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Development of an accident prediction model for Italian freeways

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A R T I C L E I N F O

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A B S T R A C T

The roadway safety management process plays an important role in the national efforts for improving road safety along the Italian freeway network. In 2016, 8.3% of the overall Italian road deaths and 6.3% of the overall road injuries occurred along the 6700 km-long freeway network. Accident Prediction Models (APMs) represent one of the best tools to perform a road safety quantitative assessment. With the aim of providing the Italian freeway agencies with a tool that allows to deal with potential safety issues, this paper defines two APMs for single- and multiple-vehicle fatal-and-injury crashes to be applied on Italian rural freeway segments, based on jurisdictional specific Safety Performance Functions (SPFs) developed in the PRACT project.

The proposed procedure is based on the Highway Safety Manual (HSM) approach, and it introduces a new methodology to transfer the HSM to European motorways.

In order to improve the prediction accuracy, the proposed APMs consist in a jurisdictional specific base SPF, developed for the base data set as a function of Annual Average Daily Traffic (AADT) and segment length, combined with Crash Modification Factors (CMFs), in order to account for differences between each site and the base conditions. The full models are then calibrated based on the total number of accidents observed in the wide data set. For both full models (one for single-vehicle and one for multiple-vehicle crashes), the goodness of fit is evaluated in terms of chi square test, root mean square error, observed Vs predicted diagram and predicted Vs residual diagram.

The results show a good aptitude of both models to describe the analysis data set. The proposed models represent a solid and reliable tool for practitioners to perform accident predictions along the Italian freeway network.

1. Introduction and objectives

In 2016, 175,791 road accidents occurred in Italy causing 3283 deaths and 249,175 injuries (ACI-ISTAT, 2017). Along the Italian freeways, 9360 accidents occurred (5.3% of the overall accidents) with 274 deaths (8.3%) and 15,790 injuries (6.3%).

Despite a general increase in the number of road accidents (+ 2% on freeways compared to 2015), the number of fatalities is decreasing (-10.2% on freeways compared to 2015). Even though the crash rate in freeways is considerably lower than in other types of infrastructure, freeway accidents are characterized by a mortality index equal to 2.9, among the highest recorded in the different types of Italian roads (ACI-ISTAT, 2017).

With the aim of reaching the 2020 target (halve the number of road deaths, compared to 2010) (United Nations Road Safety Collaboration, 2011), in the period 2017–2020 the number of road deaths in Italy needs a further reduction of about 11%.

The Italian freeway network is about 6700 km long, therefore the reduction in freeways crashes is a priority for National Road Authorities (NRAs) and freeways agencies.

The roadway safety management process plays an important role in the national efforts for improving traffic safety; within this topic, Accident Prediction Models (APMs) represent one of the best available tools for performing a quantitative safety assessment. APMs are mathematical equations that allow road engineers and National Road Authorities to relate the number of crashes expected on a site to its specific geometric and environmental characteristics (Yannis et al., 2016a,b). The use of traditional approaches, such as crash frequency and crash rate estimation, allows the identification of sites with high frequency of crashes by means of a minimum amount of data. However, these methods alone do not allow a quantitative safety assessment of specific features. On the other hand, despite the need of more detailed

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data, the use of APMs as part of the network screening process, allows a road agency to have a good insight in the safety level of its roads (Eenink et al., 2005). Indeed, APMs allow to identify locations that may benefit the most from a safety treatment, and therefore to better define strategies in safety actions and to set priorities (Srinivasan and Bauer, 2013). Another application of APMs is to determine the safety impact of design changes at project level, in order to evaluate existing alternatives or proposed new solutions in the decision making phase (Srinivasan and Bauer, 2013). APMs can also be used to evaluate the safety effects of engineering treatments, as part of a before-after study. In order to properly determine the effect of the implementation of specific safety countermeasures on crashes. APMs are often used in combination with the empirical Bayes procedure (Hauer, 1997), which allows to account for the potential bias due to the regression to the mean phenomenon.

In order to provide the Italian freeway agencies with a tool that allows to deal with potential safety issues identifying the sites with the largest potential safety improvements and helping in choosing the best treatments, this paper provides two APMs for single- and multiple-vehicle fatal-and-injury crashes to be applied on Italian rural freeways based on jurisdictional specific Safety Performance Functions (SPFs) as developed in the PRACT project (La Torre F., Domenichini L., Meocci M. et al. 2016). The proposed procedure is developed based on the approach presented in the Highway Safety Manual (AASHTO, 2010), and it introduces a new methodology to transfer the HSM Part C project-level models to European motorways.

The general level of crash frequencies may vary substantially from one jurisdiction to another for a variety of reasons, including crash reporting thresholds and crash reporting system procedures; even when a proper calibration is performed, transferring a model developed for one jurisdiction to another one may lead to misleading results. On the other hand, the SPFs developed with data for a specific jurisdiction may provide improvements in the prediction accuracy; the HSM indicates that jurisdiction-specific SPFs “are likely to enhance the reliability of the HSM predictive method” (AASHTO, 2010; Srinivasan and Bauer, 2013; Srinivasan et al., 2013). The accident prediction models here proposed for single-vehicle (SV) and multiple-vehicle (MV) fatal-and-injury crashes occurred on rural freeway segments consist in a jurisdictional specific base SPF, developed for the base data set as a function of Annual Average Daily Traffic and segment length, combined with Crash Modification Factors (CMFs), to account for differences between the base conditions and the specific conditions in each analysed section. The full models have been then calibrated based on the total number of crashes observed in the full data set.

2. Background

Nowadays the Highway Safety Manual (HSM) prediction model (AASHTO, 2010) represents the most widely used approach for road safety assessment. The HSM provides a predictive method for estimating the expected average crash frequency of a network, facility or individual site.

According to the procedure proposed by the HSM, the “reference” crash frequency of a segment can be estimated by means of the application of a regression model developed from observed crash data on a large number of sites. The regression models, called Safety Performance Functions (SPFs), are presented for different facility types with “base conditions” that are the specific geometric design and traffic control features of a “base” site. The base functions depend only on the annual average daily traffic and on the segment length, with linear or non-linear traffic effects (depending on the type of road). In order to account for the geometric design and traffic control features of the site under investigation that differ from the base conditions, Crash Modification Factors (CMFs) are used as multiplicative factors to adjust the predicted “base” crash frequency. CMFs are generally developed estimating the safety impact following an intervention or a design change, using a before-after approach. As the general level of crash frequency may vary substantially from one jurisdiction to another for a variety of reasons, including climate, driver population, crash reporting threshold and crash reporting system procedures, a calibration factor (C) is usually adopted to improve the prediction accuracy of the HSM model when transferred to different road networks (AASHTO, 2010; Bahar and Hauer, 2014).

