	12.468	15.307	17.825	0.92%
3	7.420	1.547	7.246	8.312	10.205	11.884	0%

URBAN AREA

(A) DENSITY DISTRIBUTION FOR TWO DIRECTIONAL LANES



(B) DENSITY DISTRIBUTION FOR THREE DIRECTIONAL LANES



(C) DENSITY DISTRIBUTION FOR FOUR DIRECTIONAL LANES

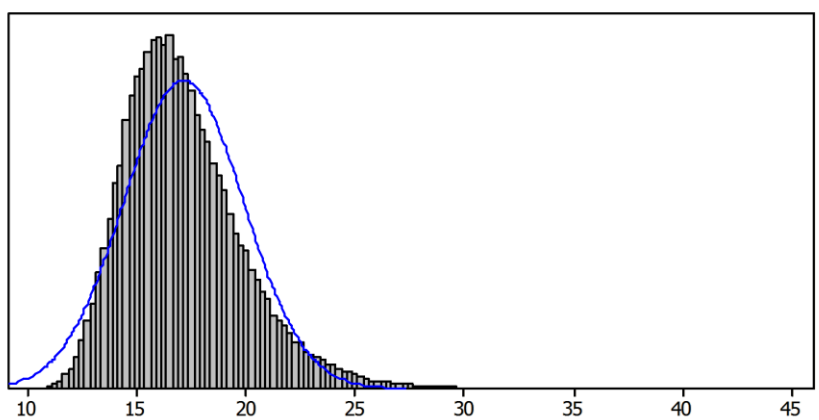
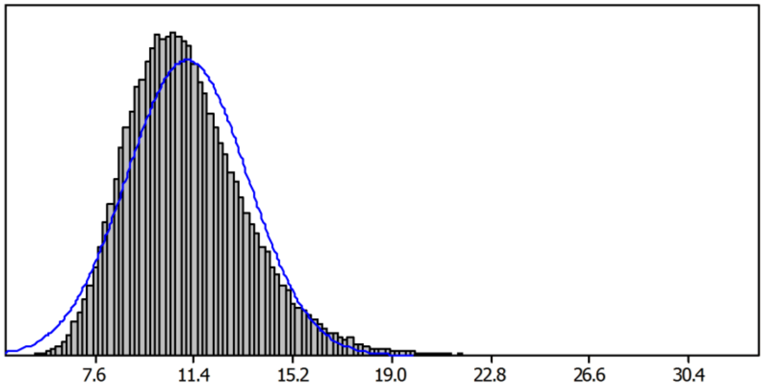


Figure 13 Vehicle Density Distributions for A) Two Directional Lanes, B) Three Directional Lanes, C) Four Directional Lanes in Urban Areas

RURAL AREA
(A) DENSITY DISTRIBUTION FOR TWO DIRECTIONAL LANES



(B) DENSITY DISTRIBUTION FOR THREE DIRECTIONAL LANES

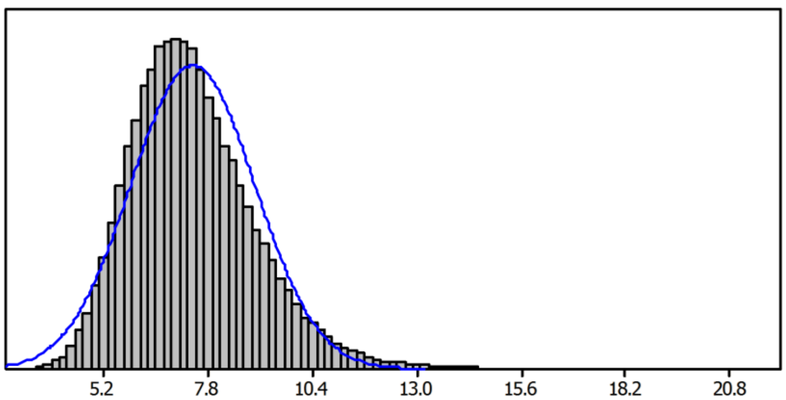


Figure 14 Vehicle Density Distributions for A) Two Directional Lanes, B) Three Directional Lanes in Rural Areas

4.2.2 *Monte Carlo Simulation using Microsoft Excel*

The vehicle density of a facility due to uncertainty in the input parameters was also obtained by Microsoft Excel to verify the results from Minitab. Microsoft Excel is used to calculate vehicle density from Monte Carlo simulation using the probability distributions developed for the input parameters. The inputs for carrying this analysis are K, D, f_{HV}, and FFS. These inputs are similar for urban and rural areas, with difference in the probability distributions for the input parameters.

