Planning Level Regression Models for Crash Prediction on Interchange and Non-Interchange Segments of Urban Freeways

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ABSTRACT

The need for safety assessment tools for long-range transportation planning at statewide and metropolitan levels received serious recognition when the Transportation Equity Act for Twenty First Century (TEA-21) established a requirement related to safety considerations in the planning process of Metropolitan Planning Organizations (MPO) and state Departments of Transportation. However, most MPOs do not currently assess the safety consequences of alternative transportation systems, and one of the reasons is the lack of suitable methodology. The goal of this research was to develop practical tools for assessing safety consequences of freeways in the context of long-range urban transportation plans. Data for crashes, identified by freeway segments, were obtained from the North Carolina Department of Transportation and Tennessee Department of Transportation. The researchers used the negative-binomial regression modeling approach to develop separate models to predict number of crashes for different level of crash severity for non-interchange segments and interchange segments. A major consideration for the selection of independent variables of the models was planners' ability to forecast future values of the variables for alternative highway networks. The research provides crash prediction models that MPO planners can use to evaluate the safety impact of alternative freeway networks. These models are appropriate for 'safety conscious planning'.

INTRODUCTION

Prediction models for assessing safety impacts of different types of highway facilities have long been of interest to transportation and traffic engineers. Several studies have investigated the effects of roadway geometrics, drivers, and environmental factors on the number and severity of crashes. The use of these models is difficult for long-range planning involving future highway networks because planners usually do not make forecasts of the values of many of the explanatory variables used for these models.

Because higher average crash rates are normally observed on non-freeways and especially intersections (Fazio et al. 1993), most crash prediction models for highways are associated with non-freeway facilities. Among the limited number of existing crash prediction models for freeways, the majority have been developed for the purpose of either identifying highly hazardous locations or evaluating the effectiveness of safety treatments, i.e., countermeasures. These models are suitable for corridor planning and analyzing specific road segments for which detailed data are available.

The need for safety assessment tools at the long-range planning level was not seriously considered until Transportation Equity Act for the Twenty First Century (TEA-21) called for Metropolitan Planning Organizations (MPOs) in urbanized areas to take into account the safety related aspects of alternative urban transportation systems in the metropolitan planning process. The statewide planning process also must consider safety. Having no reliable analytical tools, MPOs currently evaluate the safety of alternative plans based on “rules of thumb” and expert judgment (Khan et al. 1999). The weakness of the past approach must be overcome, and for that purpose there is a need to develop better tools and criteria for assessing the safety impacts and related economic consequences of long-range transportation alternatives.

Objective of Research

The objective of this research was to develop predictive models for crashes occurring on urban freeways. These crash prediction models are to be used for assessing the safety related consequences associated with alternative types of freeways included in long-range transportation plans. The independent variables used in the models are limited to those that are commonly forecasted by planners for future scenarios. For assessing the safety consequences of an entire highway network in an urban area, these models could be used in conjunction with other predictive models for non-freeway arterial highways. These models should enrich the tools available for 'safety conscious planning', which is being advocated by the Federal Highway Administration.

REVIEW OF FREEWAY CRASH PREDICTION MODELS

Most of the crash prediction models for freeways have been developed since the 1990s while those for non-freeways began to be developed decades before. In 1993, Fazio et al. used conflict rates, which were found to significantly relate to crash rates, as a measure of level of safety of freeway weaving sections. The simulation approach used in their study seems to be promising for estimating model parameters. However, the detailed characteristics of freeways needed for this modeling process are not available for long-range plans. Further, planning level applications do not deal with weaving sections.

During the same time, research by Kraus, et al. focused on the relationship between urban freeway crash rates by collision type (e.g., rear-end and run-off-the-road) and independent variables such as physical characteristics of freeways, time of day, and traffic flow rates. Their modeling approach included both bivariate and multivariate analyses. The multivariate analyses were based on non-linear modeling and assumed Poisson distribution for crashes. Their crash prediction models were developed for urban freeway sections regardless of their locations in relation to interchanges (Kraus et al. 1993).

