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Safety Performance Functions for Two-Lane Urban Arterial Segments

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Background

Background

The predictive method in the HSM is based on regression models named Safety Performance Functions (SPFs).

SPFs estimate the predicted average crash frequency N_b for certain base geometric and operational conditions.

To account for the differences between the specific base conditions and the site conditions, crash modification factors (CMFs) are utilized to adjust N_b , as follows:

$$N_e^i = N_b^i \prod_{\forall k} CMF_k^i$$

At site i, N_b^i is the predicted crash frequency for base conditions, N_e^i is the expected crash frequency, and CMF_k^i is calculated for specific geometric or operational feature k

Background (cont'd)

SPFs in the HSM were developed using historic crash data collected over a number of years at sites of the same facility type in various states in the U.S.

Therefor these SPFs cannot be transferred directly at other locations because of the expected differences in driver, environmental and geographic characteristics, crash reporting policies, etc.

To make the SPFs better accommodate the local data, two strategies are usually employed:

- Calibration of the SPFs provided in the HSM,
- Development of location-specific SPFs.

Both strategies are highly data driven.

Background (cont'd)

In calibration, a calibration factor C is calculated by:

$$C = \frac{\sum_{\forall i} N_e^i}{\sum_{\forall i} N_o^i}$$

Where, N_o^i is the observed number of crashes at site i.

Here, the difficulty lies in the calculation of N_e^i. Wide-ranging geometric and operational data are required to apply the corresponding CMFs.

There are 76 unique variables used in the HSM's predictive models, 47 of which are required, and the rest are desirable. Of the 47 required variables, 35 are roadway geometry related.

Collecting or extracting these data is labor intensive, thus it is crucial to automatically acquire as much data as possible from existing sources.

Objectives

Objectives

To present the SPF calibration and development process for the undivided two-lane urban and suburban arterial (U2) segments in New Jersey (NJ).

Data requirements, the availability of required data, and the data processing and extraction methods are presented, along with detailed results of the calibration and development process.

We also show the impact of crash location information on analyses results.

Key Take-Away: Efforts made to manually extract the missing required data can easily be offset by the inaccuracies in crash frequency databases, and the thresholds used to identify intersection related crashes.

