FINAL RESEARCH REPORT

SAFETY EVALUATION TESTBEDS -- AN ASSESSMENT OF SAFETY PROJECT PRIORITIZATION IN THE WSDOT I2 PROGRAM

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This study was conducted in cooperation with the U.S. Department of Transportation, Federal Highway Administration.

16. ABSTRACT: This study examines the feasibility of Bayesian and data envelopment techniques for robust identification of safety priorities in the Washington State DOT improvement program. Findings indicate that the methods employed in this study have potential for reliable predictions and identification of safety needs. A case study dataset of high accident locations was used to make this assessment.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

EXECUTIVE SUMMARY

The current Washington State Department of Transportation (WSDOT) method for evaluating roadway projects for safety upgrades relies on procedures that combine frequency and severity of accidents at locations in a weighted manner. This is a reasonable procedure that captures a significant portion of locations deserving of safety upgrades in a consistent manner. However, what is not apparent from the programming process is the cause of turnovers of locations from year to year. One main issue underlying the turnover rate is the reliability of predictions of accident risk. The second issue related to the turnover rate is one of efficient investment. For example, any given highway accident corridor needs to be examined in terms of benefits and costs from safety investments, and how they efficiently relate to performance measure of the location. To fully optimize the Highway Safety Management System (HSMS) at the WSDOT, both of the above-mentioned dimensions need to be addressed in conjunction with one another. Accident occurrence prediction and approaches for establishing consistent and sustainable safety programs in addressing risk through proper and timely investment are the main issues researched in this report. To this end, we analyzed a pilot subset of the WSDOT I2 program that specifically deals with safety needs. We examined 190 sections in the Northwest Region and provide findings related to both predictive reliability and programming efficiency issues.[1] The I2 program is a sub-program within

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WSDOT's "Improvement" category. The I2 program involves capital projects that are prioritized strictly on safety needs.

BACKGROUND STATEMENT

Motor vehicle accidents continue to be a major cause of death and injury in the United States. As a consequence, state and federal agencies expend considerable resources in an effort to improve safety by implementing countermeasures that include improving highway geometrics, highway signing, and right-of-ways. The goal of WSDOT, the Washington State Patrol, and the Washington Traffic Safety Commission is to reduce and eliminate deaths and disabling injuries on our state's highways and roads. Figure 1 below shows fatality rate trends for three networks – national, Washington State highway, and Washington roads. Fatality rates are measured in terms of fatalities per 100 million vehicle miles traveled.

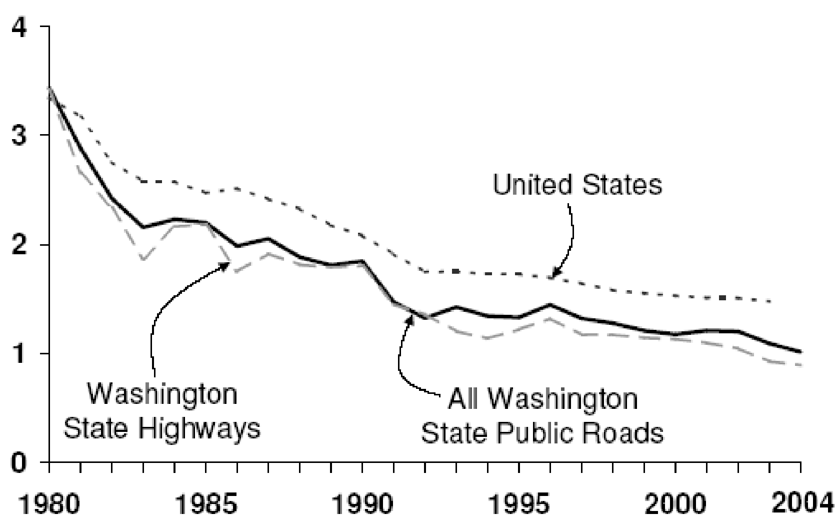

Figure E-1. Comparison of Traffic Fatality Rates from 1990 to 2000.
(Provided by: WSDOT Transportation Data Office)

The WSDOT is a leader in the management of fatal and disabling injury rates nationally. A recent internal study (highlighted in the WSDOT Gray Notebook) conducted by key WSDOT safety staff reports that

> *"Washington State has one of the lowest fatal accident rates per hundred million vehicle miles traveled among all 50 states. WSDOT evaluates past accident history to determine strategies to further reduce fatal and disabling crashes. This approach is incorporated into the state's long range plan (Washington Transportation Plan) and used to direct future capital investments."*

In recognition of its practices, the American Association of State Highway and Transportation Organizations (AASHTO) recognized WSDOT for its proactive approach to safety. In May 2005, AASHTO presented WSDOT with its Safety Leadership Award. WSDOT's approach is based upon a "local, corridor and system-wide perspective. Working with other safety agencies, WSDOT adopted a strategic safety plan, called Target Zero. As an outcome, the state has had a 56% decrease in fatal and disabling crash rates since 1990 even though vehicle miles traveled over that period have increased by 35%."

In light of such advances in safety management, the WSDOT is continually improving the safety management process through approaches that are pro-active. A proactive approach would improve potentially problematic areas before severe accidents and the infrastructure damages associated with accidents have occurred. Statistical modeling provides a proactive approach by developing a relationship between the severity or frequencies of accidents and information on road geometrics, traffic volumes and roadside features. The "proactive" capability arises from WSDOT's ability to predict accident occurrence and severity using existing infrastructure information. Applying proactive approaches in the WSDOT I2 program context requires categorization of accident locations. The Washington State Department of Transportation categorizes highway accident prevention and reduction locations in the following manner:

High Accident Location (HAL): spot locations less than a mile long with a higher than average rate of severe accidents in the past 2 years.

Pedestrian Accident Location (PAL): spot locations (0.10 mi or less) that have 4 accidents in a 6-year period.

High Accident Corridor (HAC): sections of state highway one or more miles long, with a higher than average number of severe accidents over a continuous period of time.

A detailed explanation of WSDOT's current methodology behind identification of HAL is provided in a following section on data and methodology in this executive summary.

OBJECTIVES

The objective of this study was to assess the current system of prioritizing and programming safety projects through WSDOT's I2 program, with a special focus on high-accident locations. Pedestrian accident locations and high accident corridors were not part of this study. However, the extension of the proposed methodology to those categories is straightforward. Accident risk predictive reliability and identification of methods for analysis of safety programming efficiency on the basis of multiple safety performance measures were the major goals of analysis.

BENEFITS AND CONTEXT

The major benefit of this study will be a method to address systematically the programming of all projects in the state's I2 program. This includes coverage of collision prevention and collision reduction sub-programs on a comprehensive basis. In doing so, WSDOT will be able to implement procedures that prioritize locations in terms of social costs and benefits, while providing for maximal coverage of locations in terms of identified and funded improvements. While this is a complex goal to accomplish, the benefit will be significant. As an example, if one were to consider HALs in each biennial cycle, over 600 locations are typically identified for improvements. Scoping for improvements begins with identifying trends in accident histories. Accurate identification of safety improvement priorities with a high level of certainty maximizes the efficiency of the scoping process. With WSDOT's 2005-2015 ten-year plan for Highway Safety Improvements providing for nearly a billion dollars in targeted safety enhancements, the I2 process has much to gain from systematically addressing project turnover in system plans from one biennial cycle to the next. "Turnover" is defined as a location that repeats as a high-priority accident spot or corridor. The percent of locations "turning over" from one biennium to the next varies by functional class and region. In the case of HALs for example, Northwest Region "turnovers" are the highest across three bienniums (2003-2005 to 2007-2009). Figure 2 shows the "turnover" trend.

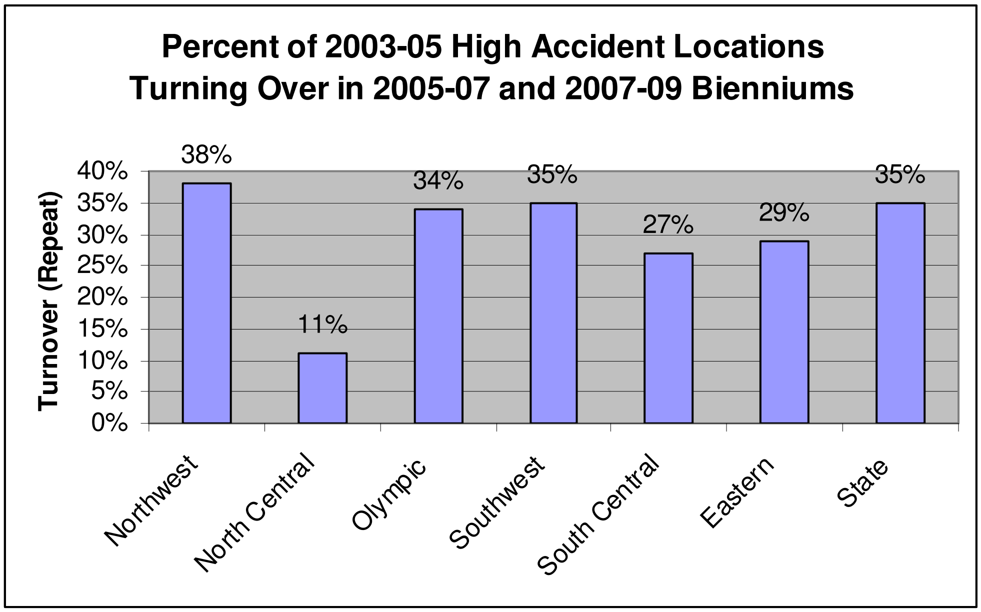

Figure E-2. High Accident Location Turnover Trends.

As seen in Figure 2, 38 percent of the Northwest Region HAL network turns over from the 2003-2005 biennium to the 2007-2009 biennium. The state as whole turns over 35 percent of the 650 high accident locations during the same period, while, North Central Region turns over the least, 11 percent. The variability in regional turnovers is attributable to the distribution of urban, high volume locations in the state network. Regardless of the variability, consistent system-level enhancements that address with a high level of certainty, necessary safety improvements at properly prioritized HALs also result in improved project life cycles, thereby enhancing investment efficiency. If the "turnover" period is limited to two bienniums, approximately 50 percent of HALs statewide turn over from the 2003-05 biennium to the 2005-07 biennium. The above mentioned trends emphasize the usefulness of a reliable predictive methodology for targeting the locations where reductions in societal costs due to accidents would be greatest.

Another benefit of this study is the development of a composite method that consistently takes into account information from both the frequency and severity dimensions of accidents. Incorporating severity will ensure that locations with high societal costs are targeted for improvement. Such a method can be consistently used throughout Washington State. This consistency may also substantially reduce the fiscal and personnel resources which are currently used to collect and analyze roadway and roadside data.

DATA AND METHODOLOGY

We used 190 roadway sections classified as high-accident locations in the Northwest Region of WSDOT as our safety evaluation testbed. Information relating to geometrics and traffic volume was compiled to correlate with the observed accident history and predicted accident risk. Roadway geometrics included information on number of lanes in cross section, number of interchanges and intersections in section, number of curves per mile, presence of a median barrier, and whether or not the highway was divided.

The existing WSDOT programming methodology examines accident histories over a two-year period to determine high-accident locations. Every odd-numbered year, the previous two years of accident data are analyzed. For example, in 2005, accident histories for the 2003-2004 period are assembled and analyzed. The analysis is intended to provide a list of HALs for the 2007-2009 biennium. The initial analysis of this data identifies locations on the basis of severity, frequency and accident occurrence proximity. Within a 0.1-mile interval, if six or more accidents are observed in a two-year period with a total severity score of 10 points or higher, then, that roadway segment is initially classified as a severe accident location (SAL). (Severity scores are assigned on a ten-point scale. An accident that results in property damage only, i.e., the lowest severity, is assigned one point, while a fatal accident is assigned 10 points. Other severity types such as possible injury, evident injury and disabling injury are assigned 3, 5 and 9 points respectively.) Adjacent or overlapping clusters that meet or exceed the above-mentioned severity and frequency criteria are then combined, and assigned to one of six roadway categories. Typically, the length of a roadway segment resulting from combining accident clusters is less than one mile. The six categories include rural and full access control, two-lane rural and no-full access control, four-lane or wider rural and no-full access control, urban and full access control, two-lane urban and no-full access control, and four-lane or wider urban and no-full access control state roadways. Average daily traffic volumes and severity scores for the accident clusters within each of the six roadway categories are used to compute severity rates per million vehicle miles. An average severity rate is computed for each roadway category in order to benchmark the individual roadway segments within a category. Any roadway segment with accident clusters exceeding the average severity rate for its category by at least one standard deviation is then designated as a HAL. A second criterion not involving the computation of severity rates can also come into play in the identification of HALs. By this criterion, within a two-year period, if two or more fatal accidents occur on the 0.1-mile roadway segment, classification as a HAL is warranted.

By description, current methodology is entirely based on histories, and targets a select group of locations. The select group of locations as mentioned previously have to exceed the "critical severity rate" criterion whereby the roadway segment severity rate is equal to or higher than one standard deviation above the average severity rate. The larger the deviation of a roadway segment's severity rate from the critical rate, the greater the segment's "severity index." By definition, a HAL's severity index has a minimum value of zero and increases as the segment's severity rates deviates from the critical rate.

The above description highlights several safety performance measures currently in place in WSDOT's I2 program. Frequency and severity index are measures directly available from the HAL identification process. In addition, societal costs of accidents are computable, using up-to-date costs used by WSDOT for accident severity types. The cost of a fatal or disabling injury is $1,100,000, with evident injury cost at $70,000, possible injury cost at $35,000 and property damage at $6,500. In addition to this measure, accident reductions, preventions and costs of those benefits and associated benefit cost ratios of potential improvements are useful safety performance measures. Agency inputs involve costs of improvements and infrastructure components contributing to the safety outcomes. Infrastructure components can be multivariate – including but not limited to travel lanes, horizontal curves, interchanges, intersections, presence of medians, and presence of centerline or median barriers. Traffic volumes are major contributors to safety deficiencies. In order to address this multidimensional problem, a methodology that can incorporate multiple outputs and inputs while providing a consistent benchmark of improvement efficiency is necessary. Toward this end, we employ data envelopment analysis (DEA). Data envelopment analysis is primarily used for the analysis of efficiency of investments. When faced with multiple outputs and multiple inputs, along with multiple decision units, DEA offers a prioritizing method that ranks decision units in terms of their "relative efficiency." (In our study, a HAL is the unit of decision making.) The HALs that perform the best in terms of relative efficiency are ranked the highest, for example an efficiency score of 100. HALs with efficiency scores less than 100 follow in descending order of priority. By this definition, one or more HALs can be ranked as highest in terms of priority. This is a useful property for WSDOT's decision making purposes with regard to I2 investments, since several HALs can simultaneously provide the greatest benefits and resulting investment efficiencies. The DEA method also has the flexibility of comparing multiple improvement scenarios for any given HAL. This is particularly useful when agency costs and benefits are evaluated in terms of benefit cost ratios. Using the DEA method, we can assess if low-cost improvements can perform with better relative efficiencies than high-cost improvements. Furthermore, DEA also provides insight on inputs that contribute the greatest to the relative efficiency of a HAL.

The second major dimension of the HAL identification process is the reliability of the identification procedure. In our earlier description of the current methodology, we noted that “turnovers” and HAL identifications were entirely history based. A predictive method that forecasts at a high level of accuracy expected accident potential is particularly useful from a pro-active standpoint. We noted that “turnovers” comprise 35 percent of the HAL sample when looking ahead two bienniums in advance. The remaining 65 percent raises the critical issue of predictability. A method that can correlate the multivariate infrastructure components to expected accident potential taking into account uncertainty and variability associated with individual HALs is necessary. By incorporating uncertainty into the analysis, we can provide “credibility levels” for predictions of expected accidents for individual HALs. The intent behind this approach is to establish prediction thresholds acceptable to WSDOT decision makers while ensuring a high level of accuracy in the prediction process. Toward this end, we employed Bayesian approaches to make use of their ability to improve risk predictability of accident count locations. Not only is the Bayesian approach advantageous for high-frequency accident locations, but also useful for injury-prone locations as well. The Bayesian method provides predictions of total number of accidents, or number of accidents by severity type depending on what the need may be, as well as credibility levels for predictions for every individual HAL. The inputs are multivariate, i.e., several infrastructure characteristics can be simultaneously used to develop the predictions. Using a predictive method such as the Bayesian technique safeguards against “regression to the mean” effects that may influence HAL identification. Regression to the mean is a phenomenon whereby locations with higher than average accident counts regress to their lifetime average without intervention. In such cases, treating them as locations with potential of improvement would appear to be misguided investments.

FINDINGS, RECOMMENDATIONS AND IMPLEMENTATION PLAN

Two main findings emerged from this study. The first finding relates to the usefulness of data envelopment analysis to the analysis of safety investments within the WSDOT programming context. This method is especially useful for analyzing the efficiency of a program in terms of relationship between design inputs and multiple performance outputs. Multiple performance outputs in a safety context typically include accident counts, severity index, societal cost of accidents and benefit cost. In combination with data envelopment analysis, we propose a method that employs hierarchical Bayesian techniques to improve significantly the predictive reliability of accident risk and hence more robustly identify sites with safety improvement potential.

Specific findings emerging from the DEA method indicate that up to 50 roadway HALs ranked as top priority locations, i.e., priority ranking of one. A priority ranking of one for 50 out of 190 locations implies approximately 26 percent of HALs are top priority locations. With enhanced data collection and multiple improvement alternatives, the possibility of assigning top priority to a broader set of locations exists. The HB method for predicting accident counts for the 190 HALs showed that the locations selected will maintain their observed accident profile at a high level of credibility. Since we noted that the current HAL methodology is primarily history-based, the prediction method's usefulness is in benchmarking the identification of HALs. As such, it should be noted from this study that the methods used are not intended to replace WSDOT methodology per se; rather, they are used as part of a parallel process to ensure current methodology is robust. The main advantage of the methods used in this study is to suggest broader coverage of top priority locations, where history-based methods are limited in their capabilities. It is hence recommended that the methods used in this study be employed as supplementary tools systemwide to maximize opportunities for I2 efficiency, while maintaining current methodology. Details on the predictive accuracy our methods and suggestions for improving the accuracy are noted below.

In a safety context, at the very least, typical design inputs relate to number of lanes, horizontal curvature, number of intersections and interchanges in the corridor. Such data are widely available and relatively straightforward and simple to collect and maintain. Using basic design inputs such as those described above, we were able to identify the design element of greatest need for a particular location. To be sure, a comprehensive set of design inputs are necessary to accurately identify contributing factors. As a systematic recourse to identification of a broader set of safety needs, a second finding emerged. This relates to the usefulness of predictive methodologies for WSDOT. In reality, historical data is currently used to determine what investments are required at specified high-accident locations. A hierarchical Bayesian (HB) approach to the issue of predicting accident propensities allows us to quantify the "degree of credibility" in our estimates of accidents at the high-accident locations. This methodology has shown the potential to be accurate in its predictions. We benchmarked the HB method against a traditional prediction method, namely the negative binomial (NB) model. The NB model has been widely used nationally and internationally in the safety literature as a predictive tool for estimating accident potential. With a very limited set of design inputs, the HB method improves prediction several-fold, with approximately 48 percent of locations estimated with accident predictions that are within 5 percent of observed counts. Comparatively, the NB method could only predict 13 percent of the locations at the 5 percent error margin. If the margin of prediction error is increased to 10 percent, then the HB method predicts 67 percent of locations correctly while the NB method predicts only 23 percent.

Some recommendations also emerged from this study. First and foremost is the recommendation to test this methodology on the entire WSDOT safety programming network to examine the robustness of prioritization under multiple performance criteria. We propose that extensions to this study involve a full-fledged benefit-cost analysis of proposed safety improvements. In concert, it is also recommended that a data envelopment approach be used to incorporate benefit cost into the efficiency analysis. We excluded benefit cost from this analysis for the reason that information on benefit cost is incomplete. For example, it was not clear as to how many improvement alternatives were considered for individual HALs. It is proposed that accident reduction factors be used to estimate safety benefits accurately first, and then benefit costs resulting from that analysis be used as a performance output in a DEA analysis. Second, one can then extend this methodology to the broader programming framework to include cross-program decision requirements such as preservation and improvement simultaneously. Such a step would be recommended once robustness and reliability of the DEA method are established within the I2 program at the statewide level. We also determined based on the limited dataset provided to us that using a societal cost approach that separates fatal accidents from disabling accidents may result in a priority scheme that could be different. Currently, WSDOT values disabling and fatal accidents equally for priority purposes; the reason being a fatal accident by weight of its societal cost could potentially skew priority schemes toward historically fatal locations.

