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Steven M. Lavrenz

Purdue University, slavrenz@ite.org

Christopher M. Day

Purdue University, cmday@purdue.edu

Jay Grossman

Elkhart County Highway, jgrossman@elkcohw.org

Rick Freije

Indiana Department of Transportation, rfreije@indot.in.gov

Darcy M. Bullock

Purdue University, darcy@purdue.edu

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Steven M. Lavrenz*
Purdue University
550 Stadium Mall Drive
West Lafayette, IN 47906
(765) 496-7314
slavrenz@purdue.edu

Christopher Day
Purdue University
550 Stadium Mall Drive
West Lafayette, IN 47906
(765) 494-9601
cmday@purdue.edu

Jay Grossman
Elkhart County Highway Department
610 Steury Avenue
Goshen, IN 46528
(574) 534-9394
jgrossman@elkcohw.org

Richard Freije
Indiana Department of Transportation
185 Agrico Lane
Seymour, IN 47274
(812) 524-3776
rfreije@indot.in.gov

Darcy M. Bullock
Purdue University
550 Stadium Mall Drive
West Lafayette, IN 47906
(765) 494-2226
darcy@purdue.edu

*Corresponding author.

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ABSTRACT

Intersection crashes are a safety concern for many transportation agencies, and those related to red-light-running (RLR) vehicles are of particular interest. Many camera-based RLR detection systems are controversial with the public, and there is relatively little published literature on the methodologies. This study proposes a methodology that combines high resolution signal controller data with conventional stop bar loop detection to identify vehicles that enter the intersection after the start of red, when many of the most serious RLR crashes occur. The methodology is validated using on-site video collection at several locations, and the algorithm was refined to reduce the incidence of false RLR indications. One case study demonstrates that an increase in side street green split from 20% to 24% of cycle length is associated with a 34% reduction in daily RLR counts, and a reduction in the likelihood of RLR by a factor of 1.7 – a substantial safety improvement for minimal cost. Additionally, law enforcement and transportation agencies can utilize this technique to more efficiently manage and deploy safety resources, especially in cases where detailed crash histories are unknown or too infrequent.

INTRODUCTION

Intersection-related crash injuries are a growing concern for many public agencies and professionals in the transportation industry. In 2012, there were approximately one million crashes at signalized intersections; of these, 422,000 resulted in injuries and 3,377 had one or more fatalities (1). Regarding red light running (RLR) crashes, the most recent figures (as of 2009) show that there were 676 fatalities directly attributable to RLR (2). The Insurance Institute for Highway Safety (IIHS) reports that approximately half of those killed in RLR crashes are not the signal violators themselves (3), which is particularly disconcerting. Very little has been done to investigate the use of ITS infrastructure outside of automated camera enforcement with respect to RLR crashes (4, 5, 6). Given this information, and the nearly- unanimous belief amongst drivers that RLR constitutes a major safety threat (7), it is critical that transportation engineers have a proactive tool for identifying locations with significant RLR activity.

Most existing research on RLR focuses on driver decision making in the dilemma zone. Many studies have investigated factors that influence the driver decision of whether to stop or go at the end of green. This includes in-vehicle factors (8), intersection features and dilemma zone safety measures (9, 10, 11), and investigations into individual driver traits (12, 13). Unfortunately, transportation agencies do not often have access to detailed vehicle or driver information on a systemic basis, and consequently rely on more widely available tools to identify high-risk intersections for RLR and RLR-related crashes.

One such tool is the existing loop detectors that many agencies use to guide demand-responsive allocation of phase green time at signalized intersections. A study by Lu et al. (2015) applied the high resolution data concept to dilemma zone analysis. The researchers utilized inductive loop detectors to identify drivers who proceeded through the intersection during the *yellow* interval. They also examined whether or not basic climate factors played a significant role in the dilemma zone stop/go decision. The highly instrumented nature of the test intersections would limit the scalability of the methodology for broader agency deployment (14).

