Factors influencing red light runners among motorcyclists in Malaysia

T. H. Law, Lin Xu and R.S. Radin Umar

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T.H. LAW
Lecturer
Road Safety Research Center
Faculty of Engineering
Universiti Putra Malaysia
43400 Serdang
Selangor Malaysia
Fax : 6-03-86567129 Fax : 6-03-86567129
Email : lawteik@eng.upm.edu.my

LIN Xu
Research Associate
Road Safety Research Center
Faculty of Engineering
Universiti Putra Malaysia
43400 Serdang
Selangor Malaysia
Fax : 6-03-86567129
Email : linxu1978@hotmail.com

R.S. RADIN UMAR
Professor
Road Safety Research Center
Faculty of Engineering
Universiti Putra Malaysia
43400 Serdang
Selangor Malaysia Selangor Malaysia
Fax : 6-03-86567129 Fax : 6-03-86567129
Email : radinumx@eng.upm.edu.my

Abstract: The objectives of this study were to identify the engineering design factors and to develop a preliminary model for red light runners among motorcyclists in Malaysia. The Random-Effect Negative Binomial (RENB) regression model has been used to determine the factors. The data collection was obtained from one-hour site observation at thirty different sites in Kajang and Serdang town, state of Selangor. In the RENB model, six independent variables were found to be significantly influencing the behaviors of the motorcyclists at signalized intersections. These variables were (i) motorcycle volume, (ii) change interval, (iii) amber time, (iv) cycle length, (v) number of signal phase and (vi) number of approach legs of intersection. Results of RENB model showed that most of the red light running violations occurred at the signalized intersections with high motorcycle volume, shorter change interval time, shorter amber time, longer cycle length, more signal phases and more approach legs.

Keywords: red light runners among motorcyclists, Random-Effect Negative Binomial model, signalized intersections

1. INTRODUCTION

About 6% of motorcycle accidents occurred at signalized intersections in Malaysia. While the reasons for this problem are varied and complex, an obvious one is that motorcyclists disregard the traffic signal control device and violate red lights. Among other factors contributing to this is the physical set up of the traffic signal systems. As such, an effective model for predicting red light runners among motorcyclists of signalized intersections is needed.

Traffic engineers rely heavily on traffic signals to control and separate conflicting traffic movements at busy intersections. Safe signal operation requires a high degree of voluntary driver compliance, and many drivers do not comply with red lights (Porter and England, 2000). Although traffic lights are installed to regulate and minimize the conflicts among vehicles, the risk of collision is still exist among the intersecting vehicles, affecting as well other road users, including pedestrians and bicyclists. When a motorcyclist approaches an intersection, whether the rider stops before the stop-line or not depends on the motorcycle approach speed and distance from the intersection. Other factors of engineering design parameters for signalized intersections such as motorcycle volume, change interval, amber time, cycle length, total phases, number of approach legs, channelization, are also deemed to affect runners behaviours.

In order to reduce the number of red light runners among motorcyclists at signalised intersections, it is necessary to understand how the engineering design factors influence them. The objective of this study was to identify the engineering design factors influencing red light runners among motorcyclists in Malaysia.

1.1 Selection of Sites

Potential intersections were identified and selected according to the following criteria:

1. Visible pavement marking;
2. Properly functioning traffic signal;
3. T or cross-intersection;
4. Adequate sight distance;
5. Pre-timed signal operation; and
6. Standard geometry layout (ie. Its approach roads intersect at an approximately 90-degree angle with relatively flat approach grades)

Based on the above criteria, 30 intersections were selected in two towns, Kajang and Serdang, which represent the typical towns in Malaysia in terms of ethnic composition of population, living standards and economic development.

1.2 Data Collection

Two observers were involved in recording the data needed for this analysis. Before conducting the observation at each site, the signal timing was measured in advance by using stopwatch. Data of red-light violators on motorcycles were obtained from one-hour observations at 30 sites during a continuous 3-hour period between 3:00 pm and 6:00 pm. Within these hours most weekly crashes occurred. At each site one observer counted the total number of motorcycles that entered the intersection after the onset of the red light during the observation period, and the other one counted the total motorcycle volume passing the intersection. The following information was recorded for this study:

1. Motorcycle volume;
2. Red light running among motorcyclists;
3. Change interval;
4. Amber time;
5. Cycle length;
6. Number of signal phases;
7. Total number of approach legs; and
8. Channelization

2. MODELLING DESCRIPTION

The Random-Effect Negative Binomial model (RENB) is applied to deal with violators data which are discrete, nonnegative, random, sporadic by introducing a random location- and time-specific effect term into the relationship between the expected dependent variable ($\bar{\mu}_{il}$) and the covariates, X_{il}, of an observation unit i in a given time period t, i.e.

