CATEGORICAL MODELING TO EVALUATE ROAD SAFETY AT THE PLANNING LEVEL

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ABSTRACT

The most efficient strategy to ensure long term road network safety is to integrate road safety analysis into the planning process of a network or a corridor. Safety planning decision-support tool outcomes should be reliable and realistic, taking into account the main characteristics of this particular level, which is characterized by scant and generalized data. However, the tools developed and presented in previous studies are based on models with a quantitative response, usually the number of accidents, which may not be appropriate for this level. In order to develop a more suitable tool while maintaining a measure assessment character, this work presents a qualitative response model whose outcome is the risk of occurring three degrees of hazards: low, medium and high. In the present study, an ordered probit model was applied to an urban road network using Porto (Portugal) data covering a 5-year period. Hazard categories were defined using accident frequency to reflect a measure of the safety of the road network studied.
The developed model provides a safety risk analysis of a road network or a corridor for a future period, considering road data that are easy to gather or estimate at the planning level, such as land use, traffic volume, etc.
This methodology was applied to various segment scenarios to provide an evaluation of changing road features. Furthermore, a comparison between qualitative and quantitative model outcomes is presented, showing the former as an appropriate model that enables a risk analysis approach.

Keywords: Ordered probit; road safety; transportation planning; risk.

INTRODUCTION

Around 85% of the EU's GDP is generated in cities (Commision of the European Communities, 2009). Efficient transport systems are needed to support their economy and the welfare of their inhabitants. Currently, urban mobility policies face a challenge in providing sustainable transport due to different principles that sometimes oppose each other. Research priorities and agendas for urban mobility are mainly focused on energy and the environment. However, road safety is a social concern that should be included especially in long term evaluations of different solutions and policies for urban road networks.

Over the last three decades, the number of road accidents in Portugal has decreased by 74%. Despite this, the Portuguese average continues to be higher than the European average in terms of the number of fatalities per million inhabitants. A total of 47% of these fatalities and 71% of accidents resulting in injury occur on urban Portuguese roads (ANSR, 2009). In this context, road safety considerations should be explicitly included and weighed at an urban planning level. In fact, ideally, road accidents should be prevented by anticipating the risk of accident occurrence when the road network is being planned. In addition, alternative network options should be recommended.

In order to provide safety planning decision-support tools, several studies have presented accident prediction models. The majority of these models are area-level models (macro-level), usually based on data aggregated at the traffic analysis zone level (TAZ) (Levine et al., 1995, Hadayeghi et al., 2003, Guevara et al., 2004, Sayed and Lovegrove, 2006, Hadayeghi et al., 2010, Naderan and Shahi, 2010). In addition, some models applied to road-level aggregation have also been developed for evaluating alternative road networks (Lord and Persaud, 2004, Tarko et al., 2008, Ferreira and Couto, 2011).

For the above-mentioned accident prediction models developed for the planning level, which is featured by a lack of road network information, the outcome is the number of accidents per year, i.e., a quantitative response. However, in the authors' opinion, this response is not consistent with the poor level of road network characterization available at the planning level. Moreover, at this level, the goal is to select the best solution among different scenarios, taking into account a safety indicator that evaluates safety in a broader manner instead of using a specific number of accidents that is dependent on many factors that are unknown at this level.

In this sense, this work presents a qualitative response model whose outcome is a qualitative measure that characterizes the road network scenario by the degree of hazards. The hazard categories were defined by a range of accident numbers to reflect the magnitude of the safety of the road network studied, independent of the characteristics of the road entity, thus providing a more appropriate tool while maintaining the measure assessment character. Three categories illustrating the degree of hazard based on a range of numbers of accidents were defined as low, medium and high. Using this qualitative approach, road entity scenarios can be assessed by the occurrence probability of the three degrees, thus providing a risk analysis that offers selection support for a safe solution. To achieve this, an ordered probit model (OPM) was developed and applied to an urban road network using Porto (Portugal) data covering a 5-year period. The independent variables used in the OPM geometrically and functionally characterize segments based on data gathered and/or estimated at the planning level: traffic volume, segment length, number of minor intersections (intersections with minor roads, usually without associated traffic data such as access roads), land use and road function classification. Although the OPM was developed for urban segments to provide a comparison between several road network scenarios, the conceptual development can be applied to an aggregate model.