Safety prediction methodologies for freeways, not included in the 2010 version of the HSM, have been published in the HSM supplement (AASHTO, 2014). Likewise to the first approach, the new predictive models for freeways, provided for rural and urban freeways with four/six/eight divided lanes, speed-change lanes, and ramps, consist of a “base” safety performance function combined with a set of crash modification factors.

Other procedures have been developed and applied to estimate road safety levels in road networks. A recent review of APM models applied worldwide has recently been published by Yannis et al. (2017).

The formulation of an APM by means of a Complete Safety Performance Function consists in the development of a statistical model that provides estimates of the average accident frequency of a unit (road segments, intersections, grade crossing etc.) as a function of its traits (traffic, geometry, operation). Recent researches, developed by Behnood and Mannering in 2015 and Cheng et al. in 2018 by means of developing complete SPFs, evaluate the effect of spatiotemporal stability of factors affecting crashes prediction. This approach is based on the assumption of independence of the explanatory variables included in the analysis. Historically, various types of statistical techniques have been used for modelling roadway crashes: Multivariate Analysis, Empirical Bayes Method (Hauer, 2001; Persaud et al., 1999), Fuzzy Logic and Neural Network (Abdelwahab and Abdel-Aty, 2001; Adeli and Karim, 2000). Among these methods, the multivariate analysis has a long and consolidated use in accident analysis. The early models developed with this technique were based on Multiple Linear Regression while, the currently used approach is based on the Generalized Linear Model technique (GLM), which allows to extend the linear modelling to stochastic variables that are not normally distributed with a constant variance. Within the stochastic processes, accident frequency in a specific location is usually treated as a random variable distributed with a Poisson distribution and a negative binomial error structure (Roque and Cardoso, 2014). The definition of a Complete Safety Performance function provides very robust and reliable predictions for the analysed sites (Behnood and Mannering, 2015; Cheng et al., 2018); however, these functions are hardly transferable to different conditions from the ones analysed in their formulation.

In Italy, one of the first approaches regarding the development of APMs referred to the national road network is dated 2007, when Caliendo et al. developed a prediction model for Italian four-lane median-divided motorways based on accident and road geometry data monitored over a period of 5 years, between 1999 and 2003. The model proposed allowed to obtain crash frequency as a function of traffic flow, infrastructure characteristics, pavement surface characteristics as well as wet or dry conditions, and sight distance. It was developed by means of a stepwise forward procedure based on the Generalized Likelihood Ratio Test (Caliendo et al., 2007).

In 2008, Montella et al. developed two separate crash prediction models for total crashes and severe crashes (fatal plus all injury) occurred in the Italian motorway network. The models were developed by means of a Generalized Linear Modelling approach, assuming an error structure described by a negative binomial distribution. A sample of 2245 total crashes occurred from 2001 to 2005 in the A16 motorway was used in order to develop a model considering the following variables: curvature, operating speed reduction, straight length, traffic, friction characteristics, downhill and uphill slope (Montella et al., 2008).

The first implementation of the HSM method in Italy was conducted in 2009 (Martinelli et al., 2009) but it was not referred to freeways. The research focused on the application of the calibration procedure to two-lane two-way rural roads in the Italian province of Arezzo in order to evaluate the practical transferability of the HSM methodology to a region characterized by a different environment and different road characteristics, driver behaviour, and crash reporting systems as compared to those on which the HSM models had been developed.

A few years later, Cafiso and D'Agostino (2012) focused their research on "ranking of high accident concentration sections". A Safety Performance Function based on the Italian road infrastructure characteristics was developed using the General Estimating Equation, including in the analysis a 76.85 km long stretch of road from the A18 Messina-Catania, with 314 crashes occurred in a 4-years period. A comparison with the HSM methodology was also performed. Statistical evaluations demonstrated that the estimations obtained with the GEE were more reliable than the HSM calibration process but the HSM model applied was the "divided highways" and not the "freeways" model (not available at the time). (Cafiso and D'Agostino, 2012).

In order to assess the potential issues that occur applying the HSM freeway model to a different road context characterized by diverse environmental conditions and a distinct crash reporting system, La Torre et al. (2014) evaluated the transferability of the HSM ay model to the Italian freeway network. The goodness of fit assessment was carried out by means of statistical tests such as mean absolute deviation, calibrated overdispersion parameter, root mean square errors and residual plots. The results obtained allowed to observe a good transferability of the HSM predictive models to the Italian network, especially for freeways fatal and injury models (La Torre et al., 2014).

With the aim of making a step forward in accident prediction methodologies and providing the European roadway agencies a tool that allows to obtain a reliable crash frequency estimation on freeway segments as a function of its geometric design, traffic control features, and traffic volumes, a new methodology was developed in the PRACT project to transfer to the European road network the HSM approach (La Torre F., Domenichini L., Meocci M. et al. 2016). This approach was considered more solid and transferable for accident prediction modelling than the use of a complete safety performance function.

In this paper, the implementation on the Italian freeways network is described in detail.

3. Database structure and data availability

The Italian freeway network is about 6700 km long with a divided carriageway cross-section of 2, 3 or 4 lanes per direction. Any accident occurring on the freeway network, including property damage only (PDO) is recorded by the Police and/or a specific traffic assistant group.

The data collected on site are recorded in an accident database managed by the management company of the freeway trunk.

The accident database available for this study refers to the data collected by "Autostrade per l'Italia S.p.A." (ASPI), company that manages a 3020 km long freeway network across Italy. Fig. 1 shows the Italian freeway network, with highlighted in green the sections managed by ASPI.

The accident data analysed within this research refers to 884 km of freeway segments in one direction of travel, covering a 5-year period, from 2009 to 2013.

All the models developed within the PRACT project refer only to fatal and injury crashes as the data availability for property damage only in the other countries for which the PRACT models are developed (UK, Germany, Greece, Netherlands) is limited and often unreliable.

Geometric data and traffic data have also been collected to perform the research.

The geometric database provided by ASPI, containing curvature and gradient information discretised into 50-meter intervals, has been integrated with additional cross-sectional data collected by the University of Florence. The traffic database contains the average daily vehicle passages in each section between two interchanges, available on a monthly basis from 2009 to 2013, for each direction of travel.

Fig. 1. Italian freeways managed by Autostrade per l'Italia S.p.A. (source: Autostrade.it).

The information contained in each database is summarised in Table 1.

