SAFETY-BASED DEPLOYMENT ASSISTANCE FOR LOCATION OF V2I APPLICATIONS PILOT: CURVE SPEED WARNING APPLICATION

Background

V2I Applications

Vehicle-to-Infrastructure (V2I) is a component of the connected vehicles program. It is a wireless-based communication technology in which the exchange of critical operational and safety data between vehicles and roadway infrastructure is intended to help avoid crashes. Previous research commissioned by the U.S Department of Transportation (DOT) has identified eight applications that can provide safety benefits. Among those applications, Red-Light Violation Warning (RLVW), Stop Sign Gap Assist (SSGA) and Curve Speed Warning (CSW) were selected for accelerated evaluation. A prototype CSW application was subsequently developed under an agreement between the Federal Highway Administration (FHWA) and the Crash Avoidance Metrics Partners, LLC (CAMP).

Curve Speed Warning (CSW) Application

The CWS application is one of the V2I accelerated-development applications. The intent of the application is to target crashes on horizontal curves by providing a warning to vehicles approaching the curve at an unsafe speed based on the conditions within the curve. An equipped location broadcasts the curve geometry and road conditions. When an equipped vehicle approaches the curve, a vehicle-based application determines if the speed is too high to safely negotiate the curve and provides a warning to the driver. The driver is expected to slow the vehicle to safely negotiate the curve. The application addresses both single and multiple vehicle crashes due to lane departure.

Vehicle Deployment

The number of vehicles equipped to receive the CSW message will affect the system's ability to prevent crashes. As more vehicles are equipped, more crashes may be prevented. The *National Connected Vehicle Field Infrastructure Footprint Analysis* presented estimates for the speed of deployment of equipped vehicles in the nation's vehicle fleet. The deployment scenarios are described as mandates (assuming a requirement is in place) or organic (assuming voluntary installation by manufacturers). Figure 1 presents three scenarios for potential deployment over a 25-year period: a 1-year mandate, a 5-year mandate, and a 15-year organic implementation. The 1-year mandate presents the most aggressive deployment with 60 percent of the vehicles equipped by year 10. The 15-year organic implementation represents the slowest deployment scenario with 20 percent of the vehicles equipped by year 10. For the purposes of this analysis, it is assumed that either a mandate or organic implementation of connected vehicle technologies in vehicles will occur beginning in 2020.

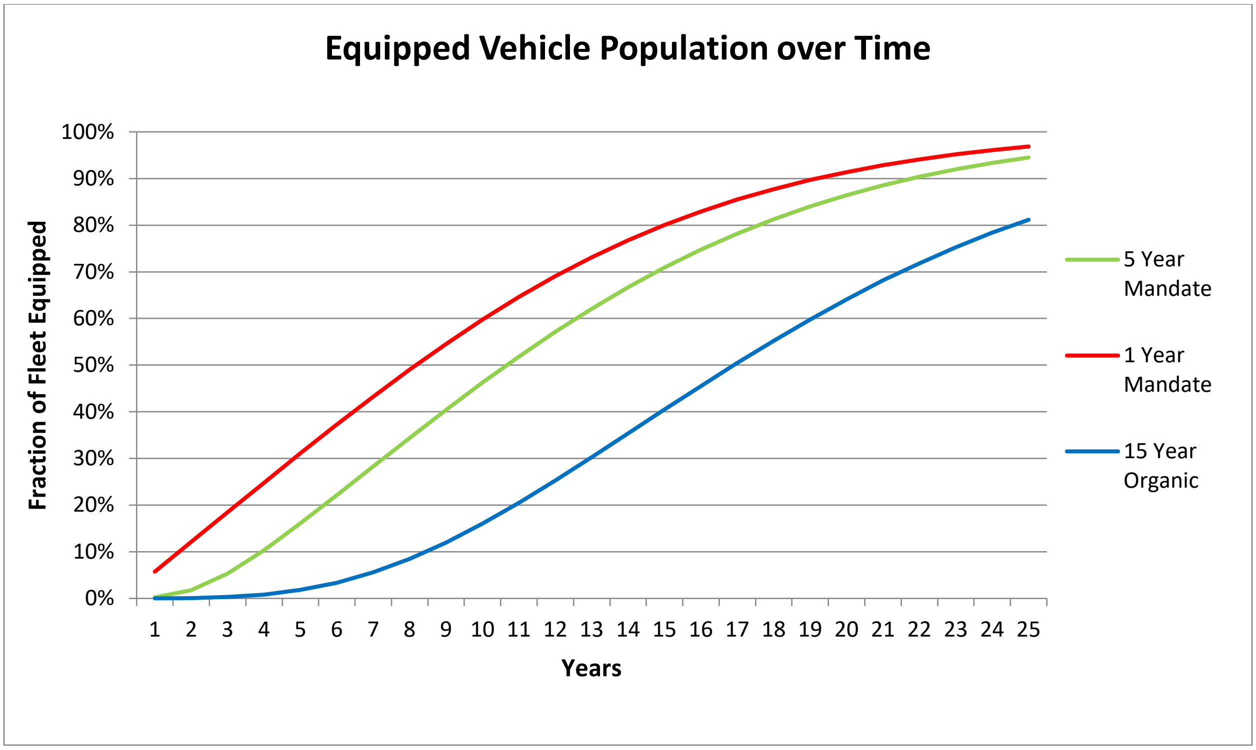

Figure 1. Three potential vehicle deployment scenarios.

(Source: *National Connected Vehicle Field Infrastructure Footprint Analysis*)

The National Highway Traffic Safety Administration (NHTSA) issued the Vehicle-to-Vehicle (V2V) Notice of Proposed Rulemaking on December 20, 2016. This NPRM proposes to mandate V2V communications for new light vehicles over a three-year period, beginning two years after issuance of a final rule.

Infrastructure Deployment

State DOTs and local transportation agencies will be the primary installers of the infrastructure component of the V2I CSW systems. They will install these systems at horizontal curves with the goal of preventing lane departure crashes. Their selection of curves for deployment of these systems will be primarily based on the expected occurrence of speed-related lane departure crashes. These agencies need guidance in identifying locations that have experienced these crashes and are expected to continue to experience these crashes unless there is an intervention such as the deployment of the CSW system.

OBJECTIVE

The objective of this effort was to develop guidance for State and local agencies on how to select locations for deployment of the CSW applications to achieve the greatest benefit to cost ratios. This was accomplished by exploring the occurrence of target crashes, the annual fluctuations in crash occurrence by curve, and the costs of the target crashes.

The selected identification-location method should have the following characteristics:

- Easy to implement by a State or local agency without rigorous statistical analysis.
- Applied using no more than five years of data.
- Results in the identification of those locations with the most opportunity to reduce target crashes.

This effort concentrated on understanding and characterizing the benefits of the application expressed as the comprehensive cost savings from preventing crashes based on historical crash occurrence or other information available in the crash and roadway inventory files.

DATA EMPLOYED

This analysis used crash, vehicle, roadway, and horizontal curve files from the Highway Safety Information System (HSIS). The economic analysis was performed based on crash cost information from the FHWA and the Office of the Secretary of Transportation. These sources of data are described in the following sections.

Curve and Crash Data

The curve and crash data for this study came as part of HSIS. The HSIS is a roadway-based system maintained by the FHWA that provides quality data on a large number of crash, roadway, and traffic variables linked to homogeneous sections of the entire highway system under State control. It is the only multi-State database that allows for the safety analysis of roadway design factors, as it is the only file system with the capability to link roadway inventory and exposure data to crash data for a large sample of primary route mileage, and the only file system to include both roadway sections with and without crashes. It is important to note that HSIS data are only available for State-maintained roadways in each State. As such, in general, HSIS represents more rural areas, because roadways in urban areas are often maintained by a municipality.

Currently, seven States are part of the HSIS: California, Illinois, Maine, Minnesota, North Carolina, Ohio, and Washington. (Historical data from Michigan and Utah are also available, but updated data are no longer captured.) HSIS also includes the City of Charlotte. This study analyzed data for the 10 most recent years of data for Washington and the three most recent years of data for Ohio.

There are six types of data files available within HSIS. All States maintain three basic files: a crash file, a roadway inventory file, and a traffic volume file. Additional roadway geometry files are also available within selected States, including a horizontal curve file, a vertical grade file, and an intersection and interchange data file. Washington and Ohio were selected for detailed curve analyses, as these States provide curve inventory data files, which are critical to this analysis to identify curves and the related crashes.

The study used ten most recent years of data available for Washington (2004 to 2013). The study also used three most recent years of Ohio data (2011 to 2013). More years of Washington data were necessary for conducting a time series analysis. All 10 years of data were no longer necessary after a recommended time frame had been established and the primary analyses only needed the most recent three years of data. Table 1 presents a summary of Washington and Ohio data used for this analysis including the years of data, the number of horizontal curves, and the number of crashes at those curves. A list of elements for each dataset is presented in Appendix A.

Table 1. Summary of HSIS data from Washington and Ohio.

Variable	Washington	Ohio
Years Analyzed (Trend Analysis)	10 (2004 – 2013)	N/A
Years Analyzed (Primary)	3 (2011-2013)	3 (2011-2013)
Total Curve Segments (single and multiple curve segments)	3,893	7,017
Single Curve Segments	2,754	3,706
Multiple Curve Segments	1,139	3,311
Average Annual Speed-Related Curve Crashes	643	1,698
Average Annual Fatal and Incapacitating Injury Speed-Related Curve Crashes	58	179
Average Annual speed-related crashes per curve segment	0.165	0.242

Crash Costs

The FHWA report *Crash Cost Estimates by Maximum Police-Reported Injury Severity within Selected Crash Geometries* provides mean comprehensive crash costs disaggregated by crash severity, location type, and speed limit.(1) The report is a useful reference for determining the cost of crashes and therefore the potential monetized benefits of preventing those crashes. However, the values in the report are based on 2001 dollars which are now out of date.

Although not disaggregated by severity, location, and speed limit, the FHWA Office of Policy provides departmental guidance on valuing reduction of fatalities and injuries by regulations or investments. The most recent guidance was provided in the 2015 memorandum, *Treatment of the Economic Value of a Statistical Life (VSL) in U.S. Department of Transportation Analyses – 2015 Adjustment.*[(2)] These values were used to modify the detailed crash costs by applying a proportion (the ratio of the 2015 fatality and the 2001 fatality costs) to the disaggregated 2001 costs to represent the costs in terms of 2015 dollars. Table 2 presents the resulting average cost per crash by the maximum injury severity in the crash in 2015 dollars. This cost represents all speed limits.

Table 2. Average cost per crash based on maximum injury severity (in 2015 dollars).

