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INJURY PREDICTION MODELS FOR ONSHORE ROAD NETWORK DEVELOPMENT

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ABSTRACT

Integrating different modes of transport (road, rail, air and water) is important for port cities. To accommodate this need, new transport hubs must be built such as airports or sea ports. If ports are to grow, they must be accessible, a feature which is best achieved by building new roads, including fast roads. Poland must develop a network of fast roads that will provide good access to ports. What is equally important is to upgrade the network of national roads to complement fast roads. A key criterion in this case is to ensure that the roads are efficient to minimise time lost for road users and safe.
With safety standards and safety management practices varying vastly across the EU, Directive 2008/96/EC of the European Parliament and of the Council was a way to ensure that countries follow procedures for assessing the impact of road projects on road safety and conduct road safety audits, road safety management and road safety inspections. The main goal of the research was to build mathematical models to combine road safety measures, i.e. injury density (DI) and accident density (DA), with road and traffic factors on longer sections, all based on risk analysis. The practical objective is to use these models to develop tools for assessing how new road projects will impact road safety.
Because previous research on models to help estimate injuries (I) or injury density (DI) on long sections was scarce, the authors addressed that problem in their work. The idea goes back to how Poland is introducing procedures for assessing the effects of infrastructure on safety and developing a method to estimate accident indicators to support economic analysis for new roads, a solution applied in JASPERS. Another reason for the research was Poland's insufficient and ineffective pool of road safety management tools in Poland. The paper presents analyses of several models which achieved satisfactory results. They are consistent with the work of other researchers and the outcomes of previous research conducted by the authors.
The authors built the models based on a segmentation of national roads into sections from 10 to 50 km, making sure that they feature consistent cross-sections and average daily traffic volumes. Models were built based on the method described by Jamroz (Jamroz, 2011). Using the available road traffic volume data, each section was assigned variables defining geometric and traffic features. Based on studies conducted on road sections, the variables were either averaged over the entire length of the section or calculated as a percentage of the variable occurring over the entire length: related to traffic volume, roadside environment or cross section

Keywords: Road safety, Polish national roads, density of injuries, log logistic and gamma distribution, risk management

INTRODUCTION

In Poland, the number of road traffic fatalities is among the highest in the European Union. In 2016, 3,026 road users died and 12,109 were seriously injured. Although national single carriageway roads account for less than 5% of the entire road network in Poland, in terms of risk they are the most dangerous. In the past three years 15 thousand accidents occurred on these roads, in which more than 20 thousand people were injured and nearly 2,600 died. The death toll is more than 27% of all fatalities in Poland, while the number of injured is 15% of the total. This indicates the need to develop methods to support a high standard of road infrastructure and its management because of the great potential to reduce the number of injuries and fatalities (The National Police Headquarters, 2015). Poland's big opportunity comes with the implementation of road infrastructure safety management principles adopted under Directive 2008/96/EC. In the document, Member States are recommended to use tried and tested road safety management tools with the Road Safety Impact Assessment as one of them (RIA).

When a new road is assessed for its impact on road safety, a strategic analysis is carried out looking at how different variants of the road will change the road safety across the public roads network. The purpose of the RIA is to determine the ranking of variants of the planned road and their impact on traffic safety across a network of interconnected roads in the road's catchment area. The results should be included in a multicriteria analysis (along with other technical, economic and environmental criteria) evaluating the variants of the analysed road.

When new roads are built, this may have a great impact on how the area will develop over the years to come. Therefore, a number of decisions are required at several stages before the optimal variant is selected. The RIA procedure can use the support of scientific methods which help to choose the best option for road safety. To that end, mathematical models combining the influence of selected factors with traffic safety measures are very helpful.

LITERATURE REVIEW

There is an extensive body of road safety research and a variety of analyses such as forecasting national trends (Broughton, 1991), the effects of the human factor on safety (Donmez et al., 2007, Deffenbacher et al., 2003) (Hewson, 2004, Zhang et al., 2006, Scott-Parker et al., 2012), the effects of junctions (Asgarzadeh et al., 2017, Xie et al., 2013, Peer and Rosenbloom, 2013), the effects of speed (Lee et al., 2006, Peer and Rosenbloom, 2013) and the effects of vehicles (Ryb et al., 2013). Since the early 1980s, a lot of the research focussed on building mathematical models of the relationship between traffic incidents and traffic volume and other roadside-related factors using generalised linear regression models.

