Cross-sectional Accident Models On Flemish Motorways Based On Infrastructural Design

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Abstract

Predictive models for accidents have been researched intensively in the world. From studies that predict all accidents to studies that predict a specific kind of accident; based on road design, environment variables, social parameters, etc. are investigated. On the dense motorway network in Flanders this has not been done yet. This paper presents a study of predictive models for accidents on motorways in Flanders based on infrastructural design. Starting with motorway accidents from 1996 to 2001, road infrastructure measurements of 2003 and traffic intensities from 1996 to 2003, a cross-sectional database is created for negative binomial regression modelling. The results found on the Flemish motorways are compared with previous studies done in other countries. Road characteristics like traffic intensity, lane width, number of lanes, outer shoulder width and maximum speed limit seem to be statistically significant associated with the number of accidents. The results are consistent with many recent studies. While a lot of research combines fatal and severe accidents, this paper gives also models that predict only fatal accidents. An important conclusion is the useful split up of motorways in three different zones: link, exit and entry zones.

Keywords: Predictive models; Motorways; Road characteristics; Negative binomial regression.

1 Introduction

Noland & Oh (2004) state that reductions in traffic casualties are linked to three general areas of transport policy: change risk-taking behaviour, regulations to improve the safety of vehicles and efforts to build and design safer road infrastructure. Accident modelling on motorways by using Negative Binomial or Poisson regression has been employed for many years now (Miaou & Lum, 1993; Bauer & Harwood, 1998; Martin, 2002; Noland & Oh, 2004; Chang, 2005; Lord, Manar & Vizioli, 2005). Statistical models have been made for intersections, road sections on urban roads, road sections on rural roads, carriageways, motorways. Different types of accidents are explored. Different types of independent variables have been investigated. This paper concentrates on the road infrastructure in Flanders.
Flanders borders onto the North Sea, and is situated between The Netherlands and France. It is the northern part of Belgium. The most important cities of Europe - London, Paris, Rotterdam, Amsterdam, Köln, Bonn and Luxembourg - are all situated within a radius of 300 km around Flanders' capital Brussels. It is populated by approximately 6 million people over an area of 13522 square kilometres. Ever since the Middle Ages, Flanders has been at the crossroads of the great European trade routes. Nowadays, a lot of foreign transport drives through Flanders and a lot of road users occupy this dense network. The motorway road density of this region is the second highest in Europe.
Accident models in Flanders are very rare, perhaps not even existing. At least, we have not found them. The only studies found in Belgium were made by Flahaut (2004) and Eckhardt & Thomas (2005). The investigation of Flahaut (2004) consisted of data from the province Walloon Brabant, one of the 10 Belgian provinces. Flahaut (2004) used

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mainly geographic measures as independent variables. The road infrastructure variables were limited to the type of road expressed in the number of lanes and the distance to a major junction. The same is true for the study of Eckhardt & Thomas (2004). They also considered mainly spatial variables. The road characteristics were limited to the number of lanes and the maximum speed limit. Their study area was the periphery of Brussels.
One of the objectives of this investigation was to offer the Administratie Wegen en Verkeer (AWV; Flemish Road & Traffic Administration) tools for further improvement of the Flemish roads. This is done by the investigation of regression models on the Flemish motorways for different accident types, based on infrastructural design. This study is based on fatal and injury crashes. Damage-only crash information is hardly reliable, since probably less than a third of the damage-only crashes are reported. We chose to investigate three kinds of models. First we searched for the best fitting model, secondly we added a time-component to that best model and finally we made traffic intensity-only models. This last model is meant as a quick tool for the people of the road administrations.
This paper is organised as follows. First the gathering, correction and combination of the different data sources is described. Next, the methodology used is explained. The third section contains the results with discussion, followed by conclusions.