In addition to loop detectors, there are a host of existing RLR identification techniques that rely on alternative forms of detection, or other technology installed at the intersection. UDOT, for instance, utilizes a radar-based approach to RLR detection; radar detection identifies instances of vehicles driving through a detection zone without stopping after the onset of red, while simultaneously estimating the vehicle speed. If the speed exceeds a particular threshold value, the vehicle is classified as RLR (15). More common, however, is the presence of RLR cameras installed at the intersection, which are often used by law enforcement to penalize drivers for RLR (16, 17). Due to their controversial nature as a revenue collection tool, the impact of RLR cameras has been the subject of scrutiny regarding their ability to reduce the occurrence of RLR crashes. Generally, the presence of RLR cameras is associated with a decrease in the most severe types of intersection crashes, while sometimes leading to a small *increase* in less severe crashes, such as rear-end collisions (18, 19, 20).

Finally, there has been limited investigation into the effects of various signal timing changes on RLR. Retting et al. (2002) investigated the impact of modified change intervals (yellow + all-red time) on RLR, and found that timing these periods in accordance with industry best practices could result in a significant reduction in crashes that occur within the red and yellow intervals (21). Subsequent studies reached similar conclusions (22, 23).

Despite the sizeable amount of research that has taken place in the area of RLR, many agencies are still left without a clear direction going forward, and lack convenient, scalable performance measures. The lack of detailed crash histories for many intersections (due to new construction or infrequent crash occurrence, for example) and a desire to avoid significant added program expenditure, has limited the prevalence of predictive RLR performance measures amongst practitioners. This study seeks to address this shortcoming, by presenting a RLR identification methodology based on existing and industry-standard signal infrastructure.

METHODOLOGY

To identify individual cases of RLR vehicles, high resolution signal controller data was utilized (24). This data has a temporal fidelity of 0.1s, is recorded through a data logger software interface, and captures all detection and phase events at a given intersection (25). The current proposed RLR detection algorithm is developed for use with in-pavement inductive loop detectors at the stop bar. However, the methodology could be easily adapted to other detector technologies, and conceivably to other types of detector placement and configurations as well.

RLR Identification Using Existing Traffic Signal Infrastructure

A simplified illustration of the algorithm used to identify RLR vehicles can be seen in Figure 1. A vehicle is flagged as a RLR when the stop bar detector records an “on” and subsequent “off” event after the start of red on the phase (the time in red to the detector on event is designated as t_{arr}). This indicates that a driver arrived at the detection zone at the approach to an intersection, traversed it (t_{on}), and exited the zone after the termination of the right of way. This definition is consistent with the FHWA’s definition of RLR under the “permissive yellow” philosophy, in that a RLR violation occurs only when the driver enters an intersection after the onset of red (26).

Figure 1 Conceptual overview of RLR detection using loop detector and phase event data

It is important to distinguish between a method of defining RLRs based on an on/off detector event pair, and a potential method of RLR definition based solely on when the detector turns off. In theory, one could simply look at detector off events, relative to the start of red, to determine if a vehicle ran the red light. However, the conventional definition of RLR is typically based on the *front* of the vehicle crossing the stop bar after the start of red. By the time a detector off event occurs after red, the front of the vehicle will have crossed the detection zone (and presumably, the stop bar) at some prior point in time. Without exact knowledge of the vehicle size, speed, and rate of acceleration, it cannot be determined if this stop bar crossing happened before or after the start of red. Furthermore, the painted stop bar and saw-cut stop loop detectors often do not perfectly align in practice, making it even more difficult to determine the position of a vehicle based on a single detector event.

For these reasons, and given that the risk of a conflicting movement crash is substantially lower if the vehicle enters the intersection during the green or yellow intervals, it was decided to focus specifically on this post-red, on/off event pairing definition of RLR for the analysis.

Validation of RLR Detection Logic

It is relatively straightforward to match detector on/off events during the red interval to identify potential RLR occurrence. However, not every *data-flagged* RLR event will correspond to an actual RLR event. For example, right turn on red (RTOR) vehicles violate the expectation that the detector will remain occupied until the end of red, once activated. Without any kind of screening process, this and other scenarios could generate a substantially higher count of RLR events than actually occur.

Consequently, it is critical that methods be undertaken to filter the results in order to avoid cases of *false* RLRs. To this end, RLRs identified in the data were validated using in-field visual observation techniques. Two separate corridors in Indiana (US231 in West Lafayette and CR17 in Elkhart County), comprising a total of five intersections, were utilized for this validation. These locations were equipped with video cameras on one or more approaches, to record RLR events and compare to the high resolution signal controller data. The equipment used for this exercise was a combination of portable video cameras and permanent pan/tilt/zoom (PTZ) camera installations, depending on the intersection. The cameras recorded continuously – they were not activated in response to any particular events on an approach – and the footage was manually synchronized with the high resolution event data. When a RLR event was flagged in the event data, the corresponding video footage was reviewed to determine whether or not the RLR event was valid.