The most frequently used model for estimating accidents is an equation which describes the expected accidents $E(Y_i)$ as a function of traffic Q, road length L, and a set of other factors referred to as risk factors x_i $(i=2, 2, 3.........n)$. The effects of traffic volume on accidents described with the traffic volume function to the power of β_0 were first described by Hauer (Hauer, 1995). By applying this approach, a power-exponential model could be used to estimate the expected accidents on sections of road with Q, L parameters representing the risk exposure and the sum of variables $\beta_i x_i$ representing the likelihood of the severity of the consequences.

When discussing the relations between road, traffic, accidents and casualties over specific road sections, the effects are usually divided into road type and location: motorways, rural single carriageways, rural multiple carriageways, and urban single and multiple carriageways. The majority of research on road sections focussed on short sections, the length of which does not exceed 2 km. Longer sections, above 5 km, are covered rarely (Hakkert, 2011; Iyinam et al., 1997).

While the majority of researchers focus on estimating accidents and types of accidents (fatality, injury and serious injury accidents), there is very little work on the number of injuries or deaths (Ivan et al., 2006; Kiec, 2009; Yannis et al., 2014).

There are numerous independent variables affecting the extent and variability of individual road safety measures on road sections. Based on the available literature, approximately 50 independent variables related to traffic and road parameters were identified and then included in the design of models for estimating the measures. The authors studied the following variables, which were also analysed in previous works: length of section (AASHTO, 2010; Anastasopoulos et al., 2012c; Bared and Vogt, 1998; Ma et al., 2008a), road class (Abdel-Aty and Radwan, 2000a), traffic parameters (Anastasopoulos et al., 2012a; Council et al., 2000; Elvik, 2008; Fernandes and Neves, 2013a; Lao et al., 2011a; Lord and Park, 2012), type of area (built-up, rural) (Abdel-Aty and Radwan, 2000b; Fernandes and Neves, 2013b; Lao et al., 2011b), roadside environment (Hauer, 2007; Lee and Mannering, 2002; Martinelli et al., 2009, Jurewicz and Steinmetz, 2012), parameters of cross-section (Anastasopoulos et al., 2012a; Cafiso et al., 2010; Hauer, 2007; Lao et al., 2011; Ma et al., 2008, Ambros and Sedoník, 2016), intersection, interchange and driveway density (Anastasopoulos et al., 2012b; Bhatia et al., 2009; El-Basyouny and Sayed, 2009; Hauer, 2007).

OBJECTIVE OF THE WORK

The main objective was to build mathematical models to combine road safety measures, such as injury density (DI) and accident density (DA), with road and traffic factors over long sections based on risk analysis. The models help to assess selected parameters for their impact on road safety. They will also support the development of tools to help with the assessment of road projects and road safety and to rank the risks when conducting road safety inspections (RSI). With Poland's road safety far from sufficient and road infrastructure standards not meeting the criteria, it is critical to have the tools and improve the quality and effectiveness of road infrastructure safety management.

MODELLING METHODOLOGY

Road safety management includes two terms which are defined as follows: hazard – the possibility that a specific type of road accident may occur and cause specific consequences (financial consequences, injuries and fatalities) when sources of that hazard are present, and risk – the product of probability and consequences as a result of a specific road accident. (Jamroz, 2011; Technical Committee 18, 2004).

The research presented in this article is based on the relationship between a source of hazard and accident consequences such as costs, injuries and fatalities. This relationship is described by the societal risk formula (1).

The level of risk on road sections is given by the formula (Jamroz, 2011):

$$RS_O = E \cdot P \cdot C \tag{1}$$

where: RS_O – overall collective risk, E – exposure to risk, P – probability of a dangerous event, C – consequence of a dangerous event.

Test site. The analysis aiming to develop models for forecasting road accident consequences was conducted on national roads. The total length of the road network managed by the GDDKIA is 17.200 km (nearest 93% of all national roads). The research focused on two types of road:

- single carriageway – main (G) and fast traffic (GP) roads, express (S) roads – length of 15.200 km,
- dual carriageway – main and fast traffic roads (G, GP), express roads (S), motorways (A) – length of 2.100 km.

For the purpose of constructing social risk models for road safety analyses at the strategic level, sections of national roads were divided into 10 to 50 km lengths. The criteria for road section division included the usual features such as: road cross-section, class, traffic volume, intersections with other national or provincial roads, change in cross-section, road discontinuity, urban county boundaries (for G and GP roads).

In this article, the authors focus on accidents on single carriageways. Table 1 shows the characteristics of the study site. The road class (G, GP, S) determines, among other things, the design parameters such as design speed, vertical and horizontal curve radius, road accessibility, intersection type (e.g. the S class road is characterised by the lowest accessibility and presence of interchanges, while the G class road is characterised by the lowest geometric parameters and the highest road accessibility).

