Systemwide Intersection Safety Prioritization Development and Assessment

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ABSTRACT

This paper presents the development and assessment of a systemwide intersection safety prioritization tool. Generation of a systemwide intersection crash list and ranking of intersections using a new intersection safety ranking methodology are the two main components. An automated, comprehensive and sustainable process of generating the intersection crash list was designed and it addresses issues such as crash location and distinguishing between intersection and corridor safety problems. The new ranking methodology uses a score that is a composite of crash frequency, crash severity and crash type. Sensitivity analyses indicate that the rankings generated from 1-year data are significantly different from the 5-year data with Percentage Different (PD) intersections ranging from 31 to 47 and correlation between the rankings varying from less than 0 to a maximum of 0.42. For 3-year data the PD varied from 14 to 21 and correlation ranged from 0.21 to 0.76. Therefore 1-year data should be used with great caution for prioritizing intersection safety and it is strongly recommended that a minimum of 3 year data is used. It was also found that weights used in the composite ranking were not as significant in altering the prioritization of safety as the number of years of data used. Using Median score was explored as an alternative to using total score for the intersection prioritization. It was found that although the PD was low (around 14) the correlation varied significantly from 0.73 to 0.21. Median ranking should be used with caution for generating larger lists of intersections for safety prioritization.

INTRODUCTION

Intersection safety is a crucial component of highway safety; intersection fatalities constitute approximately 22% of total highway fatalities and intersection crashes compose of over 45% of all reported crashes every year (1). Methods to identify and rank intersections with safety concerns, which may be addressed through engineering improvements, are commonly used by transportation agencies. These methodologies allow the development of a "ranked list" of intersections based on reported crash data. Even though many methods share the purpose of identifying intersections with the most safety concerns, the methods can have significantly different outcomes. The methods available to identify unsafe intersections could be presented in four categories: Counts, Rates, Composite, and Empirical Bayes (2-4). There are a few variations in each category such as frequency, equivalent property damage and value loss in counts. Very often, counts, rates, and crash severity measures are combined to form a severity index as part of the composite methods. A stand alone approach to measure safety is the Empirical Bayes (EB) method (5-7). In this paper the development and assessment of a systemwide intersection safety prioritization tool is presented. First the development of the intersection Crash List is presented followed by the new ranking methodology. Also presented are the results of sensitivity analyses performed on the new methodology. Finally conclusions and recommendations are presented.

SYSTEMWIDE INTERSECTION CRASH LIST

The first step in the ranking of intersections for identifying safety improvement locations is to generate a reliable intersection crash list. Although this appears to be rather straightforward, several issues need to be addressed. These issues are improper recording of crash locations (in the crash reports) at an intersection perhaps due to alias or spelling errors, and distinguishing corridor safety issues from intersection safety issues.

In this research an automated, comprehensive and sustainable process of generating the intersection crash list was designed. The list generation should be rapid and require minimum manual operations, hence the need for automation. Comprehensive indicates that intersection safety has multi-facet causes and should not solely be evaluated by crash counts. Since the crash data is subject to changes such as adding/removing/correcting crash reports or other information, the process should be designed for rapid regeneration, maintenance and updates.

Crash Data Collection and Compilation

Crash data is continually collected and archived by the Wisconsin Department of Transportation (WisDOT). Crash location information is entered manually by law enforcement agencies on the crash report form then verified manually and assigned a reference point (RP) and an offset by WisDOT staff if it is a state highway-related crash. The post process ensures that crashes that occurred on the state highway system could be spatially located using the WisDOT linear referencing system (LRS). Any crashes located more than 0.02-mile away on the intersecting non-STH roadway are considered as an off-state route crash and rarely geocoded.

Information about Intersections on the State Trunk Network (STN) is kept in a geospatial database that includes all intersecting highways. A total of 22,863 spatially unique intersections are identified and updated regularly in the Access Point Table, including driveways and various access points to the STN System. Classification of a crash as an intersection crash is made by a law enforcement official and entered as “intersection related”.

Methodology of Geocoding Intersection Crashes

Crash reference points (RPs) are employed to relate crashes to the relevant intersections spatially. The process is performed using WisDOT Location Control Manger (LCM) built upon on the department legendary LRS. The process begins by collecting the intersection-related crash data from the crash database. Each intersection-related crash is linked to the nearest intersection based on the spatial distance, resulting in an aggregation of all crashes to a particular intersection. A state highway intersections crash count map is illustrated in Figure 1 with data from 2002 through 2005. Crash records are further categorized by crash severity, crash type or manner of collision. Crash severity includes property damage only (PDO) crashes, and Type C, B, A and K crashes. These letters indicate the severity of the crash injuries starting from minor (type C) to fatal injuries (type K). The post-processed data includes intersections with data categorized by: total number of crashes, number of crashes by severity, and number of crashes by manner of collision or crash type.

Alternative Geo-coding Procedure Using Google Maps™ API

Relating crashes to the nearest intersection may result in grouping crashes to an intersection where they did not occur. In this study, the Google Maps™ API was researched as an alternative crash location tool (8). In addition, Google can be used to create a Google Map link to an intersection so that engineers can open the link and perform preliminary scans of intersection configurations using Google images or aerial maps.