Maximum Injury Severity in Crash	Cost (in 2015 dollars)
Fatality (K)	$9,901,946
Incapacitating Injury (A)	$533,666
Injury, Non-incapacitating (B)	$197,049
Possible Injury (C)	$110,374
Property Damage Only (O)	$18,374

METHODOLOGY

Identifying Horizontal Curves and Crashes

The focus of this application is horizontal curves. Both the Washington and the Ohio HSIS data files include a curve file. The Ohio curve file has data on 18,500 horizontal curves (with degrees of curvature less than 90) on inventoried segments in the roadlog file. The file contains information on curve length, degree of curve, and direction of curve. This file was used to identify horizontal curves in Ohio. Similarly, the Washington curve file contains information on approximately 16,200 curves including angle, direction, degree (and radius), length, legal speed limit, data of last change to the curve, and whether the curve overlaps with a preceding curve. This file was used to identify horizontal curves in Washington.

These horizontal curve files were linked to the crash, vehicle, and roadway file in each State. The crashes occurring on each curve segment and within 250 feet beyond both ends of the curve were calculated for each curve. The research team extended the curve influence area beyond the curve begin and ending points. This is to include crashes that may have been the result of the curve but the crash location coded in the database is just outside of the curve or to include some consideration for the precision of crash milepost reporting.

Characterizing Curve Segments

Curves were characterized as single or multiple-curve segments. **Single-curve segments** are the curve and their extended portions. If two or more curves are closely located and their 250 feet extended portions overlapped, these curves were combined to form a **multi-curve segment.** This characterization of curves as single or multiple-curve segments was necessary because it is not feasible to distinguish between crashes occurring on closely spaced curves. The project team calculated the distance from each segment to the next one using milepost information.

The research team merged study curve segments (both single curves and multi-curves) with roadway data files for the key roadway features and traffic characteristics, including: AADT, number of lanes, shoulder width, functional classification, terrain (i.e., level, rolling, mountain), and posted speed. The team reviewed these key characteristics for changes within the multi-curve segments. In the Washington dataset, there were a very small number of multi-curve segments in which the posted speed changed from one curve to another. After further examination, the team found that only 50 segments (out of 3,893 total segments and 1,130 multi-curve segments) had varied posted speeds and only 10 of those segments varied by more than 10 miles per hour. The Ohio dataset did not have posted speed information for individual curves so the team could not conduct similar examination. The team decided to retain all these segments and used the highest posted speed limit to present the merged segment. The team also removed freeway curves from the dataset.

Curves were grouped by posted speed (45 mi/hr or lower or 50 mi/hr or higher), single or multi-curve, and number of lanes (two lanes or four lanes). Table 3 presents the curve groups for the Washington data. (There were also a small number of curve segments that did not fit into any group and were not included in this table.) The final dataset includes a total of 3,893 non-freeway curve segments include 2,740 single curve and 1,130 multi-curve segments. The table displays the average annual number of total curve segment crashes for each group. The single and multi-curve groups of four lanes and under 45 mi/hr experienced more annual crashes per curve segment than the other groups although both groups are very small. Generally, groups of fewer than 30 curve segments are too small to be representative. In comparing the data in the table, it should be noted that the multi-curve segments are much longer than the single curve segments because they include multiple curves.

Table 3. Horizontal curve segment groups and crashes in Washington.

Curve Segment Group	Number of Curve Segments in Group	Average Annual Number of Total Crashes for Group	Average Crashes per Curve Segment for Group
Single-curve segments with 2 lanes and speed limit of 45 mi/hr or lower	262	150	0.57
Single-curve segments with 4 lanes and speed limit of 45 mi/hr or lower	18	92.3	5.13
Single-curve segments with 2 lanes and speed limit of 50 mi/hr or higher	2,366	509	0.22
Single-curve segments with 4 lanes and speed limit of 50 mi/hr or higher	94	77	0.82
Multi-curve segments with 2 lanes and speed limit of 45 mi/hr or lower	246	310.7	1.26
Multi-curve segments with 4 lanes and speed limit of 45 mi/hr or lower	19	107	5.63
Multi-curve segments with 2 lanes and speed limit of 50 mi/hr or higher	847	440.7	0.52
Multi-curve segments with 4 lanes and speed limit of 50 mi/hr or higher	18	31.3	1.74

Table 4 presents the same information for the Ohio data. Similar to the Washington data, the single and multi-curve groups with four lanes and speed limits of 45 mi/hr or lower experienced more crashes by curve segment. For the single-curve segment group, there were enough curve segments in the group for this to be considered representative.

Table 4. Horizontal curve segment groups and crashes in Ohio

Curve Segment Group	Number of Curve Segments in Group	Average Annual Number of Total Crashes for Group	Average Crashes per Curve Segment for Group
Single-curve segments with 2 lanes and speed limit of 45 mi/hr or lower	599	511.7	0.85
Single-curve segments with 4 lanes and speed limit of 45 mi/hr or lower	55	354.7	6.45
Single-curve segments with 2 lanes and speed limit of 50 mi/hr or higher	3,008	1,373.3	0.46
Single-curve segments with 4 lanes and speed limit of 50 mi/hr or higher	27	78	2.89
Multi-curve segments with 2 lanes and speed limit of 45 mi/hr or lower	667	558	0.84
Multi-curve segments with 4 lanes and speed limit of 45 mi/hr or lower	21	156.7	7.46
Multi-curve segments with 2 lanes and speed limit of 50 mi/hr or higher	2,607	1,601	0.61
Multi-curve segments with 4 lanes and speed limit of 50 mi/hr or higher	9	151	16.78

Identifying Target Crashes

Target crashes for this application are those that can be categorized as run-off-road, rollover, or multi-vehicle opposite direction crashes. These are crashes where one of the crash-involved vehicles lost control due to traveling through a curve faster than a safe speed for the condition. The vehicle departs its travelled lane and then runs off road or rolls over or collides with another vehicle travelling in the opposing direction.

In the Washington data files, several variables were used to identify target crashes on the candidate curve segments. The variable for crash location type (LOC_TYPE) and traffic control (TRF_CNTL) were used to identify and exclude those crashes coded as related to an intersection or a driveway. The sequence of events (EVENT1, EVENT2) were used to identify those crashes that were coded as run-off-road or roll-over (EVENT1, EVEN2=9 for run-off-road and 11 for overturn). Multi-vehicle crashes were identified using number of vehicles involved (NUMVEHS>1), accident type (ACCTYPE coded as striking or being struck by another motor vehicle), and type of first collision in the crash (COLTYPE1=24-30 for from opposite direction). The crashes identified through this process were merged to each horizontal curve segment if the crash location identifiers (i.e. roadway/curve inventory code, milepost) put them within the curve segment or 250 ft beyond both ends of the segment. As noted above, the 250 ft extension was considered to include crashes that occurred because of the curve but coded as outside of the curve (e.g. a vehicle starts losing control inside the curve but keeps going and departs the roadway or strikes another vehicle outside the curve). The resulting set is all run-off-road, rollover and multi-vehicle opposite direction crashes on horizontal curve segments.

Using a similar process, the team also identified target crashes in the Ohio data files. Crash location type (LOC_TYPE) was used to exclude intersection or driveway related crashes. A freeway indicator (FRWY_IND) was used to exclude all crashes on freeways. Variable MISCACT1 was used to identify the pre-crash actions of the involved vehicles (e.g. going straight ahead, overtaking, etc.). From here, run-off-road and rollover crashes were also identified by using the sequence of events (EVENT1, EVENT2) while the identification of multi-vehicle opposite direction crashes needed extra information concerning number of vehicles involved (NUMVEHS>1) and directions of travel (VEH_N_FROM and VEH_N_TO indicating opposite directions). As in the Washington data, a 250 ft extension beyond the ends of curve was also used to attribute crashes to each segment.

The resulting number of average annual target crashes in Washington and Ohio are presented in Table 5. Using the number of curve segments identified in Table 1, the number of average annual target crashes per curve segment is also calculated. The table also includes the number of candidate curve segments with one or more target crashes in the analysis period and the average annual target crashes for those curve segments. Notably, the number of annual target crashes is small (i.e., less than one crash per year per segment).

Table 5. Average annual target crashes by dataset

Variable	Washington	Ohio
Average Annual Target Crashes	643	1,698
Average Annual Target Crashes Per Curve Segment	0.165	0.242
Number of Curve Segments with One or More Target Crashes in Three Years	1,148	2,761
Average Annual Target Crashes per Curve Segment for Segments Experiencing One or More Target Crashes over Three Years	0.560	0.615

Crash Severity

Washington and Ohio both use the KABCO scale to identify the maximum reported injury in a crash. Table 6 presents the distribution of maximum injury severity for target crashes and other crashes on curve segments for Washington and Ohio. The totals presented here are for three years of data. Notably, the target crashes are more severe than other crashes in both Washington and Ohio with 29 percent of the target crashes in Washington resulting in K or A or B, compared to just 12.4 percent of the other crashes and 35.5 percent of the target crashes in Ohio resulting in K or A or B, compared to just 15.8 percent of the other crashes.

Table 6. Summary of crash severity distribution for Washington and Ohio data.

Maximum Reported Crash Severity	Washington		Ohio	
	Target Crashes	Other Crashes on Curve Segments	Target Crashes	Other Crashes on Curve Segments
K (fatal)	53 (2.7%)	24 (0.7%)	87 (1.7%)	40 (0.4%)
A (incapacitating injury)	121 (6.3%)	80 (2.3%)	449 (8.8%)	305 (3.2%)
B (non-incapacitating injury)	385 (20.0%)	331 (9.4%)	1275 (25.0%)	1,150 (12.2%)
C (possible injury)	310 (16.1%)	679 (19.4%)	463 (9.1%)	1,003 (10.6%)
O (property damage only)	1,059 (54.9%)	2,389 (68.2%)	2821 (55.4%)	6,944 (73.5%)

The research team explored limiting the target crashes used in the selection of candidate horizontal curve segments to the more severe crashes (e.g., fatalities and incapacitating injuries) since some agencies limit the severities used in their network screening analysis. However, the process presented in this report uses all target crashes, a narrowed focus compared to total crashes that are generally used in network screening. Narrowing the focus further to include only those target crashes that resulted in fatalities, type A, or type B injuries would base the selection on those horizontal curves that had demonstrated the most severe target crashes, but would also greatly reduce the sample of curve segments

Note that crash severity is considered in the calculation of benefit to cost. The recommended use of all severities is to identify those horizontal curves where the target crashes are occurring consistently across several years of data.

Timeframe

The overall objective of this effort was to develop a method to identify horizontal curve segments that were good candidates for the applications based on crash data. To accomplish this objective, a method was needed to identify the timeframe that State and local agencies should use in their analysis of candidate curve segments. In general, curve segment crash counts (and target crash counts) fluctuate at any given curve from year to year. One can reduce variation with more years of data, but operational or design changes may have been implemented over time. This is particularly likely at curves that experience a high frequency of crashes, as improvements may be implemented in response to crash occurrence.