Persaud and Dzbik developed crash prediction models at both macro level (in crashes per unit length per year), and micro level (in crashes per unit length per hour) using the generalized linear modeling approach with negative binomial error structure. They pointed out that the weakness of macroscopic models was that the models could not clearly capture the difference in crash potential between freeways with intense traffic flow during peak hours and freeways with the same average daily traffic but with traffic evenly spread out during the day. Their studies confirmed that the crash pattern on freeway sections during congested periods and that during uncongested periods are different (Persaud and Dzbik 1993). However, the application of their micro level models is limited in long-range planning. The traffic flow data in hour basis is difficult to forecast at a planning level.

In 1996, Shankar et al. developed models for crashes by severity using a nested logit approach, which included both single and interaction terms in predictor variables. The variables included in their models were topological features, weather conditions, pavement surface conditions, vehicle conditions, and driver related factors. Their models were developed based on freeway segments of equal length and did not distinguish between non-interchange segments and interchange segments. As with the earlier studies, difficulty with forecasting the values of predictor variables makes this modeling approach difficult to use in long-range transportation planning.

In 1997, Resende and Benekohal developed a crash prediction model for rural freeways based on volume-to-capacity ratio. Their modeling technique was multiple linear regression analysis with the number of crashes per lane per mile as the dependent variable and daily volume-to-capacity ratio and a few other variables such as median width and surface rating as independent variables. They found that crash rates could be correlated with either traffic volumes or daily volume-to-capacity ratios. The capacity of freeways was considered to be a crucial variable in their model. However, variables related to roadway characteristics are not available in long-range transportation planning.

In 1999, Khan et al. explored the relationship between crash frequencies stratified by severity and traffic volume, segment length, and vehicle miles traveled using non-linear regression. Their findings suggested that Poisson regression with log-transformed predictors performed better than Poisson regression with linear predictors for all types of severity except for fatal crashes. Segment length and traffic volume were found to be significant in the models predicting injury and property-damage-only crashes while exposure-based predictors (vehicle miles traveled) were found to be significant in models predicting fatal crashes. Their work did not separately investigate the effects of interchanges on crash frequencies.

In 2002, Konduri and Sinha developed crash prediction models for freeway segments, which extended from the center of one interchange to that of an adjacent interchange. The predictor variables included in their models were traffic volume, topological characteristics, and weather conditions. Crash rates and the number of crashes were predicted by time of the day using a non-linear modeling approach. They suggested that traffic volume and section length could not be combined as a single variable (vehicle miles traveled) in crash prediction modeling. There was no separate treatment of the effects of interchanges on crashes.

In 2003, Chatterjee, et al, developed crash prediction models specifically for application in long-range urban transportation planning. Their modeling methods included categorical tables and linear regression analysis. The predictor variables included in their models are traffic volume and segment length. Their regression models used logarithmic transformation of variables to express non-linear relations in linear forms. The crash prediction models for freeways were developed for segments that stretched from the center of one interchange to that of another. Their models did not treat interchange related crashes and segment related crashes separately. The application of these models in a case study is documented by Schwetz et al. in another article.

In 2004, Golob et al. developed a tool for real time assessment of the level of safety on freeways in terms of crash types, crash locations, and severity of crashes. A clustering technique was used to categorize the real time traffic data, collected from loop detectors, into homogeneous groups of traffic flow conditions, which were used as predictors of crash type. Their models were developed for crash surveillance on freeways and required real time traffic flows from detectors as an input; this approach is not meant for long-range planning. During the same time Kononov and Allery developed safety-based performance standards for urban freeway segments based on crash prediction models using a non-linear function predicting crash rate with annual average daily traffic as one of the independent variables. Their models were developed based on data for urban six-lane freeways only. Each segment for their model included one interchange and the distances up to the midpoints of the sections between adjacent interchanges.

Comments on Findings of Previous Studies

The ordinary least squares (OLS) regression models are not appropriate for the analysis of crash data. OLS models require that the dependent variable be continuous with errors normally distributed and with constant variance at each combination of values of the predictors. Since the number of crashes is a discrete, non-negative variable, with the variability of the distribution increasing with the mean number of crashes, modeling the number of crashes as a Poisson variable is considered a promising approach (Jovanis and Chang 1986). However, crash occurrences generally have variances larger than the expected means, a condition referred to as "over-dispersion". Therefore, the negative binomial distribution is considered to be more appropriate and was used in majority of the previous studies since negative binomial distribution allows the variance to be larger than the mean.