Figure 2 demonstrates the camera setup for several of the test intersections used for data validation. In parts *a* and *b*, the ad hoc placement of cameras on signs adjacent to the intersection can be seen. Both of these locations were along the US231 corridor in West Lafayette. It was critical to mount these cameras in discreet locations to avoid influencing driver behavior. In all cases, the collected video was of insufficient resolution to read license plates or otherwise uniquely identify vehicles, and the video was not used for enforcement purposes. Part *c* shows the field of view from one of the PTZ camera installations on CR17 in Elkhart County. These locations were particularly valuable for data validation, since the cameras were not limited by battery life or data storage restrictions.

A detailed step-through for one instance of RLR validated with video is shown in Figure 3. The example RLR event occurred on the northbound US231 approach at River Road at approximately 1640, during the PM peak period. In part *a*, the detection zone for the rightmost through lane is highlighted and denoted by callout *i*. Superimposed along the bottom of the figure is a trace of the on-off events for this detector channel. In part *b*, the detector zone is occupied by a semi-tractor trailer, denoted by callout *ii*, and the high resolution event data logs a corresponding detector on event. Part *c* shows the detector zone again unoccupied, with a detector off event recorded. In part *d*, the phase goes to yellow, and a vehicle preparing to turn left in the southbound direction can be seen at callout *iii*. In part *e*, the phase status has changed to red, and a dark-colored passenger car can be seen approaching the detector zone in the rightmost through lane. Finally, part *f* shows this vehicle passing through the detection zone during the red clearance interval, and proceeding through the intersection, denoted by callout *v*. This creates a potential collision with the waiting left-turning yellow car (callout *iv*), and the RLR vehicle is flagged by the high resolution data detection algorithm.

Figure 2 Camera setups and fields of view for video validation of RLR data at study intersections
 (a) US231 & State Street: Camera placed behind sign, facing northbound US231
 (b) US231 & River Road: Camera placed behind sign on eastbound right turn, facing westbound River Road
 (c) CR17 & SR120: Field of view from PTZ camera mounted at the intersection. The CR17 approaches were checked for RLRs.

Figure 3 Example video validation of RLR data at US231 and State Street (facing northbound US231)

(a) Normal green progression, detector zone unoccupied [callout i]

(b) Detector zone occupied [callout ii]. Note the corresponding “detector on” event from the high resolution data

(c) Detector zone unoccupied, with corresponding “detector off” event

(d) Start of yellow. Note the vehicle waiting to turn left on southbound US231 [callout iii]

(e) Start of red

(f) The vehicle in the near through lane [callout v] was flagged as a RLR in the data. Note the near-miss with the left turning vehicle [callout iv]

Based on the size of the detection zone and the duration of the detection event (t_{on}), the speed of the RLR vehicle can be estimated using the following equations:

$$z = \frac{1}{t_{on}}(x_v + x_d) \quad (1)$$

$$t_{on} = d_2 - d_1 \quad (2)$$

where

z = estimated travel speed of the RLR vehicle over the detection zone

x_v = length of the RLR vehicle (assume 20 feet for passenger cars)

x_d = length of the detection zone. INDOT uses 6-foot diameter inductive loops with 9-foot gaps, but the exact arrangement will depend on the design standards of the local agency

t_{on} = duration of the detection event

d_1 = time of “detector on” event

d_2 = time of first “detector off” event following the “detector on” event

In the example shown in Figure 3, the estimated speed was calculated as follows:

$$z = \frac{1}{t_{on}}(x_v + x_d) = \frac{1}{0.7s}(20ft + 36ft) = 80ft/s \approx 55 mph$$

The posted speed limit on this intersection approach is 50 mph. Assuming that x_v and x_d are reasonable estimates, it is likely that the driver was traveling faster than the posted speed limit upon entering the intersection.

