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STATISTICAL ANALYSIS OF RED-LIGHT VIOLATIONS ACROSS DIFFERENT TRAFFIC SIGNAL SYSTEMS AND OPERATING CONDITIONS

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Abstract

Red-light violations (RLVs) at signalised intersections continue to pose major safety challenges, especially where traffic flow characteristics vary across urban and suburban environments. This study examines how different traffic signal systems, traffic conditions, area types, and yellow-light durations influence RLV patterns at 13 intersections in Johor, Malaysia. Using video-based data collection and multiple statistical methods—including chi-square tests, binomial proportion analysis, and quasi-binomial logistic regression—the study identifies key factors influencing driver behaviour during the yellow–red transition. Results show that vehicle-actuated systems yield the lowest RLV rates, while suburban areas and peak-hour traffic exhibit higher violation tendencies. Longer yellow intervals significantly reduce the probability of RLVs. The findings contribute to improved understanding of driver decision-making and highlight the importance of adaptive signal control and context-sensitive timing strategies.

Keywords: Red-light running, Red-light violations, chi-square test, binomial proportion test, quasi-binomial logistic regression

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INTRODUCTION

Traffic signal control systems are fundamental to ensuring safe and efficient movement at intersections with high traffic demand. However, the transition to a yellow phase creates a well-documented dilemma zone, where drivers must make rapid decisions to stop or proceed. Studies such as Papaioannou et al. (2021), Juan Li et al. (2016), and Ritvik Chauhan et al. (2022) have shown that the uncertainty introduced at this phase contributes significantly to RLV incidents.

Red-light violation is defined as a vehicle entering an intersection after the onset of the red signal (Retting et al., 1999; Institute of Transportation Engineers, 2003). In Malaysia, a considerable portion of road accidents occur at intersections—about 20% in 2020 (Royal Malaysian Police, 2020), with human factors contributing to approximately 94% of crashes (Mohd Faizul, 2008).

While many international studies have explored driver behaviour, automated enforcement, and advanced signal technologies, such as AI-enabled adaptive control systems, research synthesising these insights within the Malaysian context remains limited. This study addresses these gaps by evaluating multiple intersection types and examining how signal technology, traffic demand, environment, and timing parameters collectively shape RLV patterns.

BACKGROUND

Traffic signal control systems in Malaysia follow warrants and criteria adapted from the Manual on Uniform Traffic Control Devices (Jabatan Kerja Raya, 2017). While such systems aim to improve safety and efficiency, intersections remain a critical point of conflict. International research has consistently shown that a substantial proportion of intersection crashes arises from red-light violations (RLVs), often linked to driver expectancy, risk perception, and the speed–distance dilemma created during the yellow phase (Retting et al., 1999; Institute of Transportation Engineers, 2003).

Early studies on RLVs primarily examined engineering and operational factors—such as cycle length, intersection geometry, and dilemma-zone characteristics (Porter et al., 2000; Milazzo et al., 2002; Martin et al., 2003; Law et al., 2005). However, more recent research has shifted toward a multidisciplinary perspective. Behavioural psychology studies have shown that impatience, sensation-seeking tendencies, perceived enforcement levels, and social norms heavily influence the decision to “beat the red” (AAA Foundation, 2023; Wang et al., 2023). Tien Dung Chu (2022) suggested that males, young motorists, less educated road users, and motorcyclists are more likely to run red lights. They also found out that the surrounding conditions, such as the behaviour of other violators, the absence of traffic police, and long waiting times, increase the possibility of violations. These findings suggest that RLV behaviour cannot

be explained solely by traffic conditions or signal timing, but is closely tied to cognitive and motivational processes.

Parallel advances in intelligent transportation systems have further expanded the RLV research landscape. Machine-learning and deep-learning approaches have been applied to model driver decision-making with higher predictive accuracy, incorporating real-time trajectory data and vehicle–infrastructure communication (Li et al., 2023; Komol et al., 2024). Studies evaluating automated enforcement technologies—including CCTV and red-light cameras—have demonstrated significant reductions in violation rates, particularly in developing-country contexts similar to Malaysia (Cohn et al., 2000; Satiennam et al., 2023). These international advancements underscore the importance of integrating behavioural and technological insights when analysing RLV trends.