In studies reviewed above not only the statistical approach varied but the model form and freeway segmentation scheme also were different. Some researchers developed models for freeway segments that were defined as segments between two successive interchanges and included one-half of the interchanges at the two ends on the segment (Persaud and Dzbik 1993, Konduri and Sinha 2002, and Chatterjee et al. 2003). Some developed models for freeway segments which included interchanges in full (Kraus et al. 1993 and Kononov and Allery 2004). And some developed models for freeway segments without considering the influence of interchanges (Shankar et al. 1996).

Although there is evidence that crash risks between two types of freeway segments – segments near and including interchanges and those located away from interchanges – are significantly different (Kiattikomol 2005), none of the previous studies treated these segments separately. This appears to be a weakness of the past approaches. Developing separate models for non-interchange segments and interchange segments seems to be reasonable considering the fact that traffic flow characteristics in these two areas are considerably different.

DATA PREPARATION AND MODEL FORMULATION

Data from freeway inventory files and freeway crash records for the years 2000, 2001, and 2002 were obtained from the North Carolina Department of Transportation (NCDOT) and the Tennessee Department of Transportation (TDOT) for selected urban areas in these states. The databases include counties with large to medium size urban areas. Two types of tables – segment-based tables and individual crash-based tables – were included in the database, and the data of one table were matched with those of the other using milepost information. The segments in North Carolina were taken from 2-digit numbered Interstates (e.g., I-40 and I-85) giving 138 segments with a total length of approximately 174 miles. The segments in Tennessee were taken from 2-digit (e.g., I-24 and I-75) and 3-digit numbered Interstates (e.g., I-604 and I-440) giving 207 segments with total length of approximately 204 miles. The segment-based tables were further grouped into non-interchange segments and interchange segments. For the analysis of North Carolina data, crashes occurring on freeway segments within 1,500 feet from the middle of an interchange were considered as interchange freeway crashes. Crashes occurring on freeway segments beyond 1,500 feet from the middle of interchanges were considered as non-interchange freeway crashes. Figure 1 illustrates this concept. For Tennessee data, a similar procedure was used although the length of interchange segments varied in a few cases.

Crash and Freeway Data for North Carolina and Tennessee

About 10 of the 99 counties in North Carolina include large to medium size urban areas and significant portions of Interstate highways. Of these, six were selected for this study because of the richness of complete data for these counties. These six counties are Alamance, Buncombe, Cumberland, Durham, Gaston, and Wake. All freeway segments selected for this study represent 2-digit numbered Interstates. There were almost equal numbers of four-lane and more-than-four-lane freeway segments in the North Carolina data set. Non-interchange four-lane segments were 2.15 miles long on average while non-interchange more-than-four-lane segments were 1.62 miles long on average. All interchange segments were 0.57 miles long.

The data for Tennessee cover four counties--Knox, Davidson, Shelby, and Hamilton—that contain the largest cities in the state. Similar to the case of North Carolina, two types of data tables – the table for non-interchange/interchange segments and the table for individual crashes – were needed to develop the combined data for modeling. Non-interchange segments were shorter in the Tennessee database than those in the North Carolina database. In Tennessee, the average non-interchange four-lane segment was 1.27 miles long while the average non-interchange segment with more than four lanes was 0.93 miles long. The average interchange four-lane segment was 1.00 mile long while the average interchange segment with more than four lanes was 0.88 miles long. A summary of North Carolina and Tennessee freeway segments that were used in the analysis is presented in Table 1. It should be pointed out that for both North Carolina and Tennessee data, the number of segments with eight or more lanes is very small, and thus the category of 'more than four lanes' practically represents six-lane freeways.

A summary of the North Carolina and Tennessee crash data is presented in Table 2. North Carolina crash data shown in Table 2 represent approximately 80% of total crashes in the NCDOT's crash database for two-digit numbered Interstates in the selected counties. The other 20% of crashes could not be matched successfully to any particular segment. Crash rates were calculated using the traditional approach for roadway segments in terms of crashes per million vehicle miles traveled (MVMT) as follows:

$$\text{Crash Rate} = \frac{\text{Crashes}\left(\text{in 3 years}\right)\times 10^{6}}{\text{Segment Length}\times\text{AADT}\times 365\times 3\text{ years}}$$

For both North Carolina and Tennessee crash data, the proportions of PDO crashes, injury crashes, and fatal crashes for interchange and non-interchange segments are similar. About 70% of the total is PDO crashes, while about 30% of the total is injury crashes and less than 1% of the total is fatal crashes. However, PDO crash rates and injury crash rates for interchange segments are more than twice as high as those for non-interchange segments. Fatal crash rates for interchange segments are about twice as high as those for non-interchange segments. PDO and injury crash rates for Tennessee are higher than those for North Carolina. Fatal crash rates are nearly equal for both states.

