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Original Research Paper

Evaluation of red-light camera enforcement using traffic violations

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HIGHLIGHTS

- This study compares the red-light running violations on approaches with and without red-light cameras at the same intersections.
- The presence of the red-light cameras significantly lowered the red-light running violations.
- High-volume approaches without cameras had an approximately eight times higher rate of violations than high-volume approaches with cameras.
- The number of violations on low-volume approaches was five times higher than those on high-volume approaches.

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ABSTRACT

The State of Qatar started to use red-light cameras in 2007 at key signalized intersections and the rate of installation has subsequently increased. In 2017, 19.2% of signalized intersections are equipped with red-light cameras. In many cases, the cameras are not installed on all approaches to the intersections. The purpose of this study is to compare the red-light running violations on approaches with and without red-light running enforcement cameras at the same intersections. Actual field observations were used in this study. Different variables were investigated, including the day of the week, time of day, traffic volume, the possibility of glare on an approach, and the lengths of the yellow and all-red times. A regression tree model was used to explain the characteristics associated with the violations. The results showed that the number of violations on low-volume approaches was five times higher than on high-volume approaches. The results also showed that the presence of the cameras significantly lowered red-light running violations. High-volume approaches without cameras had an approximately eight times higher rate of violations than high-volume approaches with cameras. The analysis also showed that bringing the all-red interval closer to the values recommended by the Institute of Transportation Engineers formula may bring down the rates of violations for low-volume approaches. As with any observational data mining method, the study could benefit from a larger sample size. The method used in the study was effective and is easily transferable to other locations. The results of this study can be used in developing new strategies to improve safety at signalized intersections.

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1. Introduction

Red-light running (RLR) has been identified as a serious traffic safety concern that can lead to numerous and severe crashes. For example, according to the Insurance Institute for Highway Safety, RLR was responsible for 697 fatalities and 127,000 injuries in 2013 in the United States alone (McCarthy, 2015). Different engineering and enforcement countermeasures exist for this behavior. Red-light cameras (RLCs) are one type of enforcement countermeasure used at signalized intersections for detecting vehicles passing the approach during the red phase. This method of automatic enforcement addresses the issue of the high cost of manual enforcement. It also has the potential to change drivers' behavior through both general deterrence and punishment of individual violators.

In 2007, 80 cameras were installed at key intersections in Qatar for the first time (ITS International, 2012). The penalty for running a red light is one of the highest in the region. The fine starts from $1644 (US) and can reach $13,699 plus a significant impact on the driving history depending on the speed at the time of the violation and if the driver caused a crash as a result of running the red light. The number of cameras in Qatar is growing every year, especially after the decision to convert the major roundabouts into signalized intersections equipped with RLCs on some approaches. While this policy decision to convert to signalized intersections can be debated since something closer to the opposite is happening in much of the developed world, it is nevertheless the reality in Qatar. Although cameras have been widely implemented in Qatar and are perceived to be successful among the motorists in Qatar, information about their effectiveness is not conclusive (Shaaban, 2017). No studies have been conducted in Qatar to measure the effectiveness of camera enforcement.

The effectiveness of RLCs in reducing the number of red-light violations has been evaluated in many studies. A before and after study was used to evaluate the influence of a red-light camera enforcement program on red-light violation rates in the city of Oxnard, California, USA. A total of 14 intersections (nine camera sites, three non-camera sites, and two control sites) were studied. Baseline red-light violation data were collected before the warning period and again three to four months after the actual enforcement began. The violations for each site were recorded for a single intersection approach. At the camera sites, baseline data were recorded with the same red-light cameras that would later be mounted on poles and used for enforcement. Overall, the red-light violation rate was reduced by 42% several months after the enforcement program began (Retting et al., 1999). A follow-up study from the same authors on this issue also noted a reduction in injuries following the installation of camera enforcement (Retting and Kyrychenko, 2002).