Malaysian studies, although valuable, remain limited in breadth. Many focus on single intersections, narrow temporal windows, or specific user groups such as motorcyclists. For example, Kidwai et al. (2005) reported that countdown timers reduced violations, whereas Ibrahim et al. (2008) later found higher RLV rates at countdown-equipped sites—highlighting behavioural adaptation and context dependency. Other local studies (e.g., Hawa Mohamed et al., 2012) emphasised motorcyclist prevalence and the influence of short cycle lengths but did not examine wider environmental or behavioural factors. Importantly, few Malaysian studies have compared multiple types of signal systems—such as countdown timers, flashing-green systems, and vehicle-actuated control—across both urban and suburban settings. H. Mohamed Jamil et al. (2022) reported that the implementation of the Automated Awareness Safety System (also known as “AwAS”) was undoubtedly timely and was found to be beneficial in terms of reducing the RLV in Malaysia.

Recent research reinforces the multidimensional nature of red-light running, with predictive driver-warning technologies showing promise (He et al., 2024), engineering measures remaining vital for compliance (Hossain et al., 2025), and behavioural studies emphasising risk perception, psychology, and demographics (Kumphong et al., 2024; Radzi et al., 2024). Malaysian work adds evidence on delivery-rider violations (Malik et al., 2023) and intersection operational analysis (Rahmat et al., 2023), underscoring the need for stronger intersection safety strategies. Nevertheless, RLV requires a broader, multi-site evaluation that integrates operational, environmental, and behavioural dimensions. This study addresses that gap by analysing 13 intersections with differing signal technologies, area types, and traffic conditions, offering new insights into how system design, driver behaviour, and context collectively shape red-light violation patterns in Malaysia.

RESEARCH METHODOLOGY

Measurement of Red-Light Violation

A driver is considered to violate a red light if he or she enters the intersection after the red signal appears. Only drivers who arrived at the onset of the yellow signal were analysed, based on the assumption that this group faces the highest likelihood of entering the dilemma zone.

Studied Sites and Sample Size

Thirteen intersections located in Johor Bahru, Kulai, and Simpang Renggam were selected based on the following criteria: (i) representation of multiple signal technologies (fixed-time, countdown-equipped, flashing green, vehicle-actuated), (ii) variation in urban and suburban traffic environments, (iii) physical isolation from adjacent intersections to avoid upstream/downstream signal influence, (iv) suitability for clear video recording, and (v) documented safety relevance and observed prevalence of RLV cases. These sites represent typical Malaysian conditions, though the study does not claim full national representativeness.

The sample size, i.e., the minimum number of drivers approaching the intersection at the onset of the yellow period observed for the analysis, was based on Eqn. (1) (Thomas R. C., 2001; Panagiotis P., 2007).

$$N = \frac{pqK^2}{E^2} \quad (1)$$

where N is the sample size, p is the proportion of vehicles facing a yellow signal that passed, q is the proportion of vehicles facing a yellow signal that stopped, K is the standard deviation corresponding to the desired confidence level, and E is the permitted error in the proportion estimate.

In this study, $p = q = 0.5$, $K = 1.96$ and $E = 0.05$. A value of 0.05 for E strikes a common balance between precision and sample size feasibility. Smaller error margins (e.g., 0.01) would require significantly larger sample sizes, increasing cost and time. In many survey-based or observational studies, a 5% margin of error is acceptable for estimating population proportions with reasonable confidence (Taherdoost H., 2022; Singh A.S. et al., 2022). Therefore, the minimum sample size at each intersection required for this study was 385 drivers. Only drivers who arrived at an intersection at the onset of the yellow period were considered valid samples.

