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DEVELOPMENT OF A CRASH FREQUENCY MODEL OF INDONESIAN FREEWAYS

Summary. It is imperative to comprehend the factors that contribute to traffic crashes if they are to be reduced effectively. This study aimed to develop a crash frequency model of Indonesian inter-urban freeways. Data was collected from four inter-urban freeway toll roads. The freeway toll-road operators provide traffic volumes, geometric characteristics, and crash data. To develop the crash frequency model, the author performed a negative binomial regression analysis. The predictors included certain highway geometric factors and the hourly traffic volume. The results show that the frequency of crashes was significantly associated with the volume of traffic per hour and geometric factors. Specifically, section length, hourly traffic volume, and the width of the roadway and outer shoulder positively impacted crash frequency, while horizontal curve and inner shoulder width had a negative impact. Moreover, road divider (median) type and time of day had significant impacts on inter-urban freeway crash occurrences. The results have important implications, as they reveal the relationship between freeway design parameters and traffic crash frequency. This knowledge will aid the development of new design methods that consider safety explicitly.

1. INTRODUCTION

The Jagorawi freeway toll road is the first freeway toll road in Indonesia. The Jagorawi freeway toll road was first operated in 1998 to connect the capital city of Jakarta with the cities of Bogor and Ciawi, across a distance of of more than 60 km. Indonesia aims to have over 5000 km of freeway toll-road in 2024. The total length of the operated toll road was 2391 km in April 2021. The country will build over 2500 km of freeway toll road from 2020 to 2024 [1]. The development agenda aims to develop basic service infrastructure focusing on transportation safety and security. However, as the miles traveled increase, the number of crashes on toll-road segments also increases. According to data published in 2018, the WHO estimated that 31,726 road traffic accident deaths occurred in Indonesia [2].

Traffic crashes can be reduced by understanding the circumstances that contribute to them. Excellent knowledge of efficient methods to analyze accident data is also needed. Several studies have explored the correlation between accidents and road sections' various geometric and traffic characteristics. Most research on traffic factors has concentrated on establishing the connection between accidents and traffic volume [3–6]. Some studies have also examined the safety of highway sections based on other traffic factors, such as the volume-to-capacity (v/c) ratio [7, 8] and the level of service [9]. Recent studies have assessed whether including speed data improves model performance [10, 11].

Research on the relationship between geometric characteristics and accidents was conducted by Miaou and Lump [12], who studied the relationship between road geometry and truck accidents. Shankar et al. [13] evaluated the effects of road geometric and environmental factors on rural highway

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crash frequency. Meanwhile, Poch and Mannering [14] developed models to identify the most significant traffic and geometric elements that determine the crash frequency at intersections. In another study [15], linear regression was used to estimate the truck involvement rate in accidents/mile/year. The estimation considered variables including annual average daily traffic (AADT), heavy vehicle AADT, horizontal curve, the width of the shoulder, and vertical grade.

Despite substantial progress, greater clarity is still required in comprehending the relationship between different traffic and geometric characteristics and the safety of various highways. One notable drawback of the current models is its dependence on acquiring more extensive data on traffic conditions during the accident, particularly since the traffic variables used are macroscopic, such as AADT. In addition, the lack of integration between traffic conditions and geometric characteristics constrains the model's adaptability to different locations. To be more practical, assessments are needed to clarify how microscopic traffic variables and geometric features contribute to accident occurrences on various freeway sections.

This study focuses on combining traffic conditions and geometric characteristic variables to predict the crash frequency of Indonesian freeway toll-road sections. This study combines microscopic traffic variables (hourly traffic volume) with geometric variables used to model crash occurrence. Negative binomial regression is assessed for the building models to predict crash frequency because of over-dispersion. This study assumes no inherent linear relationship between traffic volume and crash frequency. Instead, the exponent (power) in the exposure variable is estimated with the other model parameters.

2. METHOD

2.1. Framework

Traffic crashes are complex events. They rarely have only one cause. Usually, many factors influence each other at a particular point in time. Highway systems comprise three components: the roadway, the vehicle, and the driver. A traffic crash results from the interactions of these components.

The present study focuses on developing a model to estimate the frequency of crashes on the basic freeway segments of Indonesian interurban toll roads based on hourly traffic volume and road geometry factors. This observational cross-sectional study [16] compares the characteristics of different freeway sections.