The results obtained using the parameter estimates illustrate the impact of the independent variables on the probability of the three categories. Moreover, these results in agreement with those of other studies using these variables in count-data models (Mountain et al., 1996, Karlaftis and Tarko, 1997, Mountain et al., 1998, Ivan et al., 2000, Greibe, 2003, Wedagama et al., 2006, Wier et al., 2009) as well as with the results obtained from a count-data model applied to the data set used in the present study (Ferreira, 2010, Ferreira and Couto, 2011). Furthermore, a hypothetical segment scenario was defined in order to demonstrate a risk analysis of various scenarios and the consequences of changing the exogenous factors.

The rest of this paper presents the background, data and methods, estimation results, analysis of scenarios and a summary and conclusions regarding the development and application of an ordered response model as a safety planning model, in that order.

BACKGROUND

Several studies have been presented to overcome a lack of available planning-level tools as referred by De Leur and Sayed in (2002). From these studies two different levels of data aggregation have emerged: road-level and area-level. The latter are usually based on data aggregated at the TAZ and comprise the exposure and road network data represented by vehicle kilometers traveled, network density, population, number of employees, etc. However, Tarko et al. (2008) pointed out that area-level models are useful for evaluating transportation and safety-related policies and areawide solutions but less practical for evaluating specific road improvements, screening networks for dangerous roads, estimating the impact of road characteristics or merely predicting future accidents in specific road entities. In this sense, road-level models have been developed by some authors (Lord and Persaud, 2004, Tarko et al., 2008, Ferreira and Couto, 2011). In this case, the road network was characterized by a series of nodes/intersections and links/segments and therefore separate models were developed using variables such as traffic volume (usually defined as the Annual Average Daily Traffic - AADT), number of lanes, segment length, number of intersection arms, etc.

Different approaches for both types of data aggregate-level of accident prediction models have been presented being however, noteworthy that a common technique namely Generalized Linear Modeling (GLM) with the assumption of negative binomial (NB) error distribution has been widely used (Hadayeghi et al., 2003, Guevara et al., 2004, Lord and Persaud, 2004, Sayed and Lovegrove, 2006, Tarko et al., 2008, Naderan and Shahi, 2010). The GLM procedure, normally used in the above-mentioned models, comprises the estimation of parameters to represent the average relationship between the dependent variable, typically number of accidents per TAZ or per intersection and per segment depending on the level of data aggregation, and each explanatory variable. Hence, these are count-data models whose outcome is a quantitative measure of safety.

At the road planning level, especially in the decision making process, an assessment of safety by a quantitative measure is not suitable when a poor level of information of road network characteristics is available. In fact, at this level, a safety measure is needed to evaluate and compare alternative scenarios but not necessarily to predict a number of accidents whereas this can be done later applying existing models and with more accurate results.

In this sense, an alternative approach to evaluate safety at the road planning and decision level is proposed in this work. This approach is based on a categorical modeling that defines the dependent variable as an indicator of a discrete choice, i.e., the dependent variables are merely a coding for some qualitative outcome (Greene, 2008). In this approach, a general framework of probability models are used to link the outcome to a set of factors (Greene, 2008):

$$Prob(event\ j\ occurs) = Prob(Y=j)=F[effects, parameters] \quad (1)$$

where the "event" is an individual's choice among a set of alternatives.