4. Methodology

4.1. APM modelling methodology

The accident prediction models (APMs) have been developed in the following scenario:

- road type: dual carriageway;
- site type: freeway segment (not including intersections, interchanges, driveways, etc.);
- area type: rural;
- cross section: two or more lanes for each direction of travel;
- crash type: single-vehicle (SV) and multiple-vehicle (MV) crashes (two separate models);
- crash severity: fatal and injury crashes.

The models to estimate the predicted average crash frequency ($N_{predicted}$) were developed following the HSM approach (AASHTO, 2014), which combines a good flexibility and adaptability to local conditions with a reliable accident prediction. The predictive model consists of a base SPF, crash modification factors, and a calibration factor "C", according to the Eq. (1):

$$N_{predicted,x} = N_{spf,x} \times (CMF_{1x} \times CMF_{2x} \times ... \times CMF_{ix}) \times C_x \quad (1)$$

where:

- x represents a given infrastructure (rural/urban) and lane configuration (2/3 or more for each direction) and crash type (SV or MV);
- $N_{predicted,x}$ is the predicted average crash frequency for a specific year for infrastructure/crash type x;
- $N_{spf,x}$ is the predicted average crash frequency determined for base conditions for infrastructure/crash type x;
- CMF_{ix} is the crash modification factor specific to SPF for site infrastructure/crash x;
- C_x is the calibration factor to adjust the SPF to local conditions for infrastructure/crash site type x.

Within this study, the "base" crash frequencies ($N_{spf,x}$) have been determined by means of regression models developed from data from a number of "base" sites. These base safety performance functions were fitted using only sites with "base conditions", which are the specific geometric design and traffic control features of a "base" site in the analysed scenario. The "base" conditions have been defined for each dataset as the "standard" conditions that can differ from the HSM "base" conditions. The SPFs were fitted with negative binomial (NB) regression models estimated using a generalised linear model procedure

Table 1
Database information.

Geometric data *ASPI/UNIFI database*	Traffic data *ASPI database*	Accident data *ASPI database*
• Freeway ID • Direction • Beginning of the trait • End of the trait • Geometric element: presence of straight or bend (for the bends, radius and direction: left/right) • Longitudinal slope • Outside shoulder width • Median Width • Median and outside barrier • Presence of a bridge, tunnel, junction, service area, parking • Number of lanes • Presence of a Speed limit • Presence of a high friction wearing course	• Freeway ID • Direction • Beginning of the section • End of the section • Date • Passages divided by vehicle class • Presence of an average speed enforcement (section control)	• Accident ID • Date • Time • Freeway ID • Direction • Milestone (km) • Localisation on the carriageway • Type of accident • Pavement conditions • Speed limit • Weather conditions • Presence of work zone • Cause of the accident (not always available) • Number of vehicles involved • Number of injuries • Number of fatalities • Type of damaged elements • For each vehicle involved: • Vehicle id • Type of vehicle • Condition of the driver after the accident • Vehicle damage (Yes/No) • Number of people involved • Number of injuries • Number of fatalities

as a function of annual average daily traffic (AADT) volume and roadway segment length.

Crash modification factors were then used as multiplicative factors to account for the specific site conditions, which are different from the base conditions; finally, the full Accident Prediction Models were calibrated to the entire data set in order to obtain the calibration factor to account for differences in the general level of crash frequency and enhance the reliability of the predictive method. The methodology adopted for modelling the APMs is presented in Fig. 2.

4.2. *Definition of the relevant variables included in the analysis*

As proposed by the HSM procedure, the APMs developed consider separately two types of accidents occurred on rural freeway segments:

- single-vehicle fatal-and-injury crashes (SV-fi);

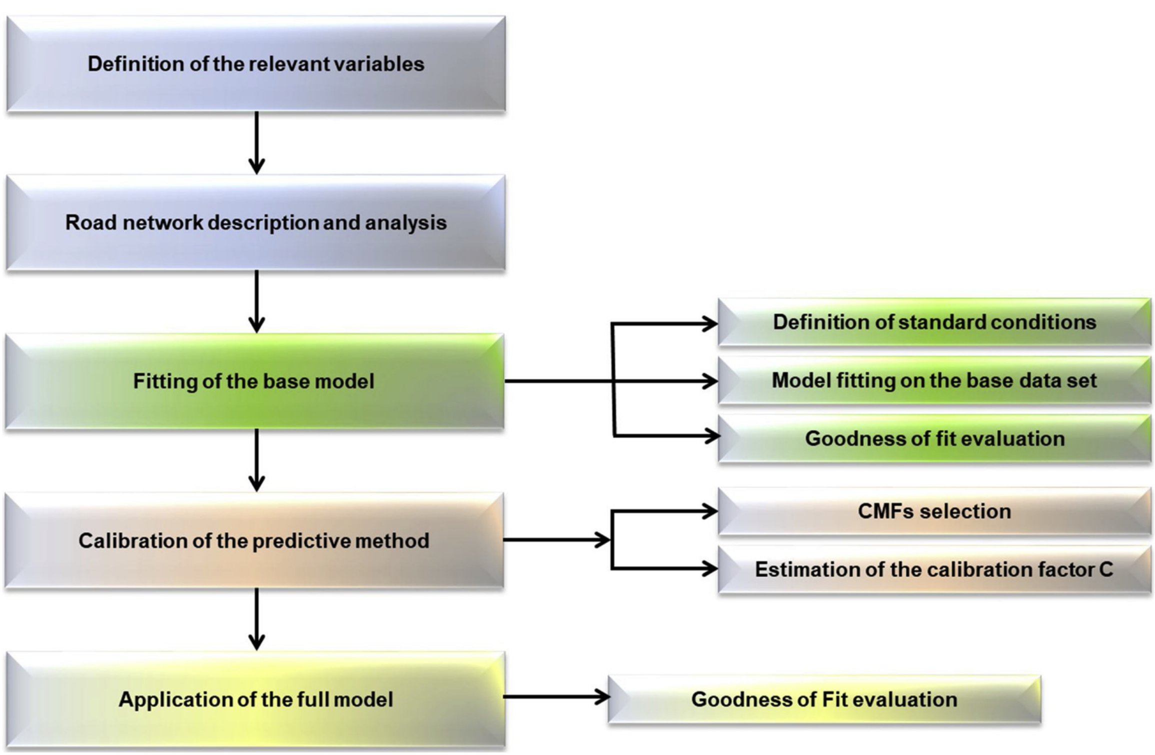

Fig. 2. Flowchart for the APM modelling methodology.

- multiple-vehicle fatal-and-injury crashes (MV-fi).