Model Formulation

A non-linear regression approach was used for developing crash prediction models. Although there is no rule to suggest the appropriate form for crash prediction models, a multiplicative form using traffic volume and segment length with exponential terms has been commonly used (Persaud and Dzbik 1993, Persaud 1991 and 1994, Lord and Persaud 2004, and Maze et al. 2005). Several variations of the suggested model form were analyzed.

For non-interchange segments:

$$N = (L)\,(AADT)^{b}$$

$$N = a\,(L)\,(AADT)^{b}$$

$$N = (L)^{b1}\,(AADT)^{b2}$$

$$N = a\,(L)^{b1}\,(AADT)^{b2}$$

For interchange segments:

$$N = (AADT)^{b}$$

$$N = a\,(AADT)^{b}$$

Where, N = expected number of crashes in a three-year period,

a, b, b_1, and b_2 = estimated parameters,

L = segment length (miles), and

AADT = annual average daily traffic (vehicles per day)

It should be pointed out that whereas the lengths of interchange segments for North Carolina are uniform, those for Tennessee varied in a few cases, and so a ‘Segment Length’ variable was used in the models for Tennessee. The models were fitted using the GENMOD procedure in SAS, assuming a negative binomial distribution for crash occurrences.

CRASH PREDICTION MODELS

All the regression model forms proposed in the previous section were fitted. For each sub-group of four-lane freeways and more-than-four-lane freeways, only the models that have significant parameters, the ratio of deviance to the degrees of freedom close to one, and a relatively high estimated R_k^2, are presented in this section. The deviance is a measure of discrepancy between actual and estimated values, which was calculated in the GENMOD procedure. The R_k^2 indicator

$$R_k^{\,2} = 1 - \frac{k}{k_{max}}$$

is used to measure the level of explanatory ability of each model (Miaou 1996). The term 'k' is the dispersion parameter estimated in the negative binomial model while k_{max} is the dispersion parameter estimated in the same negative binomial model with only an intercept term and a dispersion parameter. This measure can be used equivalently to the coefficient of determination (R^2).

Models for North Carolina Freeways

The regression models for 'PDO' crashes, 'injury' crashes, and 'fatal and injury' crashes for non-interchange segments and interchange segments of North Carolina are presented in Table 3. There were not sufficient fatal crashes to warrant separate models for that severity category.

For non-interchange segments, two model forms were selected – one for four-lane segments and the other for more-than-four-lane segments. It can be seen that all the coefficients and the exponents for ‘Segment Length’ and ‘AADT’ are estimated with a positive sign, which indicate that longer segments and/or higher freeway traffic volumes, which increase exposure, will result in more crashes of all three types on non-interchange segments. It is noted that the R_k^2 is considerably higher for the models for four-lane segments than for segments with more than four lanes.

For interchange segments, only one form of model was selected for both four-lane and more-than-four-lane segments. The variable ‘AADT’ was found significant for these models while the variable ‘Segment Length’ was omitted because all interchange segments had the same length of 3,000 feet. The magnitudes and the signs of all the coefficients and the exponents for ‘AADT’ indicate that higher freeway traffic volumes will result in more crashes of all three types on interchange segments. In addition, the models for four-lane segments were found to have higher R_k^2 than the models for more-than-four-lane segments.

Models for Tennessee Freeways

The modeling approach used for Tennessee freeways was the same as that for North Carolina. However, the models for Tennessee freeways were found to have slightly different forms. Crash prediction models for ‘PDO’ crashes, ‘injury’ crashes, and ‘fatal and injury’ crashes for non-interchange segments and interchange segments are presented in Table 4.

For non-interchange segments, it can be seen that one model form

$$N = a\,(L)^{b1}\,(AADT)^{b2}$$

was found acceptable for all six models. The magnitude and the sign of the exponents for 'Segment Length' and 'AADT' indicate that longer freeway segments and/or higher freeway traffic volume, which increase 'exposure', will result in more crashes for all three types of crashes on non-interchange segments. R_k^2 values are similar for most of the models.

