SAFETY PERFORMANCE FUNCTIONS FOR LOW-VOLUME ROADS

By:

Gianluca Dell'Acqua
Assistant Professor, Ph.D., P.Eng.
Department of Transportation Engineering "Luigi Tocchetti"
"Federico II" University of Naples
Via Claudio 21, I-80125 Naples, Italy
Phone: +39 0817683934
Fax: +39 0817683946
E-mail: gianluca.dellacqua@unina.it

Francesca Russo
Ph.D., P.Eng.
Department of Transportation Engineering "Luigi Tocchetti"
"Federico II" University of Naples
Via Claudio 21, I-80125 Naples, Italy
Phone: +39 0817683372
Fax: +39 0817683946
E-mail: francesca.russo2@unina.it

Submission date: November 15, 2010

Word count: 5,722+250x7 = 7,472

ABSTRACT

This paper analyzes roadway safety conditions using the network approach for a number of Italian roadways within the Province of Salerno. These roadways are characterized by low-volume conditions with a traffic flow of under 1,000 vehicles per day and they are situated partly on flat/rolling terrain covering 231.98 kilometers and partly on mountainous terrain for 751.60 kilometers. Since 2003, the Department of Transportation Engineering at the University of Naples has been conducting a large-scale research program based on crash data collected in Southern Italy.

The research-study presented here has been used to calibrate crash prediction models (CPMs) per kilometer per year. The coefficients of the CPMs are estimated using a non-linear multi-variable regression analysis utilizing the least – square method.

In conclusion, two injurious crash prediction models were performed for two-lane rural roads located on flat/rolling area with a vertical grade of less than 6 percent and on mountainous terrain with a vertical grade of more than 6 percent. A residuals analysis was subsequently developed to assess the adjusted coefficient of determination and p-value for each assessable coefficient of the prediction model.

CPMs are a useful tool for estimating the expected number of crashes occurring within the roads' geometric components (intersections and road sections) as a function of infrastructural, environmental, and roadway features. Several procedures exist in the scientific literature to predict the number of crashes per kilometer per year. CPMs can also be used as a tool for safety improvement project prioritization.

Keywords*:* crashes, prediction models, road safety analysis

PROBLEM STATEMENT

Roadway safety is a multidisciplinary science involving several elements: (a) the components of the roadway system - people, vehicles, and the roadways themselves, (b) the agencies and groups that plan, design, build, and use roads and promote roadway safety, and (c) the public health and safety communities that are concerned with injury prevention, response, treatment, and rehabilitation.(*1*).

While vehicle characteristics can contribute to traffic accidents (e.g., the lack of regular maintenance or vehicle overloading) human error is the most frequently cited factor contributing to both fatal and non-fatal injuries in motor vehicle accidents. Furthermore, driver behavior is improved more by enforcement and engineering than by training and education.

Low-volume roads, as analyzed in this paper, comprise a significant portion of the rural roadway network in Italy and in many other countries in the world. Because of the higher frequencies of documented crashes and more severe injuries on these roads, many researchers have examined the factors leading to these crashes.

Stamatiadis et al. (*2*) have observed that low-volume roads (e.g., roads carrying under 1,000 vehicles per day) make up 70 percent of the roadway network in the United States. Although such highways carry low volumes, historical data indicate that they have higher crash rates than other roadways. The authors found that the crash rates, and especially fatality rates, were higher for southeastern states than the national rates. Crashes in Kentucky and North Carolina for 1993 - 1995 were used for the sample. The tendency to crash among drivers grouped by age and gender and vehicles grouped by age and type were examined. The results showed that drivers under the age of 25 and drivers over the age of 65 were more likely to crash than middle-aged drivers. On average, female drivers were safer than male drivers, and young drivers (under the age of 25) experienced more single-vehicle crashes, and drivers over 65 were more likely to be involved in two-vehicle crashes. The drivers of older vehicles were more likely to be involved in two-vehicle crashes on low-volume roads than drivers of newer vehicles. In single-vehicle crashes, drivers of older vehicles were more likely to have a serious injury than drivers of newer vehicles, and large trucks had the highest two-vehicle crash rate on low-volume roads, followed by sedans, pick-up trucks, vans, and station wagons.

Achwan and Rudjito (*3*) later described the magnitude of the road crash characteristics on low-volume roads by using data from rural areas. Crash data from 1993 to 1995, recorded by the traffic police in the Purwakarta Police District were used. These data included three districts in Indonesia (Karawang, Purwakarta, and Subang). The authors found a serious road safety problem on low-volume roads in the Purwakarta region. These crashes caused significant losses in production, as well as damage and suffering. Clearly, all institutions involved in road safety should make every effort to reduce crashes. The study showed that the key vulnerable groups were motorcyclists and pedestrians, with truck casualties also being a problem on low-volume roads. Rollover was a common collision type and it appeared that this was caused by poor shoulder conditions in the majority of crashes; it was relatively rare on the national highway network. A systematic "Triple L Trial" approach - meaning data processing, crash, traffic-to crash investigation, prevention, and reduction proved successful and useful. In fact the authors found that although the number of accidents is small, it appeared that different road links do have different crash patterns. They introduced processes for identifying common contributory factors by using a stick diagram for hazardous locations.

For more than 40 years, multivariate regression techniques have been applied both in North America and in Europe to investigate the quantitative relationships between accident counts and road and traffic characteristics and to establish accident prediction models.

Several pieces of research have focused on identifying variables to account for the impact of the interactions between highway design parameters on safety (*4*).

OBJECTIVE

The research described in this paper aims to calibrate two injurious crash prediction models (CPMs) per kilometer per year for two-lane rural roads in low-volume conditions: one for roadways located on flat/rolling land with a vertical grade of less than 6 percent and the other for roadways in the mountainous area with a vertical grade of more than 6 percent.

This study illustrates a "network" approach to safety in order to identify the "black" roadway segment where the frequency of injurious crashes is higher than on the rest of the roadway.

This experimental analysis is only one component of a larger study under way for several years now on a number of rural roads in low-volume conditions within the Salerno road network with a view to improving performance and safety (*5*).

LITERATURE REVIEW

For more than 30 years, relationships between traffic crashes and geometric roadway design have been modeled by traffic safety engineers and researchers to estimate and predict accident frequency or rates under different roadway design conditions. It has been demonstrated that vehicle accidents are complex events involving the interaction of drivers, traffic, the road itself and the environment. It is believed that a significant proportion of variations in accident frequency are the result of differences in the major factors from site to site and time intervals (*6*), and that a significant portion of accidents occur due to bad infrastructure, and lack of Alignment Consistency (*7*).

