The Effect of Traffic and Road Conditions to the Fatality Rates on Rural Roads in Eastern Indonesia

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Abstract: This paper presents the effect of traffic and roads conditions to the accident rates on rural interurban roads in Eastern Indonesia. The survey was conducted in 7 provinces on 35 sections of roads. However, is only 18 sections of roads were able used for constructing the accident rates model. The multivariate regression linier with Poisson error was chosen as the best models and it concluded that the proportion of motorcycles, roughness index, road width and average speed are contributing significantly to the fatality rate in terms of fatalities over 100 million vehicle kilometre travelled. It is suggested that by limiting the number of motorcycles will have a greater impact to road safety. Increasing proportion of motorcycles by 10% will increase fatality rate by 30%. Reducing road width by 0.5 m, increasing average speed by 5 kph and increasing IRI index by 1 will increase fatality rate by 8.50%, 3.50% and 2.80% respectively.

Key Words: *Fatality rates, Poisson models, Eastern Indonesia Rural Roads*

1. INTRODUCTION

Traffic accident is one of the main causes of death in Indonesia. According to the statistics of Directorate of Traffic Police, in 2006 approximately 16,000 victims was killed in the traffic accident and if no serious counter measure efforts, it is estimated that the number of victims will increase in future. However, based on the ADB figures, the number is much higher than the police figures. It was estimated that the number of fatalities in 2004 was around 30,000 per annum (ADB, 2005). The present conditions of road safety can be seen in Figure 1.

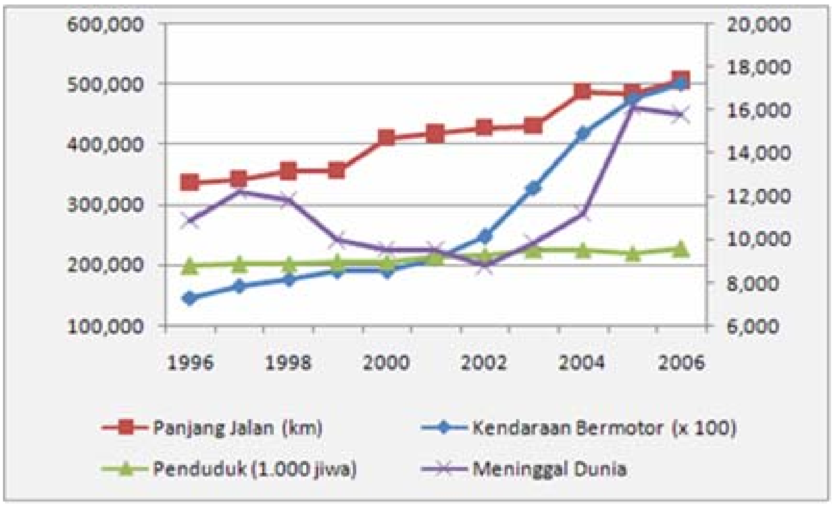

Figure 1 Condition of traffic safety in Indonesia

Figure 1 also shows a significant increased in the number of vehicles. Within five years, the number of vehicles had increased 100%. As a result, the number of traffic accidents had also increased. Furthermore, the drastic increases of the number of fatalities in the year 2004 and 2005 was also caused by the result of improvement of the traffic accident record system through out Indonesia that started in Jakarta Metropolitan Police in the mid 2003.

The rapid growth of vehicles with the significant increase of number of motorcycles can be seen in Table 1. Motorcycle is a type of vehicle has a very vulnerable towards traffic accident that can lead to fatality. The Directorate of Traffic Police is aware that motorcycle has reached the tolerance because the impact towards traffic accident can be felt throughout Indonesia. At least 60% of the traffic accident's victims associate with motorcycles as seen in Figure 2.