The dependent variable of the model is the number of crashes that occurred on freeway toll road sections per hour over three years. The model developed in the present study aimed to describe the influence of geometric characteristics and traffic factors on freeway toll-road traffic crash frequencies. The independent variables were as follows: (a) hourly traffic volume, (b) segment length, (c) horizontal alignment, (d) vertical alignment, (e) traffic lane width, (f) outer shoulder width, (g) inner shoulder width, (h) number of lanes (i) median (road divider) type, and (j) daily period. It was hypothesized that each independent variable significantly affects the occurrence of toll-roads traffic accidents.

The study collected data from four toll roads: (1) Jagorawi Toll Road, which connects the Capital Region of Jakarta and the cities of Bogor and Ciawi; (2) the Jakarta–Cikampek toll road, which connects the Capital Region of Jakarta and the city of Cikampek; (3) the Padaleunyi toll-road, which connects the cities of Padalarang and Cileunyi; and (4) the Palikanci toll-road, which connects the districts of Palimanan and Kanci. All studied freeways are in the Special Capital Region (DKI) Jakarta and West Java Province. Crash and daily traffic volume data were acquired from toll road operators. In addition, observations were made to determine the hourly traffic distribution.

2.2. Negative binomial regression

The present study's objective was to develop mathematical models to describe the relationship between traffic crash frequency on freeway toll-road segments, with independent variables that represent microscopic traffic conditions and geometric characteristics of respective freeway segments. Modeling was performed using generalized linear model techniques using R software [17]. To illustrate the use of Poisson regression in analyzing crash frequency, let us consider road segment i. If n_{ij}, a random variable, is the number of accidents during a specific period, j, then

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

where, $P(n_{ij})$ is the crash probability that occurred on-road segment i during period j, and λ_{ij} is the expected value of n_{ij}:

$$E\ (n_{ij})\ = \lambda_{ij} = \exp\ (\beta X_{ij})\ . \tag{2}$$

For a road segment i during period j, β is a regression coefficient vector that can be predicted by standard maximum likelihood methods [18]. X_{ij} represents road segment geometric attributes and other road feature conditions relevant to road segment i in period j.

One limitation of Poisson distribution is that the value of variance should be approximately equal to that of the mean. Possible over-dispersion (which occurs when variance is greater than the mean) has always been a concern in modeling accident frequency, as it results in biased and inefficient coefficient estimation. A simple regression-based test by Cameron and Trivedi [19, 20] can detect over-dispersion when testing the significance of the over-dispersion coefficient. Usually, a negative binomial distribution with Gamma distributed error factor is used to lessen over-dispersion restrictions in the Poisson models [13,21]. The negative binomial model is derived by rewriting equation (1) such that

$$\lambda_{ij} = \exp\ (\beta X_{ij} + \varepsilon_{ij}), \tag{3}$$

where $\exp(\varepsilon_{ij})$ is the Gamma distributed error factor. This addition allows the variance to exceed the mean as follows:

$$Var[n_{ij}] = E[n_{ij}]\left[1 + \alpha E[n_{ij}]\right] = E[n_{ij}] + \alpha E[n_{ij}]^2\ . \tag{4}$$

A Poisson regression model was considered a particular case of a negative binomial regression model, where α is close to zero. Hence, the choice between the two models depends on the value of α. A negative binomial distribution has the following formulation:

$$P(n_{ij}) = \frac{\Gamma((1/\alpha)+n_{ij})}{\Gamma(1/\alpha)n_{ij}!}\left(\frac{1/\alpha}{(1/\alpha)+\lambda_{ij}}\right)^{1/\alpha}\left(\frac{\lambda_{ij}}{(1/\alpha)+\lambda_{ij}}\right)^{n_{ij}}. \tag{5}$$

Standard maximum likelihood methods can estimate λ_i [18]. Based on Equation (5), the likelihood function for the negative binomial regression model is

$$L(\lambda_{ij}) = \prod_{i=1}^{N}\prod_{j=1}^{T}\frac{\Gamma((1/\alpha)+n_{ij})}{\Gamma(1/\alpha)n_{ij}!}\left[\frac{1/\alpha}{(1/\alpha)+\lambda_{ij}}\right]^{1/\alpha}\left[\frac{\lambda_{ij}}{(1/\alpha)+\lambda_{ij}}\right]^{n_{ij}}, \tag{6}$$

where N represents the total number of road segments, and T represents the last period of accident data. This maximum likelihood function is used to estimate β and 1/α.