Performing accident prediction models is a means of summarizing these complex interactive effects on the basis of information contained in the accident data, as well as using engineering judgment and analytical assumptions about the accident process.

Many types of regression models have been used over the years to develop accident prediction models: researchers are finding that conventional normal or lognormal regression models simply do not have the statistical properties necessary to adequately describe vehicle accident events on the road. Traffic accidents are better modeled by assuming a Poisson accident frequency distribution. The exponential function is a natural candidate to describe the interactive effects and at the same time ensure that the function values are always non-negative (*8*).

Miaou et al. (*8*) studied the effect of over-dispersion of accident frequency distribution on model forms. They showed that when the variance of the accident rate distributions is greater than the mean, zero-inflated Poisson or negative binomial regression models should be used. They developed an extended negative binomial model allowing variables with multiple values along a segment of road.

Fridstrøm et al. (*9*) at the Norwegian Transportation Institute developed Poisson regression models to break down the variations in accident counts into parts attributable to randomness and the systematic factors that cause accidents. They correlated the number of crashes with four variables: traffic flow, speed limits, weather and light conditions. They also proposed a set of specialized goodness-of-fit measures explicitly taking into account the inevitable amount of random variation that would be present in any set of accident counts.

Persaud and Lord (*10*) illustrated the application of the Generalized Estimating Equations (GEE) procedure to traffic-safety studies when data spanning several years are

available and when it is desirable to incorporate trend. The application is for a sample of four-legged signalized intersections in Toronto, Canada, using data for the years 1990 through 1995. GEE procedure was introduced to develop a mathematical equation incorporating a trend in accident data. The quality of fit was examined using the Cumulative Residuals (CuRe) method.

Saccomanno et al. (*11*) described an integrated and user-friendly GIS platform for road accident analysis and prediction to develop and evaluate alternative safety countermeasures. The database employed was obtained from the Ontario Ministry of Transportation. The Poisson regression and Empirical Bayesian (EB) model were used for the analyses. For illustration purposes, the authors also designated the number of BS sections along the selected highway. A BS section is defined as any section where the number of accidents observed exceeds the predicted number by at least one standard deviation from either the Poisson or the EB model estimates.

Hauer (*12*) calibrated an accident rate model for multilane urban roads by using a binominal negative regression. The variables used were the annual average daily traffic, the percentage of trucks, the vertical grade, the horizontal curve length, roadway width, the type and width of clear zones, speed limits, points of access, and the presence of, and nature of, parking areas.

Pardillo et al. (*4*) described a research project conducted at Madrid Polytechnic University, with the objective of refining the negative binomial accident prediction models that had been developed previously for two-lane rural roads in Spain. Because over-dispersion had been detected in the sample, a negative binomial regression model with an additional exponential linkage equation was adopted. Injury accident counts (IACC) were used as the dependent variable. To test the significance of the regression coefficients, a new variable in addition to the criterion based on the p-value was used: the authors also proposed a set of specialized goodness-of-fit measures, such as the deviance of the model and the log-likelihood. The final equation of the resulting model contains the total traffic flow, access density, the minimum sight distance within the 1 kilometer segment, the minimum design speed of the alignment elements included in the 1km segment, the maximum longitudinal grade, and reduction in design speed in relation to the section analyzed starting from a distance of 1km on the segment preceding the section being investigated. Cumulative scaled residuals plots were then used to identify where the model over- or underestimated accident frequencies.

EI-Basyouny and Sayed (*13*) compared two types of regression techniques: the traditional negative binomial (TNB) and the modified negative binomial (MNB). While the TNB approach assumes that the shape parameter of the negative binomial distribution is fixed for all locations, the MNB approach assumes that the shape parameter can vary from one location to another. The difference between the two approaches is investigated in terms of their goodness of fit. The study employs accident data for 58 arterials (392 segments) in the cities of Vancouver and Richmond, in British Columbia, Canada.

Tarko (*14*) presented two alternative formulations for the calibration problem in line with the maximum likelihood approach. Two methods are addressed to predict safety for the individual links and nodes of a transportation network. In both methods a planner has the freedom to portion a road network in a way that addresses expected local and sub-regional safety differences. Furthermore a planner may identify routes, corridors and areas to focus calibration on these locations if planning focuses on them. The study demonstrated the feasibility of those proposed approaches that may be helpful in developing a new class of tools for safety-conscious planning.

DATA COLLECTION

The crash data used in this research study involve 983.58 kilometers of two-lane rural roads in Southern Italy, of which 231.98 kilometers are located on flat and rolling areas with a vertical grade of less than 6 percent and 751.6 kilometers on mountainous terrain with a vertical grade greater than 6 percent.

Roadway segments on flat, rolling and mountainous terrains reflect some results of previous studies (*15*) where several processes and methodologies were developed to reach acceptable standards to classify geometric design and maintenance standards for low-volume roads. Road classification systems were examined by numerous countries, namely Australia, South Africa, the United Kingdom, and the United States. For example, *Austroads* (*16*) has defined a national system of functional classifications for urban and rural roads across Australia. The Austroads rural areas category further subdivides the road classification into five levels. For each road class there are guidelines for geometric standards that relate to design speed, cross-sectional elements, and horizontal and vertical curve requirements for flat, hilly, and mountainous terrain. The *USA Forestry Manual* (*17*) has also proposed a low-volume road classification for two-lane and single-lane roads based on the roadways' geometric and infrastructural features for rolling and hilly terrain.

A daily traffic volume is generally included in the research studies for each road class as a guide to the range of likely traffic for each class (*15*). Traffic volume is expressed as the average daily traffic (ADT) and represents traffic over the peak season. A description of the road type for each road class has also been included. In describing the road type, the service quality factor has been included to highlight the overall character of the road class which may be linked to adjacent land use or the recreational facilities it serves. The various levels of service were based on the subjective judgments of numerous practitioners closely associated with road network management. Quality of service is a qualitative term based on the concept of providing various levels of convenience, comfort, and safety to a driver.

The rural roads analyzed in Italy which are presented in this study are in low-volume conditions with an ADT of less than 1,000 vehicles per day for which a 3-year (2003-2005) crash database was used. Table 1 shows the descriptive features observed on the roads analyzed.