Two different accident prediction models provide, as dependent variable, the *number of single-vehicle* (or *multiple-vehicle) fatal-and-injury crashes per km per year*, obtained following the investigation in a 5-year period (from 2009 to 2013). Differently from the HSM, it was chosen to collect data and develop models specifically for *one-direction of travel*. This allowed more flexibility in applying the model, such as the possibility to account for differences in AADT (Roque and Cardoso, 2014), number of observed accidents and geometry in the two direction. This also provides more reliability in identifying the segments with the largest potential for safety improvements.

In order to account for data over-dispersion, the response variable is assumed to have a negative binomial distribution, better suited than the Poisson distribution for modelling crash data (AASHTO, 2014).

The variables used in the APMs, have been extracted from road alignment, cross-sectional and traffic data bases in order to evaluate the crash modification factors (CMFs) that are part of the HSM predictive process for freeways (AASHTO, 2014) and the CMFs developed within the PRACT project (Karathodorou et al., 2016; Yannis et al., 2016a), such as the presence of a high friction wearing course and the presence of an average speed enforcement (section control) or of a stationary work zone (La Torre et al., 2016, 2017, 2018). The characteristics accounted for this analysis are here summarised:

- segment length;
- number of lanes;
- horizontal curve radius and length;
- lane width;
- inside shoulder width;
- portion of segment with a barrier in the median;
- median width;
- high volume;
- portion of segment with a barrier in the outside edge;
- outside clearance;
- presence of a high friction wearing course;
- presence of average speed enforcement (section control).

Section with important work zones were removed from the analysis to develop the APM.

4.3. Description of the road network used for modelling

The sections used for the APM development are the result of the segmentation of the motorway network in 1-km-long homogeneous segments. Each segment has been assigned a weighted average of the geometric and functional variables of interest. Table 2 presents a summary of the data collected.

The experience with crash data indicates that very shorts segments or sections associated with a very low traffic volume, tend to have no reported crashes during a period of several years (Bonneson et al., 2007). When one of these segments is associated with one or more crashes, it has a tendency to exhibit undue leverage on the regression model coefficients and increases the Pearson χ^2 goodness of fit statistic in a disproportionate manner (Bonneson et al., 2007). To avoid these issues, data has been screened and only the segments with the following characteristics were included in the analysis:

- rural environment;
- mean AADT recorded in the analysis period in the specific section above the AADT 10th percentile of the sample (9279 veh/day, rounded to 10,000 veh/day);
- minimum level of exposure $E \geq E_{min}$, where E_{min} is the segment exposure associated with prediction ratio PR = 3.0, million-vehicle-miles (mvm) and E is the exposure for all segments (mvm) according to the procedure defined by Bonneson et al. (2007).

In Tables 3 and 4 the descriptive statistics of the samples used for calibrating the accident prediction single- and multiple-vehicle models are shown.

4.4. Road network analysis: identification of the “base” conditions

In order to perform an effective integration of the base models with the HSM predictive method, the final base SPFs should have the same base conditions as the ones adopted in the HSM. This will allow to apply the HSM CMFs, without the need for any further transformations. However, because the use of the same base conditions adopted by the HSM did not allow to identify a sufficient number of base segments within the data set, the base models were developed using data for a different set of conditions as compared to the HSM than the base conditions, as suggested also by the HSM procedure (AASHTO, 2010, 2014).

Analysing the descriptive statistics of the full data set, “standard” conditions were identified in the dataset by means of the use of frequency distribution plots for each analysis variable. Each CMF was evaluated for the mode value of each analysed variable; then, sections where the CMF is within ± 5% of the value calculated for the mode value are considered as “standard” and are used for developing the base models. A sample of the frequency distribution plots used for the identification of the “standard” conditions is shown in Fig. 3.

Once the standard conditions have been defined for each analysed variable and the corresponding CMF values have been estimated, a corrective coefficient was evaluated to adjust the SPFs for conditions different from the HSM base ones, according to Eq. (2):

$$\prod_{i=1}^{n} CMF_i \tag{2}$$

where, CMF_i are the crash modification factors computed for each variable i that has a standard condition different from the HSM base condition.

In Table 5 the variable ranges used to identify the “standard” segments usable for fitting the SPF base models are summarized.

4.5. Fitting of the base models

The base SPFs were fitted with negative binomial (NB) regression models estimated using a generalised linear model (GLM) procedure. A statistical software, i.e. SPSS ver. 23 (IBM, 2015) was used for this purpose.

The base models were developed according to the guidelines presented in the HSM Appendix B (AASHTO, 2014). Assuming as the response variable *fatal-and-injury single- (or multiple-) vehicle crashes per year in one direction of travel*, the base SPFs include the effect of traffic volume in terms of annual average daily traffic. The predicted average crash frequency is directly proportional to the segment length, as shown in the Eq. (3).

$$N_{spf} = L \times e^{[a + b \times ln(c \times AADT)]} \tag{3}$$

where:

- N_{spf} is the predicted average crash frequency (fatal-and-injury accidents) in one direction of travel determined for base conditions;
- L is the segment length (in km);
- AADT is the annual average daily traffic in one direction of travel [vehicles/day];
- a, b, c are the safety performance function coefficients.

According to the HSM (AASHTO, 2010), the response variable was assumed to follow a negative binomial distribution, which allowed to account for data over-dispersion. While the logarithm was assumed as a link function, the parameters of the models were estimated using the maximum likelihood method, selecting the set of parameters that

Table 2
Summary of data collected.

Crash frequency distribution	Multiple-vehicle [segments]	23 MV-fi-crashes	1
		17 MV-fi-crashes	2
		16 MV-fi-crashes	1
		15 MV-fi-crashes	2
		14 MV-fi-crashes	1
		11 MV-fi-crashes	3
		10 MV-fi-crashes	5
		9 MV-fi-crashes	6
		8 MV-fi-crashes	16
		7 MV-fi-crashes	14
		6 MV-fi-crashes	39
		5 MV-fi-crashes	45
		4 MV-fi-crashes	58
		3 MV-fi-crashes	84
		2 MV-fi-crashes	141
		1 MV-fi-crashes	201
		0 MV-fi-crashes	265
	Single-vehicle [segments]	16 SV-fi-crashes	1
		10 SV-fi-crashes	1
		9 SV-fi-crashes	2
		8 SV-fi-crashes	6
		7 SV-fi-crashes	9
		6 SV-fi-crashes	5
		5 SV-fi-crashes	18
		4 SV-fi-crashes	28
		3 SV-fi-crashes	71
		2 SV-fi-crashes	124
		1 SV-fi-crashes	267
		0 SV-fi-crashes	352
Fatal and Injury accidents	Total [# accidents]		3021
	Multiple-vehicle [#accidents]		1906
	Single-vehicle [#accidents]		1115
Segmentation process	Total length [km]		884
	Sample size [segments]		884
Accident severity	Fatal-injury crashes		
Target accident group	Multiple vehicle		
	Single vehicle		
Observed period	2009-2013 (5 years)		

Table 3
Description of the calibration dataset for Italian freeways.