Most agencies use historical crash data of some form in their network screening to identify locations that are expected to experience future crashes, and therefore require some form of remediation. In a sophisticated analysis, safety performance functions (SPFs) can be developed to predict future crashes based on past crashes and other factors such as volume. An SPF is a statistical model developed to estimate the "typical" crash frequency for a specific type of roadway entity, based on the traffic volumes and key characteristics. However, one of the goals of this effort was to develop a method that is easy to implement by a State or local agency without rigorous statistical analysis.

An analysis was conducted to select an approach to best identify those horizontal curves that were expected to continue to experience crashes and are thus potential candidates for this system. Ten years of horizontal curve data in Washington were used for this part of the analysis. The analysis used the curve segment groups and target crashes described in the previous sections. Additionally, the research team screened out curves with missing traffic volume information.

The final dataset includes a total of 3,893 non-freeway curve segments - 2,754 single curve and 1,139 multi-curve segments. All 3,893 segments have AADTs and all other key features related to horizontal curve and roadway characteristics. These are necessary variables for the analyses described below.

As previously stated, a method is needed to identify those curve segments consistently experiencing the target crashes. Several methods were considered based on the three desired characteristics outlined in a preceding section. The following measures were evaluated, using all severities:

- Annual target crash frequency
- Two-year target crash frequency
- Three-year target crash frequency
- Four-year target crash frequency
- Five-year target crash frequency
- Annual total crash frequency
- Two-year total crash frequency
- Three-year total crash frequency
- Four-year total crash frequency
- Five-year total crash frequency
- Three-year total wet weather crash frequency

All eleven measures tested met the first two characteristics (i.e., easy to implement and based on no more than five years of data).

To assess the ability of each method to meet the last characteristic (i.e., results in the identification of those locations with the most opportunity to reduce target crashes), a baseline measure or ground truth measure was needed for comparison. Instead of looking at the raw crash counts or crash rate, the team used a measure of the potential safety improvement (PSI) based on an Empirical Bayes (EB) approach as the baseline. This is the method recommended by the Highway Safety Manual and recent research.

A PSI is the difference between the expected number of crashes (long term average) for a roadway entity (in this case, a curve segment) and the “typical” number of crashes for that entity, predicted by a safety performance function (SPF). An SPF is a statistical model developed to estimate the “typical” crash frequency for a specific type of roadway entity, based on the traffic volumes and key characteristics. The EB-adjusted expected number of crashes is the long term average for a specific entity after adjusting for regression to the mean and random fluctuation over time.

EB-adjusted PSI

$$PSI_{EB} = N_{expected} - N_{predicted} = (1-w) \times N_{observed} - (1-w) \times N_{predicted}$$

Where:

- PSI_{EB} is the potential safety improvement based on the Empirical Bayes method.
- $N_{expected}$ is the expected number of crashes (long term average) for this curve segment, corrected by the EB method
- $N_{predicted}$ is the average number of crashes predicted by the SPF based on similar curve segments
- $N_{observed}$ is the number of observed crashes for this curve segment
- w is the weight for EB-based correction

The above descriptions of PSI are illustrated in Figure 2. More detailed descriptions of the SPFs and the EB method are provided in Appendix B.

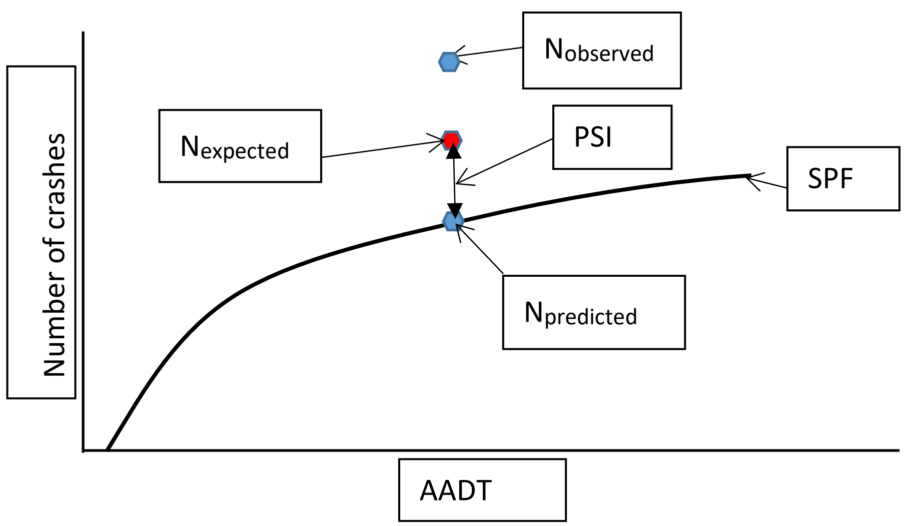

Figure 2. Concept of Potential Safety Improvement (PSI).

Two different SPFs were developed, one for single-curve segments and one for multi-curve segments. The categories presented in Table 3 are included in the development as variables. The research team estimated model parameters using several functional forms for each group of curve segments presented in Table 3. Two separate SPFs for single-curve and multi-curve segments were found to be the best among the options examined. Each SPF contained traffic volume and other curve and roadway characteristics. Using the SPFs, the team estimated the predicted numbers of target crashes (Npredicted), and then calculated the EB-adjusted expected numbers of crashes (Nexpected) and the respective PSIs for all 3,893 curve segments.

These segments were then ranked based on PSI as well as the other eleven measures being evaluated. The team followed a fractional ranking approach for breaking ties. In this approach, observations with equal values receive the same ranking number. This ranking number used in these ties is the mean of what they would have been under an ordinal ranking approach (e.g., three segments tied for rank 3 would each be given a rank of 4 – the average of ranks 3, 4 and 5).

Each of the eleven rankings was compared against the PSI-based ranking. For each pairing between an alternative ranking and the PSI-based ranking, a Spearman's rank-order correlation analysis was used to evaluate how close the alternative rankings are to the PSI method.

Table 7 shows an example of 10 fictional curve segments based on the PSI ranking and how three different alternative ranking measures are compared and evaluated. The first column is the PSI-based rankings. The second, third and fourth columns show how these same 10 curve segments are ranked based on one-year, two-year and three-year crash frequencies, respectively. The bottom row of this table is the Spearman's coefficients which indicate the strength of the statistical association between PSI-based and the other crash frequency based rankings. [Note a higher value of the Spearman's coefficient indicates a better alternative.] With a Spearman's coefficient of 0.903, the three-year crash frequency-based rankings are much closer to the PSI-based rankings than are the two-year rankings and are thus considered the better alternative to the ground truth (i.e., the PSI method) in this example. A more detailed discussion of the Spearman's rank correlation is provided in Appendix C of this report. The findings of the ranking comparisons are presented in the Results section below.

Table 7. Example of ranking evaluation method based on fictional data

PSI-based ranking	1 year crash frequency ranking	2 year crash frequency ranking	3 year crash frequency ranking
1	5	3	1
2	6	4	2
3	4	2	5
4	8	8	4
5	2	1	3
6	1	2	7
7	9	10	6
8	10	7	9
9	3	9	10
10	7	5	8
Spearman's Rank Correlation Coefficient	**0.176**	**0.485**	**0.903**

Identifying Potential Benefits

The primary anticipated benefit of the CSW application is the reduction in target crashes and the fatalities and injuries resulting from those crashes at horizontal curve segments where the systems are used. This anticipated crash benefit is the focus of this analysis. As discussed in the data section, the cost of a target crash can be monetized by the severity of a crash. This monetary cost of a crash is considered an economic benefit if a crash is avoided by the CSW application.

Differences in Candidate Curve Segments

The curves identified as priority candidates for the CSW application were reviewed to identify differences in these curve segments compared to other curve segments in the State. Specifically, the following characteristics were explored:

- Volume.
- Functional class of major roadway.
- Speed.
- Area type (i.e., urban or rural).

- Single or multi-curves.
- Degree of curvature.

This information may be useful to FHWA, States, and other agencies for future efforts in analyses of safety issues and design of countermeasures. Additionally, for this application, it could also be used to inform systemic applications of this treatment based on the curve characteristics (e.g., the treatment of all curves above a certain volume and/or above a specified degree of curvature). The findings of the comparison are presented in the Results section below.

RESULTS

The following sections present the results of Washington and Ohio data analyses, including the identification of critical horizontal curve segment types, the selection of a timeframe for use in the identification of candidates, the identification of the top ranked curve segments in each State, potential deployment scenarios for each State, and a comparison of candidate curve segments to other curve segments.

Critical Curve Segment Types

Table 8 presents the average annual target crashes for each of the eight curve segment groups in Washington that were introduced in Table 3. This table is limited to those curve segments that experienced one or more target crashes during a three-year period. The number of curve segments in each group is also displayed in the table. The majority of the groups averaged less than one target crash per year per curve segment. The table also provides an average cost per target crash based on the average severity distribution of the target crashes in the group and the average cost per crash severity presented in Table 2. The average annual number of target crashes is multiplied by the average cost of the target crash to get the average annual costs of target crashes per curve segment for each group in the final column.

The multi-curve segments generally represented higher average target crash cost and average overall higher average annual costs for the segments. The multi-curve segments with four lanes and speed limits over 50 mi/hr had the highest target crash cost and average segment costs. However, this group only included ten curve segments, much smaller than the 30 segments suggested as a minimum above.

Table 8: Average annual target crashes and average cost by curve segment group in Washington for segments with at least one target crash (number of segments in parentheses.)

Curve Segment Group (number of curve segments in group with at least one target crash)	Average Annual Number of Target Crashes	Average Cost of Target Crash	Average Annual Curve Segment Target Crash Costs
Single-curve segments with 2 lanes and speed limit of 45 mi/hr or lower (79)	0.553	$230,946	$127,654
Single-curve segments with 4 lanes and speed limit of 45 mi/hr or lower (6)	0.667	$149,355	$99,570
Single-curve segments with 2 lanes and speed limit of 50 mi/hr or higher (523)	0.437	$362,817	$158,631
Single-curve segments with 4 lanes and speed limit of 50 mi/hr or higher (51)	0.686	$173,611	$119,145
Multi-curve segments with 2 lanes and speed limit of 45 mi/hr or lower (115)	0.748	$324,684	$242,807
Multi-curve segments with 4 lanes and speed limit of 45 mi/hr or lower (13)	0.718	$469,250	$336,898
Multi-curve segments with 2 lanes and speed limit of 50 mi/hr or higher (339)	0.641	$458,139	$293,714
Multi-curve segments with 4 lanes and speed limit of 50 mi/hr or higher (10)	1.233	$608,645	$750,662

Table 9 presents similar information for Ohio. As with the Washington data, only those curve segments that experienced one or more target crashes in a three-year period are included in the table. For groups with more than 30 curve segments, the average annual curve segment target crash costs are generally consistent between $144,000 and $200,000.

Table 9. Average annual target crashes and average cost by curve segment group in Ohio for segments with at least one target crash (Number of segments in parentheses.)