Different types of categorical modeling techniques have been widely applied in economics and modeling of transportation behavior. In the field of road safety, categorical modeling techniques have been more recently used to model accident severity whereas the severity level such as no injury, injury and fatality, is a discrete outcome. The most common techniques applied to analyze accident severity were the multinomial logit, nested logit and ordered probit and logit formulation (Carson and Mannering, 2001, Kockelman and Kweon, 2002, Abdel-Aty, 2003, Eluru et al., 2008, Wang and Abdel-Aty, 2008, Savolainen et al., 2011). These models can be grouped in two response mechanisms: the ordered response (ordered probit and ordered logit) and unordered response (multinomial logit, nested logit and multinomial probit). The ordered response mechanism has the advantage of being parsimonious in structure because it imposes the restriction that the regression parameters are the same for different severity levels. Hence, the adjacent severity levels are correlated. On the other hand, the unordered response mechanism is based on a utility-maximization principle hypothesis and thus the severity levels are not presumed to correspond to the successive partition of a uni-dimension latent variable (Bhat and Pulugurta, 1997).

There is not a clear consensus in the choice of the response mechanism to apply in the accident severity analysis. Abdel-Aty (2003) compared the multinomial logit, nested logit and ordered probit models for driver's injury severity at toll plaza and concluded that the nested logit model produced the best fit. However, other authors (Kockelman and Kweon, 2002, Train, 2003) point out that such specification does not actually fit the structure of the ordinal data.

In the context of accident frequency, the discrete choice models were seldom used taking into account the "count" nature of frequency data. Qi et al. (2007) applied a random effects OPM to model and predict accident likelihood (on-line model) taking into account the preponderance of nonaccident and few accident cases in a short time period analyzed. In this study three responses (choices) were considered: nonaccident (0), one accident (1), and more than one accident (>1) per time interval. Because the responses were ordinal, ordered response model were used. The study results illustrate that the model performs well in identifying factors associated with road accidents and in forecasting the likelihood of accidents based on both time-varying and site-specific parameters.

Based on the review above, it is clear that the applications of discrete choice models were almost limited to the analysis of accident severity. Besides, on the authors' knowledge, nobody has so far examined the possibility of applying a discrete choice model to evaluate safety of different road solutions at the road planning level.

DATA AND METHODS

In order to illustrate the application of a discrete choice model for assessing safety at the road planning level using a qualitative measure as the outcome, an urban segment model was developed using data from Porto, Portugal. At the planning level, segment models can be used to analyze scenarios for a corridor or of a road network entity (an intersection model was also developed in a previous work (Ferreira, 2010) to provide a complete road network analysis). Nonetheless, the conceptual approach presented in this paper can be applied to a data aggregate model like such as an area-level model, whereas the results suggest considerable potential for further applications of these types of models.

The data used in this study consist of accident data from urban segments classified by local and principal distributor roads collected over a 5-year period (1st January 2001 to 31st December 2005). Accident data were obtained from the official Portuguese Police Security database, covering all police-recorded accidents with local information (accidents resulting in injury and accidents resulting in property damage only). All accidents were related to their specific location by applying a Geographic Information System (GIS) tool. The data consist of 5650 police-recorded accidents; of these, 1183 were personal injury accidents and 4467 were property-damage-only accidents that were related to 396 segments.

Using these injury accidents and property-damage-only accidents, hazard categories were set to reflect the magnitude of the hazard from an accident frequency standpoint (an accident severity standpoint could be used as well) of the road network studied. Taking into account the road planning context, instead of a risk factor given by the accident frequency per unit of exposure (i.e., a measure of "accident opportunity"), usually the accident frequency per length or traffic volume unit, the categories were based exclusively on accident frequency. In a planning context, when analyzing safety, one is more focused on choosing between alternative road options or assessing the factor exposure impacts, followed by a risk factor evaluation[1]. In the proposed approach, the risk of different road alternatives is analyzed after the probabilities of each category are determined.

Three categories[2] illustrating the degree of hazard by a range of numbers of accidents were defined: low, medium and high. The first category represents the 0 to 2 accidents. Such low accident numbers are less likely to be related to safe characteristics of the road entity, but rather to the unusual driver behavior, for example. The second category aims to reflect a substantial range of accident numbers that ultimately result from the unsafe features of an urban segment. The latter intends to illustrate the high range of accident frequencies that represent an unacceptable safety situation. The boundary between the last two categories can be defined by a flexible criterion that can be easily determined when applied in a jurisdiction different from the one developed. In the present study, the boundary was considered to be the accident number given by the 90th percentile of all recorded observations, which is 8 accidents. This number ensures that a serious situation as defined in terms of safety is an improbable situation. Therefore, the three responses used to model the data were: low (0-2 accidents); medium (3-8 accidents); high (> 8 accidents). The sample distribution for these responses is: low (64%); medium (28%); high (8%).