2 Motorway data in Flanders

To analyse the relationship between road safety and infrastructural design a cross-sectional database was collected for all Flemish motorways (980 km) over 6 years (from 1996 to 2001). We combined three main data sources for our investigation: the National Institute for Statistics (NIS) accident database, a traffic intensity database from AWV and road infrastructure measurements from AWV.
The accident data is collected by the National Institute for Statistics. The accident database is extra screened and corrected for accident locations by AWV. The data we used spans the period 1996 until 2001 and contains only injury accidents as shown in Table 1. We reworked the data to road segments of 100 metres.

Table 1: Number of injury accidents on Flemish motorways per type and per year.

	Fatal	Severe injured	Lightly injured	Total
1996	86	409	1667	2162
1997	86	442	1876	2404
1998	87	424	2008	2519
1999	90	489	2238	2817
2000	104	464	2239	2807
2001	98	434	2107	2639
Total	551	2662	12135	15348
Total (%)	3.59 %	17.34 %	79.07 %	100 %

Traffic density is a very important variable which can not be omitted in modelling traffic accidents. Its relevance has already been shown in several studies (Martin, 2002; Lord et al, 2005). We used the 24 hour average density, which can be compared with the commonly used Annual Average Daily Traffic (AADT).
Road characteristics were collected with the Automatic Road Analyser (ARAN) from AWV. In March 2003, with the ARAN, pictures were taken from all the motorways in Flanders. With the accompanying Surveyor software from Roadware, the dimensions of the different road characteristics were determined.
If the assumption is made that the same overdispersion parameter applies to all road segments in the database, then the maximum likelihood estimate of parameters will be seriously influenced by very short road segments and insufficiently influenced by long road segments (Hauer, 2001). In this accident modelling study, we choose for a fixed road segment length of 100 m. Further, since all motorways have a median, we considered each driving direction as a separate motorway.

Since we divided the complete Flemish motorway network in segments of 100 m, we did not have data for every segment. In order to resolve a missing data problem, imputation methods can be used. Different methods are available (Engels & Diehr, 2003). With the last observation carried forward (LOCF) method the last known value is copied further until a new measurement is found. With the linear interpolation (LI) method the missing values are calculated based on the previous and next known values and the number of empty sections in between. A third method used was a boolean filling (BOOL). We used this for example for median barriers where the raw measurements contained information like type of barrier, starting location and ending location. In between these locations, a boolean value 0 or 1 was used. Finally, in some situations we did nothing (NOTH). The specific reason is mentioned in Table 2.

Table 2: Road characteristics and the imputation methods used.

Road characteristic	Imputation method	Reason
Traffic density (AADT)	LOCF	The known traffic density is used for the next sections until another measuring point is met.
Number of lanes	LOCF	
Lane width	LI	
Outer shoulder width	LI	
Inner shoulder width	LI	
Barrier type side	BOOL	
Barrier type median	BOOL	
Number of objects	NOTH	This variable contains the number of signs in the section. It is a purely local variable.
Entry lane width	NOTH	A linear interpolation method was first considered but due to unsufficient measurements we chose to do nothing. A linear interpolation would have introduced data errors.
Exit lane width	NOTH	Same reason as for the entry lane width.
Number exit lanes	LOCF	
Number entry lanes	LOCF	
Maximum speed limit	LOCF	
Entry lane presence	BOOL	The variable has the value 1 if the segment contains an entry lane. The start and end locations were measured.
Exit lane presence	BOOL	The variable has the value 1 if the segment contains an entry lane. The start and end locations were measured.

The total number of road segments is 118896. Even with the imputation of the data, we can not complete all the sections. The reason for this is that at the beginning or the end of a motorway, we often do not have a starting value. The first and last kilometres of a motorway can be missing. This results in an underestimation of data at the intersections between motorways.

The lane width, outer shoulder width and inner shoulder width were measured between the dividing lines. A correction was made afterwards for the width of these lines. Depending on the type of line – between lanes or between a lane and a shoulder – the width is added half or completely to a specific lane.