Tab. 1. Length [km] of sections on national roads

Symbol	N	μ	Min	max	σ	ν
	[sections]	[km]	[km]	[km]	[km]	-
G	155	30.1	4.7	49.2	9.7	0.35
GP	375	27.5	1.9	55.5	10.1	0.38
S	11	14.9	2.7	28.4	8.3	0.54
Avg/sum	541	28.1	1.9	55.3	10.1	0.36

where: N – number of sections, μ – mean value, σ – standard deviation, ν – variability rate.

As we know from analyses, the accident severity is very high on S class roads (single carriageways) which suggests that such roads should no longer be designed or built. (Jamroz and Kustra, 2011) (Table 2, fig 1).

Tab. 2. Numbers and density of accidents and victims on single carriageway roads

Road type	Length	Number of			Cost of accidents	Density of			
		Accidents	Injuries	Fatalities		Accidents	Injuries	Fatalities	Cost of accidents
	L	A	I	F	AC	DA	DI	DF	DAC
T	[km]	[accidents/ 3 years]	[injuries/ 3 years]	[fatalities/ 3 years]	PLN m/ 3 years	[accidents/ km/3 years]	[injuries/ km/3 years]	[fatalities/ km/3 years]	PLN m/ km/ 3 years
G	4615.3	5166	6913	849	2694.8	1.12	1.50	0.18	0.58
GP	10361.4	17305	24206	3251	9921.0	1.67	2.34	0.31	0.96
S	163.2	108	155	43	97.0	0.66	0.95	0.26	0.59

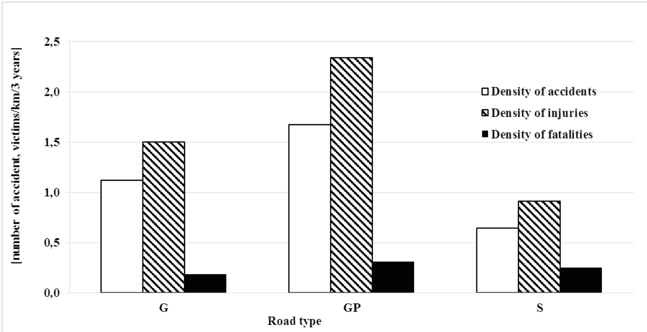


Fig. 1. Density of accidents, injuries and fatalities on Poland's national road network

RS_O^1 shows a model used for calculating overall collective risk (I) using individual risk models. The model is described with the formula:

$$RS_O^1 = E_L \cdot P_{DI} \tag{2}$$

where: P_{DI} - probability of a consequence, E_L - risk exposure.

RS_O^2 shows a three-component model used for calculating overall collective risk (I) using individual risk models. The model is described with the formula:

$$RS_O^2 = E_L \cdot P_{DA} \cdot C_{SVT} \tag{3}$$

where: E_L – exposure, P_{DA} – probability of risk occurrence, C_{SVT} – probability of occurrence of selected victim types.

The product of risk exposure obtained by converting formulas 2, 3 using the standardised road safety measures RS_N^{DI}, RS_N^{DA} is represented by the length of road (L), the probability of consequences of selected category in a unit of time (*DI, DA*), and the level of selected victim types (C_I). This approach will help to build models for standardised measures only disregarding the length of the section. The models are described with the formulas:

$$RS_O^3 = E_L \cdot P_{DI} = E_L \cdot RS_N^{DI} = L \cdot DI \tag{4}$$

$$RS_O^4 = E_L \cdot P_{DA} \cdot C_{SVT} = E_L \cdot RS_N^{DA} \cdot C_I = L \cdot DA \cdot C_I \tag{5}$$

where:
L – section length, *DA* - density of accidents, *DI* – density of injuries, C_I – injury rate.

Explanatory variables. Using the available road traffic volume data from the GDDKIA road traffic database, each section was assigned variables defining geometric and traffic features. Based on studies conducted on long road sections (from 5 to 50 km), the variables were either averaged over the entire length of the section (*DIT, DITE, DIS, DD*) or calculated as a percentage of the variable occurring over the entire length: related to traffic volume (*AADT, PHV*), roadside environment or cross section (*PBA, PWS, PNS, PUS, PEL, PCL, PAL, PST, PPPC*). A set of variables, used in the process of constructing injury prediction models on single-carriageway roads, is presented in Table 3. Due to the lack of data related to selected geometrical features (land use, transit traffic, local traffic, road network maintenance, bendiness, waviness, journey speed, speed limits) the average RLA was used.