Curve Segment Group (number of curve segments in group with at least one target crash)	Average Annual Number of Target Crashes	Average Cost of Target Crash	Average Annual Curve Segment Target Crash Costs
Single-curve segments with 2 lanes and speed limit of 45 mi/hr or lower (212)	0.593	$293,907	$174,218
Single-curve segments with 4 lanes and speed limit of 45 mi/hr or lower (30)	0.811	$245,347	$199,003
Single-curve segments with 2 lanes and speed limit of 50 mi/hr or higher (995)	0.517	$335,159	$173,250
Single-curve segments with 4 lanes and speed limit of 50 mi/hr or higher (12)	0.639	$49,891	$31,875
Multi-curve segments with 2 lanes and speed limit of 45 mi/hr or lower (297)	0.669	$215,894	$144,414
Multi-curve segments with 4 lanes and speed limit of 45 mi/hr or lower (16)	0.563	$829,714	$466,714
Multi-curve segments with 2 lanes and speed limit of 50 mi/hr or higher (1,178)	0.678	$259,934	$176,232
Multi-curve segments with 4 lanes and speed limit of 50 mi/hr or higher (9)	1.222	$53,789	$65,743

Selection of Timeframe and Candidate Curve Segments

As discussed in the methodology section, eleven measures were explored to determine the best method for State and local agencies to use crash data to identify candidate locations for CSW systems. The eleven different measures tested using Washington data included:

- Annual target crash frequency

- Two-year target crash frequency
- Three-year target crash frequency
- Four-year target crash frequency
- Five-year target crash frequency
- Annual total crash frequency
- Two-year total crash frequency
- Three-year total crash frequency
- Four-year total crash frequency
- Five-year total crash frequency
- Three-year total wet weather crash frequency

As noted in the Methodology section, in this analysis, all 3,893 curve segments were ranked using the PSI-based method and each of the alternative methods. The research team also performed an additional analysis using only the top 10 percent of segments based on PSI-ranking. The following table shows the Spearman's rank correlation coefficients between PSI-based rankings and the rankings based on the eleven options for the entire dataset and a subset of PSI-based top 10 percent.

Table 10. Comparison of eleven methods to PSI-based method for identifying priority curve segments.

	Spearman's coefficient based on all curve segments	**Spearman's Coefficient based on top 10 percent of PSI-ranked curve segments**
1 year target crash frequency rankings	0.377	0.310
2 year target crash frequency rankings	0.501	0.406
3 year target crash frequency rankings	**0.588**	**0.810**
4 year target crash frequency rankings	0.484	0.766
5 year target crash frequency rankings	0.399	0.728
1 year total crash frequency rankings	0.168	0.338
2 year total crash frequency rankings	0.238	0.465
3 year total crash frequency rankings	0.274	0.679
4 year total crash frequency rankings	0.198	0.652
5 year total crash frequency rankings	0.150	0.634
3 year total wet weather crashes frequency rankings	0.177	0.337

The results show the rankings based on three-year target crash frequency are the closest to the ones based on PSI (i.e., the largest Spearman's rank correlation coefficient). The results suggest the three-year target crash frequency is a better representation of the long term average than other alternatives, including the four-year and five-year averages. This could be a result of a greater chance of changes in operational and design characteristics in the longer time periods.

The EB-based PSI approach is considered a more reliable estimate of the long-term safety performance of an entity. If an agency has the resources and capability, this approach can provide more reliable results than average crash frequency alone. It is more sophisticated and reliable. However, it is not suggested for use by the agencies unless they have the resource and capability to perform this type of EB-based analysis. The EB-based approach violates the first among three desired characteristics: ease of implementation. Based on the analysis results, the **three-year crash frequency method holds the most promise** for providing a reliable method that achieves the desired characteristics and the results indicate it is sufficient to use the three-year average.

Based on this three-year frequency of target crashes, the curve segments in each dataset were ranked in priority order for implementation.

Demonstration of Benefits

As previously discussed, the anticipated benefit of the CSW systems is the monetized benefit of a reduction in target crashes. The potential economic benefit of a system for a specific candidate curve segment will be influenced by the number and severity of expected target crashes, the effectiveness of the system in preventing target crashes, and the deployment of equipped vehicles. This is best demonstrated by selecting example curve segments from each dataset and calculating the expected benefit.

The following section presents four examples, two for each dataset for Washington and Ohio:

- Table 11 presents a curve segment in Washington with **5 Target Crashes** per year on average. The example assumes that vehicle deployment follows the **5-Year Mandate** presented in Figure 1.
- Table 12 presents curve segment in Ohio with **8 Target Crashes** per year on average. The example assumes that vehicle deployment follows the **5-Year Mandate** presented in Figure 1.
- Table 13 presents the same Washington curve segment with **5 Target Crashes** per year on average that was presented in the first example. However, this example assumes that vehicle deployment follows the **15-Year Organic** penetration presented in Figure 1.
- Table 14 presents the same Ohio curve segment with **8 Target Crashes** per year on average that was presented in the second example. However, this example assumes that vehicle deployment follows the **15-Year Organic** penetration presented in Figure 1.

The start of system installation and vehicle penetration in all four examples is assumed to be 2020. For each scenario presented, the system is assumed to be 95 percent effective in reducing crashes when communicating with an equipped vehicle. Complete effectiveness (i.e., 100 percent) was not used because there may be some drivers who receive the warning message but do not heed the message and reduce their speed.

The examples assume that total and target crashes would continue at current levels for each curve segment without the installation of the system. Therefore, every year the same number of target crashes would be expected without the intervention. This assumption is a simplification intended for illustrative purposes. In reality, many other factors may affect the occurrence of crashes on a curve, such as changes in traffic volume or weather conditions.

The tables provide the total anticipated crashes prevented. These are represented to the nearest tenth. In reality, a tenth of a crash prevented is not possible (i.e., either a crash is prevented or it occurs). However, the table is intended to demonstrate the benefit that can be achieved over the twenty year period. The tables also provide the crash cost savings (based on the distribution of severity at the example curve segment) and the percent of target crashes reduced each year.

The number of crashes anticipated to be prevented increases each year the system is in place because there is an increase in the penetration of connected vehicle technologies in the vehicle fleet in subsequent years. As would be expected, the 5-year mandate results in more crashes being prevented sooner as a result of more aggressive penetration.

Note that all of the costs presented in these examples are presented in 2015 dollars. Inflation is not considered, again for simplification of the examples.

Table 11. Estimated number of crashes prevented and crash cost saved over time with 5-year mandate deployment scenario on a curve segment and with 5 target crashes expected without intervention (Washington).

Year	Deployment (percent)	Total crashes prevented	Crash cost saved	Percentage
2020	0.22	0	--	--
2021	1.79	0.1	$11,888	1.7%
2022	5.34	0.3	$35,464	5.1%
2023	10.33	0.5	$68,604	9.8%
2024	16.08	0.8	$106,792	15.3%
2025	22.14	1.1	$147,038	21.0%
2026	28.29	1.3	$187,882	26.9%
2027	34.42	1.6	$228,593	32.7%
2028	40.43	1.9	$268,507	38.4%
2029	46.25	2.2	$307,159	43.9%
2030	51.84	2.5	$344,284	49.2%
2031	57.14	2.7	$379,482	54.3%
2032	62.10	2.9	$412,423	59.0%
2033	66.70	3.2	$442,973	63.4%
2034	70.92	3.4	$470,999	67.4%
2035	74.76	3.6	$496,502	71.0%
2036	78.21	3.7	$519,414	74.3%
2037	81.30	3.9	$539,936	77.2%
2038	84.03	4.0	$558,066	79.8%
2039	86.43	4.1	$574,005	82.1%
2040	88.03	4.2	$584,631	83.6%
20 Year TOTAL		**43.6 Crashes**	**$6,684,643**	**48%**

Table 12. Estimated number of crashes prevented and crash cost saved over time with 5-year mandate deployment scenario on a curve segment and with 8 target crashes expected without intervention (Ohio).

Year	Deployment (percent)	Total crash prevented	Crash cost saved	Percentage
2020	0.22	0	--	--
2021	1.79	0.1	$27,665	1.7%
2022	5.34	0.4	$82,530	5.1%
2023	10.33	0.8	$159,651	9.8%
2024	16.08	1.2	$248,517	15.3%
2025	22.14	1.7	$342,174	21.0%
2026	28.29	2.2	$437,223	26.9%
2027	34.42	2.6	$531,962	32.7%
2028	40.43	3.1	$624,847	38.4%
2029	46.25	3.5	$714,795	43.9%
2030	51.84	3.9	$801,189	49.2%
2031	57.14	4.3	$883,101	54.3%
2032	62.10	4.7	$959,758	59.0%
2033	66.70	5.1	$1,030,851	63.4%
2034	70.92	5.4	$1,096,071	67.4%
2035	74.76	5.7	$1,155,418	71.0%
2036	78.21	5.9	$1,208,738	74.3%
2037	81.30	6.2	$1,256,494	77.2%
2038	84.03	6.4	$1,298,687	79.8%
2039	86.43	6.6	$1,335,779	82.1%
2040	88.03	6.7	$1,360,507	83.6%
20 Year TOTAL		**69.8**	**$15,555,956**	**47.8%**

Table 13. Estimated number of crashes prevented and crash cost saved over time with 15-year organic deployment scenario on a curve segment and with 5 target crashes expected without intervention (Washington).

Year	Deployment (Percent)	Total crash prevented	Total crash cost saved	Percentage
2020	0.02	0	-	--
2021	0.09	0.0	$598	0.1%
2022	0.31	0.0	$2,059	0.3%
2023	0.83	0.0	$5,512	0.8%
2024	1.81	0.1	$12,021	1.7%
2025	3.38	0.2	$22,448	3.2%
2026	5.60	0.3	$37,191	5.3%
2027	8.49	0.4	$56,384	8.1%
2028	11.99	0.6	$79,629	11.4%
2029	16.03	0.8	$106,460	15.2%
2030	20.49	1.0	$136,080	19.5%
2031	25.27	1.2	$167,825	24.0%
2032	30.25	1.4	$200,899	28.7%
2033	35.35	1.7	$234,769	33.6%
2034	40.47	1.9	$268,772	38.4%
2035	45.53	2.2	$302,377	43.3%
2036	50.47	2.4	$335,185	47.9%
2037	55.23	2.6	$366,798	52.5%
2038	59.77	2.8	$396,949	56.8%
2039	64.04	3.0	$425,307	60.8%
2040	68.15	3.2	$452,603	64.7%
20 Year TOTAL		**22.6 crashes**	**$3,609,865**	**26%**

Table 14. Estimated number of crashes prevented and crash cost saved over time with 15-year organic deployment scenario on a curve segment and with 8 target crashes expected without intervention (Ohio).