Number of segments in the samples		718
	2-lane segments	370
	3 or more lane segments	348
Total length covered [km]		718
Number of single-vehicle fatal-and-injury crashes		1042
Number of multiple-vehicle fatal-and-injury crashes		1826
Total number of accidents		2,868

maximise the log-likelihood function.

In order to build a model consistent with the bi-directional one developed within the HSM, the response variable for the model was set as *twice the single- (or multiple-) vehicle fatal-and-injury crashes* occurred in the segment in the analysis period; the predictors were set for *number of lanes* (developing models for *2* and *3 or more lanes*) as 'factor', and *ln (c*AADT)* as 'covariate', where c is a coefficient set equal to 0.002. The use of an *offset variable* allowed to take into account the standard conditions different from the HSM base ones and to obtain a predicted average crash frequency directly proportional to segment length and number of years of observation. The offset variable was therefore set as described in the Eq. (4).

$$offsetvariable\colon \ln(L \times CMF_{tot} \times n) \tag{4}$$

where:

- L is the segment length (km);
- $CMF_{tot} = \prod_{i=1}^{n} CMF_i$ is the corrective coefficient to account for base conditions different from the HSM base conditions;
- n is the number of years of the observation data.

Table 4
Descriptive statistics of the calibration dataset for Italian freeways.

	Minimum	Maximum	Mean	Std. Dev.
AADT [veh/day]	10,371	49,572	25,962	9,904
L [km]	1	1	1	0
Horizontal curvature [-]	0.00	32.83	1.83	5.05
Lane width [m] *	3.75	3.75	3.75	0
Inside shoulder width [m] **	0.60	0.60	0.60	0
Portion of the segment with a barrier in the median *	100%	100%	100%	0%
Proportion of AADT during hours where volume exceeds 1000 veh/h/ln	0%	41%	11%	10%
Outside shoulder [m]	1.22	4.27	2.35	0.79
Portion of segment with a barrier in the roadside	0%	100%	84%	25%
Heavy Good Vehicle (HGVs)	15%	32%	25%	4%

* due to a lack of data in this variable, it was assumed a default value according to the Ministry Decree No. 6792 of 05.11.2001 (mandatory only for new roads).

** due to the lack of data in this variable, the value 0.6 m represents the minimum value provided by the HSM for the CMF3 (inside shoulder width): 2 ft = 0.61 m.

The models' coefficients have been "corrected" to obtain a predicted average crash frequency in only one direction of travel, according to the Eq. (5).

$$a = \bar{a} + \ln(0.5) \tag{5}$$

where, $\bar{a}$ is the coefficient estimated from the fitting process.

Table 6 presents the descriptive statistics of the samples used for

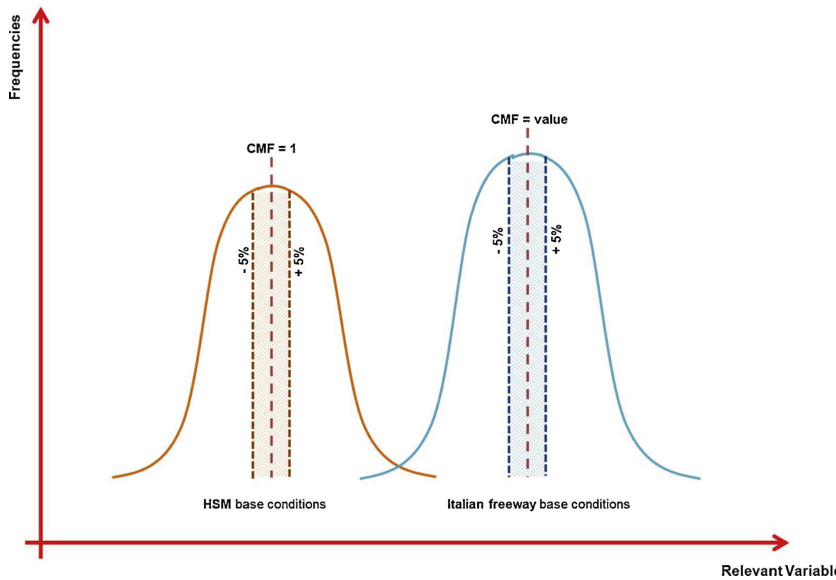

Fig. 3. Sample of the frequency distribution plots for the identification of standard conditions.

Table 5
Summary of standard conditions adopted.

	MIN	MAX
Horizontal curvature [-]	0	0.19
Average Radius [m]	4000	–
Lane Width [m] *	3.75	3.75
Inside Shoulder Width [m] *	0.60	0.60
Portion of segment with a barrier in the median [%] *	100	100
Distance from edge to barrier face [m]	0	0.20
Portion of AADT during hours where volume exceeds 1000/veh/h/ln [%]	0	30
Outside shoulder width [m] **	2.90	3.10
Portion of segment with a barrier in the roadside [%] **	90	100
Distance to upstream entrance [km] ***	0.800	–
Distance to downstream exit [km] ***	0.800	–

* variable value assumed as constant.
** only for single-vehicle models.
*** only for multiple-vehicle models.

fitting the base SPFs.

4.6. Selection of crash modification factors

In order to account for the specific site conditions that differ from the base conditions, Crash Modification Factors, or Functions, are included in the prediction models considering the relevant variables listed in Section 4.2 of the manuscript.

Consequently to the base SPF formulation, the CMFs included in the full model have the same base conditions as the base models. According to this, when a variable assumes the base condition value, the relative CMF coefficient assumes a value equal to 1, without the need of any transformations due to different base condition systems.

If the value of a relevant variable was out of range of applicability for a given Crash Modification Factor, the threshold value was selected to compute the CMF to be used.

Additional CMFs, not used in this study can be applied to the freeways base model as proposed within the PRACT project (La Torre et al., 2016, 2017, 2018; Karathodorou et al., 2016).

4.7. Estimation of the calibration factor

A calibration factor “C” is usually evaluated to improve the accuracy of the prediction of the HSM model transferred to road networks different from the one for which the model was developed. This allows to account for differences in the general level of crash frequency, which may change substantially from one country to another because of differences in climate, driver populations and trip purposes, complexity of the geometric layout, driver attitude (rate of compliance with road code rules), vehicle fleet characteristics, crash reporting threshold, and crash reporting system procedures (AASHTO, 2010; Bahar and Hauer, 2014).