Tab. 3. List of independent variables on single carriageway roads

Symbol	Unit	μ	min	max	σ	ν
T	-	4.921	2.20	5.90	-	-
RLA	-	1.503	1.00	1.97	0.29	0.19
L	[km]	27.985	5.76	55.10	10.30	0.37
AADT	[P/24h*10^{-4}]	0.817	0.04	2.67	0.44	0.54
PHV	[%]	0.172	0.03	0.64	0.08	0.49
PBA	[%]	0.259	0.00	1.00	0.18	0.68
PWS	[%]	0.234	0.00	1.00	0.33	1.40
PNS	[%]	0.049	0.00	0.87	0.14	2.95
PUS	[%]	0.561	0.00	1.00	0.35	0.62
PEL	[%]	0.005	0.00	0.93	0.05	10.67
PCL	[%]	0.004	0.00	0.23	0.02	5.02
PAL	[%]	0.013	0.00	0.48	0.05	3.53
DIT	[numbers/km]	0.004	0.00	0.78	0.04	9.40
DITE	[numbers/km]	0.016	0.00	1.17	0.09	5.69
DIS_N	[numbers/km]	0.015	0.00	0.24	0.03	1.87
DIS_R	[numbers/km]	0.065	0.00	0.63	0.06	0.90
DIS_L	[numbers/km]	0.852	0.00	7.65	0.70	0.82
DIS	[numbers/km]	0.932	0.00	7.65	0.71	0.76
DD_P	[numbers/km]	2.303	0.00	20.17	1.95	0.85
DD_R	[numbers/km]	7.641	0.00	39.06	6.48	0.85
DD_F	[numbers/km]	5.332	0.00	44.51	4.30	0.81
PST	[%]	0.4	0.00	1.00	0.31	0.77
PP_{PC}	[%]	0.205	0.00	1.00	0.16	0.78

The symbols used in Table 5: *T* - class, cross section, *RLA* – location of road, L – length of section, *AADT* – annual average traffic volume, *PHV* – share of heavy vehicles, *PBA* – share of built-up sections, *PWS* – share of sections with paved houlder width ≥ 2m, *PNS* – share of sections with paved shoulder width < 2m, *PUS* – share of sections with unpaved shoulder, *PEL* – share of sections with emergency lane, *PCL* – share of sections with climbing lane, *PAL* – share of sections with additional lane for going straight ahead (additional), *DIT* – density of interchanges, *DITE* – density of interchange entries and exits, *DIS* - density of junctions with others roads (N – national, R – regional, L – local), *DD* – density of driveway – (P – public, R – private, F – forest), *PST* – share of sections with roadside trees, PP_{PC} – share of sections with pedestrian or bike paths, *DSC* - density of speed cameras.

ANALYSIS AND RESULTS

Following the literature review (Garber and Lei, 2001; Ivan et al., 2005; Ptak-Chmielewska, 2013; Rakha et al., 2010; Son et al., 2011; Wood, 2005; Ye et al., 2013a), and the previous research (Budzynski et al., 2011; Kustra et al., 2015), it was agreed to build the safety models based on generalised models of linear regression. Each model consists of three components: probability distributions of the dependent variable, linear predictor η_i, and nonlinear link function.

For the purposes of this work the Gamma (Negative binominal) and loglogistic distributions were used. The former one is the most common probabilistic distribution used by transport safety analysts for modelling accident or injury numbers (Geedipally et al., 2012a; Hauer, 2001, 1986; Lord, 2006; Lord and Geedipally, 2012; Lord and Park, 2008; Reurings et al., 2005; Schafer, 2006; Ye et al., 2013b) transportation safety analysts have used the empirical Bayes (EB. The density function takes the form:

$$RS_O^4 = E_L \cdot P_{DA} \cdot C_{SVT} = E_L \cdot RS_N^{DA} \cdot C_I = L \cdot DA \cdot C_I \tag{6}$$

However:

$$E(Y_i) = \mu_{it} \tag{7}$$

$$Var(Y_i) = \mu_{it} + \frac{{\mu_{it}}^2}{\phi} \tag{8}$$

where $Y_i = 0, 1, 2, 3 \ldots$ N, Γ - gamma function, μ_{it} – mean value for the observation and time t, ϕ – overdispersion parameter.

The loglogistic distribution is used much less frequently in modelling accident and victim numbers. However, the authors (Li and Shang, 2014, Al-ghamdi, 2002) use it to estimate the number of accidents.

In this case, the density function takes the form:

$$P(Y_i = y_i) = f(y_i, \alpha, \gamma) = \frac{\left(\frac{\gamma}{\alpha}\right)\cdot\left(\frac{y_i}{\alpha}\right)^{\gamma-1}}{\left(1+\left(\frac{y_i}{\alpha}\right)^{\gamma}\right)^2} \quad (9)$$

However:

$$E(Y_i) = \mu_{it} = \ln(\alpha) \quad (10)$$

where γ – shape parameter, α – median of distribution.