The inputs for urban area are as follows:

- The percent of daily traffic in the design hour K, where $K \sim LN^{1}\ (\mu_K, \sigma_K^2)$
- Directional distribution of traffic D, where $D \sim 2p\ E^{2}(\mu_D, \sigma_D^2)$
- Heavy vehicle adjustment factor f_{HV}, where $f_{HV} \sim W^{3}\left(\mu_{fHV}, \sigma_{fHV}^2\right)$
- Average speed as a function of free-flow speed FFS, where

  $FFS \sim N^{4}(\mu_{FFS}, \sigma_{FFS}^2)$

Number of simulations, K= 100,000. For K = 1 to 100000, the following methodology was used:

1. Based on the underlying distribution parameters, mean and standard deviation (μ and σ) of the individual inputs, generate a set of random samples using the probability density functions for the input variables.
2. The values for AADT and PHF were assumed to be the same as described above.
3. Use Equation 3.7 to calculate the vehicle density for the simulation from this set of random samples.

Calculate the histogram, mean, variance, and percentile values for the vehicle density from the results over 100000 simulation runs. Figure 15 shows the distributions of the simulated vehicle density generated by Microsoft Excel for urban and rural areas. An urban roadway with three travel lanes in each direction and rural roadway with two travel lanes in each direction were selected to compare results obtained from Minitab and Microsoft Excel.

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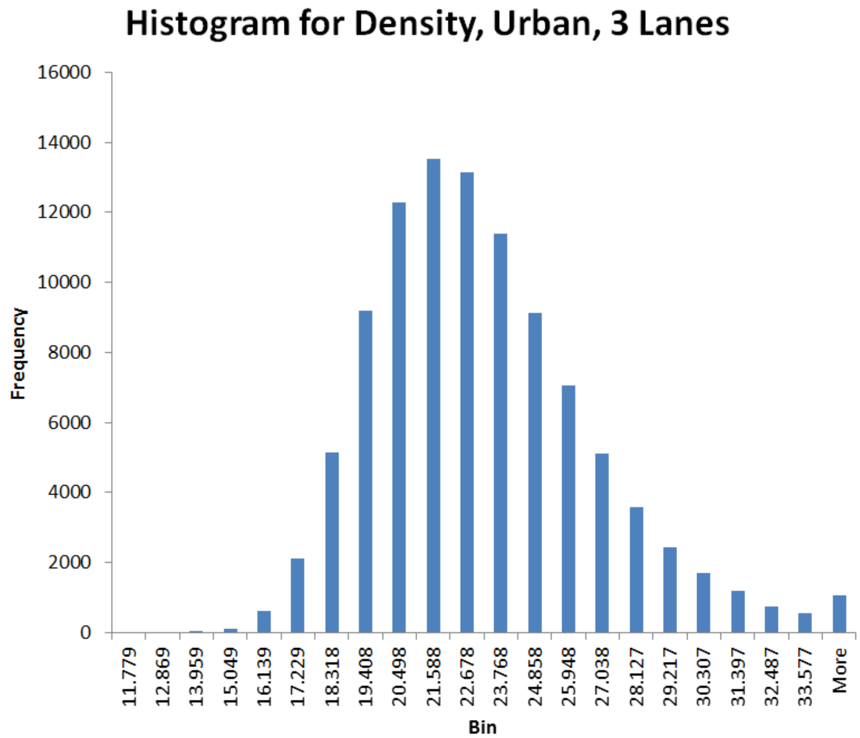
[1] Lognormal
[2] 2-parameter Exponential
[3] Weibull
[4] Normal