Data Collection and Analysis

Data were collected using video cameras placed at appropriate vantage points. Peak and off-peak periods were explicitly defined as follows: (i) Peak hours:

7:00–9:00 AM and 4:30–6:30 PM, (ii) Off-peak hours: 10:00 AM–12:00 PM and 2:00–4:00 PM. The list of the intersections studied is given in Table 1.

Since the data is in terms of the number or frequency of RLVs out of the total motorists approaching the intersection during the yellow period, a χ^2 test (Aslam M. et al., 2023) for multiple systems was used to compare the variations of red-light violations at all intersections at a significant level of 0.05. The null hypothesis for this χ^2 test is that the frequency of RLVs is independent of the type of traffic signal system or operating conditions.

A binomial proportion test (Marciniak D., 2024) was also applied to compare the proportion of violations between two types of traffic signal systems and between two different operating conditions. The null hypothesis for this test is that the proportions of RLV are equal for both systems or operating conditions. The test is based on a z-test for two proportions.

Based on the characteristics of the intersections shown in Table 1, the data, i.e., proportions of violations and no violations, are pooled for the three factors listed in Table 2.

In the χ^2 test, the observed frequencies of violation and observed frequencies of no violation based on the pooled data for each of the three factors and attributes considered are tabulated in a contingency table, i.e., also known as the Observed Contingency Table (Aslam M. et al., 2023; Marciniak D., 2024; NIST/SEMATECH, 2013).

Table 1: Characteristics of the sites studied

Site Ref. No.	Intersection Name	Traffic Signal System	Posted Speed Limit (km/h)	Cycle Time /yellow (sec)	Type of Area
<i>A</i>	Permatang/Setia Tropika	Fixed-time	70	120/3.0	Suburban
<i>B</i>	Jalan Parit Ismail/Jalan Besar (Simpang Renggam)	Fixed-time	90	120/4.9	Suburban
<i>C</i>	Jalan Persisiran Perling 1	Fixed-time	60	120/3.0	Urban
<i>D</i>	Jalan Pontian–Muar/Pontian Kecil	Fixed-time	60	120/3.1	Suburban
<i>E</i>	Jalan Seri Melaka	Fixed-time (DC)	90	120/2.0	Suburban
<i>F</i>	Jalan Teberau/Jalan Keris	Fixed-time (DC)	70	142/4.0	Urban
<i>G</i>	Jalan Johor Jaya/Jalan Anggerik	Fixed-time (DC)	60	120/2.5	Urban
<i>H</i>	Saleng/Jalan Kulai	Fixed-time (FG)	70	160/3.0	Suburban
<i>J</i>	Jalan Tun Aminah/Jalan Perwira 16	Vehicle-actuated	60	Varies/2.9	Urban

Site Ref. No.	Intersection Name	Traffic Signal System	Posted Speed Limit (km/h)	Cycle Time /yellow (sec)	Type of Area
<i>K</i>	Jalan Pontian/Jalan Tembaga	Vehicle-actuated	70	Varies/3.0	Suburban
<i>L</i>	Jalan Tun Razak (Susur 5)/Jalan Sentosa	Vehicle-actuated	60	Varies/3.1	Urban
<i>M</i>	Jalan Simpang Pasak	Vehicle-actuated	90	Varies/2.6	Suburban
<i>N</i>	Jalan Johor/Jalan Jemaluang	Vehicle-actuated	90	Varies/2.6	Suburban

Note: Fixed-time (DC) – Fixed-time with a digital countdown feature.
 Fixed-time (FG) – Fixed-time with a flashing green feature.

Table 2: Factors and attributes considered in the analysis

No.	Factors	Attributes
1	Different traffic signal systems	fixed-time, fixed-time with a digital countdown, and vehicle-actuated
2	Characteristics of the area where the intersection is	urban and suburban areas
3	Conditions of traffic flow	peak hour and off-peak hour

A quasi-binomial logistic regression model (Hilbe, 2016; Shoukri, M.M., and Aleid, M.M., 2022) was developed to examine the relationship between yellow-light duration, traffic signal system type, and the likelihood of red-light violations. This statistical approach was chosen to address overdispersion in the response variable, which occurs when the variance of the observed proportions exceeds the nominal variance assumed by the binomial distribution. Overdispersion is common in traffic safety studies due to driver behavioural variability and unobserved heterogeneity, as suggested by many researchers (Lord and Mannering, 2010; Washington et al., 2020).