TABLE 1 Geometric Features of the Low-Volume Roads Analyzed

FLAT AND ROLLING TERRAIN	Roadway Segment Length [km]	3.60	Average μ
		3.40	Standard Deviation
	Roadway Width [m]	7.20	Average μ
		1.40	Standard Deviation
	Predicted Speed [km/h]	56.00	Average μ
		12.00	Standard Deviation
	Lanes	2	
	Vertical Grade [%]	< 6%	
	Curve Radius [m]	150-500	
MOUNTAINOUS TERRAIN	Roadway Segment Length [km]	4.90	Average μ
		3.70	Standard Deviation
	Roadway Width [m]	6.80	Average μ
		1.20	Standard Deviation
	Predicted Speed [km/h]	54.00	Average μ
		7.30	Standard Deviation
	Lanes	2	
	Vertical Grade [%]	> 6%	
	Curve Radius [m]	<150	

Typical photographs of the analyzed roads are shown in Figure 1: the first picture shows an example of rural roads located on mountainous terrain, while the second illustrates roads in a flat area. The surface type of the examined roads is generally paved while in some minor cases it can be distinguished gravel roads.

Figure 1 Photographs of a typical road located on the mountainous and flat/rolling area.

The calibration of the injurious crash prediction models was performed using 63 roadway segments referring to the roads in the flat/rolling area, and 151 roadway segments for the roads in the mountainous area. In particular, the database analyzed was made available to the Department of Transportation Engineering at the University of Naples by the Administration of the Province of Salerno. The responsible Administration has divided the total length of a roadway in a number of segments based on the urbanized and no-urbanized areas crossed by roads, not taking into account the presence of intersections and junctions on the roadway length. It can be identified at each analyzed roadway segment the total number of crashes, and its percentage of fatal and injuries crashes. The examined database contains the number of injurious crashes at intersections but they weren't individually investigated due to low probability of vehicles meeting.

Each roadway segment includes the mean value of the following parameters:

Roadway Segment — the total length of the analyzed roadway is divided into a number of roadway segments according to the urban and no-urban areas crossed and where the accidents were observed

Roadway Segment Length — length of the roadway segment identified at each analyzed roadway

ADT — average daily traffic for a period of three years from 2003 to 2005 observed at each roadway segment

Curvature Indicator — measurement of the curvature change rate of the roadway segment. This indicator acquires the following three levels by using a range of values from 1 to 3 after a deep analysis and careful study of all discrete values in the database:

- low curvature for a mean value of all curve radius falling within the analyzed roadway segment between 400m and 500m: the indicator is 1
- medium curvature for a mean value of all curve radius falling within the analyzed roadway segment between 150m and 400m: the indicator is between 1 and 2

- high curvature for a mean value of all curve radius falling within the analyzed roadway segment of less than 150m: the indicator is between 2 and 3

Vertical grade the vertical grade indicator can acquire the following synthetic and simple levels by using a range of values from 1 to 3 after a deep analysis and careful study of all discrete values in the database:

- low gradient when the mean value of grades associated to the analyzed roadway segment is of less than 3 percent (the indicator is equal to 1)
- medium gradient when the mean value of grades associated to the analyzed roadway segment is between 3 percent and 6 percent (the indicator is between 1 and 2)
- high gradient when the mean value of grades associated to the analyzed roadway segment is over 6 percent (the indicator is between 2 and 3)

Roadway *Width* travel lanes plus shoulders

Predicted Speed is the mean speed at each analyzed roadway segment in which the Administration has divided the entire roadway segment length

Crashes Count number of total and injurious crashes each year

Table 2 shows the descriptive statistics of the crashes observed on the rural roads from 2003 to 2005. It can be observed that the average injury count for the 3-year period is 0.94 crashes per kilometer and 0.32 crashes per kilometer for the roads on flat/rolling and mountainous terrain respectively.

The employed database is not wholly complete: it may not learn the principal crash types at each roadways neither the accurate location or the weather conditions when the crash happened nor the eventually presence of obstructions within the lateral clearance area that may add to crash severity when vehicles exited the traveled way. Used reports refer to the general features of the analyzed crash counts; it needs to improve them for the future developments of the safety analyses and to better explain the average crashes/segment's year to year variability.

TABLE 2 Descriptive Statistics of Analyzed Crash Counts

		Total number	Average per Roadway segment	
FLAT/ROLLINGTERRAIN	INJURIOUS CRASHES IN 3 YEARS (2003-2005)	59	0.94	
		Analyzed Year	Total number	Average per Roadway segment
	INJURIOUS CRASHES	2003	9	0.14
		2004	32	0.51
		2005	18	0.29
		Total number	Average per Roadway segment	
MOUNTAINOUS TERRAIN	INJURIOUS CRASHES IN 3 YEARS (2003-2005)	49	0.32	
		Analyzed Year	Total number	Average per Roadway segment
	INJURIOUS CRASHES	2003	14	0.09
		2004	14	0.09
		2005	21	0.14

A user-friendly GIS platform for road crash analysis and prediction models has been used. A geographic information system (GIS) integrates hardware, software, and data for capturing, managing, analyzing, and displaying all forms of geographically referenced

information. GIS allows to view, understand, question, interpret, and visualize data in many ways that reveal relationships, patterns, and trends in the form of maps, globes, reports, and charts. A GIS helps answer questions and solve problems by looking at data in a way that is quickly understood and easily shared. GIS technology can be integrated into any enterprise information system framework.

This platform makes use of GIS Arc View and the Visual Basic programming language. The GIS enables the user to see the environmental conditions, as well as the geometric and accident information on the roadway segment (*11*).

DATA ANALYSIS

Two predictive injurious crash models were developed for the roadways analyzed in low-volume conditions: the first can be applied for roads located on flat/rolling terrain (vertical grade of less than 6 percent) and the second was associated with the roads on mountainous terrain with a vertical grade greater than 6 percent).

The prediction models were performed by using the only number of injurious crashes because since 1991, according to many European countries, the Italian Administrations, responsible for the collection and dissemination of crash data, recorded only the injurious accidents defined how "events that occur on public roads in which one or more people are killed or wounded and in which at least one vehicle is involved in a movement. "

Hauer suggested the possibility of stratifying the models to overcome the lack of flexibility of the most common exponential functional forms (*12*).

Specialized software - (STATISTICA 7) - was used to fit the models. The injurious crashes per kilometer per year were used as dependent variables.