Some recommendations for a vision for WSDOT's future safety programming efforts are in order. The issue of programming "turnover" raises interesting responses stemming from this research. WSDOT is actively pursuing prediction efforts to improve efficiency in investments. The qualitative sense from the preliminary findings from this study using the NB and HB techniques for safety prediction indicate that a prediction accuracy of 80 to 85 percent at a 10 percent error margin is a reasonable goal for WSDOT to strive for. We base this expectation on findings from the "visual benchmark models," which for the most part rely on information gathered from WSDOT's SR View. As such, when one factors in the added value of information from geometrics and roadside inventory databases, the improvements in WSDOT's predictive capabilities could be significant. The second recommendation issue in order is a plan for future work related to this research that will significantly benefit WSDOT's ongoing prediction efforts. A series of actions is recommended below to this purpose:

1. Develop region-by-region "visual benchmark models" using hierarchical Bayesian techniques and using variables currently used in this research. By doing so, WSDOT can establish prediction baselines that are aggressive but using minimal data collection effort.
2. Integrate current geometric, roadside and weather information from WSDOT's databases to establish a consistent statewide database for use in advanced prediction schemes to be benchmarked against the visual benchmark models such as those developed in this study. Perform a benchmark analysis region-by-region so as to ensure regional flexibility in the identification of critical safety projects.
3. Establish region-by-region data envelopment analysis methods to systematically stratify project prioritization schemes that take into account a multitude of decision making criteria such as accident counts, benefit-cost ratios of recommended safety treatments and severity indices to develop a programmatically robust prioritization list.
4. Apply the HB and DEA methods to critical I2 programming areas such as interstates, high accident locations, high accident corridors and at-grade intersections. By applying the methodologies to a broader set of I2 programs, a consistent list of safety performance measures can be identified for benchmarking I2 investment efficiencies on a statewide basis.
5. Data integration for the purpose of interstates, high accident locations, high accident corridors and at-grade intersections will require spatial scales that vary by area of application. For example, for HALs, the spatial scale is 0.1 miles with a rolling 0.01-mile window, while HACs will be determined on the basis of one-mile scales with

0.5-mile rolling windows. Interstates will require a combination of methods based on both HAL and HAC procedures, while at-grade intersections will involve localized windows specific to intersections and their vicinities. Data requirements relating to modeling will also vary between at-grade intersection and highway prioritization programs.

INTRODUCTION

The purpose of this report is to provide the Washington DOT a resource to prioritize transportation improvement projects from a safety management perspective. The report presents a methodology that is able to compare and contrast the geometric features of different collision locations and is able to identify the location specific factors contributing most to the occurrence of collisions. The methodology provides for collision predictions thus enabling the development of a priority list of locations that require safety improvements.

The current Washington State Department of Transportation (WSDOT) method for evaluating roadway projects for safety upgrades relies on procedures that combine frequency and severity of accidents at locations in a weighted manner. This is a reasonable procedure that captures a significant portion of locations deserving of safety upgrades in a consistent manner. However, what is not apparent from the programming process is the cause of turnovers of locations from year to year. **"Turnover" is defined as a location that repeats as a high-priority accident spot or corridor. The percent of locations "turning over" from one biennium to the next varies by functional class and region.** One main issue underlying the turnover rate is the reliability of predictions of accident risk. The second issue related to the turnover rate is one of efficient investment. Any given highway accident corridor needs to be examined in terms of benefits and costs from safety investments, and how they efficiently relate to performance of the location. To fully optimize the Highway Safety Management System (HSMS) at the WSDOT, both of the above-mentioned dimensions need to be addressed simultaneously. Accident occurrence prediction and approaches for establishing consistent and sustainable safety programs in addressing risk through proper and timely investment are the main issues researched in this report. To this end, we analyzed a pilot subset of the WSDOT I2 program that specifically deals with safety needs. The I2 program targets locations on the state network primarily for safety improvements. The I2 program is a sub-program within WSDOT's "Improvement" category. The I2 program involves capital projects that are prioritized strictly on safety needs. In WSDOT parlance, the I2 program is also referred to as the safety improvement program. We examined 190 sections in the Northwest Region and provide findings related to both predictive reliability and programming efficiency issues.[2]

BACKGROUND STATEMENT

Motor vehicle accidents continue to be a major cause of death and injury in the United States. As a consequence, state and federal agencies expend considerable resources in an effort to improve safety by implementing countermeasures that include improving highway geometrics, highway signing, and the roadside. The goal of WSDOT, the Washington State Patrol, and the Washington Traffic Safety Commission is to reduce and eliminate deaths and disabling injuries on our state's highways and roads. Figure 1 shows fatality rate trends for three networks – national, Washington State highway, and

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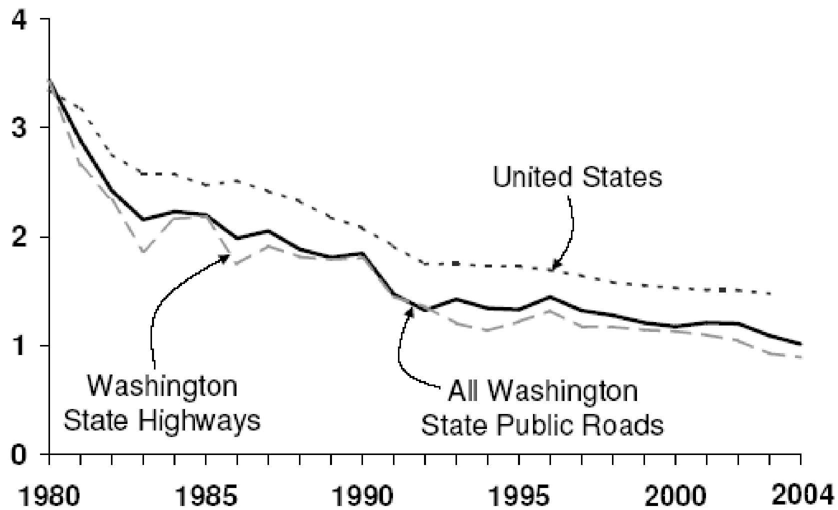

Figure 1. Comparison of Traffic Fatality Rates from 1990 to 2000.
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BENEFITS AND CONTEXT

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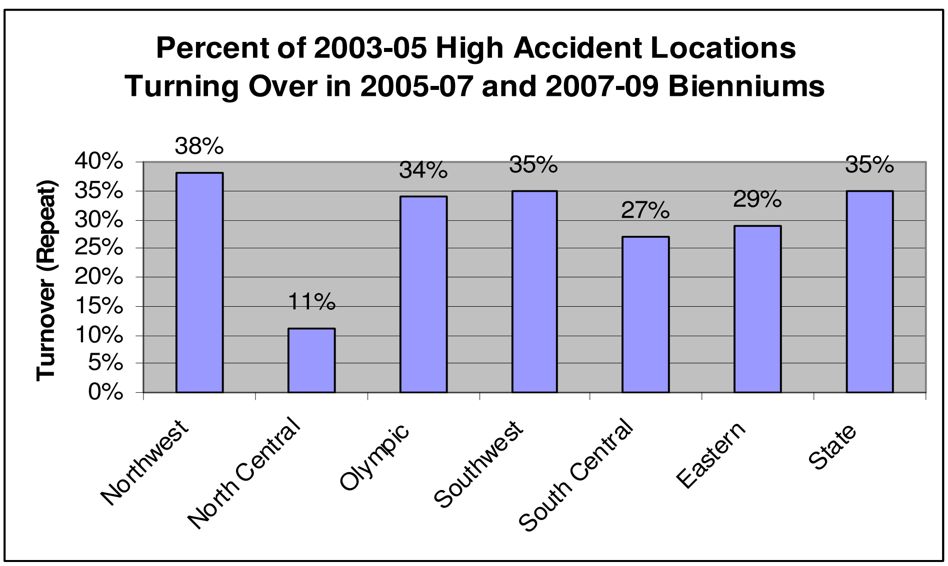

Figure 2. High Accident Location Turnover Trends.

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STUDY METHODOLOGY

We present here the general methodological approach to the assessment of WSDOT's safety programming process. In so doing, we recommend a composite framework that embodies the strengths of proven techniques such as Bayesian prediction and data envelopment analysis. To describe the methodology further, a brief description of the decision-making context of WSDOT's programming process is first necessary. Key activities relating to data, personnel, analytical and decision making issues are described. Table 1 below provides a brief overview of these activities.

Table 1. Decision Processes in a Typical Safety Evaluation System

Local Policy	Establishes policy and responsibilities for units within WSDOT as well as counties and local administration boards
Data Collection	Provides information to support decisions for identifying critical safety inventory, needs, and countermeasures, and monitoring the results of safety decisions (system performance)
Data Analysis	Converts field data into usable information to assist decision makers in identifying safety needs and countermeasures, and monitoring the results of their decisions
System Output	Presents analyzed and processed data in a format that is usable for decision makers
Project Prioritizing and Program Development	Includes final prioritizing of transportation safety needs, selecting cost effective solutions, and adopting safety policies, standards, procedures and programs
Program Implementation	Carries out funded projects resulting in safety enhancements as well as educational, enforcement, and emergency programs
Performance Monitoring	Measures and analyzes results of transportation safety decisions, countermeasures, and programs; provides information from which "base year," efforts are forecast and evaluated and future work programs are developed
Annual Safety Report	Reports, on an annual basis, the results of safety system work efforts, expenditures, and system performance

The scope of this report concentrates on Data Collection, Data Analysis, System Output and Project Prioritization (excluding project development) steps. It is recognized that within the project prioritization step, several sub programs will be involved, including interstates, high-accident locations and corridors, at-grade intersections, pedestrian locations, intersection improvements to reduce the risk of collisions, rural roadside safety improvements and corridor improvements for passing lane safety. To incorporate these issues into a framework that is eventually suitable for an on-going, long-term evaluation of WSDOT's I2 program, we present Figure 3 that follows. Figure 3 is a composite framework that employs in a parallel manner the strengths of Bayesian and data envelopment analysis methods as they relate to the various goals of the safety programming process. We note here that the main contribution of Bayesian methodologies lies in the predictive aspects of accident risks, i.e., identification of sites with promise. The data envelopment analysis procedure contributes mainly to the ranking of sites with promise on the basis of multiple performance criteria. To fully integrate the Bayesian and data envelopment techniques, feedback loops need to be established, which we discuss in the findings section of this document. As mentioned previously, this study is a safety evaluation testbed analysis, not a full-blown analysis of the entire I2 program at the WSDOT. As such, the study focuses on the feasibility, reliability and relevance of the framework presented in Figure 3.

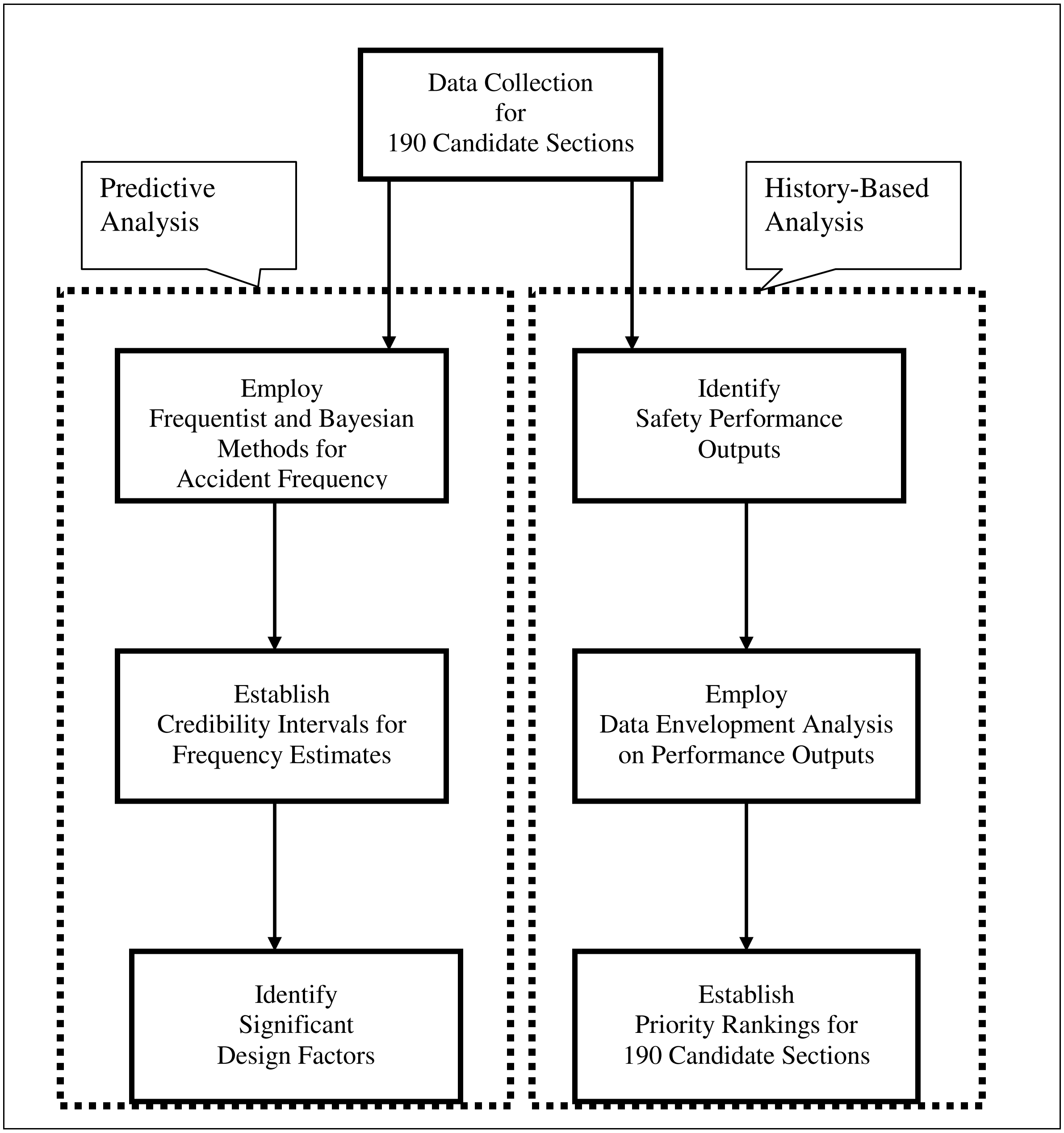

Figure 3 Analysis Methodology

The framework in figure 3 can be broken down into predictive and historical components – the Bayesian method constituting the predictive component and data envelopment analysis constituting the historical component. The main idea behind this composite approach is to maximize information that is historical as well as pro-active. With historical data, information on accident counts and severity is available. In addition, societal costs of accidents are also available. The WSDOT also computes the severity index of sites using an average severity rate as a baseline for comparison. By making use of historical information mentioned above in conjunction with computed severity indices, a method to prioritize sites allowing for the possibility that multiple sites can be ranked with equal importance, can be explored. Such an approach is beneficial in the context of fiscally constrained programming, in order to maximize the set of improvement locations under consideration, as well as the set of improvement choices for those locations. For example, two locations with identical priorities may require very different levels of investment. By pursuing investments that target locations with similar priorities, but with potentially greater returns at a smaller scale of investment, the potential for prioritization coverage in terms of locations addressed is also enhanced.

Historical information is of limited insight into how sites' accident potential changes over time. By correlating geometric and traffic volume data with observed accident counts, predictive models that estimate accident risk in upcoming bienniums are necessary. The usefulness of predictive models lies in their ability to predict with a high level of credibility the expected risk, while making use of limited data. Data collection, maintenance and continued collection in future years are significant resource issues. In this light, an objective of this study is to examine the level of predictive accuracy that can be achieved with commonly available geometric and traffic volume data. The main benefit from a programming standpoint is the identification of turnovers – sites that repeat over multiple bienniums. To complete the decision loop, a re-ranking of sites using estimated counts is necessary. By comparing priorities based on history as well as predictive models, WSDOT decision makers can visualize where safety improvement potential is greatest.

In summary, by ranking sites in order of priority, and determining how many of these sites continue to be turnovers over multiple bienniums, the WSDOT is better positioned to make judicious investments in safety while maximizing spatial coverage of their high accident locations.

LITERATURE REVIEW

A review of accident modeling literature reflects the variety of methods that have been used to model accidents. The conventional method to model accidents is using linear regression to model accident rates, a continuous number (for example Mulinazzi and Michael 1969; Shah 1968). This is a straightforward method that models the number of accidents per million vehicle miles (known as accident rate) for a given roadway segment. Research identified that linear regression has many drawbacks, such as lack of distributional properties to describe random event counts (frequencies) such as vehicle accidents. Furthermore, if linear regression is used to model accident counts as opposed to rates, then the estimated parameters associated with contributing factors are biased and inconsistent. In such a situation, predictions would be incorrect. One alternative to model accident frequencies is to use count models such as Poisson and negative binomial (and their suitable variations) models.

More recent methods used for modeling accident frequencies include models such as the Poisson and negative binomial (see for example Shankar, Mannering and Barfield 1995; Poch and Mannering 1996; Milton and Mannering 1998) and the zero inflated Poisson and zero inflated negative binomial (for example Shankar, Milton, and Mannering 1997). The Poisson model, while possessing desirable statistical properties (that linear regression lacks), is not suitable for overdispersed data. Accident data are overdispersed. Due to overdispersion, the variance of counts exceeds the mean, thereby violating the property of equality between variance and the mean inherent in the Poisson model. As a result, employment of Poisson model for overdispersed data results in underestimation of coefficient variances and likelihood of accidents. Shankar et al 1995 showed that the negative binomial model incorporates overdispersion and thus avoids the underestimation of coefficient variances and likelihoods.

Emerging research in Bayesian methods has shown that the predictive power of hierarchical Bayesian techniques may be superior to the classical frequentist approaches mentioned in the literature described above. Frequentist approaches involve the development of accident likelihoods based on observed data. Bayesian approaches incorporate subjectivity in addition to information from observed data. Subjectivity in Bayesian approaches typically involves judgments on the nature of coefficients associated with accident risk factors. The transportation safety field is not without precedent in the application of Bayesian methods, much less other fields such as pavement engineering. Hossain, Chowdhury and Gisi (2002) present a project prioritization process for the Kansas Department of Transportation (KDOT) using a pavement structural attribute termed Pavement Structural Evaluation (PSE).

Maritime traffic safety has evidenced the use of Bayesian methods (Or and Kahraman 2002). In assessing the safety of land-borne traffic particularly, Davis and Yang (2001) use Hierarchical Bayes methods combined with an induced exposure model in order to identify intersections where the crash risk for a given driver subgroup is relatively higher than that for other groups. Abdel-Aty and Pande (2005) identify freeway loop detector data patterns that potentially precede traffic accidents in order to establish a link between real-time traffic flow parameters and accident occurrence. They employ a Bayesian classifier based methodology, probabilistic neural network (PNN) to illustrate the predictive power of Bayesian-based techniques. Perhaps the most relevant and contemporarily useful work in recent years in the field of transportation safety comes from the research of McNab (2003, 2004). In 2003, McNab presented a Bayesian hierarchical methodology to model and analyze accident and injury surveillance data. The objective of that work was to help develop programs to address high risk regions for preventive programs. In 2004, McNab presented yet another study within which, analysis of accident and injury variations, risk factor effects, random spatial effects and age effects can be considered simultaneously. The modeling techniques provided extended scope and flexibility in accommodating spatial effects as well as nonlinear age effects.

There has been considerable discussion in the literature related to the identification of sites with promise and ranking of those sites. Perhaps the most compelling work to date emanates from the collection of research embodied in Hauer, Harwood, Council and Griffith (2002), Elvik (2004), and Hauer, Allery, Kononov and Griffith (2004). In the latter body of work, the authors discuss in a methodical manner the development of a program of local safety improvements. The finding they present is of great relevance to this study. The authors conclude that sites at which the most accidents or the most severity-weighed accidents are expected, lead to the most cost-effective projects. Along a parallel theme, Geurts, Wets, Brijs and Vanhoof (2004) conclude that variability exists in the identification and ranking of “accident blackspot sites." They show that use of estimates instead of historical count values on the other hand do have important consequences for the selection and ranking of black spots. They conclude this is important not only for the number of accident locations that will receive a different ranking order but also for the effect on the type of accident locations that are selected as dangerous. We believe the above-mentioned bodies of work are of eminent value to the study being undertaken in this report. Hence, the methodology presented in our report parallels this thinking, but builds on this body of work by employing state-of-the-art analysis techniques such as hierarchical Bayes and data envelopment analysis. Integrating Bayesian and data envelopment analysis methods in the safety context is without precedent in the reported literature.

Other studies of relevance in the Bayesian perspective include work on the estimation of benefits of safety improvements. Clarke and Sarasua (2003) employed a Bayesian approach to develop crash reduction factors (CRFs) for specific countermeasures. Rimiller, Ivan and Garrick (2003) apply empirical Bayesian methodology to estimate impacts of left-turn treatments. A comparison of empirical Bayes and frequentist methods to predict sites with promise is shown in Saccomano, Grossi, Greco and Mehmood (2001). Davis (2001), Melcher, Dixon, Washington and Wu (2001), Hanley, Gibby and Ferrara (2000), and Persaud, McGee, Lyon and Lord (2003) extensively discuss various aspects of safety benefits estimation using Bayesian techniques. The studies finds that fewer sites are identified using the empirical Bayes approach suggesting significant cost savings in safety investments. This body of work is of value for on-going, long-term extension of the research conducted in this report.

Finally, from a pure modeling standpoint, perhaps the most relevant contemporary work in the comparison of empirical Bayes and full Bayes research comes in the form of a study done by Miaou and Lord (2003). The authors examine classic issues of relevance to safety modelers, such as functional forms, parametric restrictions and goodness-of-fit measures.