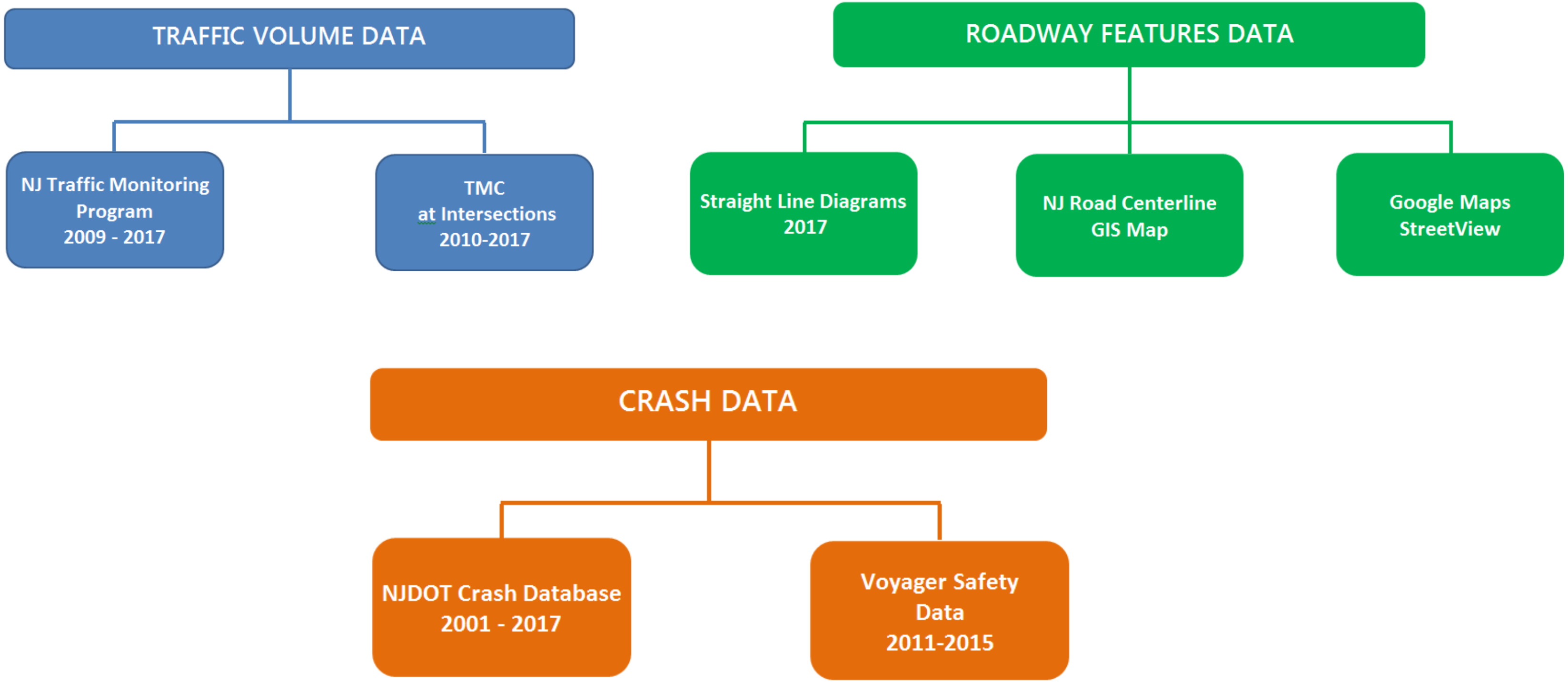
Data Requirements & Availability

HSM Data Requirements for U2

Data	Required	Desirable	Availability
Segment Length	✓		•
Annual Average Daily Traffic (AADT)	✓		•
Number of Driveways by Land Use Type	✓		+
Posted Speed Limit	✓		•
Presence of On-Street Parking	✓		+
Type of On-Street Parking	✓		+
Roadside Fixed Object Density		✓	
Lighting		✓	+
Presence of Automated Speed Enforcement		✓	

Note: • symbol means the data are readily available for NJ, + symbol means that data are manually extracted

Available Data Sources



Available Data Sources (cont'd)

The key source for roadway features data is the SLD database, maintained by the NJDOT.

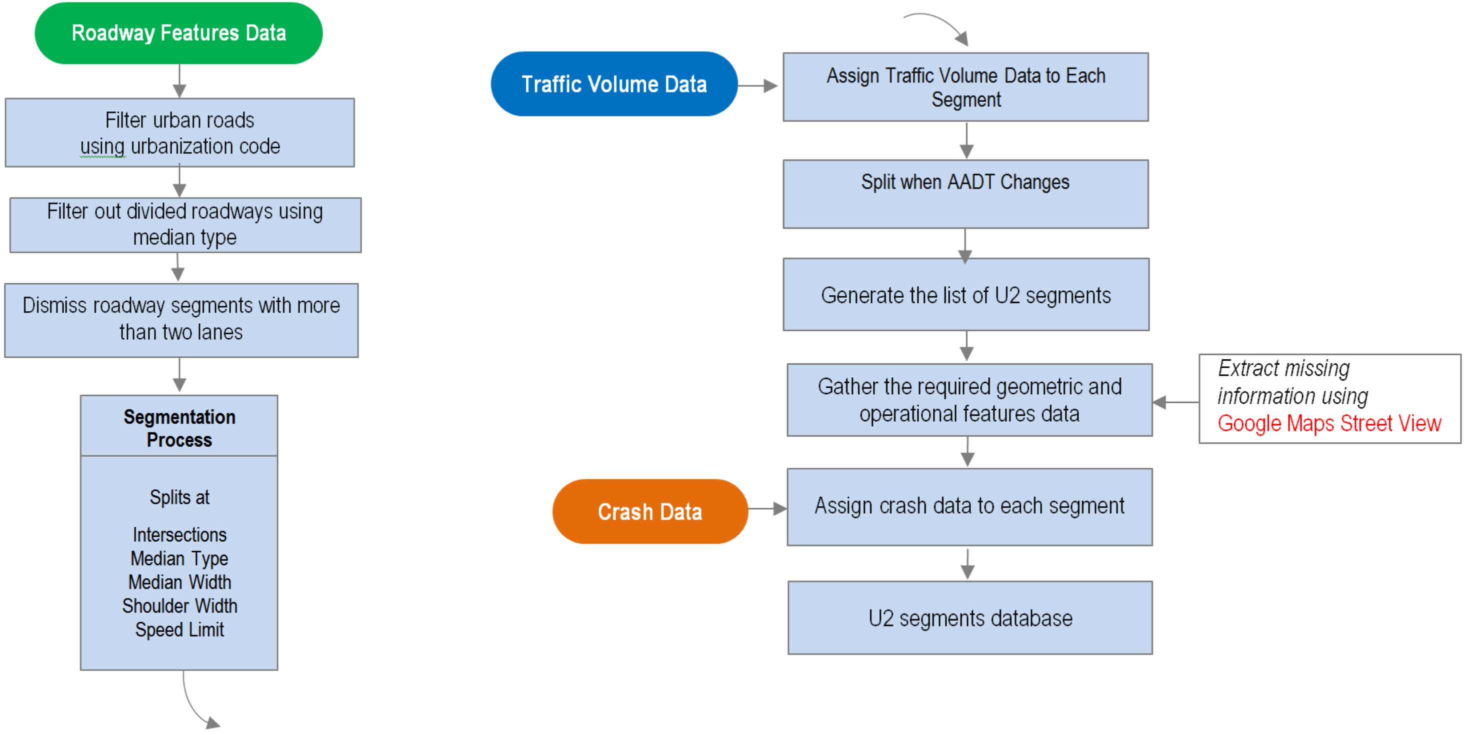
SLD includes various tables for different geometric and operational features of NJ roadways.