An iterative process was applied in the development of the two crash prediction models. Hauer (*12*) distinguished two steps in the process: (*a*) the choice of model form (model equation) and (*b*) estimating the parameters. Both steps are repeated in each phase of the model development process. In fitting the models, weighting was applied to the explanatory variables of each record in proportion to the roadway segment length. Operating in this way, emphasis was given to the key role played by the different characteristics of roadway segments into which the total road length was broken down by the Salerno Province Administration for the urbanized area. The Gauss-Newton method, based on the Taylor series, was used to estimate the coefficients of employed variables by using ordinary least-square regression. All the parameters included in the model are significant to a 95 percent confidence level. The significance of the regression equations' coefficients were investigated by using two criteria: 1) the models were kept where the *p*-value of the coefficients was under 5 percent; 2) the cumulative residual analysis, which is discussed in the next section.

Injurious Crash Prediction Models

The best *crash prediction model on low-volume roads located in areas with flat/rolling terrain*, in injurious accidents per year per kilometer, was worked out from data for 59 crashes reported over three years; the equation form is the following:

$$\mathrm{Y} = \left(\frac{ADT}{1000} \cdot 6 \cdot 10^{-5}\right) \cdot \left(6 \cdot 10^{-1.5} \cdot \mathrm{CI}\right) \cdot e^{(0.25 \cdot \mathrm{V} - 1.42 \cdot \mathrm{VGI})} \cdot e^{(0.81 \cdot \mathrm{W})} \tag{1}$$

where

Y = number of injurious crashes per year per kilometer
ADT = average daily traffic in vehicles per day
V = mean speed at each analyzed roadway segment
CI = the curvature indicator as explained above
VGI = the vertical grade indicator as explained above
W = lanes plus shoulders width in meters

A reasonably-goodness-of-fit indicator was made for this regression: the adjusted coefficient of determination ρ² is 91 percent. As can be seen from Equation 1, where all the variables are statistically significant as shown in Table 3, the ADT variable has little influence on the predicted number of crashes: as could be imagined, the road is in low-volume conditions, but its presence is due to the increase in ρ² value.

The best *crash prediction model on low-volume roads located in areas with mountainous terrain*, in injurious accidents per year per kilometer, was worked out from data for 49 crashes reported over three years; the equation form is the following:

$$Y = e^{\left[-190.48+5.98\cdot\left(\frac{ADT}{1000}\right)+0.65\cdot V\right]} \cdot e^{(224.51-13.83\cdot CI+6.81\cdot VGI-7.15\cdot W)} \tag{2}$$

where

Y = number of injurious crashes per year per kilometer
ADT = average daily traffic in vehicles per day
V = mean speed at each analyzed roadway segment
CI = the curvature change rate indicator as explained above
VGI = the vertical grade indicator as explained above
W = lanes plus shoulders width in meters

The adjusted coefficient of determination ρ² is 99 percent. The structural form of this model is close to the representative crash models presented by Vogt and Bared (*16*) calibrated from data coming from the states of Minnesota and Washington on rural two-lane highways for segments and three-legged and four-legged stop-controlled intersections on minor legs. In these models the ADT is introduced as a primary effect in the $EXPO_m$ variable (a product of ADT and time), and as a secondary effect in the exponential form.

The following visual aid shows p-values for each coefficient of the variables in the prediction Equations 1 and 2, respectively.

TABLE 3 Coefficient of the Variables in CPMs 1 and 2

Crash Prediction Model on Low-Volume Roads located in areas with Flat/Rolling terrain						
Descriptive Variable	**Estimated Coefficient**	**Standard Error**	**t-value ; df = 1**	**p-level**	**Lo. Conf. Limit**	**Up. Conf. Limit**
ADT/1,000	0.00006	0.000000	0.00	0.00	0.0001	0.00006
CI	$6\cdot(10^{-1.5})$	0.000000	0.00	0.00	0.0001	0.00006
V	0.24556	0.2546692	0.00	0.00	-2.9906	3.48172
VGI	-1.42373	2.760914	0.00	0.00	-36.5045	33.65701
W	0.80841	0.604812	0.00	0.00	-6.8765	8.49328

Crash Prediction Model on Low-Volume Roads located in areas with mountainous terrain						
Descriptive Variable	**Estimated Coefficient**	**Standard Error**	**t-value; df = 1**	**p-level**	**Lo. Conf. Limit**	**Up. Conf. Limit**
-	-190.481	0.000000	0.00	0.00	-190.481	-190.481
ADT/1,000	5.988	1.577217	0.00	0.00	-14.053	26.028
V	0.651	0.386234	0.00	0.00	-4.256	5.559
-	224.513	0.000000	0.00	0.00	224.513	224.513
CI	-13.834	7.219135	0.00	0.00	-105.562	77.893
VGI	6.807	6.639895	0.00	0.00	-77.560	91.175
W	-7.150	2.692705	0.00	0.00	-41.364	27.064

Analysis of the Residuals

Hauer recommends analyzing residual plots as an essential tool in this process (*12*). The residual is the value of the difference measured between the predicted value of injurious crashes using the model and the real value of the number of injurious crashes surveyed on the same roadway segment. The goal is to graphically observe how well the function fits the data set.

The CuRe (Cumulative Residuals) method has the advantage of not being dependent on the number of observations, as are many other traditional statistical procedures (e.g., ρ^2) (*4, 10, 12*). The CuRe method was adopted in addition to using the p-value criterion to test the significance of the regression equation,

Pardillo et al. (*4*) used cumulative scaled residuals analysis to identify the regions where models under- or over-estimated accident rates, which provides a basis for the stratification of the models. The research demonstrated the usefulness of this type of analysis in detecting redundancies in the statistical information contained in the calibration data sample and in comparing alternative prediction models calibrated with different sample sizes.

Lord and Persaud (*10*) also applied cumulative residuals analysis to evaluate prediction models showing the variation in the crash rate in consecutive years, but they rule out the use of the conventional ρ^2.

For this reason, a diagram of cumulative residuals was plotted based on the ADT values analyzed. Figure 2 shows the residuals of two prediction models where it can be seen how the models offer a correct interpretation of reality. There is a fair distribution of residuals around the mean.

Positive values in the residuals plots correspond to the regions where the model underestimates crash densities, while negative values reflect the opposite situation. For a good fit, the fluctuations must be homogeneous around the mean.

Abrupt decreases or increases in the graph may reflect lack of flexibility in the functional form in the model and, in some cases, the existence of redundant data for a given value of the explanatory variable. For roads located in the flat/rolling area, the observed residuals, in injurious crashes per year per kilometer, have a minimum value of 0.0001, a maximum value of 0.09, a mean value of 0.022 and a standard deviation of 0.023. For roads located in the mountainous area, the observed residuals, in injurious accidents per year per kilometer, have a minimum value of -0.03, a maximum value of 0.080, a mean value of 0.012 and a standard deviation of 0.021.