The calibration factor C is defined as the ratio between the total number of crashes observed (N_{obs}) and the total number of crashes predicted (N_{pred}) by the uncalibrated model as shown in Eq. (6).

$$C = \frac{\sum_{i=1}^{allsites} \sum_{j=1}^{allyears} N_{obs,i,j}}{\sum_{i=1}^{allsites} \sum_{j=1}^{allyears} N_{pred,i,j}} \quad (6)$$

The effect of several causal factors, such as driver habits, enforcement levels, vehicle technologies or safety systems, may improve over time and cause changes in crash counts unrelated to the safety

Table 6
Descriptive statistics of the sample used for modelling the base SPF.

	Single-vehicle fatal-and-injury crashes		Multiple-vehicle fatal-and-injury crashes	
Analysis period	2009 - 2013 (5 years)		2009 - 2013 (5 years)	
Number of segments	116		310	
2 lanes	58		160	
3 or more lanes	58		150	
Total length covered [km]	116		310	
Number of crashes	93		692	
	Min - Max	Mean (Std. Dev.)	Min - Max	Mean (Std. Dev.)
AADT [veh/day]	10,371 – 49,572	29,742 (11,792)	10,371 – 49,572	26,460 (10,252)

treatment. The models used within the PRACT project for developing new CMFs were calibrated separately for each year of analysis to reflect these time trends (La Torre et al., 2018).

4.8. Evaluation of the goodness of fit and residual analysis

Several statistics have been developed in accident analysis to assess how well a model fits the data. In this research, the goodness-of-fit (GoF) of the base and full models has been assessed by means of the following indicators:

- Pearson's χ^2 statistic: the χ^2 distribution with *n–p* degrees of freedom (df), where *n* is the number of observations (i.e., segments), and *p* is the number of variables; it is asymptotic to the χ^2 distribution for larger sample sizes and exact for normally distributed error structures (Bonneson et al., 2007; McCullagh and Nelder, 1993). The Pearson χ^2 statistic evaluated for a model is usually compared to the χ^2 - *value* computed for *n–p* degrees of freedom and a *p-value* equal to 0.05 ($\chi^2_{0.05,(n-p)}$). If the χ^2 statistic of the model is less than the χ^2 - *value*, the hypothesis that the model fits the data cannot be rejected.
- root mean square error (Se): this is an useful statistic for assessing the precision of a model estimate and is often used to compare the GoF of different models. It is computed using the equation suggested by Bonneson et al. (2012).
- R-squared coefficient of determination (R^2): the coefficient usually adopted to estimate the percentage of variation explained by a regression model. It may yield to controversial results for non-linear models, as typically accident prediction models are; however, it has some useful interpretation when computed using the equation suggested by Kvalseth (1985). According to this criterion, the closer to 1 the R^2 coefficient is, the better the model explains the data set.
- cumulative residuals plot (CURE): the graph consists in plotting the cumulative residuals[1] versus a variable of interest, showing at a glance how good a fit is, and what the remaining concerns are.

While the first three indicators are the most used single-number measures for generalised linear models able to describe a model overall goodness of fit, the last method (CURE plot) is commonly used for residual analysis in order to identify anomalies in a model, such as the presence of outliers or bias. A good model should have a CURE plot that oscillates around 0 and encroaches the $\pm 2\sigma$ limits only rarely (Hauer, 2015). Also, according to Hauer, "long up or down runs indicate regions of bias which demand model improvement", while "large vertical drops invite the examination of outliers".

5. Results and discussion

5.1. Base models

The base models developed for Italian rural freeway segments allow to estimate *single- (or multiple-) vehicle fatal-and-injury crashes per year in one direction of travel* for sections with base conditions as defined in the HSM model for freeway segments (AASHTO, 2014) by means of the equations (8) and (9).

SV fatal-injury crashes:

$$N_{spf,sv,fi} = L \times e^{[a+1.393\times ln(0.002\times AADT)]} \tag{8}$$

- $a = -7.924$ for 2-lane segments
- $a = -8.008$ for 3(or more)-lane segments

MV fatal-injury crashes:

$$N_{spf,mv,fi} = L \times e^{[a+1.797\times ln(0.002\times AADT)]} \tag{9}$$

- $a = -8.304$ for 2-lane segments
- $a = -8.528$ for 3(or more)-lane segments

where:

- $N_{spf,sv,fi}$ is the predicted average crash frequency (fatal-and-injury accidents) for single-vehicle crashes in rural freeway segments with base conditions, one direction of travel;
- $N_{spf,mv,fi}$ is the predicted average crash frequency (fatal-and-injury accidents) for multiple-vehicle crashes in rural freeway segments with base conditions, one direction of travel.

The over-dispersion parameter is k = 0.789 for the SV base model and k = 0.678 for the MV base model.

In order to check the soundness of the estimation, the regression parameters computed for base SPFs single-vehicle and multiple-vehicle fatal-and-injury crashes in one direction of travel are compared to the correspondent ones found in the published literature. In Table 7, the estimated regression coefficients are shown together with the ones developed in the HSM. In order to compare the coefficients developed for one-directional models with the HSM bidirectional ones, the Italian *a* coefficients are corrected inverting Eq. (5).

As shown in Table 7, the coefficients are consistent with the correspondent ones found in the published literature. The differences in absolute values reflect the different contexts in which the models have been developed.

5.2. Evaluation of the goodness of fit of the base models

The overall goodness of fit indicators for the base models are presented in Table 8.

For both SV and MV models, the Pearson's χ^2 statistic is less than the corresponding value of χ^2 computed for the respective *n–p* degrees of freedom, assuming a p-value equal to 0.05. According to these results, the hypothesis that both models fit the data cannot be rejected.

The root mean square error (Se) shows a good capability to describe the respective dataset, for both models.

The evaluation of the coefficient of determinations R^2 yields to controversial results. Being both coefficient of determinations R^2 not close to 1, the ability of the models to explain the respective data set is in doubt. However, several authors (Fridstrøm et al., 1995; Miaou et al., 1996) expressed reservations about the use of the coefficient of determination as instrument of goodness of fit measure for negative binomial models.

5.3. Cumulative residual analysis

In order to perform an additional analysis on the models goodness of fit, identifying the areas which demand for further investigation, the cumulative residuals (CURE) for the base SV and MV models were plotted. The results are presented in Figs. 4 and 5.