Table 1 Proportion of motorcycles towards the total number of vehicles

Year	Total Registered Vehicles	Annual Growth of Total Vehicles	Registered Motor-cycles	Annual Growth of Motor-cycles	Proportion of Motor-cycles
1996	14,530,095		10,090,805		69%
1997	16,821,076	16%	12,015,390	19%	71%
1998	17,644,885	5%	12651813	5%	72%
1999	18,224,149	3%	13,053,148	3%	72%
2000	18,975,344	4%	13,563,017	4%	71%
2001	21,201,272	12%	15,492,148	14%	73%
2002	24,671,330	16%	18,061,414	17%	73%
2003	32,774,929	33%	23,312,945	29%	71%
2004	41,986,814	28%	28,963,987	24%	69%
2005	47,654,826	13%	33,193,076	15%	70%
2006	50,102,492	5%	35,102,492	6%	70%
Average Annual growth		20%		19%	71%

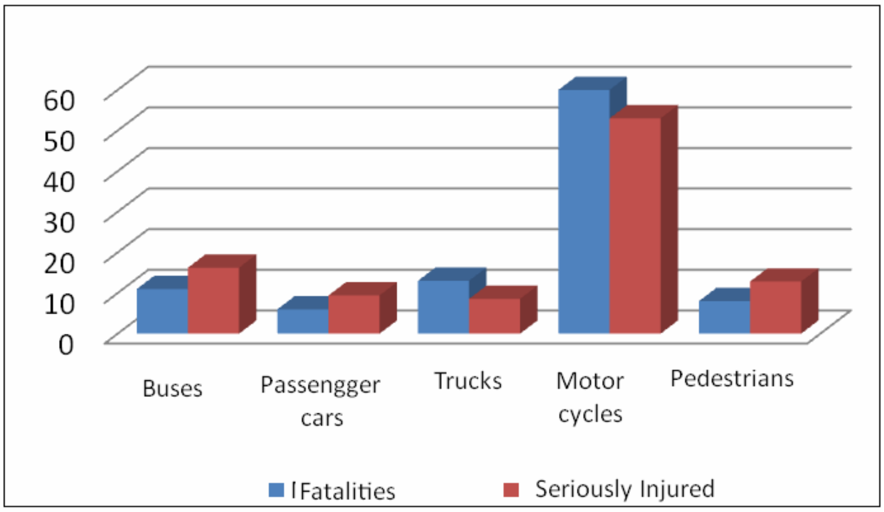

Figure 2 Percentage number of victims based of the type of vehicles

This paper was utilise the study result of the first baseline report for monitoring and evaluation the Eastern Indonesia National Road Improvement Project (EINRIP) funded by the Australian government through the Australian Aids Agency (AusAid). EINRIP surveys were carried out in 7 provinces on 35 sections of road. Some of the sections were virtually having no traffic and unpaved (EINRIP, 2008).

Researches on the effect of traffic and road conditions in Indonesia to the risk of accidents are relatively limited. For example, Tjahjono (2007a and 2007b) studied the effect of these variables to the occurrence of accident on Indonesian motorways. Moreover, studies on rural road accidents are virtually not available. The EINRIP study is the first kind in Indonesia to carry out before and after road capacity expansion to the frequency of fatal road accidents. Road improvement will increase the vehicle speeds and may lead to an increase in accidents. Therefore, the EINRIP requires all road sections have subjected to a safety audit and appropriate safety measures have been incorporated into the final design. Monitoring will be carried out between three and five years after construction. The project uses also a "double-difference" approach measuring changes on project roads both before and after construction, and using a set of control roads as a basis for establishing what would have happened in the lack of the adequate road investment. The control roads have been chosen arbitrary assuming these roads are having the same road and environment conditions as the project section of roads. From the study, it will be also a good opportunity for carrying out research on rural roads in Eastern Indonesia.

From the initial recognising survey, main problem of rural roads in Eastern Indonesia associated to the risk of accidents causes by: poor pavement conditions (IRI), sub standard geometric condition in particular road width (WIDTH), high proportion of motorcycles (MC) and high average speed (SPEED) relatively to the fact that the road conditions are very poor. Other factors are the absence of road sign and marking and other safety devices e.g. safety fence and settlements are too closed to the carriageway.

The main objectives of this paper are having two folds: First, to establish the understanding of the consequences of having sub standard road width, pavement condition, traffic conditions i.e. proportion of motorcycle and average speed to the traffic safety performance and; Second, to indicate the potential safety improvement by improving those variables.