We also discuss here extant literature on the application of data envelopment analysis to the field of transportation. The discussion is oriented toward the assessment of efficiency of transportation infrastructure operation. As such, insights related to this topic are of direct relevance to the safety programming issues considered in this report. Alder and

Berechman (2001) mention that the relative efficiency and quality of airports seems to play a strong role in airlines' decision making regarding choice of hub locations. Previous studies of airport quality and efficiency have focused on passenger responses to surveys. The Alder-Berechman article describes the development of a model to determine airport quality and efficiency based on the responses of the airlines. Several European and non-European airports were the subject of the questionnaire which was designed to measure factors such as delay data, runway capacity, local labor force availability and costs and the reliability of air traffic control.

Francis and Humphreys (2002) present a paper that examines how benchmarking is being used by airport managers as a means for internal performance comparison and improvement. Drawing on interviews with airport managers and a questionnaire survey of the world's top 200 busiest passenger airports, the paper discusses the nature, prevalence and consequences of current benchmarking practices in airports. Also included is a review of the literature on airport benchmarking and a discussion of the characteristics and relevance of best practice benchmarking.

Pels, Nijkamp and Rietveld (2003) consider the efficiencies of European airports and estimate production frontiers for these airports using both stochastic frontier and data envelopment analyses. They argue that European airports, on average, are inefficient and that airline inefficiency contributes significantly to airport inefficiency in terms of air passenger movements. The authors find that the average European airport operates under constant returns to scale in producing air transport movements and under increasing returns to scale in producing passenger movements. These operating characteristics are statistically tested in a stochastic frontier model.

Odeck (2005) uses data envelopment analysis to investigate target achievements of the Norwegian Public Roads Administration (NPRA) charged with traffic safety services. The data envelopment framework is used to measure growth in target achievements. They find that technological progress contributes most to growth in target achievements. This is a particularly useful finding for the study at hand. Technological progress at WSDOT can include improved data collection and maintenance services, technological improvements in decision models as well as improvements in the interfaces between people, process and technology. Technological progress involves a cultural shift in decision making – one that balances history-based decision making with predictive decision making.

ANALYTICAL TECHNIQUES

We present in this section a brief discussion of hierarchical Bayesian and data envelopment methods. Hierarchical Bayesian methods are discussed first followed by data envelopment methods.

Bayesian methods explicitly use probability to quantify uncertainty. After fitting a probability model to data, Bayesian inference summarizes the result by a probability distribution on unobserved quantities such as the parameters of the model, or predictions for new observations. Unobserved quantities in our study include parameters (coefficients) associated with accident risk factors, as well as predictions of accidents at high-accident locations. For example, one will be able to say that "on State Route 2, the location with milepost limits 0.00 to 0.19, and length of 0.19 miles, is expected to have at a 97.5 percent credibility level, no more than 26 biennial accidents." This is a probability statement on the predicted or estimated accident count at the stated location on State Route 2. Similarly, one can also make probability statements on the parameters (coefficients) associated with accident risk factors. Parameters (coefficients) are some measure of the marginal impact of risk factors on accident counts. One cannot say for sure that the marginal impact of intersections on accident counts is exactly a 10 percent increase for each intersection added to the network. Clearly, judgment and experience say that intersections increase exposure and hence would increase accident likelihoods. As such, it is reasonable to state the marginal impact of intersections in terms of "credibility levels." For example, the statement "the addition of each intersection to the network results in a 10 percent increase in accident counts at the 50 percent credibility level" suggests that the probability of the impact being a 10-percent increase is 50 percent. In other words, this statement quantifies the level of uncertainty underlying the increase in accident counts as a result of the addition of an intersection to the network.

These probability statements are conditioned on the observed data. The Bayesian approach to inference specifies two distributions:

- a prior distribution $P(\theta)$ for the parameters that reflects knowledge about θ before seeing the data. The "prior" is a definition of the statistical model *before observing the data*.

- a distribution $P(y|\theta)$ for the data given parameters,

The posterior distribution combines these distributions, and reflects knowledge about θ being updated after seeing the data:

$$P(\theta \mid y) = \frac{P(y \mid \theta)P(\theta)}{\int P(y \mid \theta)P(\theta)dy}$$

The posterior is a definition of the statistical model after observing the data.

<u>Predictive Distribution</u>

A future observation $\tilde{y}$ (in our case, accident counts at a given location) may be predicted using a predictive distribution $P(\tilde{y} \mid y)$ based on the posterior distribution as follows:

$$P(\tilde{y} \mid y) = \int P(\tilde{y} \mid \theta)P(\theta \mid y)d\theta$$

Importantly, this accounts for the uncertainty in the estimation of θ, the set of coefficients associated with various accident risk factors.

The advantage of Bayesian approaches is directly quantifying uncertainty when predictive models with many parameters are considered. This is especially the case in traffic safety programming where roadway geometrics, traffic factors and environmental conditions play a dominant role. Human factors are not easily measurable in terms of their association with traffic accidents. For example, measuring seat belt use for various geographic regions, or drunk driving over long periods of time requires an inordinate amount of surveys. Moreover, predicting how human factors change over time is challenging. Hence, maintaining over the long-term, sustainable sources of human factors information is an expensive proposition at state departments of transportation. Hence, to develop a predictive paradigm that maximizes predictive power with easily available DOT data, the Bayesian paradigm gives freedom to set up complex models by supplying a conceptually simple method. Although a realistic model may require many parameters, interest usually focuses on a smaller number of parameters, such as intersections and interchanges, horizontal curves, average daily traffic, presence of median barriers, whether highways are divided or not, roadway cross section, etc. Such data are readily available and viewable in digital format on WSDOT media.

HIERARCHICAL MODELS

The Bayesian approach shows its greatest practical advantage in hierarchical models. Assume that data are collected from many groups of roadway sections that have observed accident, roadway and traffic characteristics. Roadway geometrics in particular will be somewhat similar across sections. Rather than making inferences separately for each group, usually it is desirable to combine the information from the various groups in order to better understand the phenomenon under study.

Since there might be substantial variability between the groups, a natural way to approach the problem is to build a two-stage “hierarchical model” as follows:

- a set of first level models for clusters or groups of observed data. These models are sometimes known as *individual models.*

- a second level model for the parameters of the first level models. This model is sometimes known as a *structural model,* or *population distribution,* and its parameters are called *hyperparameters*.

Hierarchical models avoid overfitting the data by using the population distribution to structure dependence in the parameters. This is to say that the statistical model developed will not be confined in its predictive accuracy to the sample at hand. The predictive power can be extended to samples not used for estimation. A detailed description of the hierarchical poisson gamma model is provided in appendix B.

DATA ENVELOPMENT ANALYSIS (DEA)

Data envelopment analysis is a linear programming based technique for measuring the relative performance of decision units where the presence of multiple inputs and outputs makes comparisons feasible. A decision unit in our case is a roadway section under consideration for safety improvement. A roadway section can be viewed as a source of multiple decision options. For example, a section where runoff the road accidents are significant can be analyzed for a) guardrail placement, or b) horizontal curvature improvement. In this case, each improvement alternative is viewed as a separate decision option for the section under consideration. In this sense, DEA can allow decision makers comparisons between various improvement options for a single roadway section. The other advantage of DEA is that not all roadway sections are required to have the same set of improvement options. For example, section “a” can be analyzed with two improvement options under consideration, while section “b” can be analyzed with four improvement options under consideration. A third advantage of the DEA approach is it allows for the incorporation of multiple inputs and multiple outputs in the decision making process. For example, in the traffic safety programming context, the inputs are AADT, number of lanes, number of horizontal curves, number of interchanges, and number of intersections. Outputs are accident occurrence, severity index and societal costs as used in this analysis. Ideally, one would use some measure of agency benefit such as accident reductions and benefit cost ratios. These were not readily available from WSDOT databases, so we adapt the DEA methodology to determine areas of greatest need for improvement first. This is to say for example, that section “a” has horizontal curvature as the area of greatest need, while section “b” has intersection improvement as the area of greatest need. Greatest need is determined by the analysis of relative contribution of a roadway characteristic to a section’s accident related outputs such as accident counts, societal costs and severity index.

The issue of DEA-based efficiency in the traffic safety programming would ideally refer to efficiency in agency improvement investments as they relate to agency benefits. As mentioned previously, since this information was not available, we propose a method to identify areas of greatest need section-by-section first and then recommend using Bayesian methodology to estimate accident reduction benefits for those improvements. Hence the application of DEA methodology in this report should be viewed as an approach to prioritize the nature of the section-specific need as well as rank the sections in terms of overall need. DEA-based efficiency in this perspective takes an alternative meaning. A section with an efficiency rating of 100 percent implies it is a section deserving of highest safety improvement priority. In this sense, a higher efficiency rating indicates a level of poorer safety -- given the inputs such as roadway geometrics and traffic volumes, accident-related outputs are occurring at the highest production levels.

It should be noted that the used measures of output such as accident occurrence, societal cost and severity index are measures of agency costs. Likewise, with the exception of AADT, the other inputs are measures of agency investment that relate to accident occurrence. Ideally, one should analyze the expected number of accident reductions as a measure of efficiency of investment. Since section-specific information on accident reduction was not available, we use multiple outputs that relate to the accident occurrence, severity index, and societal costs. In this sense, the inputs are viewed as disinvestments. That is, greater the weight of a particular input, the greater disinvestment due to higher efficiencies in a non-desirable outcome such as accident occurrence, severity index or societal cost. Naturally, the recommendation associated with inputs with higher weights is to minimize their contribution. One way for example to minimize an input's contribution is to eliminate it – removal of a horizontal curve. This is a cost-prohibitive investment; as a result, alternatives may arise, such as reducing the sharpness of a horizontal curve, for example. Average daily traffic is for the most part an uncontrollable input, even though it has an impact on accident occurrence, societal cost and severity indexes. Addition of lanes may appear to decrease the impact of traffic volumes; however, the issue of latent demand remains as a counter-productive effect. The advantage with the DEA method is it is non-parametric, meaning it imposes no distributional assumptions; however it is sensitive to measurement errors. One must be careful in the choice of inputs and the measurement of inputs. It should also be noted that although non-stochastic, the type of DEA employed in this study allows us to determine in a ballpark sense the input of greatest need section-by-section. This then allows us to identify potentially more safety initiatives with the consideration set of horizontal curve mitigation, cross-section width mitigation (number of lanes) and interchange and intersection mitigation. The locations used in this study for the most part, are amenable to the above-mentioned types of improvements. On a statewide network, one would have to define a broader array of potential agency investments toward safety and use those as inputs for full-fledged safety analysis. To comparatively address the issue of relative safety need, DEA measures the relative safety ranking of the roadway sections under consideration. As safety need is an indicator of higher societal cost, locations ranking high by DEA will indicate high safety needs, in relation to all locations considered in the analysis.

The notion of DEA-based relative safety need

Relative safety need is a notion developed in this analysis to indicate the relationship of multiple safety outputs to multiple safety inputs. A need by definition implies a safety output(s) results in preventable or reducible societal costs. Technically, these outputs are a measure of a location's "unsafety." Several safety inputs can contribute to these costs, namely, ADT, number of lanes, horizontal curves, or interchanges and intersections. If two locations are identical in their safety characteristics, and one location has a higher "unsafety" output, then it is reasonable to prioritize the location with the higher output over the other. This notion is applied in the use of DEA for our analysis. A reasonable measure for relative safety need is:

$$\text{Relative SafetyNeed} = \frac{\text{Weighted sum of outputs}}{\text{Weighted sum of inputs}}$$

Relative Safety Need (RSN) can be mathematically expressed as:

$$RSN_j = \frac{u_1 y_{1j} + u_2 y_{2j} + ... + u_r y_{rj}}{v_1 x_{1j} + v_2 x_{2j} + ... + v_i x_{ij}} \leq 1$$

Where,

RSNj is relative safety need for roadway section "j"

u_r = weight of output *r, for example, weight of accident count, severity index or societal cost*

y_{rj} = amount of output *r* from unit *j, for example, accident count, severity index value, or societal cost value*

v_i = weight of input *i, for example, weight of horizontal curves, interchanges and intersections, ADT,or cross section width*

x_{ij} = amount of input *i* to unit *j, for example, number of horizontal curves, number of interchanges and intersections, ADT value, or number of lanes*

Relative safety need is usually constrained to the range [0,1]. Two versions of DEA are utilized in this analysis. One of these calculates relative safety needs on constant return to scale, and the other allows variable return to scale. In brief, the Charnes, Cooper and Rhode (CCR) version calculates relative safety needs on constant returns to scale, while, the Banker, Charnes and Cooper (BCC) version evaluates relative safety needs on variable returns to scale. Variable returns to scale implies a less restrictive form of safety needs calculation, with the practical implication being a potentially larger set of priorities in terms of locations covered. The analytical structure of the above-mentioned DEA versions is presented in detail in appendix B.

DATA USED FOR THE ANALYSIS

The data used for this analysis was derived from the Washington Sate Department of Transportation (WSDOT) I2 prioritization database provided by Northwest Region staff. There were 320 road sections in the original dataset. The lengths of sections vary from 0.01 mile to 1.52 miles. For the analysis purpose, sections whose lengths are less the 0.05 miles were ignored. Therefore, a total of 190 sections were analyzed. Table 2 provides summary statistics for the 190 sections.

Table 2. Summary Statistics of Key Variables.

Variable	Mean	Std.Dev.	Minimum	Maximum
Property Damage only (2-Yr Counts)	31.92	31.66	1	202
Possible Injury (2-Yr Counts)	15.82	15.79	0	123
Evident Injury (2-Yr Counts)	5.26	5.28	0	47
Disabling Injury (2-Yr Counts)	0.91	1.34	0	11
Fatality (2-Yr Counts)	0.11	0.33	0	2
Total Accidents (2-Yr Counts)	54.03	51.56	6	354
Societal Costs Per Pear	1,054,584	1,050,518	56,000	8,471,500
Severity Index	1.98	2.55	0	17.30
Annual Average Daily Traffic	19,551	12,172	963	57,030
Length in miles	0.271	0.204	0.06	1.39
No. of Lanes	3.78	1.10	2	6
No. of Horizontal Curves	0.72	0.74	0	3
No. of Interchanges / Intersections	1.94	1.41	0	10

The following input and output variables were used in the analysis:

Output Variables: Total number of accidents, societal cost, and severity index

Input Variables: Average Annual Daily Traffic (AADT), Number of lanes, Number of curves, Number of interchanges / intersections.

Table A-1 in the appendix provides detailed section-by-section characteristics for all 190 roadway segments.

RESULTS AND DISCUSSION

We present results from the hierarchical Bayesian and DEA applications. In the DEA analysis of the 190 sections, both CCR and BCC versions of the DEA methodology were employed. Table A-2 in the appendix details the comparison section-by-section for returns to scale that are constant versus variable. It is observed that in the CCR (Constant Returns to Scale) analysis 15 roadway segments achieve a hundred percent accident occurrence efficiency, implying that they are top priority segments from a safety investment standpoint; in the variable returns to scale analysis, a total of 56 roadway segments achieve a 100 percent accident occurrence efficiency rating. All of the segments that achieve a hundred percent accident occurrence efficiency in the constant returns to scale analysis also achieve a hundred percent efficiency rating in the variable returns to scale analysis. As a result, at a minimum, 15 segments are categorized as top priority segments, and depending on the budget allocation, up to 56 segments can be categorized as top-priority I2 segments. All of these segments are ranked 1 i.e., highest priority for safety improvement projects. One should also note in Table A-2 in the appendix that as the rankings increase beyond the value of one, the priority of the segment decreases.

We also note that the areas of greatest need for the ranked segments vary depending on the relative weights of the inputs. As mentioned previously, higher the relative input, higher the relative importance of that roadway characteristic. Average daily traffic is not a controllable input for the most part, although it contributes to the overall safety efficiency rating. Keeping that in mind, the relevant inputs in terms of greatest need are a) number of horizontal curves, b) number of interchanges, and c) number of interchanges. These needs are summarized in table 3 below. As noted in table 3, roadway cross section is noted as area of highest need in 91 sections, while number of horizontal curves is noted as the area of highest need in 138 sections. Furthermore, total number of interchanges and intersections in section is noted as area of highest need in 31 sections. The last variable refers specifically to the at-grade intersection sub-program of WSDOT's I2 program. It should also be noted that sections may have more than one area of highest need. Hence the total number of sections identified may include sections with multiple improvement needs. *This findings highlights the fact that DEA can be used to examine as a ballpark method, more than one safety improvement need for any given section.* The various improvement possibilities are directly a function of the variety of roadway characteristics that are used to examine safety efficiency ratings in the I2 program.

Table 3 Summary of Inputs of Greatest Needs (190 Sections)

Inputs	Number of Sections
Average Daily Traffic	84
Total No. of Lanes	*91*
Total No. of Horizontal Curves	*138*
No. of Interchanges / Intersections	*31*

Once an initial estimate of safety needs is conducted through DEA and sites ranked in terms of safety priority, a similar analysis can be conducted using Bayesian predictive methods to align the results. The Bayesian methods are more powerful for the identification of safety risk as well as identifying safety improvements. However the Bayesian analysis unlike the DEA approach is not well suited for examining multiple outputs in a single analysis. We hence employed the Bayesian approach to benchmark its predictive efficiency versus the classical negative binomial. Inputs including categorical variables such as presence of barriers, presence of divided highway sections as well as interactions are used in addition to the inputs as those in the DEA analysis. The Bayesian model thus is a more refined model, but fairly minimal in data demands. The predictive variable used in the Bayesian analysis was number of biennial accidents in a section. Tables 4 and 5 below summarize the benchmarked results.

Table 4 shows the statistically significant effects affecting biennial accident occurrence for the 190 sections. The overdispersion effect is significant indicating that an overdispersion model is appropriate for safety prediction. It is also noted that the hierarchical Poisson with gamma prior agrees closely with the classical negative binomial; however, the mainly useful result from the Bayesian analysis is the credibility intervals associated with the coefficient values. As expected, some variability exists between the 50th percentile credibility and 97.5th percentile credibility estimates of the coefficients in the model. Some variables such as the horizontal curve indicators are statistically insignificant in the sample used for analysis in this testbed. We retain these variables so to be able to test their significance in a large context, applied to the entire state network of highways.

Both the classical negative binomial and the hierarchical poisson with gamma prior are based on measured variables that are mainly obtained from WSDOT's SR View database. As such, these models should be viewed as "benchmark" models against which alternative prediction schemes should be calibrated in terms of their predictive accuracy. The benchmark models developed here are mainly "visual" in the source of their data – that is, variables other than traffic volumes are measured visually from SR View. Hence, we use the term "visual benchmark models" to refer to the prediction schemes used in this safety evaluation testbeds.

Table 4 Comparison of Classical Negative Binomial Model and Hierarchical Bayesian Analysis for Overall Accidents (190 sections)

	Negative Binomial Model		Hierarchical Bayesian Poisson with Gamma Prior			
	Est. Coeff. (Std. Error)	T-statistic	Est. Coeff. (Std. Error)	T-statistic	Credibility Percentiles of Coefficient	
					50 %	97.5%
Constant	-2.741 (0.376)	-7.300	-2.939 (0.118)	-25.013	-2.912	-2.766
Natural logarithm of Per-Lane-AADT	0.665 (0.044)	15.071	0.682 (0.017)	39.738	0.649	0.710
Lengths of sections in miles	1.463 (0.161)	9.072	1.365 (0.363)	3.759	1.404	1.917
Number of Interchanges / Intersections in the sections	0.061 (0.0245)	2.442	0.075 (0.053)	1.417	0.067	0.263
Curve indicator 1 (1 if the No. of horizontal curves per mile >= 2 and <= 7; 0 otherwise)	-0.039 (0.062)	-0.629	-0.030 (0.062)	-0.488	-0.032	0.092
Curve indicator 2 (1 if the No. of horizontal curves per mile > 7; 0 otherwise)	-0.149 (0.086)	-1.729	-0.148 (0.102)	-1.441	-0.140	0.030
Interaction variable 1 between undivided roadway and barrier (1 if roadway is undivided and there is no barrier; 0 otherwise)	0.425 (0.113)	3.749	0.482 (0.124)	3.881	0.490	0.733
Interaction variable 2 between undivided roadway and barrier (1 if roadway is undivided and there is a barrier; 0 otherwise)	0.194 (0.124)	1.565	0.288 (0.114)	2.537	0.284	0.519
Interaction variable 3 between divided roadway and barrier (1 if roadway is divided and there is a barrier; 0 otherwise)	0.537 (0.132)	4.057	0.615 (0.128)	4.817	0.615	0.868
Alpha	0.126 (0.014)	8.893	0.146 (0.018)	8.109	6.841	8.544
Restricted log-likelihood (Constant only)	-5,037.859					
Log-likelihood at convergence	-968.3092					

The usefulness of visual benchmark models for large-scale systemwide programming is the development of a consistent baseline against which predictions with a wider array of data can be measured. As such, the visual benchmark models represent a bare minimum predictive capability that WSDOT can achieve by solely relying on SR View data. To date, WSDOT's methods have mainly relied on classical negative binomial models to predict safety levels on its highways. The use of Bayesian methods on a statewide network is computationally demanding, considering the vast array of data that WSDOT has at its disposal to use in the development of advanced prediction models. This research attempts to establish basic procedures for systematically testing the suitability of Bayesian techniques for benchmarking future advancements in WSDOT's safety prediction capabilities. The evidence so far shows that promise exists in significantly improving WSDOT's safety prediction capabilities.