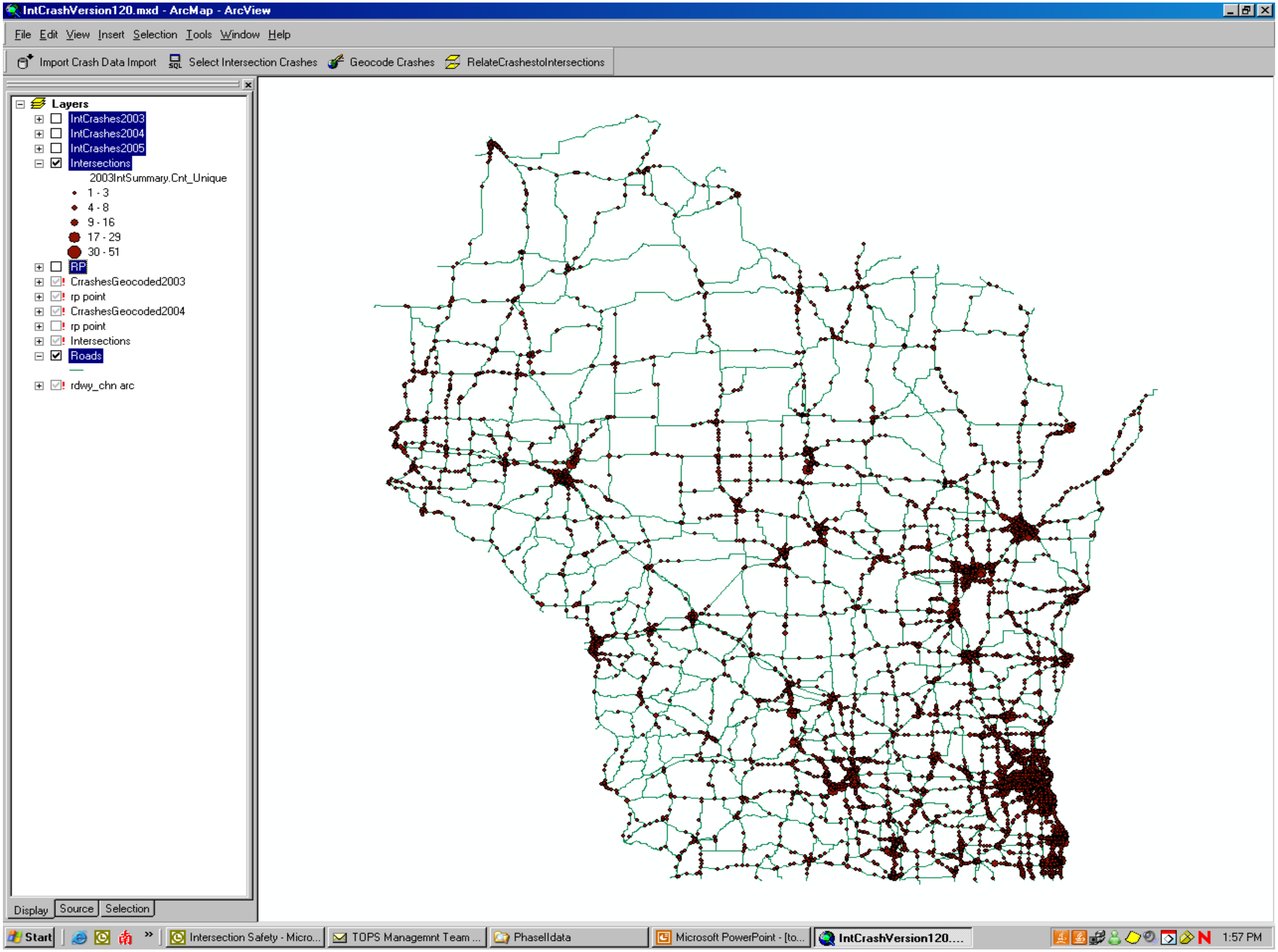

FIGURE 1 Wisconsin statewide intersection crash count map.

The location information supplied to Google Maps™ for geocoding was the list of crashes with location data. Google found matches for about 80 percent of the crashes. Despite the powerful capability provided through the Google map application, the results returned from the Google Maps™ API should be analyzed with caution. Specifically the following are issues in using Google Maps API:

1. Google applies a complicated algorithm to provide a "best guess" if the input location does not have the exact match in its database; Thus further location quality assurance might be required to ensure that the identified locations are correct.
2. Google cannot recognize some highway facilities including *from, to, on, off, median, ramp, exit, bound, eb, wb, sb, nb*, etc; therefore, the highway names in the crash reports need to be cleaned.
3. Google has a different way of spelling US highways, State highways and County highways, so a conversion is needed before mapping in Google.
4. Google's database for geocoding may be different from the one for Google Maps™ provided by NAVTAQ™. The discrepancies in two resources may cause some issues, such as different addresses in Google geocoding and a Google map link;

Quality Control Using Google Maps API

Google Maps API has also been experimented as a possible tool for QA/QC for the following:

1) To Standardize intersection name by selecting the intersection address that appeared the most in police reports; and
2) To distinguish between an intersection safety issue and a corridor safety issue.

For each intersection, all of the crashes were examined for the intersection name. The standardized name was determined based on the name that appeared most in the crashes that were assigned to that intersection. For example, in Figure 2a, 141 crashes were identified around intersection 44984 during the five-year period and about 98% were called *W Johnson St & N Pioneer Rd, Fond du Lac, WI* in police crash reports. Since the majority of crashes (98%) were coded to the same intersection, the name was standardized as *W Johnson St & N Pioneer Rd, Fond du Lac, WI* with a high level of confidence.

It is possible that the crashes are assigned to a nearby intersection rather than to the actual intersection because the crashes were aggregated to an intersection by distance from the intersection. This situation usually occurred in urban areas where intersections were closely spaced. Consequently a corridor safety issue may be categorized as an intersection safety issue. For example, intersection 10201 (shown in Figure 2b) was geocoded with 68 crashes. About 35% of them were recorded in police reports as *S Howell Ave & W Layton Ave, Milwaukee, WI* with the rest called differently. Even though the majority

(35%) indicated the poor safety performance of *S Howell Ave & W Layton*, it might rather be considered as a corridor-based safety issue than an isolated intersection problem because 44 out of 68 crashes were in the proximity of the intersection of *S Howell Ave* and *S 13St*.

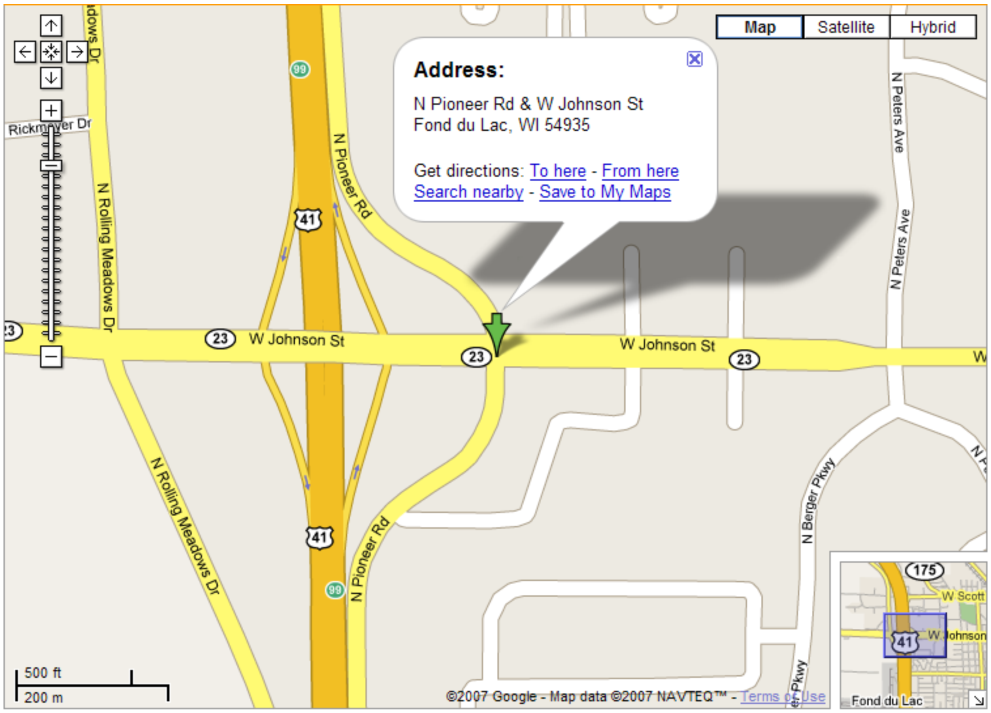

FIGURE 2a Name intersection with majority crash locations.