[1] For other purposes, such as hotspot identification, it may be useful to use risk factors as the categorical dependent variable.

[2] Other options for category definitions were analyzed, including categories that differentiate accident severity (0 accidents; injury accidents; no-injury accidents). However, based on the statistical significance of the parameter estimates, these options were rejected.

These responses were related to road network attributes represented by independent variables. The variables selected as independent variables were chosen by considering information that can be gathered and/or estimated at the road planning level. Therefore, to geometrically characterize a segment, the two most common variables besides the traffic flow were used: the segment length[3] and the number of minor intersections per segment length. These variables are usually used to homogenize segments and are easy to determine at the planning level by, for example, using a GIS tool. Furthermore, to describe the urban environment, road design and flow pattern characterizing a road network, land use and road function classification variables were included. These variables, especially the land use variable, have been extensively studied as independent variables (Ivan et al., 2000, Greibe, 2003, Wedagama et al., 2006, Dissanayake et al., 2009). In fact, the main decisions required in the urban planning process are related to land use and road function classification.

In this study, five different types of land use based on the municipal master plan were taken into consideration as dummy variables: Land Use 1 (LU1) – high density of buildings; Land Use 2 (LU2) – low density of buildings; Land Use 3 (LU3) – industrial area; Land Use 4 (LU4) – community building area (educational buildings and sports grounds); Land Use 5 (LU5) – historic center area. Figure 1 illustrates the land use classification of Porto city.

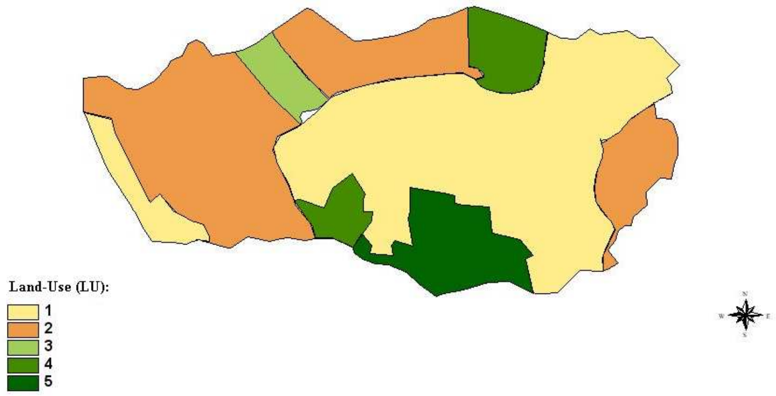

Figure 1 Land use classification of Porto city

In addition, the municipal master plan defines four road classes, namely, arterial roads, principal distributor roads, local distributor roads and access roads. However, only principal distributor roads and local distributor roads were used (also as dummy variables) due to the fact that arterial roads have characteristics similar to those of a highway and that there is a lack of traffic flow data for access roads. Figure 2 shows the road function classification of the Porto road network.

[3] Segment length was defined as part of a road network data set used under a doctoral study (Ferreira, S., 2010) where the influence area of an intersection was 15 meters from the center of the intersection.