We compare the predictive outputs from the classical and Bayesian analyses for the 190 road sections used in the evaluation of the safety testbed. Table 5 summarizes the findings below. The HB (Bayesian) method reports 48.15 percent of all segments within 5% absolute error, where absolute error is defined as the absolute percent difference between observed and predicted accident counts. Comparatively, the classical NB approach predicts 13.17 percent of all 190 segments within the five percent margin. If we increase the acceptability of prediction error to 10%, the HB captures 67.08% or more than two-thirds of all sections while the classical NB only improves to 22.63%. What this shows as a preliminary result is the "visual benchmark model" using HB techniques establishes a viable prediction baseline compared to classical methods. This is a significant return to investment for WSDOT in terms of SRView, as well as implications of SRView and related databases for improved precision in safety programming.

Table 5 Summary of Predictions Comparisons of Classical Negative Binomial Model and Hierarchical Bayesian Analysis for Overall Accidents (190 sections)

The Difference between Observed and Predicted Overall Accidents	Negative Binomial Model	Hierarchical Bayesian Analysis
Under or equal to 5 %	13.17 %	48.15 %
Under or equal to 10 %	22.63 %	67.08 %

A detailed section-by-section hierarchical Bayesian analysis of all 190 sections is provided in table A-3 in the appendix. In table A-3, the reader will note credibility intervals for the predicted variable, namely number of biennial accidents. For example, in table A-3, the reader will note that state route 2, milepost limits 14.50 to 15.11, with length 0.61 miles is expected to have at a 97.5 percent credibility level no more than 197 biennial accidents.

Route	Beginning Milepost	Ending Milepost	Length	Actual Overall Accidents	Prediction from Hierarchical Bayesian Analysis			
					50% Credible Interval	75% Credible Interval	97.5% Credible Interval	Mean of Predictions
2	14.50	15.11	0.61	181	177	185	197	177

The mean predicted biennial count for the same section is 177 whereas the observed biennial count is 181. We find this to be a very useful result for WSDOT decision makers since it allows decision makers to set acceptability limits based on credibility intervals. Such a method in combination with the DEA approach described earlier allows for decision making feedback loops to make the I2 program robust.

CONCLUSIONS AND RECOMMENDATIONS

Two main findings emerged from this study. The first finding relates to the usefulness of data envelopment analysis to the analysis of safety investments within the WSDOT programming context. This method is especially useful for analyzing the efficiency of a program in terms of relationships between design inputs and multiple performance outputs. Multiple performance outputs in a safety context typically include accident counts, severity index, societal cost of accidents and benefit cost. We excluded benefit cost from this analysis for the reason that information on benefit cost is incomplete. It is proposed that accident reduction factors be used to estimate safety benefits accurately first, and then benefit costs resulting from that analysis be used as a performance output in a DEA analysis. In a safety context, at the very least, typical design inputs relate to number of lanes, horizontal curvature, number of intersections and interchanges in the corridor. Such data are widely available and easy to collect and maintain. Using basic design inputs such as those described above, we were able to identify the design element of greatest need for a particular location. Evidently, more design inputs are necessary to fully relate to the entire menu of design investments that are usually determined based on engineering judgments by WSDOT staff. As a systematic recourse to identification of a broader set of safety needs, a second finding emerged. This relates to the usefulness of predictive methodologies for WSDOT. Currently, WSDOT proposes to use frequentist methods such as the negative binomial model to determine crash location propensities and base its high-accident corridor and location prioritization schemes. In reality, historical data is currently used to determine what investments are required at specified high-accident corridor locations. The limitation with both approaches mentioned above is that the degree of uncertainty inherent in decision making is not accounted for. A Bayesian approach to the issue of predicting crash propensities using a hierarchical methodology allows us to quantify the "degree of credibility" in our estimates of crash risk at the high-accident locations. This methodology has shown the potential to be more accurate in its predictions compared to the classical negative binomial approach. As we mentioned earlier, with a very limited set of design inputs, the hierarchical Bayesian approach improves prediction several-fold, with approximately 48 percent of locations estimated with crash risks that are within 5% of observed risk. Comparatively, the classical approach could only predict within 5% error 13% of the locations. If the margin of prediction error is increased to 10%, then the Bayesian approach predicts 67 percent of locations correctly while the classical approach predicts only 23%.

Some recommendations also emerged from this study. First and foremost is the recommendation to test this methodology embodied in this report on the entire WSDOT safety programming network to examine the robustness of prioritization under multiple performance criteria. Second, one can then extend this methodology to the broader programming framework to include cross-program decision requirements such as preservation and improvement simultaneously. We also determined based on the limited dataset provided to us that using a societal cost approach that separates fatal accidents from disabling accidents may result in a priority scheme that could be different. Currently, WSDOT values disabling and fatal accidents equally for priority purposes; the reason being a fatal accident by weight of its societal cost could potentially skew priority schemes toward historically fatal locations. More research needs to be done to examine the sensitivity of the WSDOT programming system to fatality and disabling injury costs being treated independently.

Some recommendations for a vision for WSDOT's future safety programming efforts are in order. The issue of programming "turnover" raises interesting responses stemming from this research. *WSDOT is actively pursuing prediction efforts to minimize variability in regional programming turnover so as to improve efficiency in investments.* The qualitative sense from the preliminary findings from this study using the classical and Bayesian techniques for safety prediction indicates that programming efficiency can be increased. Given the turnover trend of 50 percent in the 2005-2007 biennium and 35 percent in the 2007-2009 biennium, it can be noticed that 50 percent of HALs in the 2005-2007 biennium will be non-repeating new locations, i.e., locations that do not turn over. In the 2007-2009 biennium, the non-repeating location percentage is expected to increase to 65 percent, since 35 percent is expected to be turnovers. *So, one objective that can be systematically addressed is the objective of maximizing the predictability of turnovers over multiple bienniums. The second objective of safety programming relates to regional variability in turnovers.* The Northwest Region will turn over 38 percent in the 2007-2009 biennium, while the North Central Region will turn over 11 percent in the same biennium. This is a variability of 27 percent in turnover from the region with the highest turnover to one with the lowest turnover. *To enhance geographic equity in safety programming and proper identification of locations across regions, the methods presented in this study offer potential in terms of minimizing regional turnover variability.*

We base this expectation on findings from the "visual benchmark models," which for the most part rely on information gathered from WSDOT's SR View. As such, when one factors in the added value of information from geometrics and roadside inventory databases, the improvements in WSDOT's predictive capabilities could be significant. The second recommendation issue in order is a plan for future work related to this research that will significantly benefit WSDOT's ongoing prediction efforts. A series of actions is recommended below to this purpose:

1. Develop region-by-region "visual benchmark models" using hierarchical Bayesian techniques and using variables currently used in this research. By doing so, WSDOT can establish prediction baselines that are aggressive but using minimal data collection effort.
2. Integrate current geometric, roadside and weather information from WSDOT's databases to establish a consistent statewide database for use in advanced prediction schemes to be benchmarked against the visual benchmark models such as those developed in this study. Perform a benchmark analysis region-by-region so as to ensure regional flexibility in the identification of critical safety projects.
3. Establish region-by-region data envelopment analysis methods to systematically stratify project prioritization schemes that take into account a multitude of decision making criteria such as accident counts, benefit-cost ratios of recommended safety treatments and cross-program constraints to develop a programmatically robust prioritization list.

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APPENDIX A – Data Envelopment Analysis and Bayesian Prediction Model Results

Table A-1-1 Detailed Section-by-Section Characteristics, Part-I

SR	Begin Milepost	End Milepost	Length	Property Damage (2-Yr)	Possible Injury (2-Yr)	Evident Injury (2-Yr)	Disabling Injury (2-Yr)	Fatality (2-Yr)	Total Accidents (2-Yr)	Societal Cost Per Year	Severity Index	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
2	0.00	0.37	0.37	31	11	4	0	0	46	415500	4.2	5805	4.43	1	4
2	0.08	0.16	0.08	9	2	4	1	0	16	692000	0.9	12859	4.00	0	3
2	0.13	0.26	0.13	4	5	1	2	0	12	1132000	11.1	3286	4.00	1	3
2	13.75	13.91	0.16	22	10	3	2	0	37	1338500	0.5	22271	2.00	0	1
2	14.50	15.11	0.61	120	37	16	8	0	181	5527500	1.5	32391	4.00	1	4
5	0.00	0.12	0.12	10	9	5	1	0	25	850000	9.3	5749	6.00	0	0
5	0.10	0.21	0.11	6	6	1	0	0	13	155500	1.8	5845	6.00	0	0
5	0.11	0.23	0.12	17	14	3	1	0	35	893500	6.1	9579	6.00	0	1
5	0.15	0.30	0.15	2	2	2	0	0	6	106000	0.8	3112	6.00	0	1
5	0.18	0.36	0.18	7	3	2	0	0	12	138500	1.7	5328	6.00	1	2
5	0.19	0.38	0.19	20	8	4	0	0	32	330000	2.3	13278	6.00	1	2
5	0.20	0.41	0.21	8	4	0	0	0	12	94000	0.5	6085	6.00	1	2
9	1.47	1.70	0.23	23	13	5	2	0	43	1459000	0.6	17957	2.00	1	1
9	10.87	10.97	0.10	10	10	2	1	1	24	1270000	1.3	16908	2.00	1	1
9	13.93	14.13	0.20	13	14	8	1	0	36	1044000	2.2	17472	2.00	0	1
9	15.75	15.96	0.21	19	8	6	2	0	35	1392000	1.8	19294	4.00	0	1
9	53.16	53.36	0.20	5	4	3	1	0	13	682500	1.3	5639	2.00	3	1
9	77.87	77.97	0.10	4	3	0	0	0	7	64500	1.5	1810	2.00	1	0
11	10.78	10.84	0.06	3	0	5	0	0	8	171500	9.7	1541	2.00	1	0
18	0.00	0.33	0.33	9	3	0	1	0	13	579500	9.9	2412	4.00	1	1
18	0.09	0.18	0.09	6	3	0	0	0	9	70500	0.8	3922	4.00	1	1
18	0.13	0.26	0.13	8	7	1	0	0	16	179000	1.1	8559	4.00	1	1
18	0.14	0.28	0.14	8	2	0	0	0	10	59000	0.6	4265	4.00	1	1
18	0.17	0.34	0.17	5	4	2	0	0	11	150000	3.4	3809	4.00	1	1
18	0.20	0.40	0.20	2	4	0	0	0	6	76000	1.6	2640	4.00	1	2

Table A-1- 2 Detailed Section-by-Section Characteristics, Part-II

SR	Begin Milepost	End Milepost	Length	Property Damage (2-Yr)	Possible Injury (2-Yr)	Evident Injury (2-Yr)	Disabling Injury (2-Yr)	Fatality (2-Yr)	Total Accidents (2-Yr)	Societal Cost Per Year	Severity Index	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
18	14.55	14.76	0.21	11	9	5	1	0	26	853000	0.2	23026	2.00	0	1
18	2.61B	0.16	0.28	25	15	5	1	0	46	1000000	0.6	20702	4.00	0	1
20	26.59	26.83	0.24	4	1	2	2	1	10	1594500	0.2	9633	2.00	2	1
20	31.25	31.70	0.45	65	23	9	0	0	97	890000	1.5	18481	3.67	2	4
20	53.24	53.34	0.10	1	4	3	2	0	10	1170500	0.4	11450	4.00	1	1
20	58.67	58.96	0.29	6	4	3	3	1	17	2185500	0.0	18073	2.00	2	1
20	59.39	59.70	0.31	36	10	4	0	0	50	413000	0.2	18073	3.65	1	2
20	59.73	59.94	0.21	27	7	4	2	0	40	1333500	1.4	20440	4.00	1	1
96	1.09	1.26	0.17	15	22	5	0	0	42	592500	1.7	21720	4.00	0	2
96	1.35	1.51	0.16	20	10	6	1	0	37	930000	0.6	25424	4.00	0	1
96	2.18	2.51	0.33	38	22	3	2	0	65	1596500	1.0	28585	4.00	0	1
99	0.09	0.19	0.10	7	2	0	0	0	9	56000	2.9	2300	4.00	0	2
99	8.05	8.27	0.22	37	13	3	1	0	54	936000	3.2	18111	4.00	0	1
99	8.87	10.26	1.39	202	123	26	2	1	354	5103500	8.0	18936	4.00	0	5
99	10.29	10.79	0.50	73	33	9	1	0	116	1589000	3.0	18936	4.00	1	4
99	10.86	10.97	0.11	11	10	5	0	0	26	370500	0.6	18936	4.00	1	2
99	11.18	11.48	0.30	30	12	6	1	0	49	995000	1.0	18936	4.00	0	2
99	11.62	12.02	0.40	48	20	5	0	0	73	656500	2.5	18936	4.00	0	1
99	12.90	13.21	0.31	60	37	7	2	0	106	2055000	1.8	29960	4.00	0	1
99	13.65	13.80	0.15	28	24	4	0	0	56	634000	1.3	29960	4.00	0	2
99	13.99	14.39	0.40	26	20	6	2	0	54	1623000	0.3	30589	4.00	1	3
99	15.26	15.58	0.32	64	34	13	1	1	113	2209500	4.1	29960	4.00	1	1
99	16.40	16.78	0.38	36	15	10	2	0	63	1695500	1.3	25122	4.00	0	2
99	17.43	17.75	0.32	26	13	11	4	0	54	2663000	3.0	25122	5.00	0	1
99	18.26	18.45	0.19	22	8	4	0	0	34	336000	0.8	18577	5.00	1	1

Table A-1- 3 Detailed Section-by-Section Characteristics, Part-III

SR	Begin Milepost	End Milepost	Length	Property Damage (2-Yr)	Possible Injury (2-Yr)	Evident Injury (2-Yr)	Disabling Injury (2-Yr)	Fatality (2-Yr)	Total Accidents (2-Yr)	Societal Cost Per Year	Severity Index	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
99	19.06	19.15	0.09	13	7	5	1	0	26	824000	1.1	18577	5.00	0	1
99	19.37	19.51	0.14	17	9	0	1	0	27	708500	0.4	18577	5.00	1	2
99	19.42	19.49	0.07	27	15	7	3	0	52	2071000	5.0	18577	5.00	1	1
99	20.06	20.29	0.23	39	20	10	3	0	72	2292000	1.9	37155	4.00	1	2
99	22.85	23.02	0.18	19	5	3	0	0	27	242000	0.2	18362	4.00	1	2
99	37.18	37.80	0.62	53	45	13	2	0	113	2369000	0.1	39179	6.00	0	10
99	38.97	39.22	0.25	21	21	11	2	0	55	1788000	0.8	32983	5.00	0	2
99	39.26	39.51	0.25	25	25	2	1	0	53	1077500	0.1	32983	5.00	0	2
99	39.58	40.18	0.60	66	45	10	4	0	125	3310500	1.8	32983	5.00	0	5
99	40.21	40.59	0.38	61	40	9	4	1	115	3675500	1.2	32983	5.00	0	2
99	40.66	41.10	0.44	75	32	8	2	0	117	2045000	0.6	37340	4.00	0	3
99	41.17	41.45	0.28	31	21	7	3	0	62	2188000	0.9	40403	4.00	2	4
99	41.71	42.11	0.40	48	26	11	2	1	88	2456500	0.2	43936	4.00	0	3
99	43.39	43.57	0.17	33	16	6	0	0	55	574000	0.4	37233	4.00	2	2
99	45.35	45.84	0.49	63	21	10	1	0	95	1381500	0.1	34858	4.00	0	3
99	45.86	46.19	0.33	35	19	6	1	1	62	1632500	0.8	34858	4.00	1	2
99	46.39	46.66	0.27	27	20	10	0	0	57	756000	0.3	36557	4.00	0	2
99	46.75	47.05	0.30	60	19	5	0	0	84	675000	0.8	37746	4.00	0	3
99	48.67	49.17	0.50	67	36	11	0	1	115	1688500	0.1	41701	4.00	1	2
99	49.91	50.66	0.75	69	50	12	0	0	131	1472000	0.5	39470	4.00	0	6
99	50.75	51.40	0.65	56	33	17	1	0	107	1798000	1.6	37857	4.00	0	4
99	51.98	52.48	0.50	73	43	9	3	0	128	2764000	2.3	39119	4.00	0	3
99	52.66	52.95	0.29	28	19	6	2	0	55	1611500	1.5	31086	4.62	0	1
99	53.59	53.89	0.30	30	19	10	0	0	59	747500	3.0	16471	6.00	0	3
99	54.30	54.78	0.48	82	36	9	2	0	129	2168500	1.2	35067	6.00	0	3
99	54.80	54.89	0.09	27	11	3	1	0	42	871000	0.1	35067	6.00	1	3
99	55.00	55.20	0.20	26	18	5	0	0	49	555500	0.3	33288	6.00	2	3

Table A-1- 4 Detailed Section-by-Section Characteristics, Part-IV

SR	Begin Milepost	End Milepost	Length	Property Damage (2-Yr)	Possible Injury (2-Yr)	Evident Injury (2-Yr)	Disabling Injury (2-Yr)	Fatality (2-Yr)	Total Accidents (2-Yr)	Societal Cost Per Year	Severity Index	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
104	24.65	24.74	0.09	7	2	0	1	0	10	556000	1.7	5468	4.00	1	1
104	26.43	26.52	0.09	13	12	2	1	1	29	1314000	0.9	23537	4.00	1	1
164	0.31	1.07	0.76	94	44	19	5	0	162	4169500	4.0	21929	4.00	3	3
164	1.09	1.34	0.25	37	18	9	0	0	64	718500	1.1	32535	4.00	1	1
164	1.78	2.14	0.36	42	16	7	3	0	68	2133500	1.3	32535	4.00	1	1
164	2.24	2.41	0.17	22	10	2	1	1	36	1306000	0.1	29875	4.00	1	1
167	0.00	0.16	0.16	19	6	3	0	0	28	259500	1.5	12900	2.00	1	1
167	0.09	0.19	0.10	8	2	1	0	0	11	91500	0.3	5964	2.00	1	2
167	0.14	0.28	0.14	12	2	1	0	0	15	103500	1.4	5741	2.00	1	2
167	0.15	0.31	0.16	6	5	0	0	0	11	105500	0.1	7180	2.00	1	2
167	0.16	0.33	0.17	11	8	1	0	0	20	205500	0.5	12890	2.00	1	2
167	0.19	0.36	0.17	15	6	0	1	0	22	650000	5.9	5399	2.00	1	2
167	25.70	26.67	0.97	124	67	10	1	0	202	2369500	1.1	50999	4.00	2	3
167	26.84	27.28	0.44	66	37	6	0	1	110	1540500	0.5	37257	4.00	1	4
169	11.35	11.53	0.18	27	6	4	0	0	37	316000	1.4	10127	2.00	0	1
181	5.32	5.62	0.30	59	21	5	2	0	87	1707000	0.9	30057	4.00	0	2
181	5.83	5.98	0.15	35	9	3	1	0	48	860000	1.2	25354	4.00	1	1
181	7.62	7.80	0.18	28	16	3	1	0	48	961500	0.6	34219	4.00	0	1
181	9.68	9.84	0.16	25	19	1	0	0	45	440000	0.1	30930	4.00	1	1
202	0.13	0.34	0.21	43	16	6	0	0	65	604000	0.5	37943	4.00	3	3
202	2.66	2.73	0.07	17	2	0	0	0	19	86000	0.0	7980	2.00	1	2
202	6.76	7.06	0.30	44	8	3	2	0	57	1440500	1.0	19320	3.20	1	6
202	7.17	7.26	0.09	12	6	2	0	0	20	206000	1.1	8909	3.00	1	3
202	7.28	7.43	0.15	27	4	2	0	0	33	216000	0.1	17818	4.00	1	4
202	7.45	7.57	0.12	32	12	5	1	0	50	968500	3.4	17818	4.00	0	1
202	7.63	7.80	0.17	17	12	3	0	0	32	358500	0.7	17818	4.00	1	2
202	8.14	8.35	0.19	40	20	7	0	0	67	697500	2.3	25821	4.00	0	2