2.3. Model form

Freeway traffic crashes directly depend on traffic exposure in terms of the number of vehicles (traffic volume) and length of the trip (road segment length). They indirectly depend on road geometric characteristics and other factors [22]. A direct effect on crashes means that when the variables' values are zero, it will automatically result in zero crashes. On the other hand, the indirect effect (indirect influence) on crashes means that a value of zero for that variable does not automatically result in zero crashes. With the frameworks mentioned previously, traffic exposure is integrated into the model as a log function. In contrast, the geometry factors are integrated into the model with exponential components.

3. DATA

3.1. Freeway data

Overall, there are 65 two-lane, three-lane, four-lane, and five-lane freeway toll-road sections that cover a length of 182 km (for each direction). In this study, a road section is defined as one direction of the toll road between the exit and entrance. Table 1 presents the number and the length of each type of toll road selected for the study. A five-lane type of toll-road section was not analyzed further as the amount is inadequate. The Jagorawi Toll Road consists of 19 sections (six two-lane sections, 12 three-lane sections, and one five-lane section).

Table 1

The number of freeway toll-road sections and their lengths

Toll-roads	Length (2-way, km)	No. of sections (1 way)				
		2-lane	3-lane	4-lane	5-lane	Total
Jagorawi	47	6	12	0	1	19
Japek	73	14	4	10	0	28
Padaleunyi	36	12	0	0	0	12
Palikanci	26	6	0	0	0	6
Total	182	38	16	10	1	65

Table 2 presents a summary of geometric characteristics values for freeway toll roads used in the analysis to develop the model. In the regression analysis carried out to develop crash frequency models, 10 freeway toll-road geometric characteristics are considered as predictor candidates. Among these characteristics, freeway section length and horizontal and vertical curves are numeric variables. The road section length ranges from 1.2 km to 14.8 km, with a mean of 5.92 km and a standard deviation of 3.02 km. The selected freeway toll-road segments have relatively straight and flat alignments, with an average horizontal curve of less than 1 rad/km and a vertical change of less than 10 m/km. However, there is a segment with a vertical change value of 28.47 m/km.

Table 2

Summary of the geometric characteristic variable values obtained from selected freeway toll-road sections

Variables	Values				
	Levels	Min	Max	Means	SD
Section length (km)		1.2	14.8	5.92	3.02
Hor. curve (rad/km)		0	0.91	0.16	0.17
Vertical up+down (m/km)		1.31	28.47	6.13	5.19
No. of lanes	2; 3; 4				
Lane width (m)	3.60; 3.75				
Carriageway width (m)		7.2	14.4	9.29	2.76
Inner shoulder width (m)	0.75; 1.50; 1.75				
Outer shoulder width (m)	2.50; 3.00; 3.75				
Road divider type	Conc. wall; Guardrail; Depressed median				
Road divider width (m)	0.60; 3.00; 11.50				

Characteristics such as the number of lanes, lane width, inner shoulder width, outer shoulder width, and median type are discrete variables with limited values. For instance, the number of lanes can be 2, 3, or 4. The lane width can be 3.60 m or 3.75 m. The inner shoulder width, outer shoulder width, and median type each have three levels. The carriageway width is determined by multiplying the lane width by the number of lanes. The median type is a nominal variable with three levels: concrete wall, guardrail (fence barrier), and depressed, wide median.

3.2. Traffic data

To enhance the accuracy of the microscopic modeling, we utilized hourly traffic volumes to describe traffic conditions at the time of the accident, rather than relying on daily volumes. However, we faced a challenge given that the hourly traffic flow data at the time of the accident was unavailable. Hourly traffic flow data was derived from average daily traffic (ADT) using typical daily flow profiles. Annual average daily traffic (AADT) values ranged from 7030 to 137,000, with an average value of 44,000. The typical daily traffic flow profiles were obtained by conducting traffic surveys on typical days of a typical week. Average hourly traffic volume (Q) for 24 hours at each segment was obtained from the survey. Hourly volume for 24 hours was added together to get the total daily volume. Additionally, hourly proportions (P_q) were obtained by dividing the hourly traffic volume in question (Q) by the total volume of 24 hours.