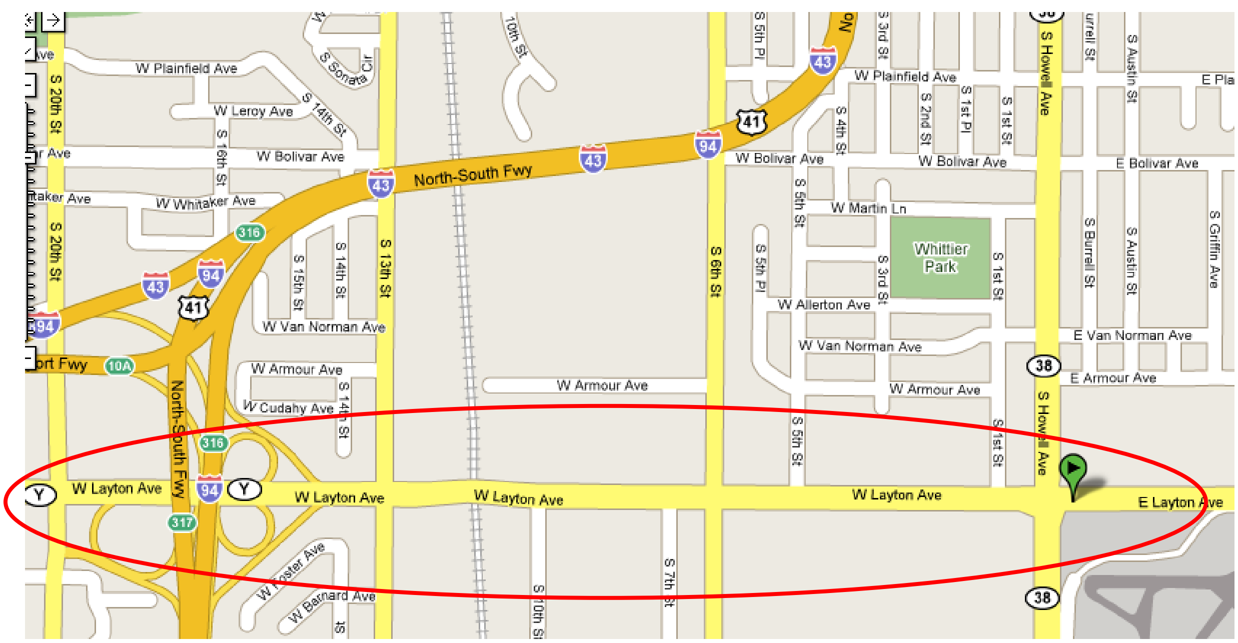

FIGURE 2b A corridor-based safety problem versus isolated intersection safety issue.

INTERSECTION SAFETY RANKING METHODOLOGY

Using the generated intersection crash list, an intersection safety methodology is proposed to identify intersections for safety improvements. This methodology used a composite ranking considering crash frequency, severity and crash type. This methodology differs from other composite methodologies because it incorporates crash type explicitly in the ranking. A final score of the scores (FS_S) was assigned to each intersection using Equation 1. The scores are summed for all years of crash history to give the FS_s for the study period. A composite rank was obtained by ranking the FS_S from highest to lowest.

$$FS_S = 100\left(\frac{1}{5} \times \frac{Crash\ Frequency}{Max(Crash\ Frequency)} + \frac{3}{5}\frac{SI}{Max(SI)} + \frac{1}{5}\frac{TypeScore}{Max(TypeScore)}\right) \qquad (1)$$

Where

FS_S = The weighted score of the scores

Crash Frequency = Total crash count over the study period (i.e., 5-years)

SI = Total Severity Index for the study period

Type Score = Total score of crash type

Max (Crash Count, SI, and Type Score) = Maximum Score of each in the study period

Equation 1 combines the total crashes of each intersection, a score for the severity of crashes at each intersection called severity index (SI), and a score based on the type of crashes that occurred at the intersections called Type Score. The details of computing these three components are elaborated in the following sections. The weights of 1/5 for crash frequency, 3/5 for SI and 1/5 for crash type were established based on the relative importance of the factors. SI was given a higher weight considering that the severity of the crashes is of highest concern.

Ranking Criteria

Crash Frequency

The total number of crashes for the study period was obtained by adding the individual crashes reported for each intersection.

Severity Index

The crash database contains information of the most severe injury of every crash, thus defining the severity of the crash. After the severity of each crash was obtained, a score-based criterion was used.

This score represented by SI, is an indicator of the total severity of the crashes that occurred at the intersection (4). In this approach each of the injury levels (K, A, B, C) are given a weight. The SI is calculated as shown in Equation 2. The weight of each injury level represents a ratio of the relative average crash cost by severity using the relative cost based on property damage only crashes. The weight values used in Equation 2 were established similar to the Illinois DOT methodology injury level weights (9). The weights for each injury level used are the same as the Illinois DOT methodology up to injury level A. Because of the tremendous impact and cost that a fatality has according to the NSC (10), the weight value of fatality was increased based on engineering judgment.

$$SI = 40N_K + 9N_A + 5N_B + 2N_C + N_{PDO} \qquad (2)$$

Where

N_K = Number of injuries of type K

$N_{A,}$ = Number of injuries of type A

$N_{B,}$ = Number of injuries of type B

$N_{C,}$ = Number of injuries of type C

N_{PDO} = Number of PDO crashes

The weighting coefficient selection for a fatality can significantly influence the SI score. Therefore, 4 combinations of weights were tested to evaluate what effect the changing of the fatality weight brings to the ranking. Combination A tests the Illinois DOT coefficients for the SI (1, 2, 5, 9 and 10 for PDO, C, B, A and K, respectively). Combinations B, C and D have weights of 100, 150 and 200 respectively for a fatality (all other weights are the same as Illinois DOT). Combination E uses the relative costs from PDO crashes as established by the NSC as weights which are 1, 11, 23, 88 and 1745 for PDO, C, B, A and K, respectively.

As shown in Figure 3, combinations A and B have the lowest risk to influence the ranking since they show the lowest percent difference (PD) from the original FS_s methodology. When combinations C, D and E are used then the risk is significantly increased. As the severity weight is increased in combinations C and D the PD increases between 30 and 40 percent. If the NSC ratios are used, as shown by combination E, then the ranking changes by more than 40 percent. Therefore, a number weight between 10 and 100 for fatality would lower the influence that fatalities have on the ranking.