Table A-1- 5 Detailed Section-by-Section Characteristics, Part-V

SR	Begin Milepost	End Milepost	Length	Property Damage (2-Yr)	Possible Injury (2-Yr)	Evident Injury (2-Yr)	Disabling Injury (2-Yr)	Fatality (2-Yr)	Total Accidents (2-Yr)	Societal Cost Per Year	Severity Index	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
202	13.00	13.13	0.13	7	7	7	0	0	21	371000	0.5	11011	2.00	0	1
202	24.46	24.68	0.22	3	4	5	1	0	13	741500	0.4	5621	2.00	3	0
204	2.05	2.35	0.30	20	14	1	0	1	36	837500	0.2	22177	4.00	1	2
405	0.00	0.39	0.39	15	12	4	0	0	31	385000	7.9	6325	5.00	2	1
405	0.06	0.12	0.06	8	3	1	0	0	12	109000	1.7	4627	5.00	1	1
405	0.12	0.24	0.12	13	9	2	0	0	24	261500	1.2	12926	5.00	1	1
405	0.15	0.31	0.16	11	3	4	0	0	18	215500	2.9	6735	5.00	1	1
405	0.16	0.32	0.16	18	13	3	0	0	34	379000	3.7	11091	5.00	1	1
405	0.19	0.38	0.19	7	4	1	0	0	12	123500	0.3	7383	5.00	1	1
509	0.00	0.44	0.44	37	24	4	1	0	66	1161000	8.7	12661	4.00	1	1
509	0.00	0.50	0.50	5	0	0	0	1	6	515000	0.6	5380	4.00	1	1
509	0.11	0.22	0.11	3	3	1	0	1	8	594000	0.3	9469	4.00	0	1
509	19.85	20.32	0.47	30	15	10	0	0	55	677500	0.0	20372	2.00	1	2
515	0.36	0.59	0.23	25	14	1	0	0	40	352500	0.1	25267	4.00	0	1
515	0.91	1.27	0.36	86	39	11	2	0	138	2298000	4.3	28282	4.00	0	1
515	3.99	4.23	0.24	25	14	1	1	0	41	852500	0.3	25756	4.00	0	1
515	4.75	5.20	0.45	50	27	10	1	0	88	1447500	0.9	27154	4.00	0	2
516	1.79	2.14	0.34	42	16	6	1	0	65	1101000	0.5	30814	4.00	1	3
516	4.90	6.04	1.14	170	73	12	1	1	257	3177500	0.6	26817	4.00	3	7
516	7.09	7.72	0.63	120	56	10	0	0	186	1665000	2.7	28175	4.00	3	4
516	10.53	10.80	0.27	24	13	4	2	0	43	1429500	1.2	26479	4.00	0	1
516	11.99	12.19	0.20	35	12	4	0	0	51	445000	0.0	29477	4.00	0	1
518	0.00	0.21	0.21	12	5	2	1	0	20	688500	4.2	7007	4.00	1	1
518	0.05	0.11	0.06	13	4	0	0	0	17	109000	7.6	2537	4.00	0	1

Table A-1- 6 Detailed Section-by-Section Characteristics, Part-VI

SR	Begin Milepost	End Milepost	Length	Property Damage (2-Yr)	Possible Injury (2-Yr)	Evident Injury (2-Yr)	Disabling Injury (2-Yr)	Fatality (2-Yr)	Total Accidents (2-Yr)	Societal Cost Per Year	Severity Index	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
519	0.34	0.51	0.17	44	13	2	1	0	60	924500	2.2	17558	4.00	0	3
520	0.00	0.22	0.22	13	7	1	0	1	22	694000	1.2	14149	4.00	1	1
520	0.01	0.21	0.20	41	6	5	0	0	52	390500	0.4	28159	4.00	1	1
520	0.06	0.17	0.11	6	3	4	0	1	14	700500	2.9	7953	4.00	1	1
520	0.14	0.28	0.14	8	4	1	0	0	13	126500	0.7	6997	4.00	1	1
520	0.20	0.40	0.20	8	4	1	0	0	13	126500	0.9	6483	4.00	1	1
520	0.23	0.46	0.23	29	13	3	1	0	46	912000	3.5	16129	4.00	2	1
522	0.00	0.31	0.31	4	4	1	1	0	10	614500	2.9	4600	2.00	2	1
522	4.09	4.51	0.42	68	25	14	0	0	107	1096500	0.6	48050	5.00	1	1
522	6.61	7.68	1.07	143	58	47	11	0	259	8471500	0.6	57030	6.00	2	3
522	16.50	16.60	0.10	14	13	1	0	0	28	302000	1.5	11610	2.00	0	1
522	16.60	16.80	0.20	20	7	2	1	0	30	747500	0.8	11610	2.00	0	1
523	0.49	0.56	0.07	14	13	5	0	0	32	432000	0.3	25684	4.00	0	5
523	0.86	1.13	0.27	27	22	1	1	0	51	998500	0.6	25684	4.00	0	6
524	4.06	4.48	0.42	61	31	8	1	0	101	1485500	0.2	32626	4.00	1	2
524	4.49	5.24	0.75	120	48	22	2	0	192	2915000	1.5	32626	4.00	1	5
524	5.57	5.96	0.39	52	17	11	1	0	81	1311000	2.2	24493	4.00	2	3
524	6.69	6.81	0.12	16	8	7	1	0	32	915500	2.3	14825	2.00	1	1
524	7.43	7.61	0.18	7	9	7	0	0	23	406000	0.1	17006	2.00	0	1
524	9.44	9.68	0.24	24	5	6	0	0	35	354500	0.4	17686	2.00	0	1
524	0.00B	0.08	0.20	11	6	2	0	0	19	203000	5.0	3265	2.00	0	2
525	0.00	0.52	0.52	9	1	3	1	0	14	642000	14.3	2193	3.00	1	2
525	0.15	0.30	0.15	7	5	1	0	0	13	141000	5.9	2895	3.00	1	1
525	3.43	4.27	0.84	88	50	12	2	1	153	3029000	2.2	23022	3.00	0	2
525	8.08	8.28	0.20	14	8	1	0	0	23	214500	0.5	9359	4.00	2	1
526	0.08	0.17	0.09	26	11	2	1	0	40	835500	3.2	14624	4.00	0	0
526	0.12	0.25	0.13	5	7	2	0	0	14	202500	3.1	5412	4.00	0	1

Table A-1- 7 Detailed Section-by-Section Characteristics, Part-VII

SR	Begin Milepost	End Milepost	Length	Property Damage (2-Yr)	Possible Injury (2-Yr)	Evident Injury (2-Yr)	Disabling Injury (2-Yr)	Fatality (2-Yr)	Total Accidents (2-Yr)	Societal Cost Per Year	Severity Index	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
526	0.32	0.40	0.08	6	4	4	0	0	14	218000	0.5	10249	4.00	1	2
526	4.35	4.52	0.17	31	21	4	0	0	56	590500	0.2	41665	4.00	1	1
527	1.52	1.66	0.14	9	7	6	1	0	23	844500	0.8	15987	2.00	1	1
527	2.24	2.84	0.60	99	47	10	1	0	157	1944500	4.5	20791	4.00	1	4
527	3.64	3.99	0.35	62	25	9	1	0	97	1416000	1.9	35834	4.00	0	2
527	5.50	5.60	0.10	27	14	4	1	0	46	956000	0.8	30667	4.00	0	1
527	6.54	6.71	0.17	43	18	5	1	0	67	1106500	2.1	28569	4.00	1	1
527	8.79	8.94	0.15	20	16	1	0	0	37	372500	1.2	15487	2.00	1	2
527	10.31	10.55	0.24	54	11	9	0	0	74	647000	2.1	26557	5.00	1	2
528	0.01	0.50	0.49	62	19	9	3	0	93	2311000	1.2	29200	4.00	0	3
529	0.19	0.67	0.48	51	20	10	2	0	83	1828000	9.0	6874	2.00	0	4
529	0.73	1.03	0.30	30	16	7	0	0	53	597500	2.7	15275	4.00	0	3
529	6.63	6.69	0.06	30	6	3	0	0	39	292500	0.9	19604	4.00	0	2
531	1.41	1.56	0.15	4	4	3	1	0	12	679500	17.3	963	2.00	1	1
536	4.49	4.92	0.43	35	18	3	2	0	58	1517500	0.4	12646	2.00	2	2
536	5.13	5.34	0.21	20	9	0	1	0	30	717500	0.4	10560	2.00	1	1
538	0.27	0.69	0.42	56	26	10	3	0	95	2448000	2.2	25427	4.00	0	1
538	1.21	1.31	0.10	23	16	7	0	0	46	576500	1.9	20580	4.00	0	1
538	2.18	2.39	0.21	8	4	4	0	2	18	1224000	3.6	6953	2.00	1	0
539	0.02	0.75	0.73	132	60	17	0	0	209	1998500	0.6	44159	4.00	0	4
547	7.30	7.40	0.10	2	2	4	0	0	8	171000	6.8	1919	2.00	1	0
599	0.00	0.20	0.20	13	3	2	0	0	18	156500	2.6	5963	4.00	1	1
900	9.75	9.86	0.11	15	7	5	1	0	28	830000	1.3	17307	5.00	1	2
900	9.99	10.15	0.16	15	1	1	0	0	17	95000	0.0	5761	2.00	0	2
900	10.20	10.34	0.14	8	5	1	1	0	15	644000	2.1	5761	2.00	0	4
900	10.40	10.56	0.16	14	10	2	2	0	28	1282000	2.9	11522	2.00	0	5

Table A-1- 8 Detailed Section-by-Section Characteristics, Part-VIII

SR	Begin Milepost	End Milepost	Length	Property Damage (2-Yr)	Possible Injury (2-Yr)	Evident Injury (2-Yr)	Disabling Injury (2-Yr)	Fatality (2-Yr)	Total Accidents (2-Yr)	Societal Cost Per Year	Severity Index	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
900	10.78	11.01	0.23	14	13	3	1	0	31	867000	1.3	16673	4.00	2	2
900	10.99	11.12	0.13	26	9	4	0	0	39	365500	0.5	23142	4.00	0	2
900	11.14	11.32	0.18	46	17	4	0	0	67	565500	0.4	38770	4.00	1	1
900	16.11	16.28	0.17	10	8	1	1	0	20	702500	1.9	8678	2.00	1	1
900	21.33	21.48	0.15	26	12	4	0	0	42	418000	3.7	12602	4.00	1	3
908	3.83	4.19	0.36	48	30	3	0	0	81	766500	0.1	35965	4.00	0	2
908	6.49	6.66	0.17	15	7	4	1	0	27	797500	5.7	5788	2.00	1	2

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Table A-2- 1 Comparison Between DEA Variable-Return-to-Scale Results and Constant-Return-to-Scale Results, Part-I

SR	Begin Milepost	End Milepost	Length	Return to Scale	ACC Occurrence	Rankings	Outputs Weights			Inputs Weights			
							Societal Costs	Severity Index	Total Accidents	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
2	0.00	0.37	0.37	CRS	0.4341	91	0.0000	0.0075	7.4538	9.8190	0.0000	0.0000	0.0000
				VRS	0.5685	155	0.0000	0.0000	7.6957	6.2232	0.0344	0.2140	0.0000
2	0.08	0.16	0.08	CRS	0.2108	189	12.2421	0.0000	0.0000	2.5679	0.0000	0.0597	0.1403
				VRS	0.5680	156	12.2421	0.0000	0.0000	1.5244	0.0740	0.3347	0.1201
2	0.13	0.26	0.13	CRS	0.8670	20	7.4837	0.0000	0.0000	11.7728	0.0000	0.3217	0.0000
				VRS	0.8678	64	7.4837	0.0000	0.0000	11.4803	0.0000	0.3385	0.0000
2	13.75	13.91	0.16	CRS	0.7868	28	6.3291	0.0000	0.0000	0.0000	0.2195	0.9899	0.5610
				VRS	1.0000	1	6.3291	0.0000	0.0000	0.0000	0.2613	0.5445	0.4775
2	14.50	15.11	0.61	CRS	1.0000	1	1.5326	0.0000	0.0000	0.2964	0.2079	0.0000	0.0000
				VRS	1.0000	1	1.5326	0.0000	0.0000	0.0000	0.2456	0.0176	0.0000
5	0.00	0.12	0.12	CRS	1.0000	1	0.0000	0.1075	0.0000	0.3884	0.1601	1.9129	1.7618
				VRS	1.0000	1	0.0000	0.0973	1.3525	0.4053	0.1599	9389051.3452	13891691.4274
5	0.10	0.21	0.11	CRS	0.5157	66	0.0000	0.0000	27.2308	4.8919	0.0831	0.0190	2.7162
				VRS	0.9431	58	6.5877	0.1714	15.5343	1.4694	0.1416	0.6202	0.3990
5	0.11	0.23	0.12	CRS	0.5970	49	2.2621	0.1248	0.0000	0.0000	0.1381	0.9498	0.1715
				VRS	0.7389	82	9.4813	0.0000	0.0000	1.8585	0.0902	0.4080	0.1464
5	0.15	0.30	0.15	CRS	0.1747	201	34.5766	0.5210	8.8810	15.4927	0.0000	1.6951	0.1546
				VRS	0.8634	65	79.8752	0.0001	0.0267	13.5463	0.0000	0.4974	0.2608
5	0.18	0.36	0.18	CRS	0.1255	229	0.0000	0.0282	28.0861	10.7038	0.0000	0.0000	0.0000
				VRS	0.4312	216	59.3457	0.0023	0.7622	4.2938	0.0492	0.2168	0.0435
5	0.19	0.38	0.19	CRS	0.1948	192	0.0000	0.0000	11.0625	0.8726	0.0107	0.0037	0.3645
				VRS	0.4003	227	0.0000	0.0000	11.0625	1.1431	0.0546	0.2086	0.0989
5	0.20	0.41	0.21	CRS	0.1062	236	0.0000	0.0292	29.0696	9.3722	0.0000	0.0000	0.0000
				VRS	0.4236	219	78.2087	0.0319	3.4295	0.9828	0.0654	0.2662	0.1183
9	1.47	1.70	0.23	CRS	0.5400	61	5.7232	0.0239	0.0000	1.7751	0.1383	0.0000	0.1645
				VRS	1.0000	1	2.7509	0.0000	4.3322	0.0000	0.4648	0.0036	0.0668

Table A-2- 2 Comparison Between DEA Variable-Return-to-Scale Results and Constant-Return-to-Scale Results, Part-II

SR	Begin Milepost	End Milepost	Length	Return to Scale	ACC Occurrence	Rankings	Outputs Weights			Inputs Weights			
							Societal Costs	Severity Index	Total Accidents	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
9	10.87	10.97	0.10	CRS	0.5030	72	5.9116	0.0875	0.0000	0.0000	0.3729	0.0000	0.2543
				VRS	1.0000	1	5.7462	0.0159	1.7396	0.0000	0.5000	0.0000	0.0000
9	13.93	14.13	0.20	CRS	0.7528	30	4.5889	0.1975	0.0000	0.0000	0.2882	1.8493	0.4236
				VRS	1.0000	1	2.1139	0.2835	1.1389	0.0000	0.3186	1.7537	0.3627
9	15.75	15.96	0.21	CRS	0.6251	44	6.0858	0.0000	0.0000	1.5495	0.0376	0.5266	0.3254
				VRS	0.8117	71	6.0858	0.0000	0.0000	1.1781	0.0934	0.4402	0.2277
9	53.16	53.36	0.20	CRS	0.4881	78	12.4125	0.0000	0.0000	6.2700	0.0554	0.0000	0.2692
				VRS	1.0000	1	9.9110	0.0025	5.3978	0.0000	0.5000	0.0000	0.0000
9	77.87	77.97	0.10	CRS	0.8178	26	0.0000	0.0000	50.5714	13.8546	0.2801	0.0000	8.1315
				VRS	1.0000	1	0.7828	0.0040	49.9640	0.0000	0.3718	0.2563	0.2563
11	10.78	10.84	0.06	CRS	1.0000	1	0.0000	0.1031	0.0000	37.0084	0.0000	0.0000	2.5433
				VRS	1.0000	1	0.0000	0.1031	0.0000	34.7676	0.0090	0.0425	103263727.3048
18	0.00	0.33	0.33	CRS	0.6360	43	13.6215	0.0069	0.0000	9.0267	0.0000	0.1669	0.4513
				VRS	0.7474	81	10.0188	0.0000	8.5683	7.5634	0.0199	0.3704	0.2302
18	0.09	0.18	0.09	CRS	0.1346	222	0.0000	0.1311	35.2072	10.2956	0.0000	0.0000	0.2920
				VRS	0.5935	146	6.5526	0.0066	36.9800	1.3771	0.0916	0.3730	0.1657
18	0.13	0.26	0.13	CRS	0.1797	198	0.0000	0.0000	22.1250	1.6102	0.0197	0.0069	0.6725
				VRS	0.5338	173	7.5961	0.1872	14.0175	1.2385	0.0824	0.3355	0.1490
18	0.14	0.28	0.14	CRS	0.1365	221	0.0000	0.0000	35.4000	4.0402	0.0000	0.0000	0.6979
				VRS	0.5886	149	27.6263	0.0358	27.8284	1.3658	0.0909	0.3700	0.1643
18	0.17	0.34	0.17	CRS	0.2242	178	0.0000	0.1561	15.0977	5.6017	0.0000	0.2648	0.3611
				VRS	0.5951	143	19.0795	0.0166	19.4883	1.3809	0.0919	0.3741	0.1662
18	0.20	0.40	0.20	CRS	0.1320	226	0.0000	0.0541	53.8932	21.6023	0.0000	0.0000	0.0000
				VRS	0.6203	131	8.6744	0.0480	49.8762	7.5208	0.0636	0.3348	0.0313
18	14.55	14.76	0.21	CRS	0.5014	74	9.9314	0.0000	0.0000	0.0000	0.2195	0.9899	0.5610
				VRS	1.0000	1	7.7812	0.3963	1.8687	0.0000	0.3717	0.2565	0.2565

Table A-2- 3 Comparison Between DEA Variable-Return-to-Scale Results and Constant-Return-to-Scale Results, Part-III

SR	Begin Milepost	End Milepost	Length	Return to Scale	ACC Occurrence	Rankings	Outputs Weights			Inputs Weights			
							Societal Costs	Severity Index	Total Accidents	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
18	2.61B	0.16	0.28	CRS	0.4637	88	6.3724	0.0000	1.9068	1.1003	0.0413	0.4739	0.4353
				VRS	0.7093	89	3.4355	0.0000	4.5748	0.3832	0.1456	0.3175	0.2786
20	26.59	26.83	0.24	CRS	0.8318	23	5.3130	0.0000	0.0000	2.8771	0.1439	0.0000	0.2263
				VRS	1.0000	1	5.3130	0.0000	0.0000	1.3390	0.3623	0.0000	0.0492
20	31.25	31.70	0.45	CRS	0.3317	142	0.0000	0.0000	3.6495	0.4816	0.0072	0.0000	0.2044
				VRS	0.6202	132	0.0000	0.0000	3.6495	0.1415	0.2266	0.0000	0.0309
20	53.24	53.34	0.10	CRS	0.4982	75	7.2375	0.0000	0.0000	3.5886	0.0000	0.0834	0.1961
				VRS	0.6230	128	7.2375	0.0000	0.0000	1.4423	0.0700	0.3167	0.1136
20	58.67	58.96	0.29	CRS	0.7996	27	3.8762	0.0000	0.0000	2.0179	0.1009	0.0000	0.1587
				VRS	1.0000	1	3.8762	0.0000	0.0000	0.0000	0.4533	0.0000	0.0934
20	59.39	59.70	0.31	CRS	0.2910	156	0.0000	0.0000	7.0800	0.8197	0.0122	0.0000	0.3479
				VRS	0.5712	153	0.0000	0.0000	7.0800	0.0777	0.2471	0.0017	0.0364
20	59.73	59.94	0.21	CRS	0.4145	96	6.3528	0.0000	0.0000	1.6642	0.0161	0.1454	0.1939
				VRS	0.5479	165	4.5477	0.0000	2.5147	0.3510	0.1025	0.2616	0.2025
96	1.09	1.26	0.17	CRS	0.2607	164	0.0000	0.2888	4.2899	0.0000	0.1299	0.8406	0.2402
				VRS	0.5297	176	5.2085	0.1481	3.2362	0.6272	0.1050	0.4416	0.1705
96	1.35	1.51	0.16	CRS	0.3820	114	7.0894	0.0000	2.1214	1.0084	0.0379	0.4343	0.3989
				VRS	0.6667	109	2.9241	0.0001	6.4956	0.0000	0.1667	0.3333	0.3333
96	2.18	2.51	0.33	CRS	0.6560	41	4.6464	0.0000	0.6773	0.0000	0.0878	0.4499	0.6488
				VRS	0.7841	74	4.6464	0.0000	0.6773	0.0000	0.1481	0.3667	0.4075

Table A-2- 4 Comparison Between DEA Variable-Return-to-Scale Results and Constant-Return-to-Scale Results, Part-IV