For interchange segments, two model forms were found acceptable. One form, for interchange segments with four lanes, is

$$N = (L)^{b1} (AADT)^{b2}$$

Another form, for interchange segments with more than four lanes, is

$$N = a (L)^{b1} (AADT)^{b2}$$

The positive sign of the exponents for 'Segment Length' and 'AADT' indicates that longer segments and/or higher freeway traffic volumes will result in more crashes for all three crash types. The R_k^2 for the model for four-lane segments is higher than that for the model for more-than-four-lane segments for the cases of 'injury' crashes and 'fatal and injury' crashes while the opposite is the case for 'PDO' crashes.

PATTERN OF VARIATION IN CRASHES WITH TRAFFIC VOLUME

Transportation engineers and planners often wonder whether the number of crashes on a freeway segment with a given number of lanes increases with the increase of traffic volume at a constant rate, increasing rate, or decreasing rate. Another related question is whether the severity types of crashes vary in their proportions to total crashes as traffic volume increases. For example, does the proportion of fatal and injury crashes increase or decrease with the increasing traffic volume? In order to provide some insight into these questions, each of the twelve regression models for each state was used to estimate the number of crashes for traffic volumes increasing at an increment of 10,000 vehicles per day. The graphs of estimated numbers of total crashes for each state are presented in Figures 2 and 3. The maximum AADT used for four-lane segments and more-than-four-lane segments were 150,000. Not all of the graphs for crashes of each severity type are presented because of the word limit for the paper. The shapes of the curves of each severity type within each state are quite similar to with those for 'total' crashes; however, the shapes of the curves are different for the two states.

For North Carolina the curve for interchange segments with four lanes stands out distinctly from the others, showing an increasing slope as AADT increases, which indicates an increasing crash rate. For AADT values more than 50,000, the number of crashes on these segments also is greater than that on other segments. The implication of this finding is that interchange segments with four lanes are less safe than other segment types as AADT exceeds 50,000, and this gap increases as AADT increases.

The graphs for Tennessee were different from those for North Carolina in several respects. The curve for interchange segments with four lanes did not stand out as prominently above the others as it did in the case of North Carolina. The slope of this curve is linear. The curve for interchange segments with more than four lanes stands out above others when AADT exceeds 60,000. The graph for non-interchange segments with four lanes has increasing slope indicating increasing crash rate beyond an AADT of 40,000.

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

The primary objective of this research was to develop practical crash prediction models for assessing the long-range safety impact of alternative freeway networks for urban areas. A group of regression models was developed which used only two independent variables – traffic volume and length of segment – both of which are predicted or known by transportation planners. It was found that crash rates for freeway segments influenced by interchanges are considerably higher than those for segments located away from interchanges, and this finding justifies the development of separate models for those two types of segments. A distinction was also made between segments with four lanes and those with more than four lanes. The 'more than four lanes' category primarily included six-lane segments.

The pattern of increase of crashes with the increase of traffic volume as predicted by the models was found to be different between North Carolina and Tennessee. For North Carolina, it was found that crash rates for interchange segments with four lanes would increase with increasing traffic volume, and these segments may be most crash prone when AADT exceeds 50,000. For Tennessee, the models indicated that the interchange segments with more than four lanes have the highest crash rates when AADT exceeds 60,000.

The models developed by this research seem suitable for use in long-range planning applications in North Carolina and Tennessee. Planners in other southeastern U.S. states with similar terrain, weather, demographics, design practices, crash reporting thresholds, etc., should consider applying these models directly if, in their current situation, crash models for freeways in their areas are poor or non-existent. Others states where conditions are significantly different from North Carolina and Tennessee perhaps would be served better if they build their own models following the methodology described in this paper.

It should be pointed out that crash prediction models for freeways alone do not provide a complete set of tools for assessing the safety consequences of a highway network that includes freeways and non-freeway arterials and collectors. Therefore, planning level models should be developed for non-freeway arterials, even though this would be a challenging task.

