World Applied Sciences Journal 25 (8): 1197-1208, 2013
ISSN 1818-4952

DOI: 10.5829/idosi.wasj.2013.25.08.13392

Modeling of Train Accidents at Unmanned Railway Crossing

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Submitted: Sep 17, 2013; **Accepted:** Oct 23, 2013; **Published:** Oct 30, 2013

Abstract: Rapid growth of transportation activities of people live near by railway areas increase traffic frequency rate. And as a result the number of vehicle collisions occurrence at unmanned railway crossing with no guards and gates has also increased. Some factors influence the number of accidents at unmanned railway crossing. Those factors are train engineering, road engineering and environment. The objective of this study is to modeling those factors. The modeling which represents the correlation of collisions at railway crossings with those factors is analyzed with Poisson regression analysis by using Gen-stat statistic program. Some observations were conducted at 33 unmanned railway crossings at DAOP VIII Surabaya, East Java, Indonesia. The results of the last Poison regression modeling show four significant factors influencing number of collisions at unmanned railway crossings. And those are train speed, flashing light, average of daily traffic (ADT) and distance traffic signs to railway crossings. Train speed seems to become the primary contributing factor to collision rates at unmanned railway crossings. However, it is recommended that besides the regulation of the train speed, other factors such as facilities and provision e.g. the distance of flashing light installation and Early Warning System (EWS) should be provided to with stand and hinder crashes at unmanned railway crossing effectively.

Key words: Railway crossing · Train engineering · Road engineering · Environment · Poisson regression

INTRODUCTION

The railway system in East Java was firstly established in the era of Dutch colonial. And based on the present data, the line is about 910 km consisting of 103 km of North lines, 204 km of central line, 273 km of South Ring lines and 329.72 km of East lines. Indonesian Railway Administration Region VII (DAOP VII), VIII (DAOP VIII) and IX (DAOP IX) operate all those lines. Figure 1 shows the railway line in East Java.

The rapid economic growth of East Java is also followed by a growing number of vehicles that cause traffic growth across the road network in East Java.

The escalation number of traffic also appears in the road system. The local government responds to this enhancement by constructing new road and improves road systems [1]. And this response covers not only the areas that do not intercept with railway lines but also in those which intercept with them. Recently the number manned and unmanned railway crossings in East Java, have increased significantly. As the result of this increasing, the number of accidents occurred at unmanned railway crossings increase as well. It is shown in Figure 3.

There are 1496 railway crossings in East Java and 903 out of them are unmanned. The current data shows that 338 of them are active railway crossings with guards and gates and 196 of them are illegal. The data is presented in the table 1.

In all, about 73,46 % of those railway crossings are highly potential for collisions [3].The opening of lots of illegal railway crossings due to the growth of the hinterland land use both on the left and the right sides in almost every railway secretes high potential occurrence of accidents as well [19]. Out of 903 unmanned railway crossings in East Java about 52, 82 % are located in DAOP VIII Surabaya. And they are highly potential for railway crossing crashes. Table 2 presents the number of potential railway crossings crashes in each operational areas of DAOP VIII Surabaya.

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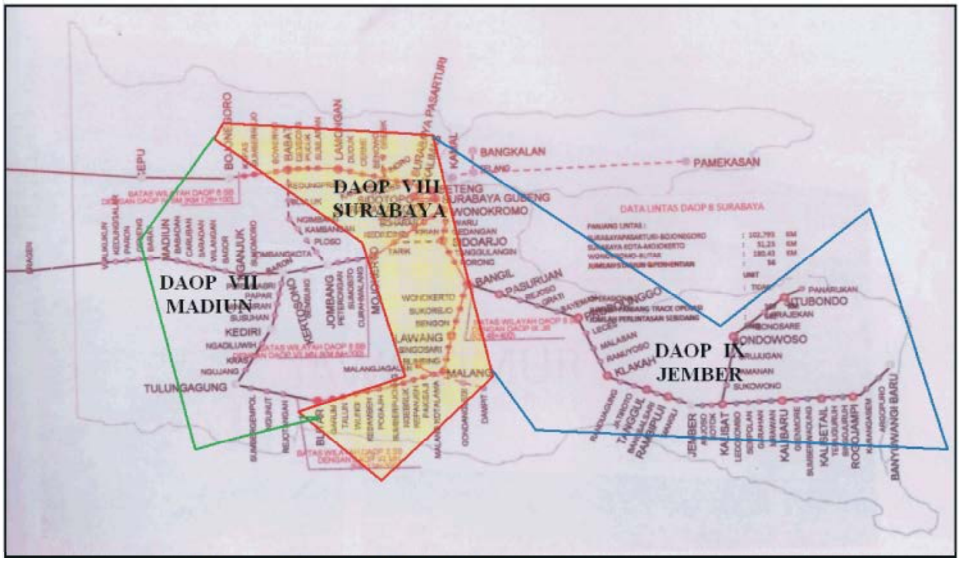