SR	Begin Milepost	End Milepost	Length	Return to Scale	ACC Occurrence	Rankings	Outputs Weights			Inputs Weights			
							Societal Costs	Severity Index	Total Accidents	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
				VRS	0.6852	102	14.1192	0.0000	0.0000	1.8972	0.0921	0.4165	0.1494
99	0.09	0.19	0.10	CRS	0.4738	84	0.0000	0.2070	15.7215	24.7957	0.0000	1.5304	0.0000
				VRS	1.0000	1	8.6075	0.0514	31.2277	24.7957	0.0000	0.6843	0.0000
99	8.05	8.27	0.22	CRS	0.5439	59	4.0289	0.1734	0.0000	0.0000	0.1828	1.1730	0.2687
				VRS	0.7747	77	1.5858	0.1280	2.7209	0.5600	0.1479	0.6868	0.2305
99	8.87	10.26	1.39	CRS	1.0000	1	0.0000	0.0000	1.0000	1.9963	0.0000	0.0565	0.0674
				VRS	1.0000	1	0.4026	0.0247	0.5600	2.9315	0.0052	38834.1389	0.0011
99	10.29	10.79	0.50	CRS	0.3942	106	0.0000	0.0000	3.0517	0.4786	0.0071	0.0000	0.2031
				VRS	0.6100	135	0.0000	0.0000	3.0517	0.1073	0.2118	0.0016	0.0289
99	10.86	10.97	0.11	CRS	0.1488	218	0.0000	0.0000	13.6154	0.8062	0.0120	0.0000	0.3421
				VRS	0.5000	192	2.9599	0.0076	11.7904	0.0000	0.2500	0.0000	0.0000
99	11.18	11.48	0.30	CRS	0.3418	136	7.7805	0.0000	0.6224	1.0152	0.0299	0.4027	0.2716
				VRS	0.6005	138	5.3693	0.0000	2.6684	1.3779	0.0695	0.2892	0.1321
99	11.62	12.02	0.40	CRS	0.6375	42	0.0000	0.0000	4.8493	1.2520	0.0154	0.0053	0.5229
				VRS	0.8169	70	0.0000	0.0000	4.8493	0.7310	0.1189	0.2565	0.2815
99	12.90	13.21	0.31	CRS	0.8724	19	3.4937	0.0000	0.5093	0.0000	0.0953	0.4724	0.6189
				VRS	0.9199	61	3.4937	0.0000	0.5093	0.0000	0.1481	0.3667	0.4075
99	13.65	13.80	0.15	CRS	0.2917	155	0.0000	0.0000	6.3214	0.0000	0.1094	0.0000	0.2813
				VRS	0.5571	161	0.0000	0.0000	6.3214	0.0000	0.1517	0.1396	0.1967
99	13.99	14.39	0.40	CRS	0.3026	149	5.2197	0.0000	0.0000	1.0284	0.0514	0.0000	0.0809
				VRS	0.5170	183	3.3397	0.0000	2.3611	0.0501	0.2165	0.0172	0.0300
99	15.26	15.58	0.32	CRS	0.8660	22	0.9746	0.0289	1.9646	0.0000	0.1494	0.0000	0.4026
				VRS	0.8719	63	0.7311	0.0000	2.5353	0.0000	0.1733	0.0000	0.3070

Table A-2- 5 Comparison Between DEA Variable-Return-to-Scale Results and Constant-Return-to-Scale Results, Part-V

SR	Begin Milepost	End Milepost	Length	Return to Scale	ACC Occurrence	Rankings	Outputs Weights			Inputs Weights			
							Societal Costs	Severity Index	Total Accidents	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
99	16.40	16.78	0.38	CRS	0.5197	65	4.9965	0.0000	0.0000	0.9230	0.0376	0.3917	0.2214
				VRS	0.6571	112	4.9965	0.0000	0.0000	0.8739	0.0693	0.3265	0.1689
99	17.43	17.75	0.32	CRS	1.0000	1	3.1812	0.0000	0.0000	1.1353	0.0370	0.5258	0.3149
				VRS	1.0000	1	2.9775	0.0213	0.0000	0.0000	0.0000	1.5396	1.0000
99	18.26	18.45	0.19	CRS	0.2932	152	0.0000	0.0000	10.4118	1.2362	0.0152	0.0053	0.5163
				VRS	0.4650	208	0.0000	0.0000	10.4118	0.3142	0.1006	0.1778	0.2170
99	19.06	19.15	0.09	CRS	0.3648	125	9.6953	0.0000	0.7756	1.3502	0.0398	0.5356	0.3612
				VRS	0.6240	127	10.2809	0.0000	0.0000	1.0922	0.0866	0.4081	0.2111
99	19.37	19.51	0.14	CRS	0.1906	193	11.9570	0.0000	0.0000	1.4401	0.0139	0.1258	0.1678
				VRS	0.4050	222	7.6654	0.0000	4.7058	0.7813	0.0902	0.1530	0.0707
99	19.42	19.49	0.07	CRS	0.6781	39	3.5826	0.0248	0.0000	1.2135	0.0463	0.1710	0.2020
				VRS	0.6921	97	3.4433	0.0316	0.0000	0.6739	0.0683	0.2419	0.1972
99	20.06	20.29	0.23	CRS	0.4917	77	3.2819	0.0590	0.0000	0.0000	0.0968	0.2624	0.1752
				VRS	0.6208	130	3.5589	0.0195	0.0000	0.0000	0.2063	0.0612	0.0568
99	22.85	23.02	0.18	CRS	0.1558	211	0.0000	0.0000	13.1111	0.8128	0.0121	0.0000	0.3449
				VRS	0.5000	192	0.4720	0.0010	12.9317	0.0000	0.2500	0.0000	0.0000
99	37.18	37.80	0.62	CRS	0.3095	146	3.5760	0.0000	0.0000	0.0000	0.1667	0.0554	0.0000
				VRS	0.3926	233	3.5760	0.0000	0.0000	0.0000	0.1419	0.0535	0.0149
99	38.97	39.22	0.25	CRS	0.4775	82	4.7380	0.0000	0.0000	0.4109	0.0596	0.3988	0.2321
				VRS	0.5759	151	4.7380	0.0000	0.0000	0.4722	0.0781	0.2778	0.1681
99	39.26	39.51	0.25	CRS	0.2966	151	5.8143	0.0000	1.7398	0.6421	0.0241	0.2766	0.2540
				VRS	0.4873	205	2.5705	0.0000	4.4955	0.2322	0.0984	0.2048	0.1869
99	39.58	40.18	0.60	CRS	0.5699	54	2.5590	0.0000	0.0000	0.0000	0.1214	0.2470	0.0786
				VRS	0.6112	134	2.5590	0.0000	0.0000	0.0691	0.1672	0.0569	0.0248
99	40.21	40.59	0.38	CRS	0.9817	15	2.3049	0.0000	0.0000	0.4109	0.0596	0.3988	0.2321
				VRS	1.0000	1	2.3049	0.0000	0.0000	0.0000	0.0000	1.8800	0.5000

Table A-2- 6 Comparison Between DEA Variable-Return-to-Scale Results and Constant-Return-to-Scale Results, Part-VI

SR	Begin Milepost	End Milepost	Length	Return to Scale	ACC Occurrence	Rankings	Outputs Weights			Inputs Weights			
							Societal Costs	Severity Index	Total Accidents	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
99	40.66	41.10	0.44	CRS	0.5054	70	1.7532	0.0000	1.7451	0.0000	0.0941	0.1716	0.2079
				VRS	0.6394	118	0.0000	0.0000	3.0256	0.0000	0.1744	0.0558	0.1008
99	41.17	41.45	0.28	CRS	0.3968	104	3.7610	0.0318	0.0000	0.0000	0.2500	0.0000	0.0000
				VRS	0.5349	172	2.5197	0.0000	1.9939	0.0000	0.2186	0.0129	0.0249
99	41.71	42.11	0.40	CRS	0.5862	50	3.4486	0.0000	0.0000	0.0000	0.1683	0.3424	0.1089
				VRS	0.6556	113	3.4486	0.0000	0.0000	0.0000	0.2281	0.0938	0.0292
99	43.39	43.57	0.17	CRS	0.2865	157	0.0000	0.0000	6.4364	0.0000	0.1094	0.0000	0.2813
				VRS	0.5254	179	0.0000	0.0000	6.4364	0.0000	0.2235	0.0000	0.0530
99	45.35	45.84	0.49	CRS	0.3862	111	0.0000	0.0000	3.7263	0.0000	0.0854	0.0000	0.2195
				VRS	0.5903	148	0.0000	0.0000	3.7263	0.0000	0.2294	0.0108	0.0275
99	45.86	46.19	0.33	CRS	0.3472	133	1.5614	0.0590	3.7220	0.0000	0.1195	0.0000	0.2610
				VRS	0.5449	166	0.0000	0.0000	5.7097	0.0000	0.2214	0.0122	0.0510
99	46.39	46.66	0.27	CRS	0.2969	150	0.0000	0.0000	6.2105	0.0000	0.1094	0.0000	0.2812
				VRS	0.5601	158	0.0000	0.0000	6.2105	0.0000	0.1517	0.1396	0.1967
99	46.75	47.05	0.30	CRS	0.3415	137	0.0000	0.0000	4.2143	0.0000	0.0854	0.0000	0.2195
				VRS	0.5706	154	0.0000	0.0000	4.2143	0.0000	0.2294	0.0108	0.0275
99	48.67	49.17	0.50	CRS	0.5990	48	0.0000	0.0000	3.0783	0.0000	0.1094	0.0000	0.2812
				VRS	0.6792	106	0.0000	0.0000	3.0783	0.0000	0.1375	0.0000	0.2250
99	49.91	50.66	0.75	CRS	0.3701	120	0.0000	0.0000	2.7023	0.0000	0.2500	0.0000	0.0000
				VRS	0.6050	136	0.0000	0.0000	2.7023	0.0000	0.2119	0.0099	0.0254
99	50.75	51.40	0.65	CRS	0.3869	109	4.7116	0.0000	0.0000	0.0000	0.1518	0.3088	0.0982
				VRS	0.5955	140	0.0000	0.0000	3.3084	0.0000	0.2232	0.0105	0.0268
99	51.98	52.48	0.50	CRS	0.6595	40	3.0649	0.0000	0.0000	0.0000	0.1683	0.3424	0.1089
				VRS	0.7024	91	3.0649	0.0000	0.0000	0.0000	0.2281	0.0938	0.0292
99	52.66	52.95	0.29	CRS	0.6248	45	5.2354	0.0000	0.0263	0.0000	0.0811	0.4604	0.6252
				VRS	0.7172	86	5.2569	0.0000	0.0000	0.0000	0.1328	0.3587	0.3862

Table A-2- 7 Comparison Between DEA Variable-Return-to-Scale Results and Constant-Return-to-Scale Results, Part-VII

SR	Begin Milepost	End Milepost	Length	Return to Scale	ACC Occurrence	Rankings	Outputs Weights			Inputs Weights			
							Societal Costs	Severity Index	Total Accidents	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
99	53.59	53.89	0.30	CRS	0.2792	159	0.0000	0.2300	1.8602	0.0000	0.1056	0.7950	0.1221
				VRS	0.4849	206	5.6115	0.0000	3.0292	1.1432	0.0570	0.2388	0.1092
99	54.30	54.78	0.48	CRS	0.4863	79	2.6197	0.0000	0.9040	0.5078	0.0179	0.2001	0.1934
				VRS	0.5408	169	0.4353	0.0000	2.4384	0.3640	0.0610	0.1318	0.1366
99	54.80	54.89	0.09	CRS	0.1602	209	4.3156	0.0000	4.6887	0.4830	0.0123	0.0546	0.1916
				VRS	0.3389	240	1.3110	0.0000	7.2925	0.0403	0.1497	0.0108	0.0221
99	55.00	55.20	0.20	CRS	0.1788	199	0.0000	0.0000	7.2245	0.5138	0.0077	0.0000	0.2181
				VRS	0.3469	238	0.0000	0.0000	7.2245	0.0474	0.1506	0.0010	0.0222
104	24.65	24.74	0.09	CRS	0.3969	103	15.2365	0.0000	0.0000	6.5180	0.0000	0.0792	0.2959
				VRS	0.6327	119	15.2365	0.0000	0.0000	2.3938	0.0758	0.3334	0.1339
104	26.43	26.52	0.09	CRS	0.3815	115	6.4471	0.0000	0.0000	0.4125	0.0342	0.2367	0.4562
				VRS	0.5298	175	6.4471	0.0000	0.0000	0.4952	0.0820	0.2914	0.1763
164	0.31	1.07	0.76	CRS	0.9214	16	2.0318	0.0000	0.0000	1.2188	0.0609	0.0000	0.0959
				VRS	0.9315	59	2.0318	0.0000	0.0000	1.6280	0.0000	0.0000	0.1247
164	1.09	1.34	0.25	CRS	0.4638	87	0.0000	0.0000	5.5312	0.0000	0.1166	0.0000	0.5335
				VRS	0.6162	133	0.0000	0.0000	5.5312	0.0000	0.1608	0.1481	0.2086
164	1.78	2.14	0.36	CRS	0.6180	47	2.7832	0.0000	1.5570	0.0000	0.0696	0.1583	0.5634
				VRS	0.6878	99	3.6304	0.0000	0.4462	0.0000	0.1237	0.2361	0.2690
164	2.24	2.41	0.17	CRS	0.3720	118	6.4866	0.0000	0.0000	0.0000	0.0595	0.2297	0.5323
				VRS	0.5271	177	0.0000	0.0000	9.8333	0.0000	0.1608	0.1481	0.2086
167	0.00	0.16	0.16	CRS	0.3209	144	0.0000	0.1235	10.3012	0.0000	0.2295	0.0000	0.5409
				VRS	1.0000	1	0.2320	0.0477	11.6492	0.0000	0.5000	0.0000	0.0000

Table A-2- 8 Comparison Between DEA Variable-Return-to-Scale Results and Constant-Return-to-Scale Results, Part-VIII

SR	Begin Milepost	End Milepost	Length	Return to Scale	ACC Occurrence	Rankings	Outputs Weights			Inputs Weights			
							Societal Costs	Severity Index	Total Accidents	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
167	0.09	0.19	0.10	CRS	0.0988	238	0.0000	0.0320	31.8729	9.5624	0.0000	0.0000	0.0000
				VRS	1.0000	1	2.6592	0.0138	31.1190	0.0000	0.5000	0.0000	0.0000
167	0.14	0.28	0.14	CRS	0.1432	219	0.0000	0.0229	22.8421	9.9335	0.0000	0.0000	0.0000
				VRS	1.0000	1	2.3571	0.0634	20.8254	0.0000	0.5000	0.0000	0.0000
167	0.15	0.31	0.16	CRS	0.0820	241	0.0000	0.0000	32.1818	7.9429	0.0000	0.0000	0.0000
				VRS	1.0000	1	4.7516	0.0557	30.0982	0.0000	0.5000	0.0000	0.0000
167	0.16	0.33	0.17	CRS	0.1341	223	0.0000	0.1918	16.0024	0.0000	0.1490	0.0000	0.3510
				VRS	1.0000	1	10.5469	0.2667	10.8116	0.0000	0.5000	0.0000	0.0000
167	0.19	0.36	0.17	CRS	0.4753	83	5.7219	0.0951	0.0000	0.0000	0.5000	0.0000	0.0000
				VRS	1.0000	1	1.5626	0.0766	6.8921	0.0000	0.5000	0.0000	0.0000
167	25.70	26.67	0.97	CRS	0.8211	25	0.0000	0.0000	1.7525	0.0000	0.0854	0.0000	0.2195
				VRS	0.8503	66	0.0000	0.0000	1.7525	0.0000	0.1122	0.0000	0.1837
167	26.84	27.28	0.44	CRS	0.3667	123	0.0000	0.0000	3.2182	0.0000	0.0700	0.0000	0.1800
				VRS	0.5945	145	0.0000	0.0000	3.2182	0.0000	0.2209	0.0104	0.0265
169	11.35	11.53	0.18	CRS	0.4446	90	0.0000	0.3387	5.0306	0.0000	0.2598	1.6812	0.4805
				VRS	1.0000	1	0.0000	0.0000	9.5676	2.2059	0.1375	0.5943	0.3332
181	5.32	5.62	0.30	CRS	0.5075	68	4.2137	0.0000	0.6142	0.0000	0.1008	0.4331	0.2985
				VRS	0.6511	116	0.7537	0.0000	3.4510	0.1124	0.1348	0.1795	0.2008
181	5.83	5.98	0.15	CRS	0.3690	122	0.6854	0.0000	6.8619	1.0849	0.0165	0.0000	0.4516
				VRS	0.5653	157	0.0000	0.0000	7.3750	0.0000	0.1608	0.1481	0.2086
181	7.62	7.80	0.18	CRS	0.4062	99	7.5039	0.0000	1.0938	0.0000	0.1167	0.5365	0.5334
				VRS	0.7000	92	0.0000	0.0000	7.3750	0.0000	0.1683	0.2633	0.3267
181	9.68	9.84	0.16	CRS	0.3261	143	0.0000	0.0000	7.8667	0.0000	0.1101	0.0000	0.5595
				VRS	0.5557	162	0.0000	0.0000	7.8667	0.0000	0.1608	0.1481	0.2086

Table A-2- 9 Comparison Between DEA Variable-Return-to-Scale Results and Constant-Return-to-Scale Results, Part-IX

SR	Begin Milepost	End Milepost	Length	Return to Scale	ACC Occurrence	Rankings	Outputs Weights			Inputs Weights			
							Societal Costs	Severity Index	Total Accidents	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
202	0.13	0.34	0.21	CRS	0.2642	162	0.0000	0.0000	5.4462	0.0000	0.0854	0.0000	0.2195
				VRS	0.5265	178	0.0000	0.0000	5.4462	0.0000	0.2294	0.0000	0.0274
202	2.66	2.73	0.07	CRS	0.1325	225	0.0000	0.0000	18.6316	0.9818	0.0146	0.0000	0.4167
				VRS	1.0000	1	8.6043	0.0000	17.0042	0.0000	0.5000	0.0000	0.0000
202	6.76	7.06	0.30	CRS	0.3418	135	5.8809	0.0000	0.0000	0.4264	0.2674	0.0000	0.0000
				VRS	0.6250	126	1.1069	0.0041	5.0158	0.0000	0.3125	0.0000	0.0000
202	7.17	7.26	0.09	CRS	0.1215	231	0.0000	0.0174	17.3607	6.4014	0.0000	0.0000	0.0000
				VRS	0.6667	109	1.0760	0.0180	16.8871	0.0000	0.3333	0.0000	0.0000
202	7.28	7.43	0.15	CRS	0.1132	233	0.0000	0.0000	10.7273	0.4832	0.0072	0.0000	0.2051
				VRS	0.5000	192	1.1654	0.0209	10.3861	0.0000	0.2500	0.0000	0.0000
202	7.45	7.57	0.12	CRS	0.5712	53	3.8366	0.1651	0.0000	0.0000	0.1828	1.1730	0.2687
				VRS	0.7773	76	1.5843	0.1279	2.7183	0.5616	0.1483	0.6888	0.2311
202	7.63	7.80	0.17	CRS	0.1861	196	0.0000	0.0000	11.0625	0.8191	0.0122	0.0000	0.3476
				VRS	0.5000	192	0.3066	0.0039	10.8891	0.0000	0.2500	0.0000	0.0000
202	8.14	8.35	0.19	CRS	0.3849	113	0.0000	0.1957	2.9059	0.0000	0.1299	0.8406	0.2402
				VRS	0.5963	139	0.0000	0.0690	4.4451	0.0755	0.1553	0.2311	0.1722
202	13.00	13.13	0.13	CRS	0.2502	169	15.5605	0.0000	5.3697	1.5516	0.0548	0.6112	0.5908
				VRS	1.0000	1	12.5204	0.1934	5.9836	0.0000	0.4022	0.1957	0.1957
202	24.46	24.68	0.22	CRS	0.8307	24	0.9147	0.0000	25.0507	7.1894	0.1457	0.0000	4.1704
				VRS	1.0000	1	11.0867	0.0014	0.7910	0.0000	0.5000	0.0000	0.0000
204	2.05	2.35	0.30	CRS	0.2145	184	4.7768	0.0000	5.1897	0.7159	0.0182	0.0809	0.2839
				VRS	0.5000	192	0.5196	0.0006	9.3271	0.0000	0.2500	0.0000	0.0000

Table A-2- 10 Comparison Between DEA Variable-Return-to-Scale Results and Constant-Return-to-Scale Results, Part-X

SR	Begin Milepost	End Milepost	Length	Return to Scale	ACC Occurrence	Rankings	Outputs Weights			Inputs Weights			
							Societal Costs	Severity Index	Total Accidents	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
405	0.00	0.39	0.39	CRS	0.3865	110	0.0000	0.0318	8.5475	7.1806	0.0000	0.0000	0.2036
				VRS	0.4353	213	0.0000	0.0000	11.4194	3.5416	0.0442	0.1680	0.0504
405	0.06	0.12	0.06	CRS	0.1691	206	0.0000	0.0926	24.8571	9.1332	0.0000	0.0000	0.2590
				VRS	0.5354	171	1.2683	0.0015	28.9448	1.2422	0.0827	0.3365	0.1495
405	0.12	0.24	0.12	CRS	0.2358	174	0.0000	0.0000	14.7500	1.4087	0.0173	0.0060	0.5883
				VRS	0.4633	209	0.0000	0.0000	14.7500	1.0886	0.0595	0.2611	0.1947
405	0.14	0.29	0.15	CRS	0.2126	186	0.0000	0.1279	12.3704	4.3512	0.0000	0.2056	0.2805
				VRS	0.5180	181	18.9083	0.0000	10.2071	1.4882	0.0742	0.3109	0.1422
405	0.14	0.29	0.15	CRS	0.3500	131	0.0000	0.0000	10.4118	1.4756	0.0181	0.0063	0.6163
				VRS	0.5150	184	0.0000	0.0000	10.4118	1.1282	0.0616	0.2706	0.2018
405	0.19	0.38	0.19	CRS	0.1368	220	0.0000	0.0000	29.5000	2.8267	0.0000	0.0148	0.6193
				VRS	0.5050	187	25.6448	0.0308	18.1990	1.1718	0.0780	0.3174	0.1410
509	0.00	0.44	0.44	CRS	0.6970	37	2.5706	0.0437	1.4349	0.6856	0.0774	0.1809	0.3572
				VRS	0.6976	93	2.5516	0.0438	1.4462	0.6925	0.0763	0.1713	0.3696
509	0.11	0.22	0.11	CRS	0.3639	128	14.2618	0.0000	0.0000	2.1138	0.0513	0.7184	0.4439
				VRS	0.8303	68	14.2618	0.0000	0.0000	2.0840	0.1107	0.4797	0.2111
509	19.85	20.32	0.47	CRS	0.3667	123	0.0000	0.0000	6.4364	0.0000	0.1400	0.0000	0.3600
				VRS	1.0000	1	0.0120	0.0000	6.4302	0.0000	0.5000	0.0000	0.0000
515	0.36	0.59	0.23	CRS	0.3067	148	0.0000	0.0000	8.8500	1.0992	0.0135	0.0047	0.4591
				VRS	0.6733	108	0.0000	0.0000	8.8500	0.0000	0.1683	0.2633	0.3267
515	0.91	1.27	0.36	CRS	1.0000	1	0.0000	0.0094	2.4612	0.0000	0.1022	0.0933	0.5911
				VRS	1.0000	1	0.3606	0.0148	2.1506	0.0000	0.0000	0.3710	1.0000
515	3.99	4.23	0.24	CRS	0.3642	127	7.3916	0.0000	2.2118	1.0025	0.0377	0.4318	0.3966
				VRS	0.6767	107	0.0000	0.0000	8.6341	0.0000	0.1683	0.2633	0.3267
515	4.75	5.20	0.45	CRS	0.4679	86	2.3905	0.0000	2.3796	0.0000	0.1188	0.2167	0.2625
				VRS	0.6532	114	0.0000	0.0000	4.0227	0.0000	0.1517	0.1396	0.1967