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NOTATIONS

The following symbols are used in the paper:

a, b, b_1, and b_2	=	Estimated parameters
AADT	=	Annual Average Daily Traffic
L	=	Segment length
MPO	=	Metropolitan Planning Organization
MVMT	=	Million Vehicle Miles Traveled
N	=	Expected number of crashes in a three-year period
NC	=	North Carolina
NCDOT	=	North Carolina Department of Transportation
OLS	=	Ordinary Least Squares
PDO	=	Property Damage Only
STC	=	Southeastern Transportation Center
TDOT	=	Tennessee Department of Transportation
TEA-21	=	Transportation Equity Act for the Twenty First Century
TN	=	Tennessee
USDOT	=	US Department of Transportation

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TABLE 1. Summary of Freeway Segments for North Carolina and Tennessee

Type of Freeway Segments	Number of Lanes	Number of Segments		Total Length (miles)	
		NC	TN	NC	TN
Non-Interchange	Four	36	36	77.34	45.65
	More Than Four	37	106	59.76	98.86
	Total	73	142	137.10	144.51
Interchange	Four	33	15	18.75	15.05
	More Than Four	32	50	18.18	44.12
	Total	65	65	36.93	59.17

TABLE 2. Freeway Crashes by Severity Type for North Carolina and Tennessee (2000-2002)

Crash Severity Type	Non-Interchange Segments						Interchange Segments					
	Crashes		%		Rates (Crashes /100MVMT)		Crashes		%		Rates (Crashes /100MVMT)	
	NC	TN	NC	TN	NC	TN	NC	TN	NC	TN	NC	TN
PDO	2,787	7,372	66.80	71.19	28.05	58.20	2,989	8,501	70.25	71.81	98.92	144.62
Injury	1,355	2,949	32.48	28.48	13.64	23.28	1,246	3,306	29.28	27.92	41.24	56.24
Fatal	30	34	0.72	0.33	0.30	0.27	20	32	0.47	0.27	0.66	0.54
Total	4,172	10,355	100	100	41.98	81.75	4,255	11,839	100	100	140.81	201.41

TABLE 3. Models for North Carolina Freeways

Type of Segments	Number of Lanes	Type of Severity	Model	Deviance /DF	Dispersion (k)	R_k^2
Non-Interchange Segments	4 Lanes	PDO	$N = 4.9x10^{-8} (L)^{1.1043} (AADT)^{1.8007}$	1.4114	0.1282	0.92
		Injury	$N = 1.9x10^{-7} (L)^{1.2675} (AADT)^{1.6010}$	1.1075	0.1729	0.90
		Fatal and Injury	$N = 2.3x10^{-7} (L)^{1.2811} (AADT)^{1.5838}$	1.1056	0.1755	0.90
	>4 Lanes	PDO	$N = (L)^{1.2127} (AADT)^{0.2935}$	1.2341	1.8649	0.41
		Injury	$N = (L)^{1.0788} (AADT)^{0.2283}$	1.2126	1.7306	0.41
		Fatal and Injury	$N = (L)^{1.0626} (AADT)^{0.2305}$	1.2140	1.7530	0.40
Interchange Segments	4 Lanes	PDO	$N = 2.1x10^{-10} (AADT)^{2.3557}$	1.0760	0.1789	0.76
		Injury	$N = 5.5x10^{-7} (AADT)^{1.5756}$	1.1196	0.2811	0.49
		Fatal and Injury	$N = 6.8x10^{-7} (AADT)^{1.5578}$	1.1202	0.2704	0.50
	>4 Lanes	PDO	$N = 1.6x10^{-5} (AADT)^{1.3167}$	1.1344	0.2957	0.27
		Injury	$N = 4.0x10^{-5} (AADT)^{1.1589}$	1.1144	0.2164	0.27
		Fatal and Injury	$N = 3.8x10^{-5} (AADT)^{1.1629}$	1.1157	0.2135	0.28