The density of injuries (Table 4) was analysed using the probability density function. Figure 2 shows the fit between the data, the gamma distribution (shape = 2.362, scale = 3.272, Chi-Square test: 45.76, Log Likelihood: -273.429), and the loglogistic distribution (median = 0.596, shape = 0.394, Chi-Square test: 39.67, Log Likelihood: -279.73).

Tab. 4. Number of injuries on a single carriageway

Symbol	Injuries	Density of injuries				
	N	μ	min	max	σ	v
G	6913	0.513	0.044	1.784	0.319	0.62
GP	24206	0.819	0.038	3.366	0.518	0.63
S	155	0.325	0.030	0.851	0.276	0.85
Sum/avg.	31274	0.721	0.030	3.366	0.488	0.68

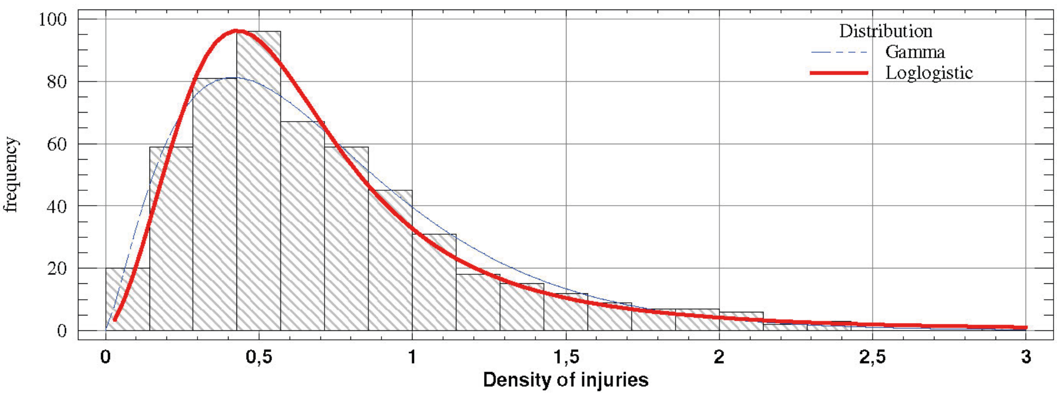


*Fig. 2 Probability density function – density of injuries (**DI**)*

In the case of the negative binominal, the logarithmic form of the copula function was used and the formula is:

$$\mu_i = E(Y_i) = \beta_0 \cdot X_{i1}^{\beta_{i1}} \cdot X_{i2}^{\beta_{i2}} \cdot exp^{(\eta_i)} \quad (11)$$

where: μ_i, – vale of expected dependent variable, η_i – linear predictor, x_{ik} – observed non-random independent variables, $\beta_{i,}$ – equation coefficient.

Linear predictor η_i:

$$\eta_i = \varepsilon + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} = \varepsilon + \sum_{i=1}^{k} \beta_i x_{ik} \quad (12)$$

where: ε – unobservable variable representing a component of random error.

By transforming the risk models RS_N^{DI} (formula 4 and 5) and adopting the probability density function we obtain:

$$\mu_i = DI = \beta_0 \cdot T \cdot AADT^{\beta_1} \cdot exp(\eta_i) \quad (13)$$

$$\mu_i = DI = (DA + \beta_0 \cdot T \cdot DA^{\beta_1}\, exp(\eta_i) \quad (14)$$

$$\mu_i = DI = Y_{max} \cdot exp(-\beta_0 \cdot exp(-\eta_i)) \quad (15)$$

In the process of building models, the following variables were statistically significant: *AADT, PHV, DA, PBA, PWS, PAL, T, RLA*. The injury density models for long sections of single carriageways which offer the best approximation of actual data to observations are represented by the equations:

$$DI = \beta_0 \cdot T \cdot AADT^{\beta_1} \cdot \exp(\beta_3 \cdot PHV + \beta_4 \cdot PBA + \beta_5 \cdot PWS + \beta_6 \cdot PAL + \beta_7 \cdot T + \beta_8 \cdot RLA) \quad (16)$$

$$DI = (DA + \beta_0 \cdot T \cdot DA^{\beta_2} \exp(\beta_4 \cdot PBA + \beta_7 \cdot \mathrm{T} + \beta_9 \cdot \mathrm{AADT_1}) \quad (17)$$

$$DI = Y_{max} \cdot \exp(-\beta_0 \cdot \exp(-(\beta_3 \cdot PHV + \beta_4 \cdot PBA + \beta_6 \cdot PAL + \beta_7 \cdot T + \beta_8 \cdot RLA) \quad (18)$$

Table 5 presents the values of equation coefficients, while Table 6 gives the characteristics of statistical parameters.