Another correction of the dataset has been done towards road works. The infrastructure measurements dated from March 2003 and initially we copied them backwards to 1996. With the knowledge of the timing and location of road works from 1996 to 2001, we then set the infrastructure information before and during the period of the road works as missing.

During the modelling process it was found that for some road characteristics the initial continuous variables were insufficient. In that case classification variables were defined in two ways: statistic classes (S) and technical classes (T). The statistical classes were created in such way that each class contains approximately the same number of observations. The technical classes were created based on the technical regulations for building motorways, which were gathered in an international review (Nuyts et al, 2004). It turned out that depending on the investigated motorway zone, which will be explained later, and accident type, the most predictive variable could differ. In Table 3 the variables which are used in this investigation are listed. Both the continuous and classification variables are listed, even for the same road characteristic. The classification variables are indicated with a "C" and the number of categories.

Table 3: Summary of continuous and classification variables used in the analysis with indication of the number of categories (C) and if statistical (S) or technical (T) categories were used.

Variable	Categories	Number of segments	Minimum	Maximum	Mean	Standard deviation
All accidents		118896	0	51	0,129	0,582
Fatal accidents		118896	0	2	0,005	0,069
Severe accidents		118896	0	5	0,022	0,157
Lightly injured accidents		118896	0	47	0,102	0,516
Traffic intensity (AADT)		75632	3812	104422	30936	15596
Traffic intensity (AADT) – C3	< 38000; 38000 – 60000; > 60000					
Year of accident		118896	1996	2001		
Year of accident – C6	1996; 1997; 1998; 1999; 2000; 2001					
Lane width (m)		84321	2,871	4,381	3,617	0,163
Lane width (m) – C3S	< 3,25; 3,25 – 3,60; > 3,60					
Lane width (m) – C2T	< 3,50; > 3,50					
Outer shoulder width (m)		83753	0,300	10,164	3,134	0,845
Outer shoulder width (m) – C4S	< 1,30; 1,30 – 2,60; 2,60 – 3,70; >3,70					
Outer shoulder width (m) – C3S	< 1,30; 1,30 – 2,70; > 2,70					
Outer shoulder width (m) – C3T	< 0,75; 0,75 – 3,00; 3,00 – 4,00; > 4,00					
Inner shoulder width (m)		84796	0,327	8,827	1,290	0,946
Inner shoulder width (m) – C2S	< 1,30; > 1,30					
Inner shoulder width (m) – C3T	< 0,75; 0,75 – 1,50; > 1,50					
Number of lanes		87367	1	4	2,447	0,544
Number of lanes – C4	1; 2; 3; 4					
Maximum speed limit (km/h)		87384	50	120	116,92	10,31
Maximum speed limit (km/h) – C4	50-60; 70-90; 100; 120					
Maximum speed limit (km/h) – C7	50; 60; 70; 80; 90; 100; 120					
Entry lane – presence	0; 1 (present)					
Exit lane – presence	0; 1 (present)					
Number of entry lanes	0; 1; 2; 3					
Number of exit lanes	0; 1; 2; 3					
Entry lane width		7948	0	5,955	1,795	1,605
Exit lane width		7185	0	6,253	1,601	1,378
Number of objects		87402	0	8		
Outer barrier type	None; concrete; metal; New Jersey					
Inner barrier type	None; concrete; metal; New Jersey					

3 Methodology

Accident data consists of counts and thus are considered as Poisson or negative binomial distributed. In order to make a decision between a negative binomial distribution and a Poisson distribution for the accidents, we calculated the T1 statistic of Dean and Lawless (1989) for several subsets of our database. We found that the negative binomial distribution fitted the data the best.

In the negative binomial distribution, an overdispersion parameter is used. Depending on the source, this parameter can be defined in two ways; one way is the reciprocal value of the other. To avoid mistakes in interpretation of the values, we mention that we used the overdispersion parameter k, as in the SAS GENMOD manual (SAS, 1999). With this version we can write: $Var(y) = E(y) + k.[E(y)]^2$. We used the GENMOD procedure in SAS 8.02 to make the models.