TABLE 4. Models for Tennessee Freeways

Type of Segments	Number of Lanes	Type of Severity	Model	Deviance /DF	Dispersion (k)	R_k^2
Non-Interchange Segments	4 Lanes	PDO	$N = 1.7x10^{-10} (L)^{0.8078} (AADT)^{2.3669}$	1.2185	0.3448	0.67
		Injury	$N = 2.2x10^{-10} (L)^{0.7856} (AADT)^{2.2600}$	1.2073	0.3540	0.65
		Fatal and Injury	$N = 2.7x10^{-10} (L)^{0.7906} (AADT)^{2.2430}$	1.2123	0.3517	0.65
	>4 Lanes	PDO	$N = 1.2x10^{-5} (L)^{0.8996} (AADT)^{1.3525}$	1.1315	0.6248	0.53
		Injury	$N = 5.0x10^{-5} (L)^{0.9649} (AADT)^{1.1480}$	1.0586	0.4562	0.62
		Fatal and Injury	$N = 6.8x10^{-5} (L)^{0.9726} (AADT)^{1.1233}$	1.0566	0.4389	0.64
Interchange Segments	4 Lanes	PDO	$N = (L)^{0.4239} (AADT)^{0.3853}$	1.2182	0.3246	0.33
		Injury	$N = (L)^{0.4803} (AADT)^{0.2977}$	1.2120	0.1779	0.53
		Fatal and Injury	$N = (L)^{0.4919} (AADT)^{0.2989}$	1.2127	0.1817	0.54
	>4 Lanes	PDO	$N = 2.5x10^{-5} (L)^{0.7059} (AADT)^{1.3502}$	1.1102	0.2852	0.40
		Injury	$N = 9.0x10^{-5} (L)^{0.8098} (AADT)^{1.1607}$	1.1028	0.2777	0.40
		Fatal and Injury	$N = 0.0001 (L)^{0.8117} (AADT)^{1.1528}$	1.1015	0.2697	0.40