A



B

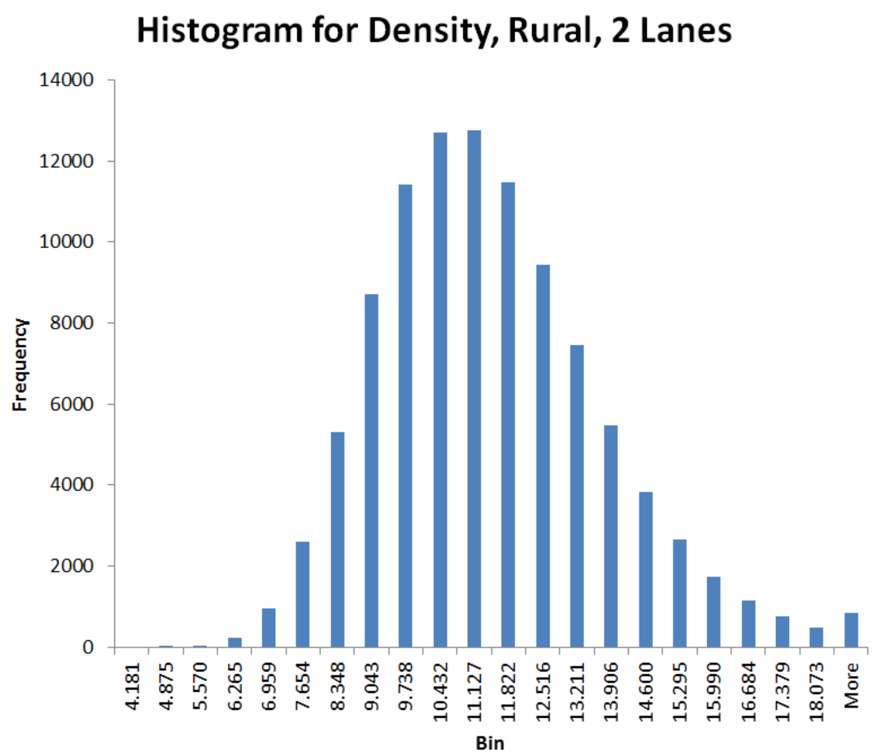


Figure 15 Vehicle Density Histograms for A) Three Lanes in Urban Areas and B) Two Lanes in Rural Areas from Microsoft Excel

As observed in Figures 13 through 15, the vehicle density obtained from the two applications is very similar. This verifies the accuracy of the estimations in Minitab. Obviously, the value and spread of the vehicle density is greater in urban areas than rural areas. In addition, a clear pattern of randomness propagation can be observed in the distribution of the vehicle density. It should be noted that, the input distributions will vary with different facilities, and the resulting vehicle density distributions will also vary.

4.2.3 Extended Analysis

The uncertainty involved in the heavy vehicle adjustment factor was quantified in this work, firstly, by considering the uncertainty in the heavy vehicle volume estimates. The work in this section allows for the quantification of uncertainty in f_{HV} by also taking into account the uncertainty associated with the passenger car equivalencies. The HCM recommends a PCE = 1.5 for level basic freeway segments, which is assumed in this study. However, Umama Ahmed (*42*) stated that this value was true when the truck presence did not exceed 3%. Higher PCE values were identified at higher truck presence levels. However, not enough data were available to study this phenomenon for definite conclusions. Thus, the previously stated finding of PCE factors based on the percentage of heavy vehicles by Umama Ahmed (*42*) was considered in this study. This is done to include the variation in the values for PCEs of trucks with the variation in percentage of trucks. The values for the passenger car equivalent factor relation with heavy vehicle percentage in traffic stream are given in Table 13. These values are used for the PCEs of trucks to completely quantify the uncertainty involved in computing the heavy vehicle adjustment factor.