RLR Data Validation Results & Algorithm Refinement

The results of the initial video comparison are shown in Figure 4. By cross-referencing the video, data-flagged RLR events were grouped into one of four different categories, shown in part *a*:

- Valid RLR: These events were flagged in the high resolution data, and the vehicles were confirmed in video as entering the intersection after the start of red.
- RTOR vehicles: The video showed these vehicles as executing a legal right turn during red. These were excluded from the pool of RLR events.
- Left Turn (LT) detector clipping: These events occurred primarily in the left turn lanes, when a left-turning vehicle from the crossing street drove over the loop detectors. Note that these events always occurred more than 5 seconds after the start of red.
- Other Invalid RLR: These constitute various misdetection errors. In some cases, detector crosstalk or splashover (27) from an adjacent lane would cause a false detection. In other cases, a smaller vehicle, such as a motorcycle, would cause the detector to erroneously flicker on and off several times in sequence (even though the motorcycle itself remained stationary).

These categories were used to refine the RLR detection algorithm, and to limit the window of the search query to a restricted temporal area, denoted by callout *i*. An upper bound of 2 seconds and a lower bound of 0.1 seconds was set on the t_{on} field. In a few cases involving large semi-trucks occupying the detector zone for longer than this time period [callout *ii*], the RLR events would be missed, but it was assumed that these events occur relatively infrequently.

In part *a* of this figure, it was also noted that the vast majority of RLR events occur within the first 2 seconds of red. This is to be expected, as most appeared to be cases of drivers “just missing” the yellow light, although several particularly severe cases are identified at callout *iii*.

Figure 4 Comparison of RLR data events and video validation, along with safety risks for valid RLRs
(a) RLR data events categorized based on video validation. [Callout i] shows the refined search area for RLR events, which captures all valid RLRs, except for two large semi-trucks [callout ii]. [Callout iii] identifies particularly high-risk RLR events, which occurred nearly 3s after the start of red
(b) Valid RLRs from part a. By assuming a fixed vehicle and detector zone configuration, speeds can be estimated for all RLR vehicles. Those RLR events with shorter detector on durations, and those occurring later in red, are considered to be higher risk

Identification of Potential RLR Safety Measures

Once a reasonably accurate count of RLRs is obtained from the data, it can be analyzed for potential patterns. A detailed analysis of individual RLR behavior is beyond the scope of this paper, but part *b* of Figure 4 shows the refined search area from part *a* at a larger scale. Plotted along the right vertical axis is an estimated speed corresponding to detector on durations, from Equations 1 & 2 above. These speeds are based on an assumed 20-ft vehicle size and a 54-ft detection zone, standard for INDOT and Elkhart County. Note that because the relationship between z and t_{on} is non-linear, the axes are logarithmically scaled.

Again, the results show that valid RLR events occurred primarily in the first 2 seconds of red, and that they resulted in t_{on} times between 0.5s and 2.0s. This corresponds to a wide range of potential speeds, although generally most RLRs appeared to be travelling between 30 and 55 miles per hour.

Plots of this nature could be used in future research or by agencies as a means of categorizing RLR events by severity. Generally, the further to the right on the plot that a RLR event occurs, the higher the risk for a potential crash with a conflicting traffic movement. Also, the closer to the bottom on the plot, the higher the approximate vehicle speed associated with the event, which implies higher potential severity for collisions risked by the RLR event. These properties provide a potential first-order screening tool for identifying high risk locations.

Video Validation of Refined Algorithm

Based on the refined RLR algorithm, a second validation was conducted to verify the results. Video was matched to high resolution event data at the aforementioned approaches for multiple time-of-day (TOD) plans, as well as weekday and weekend time periods. In total, approximately 18 different days of RLR data and associated video were considered. The results of this second validation are shown in Figure 5 for all three study corridors. The revised RLR detection algorithm performed with a high degree of accuracy and precision – across all locations and TOD plans, only 3.7% of recorded RLR events were determined to be *false positives*. The inverse occurrence – a *false negative*, in which a valid RLR event occurs, but is not detected by the algorithm – was not considered here. The resulting counts should provide agencies with an accurate, albeit potentially conservative, estimate of RLR activity occurring at an intersection.