Year	Deployment (Percent)	Total crash prevented	Total crash cost saved	Percentage
2020	0.02	0	--	--
2021	0.09	0.0	$1,391	0.1%
2022	0.31	0.0	$4,791	0.3%
2023	0.83	0.1	$12,828	0.8%
2024	1.81	0.1	$27,974	1.7%
2025	3.38	0.3	$52,238	3.2%
2026	5.60	0.4	$86,548	5.3%
2027	8.49	0.6	$131,213	8.1%
2028	11.99	0.9	$185,306	11.4%
2029	16.03	1.2	$247,744	15.2%
2030	20.49	1.6	$316,674	19.5%
2031	25.27	1.9	$390,549	24.0%
2032	30.25	2.3	$467,515	28.7%
2033	35.35	2.7	$546,335	33.6%
2034	40.47	3.1	$625,465	38.4%
2035	45.53	3.5	$703,668	43.3%
2036	50.47	3.8	$780,016	47.9%
2037	55.23	4.2	$853,582	52.5%
2038	59.77	4.5	$923,747	56.8%
2039	64.04	4.9	$989,740	60.8%
2040	68.15	5.2	$1,053,261	64.7%
20 Year TOTAL		**36.1 Crashes**	**$8,400,584**	**26%**

Large-Scale Consideration for Agency-Wide Deployment Levels

As previously discussed, this analysis illustrates how interested agencies could focus on implementing CSW systems at those horizontal curve segments that have the most target crashes based on a three-year average of target crash occurrence. For each individual curve segment, the agency can conduct a cost benefit analysis. An agency may also want to set a goal for a systemic deployment (e.g., top five percent of all curves) or a goal for reducing the number of target crashes agency-wide (e.g., reduce target crashes by 50 percent agency-wide over twenty years). For this broader scale consideration, the cumulative distribution of target crashes should be considered. The research team conducted an analysis for all candidate curve segments in Washington and Ohio to demonstrate the benefit of these simple graphs. To develop these graphs, an agency would need a listing of candidate curve segments and the average annual target crashes at each.

Figure 3 and Figure 4 present the cumulative distribution of average annual total target crashes (total target crashes over three years divided by three) compared to the number of candidate curve segments that experienced **at least one target crash** in Washington and Ohio, respectively. As shown on the graphs, 10 percent of these curve segments are responsible for nearly 30 percent of the total target crashes in Washington and Ohio. The percent is consistent for the two datasets.

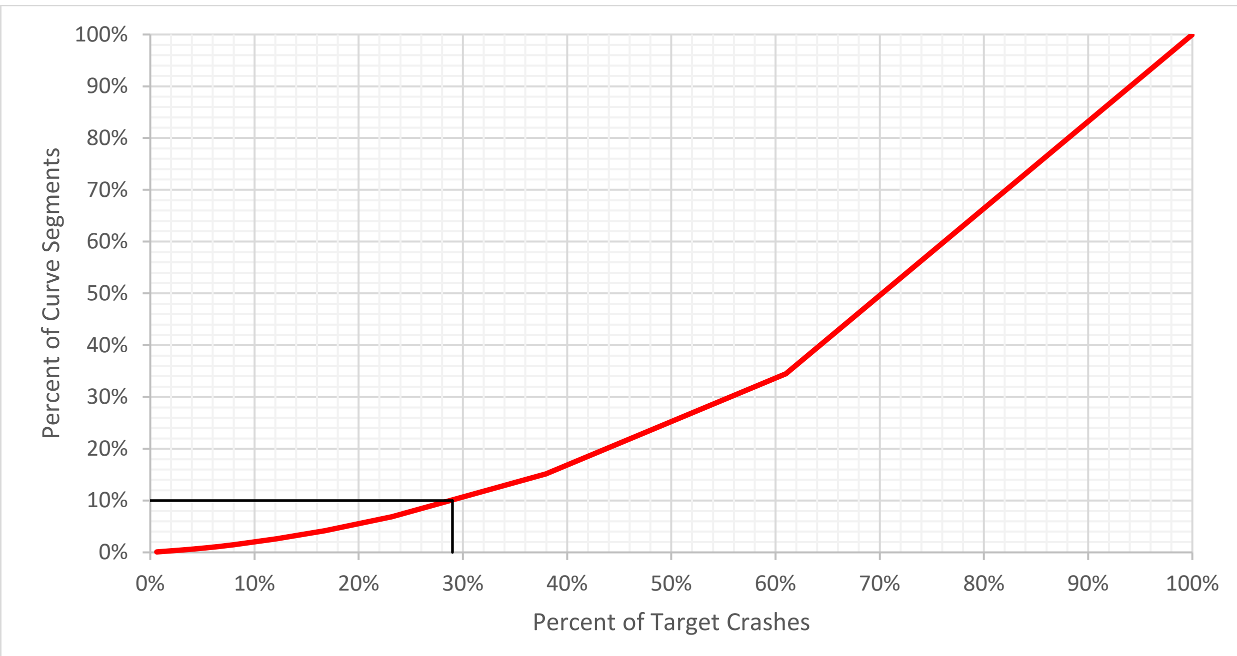

Figure 3. Relationship between cumulative number of horizontal curve segments and cumulative target crashes in Washington.

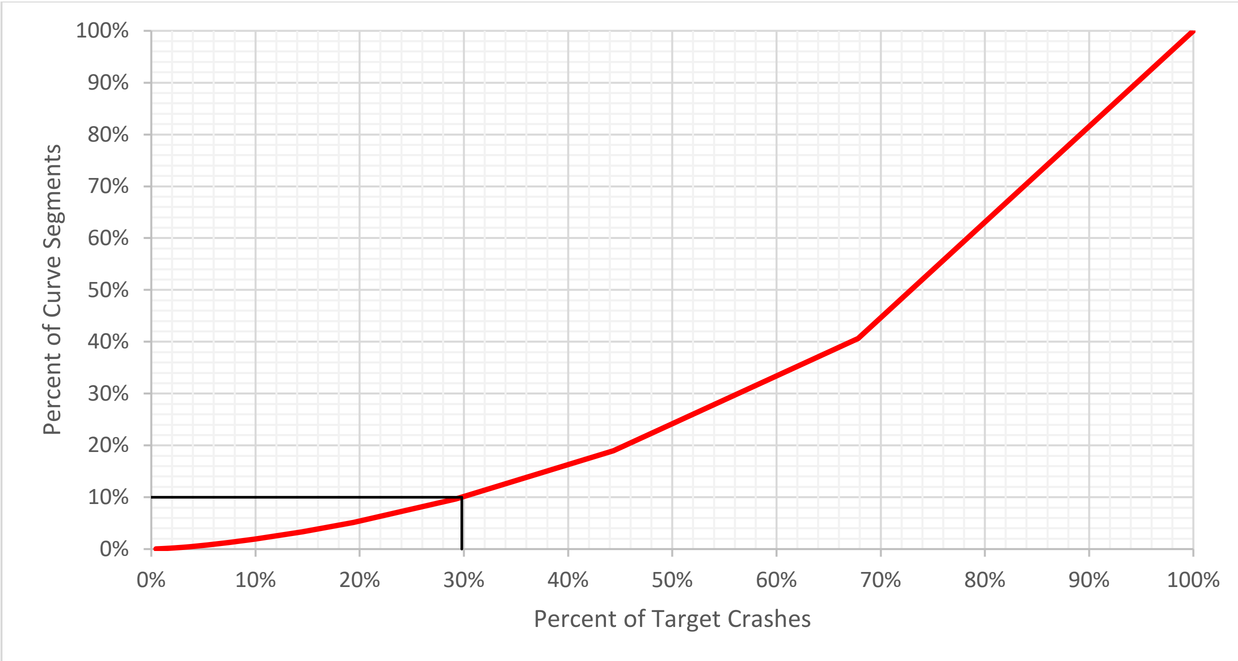

Figure 4. Relationship between cumulative number of horizontal curve segments and cumulative target crashes in Ohio.

An agency may also want to consider the severity of the target crashes. Translating the maximum injury severity of the crashes to crash costs is a useful way to account for severity in these graphs. Figure 5 presents the cumulative distribution of annualized target crash costs compared to the number of candidate curve segments in Washington that experienced at least one target crash in the last three years. The impact of deploying at the top 10 percent of curve segments is more poignantly expressed once severity is included. The top 10 percent of curve segments represent over 80 percent of total target crash cost. A similar graph for Ohio is presented in Figure 6. The top 10 percent of curve segments represent more than 70 percent of total target crash cost in Ohio.

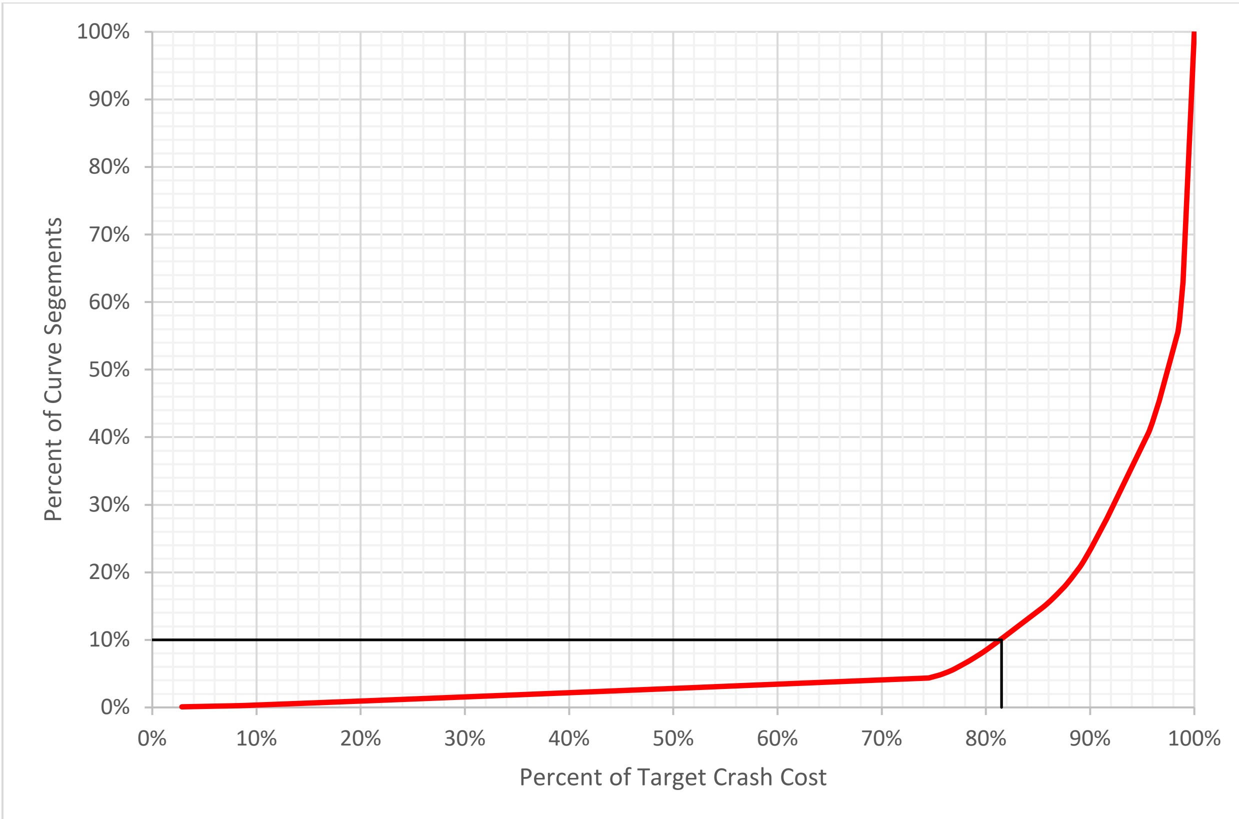

Figure 5. Relationship between cumulative number of horizontal curve segments and cumulative target crash cost in Washington.