Another study to assess the RLCs was conducted in Fairfax County, Virginia, USA. The RLC enforcement program involved ten cameras installed around the county. The data analysis identified improvements in violation rates of 36% over the first three months of automated enforcement and a 69% reduction after six months of camera operation. The crash rates data also showed a reduction of 40% in crashes (Retting et al., 2008).

Huang et al. (2006) investigated the effect of RLCs on crash risks at signalized intersections for both right-angle and rear-end crashes in Singapore. A binary logit model was preliminarily developed to examine how the stopping versus crossing decision of drivers at the onset of amber is affected by geometric, traffic, and situational variables. The results showed that the presence of RLCs is one of the five significant factors affecting a driver's decision to cross during the yellow phase. A multinomial logit model further indicated that RLCs are effective in reducing the RLR frequency. Further analysis of the fitted model revealed that while the presence of RLCs is effective in reducing the risk of right-angle crashes, it has a mixed effect on the risk of rear-end crashes. Whether the RLC reduces or increases the possibility of rear-end crashes is dependent on the speed of the trailing vehicle and the headway between vehicles.

In 2009, a study in Iowa compared the red-light violations at camera-enforced approaches against a set of control approaches at intersections where no cameras had been installed. The number of RLR violations for 21 intersection approaches for both study and control intersections was compared. The violation data were collected from the four camera-enforced intersections, and seven other non-camera enforced intersections, which were used as control sites. A cross-sectional analysis was used to compare the RLR violations at treatment locations to violations at control locations. A Poisson lognormal regression was used to evaluate the effectiveness of the cameras in reducing violations. The results indicated that RLCs substantially reduced the number of violations at camera-enforced approaches as compared to control approaches. In comparison to the camera-enforced approaches, the statistical model showed that RLR violations were 25 times higher at locations without RLCs than for locations with cameras (Fitzsimmons et al., 2009).

In 2011, another study in Iowa was conducted to assess the safety effectiveness of the RLCs installed at seven intersections. The intersections were chosen based on crash rates and whether cameras could feasibly be placed at the intersection approaches. The violations were collected before drivers were aware that the cameras were going to be installed. The data collected during this period were used as "before" data. Data used for the "after" time period were collected after the 30-d warning period and after the cameras had been active for at least a month. A comparison study was completed with the assumption that a decrease in the violations is a surrogate for a decrease in RLR crashes. Furthermore, changes in vehicles entering the intersection during the red phase and yellow phase, along with a headway analysis, were assessed to determine if the cameras had the desired effect on safety. The overall finding was a reduction in violation rates for targeted movements (i.e., left turning and through movements) (Hallmark et al., 2010).

A study in Australia aimed at evaluating the effectiveness of cameras in terms of reduction in crash frequency (presented for all reported crashes, and specifically right angle/right turn through crashes, rear-end crashes, and serious injury crashes) and the net economic benefit of these treatments. Furthermore, changes in traffic infringements targeted by red-light speed cameras, including speeding and running a red light, were presented. This evaluation included 11 sites that were upgraded from an RLC to a red-light speed camera. The preliminary results found that the upgraded red-light speed cameras significantly reduced all reported crashes, right angle/right turn through crashes, rear-end crashes, and serious injury crashes by 19%, 41%, 20%, and 72%, respectively (Chen et al., 2012).

In summary, many studies have shown that automatic enforcement through the RLCs is an effective tool in addressing RLR crashes and violations. Most of these studies have been conducted in developed countries. The purpose of this study is to investigate the effectiveness of the cameras in Qatar, a fast-growing developing country in the Arabia Gulf region. Qatar has different conditions than the countries investigated in previous studies.

While crash analysis is the preferred method of evaluating the effectiveness of the cameras, it is not possible to conduct this type of analysis in Qatar since detailed and reliable crash data are not available. Therefore, it was decided to use the rate of violations as a proposed method for evaluating the effectiveness of the RLCs. However, no studies were conducted to study the rate of violations before the cameras were installed in Qatar, which makes it not possible to conduct a before and after study in Qatar.