Fig. 1: The railway lines in some operational areas (DAOP) in East Java

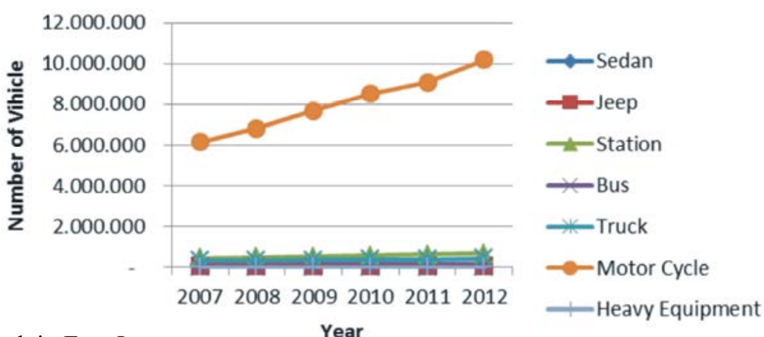

Fig. 2: The traffic growth in East Java

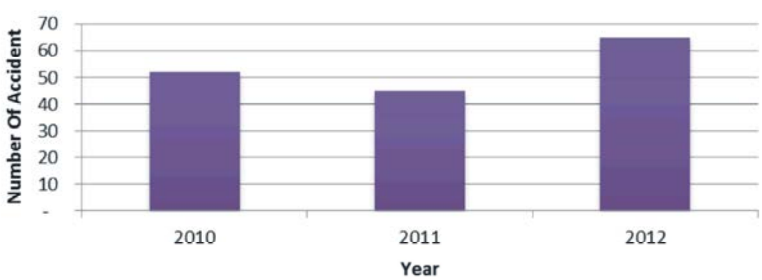

Fig. 3: The increasing number of accidents data

Table 1: Railway crossings that area potential to accidents in East Java

No.	Operational Areas (DAOP)	Railway Crossing(number-s) Official	Unmanned railway Crossing	Illegal	Explanation
1	DAOP VII Madiun	62	172	-	
2	DAOP VIII Surabaya	179	477	126	
3	DAOP IX Jember	97	254	70	
	Total Number=1496	338	903	196	

Resource: Data Base of PT. Kereta Api Indonesia 2010 [2].

Table 2: Railway Crossings that are potential to crashes at DAOP VIII Surabaya

		Unmanned railway Crossing (number-s)				
No.	District	Official	Initiative guarded railway crossing	Unmanned railway crossing	Illegal	Explanation
1	Bojonegoro	52	6	46		
2	Lamongan	74	3	71		
3	Gresik	63	2	61		
4	Surabaya	84	49	35		
5	Sidoarjo	109	51	58		
6	Mojokerto	20	5	15		
7	Pasuruan	56	12	44		
8	Malang	75	28	47		
9	Blitar	125	25	100		
	Total	658	181	477	126	

Source: Data Base of PT. Kereta Api Indonesia 2010 [2].

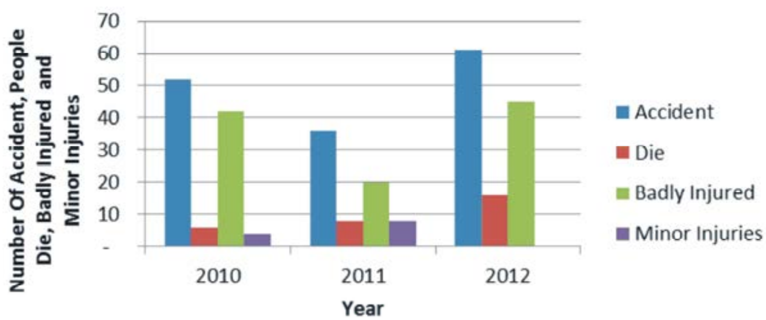

Fig. 4: Dataof the accidents at unmanned railway crossings

Since 2010 - 2012 there was about 149 crashes with 30 life less victims, 107 were badly injured and 12 were with minor injuries. The recapitulation of the accidents and the condition of the victims are shown in figure 4:

With reference to this data, which shows a tremendous number of railway crossings accidents, the research of this study was conducted at DAOP VIII Surabaya. Reviewing the number of railway crossing accident, which has increased steadily, there is an urgent need to have some actions to reduce it. One important step that needs to be conducted to study it is by having a predicted accident modeling that occurs in the railway crossing, particularly in those unmanned railway crossings that are potential to vehicle collisions.