In order to compare models during the modelling process we calculated the Akaike Information Criterion (AIC) according to Chi & Russel (1999) and the Bayesian Information Criterion (BIC) according to Zucchini (2000). When the criterions gave opposite results, we gave priority to the AIC criterion. Since neither of them is calculated

in the GENMOD procedure of SAS, we used the GENMOD results to calculate the criterions ourselves in Microsoft Excel.
We considered four accident types and three motorway zones, so we came up with 12 situations. For each of these 12 possible situations, we searched for the best model with the available variables. For a second model, we added the accident year variable in order to determine the time influence. A third model was built only with an interception term and the traffic intensity. The latter was built in order to give the Flemish road administration an easy model to continue their work faster. An R-squared measure for negative binomial models or Poisson models (Cameron & Windmeijer, 1996) was calculated after the best models were found. Only the results of the motorway zone identification, the models for all injury accidents and the models for only fatal accidents are shown in this article. The fatal accidents are investigated separately. A lot of studies combine the fatal with the severe accidents and calculate estimates for this combination. Noland & Oh (2004) also mention that this combination can be misleading since the road characteristics associated with fatalities can be quite different than those associated with injuries. In our report (Van Geirt & Nuyts, 2005) we also show the models for heavily-injured accidents and the models for lightly-injured accidents. One will also find more information and results about the zone identification. The report is in Dutch but the tables will probably be understandable for most international readers.
Three major zones were identified: link zones, entry zones and exit zones. The determination of the boundaries of the entry and exit zones was an iterative process. Regression models were made that predicted number of accidents based on traffic intensity and distance to an entry zone. It was found e.g. that for segments less than 1 km before an exit, the expected number of accidents differed significantly from the expected number of accidents of segments more than 1 km before an exit. It was also found that the expected number of accidents of segments between 1 and 1.5 km before an exit zone and more than 1.5 km before the exit zone did not differ significantly. Therefore, it was concluded that the exit zone started 1 km before the exit. In the same manner, the end boundary of an exit zone was defined. The same process was repeated for entry zones.

4 Results and discussion

The purpose of our investigation was to create predictive models for different types of accidents on motorways, based on infrastructural design and traffic intensity. Infrastructure variables like outer en inner barriers, number of poles and signs at the outer side, entry and exit lane width are found not to be statistically significant for neither accident type nor zone type. In this paper, the results for all injury accidents and fatal accidents are discussed.
The first investigation was the identification of different zones on the motorways. Three major zones on the motorways were defined: link zones, entry zones and exit zones. We found that the accident frequencies changed significantly beyond 1 kilometre upstream and 1 kilometre downstream for both the entry and exit zones. Janson et al (1998) made a similar investigation for their analysis of truck accidents on motorways. They found boundaries between 0,24 to 0,40 km.

4.1 Regression model for all injury accidents

We define all injury accidents as the sum of the fatal, severe and lightly injured accidents. The negative binomial models that predict these accidents are shown in Table 4.

Table 4: Regression models for all injury accidents in the three motorway zones.

Variable	Classes	Link zone		Entry zone		Exit zone	
		Estimate	p	Estimate	p	Estimate	p
Intercept		-14,444	<0,0001	-12.271	<0,0001	-10,911	<0,0001
AADT (log)		1,110	<0,0001	0,956	<0,0001	1,003	<0,0001
Lane width (m)	2,80 – 3,25	0,201	0,2766	0,170	0,2670		
	3,25 – 3,60	0,154	0,0016	0,169	0,0033		
	> 3.60 m	0		0			
Number of lanes	2	0,527	0,0235				
	3	0,555	0,0124				
	4	0					
Outer shoulder width (m)						-0,075	0,0083
Outer shoulder width (m) C3S	0,00 – 1,30	0,304	0,0246	0,317	0,0024		
	1,30 – 2,70	0,196	0,0165	0,173	0,0054		
	> 2,70 m	0		0			
Inner shoulder width (m)						-0,213	<0,0001
Inner shoulder width (m) C2S	0,00 – 1,30	0,280	<0,0001				
	> 1,30 m	0					
Inner shoulder width (m) C3T	0,00 – 0,75			0,364	< 0,0001		
	0,75 – 1,50			0			
Speed limit						-0,009	0,0003
Speed limit C4	70-90			0,124	0,2902		
	100			0,866	< 0,0001		
	120			0			
Entry lane presence	0			-0,174	0,0019		
	1			0			
Overdispersion		0,402		0,648		0,791	
R-square measure		86,3 %		29,3 %		25,9 %	