2. METHODOLOGY

Many traffic accident prediction models have been constructed in recent years. Early work used linear regression to model accident frequencies, with errors assumed to be normally distributed (Satterthwaite, 1981). It was found from a study carried out by Jovanis and Chang (1986) that the use of generalized linear regression with a Poisson error structure is much better than linear regression (with a normal error structure and using a least squares regression technique) for describing the nature of accident frequencies, i.e. for random, discrete, non-negative and rare events. They introduced a Poisson model to relate accident frequency to traffic and various environmental variables. They concluded that a linear regression has problems associated with non-negativity and error terms with unequal variance. If the fundamental accident process is one in which the mean accident frequency is functionally related to the variance (e.g., a Poisson distribution which assumes the mean is equal to the variance), parameters in a linear regression model will be unbiased but will have incorrect confidence limits. As the intention of the regression is to recognise factors that significantly affect accident occurrence, incorrect confidence limits will invalidate hypothesis testing of parameter significance. Comparison studies between the normal distribution and the Poisson distribution have been carried out by Joshua and Gerber (1990) and Miaou and Lum (1993) and have confirmed that the Poisson model is superior to the traditional linear regression. Lee and Mannering (2002) in their methodology review suggested that using categorical modelling techniques such as logit models is also inappropriate since these models do not take into account non-negative integer count characteristic that applies to with accident frequencies. Moreover, the Poisson model can be employed through the adaptation of generalized linear modelling techniques (for details of this technique see McCullagh and Nelder, 1983).

The Poisson distribution has the limitation that the variance and mean should be approximately equal. In the case of accident frequencies, the variance is generally much larger than the mean (described as the over-dispersion phenomenon) at which point the Poisson model becomes inappropriate. To overcome this problem, Maher and Summersgill (1996) suggested using the quasi Poisson model[1] or the negative binomial model. The quasi-Poisson model may lead to inefficient coefficients and bias results[2], so that the negative binomial model has been suggested as an appropriate model to solve the over-dispersion phenomenon. From a large number of empirical studies carried out by the U.K. Transport Research Laboratory, it was concluded that the negative binomial model is the most appropriate way by which to model over-dispersion, in particular with a large dataset (Maher and Summersgill, 1996). The negative binomial model has been used intensively by recent studies as the most appropriate methodological technique for modelling accident frequencies (for example: Walmsley *et al*., 1999 and Lee and Mannering, 2002).

The Pure Poisson Model

The basic form of model is based on the assumption that the observed number of accidents at a site is assumed to be Poisson distributed. The Poisson model is

$$P(n_{ij}) = \frac{\exp(-\lambda_{ij})\lambda_{ij}^{n_{ij}}}{n_{ij}!} \tag{1}$$

i.e. where P (n_{ij}) is the probability of n accidents occurring in a given section or segment i in time period j and λ_{ij} is the expected value of n_{ij} (for simplification of notation, the j subscript is suppressed in the following equations). The expected number of accidents per given period 'λ_I' is then related to the explanatory variables, X_i, through a log-link function by the following equation:

$$E(n_i) = \lambda_i = \exp(\beta X_i) \tag{2}$$

[1] Basically, the parameter estimates resulting from the quasi-Poisson models are similar to the pure Poisson model, the differences being in the magnitude of standard errors, which are inflated by a factor of k (Maher and Summersgill, 1996). The best prediction of k is determined by Pearson's χ^2 value divided by the degrees of freedom (Crawley, 1993).

[2] The effect of the quasi Poisson approach is that some variables would not be regarded significant under this model, because their *t* ratios would not attain the necessary level (Maher and Summersgill, 1996).

i.e., where, β is the vector of parameters that should be estimated by fitting processes and X_i is the vector of explanatory variables. In these cases, the maximum likelihood method is used to estimate the parameter rather than the standard least squares method.

The ratio between residual deviance and degrees of freedom can be used for testing the over-dispersion phenomenon. If the ratio is substantially greater than one, then the data are over dispersed.