Some previous studies have shown that variables studied by some former researchers are very prominent in influencing the prediction of the number of crashes at railway crossings. And some of correlated variables can be simulated and combined into a modeling of railway crossing accident. The prediction of accident numbers at railway crossings are influnced by some factors. And they are connected with some variables, which are related with psychological sensory behavior and the perception of passing railway crossing drivers [5]; category of the warning system, volume of the traffic, volume of the train

Fig. 5: An accident at an unmanned railway crossing

Fig. 6: One of those unmanned railway crossings, which is very potential for accident occurrences

traffic, visibility at the railway crossings [6]; Types of warning equipments, railway crossing geometry, volume of the traffic [7]; Number of passing trains at railway crossings, active traffic control equipment, warning sign of flickering light [8]; Width of railway crossing geometry, traffic control equipment, time of flickering light, speed at mounding ground, railway crossing size, traffic warning signs, volume of traffic road, speed limit [9]; Number of passing trains, tract numbers, diameter of road seperator, audit of safety, AADT, warning equipment, control management, barrier control, status or road class, types of area around road crossings (business, residential, agricultural areas etc.) [10]; Identification of number of trains, service levels, types of vehicles involved in accidents, number of damage of the vehicles, number of people injured or die in the accidents [11]; Feature of road crossing engineering, human factors, environment factors [12]; variables of road seperators, variables of drivers' behavior and response towards traffic equipment at the road crossings [13]; volume of traffic and passing trains per hour, speed of vehicles approaching road crossing areas, percentage of heavy vehicles, service leves (LOS), speed of the train approaching the road crossing areas [14];Train feature, road feature, road crossing feature and feature of traffic control [15].

There has not been many studies conducted to create a modeling of prediction of train collision at unmanned railway crossing by accommodating, collecting and developing all the explanatory variables, which have been studied by previous researchers. using different analysis in which the modeling is built to predict at any unmanned railway crossings with single track, that is commonly used in developing countries. It is commonly known that most of these countries have very limited and low budget to improve the safety at railway crossings. And this is equal with the minimum awareness of the people to ward the safety of train expedition. Consequently, this condition and the minimum awareness open some opportunities for these people to open illegal railway crossings. And this situation takes place in East Java as well. Therefore the rate of collision at unmanned railway crossings is getting higher. In spite of this, a lot of studies of accidents occurred at active double track or more modern railway crossings both automatic and manual have been performed. In these studies, only explanatory variables are studied spatially with different data analysis from one researcher to another one. It is recommended that the type of study of modeling crashes at unmanned railway crossings is conducted considering the results of the study are crucially needed and are useful for the recommendation of how to reduce the number of collision at unmanned railway crossings effectively. The objectives of study are to construct a model prediction of train accident at unmanned railway crossing and to validate the model with actual data.

MATERIALS AND METHODS

The study was conducted in 33 unmanned railway crossings in the operational area of PT. Kereta Api Indonesia (Persero) specially at DAOP VIII Surabaya. The operational area (DAOP) VIII Surabaya, East Java had a lot of train accidents since 2010 until 2012 and those accidents involved both two-wheeled and four wheeled vehicles. In details those were 11 (33.35%) railway crossings in Lamongan district, 6 (18.2%) railway crossings in Sidoarjo district, 5 (15.20%) railway crossings in Bojonegoro district, 1 (3.00%) in Gresik district, 3 railway crossings (9.10%) in Pasuruan, 1 (3.00%) railway crossings in Malang district, 3 (9.10%) railway crossings in Blitar district and the last were 3 (9.10%) railway crossings in Surabaya district. Data was taken from 8 district with 33 unmanned railway crossing spots at DAOP VIII Surabaya, where collision had occurred for the last 3 (three) years, since 2010 until 2013 and involved two (R2) and four (R4) wheeled vehicles as shown in Table 3.

There are two variables as explanatory and response variables. The explanatory variables included in this research are as follow:

- Train engineering factors contains of the following variables: width of railway crossing (X1), number of track (X2), train speed (X3), volume of passing trains (X4), traffic signs at railway crossing (X5), angle between railway to road (X6), Traffic signs distance to railway crossing (X7), sight distance (X8), the guardrail at railway crossing (X9), availability flashing light (X10) and siren (X11).

Table 3: the frequency of accident at some unmanned railway crossings

District	Accident Frequency	Percentage (%)
Kabupaten Bojonegoro	5	15.2
Kabupaten Lamongan	11	33.3
Kabupaten Gresik	1	3.0
Kota Surabaya	3	9.1
Kabupaten Sidoarjo	6	18.2
Kabupaten Pasuruan	3	9.1
Kabupaten Malang	1	3.0
Kabupaten Blitar	3	9.1
Total	33	100.0

Table 4: Continous variables data

Variable	unit	Mean	Std. Deviation
Width of railway crossing (X1)	m	3.22	0.89
Train speed (X3)	km/hour	71.82	11.97
Volume of passing trains (X4)	train/day	31.88	4.82
Traffic signs distance to railway crossing (X7)	m	11.27	8.43
Sight distance (X8)	m	736.36	230.58
Width of road (X12)	m	3.28	0.91
ADT (X14)	pcu/day	244.50	208.30
Number of accidents / 3 years (Y)	accident	1.45	0.87