Figure 5 Comparison of RLR events from algorithm and video ground truthing

(a) Combined RLR event counts for SR119, SR120, and CR38 at CR 17 in Elkhart County. All RLR events were measured on the CR17 approaches

(b) State Street and US231 in West Lafayette. All RLR events were measured on the northbound US231 approach

(c) River Road and US231 in West Lafayette. All RLR events were evaluated on the westbound River Rd approach

CASE STUDY: US31 & 126TH STREET SPLIT ADJUSTMENT

In addition to the general rating of RLR events at an intersection, the high resolution data algorithm can be utilized to evaluate intersection and signal timing treatments which have already been implemented. Here, a *post hoc* assessment of the intersection of US31 and 126th Street in Carmel, IN was performed after a green split adjustment. Of particular interest was the westbound through lanes (phase 8), which can be seen in Figure 6. In response to repeated split failures occurring during the midday TOD plan (0900-1500) as result of high retail traffic in the area, the local agency decided to increase the green split from 20% of cycle time to 24% on this approach. In Freije et al. (2014), which details the full impacts of the split increase on intersection performance, a split failure was defined as 80% occupancy on the approach during the green interval, and 80% occupancy during the first 5 seconds of the red interval (28).

The results of the split increase on RLR counts over a several-month period before and after the split change can be seen in Figure 7 and Figure 8. The split increase occurred on July 29th, 2013. Part *a* of Figure 7 shows daily counts of RLRs plotted against average time in red (t_{arr}) for

Figure 6 US31 & 126th Street intersection diagram. The change in RLR events is evaluated for a change in green split on Phase 8 from 20% of cycle length to 24%.

the before and after periods. The daily RLR count appears to have decreased after the split adjustment. Part *b* of this figure shows a comparison of the cumulative distribution functions (CDFs) of t_{arr} before and after the split adjustment. Here, it can be seen that the overall shape of the distributions does not significantly change, although the median value for t_{arr} does decrease, from 0.8 seconds in red before the split adjustment to 0.6 seconds after (a reduction of 25%).

Figure 8 shows a comparison of the before and after daily RLR counts (part *a*), along with a computation of the RLR rate per 1,000 entering vehicles (part *b*). The latter measure is arguably more useful, since it accounts for small differences in traffic volumes during the analysis periods. Based on this historical data, it appears that the increase of split time on this phase substantially reduced the occurrence of RLR vehicles; in fact, mean daily RLR counts decrease by

Figure 7 Effect of phase 8 split increase on RLR behavior during the 0900-1500 TOD plan at US31 & 126th Street.

(a) Comparison of RLR count vs. average time in red that RLR occurs. Each point represents a single day of RLR observations.

(b) Comparison of RLR time in red CDFs before and after split adjustment. Note the shift in median RLR time in red.

Figure 8 Effect of phase 8 split increase on RLR performance measures during the 0900-1500 TOD plan at US31 & 126th Street

(a) Change in daily RLR counts before/after split increase

(b) Change in average daily RLRs per 1,000 entering vehicles before/after split increase

approximately 34%. Tests of statistical significance shown in Table 1. In this table, tests of significant differences between the mean daily RLR counts, as well as the variance of the daily

RLR counts, were conducted (29). Based on these tests, the results show that an increase in green split did result in reductions to mean RLR and RLR variance. The null hypothesis of no difference in RLR behavior was rejected at the 99% confidence level.

Table 1 Test of Statistical Significance for Changes in RLR Average Daily Counts and Variance Before/After Split Adjustment

	<i>t-Test of Means</i>			<i>F-Test of Variances</i>	
	20% Split	24% Split		20% Split	24% Split
<i>Mean RLR</i>	1.063	1.500	<i>Mean RLR</i>	1.063	1.500
<i>Variance</i>	0.063	0.357	<i>Variance</i>	0.063	0.357
<i>Obs.</i>	16	22	<i>Obs.</i>	16	22
<i>d.f.</i>		30	<i>d.f.</i>	15	21
<i>t-Stat</i>	-3.083		<i>F-Stat</i>		0.175
<i>p-value</i>	0.004		<i>p-value</i>		0.001
<i>t_{critical}</i>	2.042		<i>F_{critical}</i>		0.432