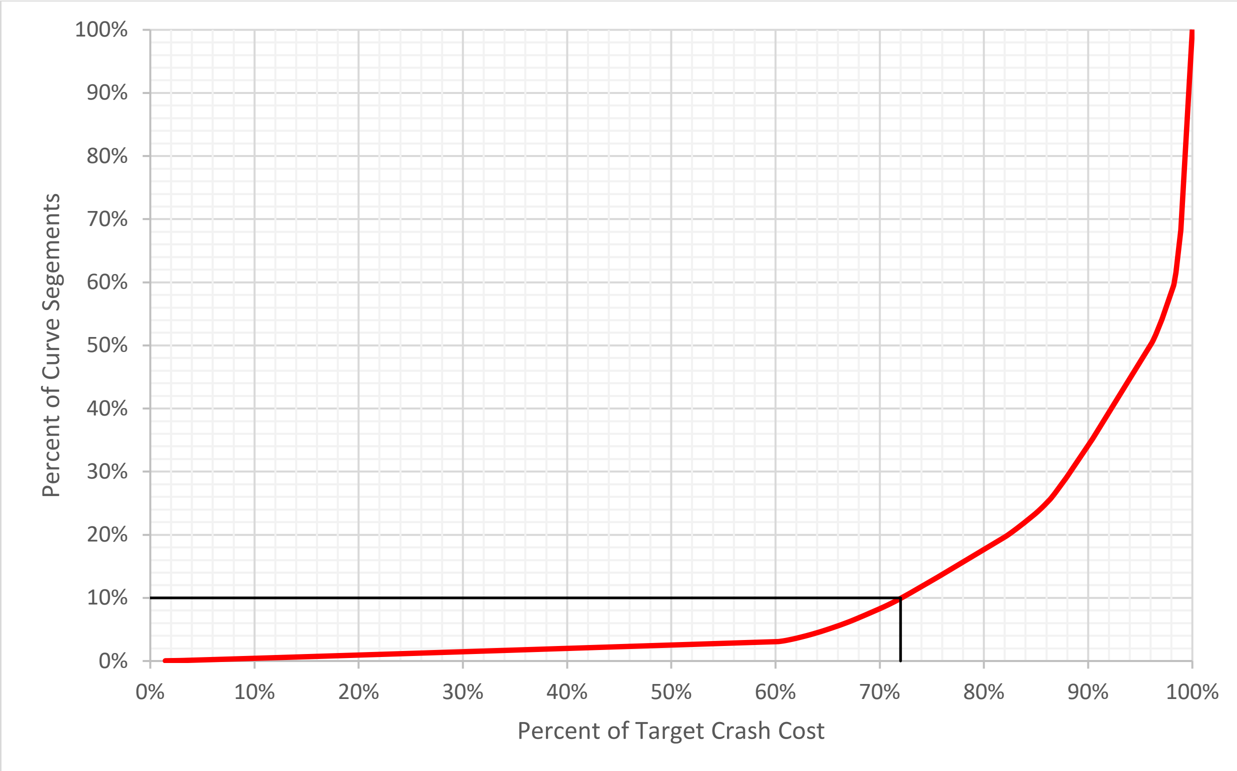

Figure 6. Relationship between cumulative number of horizontal curve segments and cumulative target crash cost in Ohio.

Difference in Candidate Curve Segments

As discussed in the methodology section, the candidate curve segments with the most target crashes in a three year period were compared to other curve segments to identify any notable differences in the characteristics of the highest priority candidate curve segments to the other segments. Specifically, in Washington there were 174 candidate curve segments that experienced three or more target crashes in a three-year period. These candidate segments were compared to those that experienced two or less target crashes in the same three-year period. There were 524 candidate curve segments in Ohio that experienced three or more crashes in a three-year period and similar comparisons were also made for Ohio data.

This information is presented for the benefit of FHWA and their partners when relevant in any of the three datasets. (Note that only notable differences are discussed.) The implementing agencies may also find this useful for the preliminary screening of curve segments or to initiate systemic improvements.

Urban/rural

The Washington dataset includes area type (urban/rural) information. Although the Ohio dataset also has a variable indicating the area type of each road segment, a vast majority of this data element is missing. This makes it impossible for identifying the area type in which a curve segment is located by using this variable alone. After further examination of the data, the research team decided to use the variable related to roadway classification as an alternative source of information for rural or urban designation. Table 15 and 16 show the comparison of urban/rural characteristics between the priority candidate curve segments and others curve segments in Washington and Ohio, respectively. The results from both state are quite consistent and show that the priority candidate curve segments are more likely to be in an urban area. This information might be helpful to agencies in the deployment process.

Table 155. Comparison of urban/rural characteristics between priority candidate curve segments and other curve segments in Washington.

Area Type	Priority Candidate Curve Segments (3 or more target crashes)	Other curve segments
Rural	84.5%	95.2%
Urban	15.5%	4.8%

Table 16. Comparison of urban/rural characteristics between priority candidate curve segments and other curve segments in Ohio.

Area Type	Priority Candidate Curve Segments (3 or more target crashes)	Other curve segments
Rural	80.2%	92.1%
Urban	19.8%	7.9

Traffic Volume

The Washington and Ohio curve data files do not include AADT information. However, the AADT values are available in the roadway files and the research team merged the AADT within each curve segments using route identifier and milepost information. The AADTs for the priority candidate curve segments were compared to the remaining curve segments and presented in Table 17 and Table 18. The priority candidate curve segments have higher average AADTs in both Washington and Ohio. This is expected as higher volume present more opportunity for crashes.

Table 17. Comparison of volume characteristics between priority candidate curve segments and other curve segment in Washington.

Variable	Priority Candidate Curve Segments (3 or more target crashes)		Other curve segments	
AADT	Minimum	279	Minimum	89
	Average	7,303	Average	3,277
	Maximum	37,138	Maximum	42,196

Table 18. Comparison of volume characteristics between priority candidate curve segments and other curve segments in Ohio.

Variable	Priority Candidate Curve Segments (3 or more target crashes)		Other curve segments	
AADT	Minimum	150	Minimum	80
	Average	4,435	Average	2,300
	Maximum	40,870	Maximum	44,390

Roadway Classification

The roadway class was compared between the priority candidate curve segments and the other curve segments in Washington and Ohio. The comparisons are summarized in Tables **19** and **20.** A vast majority of curve segments are rural two-lane roads in both Washington and Ohio. However, as the results shown in Table 19 and Table 20, the priority candidate curve segments are less likely to be on rural two-lane roads when compared to the other curve segments. Overall, around 90 percent of curve segments are on rural two-lane roads but the percent of priority candidate segments on rural two-lane roads is smaller – 72.4 percent and 80 percent for Washington and Ohio, respectively.

Table 19. Comparison of roadway classification between priority candidate curve segments and other curve segment in Washington.

	Priority Candidate Curve Segments (3 or more target crashes)	Other curve segments	Overall
Rural two-lane roads	72.4%	90.4%	89.6%
Others	27.6%	9.6%	10.4%

Table 20. Comparison of roadway classification between priority candidate curve segments and other curve segment in Ohio.

	Priority Candidate Curve Segments (3 or more target crashes)	Other curve segments	Overall
Rural two-lane roads	80.0%	91.7%	90.8%
Others	20.0%	8.3%	9.2%

Speed Limit

Both Washington and Ohio includes posted speed limit information in the HSIS roadway inventory data. The posted speed of the two groups of curve segments were compared. The Washington dataset includes curve segments with posted speeds that range from 25 mi/hr to 70 mi/hr and the range of posted speeds in Ohio dataset is from 20 to 65 mi/hr. Table 21 and Table 22 show the results for Washington Ohio, respectively. However, the results appear counterintuitive. The priority group included fewer curve segments with posted speeds of 50 mi/hr or higher (70.7 percent of the priority curve segments versus 86.4 percent for the other curve segments in Washington and 76 percent versus 81.1 percent in Ohio). One possible explanation could the fact that curves with lower posted speed limits often have less favorable conditions and are less forgiving for speeding. Therefore, going over the posted speeds through horizontal curves with lower posted speeds is more likely to result in a crash than doing the same at curves with higher speed limits.

Table 21. Comparison of posted speeds between priority candidate curve segments and other curve segment in Washington.

	Priority Candidate Curve Segments (3 or more target crashes)	Other curve segments	Overall
Posted Speed of 45 mi/hr or **lower**	29.3%	13.6%	14.3%
Posted Speed of 50 mi/hr or higher	70.7%	86.4%	85.7%

Table 22. Comparison of posted speeds between priority candidate curve segments and other curve segment in Ohio.

	Priority Candidate Curve Segments (3 or more target crashes)	Other curve segments	Overall
Posted Speed of 45 mi/hr or lower	24.0%	18.9%	19.3%
Posted Speed of 50 mi/hr or higher	76.0%	81.1%	80.7%

Single Curve and Multi-curve segments

The research team also examined the difference in number of single and multi-curve segments between the priority curve segments and the other segments. Table 23 and Table 24 show summaries of the results for Washington and Ohio data. In both states, a majority of the priority group are multi-curve segments (64.9 percent and 67.7 percent of priority group are multi-curve segments for Washington and Ohio, respectively).

Table 23. Comparison of single curve and multi-curve segments between priority candidate curve segments and other curve segments in Washington.

	Priority Candidate Curve Segments (3 or more target crashes)	Other curve segments
Total number of curve segments	174	3,719
Number of multi-curve segments	113	1,026
Percentage of multi-curve segments	64.9%	27.6%

Table 24. Comparison of single curve and multi-curve segments between priority candidate curve segments and other curve segments in Ohio.