The Negative Binomial Model

As mentioned above, the limitation of the Poisson model is that the variance and mean must be approximately equal but, in general, accident data have a variance exceeding the mean. To deal with the limitations of the Poisson model, a negative binomial based on a gamma-distributed error term is commonly used. Therefore, the basic equation is as follows (Shankar *et al*., 1995, Walmsley *et al*., 1999 and Lee and Mannering, 2002):

$$E(n_i) = \lambda_i = \exp(\beta X_i) + \varepsilon_i \tag{3}$$

where ε_i is a gamma distributed error term. This addition will make it possible that the variance is different from the mean following the next equation:

$$\mathrm{Var}\,(\mathrm{n_i}) = \mathrm{E}(\mathrm{n_i}) + \theta\ E(n_i)^2 \tag{4}$$

From equation 2, it can be seen that if parameter θ is equal to zero, then the negative binomial model becomes a Poisson model; therefore the Poisson model can be described as an absolute of the negative binomial model. The negative binomial model is described by the following equation:

$$\mathrm{P}(\mathrm{n_i}) = \frac{\Gamma((1/\theta) + \mathrm{n_i})}{\Gamma(1/\theta)\mathrm{n_i}!}\left(\frac{1/\theta}{(1/\theta) + \lambda_i}\right)^{1/\phi}\left(\frac{\lambda_i}{(1/\theta) + \lambda_i}\right)^{\mathrm{n_i}} \tag{5}$$

Model Forms

The general form of the models was followed by the following equation:

$$\begin{aligned} A \quad = \quad & k\ FLO^{\alpha 1}.LEN^{\alpha 2}.\exp\,(\beta_1 GEO_{L1}).\ \exp\,(\beta_2 GEO_{L2})\ldots\ldots \\ & \exp\,(\delta_{1.}OTH_1).\exp(\delta_2 OTH_2)\ldots\ldots. \end{aligned} \tag{6}$$

where A = Accident frequency (accidents per year)

FLO = Traffic flow (100,000 AADT in vehicles per day)

LEN = Length of segment (km)

GEO_1, GEO_2,…..= Geometric variables

OTH_1, OTH_2….. = Other variables such as streetlights indicator variable

α, β and δ = Regression coefficients

These forms followed the suggestion of Taylor et al. (2000) that the simplest functional forms for individual terms i.e. the power form and the exponential form gives a satisfactory fit, so that more complex terms are not needed. Furthermore, from the literature review, the power form was shown to fit well for the traffic flow and segment length variables, and the exponential form is well described for the road features variables (see Walmsley et al., 1999 and Taylor et al., 2000).

Fitting the Models

The procedure used in building the models was to fit the variables to the null model first and retain those which were individually significant and which, in combination, provided the best fit. The difference in scaled deviance between two nested models with degrees of freedom df_1 and df_2 will follow a chi-squared distribution (χ^2) with (df_1-df_2) degrees of freedom. Therefore, for the addition of one variable, a reduction of scaled deviance of at least 3.84 is required for statistical significance at the 5% level.

Although the calculation for estimating parameters for generalised linear models can be obtained by developing readily available programs, a comprehensive structure is required for considering the model properties. These should allow for various response distributions such as Poisson and negative binomial and for different link functions. In particular for count data, the log link is the most appropriate where negative fitted values are prohibited. In addition, the programs should be accurate.

GLIM software (a description of this software can be found in Aitkin et al., 1989) meets all of these requirements (Dobson, 1990). It was first developed to provide a software tool that would enable fitting generalised linear models to data and it is widely used in the development of traffic accident prediction models. An example is the study carried out by Maher and Summersgill (1996) for reviewing the methodology of predictive accident models. Using GENSTAT (a similar model as GLIM), Walmsley et al. (1999) carried out a study for modelling accidents on modern rural dual-carriageway trunk roads, Taylor et al. (2000) carried out a study for modelling the effects of drivers' speed on accident frequencies, and Summersgill et al. (2002) carried out a study for modelling accidents at junctions on one-way urban roads. The theoretical background of GLIM is discussed by McCullagh & Nelder (1989) and Dobson (1990).