Hourly traffic volume values for analysis (q) were determined by multiplying the road section's AADT value by the proportion of traffic volume (Pq) at that hour. Therefore,

$q_i = P_{qi}$ x AADT, (7)

where,

q_i = hourly traffic volume at hour i

P_{qi} = proportion of traffic volume at hour i to the daily traffic volume $= \frac{Q_i}{\sum_{i=1}^{i=24} Q_i.}$

Q_i = Observed traffic volume per hour at hour i

In Table 3, the statistical distribution of hourly traffic volume (qi) is presented based on the number of lanes of the road sections. For a two-lane highway, the traffic volume ranges from 150 vehicles per hour to 3500 vehicles per hour, with a mean and median of approximately 1000 vehicles per hour. On three-lane toll road sections, the traffic volume values range from 300 to 9000 vehicles per hour, with median and mean values of about 2500 vehicles per hour. In the case of four-lane toll road sections, the traffic volume ranges from 700 to 9000 vehicles per hour, with a median value of 4000 vehicles per hour and an average of 3700 vehicles per hour.

Table 3

Statistics of hourly traffic volume based on the number of lanes of the freeway section

No. of lanes	Hourly traffic volume (veh./hour)					
	Min.	Quartile-1	Median	Mean	Quartile-3	Max.
2	154	433	904	1095	1636	3483
3	293	1197	2532	2489	3150	8979
4	696	1946	4014	3720	4962	9006
Total	154	626	1386	1833	2519	9006

3.3. Crash data

Overall, 5449 crashes occurred on the selected freeway toll road sections over the analyzed three-year period. The summary statistics of the crashes that occurred along the entire length of selected freeway sections are presented in Table 4. The table shows a considerable variation in crash frequency in the freeway toll road sections. However, it also shows an inclination to the right. The number of total crashes ranges from zero to 42, with an average of 3.66, a variant of 17.93, and a standard deviation of 4.23.

Table 4
Summary statistics of section crash frequency (acc./ hr.-3yrs.)

Statistics					
Min.	Max.	Mean	Median	Std. Dev.	Variant
0	42	3.66	2	4.23	17.93

4. RESULTS AND DISCUSSION

The results of the negative binomial modeling for total accidents are presented in Table 5. The deviance value of 987.7, with nine degrees of freedom, rejects the null hypothesis that the resulting model has the same explanatory power as the model containing only constants [21]. This indicates that the resulting model has an excellent statistical fit. The log-likelihood ratio, ρ^2, of the model is 0.16, indicating that the model explains some, but not all, of the variation in accident frequency. This low value is common in crash estimation due to the many other variables involved, such as human factors, roads, environment, and vehicles [14, 23–25].

Table 5 indicates that two variables related to exposure to travel—specifically, the logarithm of traffic volume per hour and the logarithm of road length—are significant. The log traffic volume per hour has a positive effect on the crash frequency of the freeway segment. In other words, the greater the log traffic volume per hour, the greater the total number of accidents. A similar pattern can be observed with log road length, as a longer road section increases the likelihood of crashes.

Table 5
Negative binomial model for total crash frequency

Variables	Coefficient	*Std. Error*
(Intercept)	-2.440	0.325
Log hourly traffic volume (veh/hr)	0.367	0.031
Log road segment length (km)	1.086	0.045
Avg. hor. curve (rad/km)	-1.234	0.147
Carriageway width (m)	0.084	0.020
Inner shoulder width (m)	-0.788	0.070
Concrete-wall median	0.000	
Guardrail median	-0.639	0.105
Depressed median	-0.070	0.073
Period 1: 0:00–8:00	0.000	
Period 2: 8:00–16:00	-0.383	0.053
Period 3: 16:00–24:00	-0.583	0.052
Dispersion parameter (θ)	3.823	0.319
No. of segments	64	
Full-model log-likelihood	-3110	
Null-model log-likelihood	-3604	
ρ^2=1-LL(β)/LL(0)	0.16	
2(LL(β)-LL(0))	987.7	

The average horizontal curve variable (in rads per km-long segment) negatively affects crash occurrence. Crash frequency on any given freeway toll road section decreases as the value of the average horizontal curve on that section increases. Moreover, wider traffic lanes result in greater total crash frequency. However, a wider inner shoulder width results in fewer crashes.