The response variable was the proportion of red-light violations, modelled using a two-column matrix of counts: the number of red-light violations, and the number of non-violations (i.e., vehicles that did not run the red light).

This structure enables the use of a binomial-type generalised linear model (GLM), where the probability of a red-light violation is modelled as a function of explanatory variables. The predictor variables included:

- (i) Yellow-light duration (a continuous variable, in seconds), and
- (ii) Traffic signal system type (a categorical variable), with three levels, i.e., Fixed-time (used as the reference category), Fixed-time with Advanced Warning Feature (AWF), and Vehicle-actuated (VA).

Dummy (indicator) variables were created for the AWF and VA signal types to allow categorical comparison against the fixed-time baseline.

The model was structured using a logit link function, which expresses the relationship between the predictors and the log-odds of a red-light violation. The general form of the model is as given in Eqn. (2).

$$\text{Log}\left(\frac{p}{1-p}\right) = \eta = \beta_0 + \beta_1 \cdot \text{YellowDuration} + \beta_2 \cdot \text{AWF} + \beta_3 \cdot \text{VA} \quad (2)$$

where p is the probability of a red-light violation, β_0 is the intercept, β_1 is the coefficient for yellow-light duration, β_2 and β_3 are coefficients for the AWF and VA signal system types, respectively.

To compute the probability of a red-light violation from this model, the equation is transformed as Eqn. (3).

$$p = \frac{e^\eta}{1+e^\eta} \quad (3)$$

where $\eta = \beta_0 + \beta_1 \cdot \text{YellowDuration} + \beta_2 \cdot \text{AWF} + \beta_3 \cdot \text{VA}$. All variables are as described before. Eqn. (3) allows for the estimation of the probability p once the model coefficients have been obtained.

The model was estimated using a standard quasi-binomial logistic regression procedure to account for overdispersion in the response variable (Hilbe, 2016). This approach maintains the logistic regression structure while providing robust standard errors for hypothesis testing and inference. The quasi-binomial method estimates a dispersion parameter that scales the variance, thereby adjusting the confidence intervals and significance tests without changing the estimated coefficients.

RESULTS AND DISCUSSION

Effects of Types of Traffic Signal Systems

Based on the pooled data of 18,158 drivers approaching the stop line at the yellow onset at all intersections during the off-peak hour periods, 25.67% of them violated the red-light signals. The analysis revealed that vehicle-actuated systems had the lowest RLV rate (16.14%), followed by fixed-time systems with an advanced warning feature (24.87%), and traditional fixed-time systems (39.02%). The percentages of red-light violations at each intersection ranged from 2.36% to 52.94%. Table 3 presents these aggregated RLV rates, while Figure 1 graphically illustrates these differences.

Table 3: Aggregated percentage of RLV based on types of traffic signal systems

Types of Systems	No. of Intersections	Sample Size	No. of RLVs/(%)
Fixed-time	4	4,897	1,911 (39.02)
Fixed-time with an advanced warning feature (AWF)	4	6,979	1,736 (24.87)
Vehicle-actuated (VA)	5	6,282	1,014 (16.14)

(Note: Figures in parentheses are in per cent.)

The χ^2 and binomial proportion tests confirmed statistically significant differences in violation rates across traffic signal systems, where the p-value, which is a probability that measures how likely it is to observe the given result when the null hypothesis is true, is equal to 1.58×10^{-165} . Such a result implies that the RLV rates differ significantly across three types of traffic signal systems at a 5% level of significance.