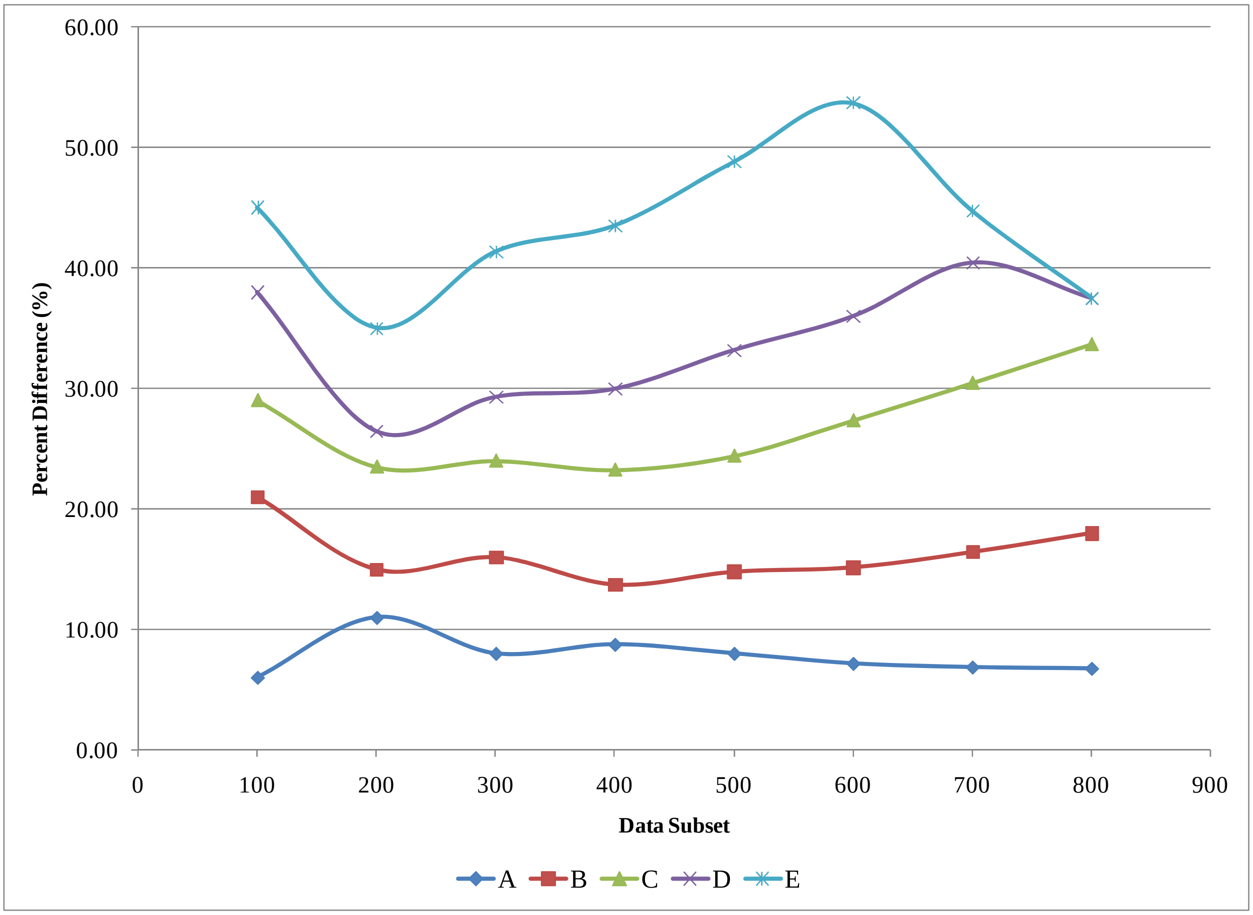

FIGURE 3 Weighting Coefficients Alternatives for SI PD to the Original SI Coefficients

Crash Type

Crash type, primarily determined by vehicle movements (e.g., angle, head-on) and crash characteristics such as the involvement of a pedestrian and the amount of vehicles, is one of the most important indicators of safety problems at an intersection. It is also the most direct lead for engineers to consider possible countermeasures. A score based on the cost of a crash per vehicle for each type of crash was used. As a result, the methodology allows ranking each intersection by crash characteristics and by the amount of damage incurred based on the type of crashes reported. As shown in Equation 11, the sum of the product of the number of involved vehicles (N_v) with the approximate cost incurred per vehicle determines the crash type score. The crash costs for each crash type were developed by Campbell and Knapp (9).

$$TypeCost = \sum Cost \times N_v \qquad (3)$$

Where

Cost = Cost of each crash type

N_v = the number of involved vehicles for each crash

Following these steps, the data necessary to apply the FS_s equation is obtained. The score of each intersection, based on the total crash frequency, severity and crash type, can be calculated for the study period. The list of ranked intersections provides a reliable starting point to the prioritization of safety improvements.

Sensitivity Analysis

The ranking methodology used in this study has many parameters for which certain values have been adopted based on past practice and the authors' knowledge. Therefore, it is important that a sensitivity analysis be performed to quantify the effect of choosing different values for the parameters. A sensitivity analysis has been performed for the following two parameters:

1. Number of years of data used
2. Weights used for the crash frequency, severity index and crash type in computing the final score of scores.

The rankings generated by the different parameters were compared using Percent Difference (PD) and Correlation similar to Miranda-Moreno et al.(12). Percent Difference quantifies the percentage of intersections that are different between the two listings. In addition to PD, it is also important to evaluate the internal variation in ranking positions. A low PD between the two ranked lists is a good indication but a low correlation could potentially influence the prioritization of safety funds because ranking positions are dramatically different between the two lists. The Pearson product moment correlation coefficient among two ranked lists was obtained with Equation 4 (11).

$$Correl(X,Y) = \frac{\sum(x-\bar{x})(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2\sum(y-\bar{y})^2}} \qquad (4)$$

Where,

$\bar{x}$ and $\bar{y}$ are the sample means of x and y

Effect of Number of Years of Data Used

This analysis was performed to evaluate the risk of misidentifying hotspots by using fewer years of crash history. There are two issues with crash history duration that need to be considered. First, as years pass, sites experience changes that are influenced by factors such as traffic volume, maintenance, land use changes, and weather. Therefore, longer crash history is usually associated with less stable safety performance functions. In contrast, short periods of data experience random fluctuations and/or regression to the mean bias on crash counts. Some jurisdictions use 1-year data for generating the ranking of intersections, although using 3-year data is a more common practice (13). This analysis provides information about the difference in the ranking generated when multiple year (1-year, 3-years, and 5-years) crash history is used. This analysis establishes the tradeoffs and benefits of using multiple year data.

Previous research by Cheng and Washington has shown that at least 3 years of crash history data and no more than 6 years should be used for a hotspot identification method (14). However, it should be noted that data generated from simulation was used by Cheng and Washington in their study. Five years of crash history is normally considered as the best and most complete data practitioners can obtain; as a result in this research, the intersections list created from 5-years data are deemed true hotspots.

Following the ranking methodology presented in this paper, intersection lists are generated using shorter periods of one-year and three-years of crash history. PD and Correlation are computed with respect to the intersection list generated from the five year data.

Figure 4a presents the PD when rankings from yearly data are compared with the 5-yr total rank. For the top 100 sites, this figure shows a significant difference of 37 to 47 PD of sites when compared to the 5-year total rank. This result gives an insight of how different and inaccurate a yearly ranking approach could be. The trend of the graph also shows that as the data subset is increased the PD decreases in general. Therefore, in order to ensure that more true hotspots are evaluated with only one year of crash data, more sites should be reviewed. The relative position of sites among ranked lists could also have a significant impact in the prioritization of hotspots. Figure 4b shows the correlation between the yearly rank and the 5-year total rank. Depending on the year, most of the correlation coefficients are between 0.0 and 0.3, suggesting a weak similarity between lists. The correlation results add more evidence to the inaccuracy of using one-year data. The chart also shows a trend of higher correlation as the data subset increases.