The graphs show that the functional form assumed for the base models is correct, and that there is no need to include other factors in the fitting process. This was expected as the sections used to develop the base models were selected with similar characteristic and standard conditions; indeed, only the exposure variable was expected to influence the crash occurrence. Both plots correctly oscillate around 0; the SV model encroaches the $\pm 2\sigma$ limit only in one point, and for a very small difference, indicating the substantial absence of any bias in both

[1] The residuals are defined as the difference between the number of crashes observed in a segment and the number of crashes predicted by the model. The residual ($\varepsilon_{i,N}$) for the segment i in the analysis period N is calculated with the Eq. (7):

$$\varepsilon_{i,N} = N_{obs,i,N} - N_{pred,i,N} \tag{7}$$

Table 7
Interpretation of SV and MV regression parameters.

Italian SPF freeway model (bidirectional)		HSM freeway model (bidirectional)	
SPF Coefficients for SV fatal-injury crashes on bidirectional Rural Freeway Segments			
Number of through lanes = 4		*Number of through lanes = 6*	
Italy	HSM	Italy	HSM
a [(*)] = -7.231	a = -2.126	a [(*)] = -7.315	a = -2.055
b = 1.393	b = 0.646	b = 1.393	b = 0.646
SPF Coefficients for MV fatal-injury crashes on bidirectional Rural Freeway Segments			
Number of through lanes = 4		*Number of through lanes = 6*	
Italy	HSM	Italy	HSM
a [(*)] = -7.611	a = -5.975	a [(*)] = -7.835	a = -6.092
b = 1.797	b = 1.492	b = 1.797	b = 1.492

[(*)] The coefficient *a* is corrected for the evaluation of a bidirectional segment inverting Eq. (5).

caused by the presence of outliers.

5.4. Calibration of the full models

The combination of the base models with the CMFs presented in the HSM (AASTHO, 2014) and the ones developed within the project PRACT allowed to estimate the number of predicted crashes (uncalibrated) for each segment during the evaluation period. In order to account for differences in the general level of crash frequency between the base data set and the calibration data set, two calibration factors were then computed for the SV and MV models. The results of the calibrations are presented in Table 9.

The calibration factors with values greater than "1" show a tendency of the uncalibrated full models to underestimate the total number of crashes in the full data set, more in the SV model than in the MV model.

These factors are applied to the "uncalibrated" full models to obtain the "calibrated" predictions.

Table 8
Goodness of fit of the base models.

	Pearson's χ^2 statistic χ^2	degrees of freedom df	Reference Pearson's χ^2 statistic $\chi^2_{(0.05,df)}$	root mean square error Se	coefficient of determination R^2
SV	64.18	112	137.68	0.177	0.138
MV	291.10	306	347.85	0.447	0.244

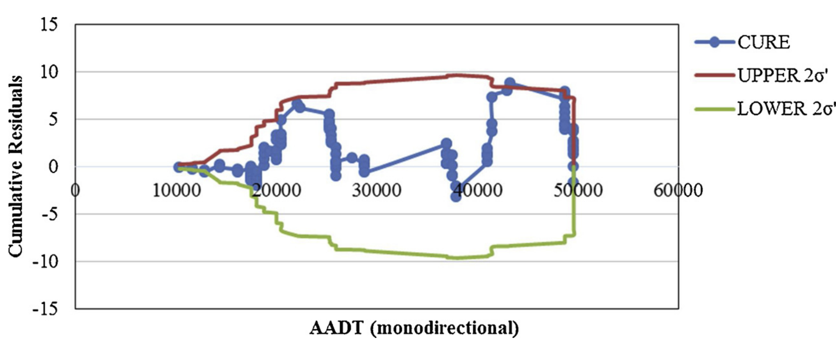

Fig. 4. CURE plot for SV base model.

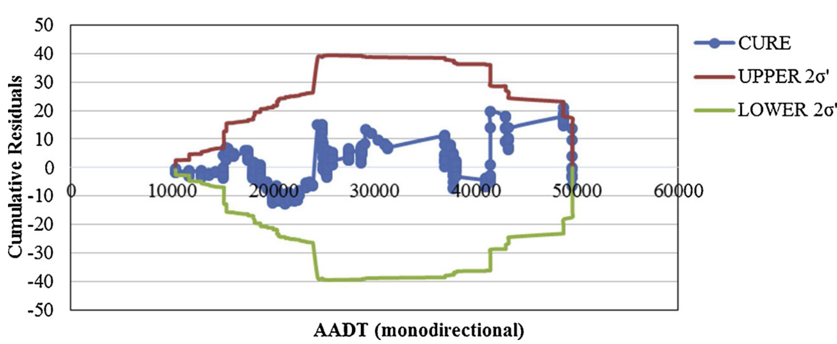

Fig. 5. CURE plot for MV base model.

Table 9
Calibration factors for the SV and MV full models.

	$N_{predicted\_uncalibrated\_tot}$	$N_{observed\_tot}$	$C = \frac{N_{observed\_tot}}{N_{predicted\_uncalibrated\_tot}}$
SV model	614	1042	1.696
MV model	1,545	1826	1.190

models. However, while the CURE plot of the MV base model does not indicate any presence of outliers, the vertical drop recorded in the SV base model in correspondence to an AADT of 40,000 veh/day could be

5.5. Evaluation of the goodness of fit of the full models

The overall goodness of fit indicators for the calibrated full models are presented in Table 10.

For both SV and MV full models, the Pearson's χ^2 statistic is less than the corresponding value of χ^2 computed for the respective *n–p* degrees of freedom, assuming a p-value equal to 0.05. According to these results, the hypothesis that both models fit the data cannot be rejected.

Table 10
Goodness of fit of the full models.

	Pearson's χ^2 statistic χ^2	degrees of freedom df	Reference Pearson's χ^2 statistic $\chi^2_{(0.05,df)}$	root mean square error Se	coefficient of determination R^2
SV	563.55	717	780.47	0.306	0.218
MV	560.48	717	780.47	0.460	0.271

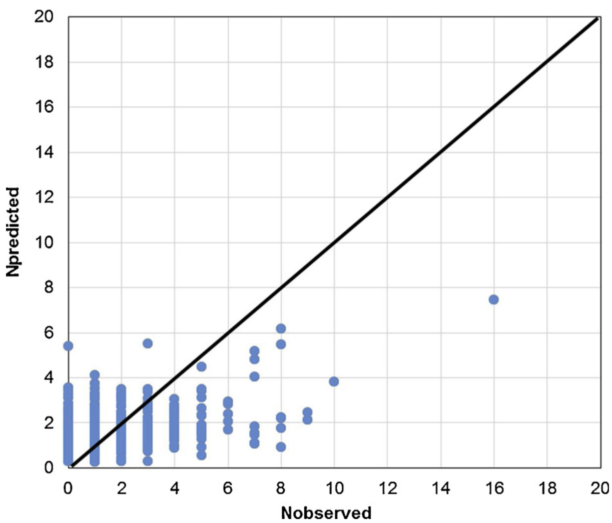

Fig. 6. Observed vs Predicted diagram for SV model.