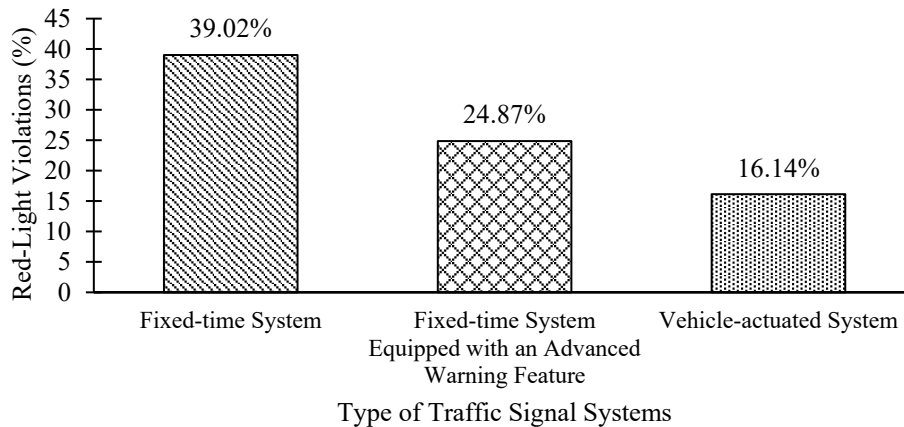


Figure 1: Effect of the type of traffic signal system on red-light violations

The superior performance of the vehicle-actuated signal system in reducing red-light violations can be attributed to its dynamic responsiveness to actual traffic conditions. Unlike fixed-time systems that follow predetermined cycles, vehicle-actuated signals detect approaching vehicles and adjust signal timing accordingly, reducing unnecessary waiting and minimising abrupt signal changes that can frustrate drivers. Although fixed-time signals equipped with countdown timers provide a warning, they lack the adaptability to traffic flow variations, limiting their effectiveness in reducing violations. By tailoring signal phases to real-time demand, vehicle-actuated systems create smoother traffic

progression and reduce driver uncertainty, thereby encouraging better compliance with traffic signals and lowering the incidence of red-light running.

Influence of Area Type

Table 4 shows that suburban intersections recorded a significantly higher RLV rate (29.05%) than urban intersections (22.03%). Both the chi-square test ($\chi^2 = 117.0$, $p < 0.0001$) and the binomial proportion test ($z = \pm 10.81$, $p < 0.0001$) confirm that this difference is statistically significant.

Although lower traffic density may partially explain this pattern, behavioural factors offer clearer insight. International studies show that drivers tend to take greater risks in low-density or low-enforcement environments—a form of risk compensation (Wilde, 1994; Elvik, 2019; Zhao et al., 2019). Suburban roads typically have wider carriageways, fewer intersections, and lower visual complexity, reducing perceived crash risk and encouraging higher speeds. These conditions make drivers less inclined to decelerate at the onset of yellow.

Perceived enforcement also plays an important role. Research indicates that drivers are more likely to run red lights where enforcement presence is low or inconsistent (Johnson & Gardner, 2020; AAA Foundation, 2023). Many suburban intersections lack automated enforcement or regular patrols, reinforcing the belief that violations carry minimal consequences.

Thus, the statistical differences observed in Table 4 align with broader evidence that reduced traffic complexity, higher operating speeds, and lower perceived enforcement collectively increase the likelihood of RLVs in suburban settings

Table 4: χ^2 statistics for the comparison of red-light violations and no violations across different types of areas

Types of Area	Total Samples	Status	Observed	Expected	χ^2	p-value
Urban	8,750	Violation	1,928 (22.03%)	2,246.05	45.0	
		No Violation	6,822	6,503.95	15.6	
Suburban	9,408	Violation	2,733 (29.05%)	2,414.95	42.0	
		No Violation	6,675	6,993.05	14.5	
Pooled	18,158		18,158		117.0	< 0.0001

Note: $\chi^2_{(\text{critical})} = 3.84$ at a 5% significance level and degree of freedom = 1

Effect of Peak-Hour and Off-Peak-Hour Conditions

As summarised in Table 5, the peak-hour conditions showed significantly higher RLV rates (36.58%) than off-peak periods (29.45%). The statistical difference is confirmed by the χ^2 and binomial proportion tests, where both tests yield a p-value of less than 0.0001. This was especially pronounced at urban intersections, likely due to: (i) platoon effects, (ii) impatience during congested periods, and (iii) shorter perceived opportunity to cross. This supports the implementation of enforcement measures such as red-light cameras during peak hours in urban settings.