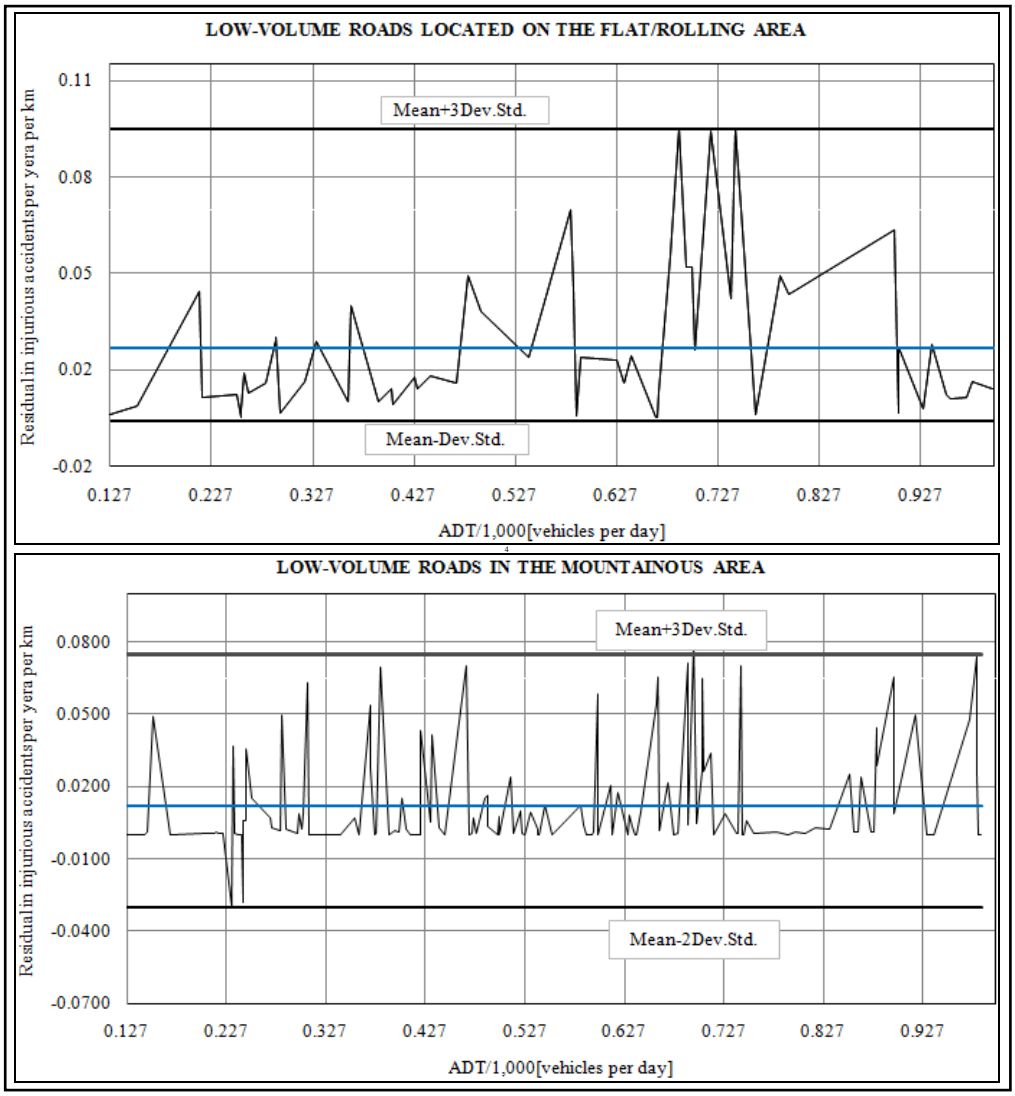

Figure 2 Residuals diagrams.

A diagram of cumulated squared residuals was plotted based on the ADT values.

Figure 3 shows two diagrams where the *x*-axis shows the ADT/1,000 values while the *y*-axis shows the cumulated squared residuals.

The first graph refers to the roads on flat/rolling terrain while the second refers to those localized on mountainous terrain.

The good prediction of two models of real injurious crashes is also confirmed by Figure 3. In fact, two plots of cumulated quadratic residuals, corresponding to the ADT/1,000 values, show no vertical jump (more correctly known as "outlier") (*12*).

The presence of an "outlier" would have indicated an observation very different from a sample data distribution and it can appear when the real crash rate is very dissimilar to the predicted value using regression equations: in this case more investigations to decide whether to use these observations or not are necessary.

In conclusion the Figure 2 shows how the residuals of the Equation 1 are slightly greater than those presented for the Equation 2; this circumstance confirms that the Equation 2 can appear better than Equation 1 also because its residuals are distributed more homogeneously around the mean. These considerations is also confirmed by Figure 3 where for the Equation 2 fewer outliers exist than Equation 1.

