Behavioral, Operational and Safety Effects of Red-Light Cameras at Signalized Intersections in Alabama

by

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Abstract

Statistics reveal that from 2007-2011 an average of 751 people died each year in red-light running (RLR) crashes in the U.S. Past studies showed that red light cameras (RLCs), as an enforcement countermeasure, can lower RLR fatalities at signalized intersections. Currently, approximately 430 individual communities run RLC programs in the U.S. and over 40 intersections in Alabama are equipped with these cameras. As more RLCs are installed at intersections in Alabama, understanding their effects and how to best implement them is of growing importance. While extensive research has investigated the safety effects of the system, very little work has been done to investigate the impacts of RLCs on driver behavior and intersection operation. To date, very few study has evaluated the effects of RLCs in Alabama. The primary objective of this study is to fill the research gap by evaluating the effectiveness of RLC program, in terms of safety, operation, and driver behavior, while also developing a novel fine structure for RLR traffic violations. In the first step, the complete process of extracting RLR crash data from Critical Analysis and Reporting Environment is presented to identify target crashes. More importantly, an extensive field observation is conducted to collect drivers' responses to clearance intervals at four intersections with RLCs and four intersections without RLCs. The increase in the intersection delays due to the presence of RLCs can be estimated. The results indicate a higher tendency to stop and a longer delay at intersections equipped with RLCs. Furthermore, a comparison among clearance lost time values, collected in the field and estimated using the Highway Capacity Manual method and Alabama Department of Transportation's Traffic Signal Design Guide and Timing Manual method, demonstrates that both manuals overestimate the intersection's capacity. An adjustment factor is estimated and recommended for improving accuracy of both methods. In the last step of the research, a novel method is developed to determine a basis for RLR fines by considering the cost of a potential RLR crash and its resulting delay, which is the first of its kind reported in the literature. Various statistical tests and simulation models are used to accomplish the objectives of this study.

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I dedicate my dissertation work to my loving parents, who have never left my side, and to my beloved husband, Hossein, who was always there for me. Not only he was a great help in collecting data, but also he gave me helpful advices throughout my Ph.D. studies. It would be much more difficult for me to finish this study without his continues motivation, enthusiasm, sacrifices, and selflessness.

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List of Abbreviations

ALDOT	Alabama Department of Transportation
ar	All red time
CARE	Critical Analysis Reporting Environment
CMP	Comparison Intersections
CPM	Collision Prediction Model
CTRL	Control Intersections
dec.	Decrease
EB	Empirical Bayes
EPDO	Equivalent Property Damage Only
freq.	Frequency
GLM	Generalized Linear regression model
HCM	Highway Capacity Manual
HCS	Highway Capacity Software
HSM	Highway Safety Manual
inc.	Increase
int.	Intersection
MARS	Multivariate Adaptive Regression Splines
mo.	Month
PDO	Property Damage Only
RA	Right Angle
RE	Rear End
REF	Reference Group
RLC	Red Light Camera
RLR	Red Light Running
RTM	Regression to the Mean

TTL	Total
UCT	Used Clearance Time
CLT	Clearance Lost Time

CHAPTER 1 INTRODUCTION

1.1 Background

Crashes due to the violation of traffic control devices result in the most severe types of police-reported crashes at signalized intersections (Retting et al. 1995). Statistics reveal that from 2007-2011 an average of 751 people died each year in red-light running (RLR) crashes in the U.S. (ATSOL 2015). The solution to the problem of RLR and resulting crashes may require a combination of engineering, education, and enforcement measures. There are numerous engineering countermeasures for various traffic safety issues (Khalilikhah et al. 2016, Jalayer and Zhou 2016, Dias & Dissanayake 2014, Khalilikhah et al. 2015, Khalilikhah 2016). In the case of RLR problem, examples are: improving sight distance, adding advance warning signs, increasing conspicuity of signals, adding intersection capacity with additional traffic lanes and flattening sharp curves (McGee 2003, Bonneson et al. 2002, Baratian-Ghorghi et al. 2016a). Public information and awareness campaigns that highlight the RLR problem and its consequences are considered education countermeasures. Since it is sometimes difficult to obtain and maintain the intensity of law enforcement presence at an intersection to reduce RLR traffic violations, considerable interest exists in new technologies to improve driver compliance with traffic control devices, prevent violations, reduce crash occurrence, and improve safety (Antonucci et al. 2004). One technology that appears to offer the potential for improving safety is the use of photo enforcement of RLR violations termed red-light camera (RLC).