As stated by Dobson (1990) GLIM is an interactive program. However the size of the matrix should be specified initially by setting the numbers of observations and covariates. Then the data are read in and elements of the design matrix $\boldsymbol{X}$ are set up. The next step is to specify the distribution and link function (for example negative binomial distribution and log link function). Based on this information, GLIM produces the linear components, $\boldsymbol{x}^T\beta$, the parameter values of β are estimated and the estimation of goodness-of-fit statistics (in terms of scaled deviance) and other information can be displayed [details of GLIM are given in NAG, GLIM Manual (1985), Aitkin et al. (1989) and Crawley (1993)].

3. STUDY AREA

As mentioned, the study area involved 7 provinces with 35 sections of road. However is only 18 sections of road in 5 provinces (see Figure 3) that can be used for constructing the models as shown in Table 2. The limitations are due to: (i) virtually some sections are having no traffic flow because of very poor unpaved road conditions and completely impassable, and (ii) no accident data is available because the locations are in the remote areas.

1. West Kalimantan 2. South Kalimantan 3. Bali 4. West Nusa Tenggara
5. South Sulawesi 6. South East Sulawesi 7 Central Sulawesi

Figure 3 Road sections locations

Table 2 Location of the road sections

No.	Province	Link ID	From	To	Length (km)	ADT
1	Bali	40.00.1	Cekik	Gilimanuk	3.20	13,149
2	Bali	40.00.2	Negara	Cekik	30.20	10,420
3	Bali	40.005	Tambanan	Antosari	19.30	28,145
4	Bali	40.039	Sidan	Klungkung	8.80	18,750
5	Bali	40.500.2	Tohpati I	Kusumba	10.40	43,024
6	South Sulawesi	54.019	Bantaeng	Bulukumba	27.00	4,766
7	South Sulawesi	54.034	Watampone	Pompanua	47.80	6,074
8	South Sulawesi	54.038	Sengkang	Impa Impa	3.20	14,222
9	South Sulawesi	54.039	Impa-Impa	Tarumpakae	21.00	3,392
10	South Sulawesi	54.053	Sidereng	Anabanua	34.10	6,084
11	South Kaimantan	36.003.1	Martapura	Ds Tungkap	19.00	16,654
12	South Kaimantan	36.011.1	Sp. Liang Angga	Liang Angga	7.50	12,880
13	West Kalimantan	30.009.2	Sei Duri	Singkawang	49.30	6,338
14	West Kalimantan	30.079.1	Tayan	Teraju	30.60	1,418
15	West Nusa Tenggara	42.030.1	Pal IV	Km 70	31.80	4,813
16	West Nusa Tenggara	42.085.11	Sumbawa Besar By Pass		8.90	2,265
17	Central Sulawesi	52.004.1	Tawaeli	Kebon Kopi	24.90	3,922
18	Central Sulawesi	52.033	Donggala	Surumana	39.40	5,112

4. ANALYSIS

4.1. The Data

Four explanatory variables were used for predicting fatalities rate (RATE) i.e. roughness index (IRI), Proportion of motorcycle (MC), road width (WIDTH) and average speed (SPEED). It should be noted that due to the absence of traffic marking on mostly road sections, road width is determined by carriageway width plus hard shoulder width (if available).

IRI values were based on the Australian Road Research Board/s (ARRB) Roughometer II. Runs were carried out in both directions. IRI values are recorded for short sections of 100 metre. In the case of the impassable road sections, a default IRI value of 25 has been assigned to the road. It should be noted that the lowest of IRI value mean the best of the road condition. Classified traffic counts were carried out over 3 weekdays of 24 hour period on all road sections and estimates of average daily traffic (ADT) then was generated. Vehicle speeds were carried out using a "floating vehicle" and speed guns at a series of sites at intervals of approximately 6 kilometres along each road. Speed for 6 classes of vehicles i.e. motorcycles, cars & vans, pickups, buses and trucks were recorded by survey team.