Motor vehicle crash data come from Safety Voyager crash database, provided by NJDOT for 2011 to 2015.

The information gathered from these three data sources can be used to generate the data required for the calibration and development of SPFs for U2 segments and intersections.

However, before generating these required datasets, the compiled data need be cleaned and corrected.

Data Processing for U2 Segments



Homogeneous Segments

An analysis ready database both for calibration and development requires homogeneous road segments.

Homogeneity means the geometric, operational characteristics and the AADT along a segment do not vary over the study period.

Homogeneous segments are determined by first splitting road segments at intersections, interchanges or any other locations where vehicles are allowed to make turns, and then at each point where there are any changes in geometric or operational characteristics.

A total of 36,008 homogeneous U2 segments were identified. It was determined that 11,610 segments were longer than 0.1 mile*.

Of the 11,610 segments, 1,639 were found to include a detector present within the segment.

Manual Data Extraction

The data required for the calibration process is not all matched by the existing database.

Manual data extraction was conducted using Google Maps™ aerial and street images.

The following attributes were extracted: (1) presence or absence of roadway lighting, (2) total number of driveways by type on the roadway segment, (3) number of driveways by type *, and (4) total number of on-street parking spaces* on the segment.

While extracting these attributes, automatically processed data was also verified visually (e.g. the number of lanes, type of segment (divided or undivided), etc.

It should be noted that due to limited time and resources, <u>the required data </u>for <u>372 U2 segments</u> out of the identified 1,639 were manually extracted.

Assigning Crashes to Segments

The distance between a crash and the closest intersection can be easily calculated, if the latitude and longitude of crashes and intersections were available (250-ft threshold).

In many crash databases the SRI (road index), milepost and travel direction information of crashes is usually incomplete.

In NJ, the police are equipped with GPS devices to record crash coordinates, yet the percent of crashes for which this information is actually included in the raw database varies from 26.4% to 45.8%.

The NJDOT post-processes the raw crashes and geocodes crashes with missing coordinates using SRI, milepost and cross street names.

After the post-processing, coordinates of nearly 95 percent of crashes from 2011 to 2015 were restored.

Final Dataset

Dataset 1: The 372 U2 homogeneous segments (out of the identified 1,639) with the required data were used for the calibration process.

Dataset 2: The remaining 1,267 segments were used for the development process.

Therefore, Dataset 2 is named as the *development dataset*.

The SPF developed using the development dataset was evaluated using Dataset 1, named as the *test dataset*. (77/23 split)

CRASH FREQUENCY

	0	1	2	3	4	5	6	7	8	9	10+
Test	0.578	0.204	0.078	0.041	0.029	0.023	0.014	0.004	0.002	0.008	0.019
Development	0.591	0.180	0.095	0.041	0.032	0.017	0.012	0.008	0.008	0.005	0.011

	CRASH MEAN	CRASH VARIANCE
Test	1.20	6.54
Development	1.15	6.32

Analysis

Analyses Outline

We demonstrated the robustness of NJ-specific SPFs using the development dataset based on its prediction accuracy on the test dataset, and to compare with the prediction accuracy of the calibrated HSM SPFs.