Since the cameras in Qatar are not installed at all intersections and are not installed on all approaches of each intersection in many cases, the assessment in this study was conducted through the comparison of camera-enforced approaches against the approaches at the same intersections where no cameras were installed. This method essentially creates an endogeneity issue for traditional statistical approaches to examine violation data. Other examples of endogeneity issues in traffic safety analysis have been discussed in the literature (Carson and Mannering, 2001; Kim and Washington, 2006). Therefore, regression tree-based analysis is used to examine the potential associations between the violations and the characteristics of approaches with and without an RLC.

It should be also noted that the data for most previous studies in the literature had been collected as part of a designed experiment. However, in developing countries most often only observational data collected outside the purview of designed experiments are available. This is what makes regression tree-based analysis more appropriate for this study. In addition, the implementation of the RLCs is also somewhat different in developing countries. In Qatar, there are no warning signs on camera-enforced approaches, which is typically not the case for camera-equipped approaches in the United States, for example. In this study, we model the rate of violations on approaches from nine different intersections in Qatar. Details of the data are provided in the next section. Moreover, while information on observed violations by turning maneuver (going through, left, or right) was available, several approaches had no violations observed at all. Hence, the violation rate had to be estimated by combining violations for all turning maneuvers. It should be acknowledged that this limitation in the data means that one cannot account for the effect of different maneuvers on red-light running behavior (Giuffrè and Rinelli, 2006). The analysis yields lessons applicable not only for camera-equipped approaches but also for approaches without them.

2. Data collection

The data from nine isolated fully-actuated signalized intersections with a combination of camera-enforced approaches and approaches without cameras were used in this study. The data was collected from a total of 18 approaches (two approaches per intersection). The intersections selected had different approach geometry, traffic signal configuration, signage, peak hour volumes, and signal timing. It should be noted that all approaches had a consistent yellow change interval of 3.0 s. All approaches had one or two left turning lanes, two through lanes, and either a shared or dedicated right turning lane. It should be noted that permitted-only and protected-permitted phases for left turns are not used in Qatar. The posted speed limits for the studied intersection approaches ranged from 60 to 100 km/h.

A red-light violation is defined as a vehicle passing beyond the approach stop bar when the traffic signal indication is a red ball or arrow then proceeding through the intersection for through, left turn, or right-turn maneuvers. The location of the stop line at each approach was defined through the field investigation. It should be noted that right turn on red is illegal in Qatar, unless there is a free right turn ramp or channelization, and overlap right turn phasing is not used in Qatar. These criteria were used to determine if a red-light violation had occurred at the studied intersections. Video cameras were used to record the violations at studied approaches for 3 h each for two days (one working day and one weekend day). The video data were reduced manually to determine whether a vehicle had run the red light.

Data for each site were recorded for two approaches, one with camera enforcement and one without a camera. The data were obtained for both approaches at the same intersection, same time, and same day. Cameras were positioned to record traffic approaching and entering these intersections with a clear view of the signal indication and the stop line or crosswalk. The recording was limited to 3 h (4:00 p.m. to 7:00 p.m.), one working day and one weekend day. Video data were reduced manually to determine whether a vehicle had run the red light. The location of the stop line at each approach was defined through the field investigation and marked in the video image for a visual reference. After completion, another group of observers who was not involved in the reduction process repeated the process, and any conflicting results were resolved by re-watching the videos.

This study explored different variables, including day of the week, time of day, left-turning volume, through volume, U-turning volume, the possibility of glare on an approach, the difference values of yellow and all-red intervals between existing and recommended by Institute of Transportation Engineers (ITE). The list of variables included in the analysis is shown in Table 1. There were no missing values in the 108 observations used for analysis.

Table 1 – List and description of the variables explored.

Characteristic	Variable	Type	Description
Time	Day of week	Binary	Weekday
			Weekend
	Time of day	Categorical	4:00 p.m. to 5:00 p.m.
			5:00 p.m. to 6:00 p.m.
			6:00 p.m. to 7:00 p.m.
Traffic	Left-turning volume	Continuous	Traffic volume (vph)
	Through volume	Continuous	Traffic volume (vph)
	U-turning volume	Continuous	Traffic volume (vph)
Traffic signal	Possibility of glare*	Binary	Yes/no
	Yellow differential**	Continuous	Second
	All-red differential***	Continuous	Second

Note: *Derived for each approach based on its location and direction; **Difference between existing and ITE recommended values of yellow time (see results section for further details); ***Difference between existing and ITE recommended values of all-red time (see results section for further details).