RLCs are installed at signalized intersections to reduce crashes due to the violation of traffic signals. They automatically capture images from vehicles that run red lights and provide evidence that assist in issuing citations to the vehicle owners. RLCs are gaining widespread popularity. The first application of RLCs in the U.S. was in New York City in 1991 (Retting et al. 1995). Thereafter, a multitude of U.S. cities began to implement enforcement cameras. As of July 2016, an estimated 430 individual communities run RLC programs (IIHS 2016). The number of intersections with RLCs, throughout the state of Alabama, has increased from seven in 2008 to over 40 in 2016. Although the use of RLCs is increasing in the nation, it is still criticized as a revenue generating instrument. There are a total of seven communities in Alabama that have installed a system of this type, including Montgomery, Tuscaloosa, Midfield, Selma, Phenix City, Center Point, and Opelika.

To date, only two related studies have been conducted in Alabama (Supriyasilp et al. 2003, Jones et al. 2015), while the overall effects of these RLCs are not yet clear. Also, relatively less efforts have been made to quantify the impacts of traffic violation policies compared to the conducted numerous researches on policy implementation in different aspects of transportation (Baratian-Ghorghi et al. 2016b). Examples are policy implementation of fuel consumption and greenhouse gas emission reduction to improve transportation sustainability (Soltani-Sobh et al. 2015a, 2016a, 2016b), road pricing to address the congestion problem (Miralinaghi and Peeta 2016), and providing traffic condition information through the use of advanced traveler information systems (Baratian-Ghorghi and Zhou 2015). Of a review of 70 studies, none looked at RLR fine policy, only one focused on the negative effects of RLCs on intersection capacity; and a few looked at the behavior of drivers at RLC intersections.

Funded by the Highway Research Center at Department of Civil Engineering of Auburn University, this dissertation contributes to RLC effectiveness studies by providing further methodological and empirical evidence on its behavioral and operational effects at signalized intersections. Furthermore, this is the first step towards developing a fine structure for RLR traffic violations.

1.2 Research Objectives

The objectives of this study are as follows:

- Examine the effects of RLCs on drivers' behavior;
- Quantify the impacts of RLCs on intersection operations;
- Evaluate the safety effects of RLCs in terms of crash severity and frequency; and
- Develop an empirical model as the basis for determining RLR fines.

1.3 Organization of Dissertation

Chapter 2 introduces the red-light safety camera program, including the red light safety acts, public awareness warning period, and civil fine. It also documents a comprehensive literature review on current practice of RLCs. Chapter 3 examines drivers' responses to clearance intervals at intersections with and without RLCs. The results of this chapter is currently under review in the journal of Transportation Research Part F: Traffic Psychology and Behaviour. Chapter 4 investigates the impacts of RLCs on intersection delay and lost time. Chapter 5 evaluates the safety effects of RLCs based on a before-and-after study and equivalent property damage only (EPDO) analysis at four intersections in Opelika, AL. The data collection method, described in this chapter, has been used in a partner study (Baratian-Ghorghi et al. 2016a). Chapter 6 presents a new fine structure for RLR traffic violations based on operational and safety evaluation results in the chapters 3 through 5. Chapter 7 summarizes all results and makes recommendations for practice and future studies.

CHAPTER 2 LITERATURE AND PROGRAM REVIEW

A red-light running (RLR) violation occurs when a motorist crosses the stop line after the traffic signal has turned red. Motorists already in the intersection when the signal changes to red, are not considered red light violators. The system activates when motion is detected just prior to the stop line after the traffic signal has turned red. The cameras capture two images of an alleged violation, taken from rear of the vehicle. Data, including the time, date, speed of vehicle and time into red is recorded. The police department reviews each violation event and makes a final determination about issuance of a citation. Finally, if the violation is approved, the owner of the vehicle would be mailed a traffic citation. The fines in Alabama vary between $60 and $100 (Jones et al. 2015, Opelika Red Light Safety Act 2011).

The following sections discuss past studies findings related to the RLR violations and red-light cameras' (RLC) effects. This chapter concludes by identifying the research gap and introducing the focus areas of this research as the starting points for further analysis.