$$\bar{\mu}_{i1} = \mu_{i1}\delta_i \tag{1}$$

Where δ_i is a random location-specific effect, to ensure a positive value, the term $\bar{\mu}_{il}$ can be written as:

$$\bar{\mu}_{i1} = \mu_{i1}\delta_i = \exp(X_{il}\beta + \mu_i) \tag{2}$$

Where β is the coefficient vector to be estimated, μ_i is the random effect across location and exp (μ_i) is gamma distributed with mean 1 and variance k, where k is also the overdispersion parameter in random-effect negative binomial model. The numbers of violators at a signalized intersection (i) for a given hour t, i.e. n_{il} is an independently and identically negative binomial model distributed with parameters $\mu_{il}\delta_i$ and Φ_I, where μ_{il} = exp ($X_{il}\beta$). The probability density function of the random-effect negative binomial model for the ith intersection is defined as

$$P(n_{i1,\dots}, n_{iT} \mid X_{i1,\dots\dots} X_{iT}) = \frac{\sqrt{a+b}\sqrt{a+\sum_T \mu_{il}}\sqrt{b+\sum_T n_{il}}}{\sqrt{a}\sqrt{b}\sqrt{a+b+\sum_T \mu_{il}+\sum_T n_{il}}} \prod_T \frac{\sqrt{\mu_{il}+n_{il}}}{\sqrt{\mu_{il}}\sqrt{n_{il}+1}} \tag{3}$$

Estimation of parameters a,b and the coefficient vector β was accomplished in GLIM using any standard ML algorithms (Cameron and Trivedi, 1998). In the random-effect negative binomial model, the random effect has been added to the negative binomial model by assuming that overdispersion parameter is randomly distributed. This formulation is better suited to account for the unobserved heterogeneity across location and time.

In order to identify significant independent variable which should be included in a violator analysis model, AIC (Akaike's Information Criterion) was used. AIC identifies the best approximating model among a class of competing models with different numbers of parameters. AIC is defined as follows:

$$AIC = d + 2q \tag{4}$$

Where d is the goodness-of-fit statistic following a chi-square distribution, and q represents the number of unknown parameters solved for in the model being fitted. The smaller the value of AIC, the better the model.

To measure the overall goodness-of-fit, the deviance value 2(LL(β)-LL(0)), which follows chi-square distribution has been used (Agresti, 2002). The test of deviance value indicates the adequacy of model in explaining red light runners among motorcyclists.

2.1 Multivariate Analysis of Red Light Runners among Motorcyclists

Exposure terms such as amber time and change interval were categorized and defined before the analyses of data were conducted. This was to prevent the problem of interpreting the effect of amber time, which was included by the length of change interval. In Malaysia, the amber duration is usually standardized to 3 seconds (Public work Technical Instruction 11/87). Therefore, amber time with the duration less than or equal to 2 seconds is categorized as "0", between 2 to 3 as "1" and more than 3 seconds as "2". All-red intervals should be at least 1 second and should not excess 3 seconds. Longer all reds can be used at the engineer's discretion where extreme conditions warrant. Therefore, 6-second change interval is deemed a reasonable design and categorized as "0" and 7-second as "1".

The data were categorized using no more than three categories. This is consistent with the approach used by Rothman (1986); he suggested that confounding can be controlled using a maximum of five categories and most of the confounding can be removed by a stratified analysis based on only two categories. Any potential confounding variables were treated in the same way as the exposures under study as a potential confounder may also have some relevance as an exposure in its own right.

Several factors were included in the model of red light runners among motorcyclists. Initially, amber time and change interval (as categorical variables) were included in the model for analysis. These variables had been identified in the literature review as the risk factors with the most evidence of strong relationships with risk (Richard et al., 1998; Retting et al., 1999). Later, other variables were added in the model to identify the effects of postulated risk factors.

Instead of using a procedure of stepwise regression to define the multivariate model, the enter approach has been used to build the single comprehensive multivariate model that included all potentially important factors.

3. ESTIMATION RESULTS

The random-effect negative binomial (RENB) result for red light running frequency among motorcyclists is presented in Table 1.

Table l: RENB model of red light running frequency of motorcyclists

Independent variables	Coefficient	Standard Error	t-value	P-value
Constant	3.2133	0.8344	3.851	0.001
Total motorcycle volume	0.1914	0.0374	5.117	0.000
Change interval	-2.5132	0.3023	-8.313	0.000
Amber time	-0.9923	0.3323	-2.986	0.006
Cycle length	0.0713	0.0313	2.278	0.008
Total approach legs of intersection	3.7132	0.3123	11.889	0.000
Signal phasing	0.613	0.2230	2.748	0.006
Overdispersion parameter	3.13			
Number of intersections	30			
$2(LL(\beta)-LL(0))$	10713.3211			
AIC value	2.326			

This table shows that all variables have the expected sign which, if positive values means increasing red light runners among motorcyclists, while negative means decreasing. The chi-square test of the deviance value (10713.321, and df = 5) rejects the null hypothesis that the obtained model contains the constant term only. Therefore, the model shows an overall good statistical fit.

For the specific variables entered in the model, six exposure variables are found to be significant at 95% significance level. The first one is total motorcycle volume entering the signalized intersection (0.01914). The result shows that red light runners of motorcyclists will increase with motorcycle volume.