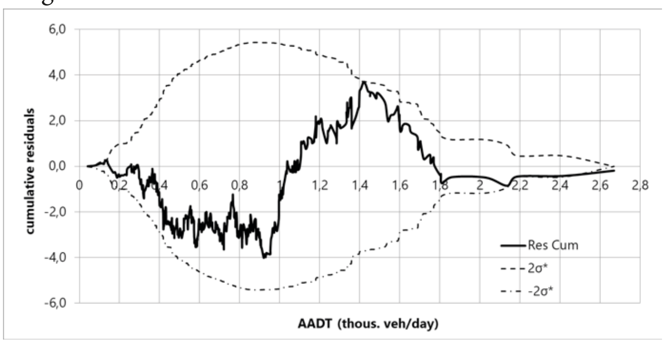
Tab. 5. Values of equation coefficients

Equation	Variable										
	Y_{max}		*AADT*	*DA*	*PHV*	*PBA*	*PWS*	*PAL*	*T*	*RLA*	$AADT_1$
		β_0	B_1	B_2	B_3	B_4	B_5	B_6	B_7	B_8	B_9
16		0.164	0.963		-0.369	-0.185	-0.313	-0.890	-0.155	0.702	
17		0.452		1.324		-1.163			-0.238		-0.153
18	2.4	9.110	0.962		-0.557	-0.240		-0.992	0.086	0.637	

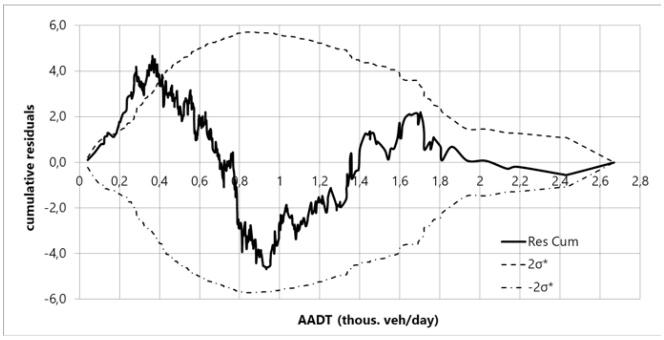
Tab. 6. Characteristics of statistical parameters

Equation	Parameters			
	R^2	R_{co}^2	SMSE	AIC
16	0.683	0.679	0.238	-628.572
17	0.958	0.957	0.093	-1056.370
18	0.635	0.630	0.251	-605.463

To test the models for their applicability to the entire range of road traffic volumes, a method proposed by Hauer was used (Hauer, 2004). Based on estimating cumulative residuals (CURE plot), the method helps to understand the extent of the AADT which the model can use to forecast injury density. In the case of models described with function 16 (figure 3a) and 18, the derived confidence limits were not exceeded across the entire traffic volume (± 2σ). However, in the case of the model described with function 17 (figure 3b) in the range of AADT 1400 – 4200, the upper limit + 2σ was exceeded, which suggests that the model should not be applied to this range of traffic volume.



a)



b)

Fig. 3. CURE plot for AADT for equation 16 (a) and 18 (b)

DISCUSSION

The effects of the selected independent variables on the models are consistent with the expectations arising from the physical interpretation of the role of these variables observed by other researchers. They are also consistent with the results of previous research conducted by the authors (AASHTO, 2010; Budzynski et al., 2013; Geedipally et al., 2012b).

All the models ensure a very good match between the actual data and those estimated from the model. The highest value of R_{co}^2 and the lowest value of AIC are found in model 17. It should be noted, however, that to estimate the density of injuries, the accident density variable (*DA*) must also be estimated. Its estimation carries an error that will cause error multiplication in model 17. The methodology for estimating this measure on single-carriageway national roads was presented by the author in his doctoral thesis (Kustra, 2016) and in the paper (Budzynski et al., 2015). An example of a function for estimating accident density can be described with the equation:

$$DA = \beta_0 \cdot T \cdot AADT^{\beta_1} \cdot \exp(\beta_2 \cdot PBA + \beta_3 \cdot PWS + \beta_3 \cdot PAL + \beta_4 \cdot DIS_N + \beta_5 \cdot DIS_R + \beta_6 \cdot T + \beta_7 \cdot RLA) \quad (19)$$

The corrected coefficient of the multi-dimensional correlation for equation 19 is 0.769. This means that the minimum R_{co}^2 value for equation 17 is 0.734, which indicates a very good match between the estimated and observed data.