One problem with Minitab is that the worksheet window in Minitab uses a fixed

Table 13 PCE Factor Relation with Heavy Vehicle Percentage, Data from Umama Ahmed (*42*)

	Vehicle Class 4 and above	
Heavy Vehicle percentage	Headway (Seconds)	Passenger Car Equivalent
>0-3%	2.14	1.50
3-6%	2.32	1.62
6-9%	2.48	1.74
>9%	2.51	1.76

structure that is more difficult to manipulate than in spreadsheet programs like Microsoft Excel. Hence, Microsoft Excel is used for this analysis. The first step in the analysis is to identify the distributions for percent of trucks in urban and rural areas. Based on the data obtained from UDOT website, the percent of trucks followed a 2-parameter exponential distribution and lognormal distribution in urban and rural areas, respectively. Then, random samples of percent heavy vehicles are generated based on the distributions, and then the PCE values for different percentages of trucks are assigned according to the values given in Table 13. Thus, the value of f_{HV} was calculated based on:

- Uncertainty in heavy vehicle volumes and
- Uncertainty in PCE values of trucks.

The vehicle density is calculated using Equation 3.7 for the simulation from the set of random samples with the new f_{HV}. Density values for this simulation for urban and rural areas are shown in Table 14.

Table 14 Statistics and Percentile Values of Vehicle Density for Different Number of Lanes Alternatives with the New f_{HV}

URBAN AREA							
Number of Lanes	**Avg. density (pc/mi/ln)**	**Standard deviation**	**50^{th} percentile**	**75^{th} percentile**	**95^{th} percentile**	**99^{th} percentile**	**Probability that design LOS C is not met**
2	35.138	6.021	34.209	38.333	46.262	53.562	97.62%
3	23.425	4.014	22.806	25.555	30.841	35.7086	22.11%
4	17.569	3.011	17.105	19.166	23.131	26.781	1.42%
RURAL AREA							
Number of Lanes	**Avg. density (pc/mi/ln)**	**Standard deviation**	**50^{th} percentile**	**75^{th} percentile**	**95^{th} percentile**	**99^{th} percentile**	**Probability that design LOS B is not met**
2	11.776	2.513	11.492	13.215	16.317	19.086	1.92%
3	7.850	1.675	7.661	8.810	10.878	12.724	0%

4.3 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 3.7, 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 mean values 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 15. Example density calculations for three directional travel lanes in an urban area and two directional travel lanes in a rural area are shown:

For an urban area:

Table 15 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

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

For a rural area:

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

4.4 Discussion

4.4.1 *Discussion of Results: Urban Segment*

The top half of Table 12 provides information on the probability distribution of operational performance that might result from basic number of lanes decisions made to achieve a design level of service 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 a 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 83% 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 a 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.

4.4.2 *Discussion of Results: Rural Segment*

The bottom half of Table 12 provides information on the probability distribution of operational performance that might result from basic number of lanes decisions made to achieve a design level of service 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 1% chance of operating at LOS B.

4.4.3 *Discussion of Results: Extended Analysis*

Table 14 provides information on the probability distribution of operational performance that might result from basic number of lanes decisions made to achieve a design level of service on an urban and rural freeway. This analysis considers the uncertainty associated with passenger car equivalencies in f_{HV} estimation, with a design year AADT of 75000 in urban area and 14000 in rural area per day. As with the former analysis, the results account for uncertainty in estimates of K_{30}, D, FFS, f_{HV}. The uncertainty associated with f_{HV} in the former analysis was partially quantified by accounting for uncertainty in heavy vehicle volume estimates. In this section of extended analysis, the uncertainty of f_{HV} is fully quantified by accounting for the uncertainty in PCE's along with heavy vehicle volume uncertainty. The results from extended analysis show that the average vehicle density value for urban and rural area for different number of lanes alternatives increases almost by 1pc/mi/ln when compared to the value obtained through former analysis.

Greater variations in the values of density were not seen because of the fact that PCE values were based on the headway and percent of trucks. The percent of trucks in urban and rural areas is mostly higher than 9% in this study. This results in a PCE value of 1.76, applicable to almost all the observations. Hence, there was only a slight increase in the density value. This analysis would have been significant in situations where there is a greater range in the value of percent of trucks.

4.4.4 *Comparison of Results: Probabilistic and Deterministic Approach*

As noted earlier, "one number" and "one letter" represent the estimates for density and level of service in a deterministic analysis. Density is considered to be a "possible range" in probabilistic 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 an 83% chance that the segment would operate at or better than the design LOS C;
- There is a little more than a 16% chance that the segment would operate at LOS D; and
- 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 level of service. 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.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

This chapter summarizes the work carried out in this study and the findings of the reliability analysis performed. Recommendations for future improvements in the analysis are also presented in this section.