Table A-2- 11 Comparison Between DEA Variable-Return-to-Scale Results and Constant-Return-to-Scale Results, Part-XI

SR	Begin Milepost	End Milepost	Length	Return to Scale	ACC Occurrence	Rankings	Outputs Weights			Inputs Weights			
							Societal Costs	Severity Index	Total Accidents	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
516	1.79	2.14	0.34	CRS	0.2675	160	0.8467	0.0000	4.8468	0.0000	0.0876	0.0000	0.2165
				VRS	0.5308	174	0.0000	0.0000	5.4462	0.0000	0.2269	0.0107	0.0272
516	10.53	10.80	0.27	CRS	0.5839	51	5.9262	0.0000	0.0000	0.0000	0.0972	0.5219	0.6112
				VRS	0.7482	80	5.9262	0.0000	0.0000	0.5546	0.1163	0.3993	0.2775
516	11.99	12.19	0.20	CRS	0.3696	121	0.0000	0.0000	6.9412	0.0000	0.0894	0.0000	0.6423
				VRS	0.7100	88	0.0000	0.0000	6.9412	0.0000	0.1683	0.2633	0.3267
518	0.00	0.21	0.21	CRS	0.4183	94	11.9909	0.0061	0.0000	5.2259	0.0000	0.0966	0.2613
				VRS	0.6227	129	11.4734	0.0000	1.1953	2.2653	0.0715	0.3093	0.1263
518	0.05	0.11	0.06	CRS	1.0000	1	0.0000	0.1316	0.0000	19.8281	0.0295	3.5902	0.0000
				VRS	1.0000	1	0.0000	0.1316	0.0000	22.4793	0.0000	3.9365	0.0000
519	0.34	0.51	0.17	CRS	0.2918	154	4.3380	0.2394	0.0000	0.0000	0.1294	0.8904	0.1607
				VRS	0.5521	164	5.1716	0.0000	2.5702	1.2540	0.0633	0.2632	0.1203
520	0.00	0.22	0.22	CRS	0.2642	163	12.2068	0.0000	0.0000	2.0384	0.0197	0.1781	0.2375
				VRS	0.5174	182	9.5350	0.0000	3.5219	1.3386	0.0671	0.2750	0.1244
520	0.01	0.21	0.20	CRS	0.3776	117	0.0000	0.0000	6.8077	1.0227	0.0152	0.0000	0.4341
				VRS	0.5780	150	0.0000	0.0000	6.8077	0.0000	0.1608	0.1481	0.2086
520	0.06	0.17	0.11	CRS	0.3895	107	12.0935	0.0000	0.0000	5.0763	0.0000	0.0617	0.2304
				VRS	0.6011	137	12.0935	0.0000	0.0000	2.1677	0.0686	0.3019	0.1213
520	0.14	0.28	0.14	CRS	0.1528	214	0.0000	0.0000	27.2308	1.6845	0.0207	0.0072	0.7035
				VRS	0.5525	163	56.6583	0.0343	3.5390	1.2819	0.0853	0.3472	0.1542
520	0.20	0.40	0.20	CRS	0.1551	212	0.0000	0.0000	27.2308	1.7124	0.0209	0.0073	0.7143
				VRS	0.5590	160	46.6592	0.0875	6.1143	1.2969	0.0863	0.3513	0.1561
520	0.23	0.46	0.23	CRS	0.4321	92	0.7099	0.0000	7.1075	1.3158	0.0200	0.0000	0.5478
				VRS	0.5362	170	0.0000	0.0000	7.6956	0.0695	0.2360	0.0000	0.0363
522	0.00	0.31	0.31	CRS	0.4961	76	13.7860	0.0000	0.0000	7.0786	0.0626	0.0000	0.3039
				VRS	1.0000	1	8.1001	0.1323	1.0231	0.0000	0.5000	0.0000	0.0000

Table A-2- 12 Comparison Between DEA Variable-Return-to-Scale Results and Constant-Return-to-Scale Results, Part-XII

SR	Begin Milepost	End Milepost	Length	Return to Scale	ACC Occurrence	Rankings	Outputs Weights			Inputs Weights			
							Societal Costs	Severity Index	Total Accidents	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
522	4.09	4.51	0.42	CRS	0.7230	34	0.0000	0.0000	3.3084	0.0000	0.0676	0.0000	0.6622
				VRS	0.7255	84	0.0000	0.0000	3.3084	0.0000	0.0719	0.0000	0.6405
522	6.61	7.68	1.07	CRS	1.0000	1	0.8346	0.0000	0.2260	0.0000	0.0953	0.0000	0.1428
				VRS	1.0000	1	1.0000	0.0000	0.0000	0.0018	0.0003	0.0007	0.3317
522	16.50	16.60	0.10	CRS	0.4121	97	0.0000	0.4673	3.7800	0.0000	0.3169	2.3849	0.3662
				VRS	1.0000	1	0.2563	0.6516	0.1710	0.0000	0.3882	0.2237	0.2237
522	16.60	16.80	0.20	CRS	0.4728	85	11.3331	0.0000	0.0000	1.9045	0.0777	0.8082	0.4569
				VRS	1.0000	1	11.3331	0.0000	0.0000	1.8302	0.1628	0.6976	0.3018
523	0.49	0.56	0.07	CRS	0.0904	240	0.0000	0.0000	11.0625	0.0000	0.2136	0.0000	0.0291
				VRS	0.5000	192	10.6211	0.1481	4.5793	0.0000	0.2500	0.0000	0.0000
523	0.86	1.13	0.27	CRS	0.1957	191	8.4842	0.0000	0.0000	0.0000	0.2500	0.0831	0.0000
				VRS	0.5000	192	0.2235	0.0227	6.6640	0.0000	0.2500	0.0000	0.0000
524	4.06	4.48	0.42	CRS	0.5260	63	0.0000	0.0000	3.5050	0.0000	0.1094	0.0000	0.2813
				VRS	0.6298	121	0.0000	0.0000	3.5050	0.0000	0.1826	0.0584	0.1056
524	4.49	5.24	0.75	CRS	0.5662	56	2.4265	0.0000	0.3043	0.0000	0.2500	0.0000	0.0000
				VRS	0.7207	85	0.0000	0.0000	1.8437	0.0000	0.2201	0.0021	0.0235
524	5.57	5.96	0.39	CRS	0.3368	140	1.2765	0.0483	3.0430	0.0000	0.0948	0.0000	0.2070
				VRS	0.5599	159	0.0000	0.0054	4.3183	0.0607	0.2197	0.0017	0.0305
524	6.69	6.81	0.12	CRS	0.4545	89	3.0037	0.1038	4.8309	0.0000	0.2674	0.0000	0.4652
				VRS	1.0000	1	0.1469	0.0548	9.4936	0.0000	0.5000	0.0000	0.0000
524	7.43	7.61	0.18	CRS	0.2519	167	8.8810	0.0000	8.8404	0.0000	0.2375	0.4333	0.5249
				VRS	1.0000	1	15.8601	0.0936	3.5482	0.0000	0.3895	0.2210	0.2210
524	9.44	9.68	0.24	CRS	0.3646	126	0.0000	0.0000	10.1143	0.0000	0.2187	0.0000	0.5625
				VRS	1.0000	1	0.2670	0.0040	9.9853	0.0000	0.3951	0.2097	0.2097

Table A-2- 13 Comparison Between DEA Variable-Return-to-Scale Results and Constant-Return-to-Scale Results, Part-XIII

SR	Begin Milepost	End Milepost	Length	Return to Scale	ACC Occurrence	Rankings	Outputs Weights			Inputs Weights			
							Societal Costs	Severity Index	Total Accidents	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
524	0.00B	0.08	0.20	CRS	0.8846	18	0.0000	0.2000	0.0000	9.3602	0.2321	2.4386	0.0000
				VRS	1.0000	1	0.0000	0.2000	0.0000	7.7317	0.2787	0.9829	0.0000
525	0.00	0.52	0.52	CRS	0.7240	33	0.0000	0.0699	0.0000	2.6784	0.0664	0.6978	0.0000
				VRS	0.7496	79	10.3932	0.0149	0.0000	8.4696	0.0440	0.5422	0.0000
525	0.15	0.30	0.15	CRS	0.3635	129	0.0000	0.1058	10.2313	6.1542	0.0000	0.2909	0.3967
				VRS	0.6975	94	0.0000	0.0000	27.2308	6.6740	0.0832	0.3166	0.0949
525	3.43	4.27	0.84	CRS	1.0000	1	2.5116	0.0000	0.2359	0.0000	0.1539	0.6395	0.2691
				VRS	1.0000	1	2.7799	0.0000	0.0140	0.0000	0.1850	0.5937	0.2225
525	8.08	8.28	0.20	CRS	0.2520	166	0.0000	0.0000	15.3913	1.5430	0.0230	0.0000	0.6549
				VRS	0.5021	190	0.0000	0.0000	15.3913	0.2114	0.2332	0.0000	0.0327
526	0.08	0.17	0.09	CRS	1.0000	1	0.3519	0.0000	8.5429	0.0000	0.2500	0.6397	7.0464
				VRS	1.0000	1	0.3686	0.0000	8.5280	1.2333	0.1743	0.0000	904237.2269
526	0.12	0.25	0.13	CRS	0.4039	101	0.0000	0.3226	0.0000	0.0000	0.2020	1.6580	0.1922
				VRS	0.9048	62	41.8346	0.0000	0.0000	2.0539	0.1275	0.5916	0.2952
526	0.32	0.40	0.08	CRS	0.0916	239	2.4220	0.0000	23.7097	0.9371	0.0135	0.0012	0.3881
				VRS	0.5000	192	1.5441	0.0254	23.9599	0.0000	0.2500	0.0000	0.0000
526	4.35	4.52	0.17	CRS	0.4058	100	0.0000	0.0000	6.3214	0.0000	0.1241	0.0000	0.5037
				VRS	0.5908	147	0.0000	0.0000	6.3214	0.0000	0.1608	0.1481	0.2086
527	1.52	1.66	0.14	CRS	0.3392	138	9.7063	0.0405	0.0000	1.8911	0.1473	0.0000	0.1753
				VRS	1.0000	1	1.6392	0.0108	12.7430	0.0000	0.5000	0.0000	0.0000
527	2.24	2.84	0.60	CRS	0.5336	62	0.0000	0.0241	2.0103	0.0000	0.0745	0.0000	0.1755
				VRS	0.6804	104	0.0000	0.0028	2.2264	0.0592	0.2144	0.0017	0.0298
527	3.64	3.99	0.35	CRS	0.5052	71	0.0000	0.0000	3.6495	0.0000	0.1094	0.0000	0.2812
				VRS	0.6802	105	0.0000	0.0000	3.6495	0.0000	0.1517	0.1396	0.1967
527	5.50	5.60	0.10	CRS	0.4017	102	7.5878	0.0000	1.1061	0.0000	0.0963	0.4754	0.6148
				VRS	0.6933	95	0.0000	0.0000	7.6957	0.0000	0.1683	0.2633	0.3267

Table A-2- 14 Comparison Between DEA Variable-Return-to-Scale Results and Constant-Return-to-Scale Results, Part-XIV

SR	Begin Milepost	End Milepost	Length	Return to Scale	ACC Occurrence	Rankings	Outputs Weights			Inputs Weights			
							Societal Costs	Severity Index	Total Accidents	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
527	6.54	6.71	0.17	CRS	0.4858	80	0.0000	0.0559	4.6634	0.0000	0.1573	0.0000	0.3707
				VRS	0.6261	123	0.0000	0.0000	5.2836	0.0000	0.1757	0.0541	0.1902
527	8.79	8.94	0.15	CRS	0.2551	165	0.0000	0.1008	8.4101	0.0000	0.1490	0.0000	0.3510
				VRS	1.0000	1	0.3462	0.0492	8.8568	0.0000	0.5000	0.0000	0.0000
527	10.31	10.55	0.24	CRS	0.3783	116	0.0000	0.0000	4.7838	0.7200	0.0107	0.0000	0.3056
				VRS	0.4781	207	0.0000	0.0000	4.7838	0.2770	0.0893	0.1184	0.1530
528	0.01	0.50	0.49	CRS	0.5514	58	3.6657	0.0000	0.0000	0.0000	0.1683	0.3424	0.1089
				VRS	0.6512	115	3.6657	0.0000	0.0000	0.4071	0.1547	0.1522	0.0576
529	0.19	0.67	0.48	CRS	1.0000	1	0.3689	0.1023	0.0000	0.0000	0.5000	2.4581	0.0000
				VRS	1.0000	1	0.0000	0.1111	0.0000	0.0000	0.5000	8.1539	0.0000
529	0.73	1.03	0.30	CRS	0.3183	145	0.0000	0.2557	2.0681	0.0000	0.1339	1.0079	0.1548
				VRS	0.5424	168	0.0000	0.0000	6.6792	1.3922	0.0665	0.2541	0.1204
529	6.63	6.69	0.06	CRS	0.2215	179	0.0000	0.0000	9.0769	0.8143	0.0100	0.0035	0.3401
				VRS	0.5135	185	0.0000	0.0000	9.0769	1.3067	0.0565	0.2709	0.1623
531	1.41	1.56	0.15	CRS	1.0000	1	0.0000	0.0578	0.0000	59.2212	0.0000	0.0000	0.0000
				VRS	1.0000	1	0.6551	0.0548	0.0000	0.3314	0.0106	0.0146	0.9587
536	4.49	4.92	0.43	CRS	0.5743	52	5.5825	0.0000	0.0000	2.0874	0.1044	0.0000	0.1642
				VRS	1.0000	1	0.0288	0.0000	6.0719	0.1573	0.4261	0.0000	0.0565
536	5.13	5.34	0.21	CRS	0.3612	130	3.3483	0.0000	8.4537	0.9981	0.1042	0.0000	0.6068
				VRS	1.0000	1	0.6935	0.0011	11.1016	0.0000	0.5000	0.0000	0.0000
538	0.27	0.69	0.42	CRS	1.0000	1	3.3979	0.0000	0.0675	0.0000	0.1375	0.7308	0.4498
				VRS	1.0000	1	3.4606	0.0000	0.0000	0.2845	0.1254	0.4059	0.3714
538	1.21	1.31	0.10	CRS	0.3877	108	0.0000	0.0000	7.6957	1.2084	0.0148	0.0051	0.5047
				VRS	0.6933	95	0.0000	0.0000	7.6957	0.0000	0.1683	0.2633	0.3267

Table A-2- 15 Comparison Between DEA Variable-Return-to-Scale Results and Constant-Return-to-Scale Results, Part-XV

SR	Begin Milepost	End Milepost	Length	Return to Scale	ACC Occurrence	Rankings	Outputs Weights			Inputs Weights			
							Societal Costs	Severity Index	Total Accidents	Average Daily Traffic	Total No. of Lanes	Total No. of Horizontal Curves	No. of Interchanges / Intersections
538	2.18	2.39	0.21	CRS	1.0000	1	6.1656	0.0303	0.0000	0.0000	0.4207	0.1585	3.9726
				VRS	1.0000	1	6.9211	0.0000	0.0000	1.9833	0.3695	0.0192	11057881.1419
539	0.02	0.75	0.73	CRS	0.6967	38	0.0000	0.0000	1.6938	0.0000	0.0700	0.0000	0.1800
				VRS	0.7791	75	0.0000	0.0000	1.6938	0.0000	0.1584	0.0506	0.0916
547	7.30	7.40	0.10	CRS	0.9106	17	1.5646	0.0000	42.8525	13.4805	0.2732	0.0000	7.8197
				VRS	1.0000	1	0.8013	0.0011	43.2146	0.0000	0.3390	0.3219	0.3219
599	0.00	0.20	0.20	CRS	0.2207	181	0.0000	0.0000	19.6666	3.0407	0.0000	0.0159	0.6661
				VRS	0.5736	152	0.0000	0.0000	19.6667	1.7713	0.0846	0.3233	0.1532
900	9.75	9.86	0.11	CRS	0.2306	175	10.2066	0.0000	0.0000	1.4878	0.0144	0.1300	0.1733
				VRS	0.4254	218	7.8622	0.0000	2.9040	1.0576	0.0530	0.2173	0.0983
900	9.99	10.15	0.16	CRS	0.1578	210	0.0000	0.0000	20.8235	9.8993	0.0000	0.0000	0.0000
				VRS	1.0000	1	9.2190	0.0000	18.6695	0.0000	0.5000	0.0000	0.0000
900	10.78	11.01	0.23	CRS	0.2420	172	9.7710	0.0000	0.0000	1.5392	0.0770	0.0000	0.1211
				VRS	0.5000	192	0.5509	0.0007	10.7652	0.0000	0.2500	0.0000	0.0000
900	10.99	11.12	0.13	CRS	0.2109	188	0.0000	0.0000	9.0769	0.7751	0.0095	0.0033	0.3237
				VRS	0.5060	186	0.0000	0.0000	9.0769	0.0000	0.1517	0.1396	0.1967
900	11.14	11.32	0.18	CRS	0.4855	81	0.0000	0.0000	5.2836	0.0000	0.1294	0.0000	0.4825
				VRS	0.6261	123	0.0000	0.0000	5.2836	0.0000	0.1757	0.0541	0.1902
900	16.11	16.28	0.17	CRS	0.3948	105	11.0066	0.0459	0.0000	2.4961	0.1944	0.0000	0.2313
				VRS	1.0000	1	0.0630	0.0319	16.5353	0.0000	0.5000	0.0000	0.0000
900	21.33	21.48	0.15	CRS	0.2196	182	0.0000	0.0978	5.3785	0.0000	0.1175	0.0000	0.1766
				VRS	0.5024	189	0.0000	0.0000	8.4286	0.1943	0.2133	0.0077	0.0320
908	3.83	4.19	0.36	CRS	0.4219	93	0.0000	0.0000	4.3704	0.0000	0.1094	0.0000	0.2813
				VRS	0.6321	120	0.0000	0.0000	4.3704	0.0000	0.1517	0.1396	0.1967
908	6.49	6.66	0.17	CRS	0.5136	67	5.2950	0.0880	0.0000	0.0000	0.5000	0.0000	0.0000
				VRS	1.0000	1	6.0499	0.0749	0.0469	0.0000	0.5000	0.0000	0.0000

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Table A-3- 1 Predictions of Hierarchical Bayesian Analysis for Overall Accidents, Part-I

Route	Beginning Milepost	Ending Milepost	Length	Actual Overall Accidents	Prediction from Hierarchical Bayesian Analysis			
					50% Credible Interval	75% Credible Interval	97.5% Credible Interval	Mean of Predictions
2	0.00	0.37	0.37	46	41	45	51	41
2	0.08	0.16	0.08	16	19	22	26	19
2	0.13	0.26	0.13	12	11	13	15	11
2	13.75	13.91	0.16	37	41	45	50	41
2	14.50	15.11	0.61	181	177	185	197	177
5	0.00	0.12	0.12	25	19	22	25	20
5	0.10	0.21	0.11	13	13	14	18	13
5	0.11	0.23	0.12	35	29	32	37	29
5	0.15	0.30	0.15	6	8	9	11	8
5	0.18	0.36	0.18	12	13	15	18	13
5	0.19	0.38	0.19	32	30	34	39	31
5	0.20	0.41	0.21	12	13	16	19	14
9	1.47	1.70	0.23	43	45	50	56	46
9	10.87	10.97	0.1	24	27	31	36	28
9	13.93	14.13	0.2	36	39	43	49	39
9	15.75	15.96	0.21	35	36	39	45	36
9	53.16	53.36	0.2	13	16	18	22	16
9	77.87	77.97	0.1	7	8	9	12	8
11	10.78	10.84	0.06	8	8	9	11	8
18	0.00	0.33	0.33	13	11	13	15	11
18	0.09	0.18	0.09	9	8	10	12	8
18	0.13	0.26	0.13	16	15	17	21	15
18	0.14	0.28	0.14	10	9	11	13	9
18	0.17	0.34	0.17	11	10	12	14	10
18	0.20	0.40	0.2	6	7	9	11	7
18	14.55	14.76	0.21	26	32	35	41	32
18	2.61B	0.16	0.28	46	44	48	54	44
20	26.59	26.83	0.24	10	16	18	22	16
20	31.25	31.70	0.45	97	93	99	109	93
20	53.24	53.34	0.1	10	11	13	16	12