The analyses were structured as :

(1)The test dataset was used to compute the calibration factor for the U2 segments in NJ.

(2) The development dataset was used to estimate SPFs specific to NJ. Four different count regression models, namely negative binomial, Poisson, zero inflated negative binomial and Hurdle models were developed and compared.

(3) The prediction accuracy of the SPFs were then compared to the ones of the calibrated HSM SPFs using absolute residual statistics on the test dataset.

Calibration Results

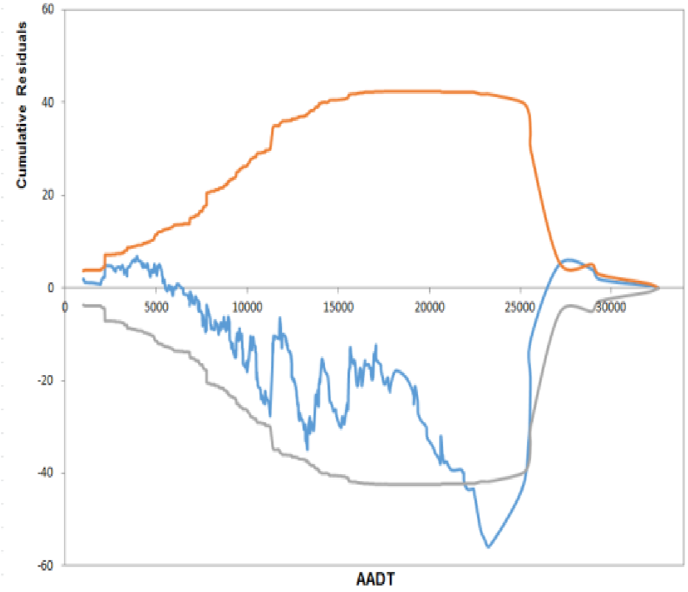
The Calibrator tool developed by the FHWA was used to calculate the calibration factor and measure its goodness of fit.

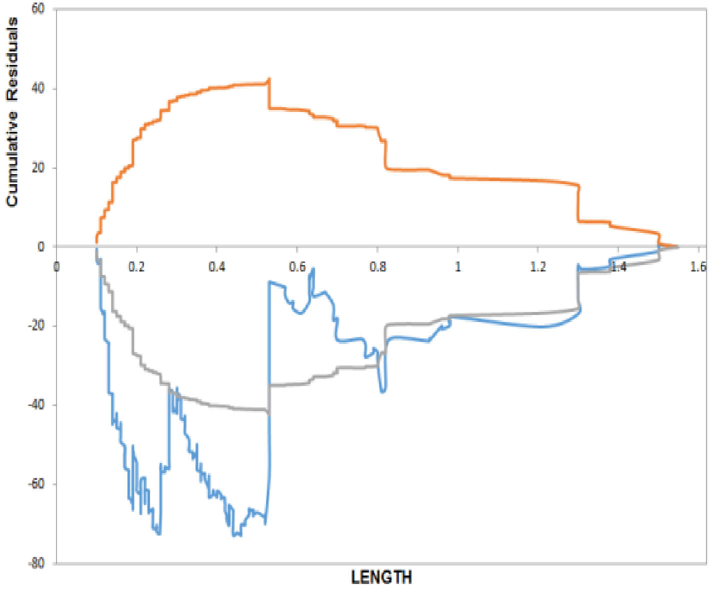
Using the compiled dataset, the calibration factor for U2 segments was found to be 1.35 with a coefficient of variation of 0.11.

The commonly accepted upper threshold for the coefficient of variation is 0.10 to 0.15.

In addition, to assess the validity of the calculated calibration factor, the cumulative residual (CURE) plots with respect to AADT and segment length were generated.

Calibration Results (cont'd)





The cumulative residuals deviate significantly from the allowable upper and lower bounds.

Though the calibration factor is close to 1.0 and that coefficient of variation is within acceptable bounds, the calibrated SPF for U2 segments is not statistically acceptable.