Table 3 shows the variables for constructing the models and Table 3 shows the summary of the data that were used to construct these models. The minimum fatality rate was 5.55 deaths per 100 million vehicle kilometre travelled (VKT) on Tambanan-Antosari section in Bali and the highest was 40.77 million VKT on Sumbawa Besar bypass in West Nusa Tenggara Province, with mean of 13,52 million VKT. Minimum average speed was 28.20 kilometre per hour (kph) on Pal IV-Km 70 in West Nusa Tenggara Province and the maximum average speed of 51,00 kph was on Sindereng-Anabauna in South Sulawesi Province, with the mean average speed of 41.10 kph. The average speed was relatively very high for the narrow road in the study area. Proportions of motorcycles were minimum of 36% and maximum of 80%, with the mean of 58.50%. Minimum road width is 4.50 metre and the maximum is 9.00 metre makes up the average road width of 5.67 metre. Finally, IRI values were between 3.6 and 10.4, with the mean of 5.4.

Table 3 Variables of the models

No.	Province	Fatal	Exposure (100 M VKT)	Ratio Fatal/100 M VKT	% of motor cycles	IRI	Width (m)	Speed (Kph)
				Rate	MC	IRI	Width	Speed
1	Bali	3	0.15	19.53	41	4.6	7.00	48.6
2	Bali	16	1.15	13.93	45	3.7	7.00	49.3
3	Bali	11	1.98	5.55	60	3.6	6.00	34.1
4	Bali	8	0.60	13.28	69	4.1	7.00	37.2
5	Bali	12	1.63	7.35	63	4.3	9.00	38.3
6	South Sulawesi	7	0.47	14.90	48	4.6	6.00	48.9
7	South Sulawesi	7	1.06	6.61	67	4.4	4.50	46.8
8	South Sulawesi	2	0.17	12.04	64	7.4	4.50	35.2
9	South Sulawesi	3	0.26	11.54	58	7.5	4.50	38.7
10	South Sulawesi	13	0.76	17.17	42	3.9	4.50	51.0
11	South Kaimantan	10	1.15	8.66	36	3.7	6.00	45.3
12	South Kaimantan	9	0.35	25.53	41	3.6	6.00	42.3
13	West Kalimantan	11	1.14	9.64	54	4.5	6.00	48.6
14	West Kalimantan	2	0.16	12.63	78	8.6	4.50	40.0
15	West Nusa Tenggara	5	0.56	8.95	76	7.0	4.50	28.2
16	West Nusa Tenggara	3	0.07	40.77	80	10.4	6.00	29.1
17	Central Sulawesi	3	0.36	8.42	53	6.0	4.50	41.0
18	Central Sulawesi	5	0.74	6.80	78	5.6	4.50	37.2

Traffic flow was derived from the segment traffic flow, the same as the Stage 1 models. The minimum traffic flow was 13,180 vehicles per day on dual-2 toll roads and the highest was 94,540 vehicles per day (in terms of AADT) on dual-3 toll roads, with means of 22,920 and 48,120 vehicles per day for dual-2 and dual-3 toll roads respectively. Correlation between variables can be seen in Table 5. The highest correlation rate of 0.74 is between proportion of motorcycles to the traffic and average traffic speed. The lowest correlation rates of 0.13 are among road width, speed and fatality rate.

Table 4 Summary of the data

	Fatality Rate	*% of Motor Cycles*	*IRI*	*Width (m)*	*Speed (kph)*
Mean	13.52	58.50	5.4	5.67	41.10
Standard Deviation	8.49	14.35	2.0	1.28	6.99
Range	35.22	44.00	6.8	4.50	22.80
Minimum	5.55	36.00	3.6	4.50	28.20
Maximum	40.77	80.00	10.4	9.00	51.00
Count	18	18	18	18	18

Table 5 Correlation between variables

	Rate	*MC*	*IRI*	*Width*	*Speed*
Rate	1				
MC	0.00	1			
IRI	0.42	0.67	1		
Wid	0.13	-0.25	-0.41	1	
Spe	-0.13	-0.74	-0.61	0.13	1

4.2. Model Result

Crawley (1993) noted that two variables may both appear to be insignificant and yet both of them may make a significant contribution to explaining the deviance on their own. Backwars elimination does not lead to the mistake of concluding that neither variable is important nor to leads to acceptance of the variable that explain the greater deviance when removed from the maximal models. It found that the most appropriate model was followed the Poisson error distribution and all explanatory variables are significant (changed of scale deviance is greater than 3.84). The Mode result and comparison between actual and model result are shown in Tables 6 and 7 respectively.