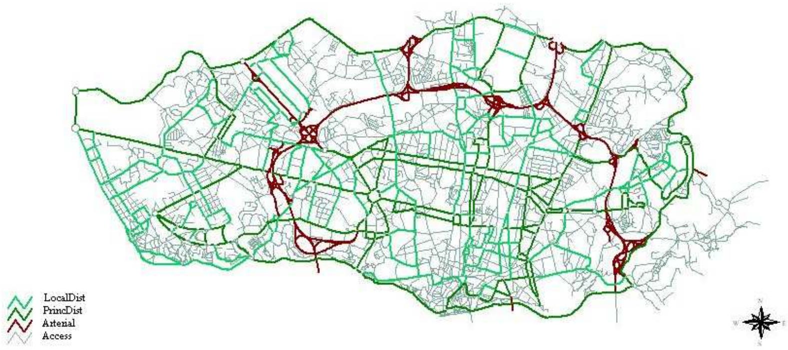

Figure 2 Road function classification of the Porto road network

A time trend variable was also included in this study in order to reflect a potential change in the overall accident level over time. A number of studies have included a time trend variable that allows for changes in terms of risk over time (Fridstrom et al., 1995, Mountain et al., 1998, Greibe, 2003). It has been previously demonstrated that this variable has a negative effect on the frequency of accidents, thus leading to an overall improvement in relation to safety education, enforcement, vehicles, etc. In this model, a geometric form was used, assuming that the "general safety development" is the same from year to year (Mountain et al., 1998). To test for possible temporal correlations, a likelihood ratio test was conducted as described by Poch and Mannering (1996), revealing that this issue does not significantly affect the resulting estimates.

Finally, because traffic flow values are not available for all road networks, the AADT was estimated by the Porto "SATURN" traffic model and data provided by permanent counting stations located throughout the principal city zones belonging to the Urban Traffic Center were used. Traffic simulations have been used in other studies related to the planning level (Lord and Persaud, 2004, Hadayeghi et al., 2010), and it was noted by Lord and Persaud (2004) that the accuracy of such predictions is directly related to the precision of the traffic flow estimates. Table 1 presents a statistical description of the dependent and independent variables used in the frequency models[4].

Table 1 Statistical description of variables used in accident frequency models (5-year)

Variable	Min.	Max.	Average	S.D.
Accident frequency	0	27	2.85	3.90
AADT	142.37	64067.80	15240.38	11699.49
Segment length (in meters)	20.71	3342.78	313.18	352.56
Number of minor intersections per kilometer	0.00	32.04	4.57	5.18
High density of buildings (LU1)	0	1	0.55	0.50
Low density of buildings (LU2)	0	1	0.22	0.42
Industrial (LU3)	0	1	0.03	0.17
Community buildings (LU4)	0	1	0.06	0.23
Historic center (LU5)	0	1	0.14	0.35
Local distributor roads	0	1	0.50	0.50
Principal distributor roads	0	1	0.50	0.50

[4] Correlations among the variables were analyzed using a correlation matrix. This allows one to assume that the explanatory variables are not correlated ($\rho \leq 0.3$) (Ferreira, S., 2010).

As is shown in Table 1, a high degree of heterogeneity is present in some of the variables, namely, the density of minor intersections and the segment length, reflecting the urban environment. The former has a maximum value that implies an average distance between minor intersections of about 30 meters. However, only about 2% of the segments have a minor intersection density greater than 20 per kilometer. Additionally, low segment length values (less than 50 meters) are exhibited by only 11% of the segments studied. These extreme value observations were maintained in the data set to describe all of the urban road network.

Because the three responses (choices) mentioned above are ordinal and have an eventual correlation between adjacent categories, ordered response models were selected. Both ordered response probit and logit models were tested. As expected, the results obtained were very similar because both these ordinal model forms are essentially equivalent and differ only in whether a logistic or a normal distribution is used for the stochastic component in the latent propensity that is assumed to underlie the observed accident frequency. Because the ordered response probit model (OPM) results were slightly better, this form was selected.
This model is specified based on a latent regression model as illustrated below:

$$y_n^* = x'_n\beta + \varepsilon_n \qquad n = 1,\ldots,N \tag{2}$$

where:
y_n^* unobserved components
x'_n vector of independent variables
β vector of parameters
N total number of road segments

In Eq. (2), the unobserved component y_n^* is associated with impacting factors, and based on y_n^*, the observed accident frequency y_n is associated with impacting factors as defined below:

$$y_n = \begin{cases} 0 & if \;\; y_n^* \le 0 \quad (low) \\ 1 & if \;\; 0 < y_n^* \le \mu \quad (medium) \\ 2 & if \;\; y_n^* > \mu \quad (high) \end{cases} \tag{3}$$

where:
μ positive threshold

In Eq. (3), the three coded responses 0, 1 and 2 represent the (un)safety categories discussed above.