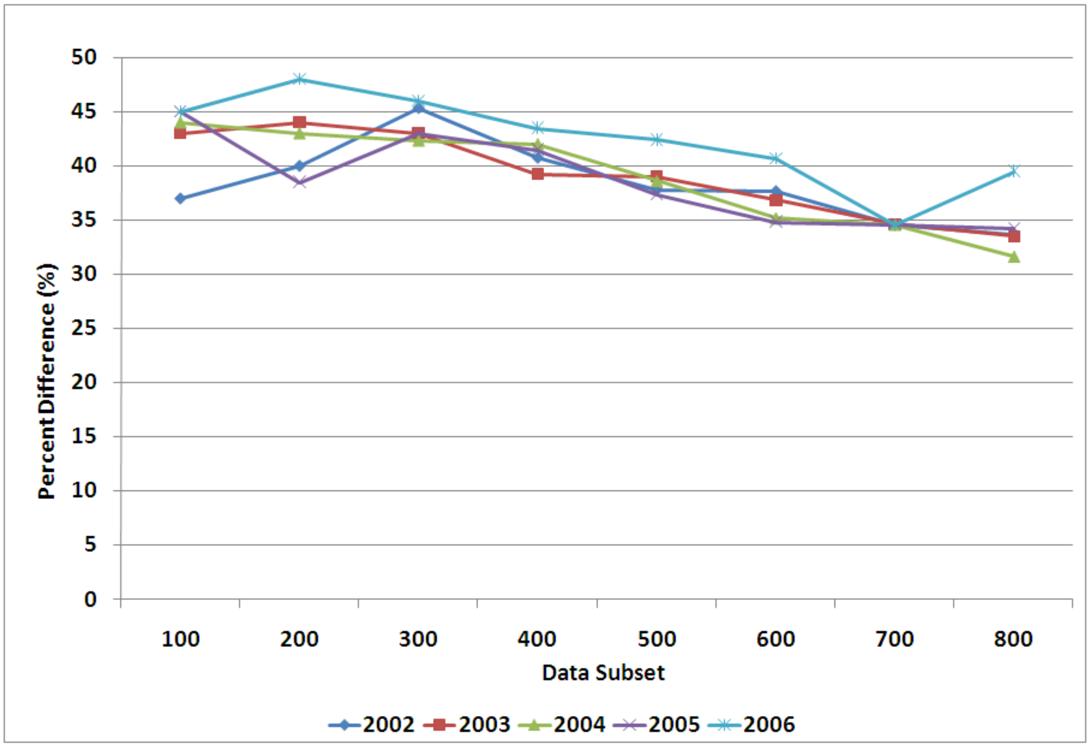

FIGURE 4a Yearly Ranks PD with 5-years Total Rank

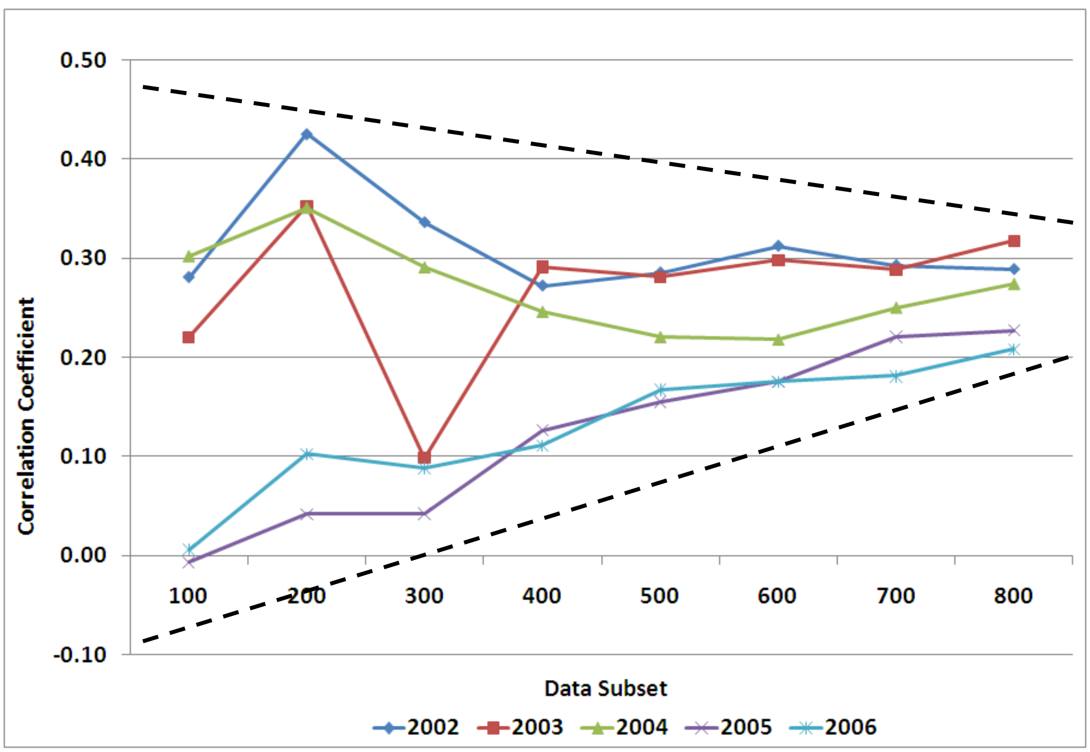

FIGURE 4b Yearly Ranks Correlation with 5-years Total Rank

When the crash history data used is increased to three years, PD decreases considerably when compared to yearly ranks as shown in Figure 5a. Generally speaking, the variability of 3-year ranks' PD is between 14 and 20. These results are very stable when compared to yearly ranks. In order to agree with more certainty that a 3-year total ranking approach yields comparable and acceptable results to a 5-year total rank, the correlation coefficient was determined and analyzed. Figure 5b shows the correlation between the 3-year total ranks and the 5-year total rank. For the top-100 ranked sites the correlation coefficients of all moving time window three year combinations is around 0.7. Therefore any three year combination strongly agrees with the ranking positions of the 5-year total ranking approach for the top-100 sites. The top 200 and 300 ranked sites strongly agree with the 5-yr total rank with a correlation coefficient over 0.7 for the 2002-2004 and 2003-2005 three year ranking combinations. The most recent combination of three year data (2004-2006) has a correlation coefficient around 0.4, indicating that the randomness of crash occurrence still could have a significant impact in the ranking order. For the rest of the data, between the top-400 and 800 sites, the correlation coefficient has a range between 0.2 and 0.55 that outperforms yearly data. Very often the top-100 ranked hotspots are the sites that transportation agencies are most interested in. In short, the 3-year total ranking approach results in similar ranking positions for hotspots, especially within the top-100 ranked intersections. In summary, a yearly rank fails to provide sufficient accuracy required to identify true hotspots. Therefore, an effort to use at least 3 years of data should be made.