2.1 Past Studies Findings

Several past studies have identified contributing factors regarding RLR crashes. Increase in traffic volume is known to be associated with an increase in RLR (Council et al. 2005, Wang et al. 2016); delays caused by congestion negatively affect drivers' behavior, contributing to the number of RLR instances; fully actuated traffic signals experience more crashes than pre-timed signals (Mohamedshah et al. 2000); and inadequate signal timing generally seems to be related to RLR (Retting et al. 2008). Several research is also available focusing on the RLR violation prediction

(Jahangiri et al. 2016, Machiani & Abbas 2015, Elhenawy et al. 2015), but very little has been known about the risk of potential crashes. With regard to the effectiveness of RLCs, there have been numerous studies focused on the safety effects, some researchers have examined drivers' behavior, but very few studies have investigated the impacts of RLCs on the operation of intersections. The next sections summarize some of these research results.

2.1.1 Research on Intersection Safety

Safety consequences of RLCs are known to be significant. The most severe type of police-reported crashes at signalized intersections is RLR related. Due in part to the diversity of evaluation methods, past studies provided mixed findings of safety effects. Most studies have shown that RLC systems can be a very effective enforcement tool. Some (Hallmark et al. 2010, Ko et al. 2013, Sayed and de Leur 2007, Persaud et al. 2005, Walden et al. 2011, McCartt and Hu 2014, Fitzsimmons 2007, Retting and Kyrychenko 2001, Hadayeghi et al. 2007) used reliable data and incorporated control for regression to the mean (RTM) in the evaluation methodology in order to focus on the safety effect of RLCs. Studies, reported that angle crashes (injury and fatal) were reduced between 17 to 32 percent (Sayed and Leur 2007, Retting and Kyrychenko 2001). However, the issue of whether rear-end collisions will increase or decrease with the implementation of RLCs has not yet been resolved. In some cases, rear-end (RE) crashes increased up to 43% (Walden and Bochner 2011) where a camera was implemented. Several studies (Council et al. 2005, Persaud et al. 2005, Hadayeghi et al. 2007, Walden and Bochner 2011, and Ko et al. 2013) highlight that the abrupt stop action to avoid committing RLR violation contributes to the increased risk of RE crashes, and is acknowledged as negative byproduct of RLCs. However, a few studies reported slight reductions in RE injury crashes (Sayed and de Leur 2007).

Hallmark, et al. (2010) performed a before-and-after Bayesian analysis in order to evaluate the effectiveness of Davenport, Iowa's red light running (RLR) camera system. Results of the analysis yielded a reduction of total crashes around 20% at RLC intersections with an almost 7% increase in crashes at the control intersections. They also found that RLR rear-end crashes did not increase at RLC intersections, while increased 33% for the control intersections. Instead of using yearly numbers, the researchers used quarterly numbers due to a short "after-crash period." There are 12 quarters of before implementation data and 8 quarters of after data.

Ko, et al. (2013), on the other hand, found that there was a 20% decrease in all type and 24% decrease in RA crashes, while rear end RLR crashes significantly increased by 37%. A length of 150ft on any approach was considered as a possible location for red-light related RE crashes, as was used in a study conducted by Council et al. (2005).

Regarding the overall effect in crash numbers, various studies have produced mixed results. Some studies concluded that there is a reduction in crash levels (e.g. Fox, 1996) while some found only small effects, or even increase in crash counts (Burkey and Obeng, 2004 and Helai et al., 2008). An analysis of RLCs in large U.S. cities by IIHS in 2011 showed a significant reduction in RLR fatality rates (Hu, McCartt, & Teoh, 2011).