The probabilities associated with the coded responses of the OPM are as follows:

$$P_n(0) = \Pr(y_n = 0) = \phi(-x'_n\beta), \tag{4}$$
$$P_n(1) = \Pr(y_n = 1) = \phi(\mu - x'_n\beta) - \phi(-x'_n\beta), \tag{5}$$
$$P_n(2) = \Pr(y_n = 2) = 1 - \phi(\mu - x'_n\beta). \tag{6}$$

where:
$\phi(.)$ standard normal cumulative distribution function

Using these probabilities, the parameters β and μ can be estimated using the maximum likelihood method.

Taking into account the increasing nature of the ordered classes, the interpretation of the β parameters is as follows: positive signs indicate a higher risk as the value of the associated variable increases, while negative signs suggest the reverse. However, in probability models such as the OPM, the sign of β does not always determine the direction of the effect on the intermediate outcomes. In that sense, the marginal effects can provide a better interpretation of changes in the independent variables X_n as follows:

$$\frac{\partial Prob(y=0)}{\partial x} = -\phi(x'_n\beta)\beta, \quad (7)$$
$$\frac{\partial Prob(y=1)}{\partial x} = [\phi(x'_n\beta) - \phi(\mu - x'_n\beta)]\beta, \quad (8)$$
$$\frac{\partial Prob(y=2)}{\partial x} = \phi(\mu - x'_n\beta)\beta. \quad (9)$$

where:
φ(.) probability mass function of the standard normal distribution

Note that the marginal effect of a dummy variable is the difference between the two probabilities associated with the dummy values 0 and 1 (without and with the variable, respectively): *Pr[y|x=1] - Pr[y|x=0]*.

ESTIMATION RESULTS

The estimation results of the OPM and the marginal effects for each variable are presented in Table 2. The parameter estimates and the threshold parameter are significant at the 95% level, indicating a possible relationship between these variables and the occurrence probability of the three categories. The parameter estimates indicate the effect of the independent variables on the latent propensity of accident occurrence for the segments. The marginal effects represent the directionality and magnitude of the effects of the variables on the probabilities of each category. Note that the sum of the marginal effects is zero, which follows from the requirement that the probabilities add to one (Greene, 2008).

The marginal effects of the traffic volume (AADT), segment length and minor intersection density are positive for categories 1 (medium) and 2 (high), suggesting the likelihood that these variables are associated with a high risk of an accident occurring. These findings are in line with those reported by various studies based on count-data models (Mountain et al., 1996, Karlaftis and Tarko, 1997, Mountain et al., 1998, Ivan et al., 2000, Greibe, 2003, Wedagama et al., 2006, Wier et al., 2009) as well as with the results obtained from a count-data model applied to the data set used in the present study (Ferreira, 2010, Ferreira and Couto, 2011). The time trend effect represented by the time trend variable is negative for the two last categories (1 and 2), thus indicating an annual decline in accident frequency for the segments with higher risk.

Table 2 Ordered probit model results

Parameter	Estimated Value	Standard Error	P[Z>z]	Marginal Effects		
				Low	Medium	High
Constant	-9.984	0.505	0.0000	-	-	-
LnAADT	0.393	0.045	0.0000	-0.129	0.116	0.013
LnLength	1.107	0.047	0.0000	-0.364	0.328	0.036
TimeTrend	-0.056	0.022	0.0119	0.018	-0.017	-0.002
Minor intersections	0.038	0.007	0.0000	-0.012	0.011	0.001
Low density of buildings (LU2)	-0.287	0.082	0.0005	0.089	-0.081	-0.008
Industrial (LU3)	0.614	0.175	0.0005	-0.229	0.190	0.038
Community buildings (LU4)	-0.494	0.132	0.0002	0.138	-0.128	-0.010
Historic center (LU5)	0.299	0.093	0.0012	-0.104	0.092	0.013
Local distributor roads	-0.186	0.069	0.0076	0.061	-0.055	-0.006
μ	1.614	0.062	0.0000	-	-	-
Log-likelihood at zero	-1682.965					
Log-likelihood at convergence	-1158.103					
Percentage correctly predicted	73%					