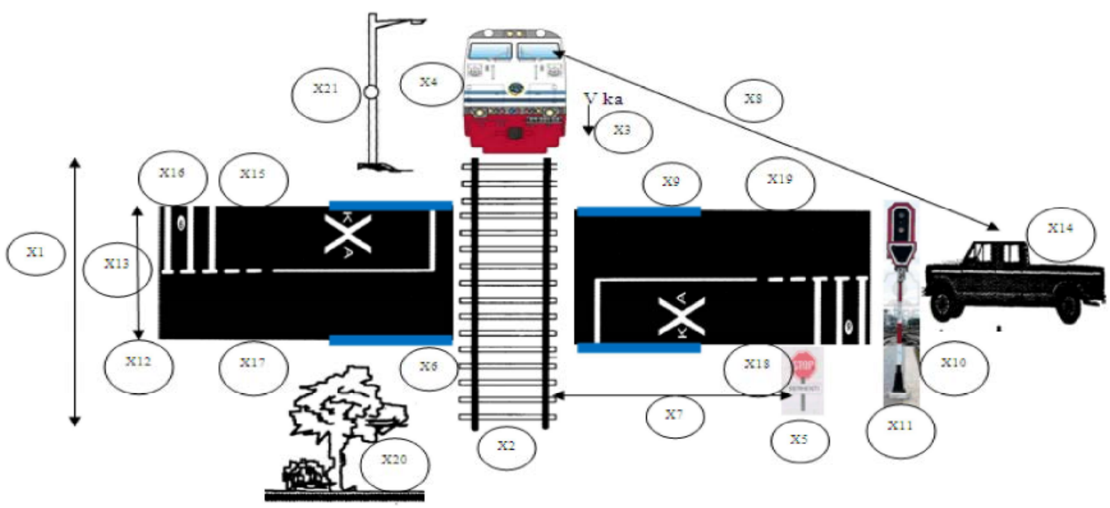

Fig. 7: Data collection for each variable at unmanned railway crossings

- Road engineering factors consists of the following variables: width of road (X12), number of lanes (X13), Average Daily Traffic / ADT (X14), road class (X15), road performance surface (X16), road construction type (X17), road traffic mark and signs (X18), sidewalk (X19).
- Environment condition consists of the following variables: agricultural, business, residential, industrious areas (X20) and road lighting (X21) [16].

These are used to determine the prediction number of collisions at unmanned railway crossings (Y).

There are two characteristics of the variable data on the site, the first variable data that is continuous as shown in table 4 and the second that is category as shown in figure 8.