	Priority Candidate Curve Segments (3 or more target crashes)	Other curve segments
Total number of curve segments	524	6,493
Number of multi-curve segments	355	2,956
Percentage of multi-curve segments	67.7%	45.5%

Degree of curve

The degree of curve was examined and compared between priority curve segment and other groups. Specifically, the team calculated and compared the average degree of curve and maximum degree of curve. In the case of single-curve segments, the average and maximum values for each segment are the same. For multi-curve segments, the average degree of curve is arithmetic mean of all curves within each segment. Similarly, the maximum degree of curve is the largest value among those constituent curves. The comparisons summarized and presented in Table 25 and Table 26 for Washington and Ohio, respectively. As expected, the priority curve segments have large values in both average and maximum degree of curves when compared to the other curve segments.

Table 25. Comparison of degree of curve between priority candidate curve segments and other curve segments in Washington.

Variable	Priority Candidate Curve Segments (3 or more target crashes)		Other curve segments	
Average degree of curve	Minimum	0.11	Minimum	0.13
	Average	8.64	Average	5.23
	Maximum	81.85	Maximum	100.52
Maximum degree of curve	Minimum	0.11	Minimum	0.13
	Average	13.84	Average	6.30
	Maximum	130.22	Maximum	163.7

Table 26. Comparison of degree of curve between priority candidate curve segments and other curve segments in Ohio.

Variable	Priority Candidate Curve Segments (3 or more target crashes)		Other curve segments	
Average degree of curve	Minimum	2	Minimum	1
	Average	11.51	Average	10.68
	Maximum	29.00	Maximum	89.3
Maximum degree of curve	Minimum	2	Minimum	1
	Average	15.10	Average	12.64
	Maximum	64	Maximum	90

CONCLUSIONS AND DISCUSSION

This report presents a method for State or local agencies to screen horizontal curves and develop a first prioritization of these curve segments for deployment of a vehicle-to-infrastructure Curve Speed Warning (CSW) system. This effort was based on data from Washington and Ohio. The effort included several assumptions for ease of analysis and to demonstrate the approach including the system effectiveness, vehicle penetration rates, and crash levels that are expected stay the same over time if no intervention is implemented. Additionally, three system cost scenarios were presented. All of these assumptions were inputs to the analysis and can be changed as more refined inputs are available.

Based on the analysis conducted, the following process could be used by agencies in identifying potential horizontal curve segments for the installation of V2I CSW systems:

Step 1. Identify horizontal curve segments

This analysis used two States that maintain a horizontal curve inventory that provided information on horizontal curves. Without such an inventory, agencies can use local knowledge, or manual review of aerial maps or photo logs to identify these horizontal curves and determine the key curve characteristics. (In absence of any horizontal curve information, the agency could also conducted a curve-related crash cluster analysis to find curves by identifying clusters in the police-reported crash data of crashes identified as curve related.)

Step 2. Attribute Crashes to horizontal curve segments

This is generally done by identifying crashes within and 250 ft beyond both ends of each curve segment. The process might vary by agency and the method should reflect agency practices for similar efforts. The target crashes for the CSW system are run-off-road, roll-over and multi-vehicle, opposite directions.

Step 3. *Remove curves Improved in the Last Three Years or Planned for Future Improvement*

This step will likely require an agency to seek additional information beyond what is available in a roadway inventory.

Step 4. Determine a Method to Identify Target Crashes in Crash Data

Target crashes for this application are those resulting from vehicles traveling through a curve faster than a safe speed and losing control. The vehicle departs its travelled lane and then runs off road or rolls over or collides with another vehicle travelling in the opposing direction. Based on the analysis conducted here, this should be defined in the crash data using information on the involved vehicles including manner of the crashes (i.e. run-off-road, roll-over or colliding with motor vehicle in transport), number of vehicles involved, and some information on either the movement preceding the crash or the accident type. Some dataset might have information indicating if a crash is curve-related. This might be very helpful in determining crashes on curves.

Step 5. Calculate Three-Year Average Annual Target Crashes and Target Crash Costs

Using the three most recent years of available crash data, calculate the average number of target crashes on each horizontal curve segments and the average annual cost of the target crashes. The research team suggests that agencies include all severities in their screening efforts and apply the crash costs presented in this report (or their own agency developed costs) by severity to calculate the costs.

Step 6. Combine curve segments into Related Groups (Optional)

If desired, the agency could use several variables to group curve segments including number of lanes, number of curves (single-curve or multi-curve segments) and area type (urban/rural). Groups of 30 segments or more is a reasonable base. The purpose of this step is to identify groups that may need separate consideration, particularly if separate funds are available for certain function classes such as rural two-lane roads.

Step 7. Develop Prioritized List

The analysis here developed a prioritized list based on a three-year average of target crash frequency. The list could also be prioritized by the monetized cost of the target crashes or subdivided by the groups identified in step 6.

This method is based on the reported crashes and operational and geometric data available in a horizontal curve and roadway inventory. The agency would use this list as an initial step in their efforts. The next step in prioritization would likely involve a detailed review (including field collection and observations) of horizontal curves that the agency intends to move forward. The costs for individual curve systems would be compared to the monetized benefit of the crashes that the system is expected to prevent. The ability of the system to prevent crashes will increase every year as more and more vehicles are equipped.

There are additional considerations that an agency may have in prioritizing curve segments for these systems that could be incorporated into the initial prioritization efforts. The largest consideration is the agency's existing future plans for the curve. For example, if the curve is part of a planned large-scale improvement such as a large corridor improvement program, the agency may remove the curve from consideration for the system or consider how the system implementation could be scheduled as part of other construction at the curve. Other considerations may include equity by district or region.

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APPENDIX A: DATA ELEMENTS

HSIS Data Elements for Analysis: Washington

Washington Accident Subfile

Variable Name	Description
ACCTYPE	ACCIDENT TYPE
CASENO	CASE NUMBER
COLTYPE1	COLLISION TYPE 1
COLTYPE2	COLLISION TYPE 2
COUNTY	COUNTY NUMBER
DISTRICT	DISTRICT NUMBER
FUNC_CLS	FUNCTIONAL CLASS
IMPACT	IMPACT LOCATION
LIGHT	LIGHT CONDITION
LOC_CHAR	LOCATION CHARACTERISTICS
LOC_TYPE	ACC LOCATION TYPE
MILEPOST	ACCUM ROUTE MILEPOST (ARM)
NO_PEDS	NUMBER OF PEDESTRAINS
NUMVEHS	NUMBER OF VEH
OBJECT1	OBJECT STRUCK 1
OBJECT2	OBJECT STRUCK 2
RD_CHAR1	ROADWAY CHARACTERISTICS
RD_INV	ROADWAY INVENTORY
RD_REL	ON/OFF ROAD
RDSURF	ROADWAY SURFACE
REPORT	ACC SEVERITY
RODWYCLS	ROADWAY CLASS
RTE_NBR	STATE ROUTE NUMBER
RUR_URB	RURAL URBAN
SEVERITY	MOST SEVERE INJURY
TIME	ACCIDENT TIME
V1CMPDIR	V1 COMPASS DIRECTION
V2CMPDIR	V2 COMPASS DIRECTION
V1DIRCDE	V1 DIRECTION
V2DIRCDE	V2 DIRECTION
V1EVENT1	V1 MOVEMENT
V2EVENT1	V2 MOVEMENT
WEATHER	WEATHER CONDITION
WEEKDAY	DAY OF WEEK
WKZONE	WORK ZONE STATUS

Washington Vehicle Subfile

Variable Name	Description
CASENO	ACC REPORT NUMBER
CONTRIB1	DRV CONTRIB CIRCUMS 1
CONTRIB2	DRV CONTRIB CIRCUMS 2
DRV_ACTN	DRIVER ACTION
EVENT1	SEQUENCE OF EVENTS 1
EVENT2	SEQUENCE OF EVENTS 2
EVENT3	SEQUENCE OF EVENTS 3
EVENT4	SEQUENCE OF EVENTS 4
MISCACT1	DRV MISC ACTION 1
MISCACT2	DRV MISC ACTION 2
SPDLIMIT	VEH POSTED SPEED
TRF_CNTL	VEH TRAFFIC CONTROL
VEHNO	VEHICLE NUMBER

Washington Roadway File

Variable Name	Description
AADT	AVERAGE ANNUAL DAILY TRAFFIC
BEGMP	BEGINNING MILEPOST
CITY	CITY NUMBER
CNTL_SEC	CONTROL SECTION
COUNTY	COUNTY NUMBER
DISTRICT	DISTRICT NUMBER
ENDMP	CALCULATED ENDING MILEPOST
EW_IND	EAST WEST IND
FUNC_CLS	FEDERAL FUNC CLASS
LANEWID	CALCULATED LANE WIDTH
LSHL_TY2	LEFT SHOULDER TYPE RD2
LSHL_TYP	LEFT SHOULDER TYPE RD1
LSHL_WD2	LEFT SHOULDER WIDTH RD2
LSHLDWID	LEFT SHOULDER WIDTH RD1
MED_TYPE	MEDIAN TYPE
MEDWID	MEDIAN WIDTH
NO_LANE1	NUMBER LANES INC

Variable Name	Description
NO_LANE2	NUMBER LANES DEC
NO_LANES	TOTAL NUMBER OF LANES
PGRP_DT	POPULATION GROUP DATE
POP_GRP	CITY POPULATION
RD_LIGHT	INTERSECTION ILLUM-ND
RD_SRMP	RDWY STATE ROUTE MP
RD_TYPE	RELATED RD TYPE
RDWY_WD1	ROADWAY WIDTH RD 1
RDWY_WD2	ROADWAY WIDTH RD 2
RDWY_WID	TOTAL ROADWAY WIDTH
ROAD_INV	ROUTE TYPE ID
RODWYCLS	ROADWAY CLASSIFICATION
RSHL_TY2	RIGHT SHOULDER TYPE RD2
RSHL_TYP	RIGHT SHOULDER TYPE RD1
RSHL_WD2	RIGHT SHOULDER WIDTH RD2
RSHLDWID	RIGHT SHOULDER WIDTH RD1
RTE_NBR	ROUTE NUMBER
RURURB	RURAL URBAN
SEG_LNG	RD CALCULATED SECT LNGTH
SPD_LIMT	LEGAL SPEED LIMIT
ST_FUNC	STATE FUNC CLASS
TERRAIN	TERRAIN TYPE
TRF_CNTL	INTERSECTION CONTROL TYPE
TRKPCTS	TRUCK PERCENTAGE

Washington Curve File

Variable Name	Description
BEGMP	HORIZ CURVE BEGIN MLPOST
CURV_ANG	HORIZ CURVE CENTER ANGLE
CURV_INV	STATE ROUTE TYPE ID
CURV_MAX	HORIZ CURVE MAX SUPER
CURV_NUM	HORIZ CURVE CONTRACT NUM
CURV_RAD	HORIZ CURVE RADIUS
DEG_CURV	DEGREE OF CURVATURE
DIR_CURV	HORIZ CURVE DIRN
ENDMP	HORIZ CURVE END MLPOST