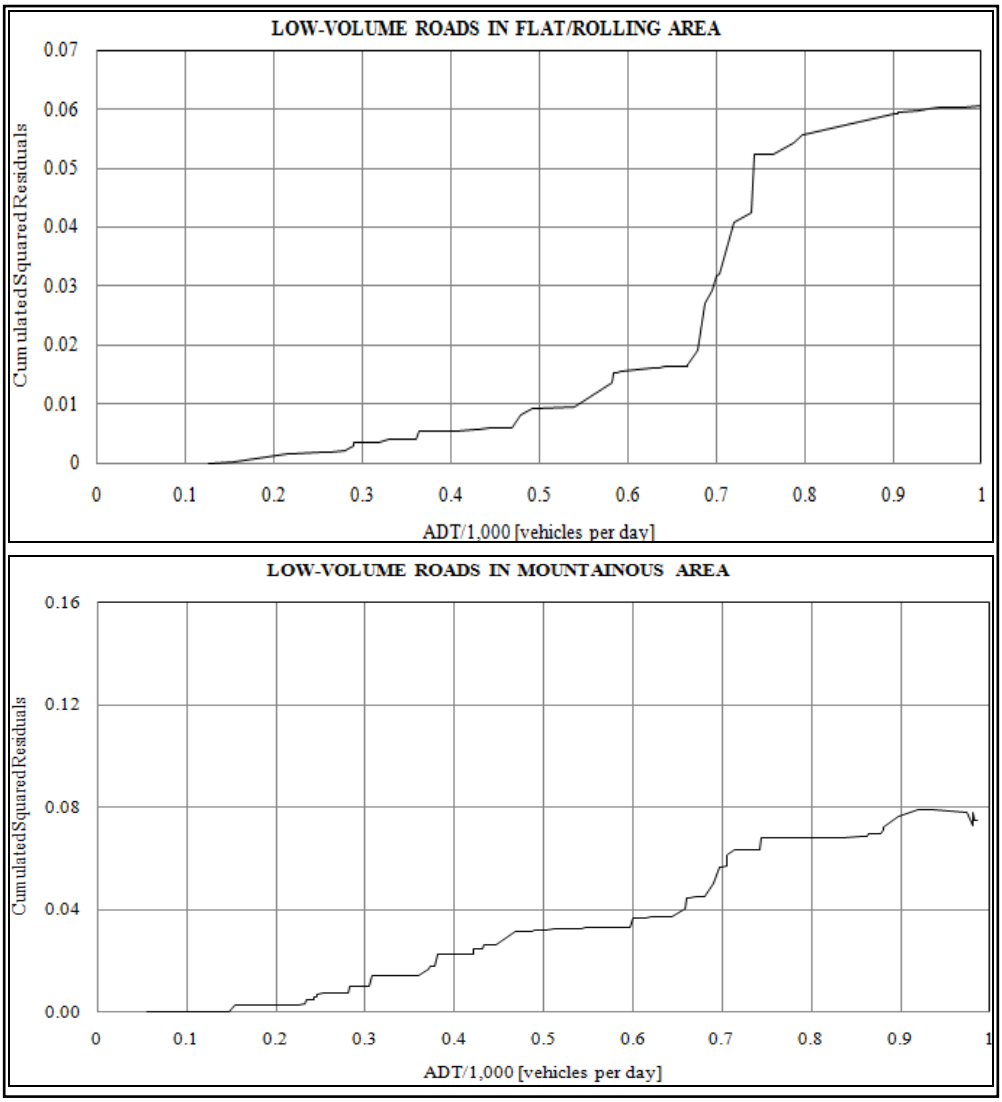

Figure 3 Cumulated squared residuals plots.

RESULTS

Two crash prediction models for injurious crashes per year per kilometer were calibrated for low-volume roads (with an ADT of less than 1,000 vehicles per day) located on flat/rolling and mountainous terrain within the roadway network of the Province of Salerno in Southern Italy. The data set includes 983.58 kilometers of roads: 231.98 kilometers on flat/rolling terrain (vertical grade < 6 percent) and 751.60 kilometers on mountainous terrain (vertical grade > 6 percent). A 3-year (2003-2005) crash database was used.

The Gauss-Newton method, based on the Taylor series, was used to estimate the coefficients of the variables employed by using an ordinary least-square regression. All the parameters included in the models are significant to a 95 percent confidence level. In addition to the *p*-value criterion to test the significance of the regression coefficients (the models were kept when the *p*-value of the coefficients is less than 5 percent), cumulative residual analysis was used as above. The observed residuals for the rural roads located in the flat/rolling area have a maximum value of 0.09, while for the roads located on the mountainous terrain, the maximum value is 0.08 for injurious accidents per year per kilometer.

Figure 3 shows the Cumulated Squared Residuals analysis to identify the outliers where the models were not able to interpret the calibration data sample perfectly. The results

proved the reliability of the regression equations and the complete absence of jumps.

Figure 4 illustrates an example of the profile of the two models. In the diagrams, the *y*-axis shows the number of injurious crashes predicted per year per kilometer, while the *x*-axis shows an independent variable of the predictive model. Each graph also presents a series of straight lines with a constant value for the remaining independent variables of the model in appropriate combination. The first graph refers to roads located on the flat/rolling area, and the second to the roads on the mountainous terrain.

The two graphs refer to a particular ADT range below 300 vehicles per day. Indeed the number of possible profiles of the two models is equal to the number of available variables employed in the model on which it can actually work to improve road safety conditions.

For example, to lower crash density on low-volume roads located in flat/rolling terrain, variations can be carried out (fixing an ADT range) on the speed, curvature rate and roadway width. Here, the profile type of the crash density function of the mean speed on the roadway segment may be seen: it can be observed how for a specific combination of roadway curvature and width (respecting their range in the calibration procedure), the number of injurious crashes per year per kilometer increases with speed. Therefore by using the straight line which represents the combination of width and curvature associated with the analyzed roadway segment, and knowing the mean speed on the roadway segment, it is possible to predict the number of injurious crashes per year per kilometer. Among other things, if it is possible to reduce the density of crashes on the roadway segment without changing its width and curvature, by reducing speed through advisor signage and/or changing the geometric features of whole segments or defined elements, one must move along the same straight line to the left. In the same way, there can be a reduction in crash density on the roadway segment with no change in speed but only in roadway width and curvature, moving downward along a vertical line. Therefore a change in speed, curvature and width may be needed.

The practitioners can apply this crash prediction model when the geometric and cinematic features of the examined roadways reflect those employed in the experimental analysis presented here. As it can see in the Figure 4 below, potential safety problems may exist on the analyzed Italian rural roads located in flat/rolling area when the Curvature Indicator is medium, Vertical Grade Indicator is medium and the road width is maximum: the number of predicted crashes can touch 2 injurious crashes per year per kilometer.

The crash prediction models presented here cannot be employed to find potential unsafe pints on the examined roadway but to analyze crash phenomenon on the road network.

The same considerations can be applied to the model for roads located in the mountainous area. The graphs in Figure 4 are represented logarithmically on the *y*-axis.

The countermeasures previously indicated to improve the safety conditions of drivers moving on the roads located in the flat/rolling area were chosen among various efficient operations. To reduce the frequency of the road injurious events, potential cheaper procedures also exist as delineations, rumble strips, advisor signage, isolated friction treatments, etc how many researchers in the scientific literature suggest. However the purpose of this experimental analysis was addressed to recognize on the existing roadways that potential mixture of the values of geometric, cinematic, and traffic features can be contributed to the occurrence of a crash. The helpfulness of these variables to decrease the number of crashes was examined by an experimental analysis with a statistical approach. Two proposed crash prediction models have confirmed how varying the values of some scheduled variables the number of crashes can reduce.

Future developments will be devoted to the investigations of driver behavior in the presence of defined countermeasures to implement or existing on the observed roads also including low-cost procedures. These advances is significant to analyze the impact of stated

devices on the public that may not initially appear ease and inclined to these safety strategies. So improving the features of crash database (e.g., the crash type, the types of involved vehicles, the environmental and surface conditions when the crash happened) it can develop a complete analysis to research the best solutions to improve the roadway safety optimizing the realization costs.