Table 2.1 RLC Safety Effectiveness Studies at a Glance

Reference	Location	Number of Sites	Evaluation Method	Data	Results
McCartt and Hu 2014	Arlington, VA	4 RLC, 4 REF, 4 CTRL	Regression models	2 days during warning period, after 1 mo., and 1 year	After 0.5s: -14% RLR After 1.0s: -25% RLR After 1.5s: -63% RLR
Ko, et al. 2013	Texas	245 RLC, 66 REF	EB	1-4 years before and 1-4 after	TTL crash: -20% (RLC) RA: -24% RE: +37%
Walden and Bochner 2011	Texas	275 RLC	Simple Before and After comparison	1, 2, and 3 year periods before/after	TTL: -23%; RA: -19-20% RE: doubled in freq.
Walden et al. 2011	39 Texan communities and College Station	296 RLC	Before and After with CMP group College Station: Wilcoxon Matched-Pairs Signed Test	2 years before, 1 year after	TTL: -26.4% ; RA: -19% RE: +43.6%; College Station: Post removal inc. in RLR
Hallmark, et al. 2010	Davenport, IA	4 RLC, 5 CTRL	Bayesian model assuming a Poisson Distribution	12 quarters before, 8 quarters after	TTL: -20% (RLC),+7% (CTRL) RE: 0% (RLC), +33% (CTRL)
Fitzsimmons 2007	3 Communities in Iowa	13 RLC, 16 CTRL	Cross-sectional analysis, GLM	varied per int.	Council Bluffs: TTL: -44% Non RE: -90%; RE: -40% Davenport: TTL: -20%
Hadayeghi et al. 2007	Halton, Ontario, Canada	447 non-RLC	CPM with EB	5 years	-0.51 RA crash/year +0.74 inc. RE crash/ year
Sayed and de Leur 2007	Edmonton, Canada	25 RLC, 47 CMP, 100 REF	CPM with EB	3 years before, 2-3 years after	TTL: -11.1% (RLC); PDO: -14.135%; RA: -17.2%; RE: -12.4%
Persaud et al. 2005	7 Jurisdictions	132 RLC, 509 REF, 296 CMP	EB	--	RA: -24.6% RE: +14.9%
Retting&Kyrychenko 2001	Oxnard, CA	125 TTL, 11 RLC, 3 CTRL cities	GLM	29 mo. before/ 29 mo. after	City wide effects: Injury crash: -29% RA: -32%

The reason behind contradictory findings may be explained by differences in either evaluation methods or data (Langland et al. 2014). Studies might or might not treat regression to the mean (RTM) and spillover effects. Failure to control RTM overestimates the effectiveness of RLCs while the effects of RLCs can be underestimated if spillover effects are neglected. Hence, before accepting the study's results, the methods should be investigated in details.

Although the relationship between red light violations and crashes at an intersection has not been quantified, some researchers have assumed that intersection safety will improve if violations reduce.

2.1.2 Research on Drivers' Behavior

Past studies in communities that have installed RLCs suggest that implementing RLC has a generalized effect on RLR behavior. For example, Retting et al. (1999) showed that the violation rate is reduced by about 40% during the first year after the RLCs were installed. Bonneson et al. (2002) divides red light runners into two categories. The first are the intentional violators who could avoid RLR event but still proceed through the intersection. The second type of drivers are the unintentional drivers for whom RLR is an unavoidable event. This type of drivers is incapable of stopping or are unaware of the need to stop. This may occur as a result of poor judgment by the driver, an insufficient yellow interval length, or deficiency in the intersection design. The authors further indicate that avoidable RLR events are most affected by enforcement countermeasures, such as RLCs, while unavoidable events are most affected by engineering countermeasures, such as signal timing improvement. Several studies have examined changes in driver behavior with respect to a combination of engineering and enforcement countermeasures (Fitzsimmons et al. 2009, Llau & Ahmed 2014). They have focused on the impact of changes in signal timing (especially the yellow change interval) in the presence of RLCs on drivers' decision-making tendencies (Hurwitz et al. 2016). Retting and Greene (1997) used data collected by RLCs to record the number of drivers taking a defensive approach when confronted with a yellow signal and concluded that safety benefits are associated with longer change intervals. A similar study conducted by Van Der Horst (1988) at non-camera intersections in the Netherlands concluded that a one-second extension of yellow interval resulted in about a 50% reduction in RLR violations. Another study explored the effects of lengthening the yellow signal phase on RLR and the additional incremental effect of RLC enforcement (Retting et al. 2008). The researchers used video cameras to examine two intersections and six approaches in Philadelphia, Pennsylvania, along with an additional three comparison intersections in Atlantic County, New Jersey. The yellow interval times increased by approximately one second at each of the intersections based on pre and post RLC implementation. Using logit regression analysis to model driver behavior and to predict whether or not the driver would run the red light, they showed that after increasing the yellow time, RLR declined 36%, and there was a 96% RLR reduction after the installation of RLCs.