As required, freeway toll roads are separated. Three types of road dividers (medians) are used: concrete walls, guardrails, and a 10-m-wide depressed median. Road divider type was treated as a categorical variable in the model. The concrete wall is used as a base with which other types were compared. As shown in Table 5, the coefficient for guardrail and depressed medians is negative. Compared with concrete walls, toll roads with a guardrail and depressed median have a lower crash frequency. However, only the crash frequency difference between the concrete wall and guardrail was statistically significant.

The text below explains how different times of day impact the frequency of car accidents. It is known that certain times of the day are associated with different lighting conditions and the driver's physical condition. The day was divided into three periods: Period 1 (0:00–08:00), Period 2 (08:00–16:00), and Period 3 (16:00–24:00). There were significantly fewer accidents during Periods 2 and 3 compared to Period 1.

An empirical model of the effect of hourly traffic volume and geometric factors on inter-urban toll-roads traffic accident frequency can be expressed as follows:

$$C_j=q^{0.367}L^{1.086}\exp(-2.44+\boldsymbol{\alpha X}+\sum\boldsymbol{\beta}\ \mathbf{T_{PER}}),$$

where:

C_j = the crash frequency on segment j (crash/hour-3 years);
q = hourly traffic volume (vehicle/hour);
L = road segment length (km);
$\boldsymbol{X}$ = vector of road geometry factors;
$\boldsymbol{T_{PER}}$ = vector of daily period;
$\boldsymbol{\alpha}, \boldsymbol{\beta}$ = coefficients to be estimated.

Independent variable elasticity estimates were conducted to determine the influence of each independent variable on crash frequency. Elasticity can be interpreted as the percentage change in the average crash frequency λ_{ij} due to 1% changes in independent variables [13, 19]. The average elasticity of each significant continuous variable in the crash frequency model is presented in Table 6.

Table 6

Elasticity estimates of crash frequency caused by changes in independent variable values

Variables	Elasticity
Hourly traffic flow (veh./hour)	0.37
Segment length (km)	1.09
Average hor. Curve (rad/km)	-0.20
Carriageway width (m)	0.78
Inner shoulder width (m)	-0.96

The findings presented in Table 6 show that a 1% increase in traffic volume is linked to a 0.37% increase in crash frequency. Likewise, a 1% rise in segment length leads to a 1.09% rise in crash frequency. A 1% increase in traffic lane width resulted in an increase in crash frequency by 0.78%. A wider lane tends to increase the average and variation in speed, which leads to a higher accident risk. Conversely, if the value of the average horizontal curve is 1% higher, the crash frequency is reduced by 0.20%. Similarly, if the inner shoulder is 1% wider, the total accident frequency decreases by 0.96%.

Table 6 also shows that all variables except the length of the segment are inelastic, as their elasticity is smaller than 1. This means that while these variables had a statistically significant impact on crash frequency, changes in these variables may have a relatively weak effect on crash frequency. In contrast, the segment length variable has a relatively high elasticity (1.09), confirming its significant influence on crash frequency.

Table 7 displays the percentage change in overall crash frequency resulting from adjustments in categorical variables. It can be seen that among the three road divider types, the concrete wall was the most strongly associated with accidents, whereas the guardrail is the safest median type. On the other hand, the period between 0:00 and 8:00 is the most strongly associated with crashes. In contrast, the period between 16:00 and 24:00 has the lowest crash frequency.

Validation was done by comparing the predicted values produced by the model with the actual values. Validation was performed using independent data not utilized to develop the model to evaluate how well the model represented the data. Data from 20 segments of the Jakarta - Cikampek Freeway Toll Road from 2002 to 2004 was used for the validation procedure.

Fig. (1a) presents the relationship between expected values produced by the crash frequency model and observed crash frequency values over three years. As shown in the figure there is a linear trend in the relationship between the observed values and expected values predicted by the model for twenty freeway toll road segments. A perfect match occurs when data points fall in a straight line that forms a 45-degree angle to the horizontal, which indicates 100% equality between the predicted and the observed values. Fig. (1b) presents the relationship between the predicted values versus the error rate. Five of the 20 values estimated by the model are underestimated, with error rates ranging from -27.7% to -3.6%. In contrast, 15 out of 20 predictions (75%) are overestimated, with error rates ranging between 4.8% and 238.3%. A high error rate tends to coincide with low predictive values.