The impact of all describing variables on the described variable was assessed using the arc elasticity index (*AE*). Where the models of selected measures are concerned, the *AE* index determines the average percentage change of dependent variable *Y* when the independent variable x^i changes by one percent in the interval $t_1 - t_2$ (Abdel-Aty and Radwan, 2000c; Litman, 2010; Mannering et al., 1996; Vaziri, 2010).

When analysing the elasticity indicator of the independent variables' influence on a selected road safety measure (*DI*), the variables that proved to be statistically significant in the constructed models were the following (Figure 4):

– variables influencing an increase in the value of the measure: *AADT, DA, RLA, T,*
– variables influencing a decrease in the value of the measure: *PAL, PBA, PHV.*

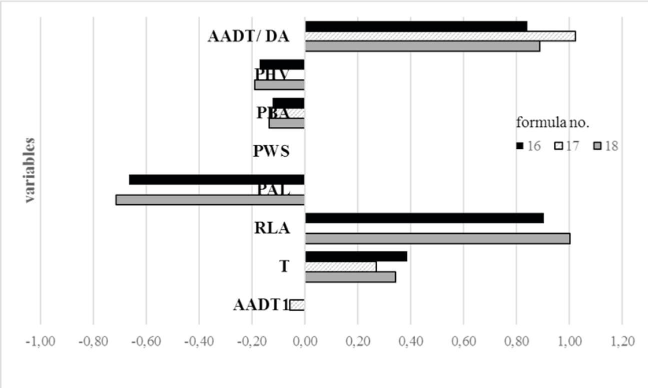


Fig. 4. Density of injuries – arc elasticity (equations 16–18)

Figure 5 shows a chart of the relations between *DI* on national roads and *AADT* for different classes of road, Figure 6 – a chart of the relations between *RLA* and *DI*, Figure 7 – between *PBA* and density of injuries (*DI*), and Figure 8 – between *PHV* and *DI*. Based on the results of the study, it is possible to determine the impact of those factors that have the greatest influence on the level of road traffic hazards.

Annual average traffic volume (AADT). The most commonly encountered models for estimating the predicted number of accidents are power-exponential models, the most important element of which is the risk exposure variable represented by AADT. An increase by 1% of this variable results in a 0.84-0.9% increase in the number of injured.

Location of road (RLA). The RLA variable has a significant impact on the risk on single carriageways. It contains factors which were not included in the model due to the lack of data (land use, transit traffic, maintenance of the road network, curvature, share of pedestrian traffic, etc.).

Share of built-up sections (PBA). An increase by 1% in built-up areas results in a decrease in casualties by 0.12-0.14%. The built-up areas are typically more accessible to a larger number of road users (number of exits, intersections, pedestrian crossings, etc.) with more traffic on side roads, all this resulting in the increased exposure (increase in accidents). On the other hand, the speed limits in these areas determine the accident severity.

Share of heavy vehicles (PHV). An increase by 1% in the share of heavy-duty vehicles results in a decrease in casualties ranging from 0.17 to 0.19%. Paradoxically, this situation is not favourable. The decline in injuries may result from an increase in the number of fatalities. The reason for this is the greater need for overtaking, which unfortunately results in an increase in the number of head-on accidents, having some of the highest rates of severity in relation to fatalities.

Technical grade and road cross-section type (T). The important role of this variable is confirmed in research by other authors who point to the significant impact of this feature on the number of road accidents and victims. The technical class and cross-section of the road have an impact on road parameters (curvature, waviness, design speed, road accessibility, etc.) and indirectly affect the speed of travel that affects the road safety level.

Share of sections with additional lane for going straight ahead (additional) (PAL). An increase in the share of sections with additional lanes allows for safe overtaking, among other things. Furthermore, on such sections there are traffic separation and limited accessibility lanes, which result in higher levels of road safety.