Table 8 shows elasticities of all of the explanatory variables. They were estimated to determine the sensitivity impact on accident frequencies. Elasticity can be defined as the percentage change in the average frequency of a dependent variable due to a one-percent change in the independent variable. For example, the elasticity of accident frequency (λ_i), with respect to x_{ik} (the *k*th independent variable for segment i) is defined as,

Table 6 Model sesult

Fatlity Rate = $k_0.\exp(\alpha^1 IRI+\alpha_2 MC+\alpha_3 WIDTH+\alpha_4 SPEED)$				
Model	Model Terms	Parameter Values	*s.e.*	Deviance Difference
Null	ln k_o	2.604	0.06411	
Full	ln k_o	1.588	1.1640	
	IRI	0.2803	0.0497	14.850
	MC	0.02646	0.0084	10.240
	WIDTH	-0.1756	0.0564	8.286
	SPEED	0.006751	0.0163	4.643

Table 7 Comparison between actual and model result

IRI	MC	WIDTH	SPEED	RATE		Deviation	
				ACTUAL	MODEL	Absolut	Relative (%)
4.6	41	4.6	7.00	9.53	7.70	1.83	19.20
3.7	45	3.7	7.00	13.93	9.78	4.15	29.82
3.6	60	3.6	6.00	5.55	4.66	0.89	16.01
4.1	69	4.1	7.00	13.28	17.39	-4.11	30.92
4.3	63	4.3	9.00	7.35	14.60	-7.25	98.74
4.6	48	4.6	6.00	14.90	9.21	5.70	38.23
4.4	67	4.4	4.50	6.61	5.52	1.09	16.43
7.4	64	7.4	4.50	12.04	9.21	2.83	23.54
7.5	58	7.5	4.50	11.54	7.74	3.80	32.93
3.9	42	3.9	4.50	17.17	8.62	8.55	49.78
3.7	36	3.7	6.00	8.66	7.65	1.01	11.61
3.6	41	3.6	6.00	25.53	8.87	16.66	65.27
4.5	54	4.5	6.00	9.64	10.95	-1.30	13.52
8.6	78	8.6	4.50	12.63	11.17	1.46	11.55
7.0	76	7.0	4.50	8.95	13.41	-4.46	49.88
10.4	80	10.4	6.00	40.77	9.12	31.65	77.63
6.0	53	6.0	4.50	8.42	8.46	-0.04	0.52
5.6	78	5.6	4.50	6.80	7.39	-0.59	8.66

$$E^{\lambda_i}_{x_{ik}} = \frac{\partial \lambda_i}{\lambda_i} \mathrm{x} \frac{x_{ik}}{\partial x_{ik}} \qquad (7)$$

Table 8 Summary of elasticity of explanatory variables

Variable	Minimum	Maximum	Unit	Range of Elasticities
IRI	3.60	10.40		0.05 to 0.14
MC	36.00	80.00	%	0.35 to 0.78
WIDTH	4.50	9.00	metre	0.05 to 0.11
SPEED	28.20	51.00	kph	0.28 to 0.51

Proportion of motorcycles was found the highest elasticities to the fatality rate, followed by average speed and road width. Roughness index was the lowest elasticity to the fatality rate. Through this model and its elasticities, it is possible to give plausible and intuitive main factors that influence fatality rate. It is not surprising that proportion of motorcycle should be considered as the most important factor for improving road safety in this study.