In addition to tests of statistical significance on the RLR counts, an *odds ratio* test was conducted for the before and after RLR rates in to discern any changes. Here the odds ratio is defined according to the following:

$$q = \frac{r_b}{r_a} \quad (5)$$

where

$$r_i = w_i / v_i \quad (6)$$

and

q = odds ratio

r_b = odds of a RLR in the “before” period

r_a = odds of a RLR in the “after” period

w_i = count of RLRs in period i

v_i = count of total entering vehicles in period i

Thus,

$$q = \frac{w_b / v_b}{w_a / v_a} \quad (7)$$

A test of significance, similar to that described previously, is conducted to determine if the resulting ratio from Equation 7 is significantly different than 1. The results for the odds ratio test are shown in Table 2. They indicate that a vehicle operating under the 20% split condition is approximately 1.6 times as likely to run a red light as a vehicle operating under the 24% split condition, *ceteris parabis*. A 99% confidence interval for the odds ratio was also estimated, and it

can be seen that the lower bound of this range is significantly above a value of 1 (which would indicate no difference in RLR odds). Thus, it can be reasonably concluded that the split increase on this phase was associated with a significant reduction in the occurrence of RLR activity on this phase, for the time periods under consideration.

Finally, Table 3 shows the impact of the phase 8 split increase on RLR daily counts for other approaches at the intersection. The major street through movements are not included, due to the lack of stop bar detection, nor are the side street protected left turns, as these phases are immediately followed by a permitted left. Overall, it does not appear that the split increase had significant adverse impacts on other approaches – the side street permitted left turns saw slight changes in average RLRs and RLR variance, while the northbound protected left saw a moderate increase in average RLR. Other approaches saw no appreciable change. The figures in this table underscore the importance of considering RLR in a holistic sense – that is, when performing signal timing interventions to reduce RLR, engineers must weigh the impacts to the intersection as a whole.

Table 2 Odds Ratio Test for RLR Rates per 1,000 Entering Vehicles Before/After Split Adjustment

	<i>Odds Ratio</i>	
	20% Split	24% Split
<i>RLR Odds</i>	0.006	0.003
<i>Odds Ratio</i>	1.672	
<i>Upper 99% CI</i>	1.707	
<i>Lower 99% CI</i>	1.637	

Table 3 Impacts of Phase 8 Split Increase on RLR Counts for All Movements Except Major Street Thru, US31 & 126th St.

Phase & Movement	Δ Mean Daily RLR	Δ Variance Daily RLR
<i>Phase 1 – NB Protected Left</i>	1.902*	2.764
<i>Phase 4 – WB Thru</i>	0.168	5.661
<i>Phase 4 – WB Permitted Left</i>	-0.141	-0.349*
<i>Phase 5 – SB Protected Left</i>	-0.231	1.216
<i>Phase 8 – EB Thru</i>	-2.389**	-9.425**
<i>Phase 8 – EB Permitted Left</i>	0.438**	0.295**

* Significant at the 0.05 Confidence Level

** Significant at the 0.01 Confidence Level

TRANSFERABILITY/CALIBRATION

The methodology presented in this paper underwent a great deal of refinement in order to reduce the likelihood of identifying false RLRs. However, there are important considerations that agencies must make when considering this methodology for their own systems.

Perhaps the most significant is the calibration of the data search window. The detector on duration (0.2s – 2.0s) and time within red (first 5s) used in this study were set based on INDOT detector zone configurations and signal timing practices. Other agencies considering this RLR

identification methodology should conduct their own field calibrations in order to define corresponding search parameters for their own systems. Additionally, emerging research suggests that different types of detection have varying latencies (time between actual vehicle arrival and detector actuation) (30). The implications of latency on RLR detection accuracy should be evaluated by agencies prior to full-scale deployment.

Depending on the detection configuration, agencies may also have trouble applying this methodology during heavily congested periods. The current RLR definition relies on a detector on event occurring after the start of red. However, in certain cases of saturated flow with longer detection zones, it may be that the detector remains on constantly through the green interval and into the red/yellow periods. In this case, although there may be legitimate RLRs, they will be missed by the data search algorithm. One approach to reducing this occurrence is to maintain shorter detection zones, perhaps setting a single front loop detector on a separate channel to monitor RLR.

Finally, while this methodology can be used to identify RLR occurrences, it does not necessarily indicate *why* the RLR occurred. However, as a first-order screening and triage tool for agencies to quickly identify high-risk intersections, this technique is particularly well-suited.