Adding the accident year variable to the predictive models for all injury accidents makes the models worse. The year variable is not statistically significant and the AIC and BIC measures increase. The further discussion of the results is in order of appearance of the independent variables. For each variable we discuss the results for all three motorway zones.

In all three zones the traffic intensity is positively correlated with the number of accidents. This is in fact a known and generally accepted result.

Hadi et al (1995) found a negative association between the number of accidents on motorways and the lane width, with a lane width of 4,00 m category which minimizes crashes. We found also a similar statistically significant correlation in the link and entry zones. Road segments with a mean lane width smaller than 3,60 m are statistically significant associated with more accidents than segments with a mean lane width above 3,60 m. In the exit zones the lane width was not found to be statistically significant.

The number of lanes is statistically significant in the link zone. The two and three lane segments are statistically significant associated with more accidents than the four lane segments. No explanation is found for this result, since it is contradictory to the intuitive expected result that the increase of number of lanes will also increase the number of lane changes and thus the number of conflicts between traffic. Noland & Oh (2004) and Chang (2005) find that the number of accidents increase with the number of lanes.

In order to find statistically significant association between the outer shoulder width and the number of accidents, we had to use different variables. In the link and entry zones a three class variable fitted the data the best; in the exit zones the continuous variable fitted the data the best. In all zones a decreasing number of accidents is statistically significant associated with an increasing outer shoulder width. Noland & Oh (2004) found

the same effect, although not significant. Hadi et al (1995) give an outer shoulder width of 4,00 m as the width that minimizes crashes. This combined decreasing and increasing effect with an optimal width was not found on the Flemish data.
In all three motorway zones an increasing inner shoulder width is found to be statistically significant associated with a decreasing number of injury accidents.
In the link zones we do not find a statistically significant correlation between the number of accidents and the maximum speed limit. In the exit zones we find an increasing maximum speed limit statistically significant associated with a decreasing number of accidents. For the entry zone the best variable was a class variable. For this one, we find only the 100 km/h class statistically significant different from all the other ones. In these entry zones the segments with the lower speed limit of 100 km/h have more accidents than the segments with a speed limit of 120 km/h. We can give two possible explanations for this. The first explanation is that these segments are really more dangerous because they provide a sudden speed change with extra decelerating and accelerating vehicles and thus extra conflicts. A second explanation is that specific areas were more dangerous due to other factors, the road administration therefore lowered the speed limit in these areas and thus the regression analysis identified these areas because of the accident history and found the lower speed as a correlated factor. The data do not allow to say which explanation is the best one.
The presence of an entry lane is statistically significant related with the number of injury accidents. There are more accidents at an entry lane, which can be explained by an increasing number of conflicts due to lane changes.

4.2 Regression models for fatal accidents

In Table 5 the models that predict the number of fatal accidents in the different motorway zones are shown.

Table 5: Regression models for fatal accidents in the three motorway zones.