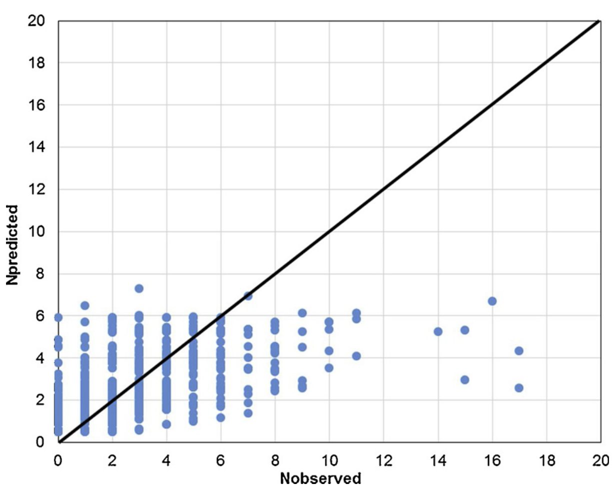

Fig. 7. Observed vs Predicted diagram for MV full model.

The root mean square error (Se) shows also a good capability to describe the respective dataset, for both models. The final results of the full model calibrations are shown in Figs. 6 and 7 by means of observed vs predicted diagrams.

The graphs show a tendency of both models to under-predict the number of crashes for those sections, where record a number of observed crashes higher than the mean values is recorded, this tendency is more clear in the MV model. These groups of segments, which represent outliers of the calibration data set, should be investigated in more details (e.g. by means of a disaggregate analysis) to understand if variables not considered in this study are involved in the high frequency records.

Another graphical representation that allows to evaluate the presence of some sources of anomalies in the model is the plot of the residuals versus the number of accidents predicted. The residual plots in Figs. 8 and 9 show a particular point distribution that is due to the presence of heteroscedasticity, which means that a non-random

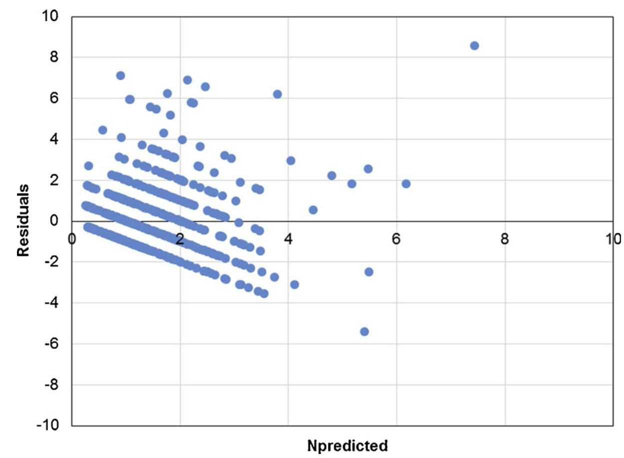

Fig. 8. Predicted vs Residuals diagram for SV full model.

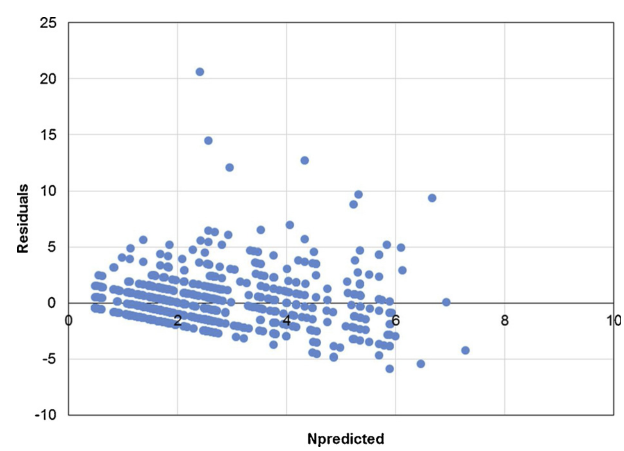

Fig. 9. Predicted vs Residuals diagram for MV full model.

distribution of residuals is observed (La Torre et al., 2014), more evident in the SV model. As a matter of fact, increasing in the number of expected crashes tends to increase the residuals. According to Shankar et al. (1995), heteroscedasticity is an important issue often associated with the negative binomial models.

6. Conclusions

In order to provide the Italian freeway agencies with a tool that allows to deal with potential safety assessments, identifying the sites with the largest potential safety improvements and helping in choosing the best treatment to apply, this paper describes two accident prediction models (APMs) for single- and multiple-vehicle fatal-and-injury crashes. Following the HSM approach, these models are based on jurisdictional specific Safety Performance Functions (SPFs) and a set of CMFs, applying the procedure defined in the PRACT Project.

The accident prediction models were developed using a dataset including information about fatal and injury crashes occurred on 884 km of freeway segments in a 5-year period (2009–2013). The models allowed to estimate *fatal-and-injury single- (or multiple-) vehicle crashes per* *year in one direction of travel*. The base SPFs developed have the same base conditions than the ones used in the HSM; this allows to account for differences between a given section and the HSM base conditions by means of CMFs without the need of any further transformations due to different base conditions. In order to improve the reliability of the prediction accounting for differences in sites where the CMFs were developed, a calibration factors (C) was then computed for each APM.

The goodness of fit of the base models and of the full models was investigated by means of Pearson's χ^2 statistic, root mean square error, and residual analysis.

For both SV and MV full models, the Pearson's χ^2 statistic is less than the corresponding value of χ^2 computed for the respective *n–p* degrees of freedom, assuming a p-value equal to 0.05. According to these results, the hypothesis that both models fit the data cannot be rejected. The root mean square error (Se) shows a good capability to describe the respective dataset, for both models. The observed vs predicted diagrams show a tendency of both full models to under-predict the number of crashes in those sections where the number of observed crashes are higher than the mean values; this tendency is more evident in the MV model. These groups of segments, which represent outliers of the calibration data set, will be investigated in further research by means of a disaggregate analysis to understand if variables not considered in this study are involved in the high frequency records.

The residuals versus the number of predicted accidents diagrams show a particular point distribution that is due to the presence of heteroscedasticity, which means that a non-random distribution of residuals is observed. This tendency, typical of Negative Binomial models, is more evident in the SV model.

The results show a good aptitude of both models to describe the respective data set. The models proposed represent a solid and reliable tool for practitioners to perform accident prediction along the Italian freeway network.

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