Development Results

The base SPFs for multi vehicle and single vehicle crashes for U2 segments in HSM have the following functional form:

$$N = \exp[a_0 + a_1 . ln(AADT) + a_2 . ln(L)]$$

L: length is used as an offset variable in the HSM (i.e. $a_2 = 1$)

HSM's predictive model follows this functional form only for multi-vehicle and single vehicle crashes.

Multi-vehicle driveway related crash counts are estimated by a simple power function with AADT as a covariate.

Pedestrian and bicycle crashes are computed as a percentage of the total predicted non-pedestrian and non-bicycle crashes.

Development Results (cont'd)

Variable	Estimate	Std Error	z-value	Pr(> |z|)	95% Confidence Interval
U2 Segments NB Model (n = 1,596)					
Intercept	-8.616	0.6385	-13.49	< 2e-16***	[-9.878, -7.382]
log(*AADT*)	1.114	0.0702	15.88	< 2e-16***	[0.979, 1.253]
log(*L*)	1.402	0.0576	24.34	< 2e-16***	[1.284, 1.522]
Null Deviance: 2,282.3, Residual Deviance: 1,362.2 with 1,593 dof, *AIC*: 3,860.8, *BIC*: 3,882. 3, α= 0.918					
U2 Segments Poisson Model (n = 1,596)					
Intercept	-8.301	0.5664	-14.655	< 2e-16***	[-9.419, -7.199]
log(*AADT*)	1.160	0.0448	25.89	< 2e-16***	[1.073, 1.249]
log(*L*)	1.318	0.0350	37.62	< 2e-16***	[1.249, 1.387]
log(SPD)	-0.226	0.1154	-1.958	0.0502	[-0.450, 0.002]
Null Deviance: 4,748.6, Residual Deviance: 2727.4 with 1,592 dof., *AIC*: 4450.3, *BIC*: 4,471.8					
U2 Segments ZINB Model (n = 1,596)					
Intercept	-8.409	0.6880	-12.22	< 2e-16***	[-9.757, -7.060]
log(*AADT*)	1.070	0.0756	14.15	< 2e-16***	[0.922, 1.218]
log(*L*)	1.035	0.0765	13.52	< 2e-16***	[0.885, 1.185]
Zero-inflation component (binomial)					
Intercept	-4.4610	3.1289	-1.426	0.154	[-10.594, 1.672]
log(*AADT*)	-0.1905	0.3046	-0.625	0.532	[-0.787, 0.406]
log(*L*)	-3.1537	0.4972	-6.343	2.26e-10	[-4.128, -2.179]
AIC: 3,820.6, *BIC*: 3,858.2, α= 0.672					
U2 Segments Hurdle Model (n = 1,596)					
Intercept	-9.0308	0.9939	-9.086	< 2e-16***	[-10.979, -7.083]
log(*AADT*)	1.1185	0.10703	10.451	< 2e-16***	[0.908, 1.328]
log(*L*)	1.0217	0.0878	11.637	< 2e-16***	[0.849, 1.194]
Zero-hurdle component (binomial)					
Intercept	-8.3774	0.9383	-8.928	< 2e-16***	[-10.216, -6.538]
log(*AADT*)	1.1713	0.1071	10.933	< 2e-16***	[0.961, 1.381]
log(*L*)	1.956	0.127	17.353	< 2e-16***	[1.735, 2.177]
AIC: 3,817.8, *BIC*: 3,855.4, Dispersion parameter, α= 1.054					

Development Results (cont'd)

The model estimation was performed in R statistical package.

The results shown are the best fitting model parameters after experimenting with models that included shoulder width and speed limit on each segment.

Only AADT and length variables came out statistically significant in the count models except in the Poisson model.

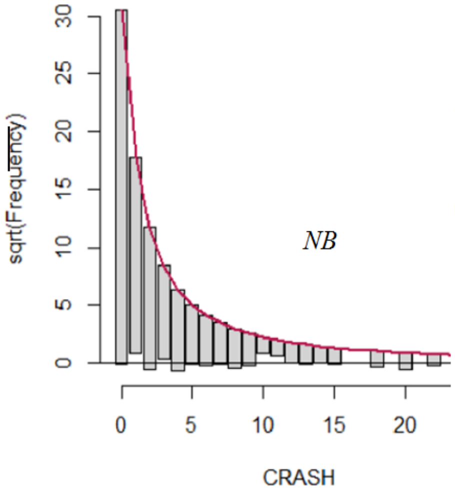
In the ZINB model, only the length variable came out significant in the zero-inflation component.