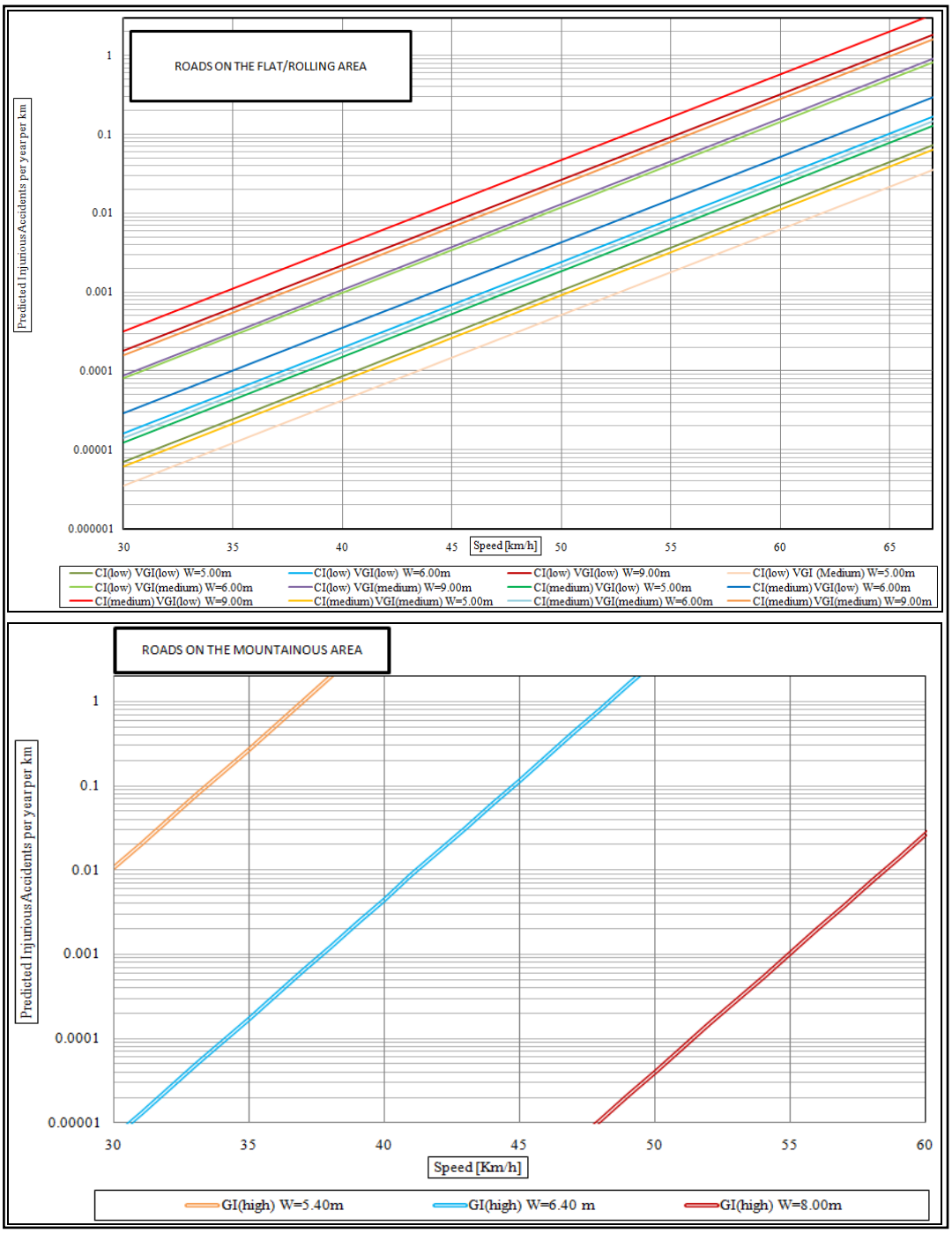

FIGURE 4 Abacus type for predicting the injurious crashes number per year per km

CONCLUSIONS AND FUTURE DEVELOPMENT

The proposed objective was to identify the relationship between the existing causality events among the geometric and functional characteristics of the observed roadway network

(Province of Salerno) and the number of recorded injurious crashes. Once the data had been gathered, a database was created to process the crash information. The proposed models can be used to analyze crashes on the road network and they can become a starting point for detailed models (e.g. crashes at intersections) also through *ad hoc* investigations of specific sites.

The models presented here predict the expected number of injurious crashes per unit length of roadway per year for rural roads in low-volume conditions located on the flat/rolling area and on mountainous terrain. The adjusted coefficient of determination ρ^2 has been used in this paper as well as the traditionally used criterion to determine how well the developed model fits the observed data, in addition to the CuRe (Cumulative Residuals) analysis.

Miaou et al. (*6*) demonstrated that the ρ^2 measurement, that was used for many years to determine the overall quality and usability of the model can lead to pitfalls. Because accident prediction models are non-normal, alternative measures such as scaled deviance and the Akaike information criterion were performed by these authors to determine the goodness of fit of regression models, (*4*).

The analyzed residual plots, an essential tool in the assessment procedure for the prediction of crashes, will be combined with other goodness-of-fit measurements to determine the reliability of the results different from ρ^2 in the future development of this research.

The results obtained may be said to be satisfactory, but the structural form and the analysis of the models to fit the data must be improved (i.e. the application of a generalized estimating equation procedure to develop an CPMs). These injurious crash prediction models can also be used to compare the safety performance of alternatives in a rural road improvement project by estimating the total expected number of crashes for each potential alternative.

M. Banihashemi et al. (*19*) have presented, for example, a linear optimization model that maximizes the safety benefits of improvements on an existing highway within specific budget constraints. The results obtained help designers maximize safety benefits, given a fixed amount of funding available for improvements.

Gerald T. Coghlan of the U.S. Department of Agriculture Forest Service stated that many LVRs around the world consist of a single lane with gravel or even native surfacing, in some remote areas of the world LVRs follow travel routes many centuries old, while in developing areas LVRs may be the first steps up from human and animal pack trails or they may be all-new roads opening up new territory. Traditionally, LVRs have not provided the volume of business, funding, or glamour to attract and support a specialized field of engineering. When involved with LVRs, the engineers used the best information available and they extended their experience and training in higher-standard roads, pavements, or structures to LVR situations, even though they may have recognized the standards as excessive.

It is therefore very difficult to classify these components of a transportation network because of the lack of standards, and it remains a very complex task to understand how to improve and repair them since there may be environmental and financial constraints, while huge sums of money are typically spent on ordinary roadways. Therefore it is necessary to establish some solutions and instruments to optimize roadway construction and management standards.