CONCLUSIONS

RLR vehicles and associated crashes are a universal concern. Besides identifying driver characteristics and using crash histories to flag dangerous intersections, there is a need for agencies to more proactively identify “at risk” locations for appropriate resource allocation, using currently available methods whenever possible. This paper proposes a methodology developed using high resolution event data to identify counts and characteristics of RLR vehicle occurrence at signalized intersections. The following conclusions were reached in the course of this study:

- High resolution signal controller data can adequately characterize RLR violations in a variety of conditions, using existing stop bar detection.
- Numerous cases can potentially skew the RLR detection algorithm, including RTOR vehicles, detector clipping, and detector malfunction. This necessitates a more intelligent search algorithm, refined based on a video validation approach.
- Based on observed detector zone configurations, the video validation resulted in an effective search window for RLR corresponding to detector on events between 0.2s and 2.0s.
- The RLR performance measure showed that a split increase on a heavy-volume side street through movement reduce the incidence of RLR vehicles by 34%, and the average time in red for RLRs by 25%.
- Further analysis showed that the addition of 4% green split on the side street was associated with a reduction in RLR rates per 1,000 entering vehicles by a factor of 1.7.

One key advantage of this methodology is its applicability to existing signalized intersection stop bar infrastructure. Consequently, it can be easily scaled to a large number of intersections across a wide geographic area, and can complement high-level agency reports of intersection performance and operations based on the same high resolution data.

The safety implications of this research are significant. Based on the results presented here, it is evident that signal timing interventions can be used to not only enhance intersection performance (in terms of reduced split failures), but also reduce the potential for crashes. Further study will more explicitly consider the linkage between RLR crash exposure, operational performance and lane occupancy, and various signal timing interventions (such as split adjustment and cycle length).

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REFERENCES

1. National Highway Traffic Safety Administration. Traffic Safety Facts 2012. *Traffic Safety Facts 2012*, 2014. <http://www-nrd.nhtsa.dot.gov/Pubs/812032.pdf>.
2. Federal Highway Administration. How Red-Light Running is Defined and How Crash Figures Are Determined. September 4, 2014. <http://safety.fhwa.dot.gov/intersection/redlight/howto/>. Accessed April 22, 2015.
3. Insurance Institute for Highway Safety. Red light cameras in Philadelphia all but eliminate violations. *Status Report*, Vol. 42, no. 1, January 2007.
4. Erke, A. Red light for red-light cameras?: A meta-analysis of the effects of red-light cameras on crashes. *Accident Analysis & Prevention*, Vol. 41, no. 5, 2009, pp. 897-905.
5. Hu, W., A. T. McCartt, and E. R. Teoh. Effects of red light camera enforcement on fatal crashes in large US cities. *Journal of Safety Research*, Vol. 42, no. 4, 2011, pp. 277-282.
6. Ahmed, M. M., and M. Abdel-Aty. Evaluation and spatial analysis of automated red-light running enforcement cameras. *Transportation Research Part C: Emerging Technologies*, Vol. 50, 2015, pp. 130-140.
7. Schulman, Ronca, & Bucuvalas, Inc. National Survey of Speeding and Other Unsafe Driving Actions, Volume II: Driver Attitudes & Behavior. Washington, D.C., 1998.
8. Lavrenz, S. M., V. D. Pyrialakou, and K. Gkritza. Modeling driver behavior in dilemma zones: A discrete/continuous formulation with selectivity bias corrections. *Analytic Methods in Accident Research*, Vol. 3-4, 2014, pp. 44-55.