Among the signal design parameters, several factors were found to contribute to red light running frequency at intersections significantly. The estimated coefficient show that longer change intervals (-2.5132) have the potential effect of reducing the number of red light running frequency. As for amber time (-0.9923), there is indication of discouraging red light running of motorcyclists while increasing it. Long cycle time (0.0713) increases the frequency of red light violating, at the same time, the researcher notice that long cycle time deals with heavy traffic volume.

Among geometric layout elements, the number of approach legs of a signalized intersection was found to contribute to running frequency at intersections significantly. The coefficient (0.613) indicates that it has an influence on encouraging red light runners among motorcyclists. The term of channelization was excluded from this model because it was found not significant at a 95% significance level.

4. DISCUSSION AND CONCLUSION

Results of this study support findings of previous research that increasing change interval and amber time will decrease the frequency of red light running of motorcycles (Retting at., 1997). The reduction of motorcycle red light running by using longer amber time and using longer change interval must be considered as highly successful countermeasures. One of the reasons for the marked reduction is that they reduce the occurrences of late exits. Riders do not appear to become habituated to longer amber time or increased change interval and may not even be aware of these changes (Retting et al., 1997). Further research would be useful to determine if this effect hold up during peak periods and at night, when riders may have a better view of the cross-street signal. In addition to reducing potential runners, longer change interval might reduce motor vehicle crash rates. Stein (1986) reported that inadequate change interval timing relative to the ITE proposed recommended practice was associated with higher crash rates. Retting et al. (1995) reported evidence that late exits tended to occur shortly after red-light onset, suggesting that increasing the all-red period might reduce right-angle crashes. Although the influence of longer amber time and change interval on red-light violation may partially erode over time, the finding of this research suggests that loner amber time and change interval can reduce red light running of motorcycles.

Longer cycle time, four-phase signal timing and more approach legs of a signalized intersection were proved increasing motorcycle red light running. Four-approach legs and signal timing with four phases provide more stops to traffic movement at intersections. These lead to frustrations among them. Riders lose patience due to longer delay and then beat the red light. The result that four-phase signal timing increases red light running is consistent with Hoong's study (2001) that having a higher number of phases per cycle may increase the number of accident at signalized intersections.

The greater the motorcycle volume, the more red light runners are among motorcyclists. This result is also consistent with previous study on accident rate at signalized intersection (Hoong, 2001). Exposure to red light running of motorcycles is likely to depend on motorcycle volume. The motorcycle volume correlates total traffic volume, which determines the length of cycle time at a signalized intersection. As a guideline, the optimum cycle length may be decided according to the relationship between motorcycle red light running and motorcycle volume.

The models developed can be used to evaluate the effectiveness of specific countermeasures, such as providing a longer change interval time and amber time, shorter cycle length, less number of signal phase, or all of them, for different traffic volumes at signalized intersections. The model can therefore be used to evaluate the feasibility of implementing these countermeasures to discourage red light runners among motorcyclists.

This study has its limitations. For instance, the frequency analysis of red light runners among motorcyclists did not account for numerous intersection influencing factors such as weather, human, sight distant, motorcycle type, approach speed, the gradients of approaching legs, which all have effect on speed and sight distant, and presence or absence of right-turn and left-turn lanes, type of left-turn control (protected, permissive, and protected and permissive). Also, long-term effects on red light running are not known and may differ from those noted during the observation period.

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REFERENCES

Agristi, A. (2002) **Categorical Data Analysis**, John Wiley and Sons, 2nd edition, New York.

Cameron, A.C. and Trivedi, P.K. (1998) **Regression Analysis of Count Data**. Cambridge University Press, New York.

Porter, B.E. and England, K.J. (2000) Predicting Red-Light Running Behavior: A Traffic Safety Study in Three Urban Settings, **Journal of Safety Research, Vol. 31, No. 1,** 1-8.

Public Work Department of Malaysia (1987) **Public Work Technical Instruction 11/87.** Public Work Department, Malaysia.

Richard A. Retting, Allan F. Williams, and Michael A. Greene (1998) Red-light Running and Sensible Countermeasures, **Transportation research record, Issue. 1640**, 23-26.

Retting, R.A., Williams, A.F., Preusser, D.F., and Weinstein,H.B. (1995) Classifying Urban Crash For Countermeasure Development, **Accident Analysis and Prevention, Vol. 2, No. 27,** 283-294.

Retting R. A. and M.A. Greene. (1997) Influence of Signal Timing on Red-light running and Potential Vehicle Conflicts at Urban Intersection, **Transportation Research Record, Issue. 1595**, 1-7.

Retting, R.A., Williams, A.F. Farmer, C.M. and Feldman, A. (1999) Evaluation of Red Light Camera Enforcement in Fairfax Va., USA. **ITE Journal**, 30-34.

Rothman, K.J. (1986) **Modern epidemiology.** Little Brown and Company, Boston/Toronto.

Stein. H. S. (1986) Traffic Signal Change Intervals: Policies, Practice, and Safety, **Transportation Quarterly, Vol. 40, No.3**, 433-455