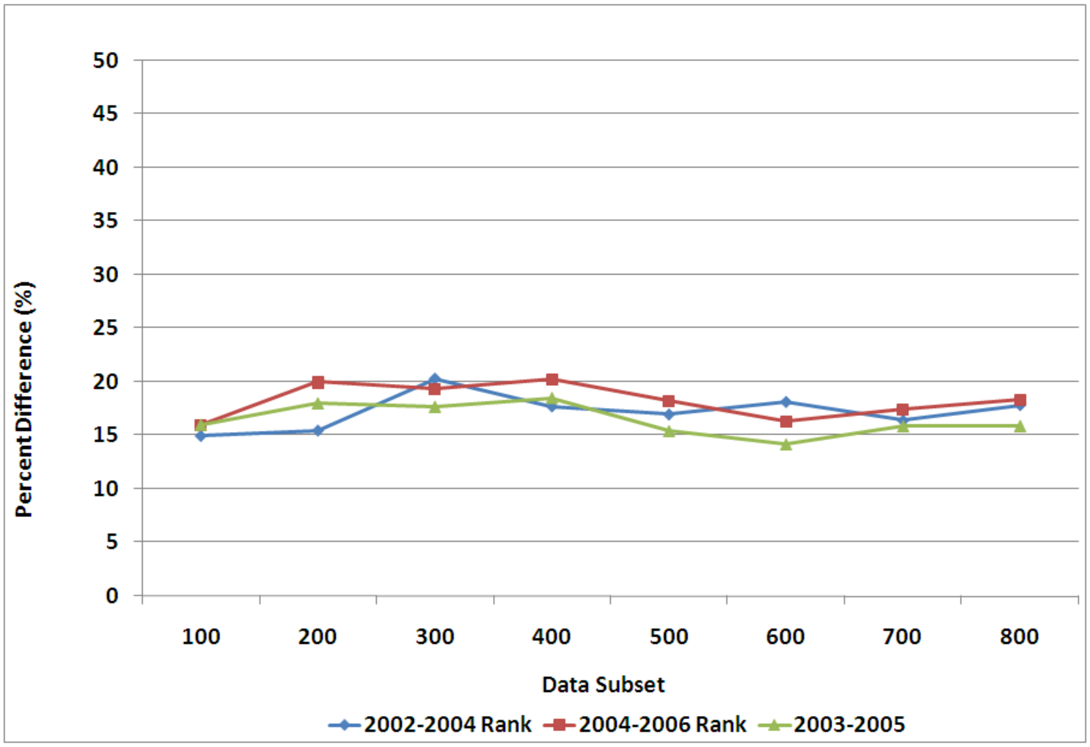

FIGURE 5a Total Rank of 3-years PD with 5-years Ranks

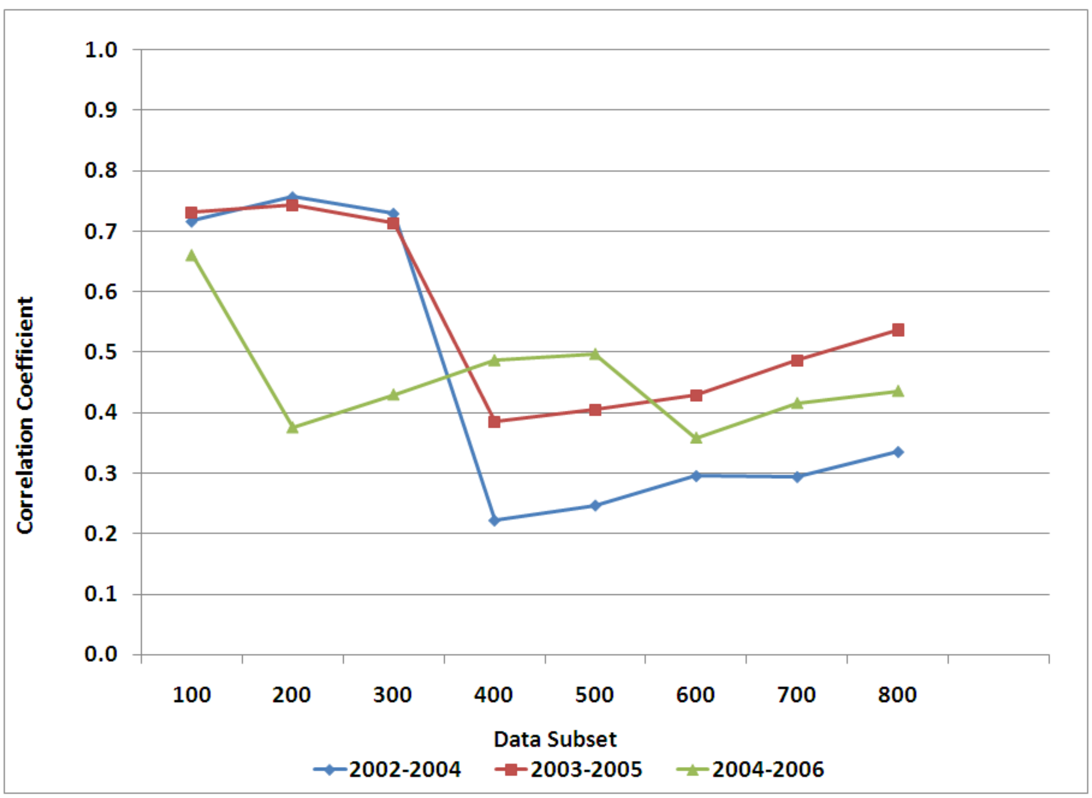

FIGURE 5b Total Rank of 3-years Correlation with 5-years Total Rank

Effect of Alternative Weighting Coefficients

The ranking methodology uses a weighted index method based on the relative importance of crash frequency, severity index and crash type. Therefore, it is essential to determine the influence that the weighting coefficients have on the ranking of intersection hotspots when compared to the weighting coefficients used in the methodology of this research. In addition, it was important to confirm that the weighting coefficients originally established are acceptable when compared to other weighting combinations.

A similar approach to Hallmark and Basavaraju (10) is taken where a higher weight was given to crash frequency or crash type, almost equal weights are used, or a higher priority is given to severity.

The weighting factors used are 1/5 for the crash frequency, 3/5 for the severity index and 1/5 for the crash type ranking approach. The factors chosen give a significant priority to the severity of the crashes. In this analysis, a test of the combinations of weighting factors shown in Table 1 is performed. The PD between the weighting coefficient combinations and the original weighting coefficients ranking was determined. Combination of coefficients (A) and (C) tests the same weighting factors of the research methodology but with the priority changed to either crash type or crash frequency instead of severity. Combination of coefficients (B) aimed to learn about the differences that might be obtained if the methodologies are given almost equal weight. Combination of coefficients (D) tested the effects of giving even more priority to severity. The main issue to be answered is the possibility of a bias towards severity. The correlation among the ranked lists was determined to learn if changing the weighting factors affected the prioritization of sites by significantly altering the ranking order.

TABLE 1 Final Score of the Scores Equation Weight Combinations

Weight Coefficients Combinations			
Combination	**Crash Frequency**	**Severity Index**	**Crash Type**
A	**0.2**	**0.2**	**0.6**
B	**0.3**	**0.4**	**0.3**
C	**0.6**	**0.2**	**0.2**
D	**0.1**	**0.8**	**0.1**

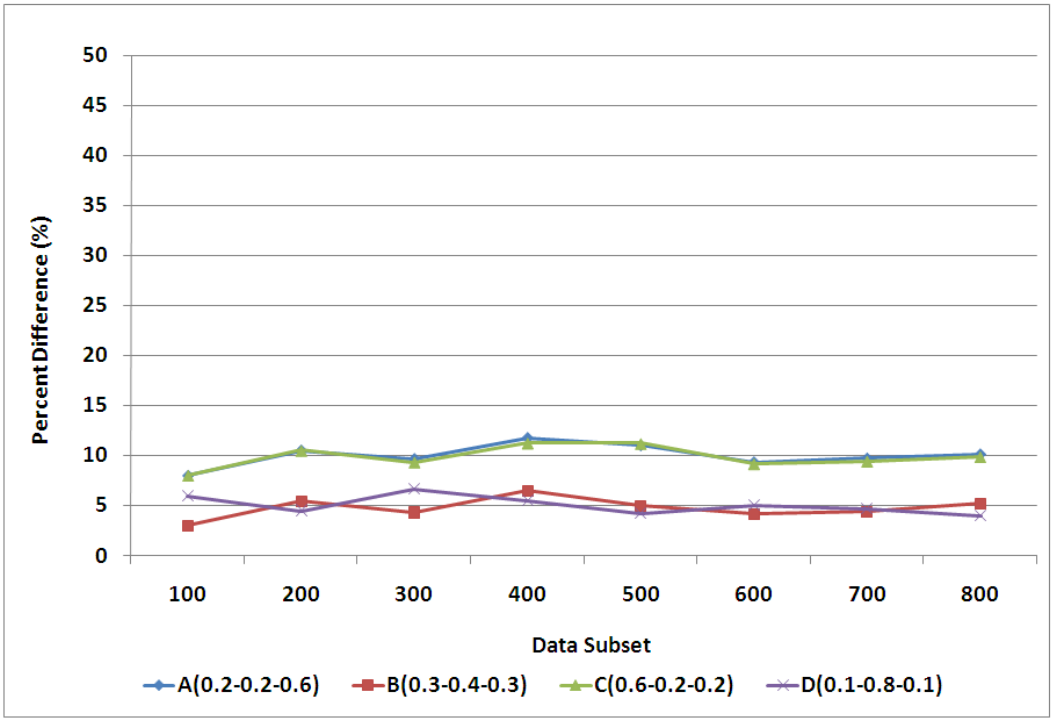

FIGURE 6a PD of Alternative Weighting Coefficients to Original Weighting Coefficients for Total Ranking of 5-years