9. Köll, H., M. Bader, and K. W. Axhausen. Driver behaviour during flashing green before amber: a comparative study. *Accident Analysis & Prevention*, Vol. 36, no. 2, 2004, pp. 273-280.
10. Yan, X., E. Radwan, D. Guo, and S. Richards. Impact of “Signal Ahead” pavement marking on driver behavior at signalized intersections. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 12, no. 1, 2009, pp. 50-67.
11. Long, K., Y. Liu, and L. D. Han. Impact of countdown timer on driving maneuvers after the yellow onset at signalized intersections: An empirical safety study in Changsha, China. *Safety Science*, Vol. 54, 2013, pp. 8-16.
12. Papaioannou, P. *Driver behaviour, dilemma zone and safety effects at urban signalised intersections in Greece*. *Accident Analysis and Prevention*, vol. 39, 2007.
13. Elmitiny, N., X. Yan, E. Radwan, C. Russo, and D. Nashar. Classification Analysis of Driver's Stop/Go Decision and Red-Light Running Violation. *Accident Analysis & Prevention*, Vol. 42, no. 1, 2009, pp. 101-111.
14. Lu, G., Y. Wang, X. Wu, and H. K. Liu. Analysis of yellow-light running at signalized intersections using high-resolution traffic data. *Transportation Research Part A*, Vol. 73, 2015, pp. 39-52.
15. Utah Department of Transportation. Red Light Monitoring [RLM] Explained In Detail. 2015, Internal Memorandum.
16. American Traffic Solutions. Red-Light Safety. 2015. <http://www.atsol.com/solutions/red-light-safety/>.
17. SRF Associates. Red Light Camera Effectiveness Evaluation: City of Rochester, New York. Rochester, 2014.
18. Hallmark, S., N. Oneyear, and T. McDonald. Evaluating the Effectiveness of Red Light Running Camera Enforcement in Cedar Rapids and Developing Guidelines for Selection and Use of Red Light Running Countermeasures. Institute for Transportation, Iowa State University, Ames, Monograph 2011.
19. Eccles, K. A., R. Fiedler, B. Persaud, C. Lyon, and M. Griffith. Automated enforcement for speeding and red light running. National Cooperative Highway Research Program, Washington, D.C., 729, 2012.
20. Council, F. M., B. Persaud, K. Eccles, C. Lyon, and M. Griffith. Safety Evaluation of Red-Light Cameras. Battelle Memorial Institute, Columbus, FHWA-HRT-05-048, 2005.
21. Retting, R. A., J. Chapline, and A. Williams. Changes in crash risk following re-timing of traffic signal change intervals. *Accident Analysis & Prevention*, Vol. 34, no. 2, March 2002, pp. 215-220.
22. Retting, R., S. Ferguson, and C. Farmer. Reducing red light running through longer yellow signal timing and red light camera enforcement: Results of a field investigation. *Accident Analysis & Prevention*, Vol. 40, no. 1, January 2008, pp. 327-333.

23. Bonneson, J. A., and K. Zimmerman. Effect of yellow-interval timing on the frequency of red-light violations at urban intersections. *Transportation Research Record*, Vol. 1865, 2004, pp. 20-27.
24. Smaglik, E. J., A. Sharma, D. M. Bullock, J. R. Sturdevant, and G. Duncan. Event-Based Data Collection for Generating Actuated Controller Performance Measures. *Transportation Research Record*, no. 2035, 2007, pp. 97-106.
25. Sturdevant, J. R., T. Overman, E. Raamot, R. Deer, D. Miller, D. Bullock, C. Day, T. Brennan, H. Li, A. Hainen, and S. Remias. Indiana Traffic Signal High Resolution Data Logger Enumerations. West Lafayette, Indiana, doi: <http://data.datacite.org/10.4231/K4RN35SH>, 2012.
26. Federal Highway Administration. *Red-Light Running Fatalities (2000-2009)*, 2014. http://safety.fhwa.dot.gov/intersection/redlight/data/rlr_fatal/. Accessed Apr. 22, 2015.
27. Ernst, J. M., D. Lamba, J. V. Krogmeier, and D. Bullock. Crosstalk Detection in Signalized Intersection Loop Detectors. *Transportation Research Record*, no. 2192, 2010, pp. 50-63.
28. Freije, R., A. Hainen, A. Stevens, H. Li, W. Smith, H. Summers, C. Day, J. Sturdevant, and D. Bullock. Graphical Performance Measures for Practitioners to Triage Split Failure Trouble Calls. *Transportation Research Record*, no. 2439, 2014, pp. 27-40.
29. Washington, S. P., M. G. Karlaftis, and F. L. Mannering. *Statistical and Econometric Methods for Transportation Data Analysis*, 2nd ed. Taylor & Francis Group, Boca Raton, FL, 2011.
30. Day, C., H. Premachandra, T. Brennan, and D. Bullock. Operational Evaluation of Wireless Magnetometer Vehicle Detectors at Signalized Intersection. *Transportation Research Record*, Vol. 2192, 2010, pp. 11-23.