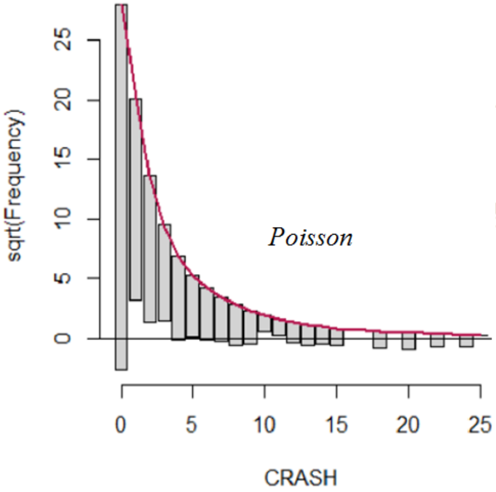
Therefore, NB, Poisson and hurdle models were selected for further exploration.

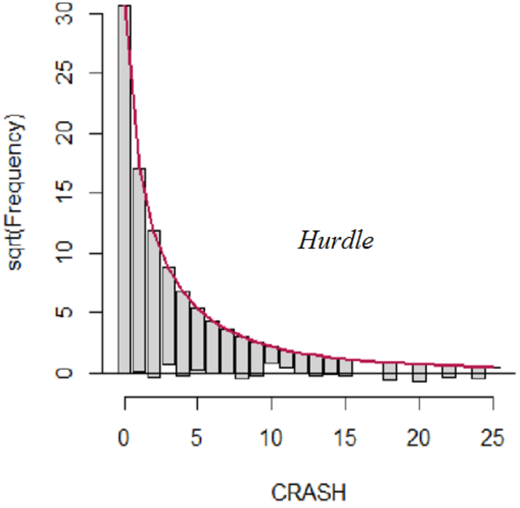
Development Results (cont'd)

Hurdle model has a slightly lower AIC and BIC values than those of the NB model, which is also significantly lower than the Poisson model, as expected.

This was also evidenced from the rootogram plots, which compare the observed and expected values graphically by plotting histogram-like rectangles for the observed frequencies and a curve for the theoretical fit.



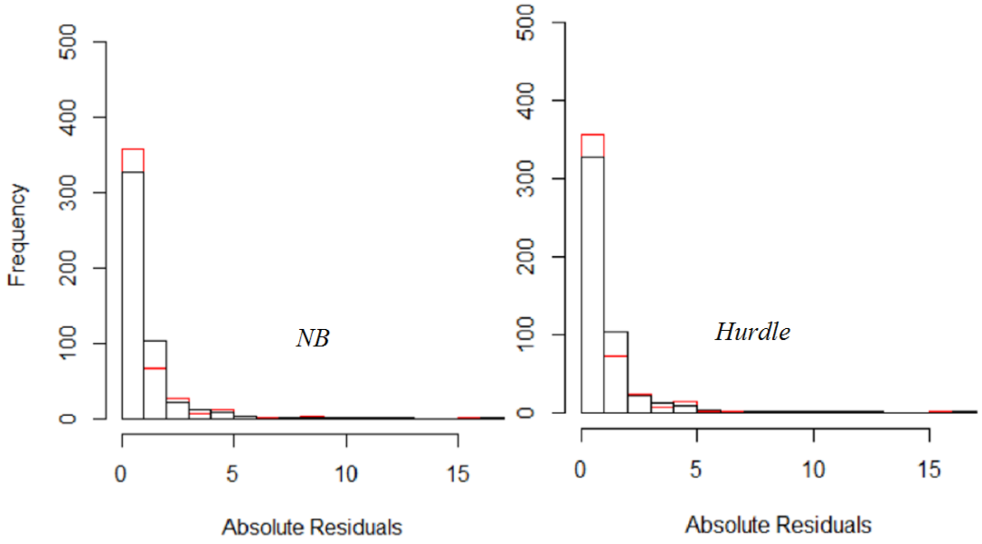




Development Results (cont'd)

The test dataset was used to test the prediction accuracy of the SPFs generated using the development dataset, and to compare those of the HSM SPFs.

The histograms of the absolute value of residuals of the SPFs' predicted values and those of calibrated HSM SPFs are:



The red line indicates the histogram of absolute residuals obtained from the NJ-specific SPFs.