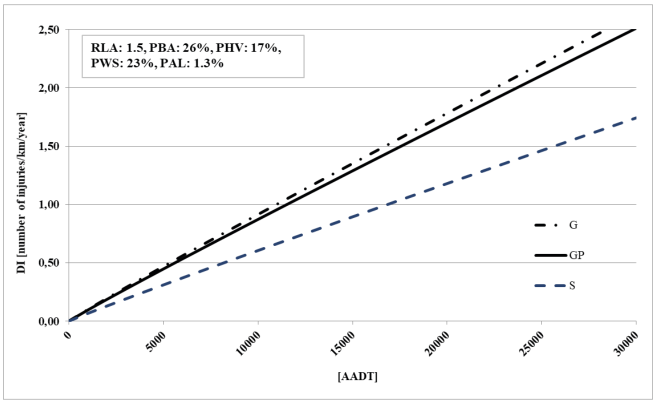


Fig. 5. Density of injuries – effects of traffic volume (AADT) - equation 16

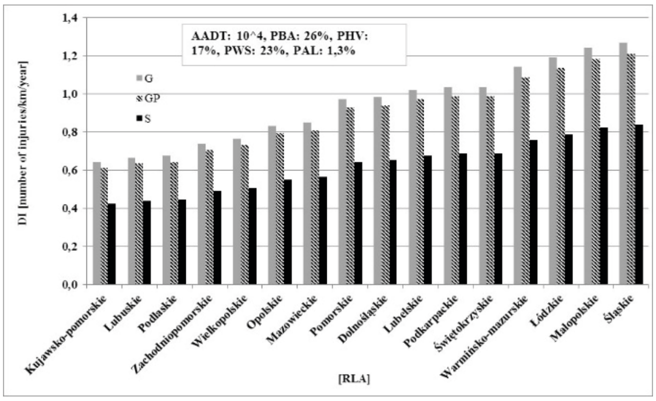


Fig. 6. Density of injuries – effects of location of road (RLA) - equation 16

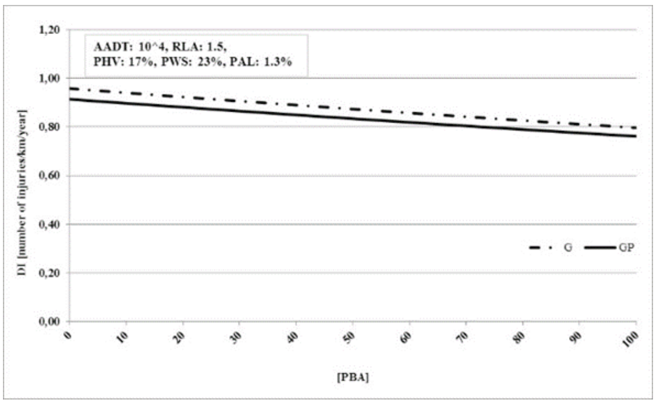


Fig. 7. Density of injuries – effects of share of built-up sections (PBA) – equation 16

** Class S roads cannot pass through built-up areas (PBA), so they do not appear on the chart.*

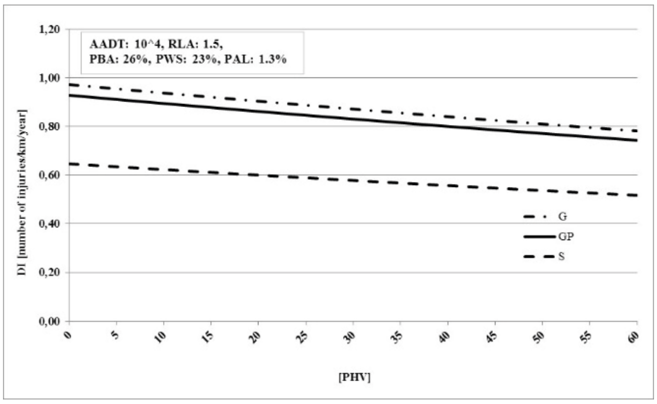


Fig. 8. Density of injuries – effects of share of heavy vehicles (PHV) – equation 16

CONCLUSIONS AND RECOMMENDATIONS

As well as explaining how mathematical models should be built, the article presents a model of injury density (DI), based on a number of road and traffic factors. The design of the model includes variables of traffic (AADT, PHV), location (PBA), cross-section (PWS, PNS, PUS, PEL, PCL, PAL), density of junctions and exits (DIT, DITE, DIS, DD), roadside (PST), pedestrian and cyclist facilities (PP), and automatic enforcement (DCS). The results are consistent with those reported by other researchers and help to fill the gap when it comes to research on long sections and modelling road safety measures for accident victims.

The main goal of the research has been achieved which was to estimate, based on risk analysis, the effects of selected road and traffic factors on the density of injuries (DI) on long sections. All the models offer a very good match between the data observed and those estimated from the model. This helps to achieve a practical objective which is to build tools for road safety management, primarily to understand how new infrastructure projects will impact road safety. The models can also be used as a component of the road safety analysis method in multi-criteria analyses and in software for estimating the number of accidents depending on traffic distribution within the road network.

The next stage of the work will be to build models for fatality and serious injury numbers and density which will help to estimate potential accident severity. The authors are planning to improve short section models (less than 5 km). While the literature on this is quite rich, the specificity of Poland's road network calls for dedicated models for a more effective operational risk management. This will support road safety inspections and ranking of road and roadside hazards.

A key element to the continued work will be the implementation of selected road safety management tools for regional roads whose safety standards are inferior to those of national roads and accident risks are higher.

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