Table 7

Total crash frequency changes caused by categorical variables

Variables	Changes	% change in average accident frequency
Median Types:	From Concrete-wall to Guardrail	-47
	From Concrete-wall to Depressed median	-7
Periods:	From Period-1 to Period-2	-32
	From Period-1 to Period-3	-44

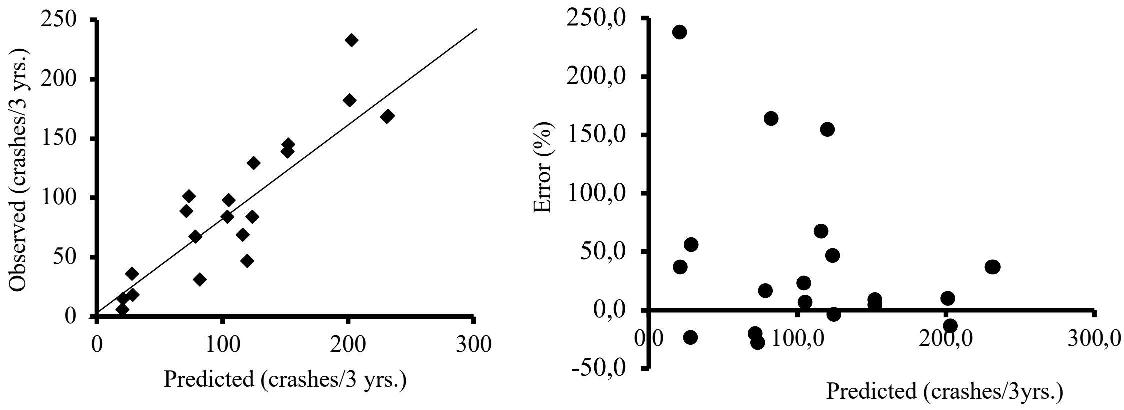

Fig. 1. a) Expected vs. observed crash frequencies and b) expected values vs. error rates

Three total crash frequency estimates with error values above 100% deserve note. Some roads may have much better above-average conditions. There is a possibility that those three road segments belong to this category. Estimated values from crash frequency prediction models can be viewed as the average accident frequency. In the present study, the estimate is based on the hourly traffic volume, segment length, horizontal curve, lane width, inner shoulder width, median type, and daily period. Some segments have geometric characteristics that are better than average and may have a low observed crash frequency while the predicted value is higher than the observed values. The second possibility is just a coincidence, which is part of a random phenomenon. During the study period, these segments experienced very low total crash incidences by chance. In the long term, these segments may have total accident frequencies approaching the average estimated by the model. Table

8 presents the proportions (percentages) of estimates for different levels of error. The validation results showed a reasonable prediction accuracy rate. Half of the estimates had an error rate of less than 25%, and only 15% of estimates had error rates exceeding 100%.

5. CONCLUSIONS

The validation results show that the model developed in the present study can reasonably describe the influence of hourly traffic flow and some geometric elements on traffic crash frequency on basic segments of Indonesian inter-urban freeway toll roads. The study found that a negative binomial distribution is suitable for describing inter-urban freeway traffic crash data. Hourly traffic volume and segment length have direct effects on crash frequency. Geometric characteristic variables and daily period have indirect effects on crash frequencies. This study helps quantify the correlation between accident occurrences using the response and the traffic flow geometric characteristic variables as predictors. For example, according to the resulting model, providing a wider toll-road right-of-way is essential for a safer road divider-type design.

Table 8

Prediction accuracy for various error levels

Error level	Number of estimates (%)
≤ 25%	50
≤ 50%	75
≤ 75%	85
≤ 100%	85
>100%	15

However, this study has limitations. For example, it does not presume to develop a crash occurrence model in an ideal or comprehensive manner. Instead, this research was performed to determine the relative influences of hourly traffic volume and some freeway geometric components on the number of traffic accidents that occur on Indonesian freeways. Thus, there may be several other factors or variables (e.g., speed) that influence crash occurrence. The actual relationship between crash occurrences and speed is complex and depends on numerous factors. Data and methodological limitations did not allow the inclusion of the effect of speed in the present study; the estimated results are isolated only to the effect of hourly traffic volume and some geometric elements.

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