Discussion & Conclusions

Discussion

The validity of the number of observed crashes depends on:

(1) the results of the geocoding post-process performed by NJDOT, and
(2) the 250-ft threshold used to identify intersection-related crashes.

In 2019, the NJDOT updated its post-processing procedure based on a tighter threshold used in geocoding process to increase the accuracy of crash coordinates, which resulted in 14.7 % less number of crashes state-wide compared to its previous version.

The calibration process was performed again using the test dataset, but with the previously estimated crashes, and the calibration factor was calculated as 1.74, a significant deviation from the current value of 1.35, stated before.

Discussion (cont'd)

The correct identification of intersection-related crashes is of upmost importance yet this distinction is not possible in most crash databases, including the Safety Voyager data.

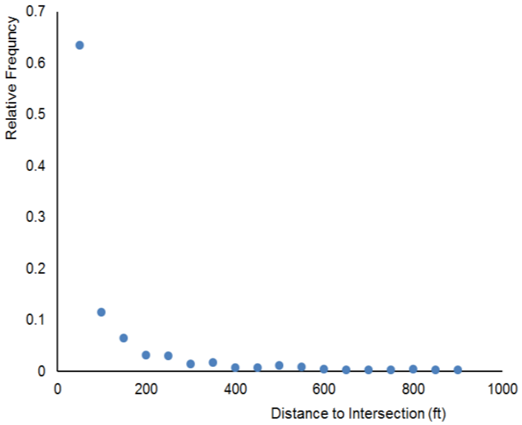
A detailed investigation of the model residuals showed that many crashes, identified as <u>segment-related</u> as per the 250 ft. threshold, appeared to be <u>intersection-related</u> based on crash characteristics (e.g. cluster of rear-end crashes in the peak periods).

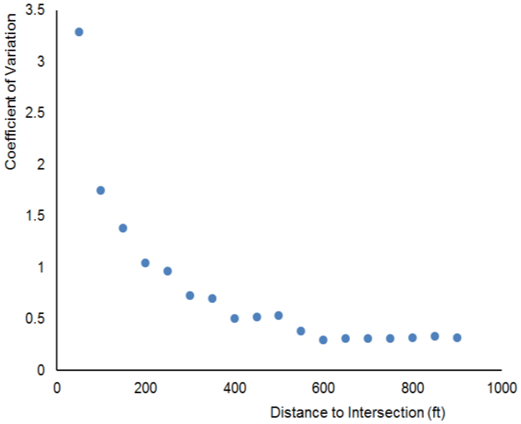
The frequency of crashes in the vicinity of each intersection was determined at 50 ft. intervals using the available crash database at a total of 5,672 urban intersections .

It is assumed that the "effect" of an intersection would reduce as the crash distance to the intersection increases, and there would be a somewhat uniform spatial distribution of segment related crash frequencies.

Discussion (cont'd)

The left plot in shows that the majority of the crashes are clustered within 100 ft. of intersections, and that 87.5 percent were reported within 250 ft. of intersections.





The right plot in shows the distribution of coefficient of variation (CV) of crash frequencies as the threshold is increased.

When the threshold is 50 ft. the CV of crash frequencies within the remaining segment is nearly 1.75. Notice that the CV attains a fixed value as the threshold is near 550 to 600 ft. from the intersection

Conclusions

We presented the SPF calibration and development process for the U2 segments in NJ. The available datasets were grouped into development and test datasets.

The test database was used to calculate the calibration factor for U2 segments, following the calibration process presented in the HSM.

Four generalized linear models, specific to NJ, were generated using the development database.

The prediction of the generated models were then evaluated and compared to those of calibrated HSM model, using the test dataset

The results showed that the negative binomial and hurdle models yield nearly 10 percent improvement in average absolute residual statistic compared to that of HSM SPF.

Conclusions (cont'd)

The impact of crash location on calibration factors was investigated, and shown that calibration factor varies significantly with the crash location assumptions.

When the calibration process was repeated for the test dataset with the 550 ft. threshold, for example, the calibration factor was calculated as 0.71.

The significance range of fluctuation of the calibration factor, from 0.71 to 1.74, when certain assumptions are modified, sheds light on the fact that efforts made to manually extract the required roadway geometry and operational features data not included in available data repositories can easily be offset by the inaccurate or incomplete entries in crash databases.

Thanks for Listening !

For questions, suggestions, feedback:

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