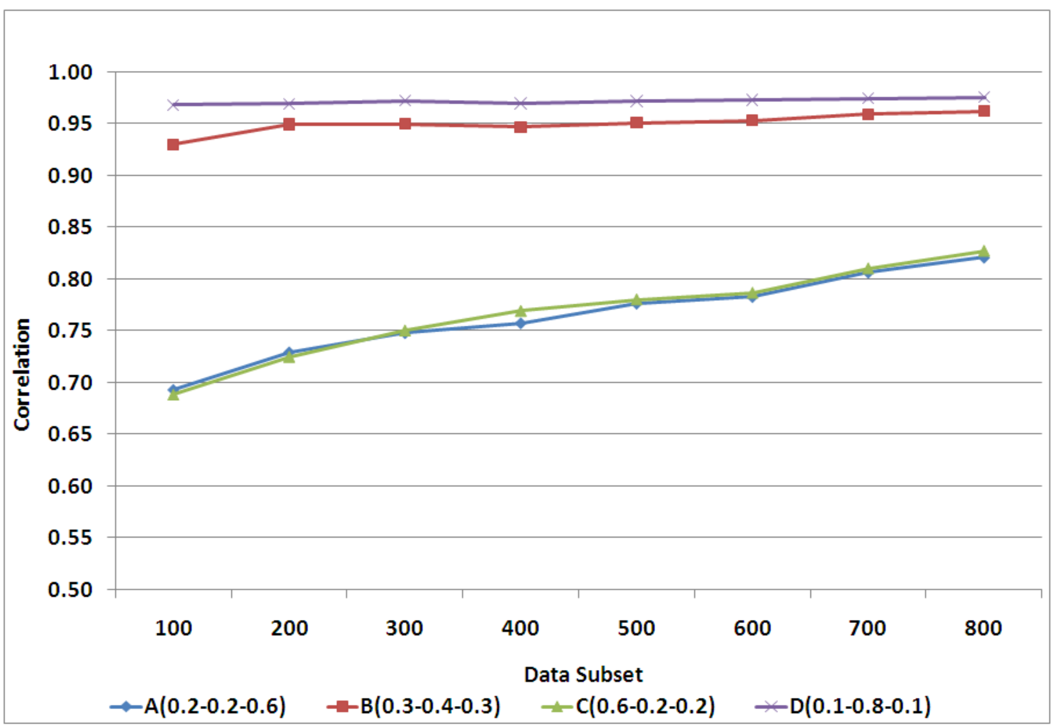

FIGURE 6b Correlation of Alternative Weighting Coefficient Combinations Ranking to Original Ranking Combination (5-yr Total Rank)

Figure 6a depicts the percent difference of the 5-yr ranking approach for the four weighting coefficient combinations to the 5-year ranking methodology proposed in this research. Overall, the PD is lower when the weights are changed than when crash history is varied. As mentioned in the literature review, the assignment of the weights can be subjective. The results quantitatively demonstrate what changes are expected if the priority has been changed. For example, when the same coefficients as in the proposed methodology are used but the priority is changed, then alternatives (A) and (C) show the highest percentage difference with the PD between 8 and 12. Alternative (B) will give significant results to accept or reject if the weights used on this research give a considerable bias towards severity (i.e., fatalities). Similarly, alternative (D) gives information of the extent of the bias when the maximum possible priority is given to severity. The PD shown by alternative (B) and (D) are similar and range between 3 and 6. It means that if the sites are given similar weights, or a higher priority is given to severity, the difference is negligible.

If the correlation among ranking lists shows a dramatic change in the ranking order, it could raise concern about the prioritization of safety. Figure 6b shows the correlation that the four weight coefficients combinations have compared to the original weights combination. In general the correlation coefficient is high, between 0.7 and 1.0. Alternatives (A) and (C), as expected have the lowest correlations that range between 0.7 and 0.825. These numbers are still high enough to conclude that even by shifting the priority, the ranking generally agrees on the most unsafe intersections. The results shown for alternatives (B) and (D) indicate that the ranking positions are almost completely unaltered. Therefore, there is no bias towards severity and the ranking differences are very limited.

The results found for PD and correlation indicate that changing the weights has minor influence on sites that appear similar among ranking lists as well as the relative position of the ranked sites. Thus, weights are not as significant in altering the prioritization of safety as crash history.

Median Alternative Ranking

Many hotspot identification methodologies use the mean as part of their method. In concept the mean is just a weighted sum of all possible values and it is also the long-term average of the distribution of the data (27). In contrast, the median is the point that divides a distribution into two equal probability masses. It is also the 50th percentile of a distribution. In data sets where the distribution is not symmetrical, the mean tends to be located away from the concentration of the observations. Also, when a data set contains one or more outlying observations, the mean can be unduly influenced by them. A median is not affected by outlying observations in a data set. Crash frequency data is often Poisson distributed therefore it is skewed to the right and the mean lies to the right of the mode. Therefore, the purpose of using mean to rank hotspot locations instead of median is to add more weight to the crash counts with outstanding values. However, the exact number of years for analysis is uncertain. Thus the question lies in learning if using median improves the stability of the ranking when different numbers of years of crash history are used. Ranking based on the median (of the yearly scores) score was evaluated as an alternative method to the ranking based on total score.

The median of the yearly “final score of the scores” for 5-years of crash history data were determined. Figure7a shows the PD of 5-year median rankings when compared to total rankings of 5-years. The striking feature is that the PD is significantly low, around 14, even when the median rank is used for ranking instead of the total rank. Figure 7b shows the correlation between the median ranking and the total ranking. Correlation is over 0.7 for 100 intersections however the correlation drops significantly as the size of the data subset increases. For 200 or 300 intersections the correlation is around 0.5, however it drops to less than 0.25 when the subsets have 400 or more intersections. These results indicate that either of the methods would return similar prioritizations for a smaller subset such as 100 intersections. However, although the PD was significantly low for all sizes of subsets the low correlations for larger subsets indicates that ranking methodology (median or total) can give significantly different prioritizations for larger subsets. Therefore it is recommended that the choice of total ranking versus median ranking should be done carefully.