Effect of Duration of Yellow Period

A quasi-binomial logistic regression model was developed to estimate the probability of red-light violations as a function of yellow-light duration and type of traffic signal system. This approach was adopted to account for overdispersion observed in the binary outcome data. The model was specified with Fixed-time signals as the reference category, allowing comparisons of the other two signal types—Fixed-time with Advanced Warning Feature (AWF) and Vehicle Actuated (VA)—against this baseline. The estimated model coefficients are tabulated in Table 6.

Table 5: Pooled data of violations during off-peak and peak-hour traffic conditions in urban and suburban areas

Types of Area	No. of Intersections	Off-Peak Hour Data		Peak-Hour Data	
		Total Samples	Violations	Total Observations	Violations
Urban	4	7,266	1,893 (26.05%)	4,504	1,539 (34.17%)
Suburban	4	2,419	959 (39.64%)	2,180	906 (41.56%)
Pooled	8	9,685	2,852 (29.45%)	6,684	2,445 (36.58%)

Table 6: Estimated model coefficients

Variable	Coefficient (β)	Std. Error	z-value	p-value
Intercept (β_0)	2.749	0.030	91.12	<0.001
Yellow Duration (β_1)	-1.007	0.009	-106.70	<0.001
AWF (β_2)	-1.136	0.011	-102.63	<0.001
Vehicle Actuated (β_3)	-1.454	0.011	-131.99	<0.001

All predictor variables were found to be statistically significant (p-value < 0.001), indicating that both the duration of the yellow-light interval and the type of signal control system significantly affect the likelihood of red-light violations. The estimated logistic regression model for observed data is expressed as in Eqn. (4).

$$\text{Log}\left(\frac{p}{1-p}\right) = \eta = 2.749 - 1.007 \cdot \text{YellowDuration} - 1.136 \cdot \text{AWF} - 1.454 \cdot \text{VA} \quad (4)$$

where p is the probability of an RLV, AWF, and VA are binary indicator variables (1 if present, 0 otherwise), and the Fixed-time is the reference category.

The performance measures used to evaluate the adequacy of the quasi-binomial logistic regression model are summarised as follows:

- Dispersion parameter of 2.14 indicated overdispersion in the data, validating the use of a quasi-binomial model (Hilbe, 2016).
- McFadden's Pseudo R^2 of 0.437 indicates that the model explains approximately 43.7% of the variability in violation rates. The model is considered strong, particularly for behavioural or observational studies, such as traffic behaviour (McFadden, 1974; Long, 1997).
- Quasi-Akaike Information Criterion (QAIC) was used to assess model strength and compare alternative model structures (Pan, 2001; Burnham and Anderson, 2002). Although the QAIC was 310.5, no alternative models were evaluated, as the selected structure was theoretically grounded and designed to balance interpretability and statistical robustness. The focus was on explaining key predictors—yellow-light duration and signal type—based on prior studies. QAIC served primarily as a diagnostic metric rather than for model selection.