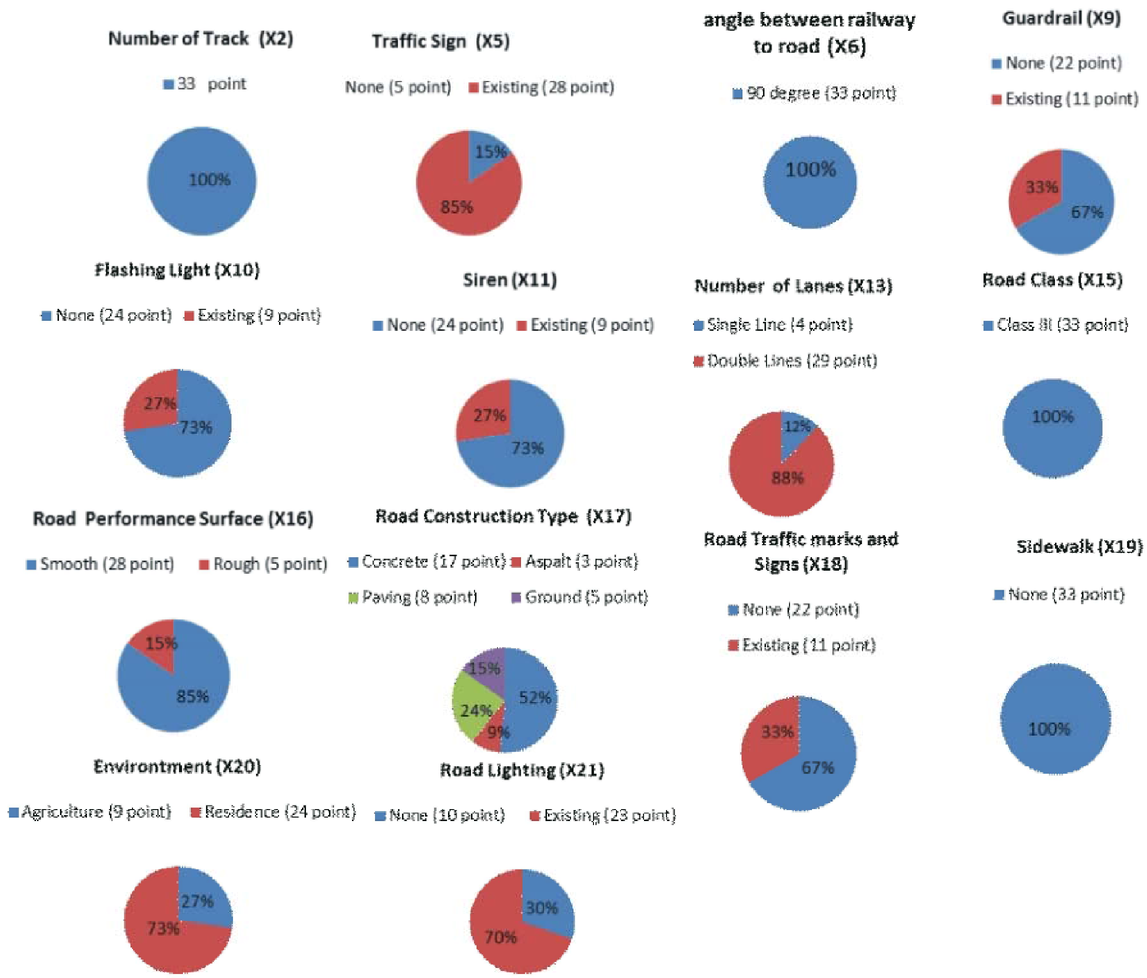

Fig. 8: Category variables data

RESULT AND DISCUSSION

Data Analysis: Description of variables with category characteristic is presented based on the results of frequency distribution. Variables with homogenous characteristic are not included in the next analysis. These variables are number of track (X2), angle between railway to road (X6), road class (X15) and sidewalk (X19).

In some characteristic, some variables have perfect level of correlation (1 value) and or close to perfect. In this case only one variable is used. Flashing light (X10) correlates perfectly with siren (X11), therefore flashing light is picked. Mean while, width of railway crossing (X1) highly correlates with width of road (X12), thus width of road (X12) is used in the modeling. So that the explanatory variables used in the modeling process is:

1. Train Speed (X3)
2. Volume of passing trains (X4)
3. Traffic signs at railway crossing (X5)
4. Traffic signs distance to railway crossing (X7)
5. Sight distance (X8)
6. Guardrail (X9)
7. Flashing light (X10)
8. Width of road(X12)
9. Number of lanes (X13)
10. ADT (X14)
11. Road performance surface (X16)
12. Road construction type (X17)
13. Road traffic mark and signs (X18)
14. Environment (X20)
15. Road lighting (X21)

Data distribution, which follows Poisson dissemination, has specific characteristics such as descriptive observation, limited to time limit and or certain area. Occasion of the observation is very little and this means that vehicles passing the road crossing have little chance to experience accidents.

Table 5: Data Distribution Test towards Poisson distribution

Statistic		Y Number of accidents / 3 years
N		33
Poisson Parameter[a,b]	Mean	1.450
Most Extreme Differences	Absolute	0.234
	Positive	0.154
	Negative	-0.234
Kolmogorov-Smirnov Z		1.341
Asymp. Sig. (2-tailed)		0.055

Table 6: Result Poisson Regression Analysis

Variable	Test results	Variable	Test results
Train speed (X3)	Significant	Width Of Road (X12)	Not Significant
Volume of passing trains (X4)	Not Significant	Number of lanes (X13)	Not Significant
Traffic signs (X5)	Not Significant	Average Daily Traffic /ADT (X14)	Significant
Traffic signs distance to railway crossing (X7)	Significant	Road Performance Surface (X16)	Not Significant
Sight distance (X8)	Not Significant	Road Construction Type (X17)	Not Significant
Guardrail (X9)	Not Significant	Road marks and traffic signs (X18)	Not Significant
Flashing Light (X10)	Significant	Environment (X20)	Not Significant

In this study, the observation of the number of collisions is counted based on the accidents happened for the last 3 (three) years. Therefore it based on the characteristic and data distribution modeling calibration with Kolmogorov-Smirnov test [17].

The mean number of accident is 1.45, which means that for the last three years around 1-2 accidents occurred at one spot area. Kolmogorov Smirnov test shows 1.341 value of *Kolmogorov-Smirnov Z* with *asymp. Sig.(2-tailed)* or *p-value* as much as 0.055 brings a conclusion that number of crashes data meets Poisson distribution. Further the modeling which represents the correlation of collisions at railway crossings with 15 explanatory variables is analyzed with Poisson regression analysis by using Gen-stat statistic program.

Development of Accident Modeling: The modeling, which represents the correlation of collisions at railway crossings, is analyzed with Poisson regression analysis. The Analysis is divided into three stages. The first stage is where modeling is performed for the explanatory variables, the second one is the stage when combined modeling is performed towards variables that significantly influence the first modeling and the last stage is selection of determining variables, which completely and entirely are significant in the second stage.