LEGAL_SP	LEGAL SPEED LIMIT
OVERLAP	CURVE OVERLAP IND
RTE_NBR	ROUTE NUMBER
SEG_LNG	HORIZ CURVE LGT (MI)

HSIS Data Elements for Analysis: Ohio

Ohio Accident file

Variable Name	Description
ACC_DATE	ACCIDENT DATE YYYYMMDD
ACCTYPE	TYPE OF CRASH(FIRST HARMFUL EVENT)
ACCYR	ACCIDENT YEAR
ANGLE	TURN CRASH INDICATOR
CASENO	UNIQUE ACCIDENT CASE NUMBER
CNTYRTE	COUNTY ROUTE
COUNTY	COUNTY
DISTRICT	DISTRICT
DIV_CODE	ROAD IDENTIFICATION
FAULT	VIOLATOR
FIPSMUNI	FIPS CODE
FLIP_IND	INDICATES DUPLICATE RECORD GENERATION
FRWY_IND	FREEWAY / NON-FREEWAY INDICATOR
FUNCLS	FUNCTIONAL CLASSFICATION
HOUR	HOUR OF DAY
LIGHT	LIGHT CONDITION
LOC_TYPE	LOCATION
MILEPOST	MILEPOST
NO_LANES	NUMBER OF LANES
NUMPEDS	NUMBER OF PEDESTRIANS
NUMVEHS	NUMBER OF VEHICLES
POP_GRP	POPULATION
REL_RD	RELATION TO ROADWAY
RD_CHAR1	CONTOUR OF ROADWAY

Variable Name	Description
RDSURF	ROAD CONDITION
RODWYCLS	ROAD TYPE
RTE_NBR	ROUTE NUMBER
SEVERITY	CRASH SEVERITY (GENERATED)
STREET_1	STREET ON
STREET_2	STREET AT/CROSS ROUTE
WEATHER	WEATHER CONDITION
WEEKDAY	DAY OF WEEK

Ohio Vehicle Subfile

Variable Name	Description
CASENO	UNIQUE ACCIDENT CASE NUMBER
CONTRIB1	CONTRIBUTING FACTOR OF VEHICLE
DIR_TRVL	DIRECTION OF VEHICLE
EVENT1	SEQUENCE OF EVENTS 1
EVENT2	SEQUENCE OF EVENTS 2
EVENT3	SEQUENCE OF EVENTS 3
EVENT4	SEQUENCE OF EVENTS 4
F_HARM	FIRST HARMFUL EVENT
MISCACT1	PRE-CRASH ACTIONS
MOSTHARM	MOST HARMFUL EVENT
MOVMNT	MOVEMENT OF VEHICLE
NUMVEH	NUMBER OF VEHICLES
SPD_LIMT	SPEED LIMIT OF ROAD
VEH_N_FROM	VEHICLE/NON-MOTORIST DIRECTION FROM
VEH_N_TO	VEHICLE/NON-MOTORIST DIRECTION TO
VEHNO	VEHICLE NUMBER

Ohio roadlog file

Variable Name	Description
AADT	WEIGHTED AVERAGE TOTAL ADT
AADT_YR	YEAR OF ADT COUNTS
ACCESS	ACCESS CONTROL
BEGMP	BEGINNING MILE POST
CNT_TLOG	COUNTY TRUE LOG
CNTY_RTE	COUNTY ROUTE
COUNTY	COUNTY
DISTRICT	DISTRICT
DIVIDED	DIVIDED/UNDIVIDED
ENDMP	END MILE POST
FUNC_CLS	FUNCTIONAL CLASS
MED_TYPE	FHWA MEDIAN TYPE
MED_WID	MEDIAN WIDTH
NO_LANES	NUMBER OF LANES
PAV_ROUG	PAVEMENT ROUGHNESS
PAVECOND	PAVEMENT CONDITION
POP_GRP	POPULATION
RD_WIDTH	ROADWAY WIDTH THRU LANES N/MEDIANS
RODWYCLS	ROADWAY TYPES
RTE_NBR	STATE ROUTE NUMBER
RTE_SUFX	STATE ROUTE NUMBER SUFFIX
RTE_TYPE	ROUTE TYPE
RURUID	POPULATION (OVE/UNDER 5000)
SEG_LNG	SEGMENT LENGTH
SEQ_NBR	SEQUENCE NUMBER
SHWD_LEFT_INSIDE	SHOULDER LEFT INSIDE
SHWD_LEFT_OUTSIDE	SHOULDER LEFT OUTSIDE
SHWD_RIGHT_INSIDE	SHOULDER RIGHT INSIDE
SHWD_RIGHT_OUTSIDE	SHOULDER RIGHT OUTSIDE
SPDLIMT	SPEED LIMIT
STN_SUF	STREET NAME SUFFIX
STR_PFX	STREET NAME DIRECTIONAL PREFIX
STRT_DIR	STREET NAME DIRECTIONAL SUFFIX
STRT_NAM	STREET NAME

Variable Name	Description
SURF_TYP	STANDARD SURFACE CLASSIFICATION
SURF_WID	SURFACE WIDTH THRU LANES N/SHOULDERS
SURFWIDL	LEFT SIDE SURFACE WIDTH IN FEET
SURFWIDR	RIGHT SIDE SURFACE WIDTH IN FEET

Ohio Curve file

Variable Name	Description
BEGMP	BEGIN LOG POINT OF CURVE
CNTY_RTE	COUNTY ROUTE
COUNTY	COUNTY
DEG_CURV	DEGREE OF CURVE
DESC	DESCRIPTION
DIR_CURV	DIRECTION OF CURVE
DIVIDED	DIVIDED HIGHWAY INDICATOR
ENDMP	END LOG POINT OF CURVE
FUNC_CLS	FUNCTIONAL CLASS
NO_LANES	NUMBER OF LANES
RTE_NBR	STATE ROUTE NUMBER
RTE_SUFX	STATE ROUTE SUFFIX
SEG_LNG	SEGMENT LENGTH

APPENDIX B: SAFETY PERFORMANCE FUNCTION AND EMPIRICAL BAYES (EB) CALCULATION

Safety Performance Function for single-curve segments

$$Target3yrs = AADT^{\beta_1} \times e^{(\beta_2 \times LVL + \beta_3 \times SHDWD + \beta_4 \times LN11LESS + \beta_5 \times MNANG + \beta_6 \times MNRAD + \beta_7 \times SPD50PLUS + \beta_8)}$$

Coefficient	Description	Estimated value	Standard Error
β_1	Average AADT over 3 years (veh/day)	0.707	0.047
β_2	Indicator for level terrain	-0.163	0.120
β_3	Shoulder width (ft)	-0.072	0.021
β_4	Indicator for 11 ft or narrower lane-width	0.169	0.087
β_5	Horizontal curve angle (degree)	3.12E-03	2.34E-03
β_6	Horizontal curve radius (ft)	-4.64E-05	1.61E-05
β_7	Indicator for posted speed of 50 mi/hr or higher	-0.352	0.132
β_8	Intercept	-3.853	0.426
k	Dispersion parameter	0.928	0.128

Safety Performance Function for multi-curve segments

$$Target3yrs = AADT^{\beta_1} \times e^{(\beta_2 \times LVL + \beta_3 \times SHDWD + \beta_4 \times LN11LESS + \beta_5 \times MNANG + \beta_6 \times MNRAD + \beta_7 \times SPD50PLUS + \beta_8 \times CURV + \beta_9)}$$

Coefficient	Description	Estimated value	Standard Error
β_1	Average AADT over 3 years (veh/day)	0.855	0.047
β_2	Indicator for level terrain	-0.241	0.145
β_3	Shoulder width (ft)	-0.067	0.024
β_4	Indicator for 11 ft or narrower lane-width	0.209	0.087
β_5	Average horizontal curve angle (degree)	8.77E-03	2.53E-03
β_6	Maximum horizontal curve radius (ft)	-2.55E-04	5.26E-05
β_7	Indicator for posted speed of 50 mi/hr or higher	0.242	0.106
β_8	Number of horizontal curves	-0.016	0.007
β_9	Intercept	-5.852	0.439
k	Dispersion parameter	0.462	0.076

The variables are defined as follows:

- Target3yrs is the predicted number of crashes on each horizontal curve segment (crashes/3 years)
- AADT is the average annual daily traffic through the curve segment (both directions, veh/day)
- LVL is an indicator variable for level terrain (=1 if the curve segment is in a level area, =0 otherwise)
- SHDWD is the paved shoulder width of the curve segment (ft)
- LN11LESS is an indicator variable for 11 ft or narrower lane (=1 if lane-width is 11 ft or narrower, =0 otherwise)
- MNANG is the curve angle of single-curve segment or average curve angle of multi-curve segment (degree)
- MNRAD is the curve radius of single-curve segment or average curve radius of multi-curve segment (ft)

- SPD50PLUS is an indicator variable for posted speed of 50 mi/hr on curve segment (=1 if the posted speed limit on the mainline is 50 mi/hr or higher, =0 otherwise)
- CURV is number of horizontal curves in the curve segment (for multi-curve segments only)

Empirical Bayes (EB)-adjusted number of expected crashes:

$$N_{expected} = w * N_{predited} + (1 - w) * N_{observed}$$

Where:

- $N_{expected}$ is the EB-adjusted number of expected crashes
- $N_{predicted}$ is the number of crashes predicted by the Safety Performance Function
- w is SPF weight, accounting for the accuracy of the SPF prediction:

$$w = \frac{1}{1 + k * N_{predicted}}$$

- k is the dispersion parameter of the SPF model

APPENDIX C: SPEARMAN'S RANK CORRELATION

The Spearman's rank correlation coefficient measures the statistical association between two rank variables. It is a non-parametric version of the Pearson correlation coefficient. The value of Spearman's coefficient ranges from -1 to +1 with the sign of the coefficient indicating the direction of the relationship. If a variable increases and the other variable also tends to increase, the association is represented by a positive value. If a variable increases while the other variable tends to decrease, the inverse relationship is presented by a negative value of the Spearman's coefficient. A Spearman's coefficient of +1 or -1 represents a perfect correlation, either on the positive or negative sides. When the coefficient increases in magnitude (closer to +1 or -1), the association between the two rank variables get stronger.

The Spearman's coefficient is calculated by the following equation:

$$\rho_{RX,RY} = \frac{COV(RX,RY)}{\sigma_{RX}\sigma_{RY}}$$

Where

- $\rho_{RX,RY}$ is the Spearman's correlation coefficient between two rank variables RX and RY
- COV(RX,RY) is the covariance of the rank variables RX and RY
- σ_{RX} is the standard deviation of rank variable RX
- σ_{RY} is the standard deviation of rank variable RY

If there are no ties in both rank variables, the coefficient can also be calculated by the following:

$$\rho_{RX,RY} = 1 - \frac{6\sum d_i^2}{n^3 - n}$$

Where:

- d_I is the difference between two ranks, d_I=RX-RY
- n is the number of observations