4.3. Discussion

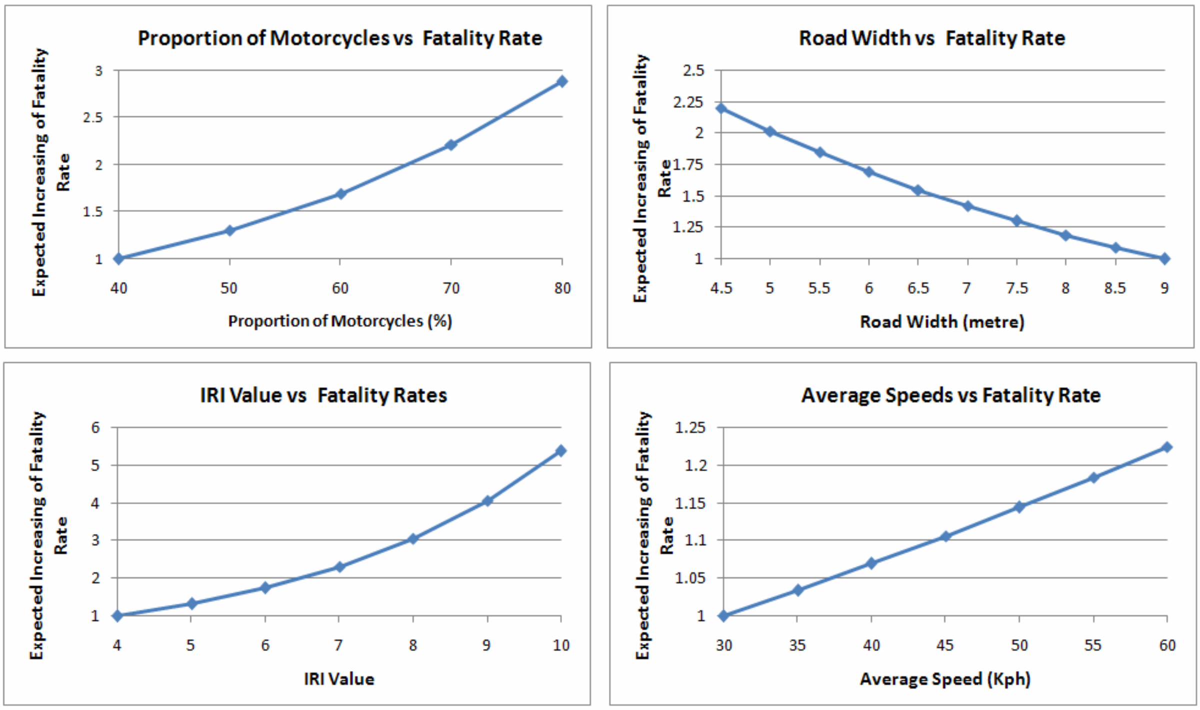

Figure 4 Risk of fatality accident by individual explanatory variables

As shown in Figure 4, some results can be drawn as follows:

1. Proportion of motorcycles to total traffic flow has the greater effect to fatality rate, followed by road width, average speed and roughness index.
2. Increasing proportion of motorcycles by 10% will increase 30% fatality rate.
3. Decreasing road width by 0.5 m will increase fatality rate of around 8.50%
4. Increasing average speed by 5 kph will increase fatality rate of around 3.50%
5. Finally, increasing roughness index by 1 factor of IRI index will increase fatality rate of around 2.80%.

The greatest effect by motorcycles was not surprising. As shown from Figure 2 that fatality associated with motorcycles was around 70% to the total number of fatalities in Indonesia. Moreover, roughness index is not giving the high elasticity because the majority of the traffic is motorcycle that can easily negotiate with the poor pavement condition. Road width is also play important role to the road safety. The sub standard road width of 4.50 m must be avoided regardless the traffic volume

Speed limit must be regulated strongly. Currently, no speed limit sign is available on all section of roads that can be difficult to regulate. Study by Nillson (2004) suggested that increasing average speed by 1% will increase the risk of number of accidents and fatalities by

3% and 5% respectively. The speed trends in this study suggested the same direction as Nilsson study.

5. CONCLUSION

This paper presents an initial model to explore the accident rates on rural road in Eastern Indonesia on the basis of a multivariate analysis to the four main factors i.e. roughness index, proportion of motorcycles, road width (summation of carriageway and hard shoulder if available) and average speed. A Poisson model of overall accident frequency is estimated the fatality rate in terms of number of fatalities over 100 million vehicle kilometres travelled. This paper is also suggested the initial strategy for improving rural road safety. The greatest improving is through, limited the number of motorcycles, and followed by improving the substandard road width, managing the speed limit and improving road pavement quality.

ACKNOWLEDMENT

This paper is based on the data collected and surveyed by EINRIP project which the author has some contribution to the project.

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