Some researchers have focused on the characteristics of RLR (Wang et al. 2016, Huang et al. 2006). For example, Huang et al. (2006) examined the factors that affect a driver's decision to run a red light and the effects RLCs have on reducing such violations. The researchers selected 15 intersections in Singapore with varying characteristics, five of which had RLCs installed. Five significant variables were identified: the percentage of green time to total cycle length, estimated time to stop line, estimated time to cross the intersection, whether the vehicle is a leader or a follower, and the presence of a RLC. The findings revealed that drivers augmented their behavior such that potential red light violators were deterred from running a red light in the presence of a RLC (40% reduction in RLR). Yang and Najm (2006) analyzed 47,000 RLR records collected from 11 intersections in the City of Sacramento, California, by RLCs. They investigated the correlation between RLR violations and various driver, intersection, and environmental factors. They found that drivers under 30 were the most likely to run red lights; most violators were not speeding at the time of the infraction; and 94% of violations happened within 2 seconds of the light turning red.

Moreover, some studies compared RLR violation rates pre and post camera installation. For example, McCartt and Hu (2014) examined the pre and post effects of RLCs on RLR based on the number of violations. Using a regression analysis, the researchers found a statistically significant reduction in the number of violations occurring 0.5 seconds (39%) and 1.5 seconds (86%) after the lights had turned red. Moreover, the probability of violations at non-camera intersections along the same corridor decreased 14%, 25%, and 63% for 0.5 seconds, 1 second, and 1.5 seconds, respectively, after the onset of red light indicating that the RLCs had a positive impact on increasing the number of stopping decisions.

Some researchers have also studied the changes in driver behavior regarding RLR occurrences after RLCs were removed from the treated intersections (Walden et al. 2011, Porter et al. 2013, Pulugurtha and Otturu 2014). They utilized data from “after the installation” and “after the termination” time periods and showed that RLR violations dramatically increased when the treatments cameras were removed.

There is limited research examining driver’s stopping behavior in the presence of RLCs without a pre-post study. Gates et al. (2014) studied 82 intersections in four regions of the United States, 10 of which had RLCs. Video cameras captured the driver’s behavior of 7,306 vehicles. Their results revealed the following: at RLC intersections, drivers tended to react 5% (0.05

seconds) quicker to a yellow light change when stopping; the deceleration rate was not affected by RLCs; the likelihood of a driver stopping increased by 2.4% with an RLC present; entry time during a red light was reduced by 43% (0.24 seconds) with RLCs; and RLR rates almost doubled at intersections with yellow times less than or equal to 4.5 seconds.

2.1.3 Research on Intersection Operation

Having knowledge of being monitored by cameras, drivers are more likely to brake sooner during the yellow or all-red intervals. This change in driver stopping behavior results in the reduction of the usable amount of yellow time, longer delay and a decline in the intersection capacity. Jha and Weldegiorgis (2014) examined the effect of behavioral change on the use of yellow intervals resulting in a possible reduction in the service capacity of the intersection. They used field data from Baltimore, Maryland for ten RLC and non-RLC intersection pairs. Their findings showed a 2% reduction in capacity at RLC intersections. The capacity reduction scenarios are not addressed in the Highway Capacity Manual (HCM) at present because the research efforts related to this issue are still emerging topics.

2.1.4 Research on Economic Aspects of RLCs

Some of the past studies focused on the economic benefits of RLC programs (Council et al. 2005, Royal 2004, De Leur and Milner 2011, Fleck and Smith 1999, Mohamedshah 2000). They found that since the right-angle (RA) crashes prevented by cameras are more severe and costly than rear-end (RE) crashes, the economic costs from the increase in RE crashes were often offset by the economic benefits from the decrease in RA crashes.

In the presence of enforcement programs drivers adhere to established traffic laws because they realize risk of fines and penalties if they are not in compliance (Wong 2014). The process of

RLR violation fine determination has yet to be examined. The fine is generally pre-determined based on the violation that has been committed. The driver pays a pre-determined monetary fine and/or accepts a predetermined number of violation points; they could also appeal the violation in order to challenge it (Sharma et al. 2007). Little effort has been made to link results, costs, and fines that violators should pay.

Over the past couple of decades, several studies have sought to measure deterrent effects, in the form of lower recidivism and/or crash rates, due to increases in fines (Walter and Studdert 2015, Tavares et al. 2008, De Paola et al. 2013, Redelmeier et al. 2003). For instance, Abay (2014) showed that drivers with one or more demerit points reduced their likelihood of committing a traffic violation by 11 to 20 percent. However, few studies have considered RLR violations and the effects of penalties (e.g. fines, demerit points) used to sanction those programs (Porter et al. 2013, Pulugurtha and Otturu 2014).