The yellow interval plays a major role in the decision to run a red light. When a driver approaches a signalized intersection during the yellow interval, the driver has to decide whether to stop or proceed through the intersection. The decision is made in either the “option zone” or the “dilemma zone”. In the option zone, the driver can either safely go through the intersection at their pre-existing speed before the signal changes to red, or slow their vehicle and brake effortlessly to stop at the intersection. The dilemma zone reflects a driver's difficult decision where both entering the intersection at the pre-existing speed and braking to halt at the stop line are dangerous options in terms of crash risk (Allos and Al-Hadithi, 1992). The concept of the dilemma zone is used to decide the yellow interval. A study conducted by Van der Horst and Wilimink found a relationship between RLR and yellow interval duration. The study found that yellow intervals of at least 3.5 s are associated with minimal RLR cases (Van der Horst and Wilmink, 1986). Bonneson et al. found that increasing the yellow time was inversely related to the frequency of RLR (Bonneson et al., 2002).

3. Methodology

This study employs the regression tree model to explain the characteristics associated with the violations. The advantage of trees models (e.g., the logit model employed by Hunt and Teply (1993)) is that these models do not rely on underlying assumptions about the data distribution. Hence, they are better suited for observational data collected outside the purview of a designed experiment. The advantage of the regression tree over other data mining tools, such as neural networks, used for observational data is that it produces a model that is represented by interpretable logic statements. These logic statements are very helpful in understanding the effect of independent variables on the target variable. It also makes it easy for researchers and analysts to present results to the decision makers. The tree-based algorithm has been used extensively for understanding and predicting consumer behavior (Currim et al., 1988; Lemmens and Croux, 2006).

A regression tree for estimation of the continuous target variable (i.e., the rate of violations on an approach in this case) is similar to the trees used for binary classification problems. The tree represents the segmentation of the data created by applying a series of if/then rules. Each rule assigns a set of observations to a group based on the value of one or more input variables. One rule is applied after another, resulting in a hierarchy of groups within groups. The hierarchy is called a tree, and each group is called a node. The final or terminal nodes are called leaves. For each leaf, the average of the dependent variable for all observations in that leaf is the predicted value. There are several methodologies that can be used to derive the rules, but the basic idea of building a tree model involves splitting each (non-terminal) node such that the descendant nodes are “purer” than the parent node. To achieve this, a set of candidate split rules is created, which consists of all possible splits for all variables included in the analysis. For example, for a dataset with 200 observations and six input variables, there would be $200 \times 6 = 1200$ splits available at the root node. These splits are then evaluated based on a chi-square test criterion to choose among various available splits at every non-terminal node (including the root node). Use of the Chi-squared test for the variability of parent and child nodes, as the split criteria were proposed by Breiman et al. (1984) in their classic work on Classification and Regression Trees. The regression tree algorithm is implemented using R (R Development Core Team, 2011). Chi-squared test variance reduction criterion is applied recursively to the descendants, which become the parents to the successive splits, and so on. The splitting process is continued until the criterion of a minimum size of a node is satisfied.

Classification and regression trees have been used in several transportation applications, such as traffic safety (Pande and Abdel-Aty, 2006) and pavement management (Zhou et al., 2009). Additionally, this approach has been used to model drivers' decisions to either stop or go in response to the yellow traffic light turning (Elmitiny et al., 2010).