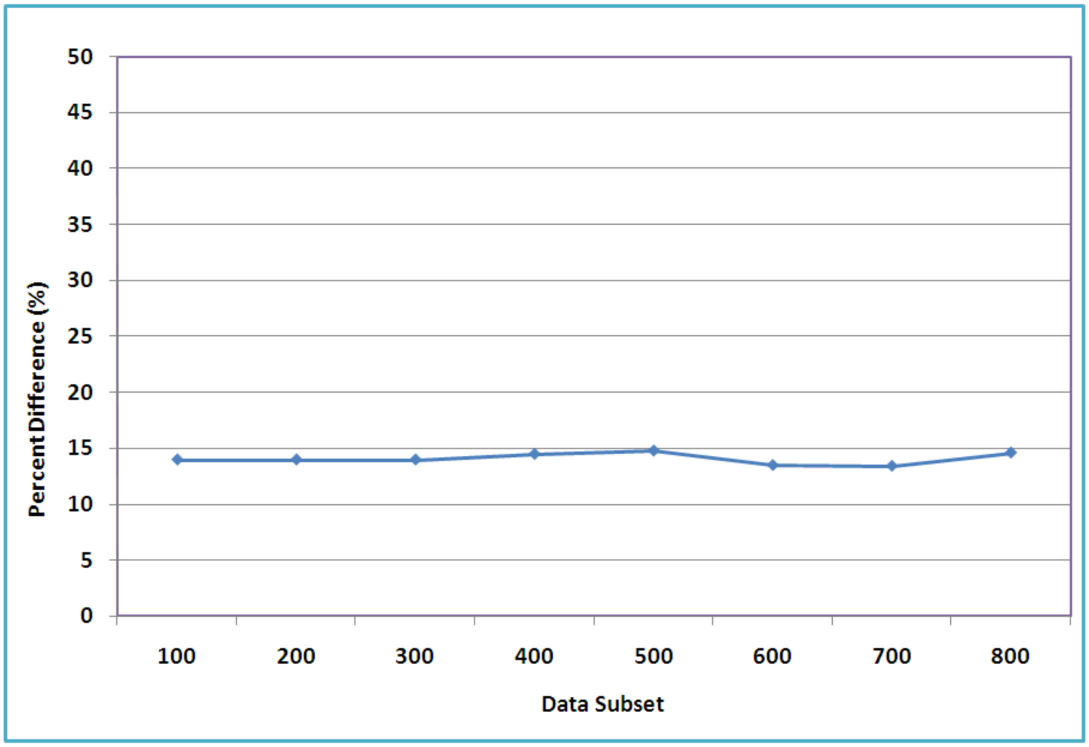

FIGURE 7a PD of 5-year Median ranking to Total Ranking of 5-years

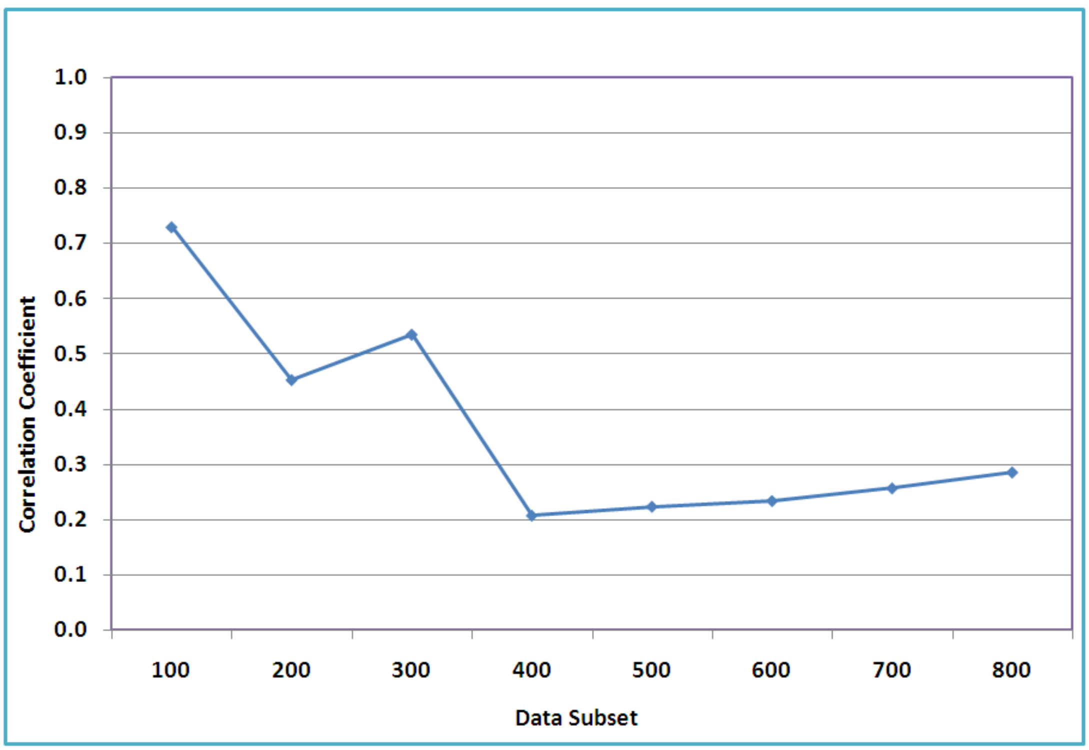

FIGURE 7b Correlation of 5-year Median ranking to Total Ranking of 5-years

CONCLUSIONS AND RECOMMENDATIONS

This paper presented the development and assessment of a systemwide intersection safety prioritization tool. The two main components of this tool are generation of a systemwide intersection crash list and ranking of intersections using a new intersection safety ranking methodology. An automated, comprehensive and sustainable process of generating the intersection crash list was designed and it addresses issues such as crash location and distinguishing between intersection and corridor safety problems. The new ranking methodology uses a score that is a composite of crash frequency, crash severity and crash type. This approach differs from previous approaches in that crash type is explicitly considered in the ranking by attributing costs to different common crash types.

Sensitivity analyses were performed, using five year crash data, to quantify the effect of duration of data used and weights used in the composite ranking on the ranking of intersections. Percentage Difference (PD) and Correlation were used to quantify the difference in the number of intersections and the relative position of the intersections in the ranking. Rankings obtained by using five year data were considered as the base. As expected the rankings generated from 1-yer data were significantly different from the 5-year data with PD ranging from 31 to 47. In addition the correlation varied from less than 0 to a maximum of 0.42. For 3-year data the PD varied from 14 to 21 and correlation ranged from 0.21 to 0.76. Therefore 1-year data should be used with great caution for prioritizing intersection safety and it is strongly recommended that a minimum of 3 year data is used.

In this research weights of 0.2, 0.6, 0.2 were used for crash frequency, crash severity and crash type respectively. The results found for PD and correlation indicate that changing the weights has minor influence on sites that appear similar among ranking lists as well as the relative position of the ranked sites. Weights used in the composite ranking were not as significant in altering the prioritization of safety as the number of years of data used.

In addition to using the total score for ranking, an alternative ranking using Median score was also researched. Using the Median score has the advantage of not being affected by outliers. Comparison of rankings generated using total score and median score indicate that although the PD was low (around 14) the correlation varied significantly from 0.73 to 0.21. In general the correlation decreased as the number of intersections ranked increased. This could possibly be due to the fact that the really unsafe intersections (top 100, for example) do not change significantly regardless of using total or median score. Median ranking should be used with caution for generating larger lists of intersections for safety prioritization.

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