From the modeling processing there are 4 significant influencing variables towards the number of crashes at unmanned railway crossings *p-value* < 0.05 which are: Train speed (X3), Traffic signs distance to railway crossing (X7), Flashing light (X10) and Average Daily Traffic / ADT (X14), in which the final model gained is Poisson Regression modeling with following equivalency:

$$\text{Log } Y = -0.591 + 0.01302\, X3 - 0.01253\, X7 - 0.2575\, X10 + 0.001122\, X14$$

or

$$Y = \exp(-0.591 + 0.01302\, X3 - 0.01253\, X7 - 0.2575\, X10 + 0.001122\, X14)$$

Where:

Y = Number of collision at unmanned railway crossings (incidents);
X3 = Passing train speed (km/hour);
X7 = Traffic signs distance to railway crossing (m);
X10 = Flashing light(available/unavailable)
X14 = Average Daily Traffic/ADT (pcu/day);

Modeling Validation: Modeling validation measures the level of compatibility of modeling with the actual observation outcome. Final modeling observation obtained is considerate through the result of deviation analysis between estimation value and actual value, calculating correlation value and conducting different tangible value between prediction result and actual value (observation).

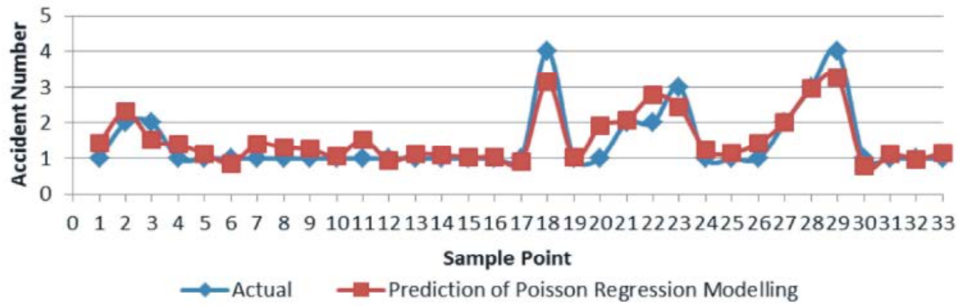

Fig. 9: The Prediction Value of Number of Accident base on Poisson Regression Modeling

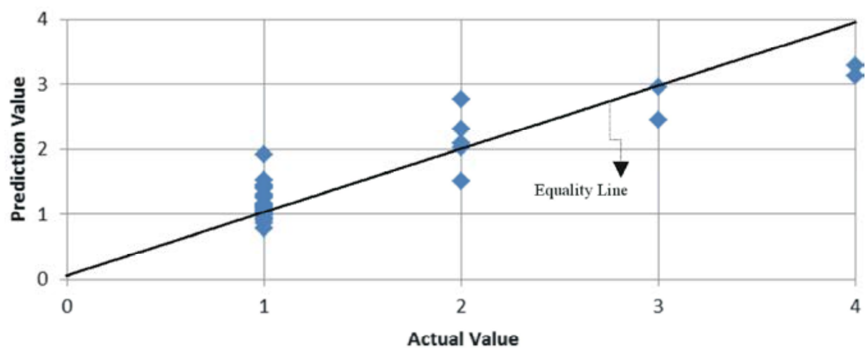

Fig. 10: Prediction Value and Actual Value Correlation of Number of Accidents

Table 7: The Analysis of Differences Test of Average Prediction and Actual Value

No	Actual	Prediction	Deviation	No	Actual	Prediction	Deviation
1	1	1.45	-0.45	18	4	3.13	0.87
2	2	2.31	-0.31	19	1	1.04	-0.04
3	2	1.51	0.49	20	1	1.92	-0.92
4	1	1.39	-0.39	21	2	2.08	-0.08
5	1	1.14	-0.14	22	2	2.77	-0.77
6	1	0.86	0.14	23	3	2.45	0.55
7	1	1.41	-0.41	24	1	1.25	-0.25
8	1	1.30	-0.30	25	1	1.16	-0.16
9	1	1.27	-0.27	26	1	1.44	-0.44
10	1	1.06	-0.06	27	2	2.03	-0.03
11	1	1.53	-0.53	28	3	2.96	0.04
12	1	0.94	0.06	29	4	3.29	0.71
13	1	1.12	-0.12	30	1	0.78	0.22
14	1	1.10	-0.10	31	1	1.11	-0.11
15	1	1.03	-0.03	32	1	0.99	0.01
16	1	1.02	-0.02	33	1	1.15	-0.15
17	1	0.90	0.10	Average	1.455	1.485	-0.0303

Counted T = -0.44; p-value = 0.662

Figure 9 describes that the estimation of number of accidents approaches actual value. When the value of prediction of accident number is rounded, then 27 spots (81.8%) present equal value between prediction value and actual value and there are differences among 6 other spots. Those different points sample no 11, 18, 20, 22, 23 and 29, for more detail can be seen in table 7.

The correlation between estimation value and actual value is 0.892 and is sufficient. This high correlation value explains that Poisson regression modeling is adequate to predict that railway crossings with highly potential accident characteristics are predicted with high value of collision rates, conversely those spots with low potential or with no accident potential characteristic, they are predicted with low value.