4. Analysis

The purpose of the regression tree analysis is to explain the interaction between different variables. The tree resulting from the variables chosen for analysis herein is shown in Fig. 1. Each terminal node (or leaf) of the tree shown in the figure depicts the average violation for approaches belonging to that leaf. It also shows the percentage of approaches from the dataset contained within that leaf in parenthesis. Each leaf is also numbered 1 through 5 increasing going from left to right. The leaves of the tree have the information contained bold and underlined. This information is also provided for the initial root node, which represents the complete dataset. Note that regression tree models were estimated with 80% (randomly drawn) data used for training, and the remaining 20% used for validation.

The regression tree was used to estimate the percentage of violations. The average percentage of violations for all observations in the dataset (root node at the top) was 0.16% as shown in Fig. 1. A “purer” descendant node for this parent would have a set of observations with a violation rate significantly lower or higher than 0.16%. The analysis identified patterns between high- and low-volume approaches. Therefore, the results of the tree analysis are presented below and categorized by the through volumes. Based on the results of the regression tree model, the day of the week, time of the day, the possibility of sun glare, left-turning volume, U-turning volume, and the differences between the recommended and provided yellow intervals were not significantly associated with the rate of violations.

4.1. *High through volume approaches*

The percentage of violations in the leaf with a through volume of more than or equal to 535 vehicles per hour (vph) was found to be lower than the total rate of violations (0.061%). Based on the tree results, higher-volume approaches (hourly volume $\geq$ 535 vph) with cameras were found to have a much lower average rate of violations (0.021%) compared to approaches without a camera (0.16%, see Leaf 2 in Fig. 1). Note that for higher-volume approaches with no camera (Leaf 2) the violation rate is the same as the overall dataset (i.e., Root node). Hence, on these approaches, lower violation rates may be attributable to camera enforcement. It should be noted that a high percentage of higher-volume approaches (44 out of 62) were equipped with a camera.

4.2. *Low through volume approaches*

For low through volume approaches, a pattern related to the yellow and all-red intervals was identified. The recommended value for the yellow and all-red intervals was calculated for all approaches based on the equations below. The basis for the recommended yellow interval duration is the formula presented in Eq. (1) (Pande and Wolshon, 2016).

$$Y_{\mathrm{Rec}} = t + \frac{v}{2(a + 9.81G)} \tag{1}$$

where Y_{Rec} is the yellow interval time recommended by the ITE manual (s), t is the driver perception-reaction time (usually 1 s), v is the approach speed (m/s), a is the deceleration rate (3 m/s^2), and G is percent of grade divided by 100 (plus for upgrade, minus for downgrade).

The all-red interval is the time needed to clear the intersection from the vehicles that legally entered before the termination of the yellow phase. The equation, from ITE (Pande and Wolshon, 2016), is shown in Eq. (2). The width of the intersection was measured in the field. The length of the vehicle was taken as 6.1 m.

$$AR_{\mathrm{Rec}} = \frac{W + L}{v} \tag{2}$$

where AR_{Rec} is the all-red interval time recommended by the ITE manual (s), W is the width of the intersection (m), L is the length of the vehicle (m).