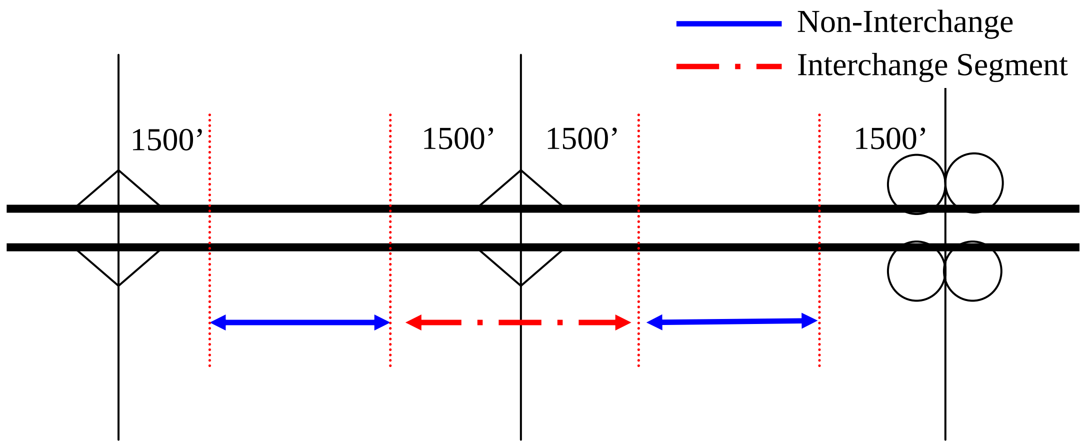

FIGURE 1. Coverage Areas for Non-Interchange Segments and Interchange Segments

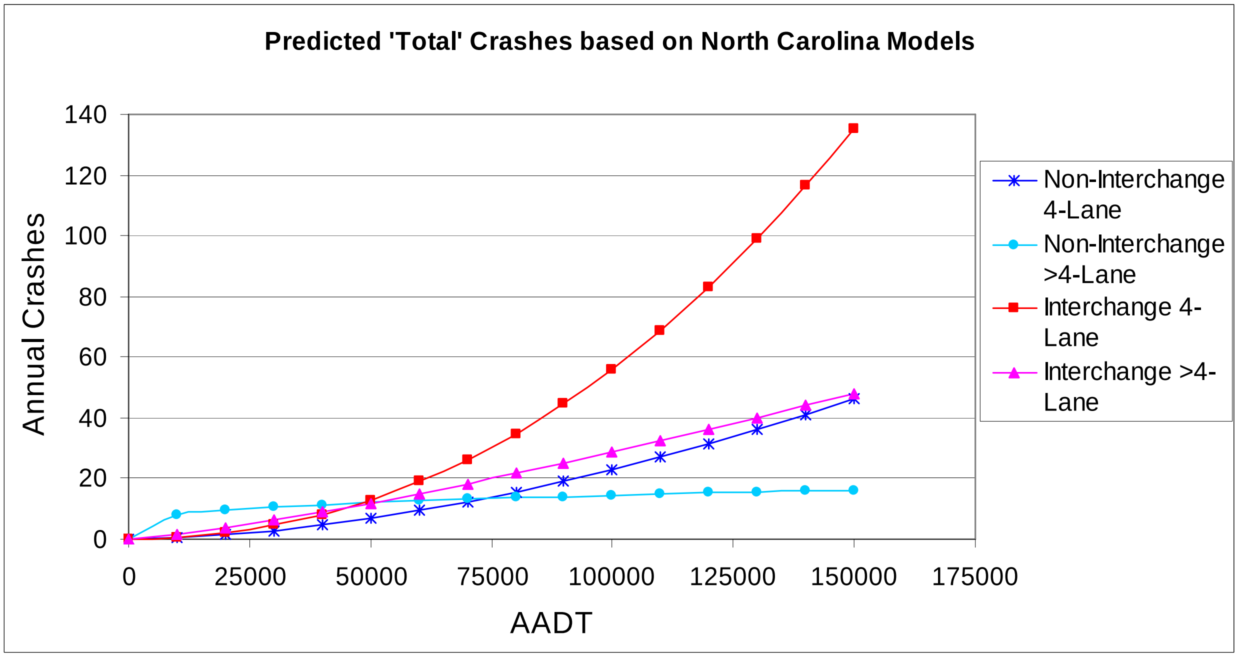

FIGURE 2. Predicted Pattern of Annual 'Total' Crashes Based on North Carolina Models

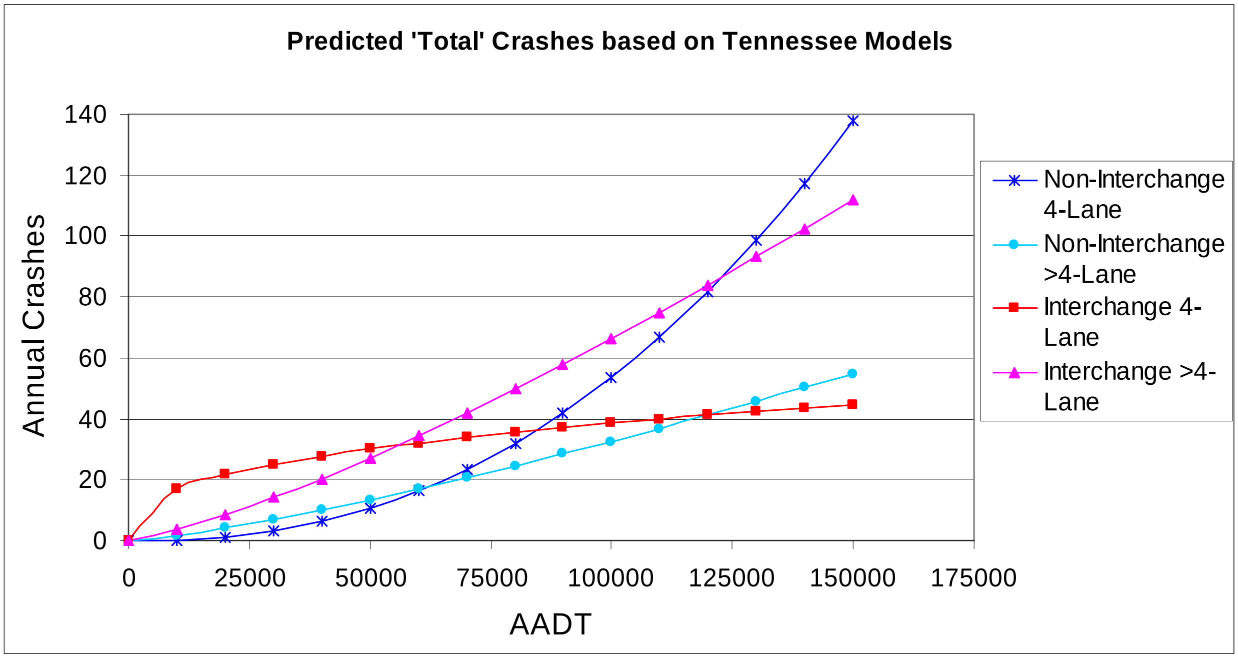

FIGURE 3. Predicted Pattern of Annual 'Total' Crashes Based on Tennessee Models