Parameter	Classes	Link zone		Entry zone	Exit zone	
		Estimate	p		Estimate	p
Intercept		-5,310	0,1427		-11,785	<0,0001
AADT (log)		0,680	0,0029		0,643	0,0059
Lane width		-1,980	0,0123			
Overdispersion		4,244			0 (Poisson)	
R-square measure		67,8 %			27,0 %	

When we add the accident year variable we did not find any model to converge. No further investigation of this effect is done.
We did find a negative binomial model in the entry zone to predict fatal accidents and we did find some statistically significant associations with some variables, but at the end the R-square measure was 0%. For that reason, we exclude the results from this paper.
For the exit zone, we did not find at all a converging negative binomial model to predict the number of fatal accidents. Since the mean ($5{,}9\ 10^{-3}$) and the variance ($6{,}0\ 10^{-3}$) of the fatal accidents in the exit zone were almost equal, we considered a Poisson distribution. In that case the SAS GENMOD, with the Poisson distribution option, did converge. Only the AADT was statistically significant. An R-squared measure of 27% was found. A negative estimate for the intercept and a positive one for the traffic density were in the line of expectations.
The fatality models of Noland & Oh (2004) find a strong statistically significant positive association with increased lane widths. In the link zones we find the opposite effect. An increasing lane width seems to be statistically significant associated with fewer fatal accidents. Hauer (2000) combines a lot of research results and concludes that the safety benefit of lane widening bottoms out somewhere between 3,35 m (11 ft) and 3,65 m (12 ft). This might explain the different results, since different studies use different datasets in which the majority of data can be situated on different sides of the minimum.

Ossiander & Cummings (2002) investigated the impact of an increased speed limit on motorways and found an increasing speed limit associated with an increasing number of fatal accidents. We did not find any correlation between the maximum speed limit and the number of fatal accidents.

The major differences found between the models for all accidents and the models for fatal accidents are the number of independent variables and the usage of Poisson modelling in the exit zone for fatal accidents. The smaller number of statistically significant variables for the fatal accident models can be explained by the much less available data. Secondly, the non convergence of the negative binomial model for fatal accidents can not be explained but was also found in other studies (De Brabander et al, 2005).

To end this result section, the R-squared measures are compared. For the all injury accident models in the link, entry and exit zones the R-squared measures are respectively 86%, 29% and 26%. The R-squared measures for the traffic intensity only models for the all injury accident models in the same zones are 38%, 25% and 22%. For the fatal accident models in the link and exit zones the R-squared measures are 68% and 27%. The R-squared measures for the traffic intensity only models are 47% and 27%, the latter being the exact same model. These results follow the conclusion of Bauer & Harwood (1998) who state that the literature has consistently shown traffic volumes to be the strongest predictor of accidents. The traffic intensity explains the biggest proportion in the models of this paper. Lord et al (2005) made an investigation of the traffic intensity only models and concluded that regression models developed solely from traffic intensity may not adequately predict accidents on motorways. According to the results in this paper this is not true. Models with an R-squared measure of up to 47% can be used to predict accidents.

5 Conclusions

This paper analysed Flemish motorway data to evaluate the association between road infrastructure and accidents. Our results are not inconsistent with many recent studies that have used more sophisticated statistical techniques and also those that control for other confounding effects. The purpose was to come to models that can be used by the road administration in Flanders. They need useful tools for their improvement works on the motorways. The models will mainly be used for before-after studies and to improve their traffic models.

An important result is the split up of the motorways in three major zones: link zones, entry zones and exit zones. The accident frequencies changed significantly beyond 1 kilometre upstream and 1 kilometre downstream for both the entry and exit zones. The predictive models differ between different zones. Sometimes the same road characteristic is statistically significant, but the way the variable is used (continuous or classification) for the best fit can differ. The advantage of modelling accidents in different motorway zones is that the road administration can improve the roads more locally. The lane width is statistically significant in the link zones and the entry zones; not in the exit zones. Thus it is more important to keep the right width in the first zones, while in the exit zones less attention can be given to the lane width and perhaps more to the shoulder widths, since the total road width is mostly limited in space. The maximum speed limit is not statistically significant in the link zones, but it is in the exit and entry zones. Future research about the maximum speed limits can be limited or specifically concentrated to these zones.

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