Table A-3- 2 Predictions of Hierarchical Bayesian Analysis for Overall Accidents, Part-II

Route	Beginning Milepost	Ending Milepost	Length	Actual Overall Accidents	Prediction from Hierarchical Bayesian Analysis			
					50% Credible Interval	75% Credible Interval	97.5% Credible Interval	Mean of Predictions
20	58.67	58.96	0.29	17	23	27	31	24
20	59.39	59.70	0.31	50	50	54	61	50
20	59.73	59.94	0.21	40	40	44	50	40
96	1.09	1.26	0.17	42	42	46	52	42
96	1.35	1.51	0.16	37	38	42	48	39
96	2.18	2.51	0.33	65	64	69	78	65
99	0.09	0.19	0.1	9	9	10	13	9
99	8.05	8.27	0.22	54	50	55	62	51
99	8.87	10.26	1.39	354	352	364	384	352
99	10.29	10.79	0.5	116	110	117	127	110
99	10.86	10.97	0.11	26	25	29	33	26
99	11.18	11.48	0.3	49	48	53	60	49
99	11.62	12.02	0.4	73	69	74	83	70
99	12.90	13.21	0.31	106	100	106	115	100
99	13.65	13.80	0.15	56	55	60	67	55
99	13.99	14.39	0.4	54	56	61	68	57
99	15.26	15.58	0.32	113	105	111	122	105
99	16.40	16.78	0.38	63	63	68	76	63
99	17.43	17.75	0.32	54	54	58	66	54
99	18.26	18.45	0.19	34	34	37	43	34
99	19.06	19.15	0.09	26	27	30	35	27
99	19.37	19.51	0.14	27	28	31	36	28
99	19.42	19.49	0.07	52	45	49	55	45
99	20.06	20.29	0.23	72	70	76	84	71
99	22.85	23.02	0.18	27	28	31	35	28
99	37.18	37.80	0.62	113	115	122	133	115
99	38.97	39.22	0.25	55	55	59	67	55
99	39.26	39.51	0.25	53	53	58	66	53
99	39.58	40.18	0.6	125	124	131	142	124
99	40.21	40.59	0.38	115	109	115	126	109
99	40.66	41.10	0.44	117	115	122	132	115
99	41.17	41.45	0.28	62	63	68	76	64
99	41.71	42.11	0.4	88	89	95	104	89
99	43.39	43.57	0.17	55	50	55	62	51
99	45.35	45.84	0.49	95	95	102	112	96
99	45.86	46.19	0.33	62	63	69	77	63
99	46.39	46.66	0.27	57	58	63	70	59
99	46.75	47.05	0.3	84	84	90	99	84
99	48.67	49.17	0.5	115	114	121	132	114
99	49.91	50.66	0.75	131	134	142	154	134
99	50.75	51.40	0.65	107	109	116	126	109
99	51.98	52.48	0.5	128	126	133	144	126
99	52.66	52.95	0.29	55	55	59	67	55
99	53.59	53.89	0.3	59	54	58	65	54
99	54.30	54.78	0.48	129	123	130	141	123
99	54.80	54.89	0.09	42	41	45	51	41
99	55.00	55.20	0.2	49	47	52	58	47
104	24.65	24.74	0.09	10	11	13	16	11
104	26.43	26.52	0.09	29	30	33	38	30
164	0.31	1.07	0.76	162	157	166	178	158
164	1.09	1.34	0.25	64	63	68	76	63
164	1.78	2.14	0.36	68	68	73	81	68
164	2.24	2.41	0.17	36	38	42	48	38
167	0.00	0.16	0.16	28	28	31	36	28

Table A-3- 3 Predictions of Hierarchical Bayesian Analysis for Overall Accidents, Part-III

Route	Beginning Milepost	Ending Milepost	Length	Actual Overall Accidents	Prediction from Hierarchical Bayesian Analysis			
					50% Credible Interval	75% Credible Interval	97.5% Credible Interval	Mean of Predictions
167	0.09	0.19	0.1	11	12	14	17	13
167	0.14	0.28	0.14	15	15	17	21	15
167	0.15	0.31	0.16	11	14	16	20	14
167	0.16	0.33	0.17	20	22	25	30	23
167	0.19	0.36	0.17	22	20	23	27	20
167	25.70	26.67	0.97	202	201	211	225	202
167	26.84	27.28	0.44	110	109	116	125	109
169	11.35	11.53	0.18	37	37	41	47	38
181	5.32	5.62	0.3	87	84	90	98	84
181	5.83	5.98	0.15	48	47	51	58	47
181	7.62	7.80	0.18	48	49	54	60	49
181	9.68	9.84	0.16	45	45	49	56	45
202	0.13	0.34	0.21	65	59	65	72	60
202	2.66	2.73	0.07	19	21	24	28	21
202	6.76	7.06	0.3	57	58	63	71	59
202	7.17	7.26	0.09	20	22	24	29	22
202	7.28	7.43	0.15	33	34	38	44	35
202	7.45	7.57	0.12	50	46	50	56	46
202	7.63	7.80	0.17	32	33	36	42	33
202	8.14	8.35	0.19	67	64	69	76	64
202	13.00	13.13	0.13	21	24	28	33	25
202	24.46	24.68	0.22	13	16	18	22	16
204	2.05	2.35	0.3	36	38	42	49	39
405	0.00	0.39	0.39	31	25	28	33	26
405	0.06	0.12	0.06	12	9	11	13	9
405	0.12	0.24	0.12	24	21	23	27	21
405	0.15	0.31	0.16	18	17	20	24	18
405	0.16	0.32	0.16	34	31	34	39	31
405	0.19	0.38	0.19	12	14	16	20	14
509	0.00	0.44	0.44	66	57	62	69	58
509	0.11	0.22	0.11	8	12	14	17	12
509	19.85	20.32	0.47	55	59	64	72	59
515	0.36	0.59	0.23	40	41	46	52	42
515	0.91	1.27	0.36	138	127	135	145	128
515	3.99	4.23	0.24	41	42	47	53	43
515	4.75	5.20	0.45	88	86	92	101	87
516	1.79	2.14	0.34	65	62	66	74	62

Table A-3- 4 Predictions of Hierarchical Bayesian Analysis for Overall Accidents, Part-IV

Route	Beginning Milepost	Ending Milepost	Length	Actual Overall Accidents	Prediction from Hierarchical Bayesian Analysis			
					50% Credible Interval	75% Credible Interval	97.5% Credible Interval	Mean of Predictions
516	10.53	10.80	0.27	43	44	49	55	45
516	11.99	12.19	0.2	51	51	55	62	51
518	0.00	0.21	0.21	20	18	20	24	18
518	0.05	0.11	0.06	17	11	12	15	11
519	0.34	0.51	0.17	60	56	60	67	56
520	0.00	0.22	0.22	22	23	25	30	23
520	0.01	0.21	0.2	52	49	53	60	49
520	0.06	0.17	0.11	14	13	15	19	14
520	0.14	0.28	0.14	13	13	15	18	13
520	0.20	0.40	0.2	13	13	16	19	14
520	0.23	0.46	0.23	46	40	43	50	40
522	0.00	0.31	0.31	10	13	15	18	13
522	4.09	4.51	0.42	107	104	111	121	104
522	6.61	7.68	1.07	259	258	269	285	258
522	16.50	16.60	0.1	28	30	33	39	30
522	16.60	16.80	0.2	30	33	36	42	33
523	0.49	0.56	0.07	32	35	39	45	35
523	0.86	1.13	0.27	51	53	58	66	54
524	4.06	4.48	0.42	101	98	105	115	98
524	4.49	5.24	0.75	192	190	199	213	190
524	5.57	5.96	0.39	81	79	84	93	79
524	6.69	6.81	0.12	32	33	37	43	34
524	7.43	7.61	0.18	23	28	31	36	28
524	9.44	9.68	0.24	35	39	43	49	39
524	0.00B	0.08	0.2	19	20	22	26	20
525	0.00	0.52	0.52	14	14	17	20	15
525	0.15	0.30	0.15	13	11	13	15	11
525	3.43	4.27	0.84	153	152	160	173	152
525	8.08	8.28	0.2	23	22	25	30	23
526	0.08	0.17	0.09	40	36	40	45	36
526	0.12	0.25	0.13	14	14	16	20	14
526	0.32	0.40	0.08	14	16	18	22	16
526	4.35	4.52	0.17	56	56	61	69	57
527	1.52	1.66	0.14	23	27	30	35	27
527	2.24	2.84	0.6	157	150	158	170	150
527	3.64	3.99	0.35	97	95	101	110	95
527	5.50	5.60	0.1	46	46	50	57	46
527	6.54	6.71	0.17	67	63	68	76	63
527	8.79	8.94	0.15	37	39	43	50	39
527	10.31	10.55	0.24	74	69	74	82	69
528	0.01	0.50	0.49	93	92	98	108	93
529	0.19	0.67	0.48	83	79	85	93	79
529	0.73	1.03	0.3	53	51	56	63	52
529	6.63	6.69	0.06	39	37	41	47	38
531	1.41	1.56	0.15	12	9	11	13	10
536	4.49	4.92	0.43	58	59	64	72	59
536	5.13	5.34	0.21	30	32	36	41	32
538	0.27	0.69	0.42	95	90	96	106	91
538	1.21	1.31	0.1	46	44	48	54	44
538	2.18	2.39	0.21	18	21	24	28	21
539	0.02	0.75	0.73	209	208	216	231	207
547	7.30	7.40	0.1	8	9	10	13	9
599	0.00	0.20	0.2	18	15	17	20	15
900	9.75	9.86	0.11	28	27	30	35	27
900	9.99	10.15	0.16	17	20	23	27	20

Table A-3- 5 Predictions of Hierarchical Bayesian Analysis for Overall Accidents, Part-V

Route	Beginning Milepost	Ending Milepost	Length	Actual Overall Accidents	Prediction from Hierarchical Bayesian Analysis			
					50% Credible Interval	75% Credible Interval	97.5% Credible Interval	Mean of Predictions
900	10.78	11.01	0.23	31	32	35	40	32
900	10.99	11.12	0.13	39	39	43	49	40
900	11.14	11.32	0.18	67	66	71	79	66
900	16.11	16.28	0.17	20	23	26	31	24
900	21.33	21.48	0.15	42	39	43	49	39
908	3.83	4.19	0.36	81	81	87	95	81
908	6.49	6.66	0.17	27	23	26	31	24

APPENDIX B – ANALYTICAL TECHNIQUES

Hierarchical Poisson Model

The hierarchical Poisson model follows a two-level structure illustrated by the following example. Suppose there are "k" total roadway sections in Washington. Associated with each section "i" is a Poisson parameter λ_i, i = 1, 2, …, n that determines the biennial accident rate. We use biennial counts and an exposure variable of two years to determine annual rates. Biennial rates are used for the purpose of biennial programming. The rates λ_i, i = 1, 2, …, n, are called "individual parameters" and correspond to individual section intensity rates.

The individual parameters may be predicted by section-level covariates through a link function as a linear combination with regression coefficients β. The regression coefficient β_0 is a constant intercept. These regression parameters are known as "structural parameters", or "population parameters". The analysis of the population parameters is appropriate when groups, clusters, or correlated observations are present in the data, and/or when over dispersion exists. Usually an additional parameter describes the "overdispersion" effect prevalent in accident counts.

Individual Models

The level 1 model specifies the distributions of the observed data vector (z_1, z_2, …, z_k) given the individual parameters λ_i's:.

$$z_i|\lambda_I \sim \text{Poisson}(e_i, \lambda_i), \; i = 1, 2, \ldots, k$$

where the parameter λ_i is the rate, and e_i is called the exposure of the i^{th} group (in this case two years since we are computing average annual rates), and z_i is the accident count for the i^{th} section.

Population Model

A popular population model is the Gamma distribution, conjugate to the Poisson. In this model, the individual Poisson parameters λ_i follow a Gamma distribution

$$\lambda_i|\zeta, \mu_i \sim \text{Gamma}(\zeta, \zeta/\mu_i), i = 1, 2, \ldots, k$$

where $\zeta > 0$ corresponds to an unobserved prior count, not necessarily an integer, and μ_i is the mean of the Gamma distribution. When there are roadway characteristics

$x_i^T = (x_{i0}, x_{i1}, \ldots, x_{ir-1})$

available for prediction, the mean μ_i is usually modeled through the link equation

$$\log \mu_i = x_i^T \beta$$

which is usually referred to as the log-linear model. Using the gamma conjugate prior and the likelihood function of the observed data, we can postulate a posterior that accommodates overdispersion akin to a negative binomial model in the frequentist sense. Comparisons of the predictions can then be made between the classical negative binomial and Hierarchical Poisson with Gamma conjugate prior.

Data envelopment analysis (DEA)

Data envelopment analysis is a fractional programming model that can include multiple outputs and inputs without recourse to a priori weights (as in index number approaches) and without requiring explicit specification of functional relations between inputs and outputs (as in regression approaches). It computes a scalar measure of efficiency and determines efficient levels of inputs and outputs for the organizations under evaluation. Data envelopment analysis (DEA) was first introduced in the literature in 1978 (Charnes *et al*. 1978).

Charnes, Cooper, and Rhodes (CCR) Version:

Following the concept of relative efficiency, Charnes, Cooper and Rhodes (1978) developed the following model, which is often called CCR (abbreviated term of Charnes, Cooper and Rhodes) version of DEA model:

Model 1: Maximize: $h_0 = \dfrac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}}$;

Subject to, $\dfrac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1$; $j = 1, 2, 3, \ldots, n$

$\dfrac{u_r}{\sum_{i=1}^{m} v_i x_{i0}} > \varepsilon$; $r = 1, 2, 3, \ldots, s$

$\dfrac{v_i}{\sum_{i=1}^{m} v_i x_{i0}} > \varepsilon$; $i = 1, 2, 3, \ldots, m$

$$\varepsilon > 0;$$

Where,

y_{rj} = Amount of output r produced by decision making unit (DMU) j

x_{ij} = Amount of input i utilized by DMU j

u_r = Endogenous weight of output r

v_i = Endogenous weight of input i

A DMU in our study refers to a roadway section. The $(y_{rj}, x_{ij}) > 0$ in the model are constants which represent observed amounts of the r^{th} output and the i^{th} input of the j^{th} decision making unit, where, $j = 1,2,3,\ldots n$ number decision making units (DMU) to convert inputs into outputs. The term h_0 is the efficiency of j_0, the DMU whose relative efficiency is to be calculated with respect to other DMUs. The solution to the above model gives the optimal value of h_0 and the weights leading to that efficiency. This optimal value satisfies $0 \leq h_0 \leq 1$ and can be interpreted as an efficiency rating, where, $h_0 = 1$ represents full or 100 percent efficiency and $h_0 < 1$ means the presence of inefficiency. Also, the calculated value of h_0 is independent to the units of measurement used for input and output variables.

The weights thus calculated are also the optimal values of the respective weights u_r and v_i. It should also be noted that these weights are determined in the solution of the model and not a priori. Due to this difference, from more customary (a priori) weighting approaches, the calculated u_r and v_i values (u_r^* and v_i^*) are called virtual multipliers and interpreted in DEA so that they yield a virtual output, $Y_0 = \Sigma u_r^* y_{r0}$ (summed over $r = 1, 2, 3, \ldots, s$), and a virtual input $X_0 = \Sigma v_i^* x_{i0}$ (summed over i = $1, 2, 3, \ldots, m$), which allows to compute the efficiency ratio $h_0 = Y_0 / X_0$.

The calculated value of h_0 (which is h_0^*), is the highest rating that the data allow for a DMU. No other choice of u_r^* and v_i^* can yield a higher value h_0^* and satisfy the constraints of model 1. These constraints make this a relative evaluation with:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} = 1, \text{ for some } j \text{ as a condition of optimality.}$$

For each of the $j = 1, 2, 3, \ldots., n$ number of DMUs similar efficiency evaluations can be obtained by positioning them in the functional form as DMU_0, one by one, while also subjecting them in the constraints. An important point is that DEA calculates relative efficiency of any DMU with respect to other DMUs in the set by the above optimization applied to the data. Therefore, the optimization implies that for any DMU_0 being evaluated, the evaluation will be effected by reference to the subset of $j = 1, 2, 3, \ldots, n$ DMUs for which:

$$\frac{\sum_{r=1}^{s} u_r^* y_{rk}}{\sum_{i=1}^{m} v_i^* x_{ik}} = 1, \; k \varepsilon K \qquad \ldots(3)$$

The stars (*) indicate that these values of u_r and v_i are optimal; and therefore, make h_0 maximal for DMU_0. Also, $k \varepsilon K$ indicates the subset of DMUs that have attained the value of unity, which is the maximum value allowed by the constraints. These $k \varepsilon K$ DMUs have attained the efficiency value of unity (efficient DMUs) with the same u_r^* and v_i^* that are the best for DMU_0 (Bowlin, 1998).

The model described above is a fractional linear program. To solve the model it is necessary to convert-it into linear form so that the methods of linear programming can be applied. In the objective function it can be observed that while maximizing a fraction or ratio it is the relative magnitudes of the numerator and denominator that are of interest rather than their individual values. It is thus possible to achieve the same effect by setting the denominator equal to a constant and maximizing the numerator. The resulting linear programming (LP) model is shown below (model *2*):

Model 2: Maximize, $h_0 = \sum_{r=1}^{s} u_r y_{r0}$

Subject to, $\sum_{i=1}^{m} v_i x_{i0} = 1$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0,$$

$$v_i,\ u_r \geq \varepsilon > 0, \forall r, i$$

The solution to this LP provides a measure of the relative efficiency of the target unit and the weights leading to that efficiency. These weights are the most favorable ones from the point of view of the target unit. To obtain the efficiencies of the entire set of units it is necessary to solve a linear program focusing on each unit in turn. Clearly as the objective function is varying from problem to problem the weights obtained for each target unit may be different. In solving each linear program the solution technique will attempt to make the efficiency of the target unit as large as possible. This search procedure will terminate when either the efficiency of the target unit or the efficiency of one or more other units hits the upper limit of 1. Thus for an inefficient unit at least one other unit will be efficient with the target unit's set of weights. These efficient units are known as the *peer group* for the inefficient unit. It is sometimes useful to scale the data on the peer units so that a better comparison of the inefficient unit with the peer units can be made. Input data of the peer units are to be scaled in such a way so that each peer unit may use no more of an input than the inefficient unit. The solution to the DEA model thus provides a relative efficiency measure for each unit in the set, a subset of peer units for each inefficient unit, and a set of targets for each inefficient unit.

The dual of the linear program, presented above in Model 2, provides useful information and knowledge regarding the mechanism of efficiency estimation and significance of the parameters. It also involves fewer constraints than the primal and hence generally preferred to solve. The dual is shown below in Model 3.

Model 3: $$Min_{\theta,\lambda} \quad \theta_o$$

Subject to, $$-y_{ro} + \sum_j y_{rj}\lambda_j \geq 0, \; r = 1, 2, \ldots\ldots\ldots, m$$

$$\theta \; x_{io} - \sum_j x_{ij}\lambda_j \geq 0, \; i = 1, 2, \ldots\ldots\ldots\ldots, k$$

Here θ provides efficiency score of the o-th unit (Farrell 1957). Each of the constraint of Model 3 is associated with either the inputs or the outputs. Using the principle of complementary slackness, from the results of Model 2 and Model 3 the following sets of identities can be obtained at optimum solution which imply that the values of the weight factors u_r and v_i provide the shadow prices for the relevant output and input respectively. The identities demonstrate that values of the weight factors provide the effect of marginal change in constraint boundary on the value of DMU's efficiency.

$$u_r\left(-y_{ro}+\sum_j y_{rj}\lambda_j\right)=0,\quad r=1, 2, \ldots\ldots, m$$

$$v_i\left(\theta\ x_{io}-\sum_j x_{ij}\lambda_j\right)=0,\quad i=1, 2, \ldots\ldots, k$$

Banker, Charnes, and Cooper (BCC) Version:

Another version of DEA that is in common use is the Banker, Charnes, and Cooper (1984) abbreviated as the BCC version of DEA. The primary difference between the CCR and BCC versions is that the CCR version bases the evaluation on constant returns to scale and the BCC version allows variable returns to scale.

The BCC version of DEA can be expressed as:

Model 4: Maximize, $h_0=\sum_{r=1}^{s} u_r y_{r0} - u_0$

Subject to, $\sum_{i=1}^{m} v_i x_{i0} = 1$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - u_0 \leq 0,$$

$$v_i,\ u_r \geq \varepsilon > 0, \forall r, i$$

In this model, the optimal value of u_0 (u_r^*), indicates the return to scale possibilities. An $u_r^* < 0$ implies local increasing returns to scale. If $u_r^* = 0$, this implies local constant returns to scale and an $u_r^* > 0$ implies local decreasing returns to scale.

As formulated here the BCC model allows variable returns to scale and measures only technical efficiency for each DMU. This implies that for a DMU to be considered as CCR efficient, it must be both scale and technically efficient. For a DMU to be considered BCC efficient, it only needs to be technically efficient.