Therefore a further problem which affects rural roads, in addition to maintenance, is the impact that the various structural and non-structural operations can have on the surrounding environment, modifying natural terrain, disturbing large areas, and leading to major cultural and land use changes. Thus, rural roads need to be well planned, well

designed, well constructed, and properly maintained for minimal adverse impact and to be cost effective in the long term with acceptable maintenance and repair costs.

Roadway construction and maintenance procedure is widely influenced by the material and financial resources available to the Administration or whoever is responsible for planning. The construction and maintenance of low-volume roads are considered very complicated because they have particular features and include trails, mule tracks or gravel roads.

In conclusion the models presented here predict the expected number of injurious crashes per unit length of highway per year; the available variables reflect geometric and no-geometric features of the analyzed roadway. The statistical approach has shown how values of combined variables can really generate a situation where may arise the crash.

The abacus in Figure 4 shows for example how it's really feasible to lower accident density on low-volume roads located in flat/rolling terrain by carrying out (fixing an ADT range) some variations on the design speed, existing curvature rate and roadway width. Thus by the assessment of the operations' costs to plausibly reduce the number of crashes to a desired value, each Administration can plan the preeminent maneuvers considering the material and financial available resources.

In conclusion it can be said that an improvement of the management of rural roads can promote improved safety conditions for drivers. Highway safety management systems (SMSs) in the United States are defined, in part, as a systematic process, the goal of which is to reduce the number and severity of traffic crashes by ensuring that all opportunities to improve safety are identified, considered, and implemented as appropriate, and evaluated in all phases of highway planning, design, construction, operations, and maintenance and by providing information for selecting and implementing effective highway safety strategies and projects (*1*).

ACKNOWLEDGEMENTS

The research was conducted under Italian National Research Project 2008 "*Driver speed behaviour evaluation using operating speed profile and accident predicting models*".
The authors wish to thank the Center for Road Safety of the Province of Salerno for the support in the research.

REFERENCES

1. Kagoro Chobya, L. A., R. W. Eckand, and W. D. Wyant. Teamwork and Technology Transfer in Low-Volume Road Safety. In *Transportation Research Record*, No.1652, TRB, Washington, D.C. 1999, pp. 59–67.
2. Stamatiadis, N., S. Jones, and L. Aultman-Hall. Causal Factors for Accidents on Southeastern Low-Volume Rural Roads. In *Transportation Research Record 1652,* TRB, Washington, D.C., 1999, pp. 111-117.
3. Achwan, N., and D. Rudjito. Accident Characteristics On Low-Volume Roads In Indonesia. In *Transportation Research Record 1652,* TRB, Washington, D.C., 1999, pp. 103-110.
4. Pardillo Mayora, J. M., R. B. Manzo, and A. C. Orive. Refinement of Accident Prediction Models for Spanish National Network. In *Transportation Research Record,* N.1950, TRB, Washington, D.C. 2006, pp. 65–72.
5. Dell'Acqua, G., and F. Russo. Speed Factors on Low-Volume Roads for Horizontal Curves and Tangents. *The Baltic Journal of Road and Bridge Engineering,* Vol. 5,No. 2, 2010, pp.89-97.
6. Miaou, S.-P., A. Lu, and H. S. Lum. Pitfalls of Using R^2 To Evaluate Goodness of Fit of Accident Prediction Models. In *Transportation Research Record*, No.1542, TRB, Washington, D.C 1996, pp. 6-13.
7. Mattar-Habib, C. A. Polus, and H. Farah. Further Evaluation of the Relationship between Enhanced Consistency Model and Crash-Rates of Two-Lane Rural Roads in Israel and Germany. *European Journal of Transport and Infrastructure Research – EJTIR*., Issue 8(4), Dec. 2008, pp. 320-332.
8. Miaou, S.-P., P. S. Hu, T. Wright, A. K. Rathi, and S. C. Davis. Relationship Between Truck Accidents and Highway Geometric Design: A Poisson Regression Approach. In *Transportation Research Record 1376,* TRB, National Research Council, Washington, D.C., 1992, pp. 10–18.
9. Fridstrøm, L., J. Ifver, S. Ingebrigtsen, R. Kulmala, and L. K. Thomsen. Measuring the Contribution of Randomness, Exposure, Weather, and Daylight to the Variation in Road Accident Counts. *Accident Analysis and Prevention,* Vol. 27, No. 1, 1995, pp. 1–20.
10. Lord, D. and B. N. Persaud. Accident Prediction Models With and Without Trend - Application of the Generalized Estimating Equations Procedure. . In *Transportation Research Record*, No.1717, Transportation Research Board of the National Academies, Washington, D.C., 2000, pp. 102-108
11. Saccomanno, F. F., L. Fu and R. K. Roy. Geographic Information System-BasedIntegrated Model for Analysis and Prediction of Road Accidents. In *TransportationResearch Record,* No.1768, Transportation Research Board of the National Academies,Washington, D.C., 2001, pp. 193-202.
12. Hauer, E., F. M. Council and Y. Mohammedshah. Safety Models for Urban Four-lane Undivided Road Segments. In *Transportation Research Record*, No.1897, Transportation Research Board of the National Academies, Washington, D.C., 2004, pp. 96-105.
13. El-Basyouny, K., and T. Sayed. Comparison of Two Negative Binomial Regression Techniques in Developing Accident Prediction Models. In *Transportation Research Record 1950,* TRB, Washington, D.C., 2006, pp. 9–16.
14. Tarko, A. Calibration of Safety Prediction Models for Planning Transportation Networks. In *Transportation Research Record 2103,* TRB, Washington, D.C., 2006, pp. 83-91.

15. Giummarra, G. J. Establishment of a Road Classification System and Geometric Design and Maintenance Standards for Low-Volume Roads. In *Transportation Research Record 1819,* TRB, Washington, D.C., 2003, pp. 132-140.
16. *Rural Road Design: Guide to the Geometric Design of Rural Roads, 7th ed. Austroads*, Sydney, New South Wales, Australia, 1989.
17. National Forestry Manual, United States Department of Agriculture, Natural Resources Conservation Service, 190-V-NFM, 1998.
18. Vogt, A., and J. Bared.. Accident Models for Two-Lane Rural Segments and Intersections. In *Transportation Research Record 1635,* TRB, Washington, D.C., 1998, pp. 18-29.
19. Banihashemi, M., and M. Dimaiuta. Maximizing Safety Improvement Benefits in Crash Prediction Models with Accident Modification Factors. In *Transportation Research Record,* No.1908, *TRB*, Washington, D.C. 2005, pp. 9–18.