The parameter estimates for LU3 (industrial area) and LU5 (historic center area) are positive and are thus associated with a higher risk of an accident occurring, with positive marginal effects for categories 1 and 2. This is consistent with the findings of previous research (Ivan et al., 2000, Greibe, 2003) and is logical considering the local analysis. LU3 is only composed of one zone in the city although there are various trip attractors depending on the hour and the day of the week. During working hours, this zone is associated with the presence of heavy vehicles and goods deliveries for the industry sector there. On weekends and non-working hours, this zone is related to risk behaviors associated with driving (alcohol, speeding, etc.) due to the fact that there are bars and restaurants in the area. This may explain the positive value of the parameter estimates, which demonstrates an increase in the probability of an accident occurring in the segments located in this type of land use area. Furthermore, in the case of LU5, the positive value of the parameter estimates may be related to the fact that this is a historic center area with a high-density building zone with old and outdated road infrastructures. In addition, there is also a high pedestrian volume and various forms of public transport. The negative values of the parameter estimates for LU2 and LU4 are also in line with expectations. In fact, zones with low densities of buildings, as is the case for LU2, are associated with a decrease in terms of accident risk. In addition, in Porto city, the community building areas (LU4) encompass two zones that include a hospital, a sports hall and university buildings. The reduced accident risk in these zones may be explained by the low density of buildings with suitable road infrastructures and perhaps by highly seasonal movements associated with fewer traffic conflicts in this zone.

Moreover, the effect of road function classification on accident occurrence probability was also as expected. Thus, the negative value for the parameter estimates of the local distributor segments reveal a decrease in accident risk that may be associated with narrower streets, which promote better driving behavior (e.g., lower speeds).

Finally, the analysis of the distribution of the three category probabilities of the 396 segments used in this study indicates that, in 69% of the segments, the "low" category is more likely to occur (27% and 4% for “medium” and “high”, respectively). For road network evaluation purposes, this kind of result can be compared to the results of other possible scenarios while maintaining the ability to identify segments that can be improved, based on a road safety perspective.

Table 3 – Cross tabulation of predicted versus actual observations

Actual observations	Total actual observations	Predicted values		
		0	1	2
0	1260	**1101**	155	4
1	557	249	**283**	25
2	163	12	99	**52**
Total predicted values	1980	1362	537	81

These results correspond to a correct prediction percentage of 73% (bold values in Table 3). Table 3 shows the accuracy of prediction for each category. The “high” category (represented in the table by the number 2) has the highest rate of misclassification of observations predicted by the model, which may be due to the fact that there are fewer observations for this category, thus resulting in heterogeneity phenomena.

ANALYSIS OF HYPOTHETICAL SCENARIOS

The qualitative response model outcome is a set of probabilities of each category for specific features of a segment, thus providing the possibility for a risk analysis. In order to demonstrate this novel qualitative outcome interpretation, the OPM was applied to a hypothetical scenario of an urban segment based on the independent variables used in this study. Table 4 presents the percentage of probabilities computed for a segment 600 meters in length through which 40,000 AADT have passed, with 1 intersection per km. The segment is classified as a local distributor road and is located in a low density building area (LU2). With these characteristics, this segment is associated with a 73% probability of being in the “high” category; thus, this segment may be classified as high risk.

Table 4 Scenario effects: results of the OPM and count-data model

	Prob(y=0) %	Prob(y=1) %	Prob(y=2) %	$Y^{a)}$ (accident number)
S_0: Reference segment scenario- AADT=40000;Length=600;1.67 minor inter. per km; LU2; local distributor road	1	26	73	5.2
S_1: +30% of AADT	1	19	80	5.7
S_2: From LU2 to LU4	9	52	39	5.3
S_3: From local dist. to principal dist.	0	14	86	6.2
S_4: Cumulative effects = S_1+S_2+S_3	1	21	78	6.9

a) These predicted values were based on a NB model, of which, the parameter estimates were statistically significant with R^2_{FT} = 67% (Ferreira, 2010).