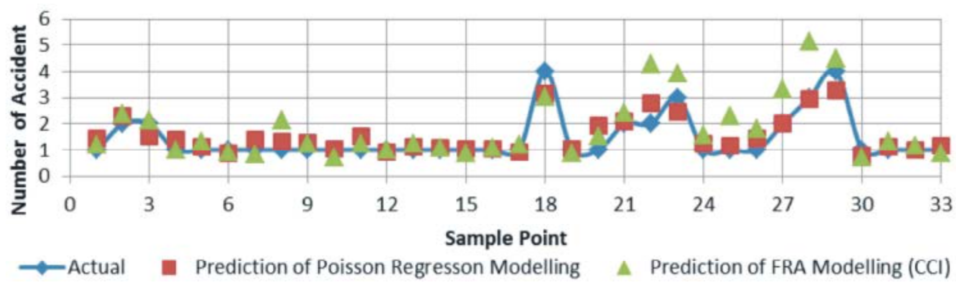

Fig. 11: The Comparison of Prediction Value of Poisson Regression Modeling and CCI Value

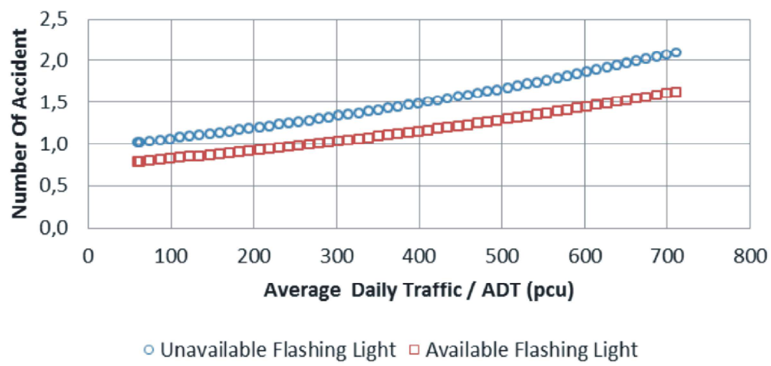

Fig. 12: Prediction of Collision Number at Various Average Daily Traffic (ADT) Value

Modeling observation is also conducted by counting the outcome of actual differences test of number of accidents between prediction value and actual value. Testing is performed with two paired sample t test (*paired t test*). The result of the analysis, shows that in average the deviation of prediction value and actual value obtained is -0.0303 with p-*value* as mush of 0.662 (bigger than 0.05). And this result concludes that there are not actual differences between prediction value and actual value.

The observation of Poisson regression shows that this modeling area is able to be used to predict the number of crash, due to the average deviation test result performed to group of Poisson modeling which is not significantly different from the actual data.

Modeling observation is also performed to prediction value which is resulted by Poisson regression and done by comparing the result of CCI value calculation CCI (Combined Casualty Index) following FRA (*Federal Railroad Administration*).

The outcome of the observation of collision rates modeling based on CCI showed it is not much superior compared with the modeling of accidents at unmanned railway crossings set up for this study. The deviation value the actual number of crashes using CCI calculation is bigger that the prediction of the result of Poisson regression, as shown in this following figure 11.

Sensitivity Analysis: The final Poisson regression modeling has four determining variables that are significantly influence number of crashes. They are Train speed (X3), Traffic signs distance to railway crossing (X7), Flashing light (X10) and Average Daily Traffic/ADT (X14). Flashing light variable is the highest regression coefficient. Based on the modeling, number of collision reduction can be obtained by implementing these:

- Reducing the train speed when approaching railway crossing
- Further distant traffic sign installation before railway crossing
- Flashing light maintenance for its good function
- Railway crossing guard stationing at unmanned railway crossing especially at the busy hours in the morning and evening.

At this phase, the level of sensitivity of some variables is evaluated with assumption that other variables do not change. And this analysis is shown through graphic by setting the data into two conditions of available and unavailable flashing lights. The train speed is 65-90 km/hour, traffic sign distance to the railway crossing is 4-30 meters, where are ADT value is 33.8-919.6 pcu. Collision rates should be low when flashing light is

Table 8: Comparisons of Actual and Predicted Values from the Poisson Model

Spot	Actual	Prediction	Information	Spot	Actual	Prediction	Information
1	1	1.45	False Positive	18	4	3.13	Correct Positive
2	2	2.31	False Positive	19	1	1.04	False Positive
3	2	1.51	Correct Positive	20	1	1.92	False Positive
4	1	1.39	False Positive	21	2	2.08	False Positive
5	1	1.14	False Positive	22	2	2.77	False Positive
6	1	0.86	Correct Positive	23	3	2.45	Correct Positive
7	1	1.41	False Positive	24	1	1.25	False Positive
8	1	1.30	False Positive	25	1	1.16	False Positive
9	1	1.27	False Positive	26	1	1.44	False Positive
10	1	1.06	False Positive	27	2	2.03	False Positive
11	1	1.53	False Positive	28	3	2.96	Correct Positive
12	1	0.94	Correct Positive	29	4	3.29	Correct Positive
13	1	1.12	False Positive	30	1	0.78	Correct Positive
14	1	1.10	False Positive	31	1	1.11	False Positive
15	1	1.03	False Positive	32	1	0.99	Correct Positive
16	1	1.02	False Positive	33	1	1.15	False Positive
17	1	0.90	Correct Positive				

available at railway crossing, passing trains are in low speed, traffic sign distance to railway crossing is far enough and the daily traffic is low too.