Lu et al. (2012) implemented a randomized experiment in China and showed that informing drivers that they were observed committing traffic violations by automatic detection devices deterred drivers from committing the same traffic violation in the future. Reeves and Kreiner (2008) invented a new system for assessing a monetary fine based on the number of vehicles that were impacted as a result of traffic violation. First, a traffic violation is discovered by a violation analyzer. Then, the data (i.e., a traffic violation code number and data representative of the impact of traffic disturbance from data collection sensors) are sent to a penalty calculator to determine the associated fine. The data representative of the impact may include the number of vehicles that were present in the resulting traffic congestion. However, the economic value of those impacts was not investigated in an effort to link them to the appropriate amount of the monetary fine.

One preliminary study, in conjunction with the current study, has been conducted by Wasilefsky et.al (2016). A Monte Carlo simulation model was used to generate a crash probability distribution for a discrete time after red that a vehicle entered an intersection. However, no applicable RLR fine structure was suggested.

2.1.5 Related Research in Alabama

In 1999, a 58 question telephone survey was administered to assess driving behaviors in 10 states including Alabama (Porter et al. 1999). Overall, 5,024 respondents completed the survey; of those 1,017 were concentrated in the remaining 40 states as a comparison group. In this study, self-reported data were collected by surveys. Inspection of the data showed that drivers in Alabama and Texas had the highest rates of running red lights. The researchers have also found that more females in Alabama (58.9%) reported running red lights than females in the remaining 40 states (51.7%). Similarly, Alabama females were more likely to have run one red light in the last 10 intersections (26.8%) than females in the comparison group (19.6%).

A pilot study of the feasibility of using RLCs conducted by the University Transportation Center of the University of Alabama indicates that the severity and risk of RLR crashes are associated with the time vehicle enters the intersection after onset of red (Supriyasilp 2003). The analysis of red light violation data conducted in Tuscaloosa suggested that RLR violation rate ranges from 0.47 to 29.0 per 1,000 vehicles. A general guideline was published in 2014 in order to assist site selection in Alabama (Jones et al. 2015). The purpose of this study was to provide consistent guidance for Alabama Department of Transportation (ALDOT) Region/Division/District Offices as well as local agencies for the implementation of RLCs at signalized intersections.

2.2 Opelika RLC Program

On April 1, 2013, RLCs officially began monitoring traffic at four signalized intersections in Opelika, Alabama. The treated intersections include US 280/Gateway Drive at Pepperell Parkway; Frederick Road at US 280/Gateway Drive; US 280/Gateway Drive at I-85 Off-ramp/Interstate Drive; and West Point Parkway at Fox Run Parkway/Lafayette Parkway/Samford Avenue. Monitored approaches were marked with advance signs, informing approaching motorists that they would be monitored by RLCs (Figure 2.1). The signs used for this purpose meet the requirements specified in the Manual on Uniform Traffic Control Devices (MUTCD 2009).

Figure 2.1 Photo Enforced Sign Used in Opelika

Prior to initiating a RLC program, legal aspects and requirements should be identified. Red light violations enforced by cameras are considered civil offense, rather than criminal citation. Signs are required to be posted at a minimum of five roads entering the city, notifying that red lights are photo enforced (Opelika, Al. Code of Ordinances 2016, Opelika Red Light Safety Act 2011). Before becoming active, the city must have a minimum of 30 days of a public awareness campaign. However, Opelika may move, add, remove, or install decoy installations without needing to notify the public. Opelika determined $60 for the first two violations and $100 for each subsequent one per twelve-month period would be applied. Fines can be waived if a driver can prove that the alleged violation occurred in the following situations: a traffic signal not being properly positioned or not sufficiently visible, the driver was following the direction of a police officer, emergency vehicle was approaching, the vehicle was an emergency vehicle, the vehicle or the license plate was stolen, poor driving conditions (ice, snow, heavy rain) made compliance dangerous, or the person did not own the vehicle at the time of infraction.