Additionally, in Table 4, the probabilities associated with the different scenarios are presented, representing changes regarding the reference scenario identified above. As shown in Table 4, a

30% increase in traffic volume produces a slight change in the probability percentage while keeping category 2 as the most likely. It should be noted that major changes in the road safety level mainly arise from changes in the land use (from the low-density building area - LU2 - to the community building area - LU4). In fact, with this change in the reference scenario, the highest percentage probability changes greatly, sufficiently lowering the probability of the "high" category such that the "medium" category has the highest probability.

The cumulative impacts arising from the analyzed scenarios are shown in Table 4 as scenario S_4. This final scenario may be high risk because the "high" category has the highest probability of occurring. By comparing this risk analysis with the quantitative response presented in Table 4 resulting from a count-data model (NB model) applied to the same data set, one can see that the number of accidents expected for the reference segment scenario is 5.2. This number fits in the "medium" category (3-8 accident), which is not the category with the highest probability of occurring according to the OPM. Although a proper calibration methodology for comparing the results is needed to assess this simple comparison, the main point is the general outcome that a qualitative response model allows for a risk analysis based on probability results instead of a unique number. Note that for an urban planner, a safety tool is one of many tools used to analyze a road network, which should provide simple and reliable results that are consistent for a wide level of analysis.

SUMMARY AND CONCLUSION

A common technique used for safety planning models is the GLM procedure with the assumption of a NB or Poisson error distribution. With this technique, the dependent variable is usually the number of accidents per TAZ or per segment and intersection in the case of area-level or road-level models, respectively. Thus, the model outcome is a quantitative response. However, at the road planning level, there is a lack of data for properly assessing safety by predicting the number of accidents because such a value is associated with a series of factors that are unknown at this point. Furthermore, the main point of a safety planning model is to compare and evaluate alternative solutions rather than to predict/forecast a number.

In this sense, this work presents an alternative approach based on a qualitative response model. Three responses were defined in order to reflect different categories based on a range of accident numbers that can be associated with degrees of hazard. The methodology for defining the response is flexible and can be adjusted to other jurisdictions. Thus, an OPM was applied to estimate the parameters and compute the marginal effects. All of the parameter estimates were statistically significant, and the marginal effect values were in line with findings reported by several count-data models and with the results obtained from a count-data model applied to the same data set used in the present study. Moreover, the results of the case studied demonstrate that, in 69% of the segments, the "low" category, defining a low degree of hazard, is more likely to occur (27% and 4% for "medium" and "high", respectively), with a correct prediction percentage of 73%. In addition, an analysis of hypothetical scenarios for a segment was presented to illustrate an application of the OPM in typifying a risk analysis of scenarios. Hence, the probability of each response (category) occurring was computed, taking into account the attributes of the segment. In order to highlight the advantage of this approach, gradual changes in those attributes were analyzed in terms of affecting risk. Furthermore, the probabilities obtained for each category by the OPM were compared to the expected number of accidents determined by a NB model (count-data model) applied to the same data set. Besides the fact the latter did not match the category with the highest probability of occurrence, the quantitative response constraining the analysis did not allow for a broader risk analysis. Based on these issues, it can be concluded that the OPM presents an alternative approach as a safety tool for road planners, providing a risk analysis with a simple and realistic interpretation of the variable effects. The OPM outcomes can be used among other traditional evaluation criteria in the strategic planning process of a road network or a corridor, thus enabling safety to be included. Note that the concept of this approach can be applied to an aggregate model.

This research represents a step towards an appropriate and reliable safety analysis at the planning level. However, further research should be done, focusing on applying alternative discrete choice models to compare the ordered response mechanism and the unordered response mechanism (represented by, for example, a multinomial logit model) in order to select the more appropriate mechanism.

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