The calculation of collision rate is conducted by adding 70 km/hour value into train speed variable with 30 meters traffic sign distance. As the result, the prediction of railway crossing accidents with various ADT shows that extensive traffic density increases number of collisions. And well functioned and good condition flashing light is very helpful to push them down. The sensitivity of ADT value correlation with number of railway crashes is obtained that the calculation of up to 100% ADT rising generates 8% of number of crashes, while up to 200% ADT rising increases 17% of the number.

The results of modeling using the Poisson regression will be used to predict the point at which a railway crossing should be paid attention. A "black spot" status for a railway crossing with high level of accidents will be able to help reduce accidents. The results of prediction of the number of accidents in each spot may be used to attribute certain characteristics to the spot. Another indicator to choose the best criteria is comparing the number of expected accidents and that of observed accidents [18]. The results of the comparison may be in the form of :

- Location which is predicted to be dangerous is actually harmful (*correct positive)*.
- Location which is predicted not to be dangerous is actually not harmful (*correct negative)*.
- Location which is predicted to be dangerous is actually not harmful (*false positive)*.
- Location which is predicted not to be dangerous is actually harmful (*false negative)*.

In this case, if the observed number of accidents is higher than the expected one, it can be categorized into *correct positive (CP)*. If the observed number of accidents is lower than the expected one, it is categorized as *false positive (FP)*.

In Table 8, it is shown that there are 10 spots which are really dangerous namely spot 3 (Bojonegoro district;140+135, SRJ-BWO), spot 6 (Lamongan district; 162+681, BBT-GEB), spot 12 (Lamongan district; 179+735, SLR-LMG), spot 17 (Gresik district; 199+790, LMG-DD), spot 18 (Surabaya district;222+603, KDA-TES), spot 23 (Sidoarjo district; 26+121, SPJ-BH), spot 28 (Pasuruan district; 43+629,PR-BG), spot 29 (Pasuruan district, 44+610, PR-BG), spot 30 (Malang district; 29+128, SN-LW) and spot 32 (Blitar district; 76+158, NB-SBP).

CONCLUSION

The conclusions of the study described above the modeling processing there are 4 significant influencing variables towards the number of crashes at unmanned railway crossings *p-value* < 0,05 which are : Train speed (X3), Traffic signs distance to railway crossing (X7), Flashing light (X10) and Average Daily Traffic / ADT (X14), in which the final modeling gained is Poisson modeling with following equivalency:

Log Y = -0.591+0.01302 X3-0.01253 X7-0.2575 X10+0.001122 X14

Or

Y = exp (-0.591+0.01302 X3-0.01253 X7-0.2575 X10+0.001122 X14)

Where:

Y = Number of collision at unmanned railway crossings (incidents);

X3 = Passing train speed (km/hour);

X7 = Traffic signs distance to railway crossing (m);

X10 = Flashing light (available/unavailable)

X14 = Average of Daily Traffic / ADT (pcu/day);

The estimate modeling result based on Combined Casualty Index (CCI) calculation by Federal Railroad Administration (FRA) presents that accuracy level is weaker compared to the estimate Poisson regression modeling set in this study. The deviation value of actual crashes from CCI is bigger than the result of estimate Poisson regression outcome in this study.

Recommendation: Some recommendation given based on the modeling output of the study is:

It is proven and presented from the study that flashing light installation at unmanned railway crossings contributes in the alleviation number at unmanned railway crossing crashes. It is recommended that flashing light should be installed with 100 and or 50 meters distance before railway crossings;

Train speed rising is proven to generates collision number at unmanned railway crossings. There are some recommendation of this condition:

- Installing 35 traffic signs in every unmanned railway crossing and setting up an obligation for train operators to serene their train once but longer to attract attention;
- Installing speed limit sign in order to lower train speed to the appropriate speed limit whenever trains pass unmanned railway crossings;
- Improvement of free sight distance by following and based it on the implemented regulation.

Aviation of traffic signs distance (closer to railway crossing) is proven to causing the rate of collision at unmanned railway crossings. Therefore, it is recommended that:

- Complete the railway crossing warning signs installation regulation at unmanned railway crossings should follow prevailed regulation and guidance in which the installation should not be too closed with railway crossings;
- Setting up cross wise traffic marks as waiting signs while waiting for passing trains to pass and based it on the present regulation;
- Installing speed trap with appropriate distance and measurement based on the present regulation.

ADT value rising is proven to be able to level up number of accidents at railway crossings. Thus it is recommended that:

- Officers should be placed and duties at peak hours in the morning and evening and they can leave the railway crossings when the traffic is not busy;
- Conducting analysis and evaluation towards passive railway crossings with priority to those which have high and low multiplication of ADT and train travelling frequency outcome, with automatic or non automatic gates, in order to improve the condition. And close those which are open and have no gates.

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