2.3 Summary

The literature reviews various aspects of RLCs: behavior, operation, economy and safety:

- Several researchers examined drivers' behavior, however primarily focused on the impact of signal timing in the presence of RLCs. Still, there is limited research examining driver's stopping behavior in the presence of RLCs without a pre-post study.
- The literature review revealed that relatively little is known about the impacts of RLCs on the operation of signalized intersections.
- Little effort has been made to link results, costs, and fines that violators should pay. Considering the controversial nature of RLCs and the increased use of cameras, developing a fine structure that closely reflects the risk a RLR vehicle poses to society is needed.
- Regarding the safety effects of RLCs, numerous studies have been conducted since the first camera was installed in New York City in 1991.

Figure 2.2 summarizes the past findings and Figure 2.3 shows the significance of this research which will make efforts to fill the gap in the literature. In both figures, the size of each colored area indicates the size of literature in that area of study.

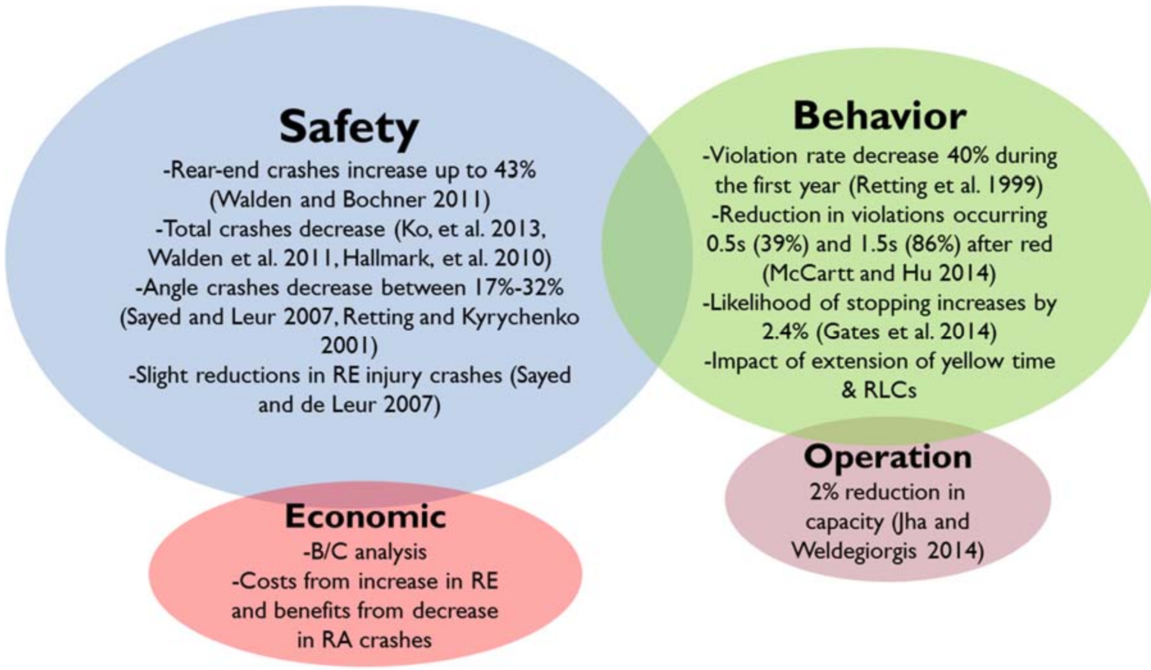

Figure 2.2 Summary Review of the Literature

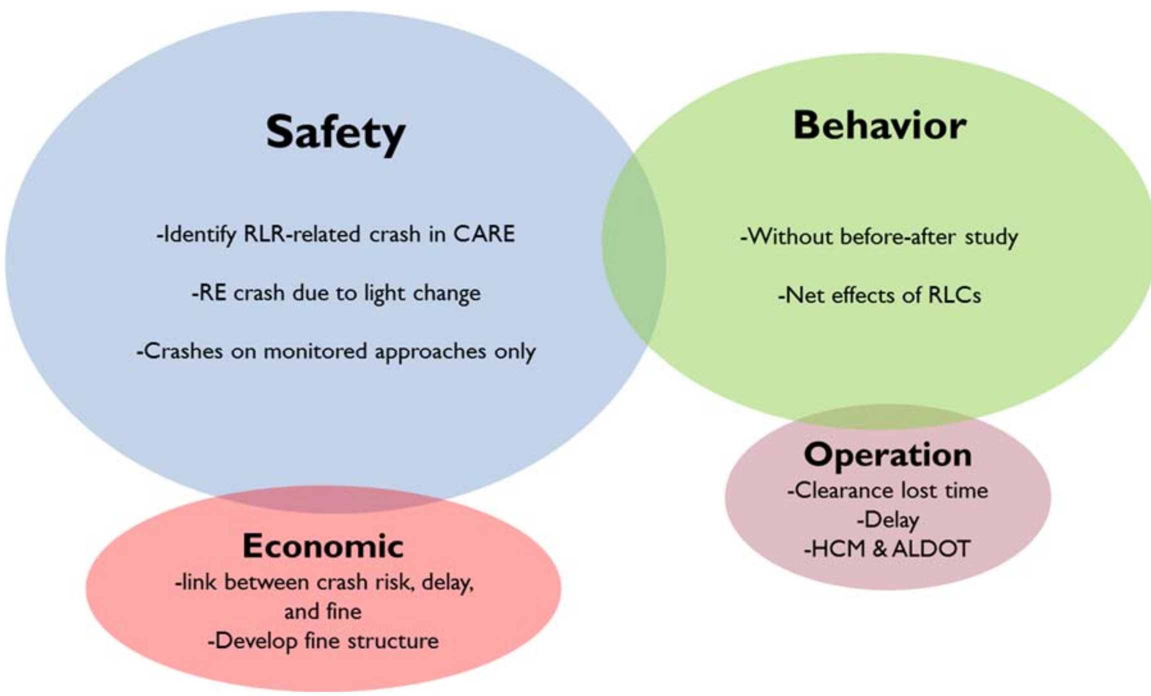

Figure 2.3 Focus Areas of This Study

This research mainly focuses on the effects of RLCs on drivers' behavior change and intersection operations based on field observations and computer simulations. Based on the results, a new fine structure will be developed. Due to limited number of study intersections, the safety evaluation based on four case studies in Opelika may not give a whole picture of safety effectiveness of RLCs in the whole state of Alabama. A more comprehensive statewide safety evaluation is recommended for further study.

CHAPTER 3 EFFECT OF CAMERA ON DRIVER'S BEHAVIOR

3.1 Introduction

At every signalized intersection, drivers from any direction might cross the intersection during a portion of clearance interval (i.e. yellow change interval and subsequent all-red interval[1]). In this study, this portion is referred to as the Used Clearance Time (UCT). When a driver approaches a signalized intersection with a steady yellow signal, he/she is being warned that the right-of-way is about to change from their phase to some other phase with which they will be in conflict. Drivers who cross the stop line