The model, i.e., Eqn. (4) can be used to estimate the probability of red-light violations, p , under different signal settings and yellow-light durations by substituting Eqn. (4) into Eqn. (3) to yield the following Eqn. (5). Using Eqn. (5), the predicted probability of RLVs based on yellow-light duration and signal type is exhibited in Figure 2.

$$p = \frac{e^{(2.749 - 1.007 \cdot \text{YellowDuration} - 1.136 \cdot \text{AWF} - 1.454 \cdot \text{VA})}}{1 + e^{(2.749 - 1.007 \cdot \text{YellowDuration} - 1.136 \cdot \text{AWF} - 1.454 \cdot \text{VA})}} \quad (5)$$

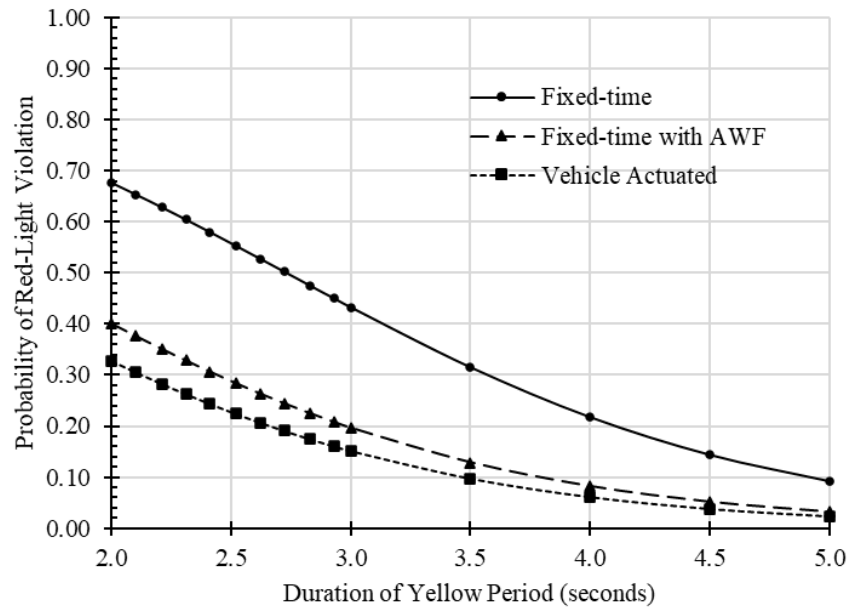


Figure 2: The predicted probability of red-light violations based on yellow-light duration and signal type

The interpretation of the model developed can be summarised as follows:

- (a) Yellow-Light Duration: A coefficient of 1.007 confirms that longer yellow intervals significantly reduce red-light violations, aligning with studies by Law et al. (2005) and Bonneson et al. (2002). However, yellow times should be capped based on approach speed and intersection size—typically 3 to 6 seconds (Transportation Research Board, 2022).
- (b) Signal Type:
 - AWF systems lower violations by improving driver anticipation.
 - Vehicle-actuated signals (VA) further reduce violations due to their adaptive nature.

Figure 2 illustrates sharper declines in violations with longer yellow durations, especially under AWF and VA systems. Predicted relationships show diminishing marginal effects beyond typical yellow durations (3–6 seconds), consistent with Transportation Research Board (2022) recommendations. The findings validate the effectiveness of combining advanced signal technologies with well-calibrated yellow intervals to improve compliance and safety.

CONCLUSION

This study offers comprehensive insight into the behavioural and operational factors influencing red-light violations in Malaysia. Key findings indicate that vehicle-actuated signals significantly reduce RLVs relative to fixed-time systems; suburban intersections experience higher violation rates due to lower traffic density and behavioural–environmental influences; peak-hour conditions intensify RLVs, particularly in urban areas; and longer yellow intervals reduce violations, though with diminishing marginal effect.

These results highlight the need for intelligent traffic systems, improved enforcement, and targeted educational measures tailored to local contexts. Priority should be given to upgrading high-risk intersections to vehicle-actuated control, with countdown timers or flashing-green displays as interim options where upgrades are not immediately feasible. Peak-hour enforcement—particularly through automated means—is vital in urban settings, while behavioural campaigns may be more effective in suburban areas. The study further underscores the importance of context-sensitive yellow timing based on approach speed and geometry.

Future research should explore machine-learning models for predicting RLV behaviour, incorporate demographic variables, conduct multi-state comparisons, differentiate vehicle types (especially motorcycles), and evaluate optimal deployment strategies for automated enforcement.

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