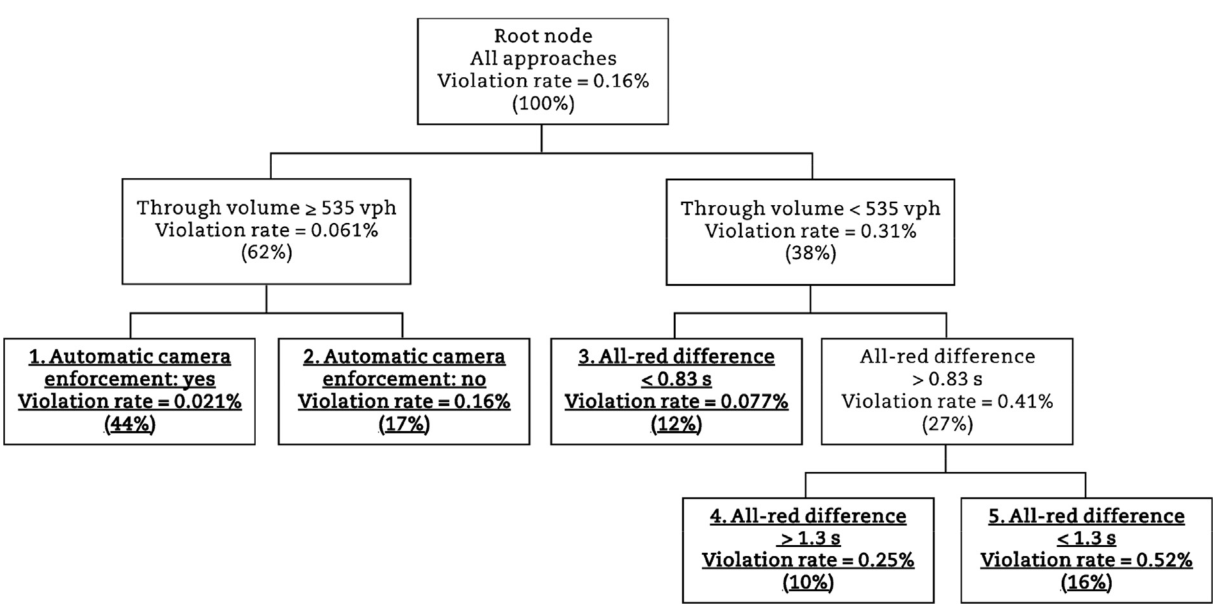

Fig. 1 – Regression tree for the rate of violations.

The differences between the time recommended by the ITE manual and the actual time for the yellow interval (Y_{Diff}) and all-red interval (AR_{Diff}) were calculated according to the Eqs. (3) and (4) below.

$$Y_{Diff} = Y_{Act} - Y_{Rec} \tag{3}$$

$$AR_{Diff} = AR_{Act} - AR_{Rec} \tag{4}$$

The all-red interval provided on intersection approaches was consistently higher than the recommended value obtained from Eq. (2). Based on the tree leaves, it may be observed that for lower-volume approaches when the all-red difference was within 0.83 s from the recommended value, the rate of violations was the lowest (0.077%). For approaches with a higher difference, the rate of violations increased to 0.41%. For approaches with all-red intervals between 0.83 and 1.3 s from the recommended ITE all-red interval, the rate of violations was higher (0.52%) than that for approaches with an all-red difference higher than 1.3 s (0.25%). It indicates that one countermeasure on low-volume approaches may be to maintain the all-red interval close to the ITE recommended value.

5. Conclusions

This study used an observational data analysis-based approach to not only assess the effectiveness of cameras but also discover strategies that may potentially work on approaches without a camera. As with any observational data mining method, the study could benefit from a larger sample size. The method should be easily transferable to other locations where automatic enforcement methods are being implemented outside the purview of a designed experiment.

In addition, analysis of these data provided lessons that authorities can learn to improve the effectiveness of future evaluations. For example, it is important to account for proneness of red-light running for traffic analysis, e.g., as Giuffrè and Rinelli (2006) pointed out using Potential Conflict Analysis, proneness to red-light running changes based on maneuver type (going through, right, or left) and time of day. It means that the period of observation needs to be longer and cover different times of day for a more effective evaluation.

The results show that RLR violations were five times higher on low through volume approaches. On high through volume approaches, the presence of the RLCs significantly lowered the red-light violations. Higher-volume approaches without cameras had an approximately eight times higher rate of violations than high-volume approaches with a camera. The analysis also showed that bringing the all-red interval closer to the values recommended by the ITE formula may reduce the rates of violations for low-volume approaches.

The researchers also identified two limitations in the data used for this study that could potentially be overcome for future RLR camera installations by the Qatar authorities. First, longer recording period would be helpful for investigators to break down the violation data by time of day and/or by signal cycle. Moreover, a robust statistical before-after analysis may be conducted using quasi-experimental study if the violation data were also available from the RLR equipped approaches prior to installation of the cameras.

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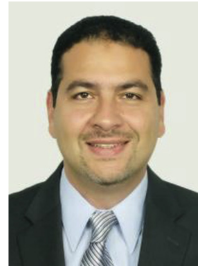

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