5.1 Summary

Designers have to deal with the challenge of designing for a broad range of driver, vehicle, and roadway conditions and capabilities. In other words, there is natural randomness associated with the input variables. While almost all the factors involved in geometric design process (i.e., speed, friction, reaction time, etc.) are stochastic in nature and are fully distributed among the road users, the current deterministic approach relies on a single value to represent each factor (*43*). This study proposes a methodology to explicitly address the level of variability and uncertainty associated with the design inputs, in the context of probabilistic analysis. This approach utilizes a full distribution of input parameters and attempts to achieve a reliable road geometric design. A literature review conducted as part of this work showed that previous studies focused mainly on safety-related concerns (e.g., available versus required sight distance, vehicle skidding and rollover) and not in an operational context.

The objective of this work is to demonstrate a reliability-based geometric design approach that incorporates the uncertainty associated with traffic-related characteristics to making decisions regarding the basic number of lanes on freeways. This analysis is executed in an operational context. This work was tested using the data from the State of Utah. Data were obtained from 14 ATR sites on Interstate 15 and Interstate 80 for the years 2002 through 2012. For all the 14 ATR sites, data were available on an hourly basis and UDOT ATR maps were used to associate area type with each site. Probability distributions were identified for each of the design input variables using the obtained data for both urban and rural freeway segments. Then, the contributions of uncertainty in the traffic-related variables to the variation of vehicle density were evaluated using Monte Carlo simulation.

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 that were developed to obtain a distribution of the vehicle density.

5.2 Findings

The analysis presented here in this work offers a rational framework for addressing the uncertainty in the geometric design process. Designers can use this method to explicitly consider uncertainty in the evaluation of vehicle density and LOS (i.e., operational performance). This research provides a different perspective on the development and usability of a performance-based design approach. The methodology is a step towards not only allowing a check and feedback of highway operational information at highway geometric design stage, but of also being able to explicitly consider the impact of design decisions on the future variability in operational performance. Several conclusions are drawn from the analysis and discussions are presented:

For the urban case study:

- The proportion of daily traffic in the design hour, the 30th highest hour, (K_{30}) ranged from 0.09 – 0.11.
- The probability that the value of directional distribution (D) exceeded 0.55 was 47%.
- The probability of having LOS C or better was 3% if two lanes per direction are provided and increased to a value of 83% if three lanes per direction are provided.
- The probability of operating at LOS B or better was 75% if four directional lanes are provided.

For the rural case study:

- The proportion of daily traffic in the design hour (K_{30}) in this study ranged from 0.08 – 0.15.
- The probability that the value of directional distribution of traffic (D) exceeded 0.70 was 9%.
- The probability of having LOS B or better was 99% if two lanes per direction are provided.
- Probability of having LOS A or better was 50% if two directional lanes are provided.

The probability of not meeting design LOS increases as the basic number of lanes decreases. Based on the probability values in the output distribution of density, scenarios corresponding to a specified “worst case”, “expected case”, and “best case” are easily determined.

Uncertainty is present in every stage of highway geometric design and can be best addressed through a probabilistic framework. 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. 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.

5.3 Future Work

This work adds to the existing knowledge base by developing and executing reliability analysis of geometric design in an operational context. The framework allows designers to explicitly consider the probability distribution of operational performance that might result from different basic number of lanes decisions. While the research conducted here offers valuable information and represents a significant departure from much of the research in this area, there are a variety of ways in which the data and the proposed methodology can be improved. The analysis in the paper can be further improved by

- Incorporating uncertainty involved in the projection of AADT by considering annual growth rate as a random variable;
- Incorporating uncertainty into the PCEs of trucks, due to different truck performance characteristics based on truck weight and power.
- 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 as well as in different operational settings (e.g., providing auxiliary lanes, selecting maximum vertical grade, selection of intersection control type and lane arrangement);
- Repeating the research on other freeway segments to determine if the results can be generalized; and
- Incorporating uncertainty involved in lane-wise density by taking into account the lane changing behavior of vehicles, which affects lane-wise density significantly.

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