and proceed through the intersection after the onset of the red light can be identified by police enforcement or a RLC. To avoid committing violation in the presence of RLCs, some drivers stop abruptly, even if they could have crossed the line legally during the yellow change interval, leading to the reduction in entry time during the clearance interval (Palat and Delhomme 2016, Baratian-Ghorghi et al. 2015a). In the HCM (2010), the UCT is considered to be an extension of the green light and is defined as "*The time, in seconds, between signal phases during which an intersection is still used by vehicles.*" Based on this definition, in this research, UCTs were recorded for 1,613 traffic signal phases at eight intersections with and without RLC, to estimate the amount of clearance time typically used by drivers. A cross-sectional analysis was then conducted to compare the range of actual UCTs for both site groups. Also a total of 2,391

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[1] The period in a signal cycle during which all approaches have a red light indication.

drivers' response data was collected to examine any change in drivers' behavior during the clearance interval.

The method applied in this study is informative for evaluating the effect of RLCs on drivers' behavior even when access to the before RLC data is not available. In the following sections, a description of data collection process is presented, followed by the definitions and variables applied to the current study. Lastly, the quantification and effects of RLCs on drivers' stopping behavior based on the amount of usable yellow time at intersections with and without RLCs is addressed.

3.2. Data Collection

3.2.1 Selection of Intersections

To investigate the effect of RLCs on driver behavior, it is imperative for comparison purposes to gather data at intersections where no RLCs had been installed, and geometric and traffic characteristics are similar to the RLC intersections. For this purpose, four non-RLC intersections, located in the neighboring city of Auburn, were selected. The intersections for inclusion in the comparison group are: Wire Road at Shug Jordan Parkway; East University Drive at Opelika Road; University Drive at East Glenn Avenue; and South College Street at Shug Jordan Parkway. Figure 3.1 shows the location of treated sites (Black) and comparison group (White) and AADT in 2012.

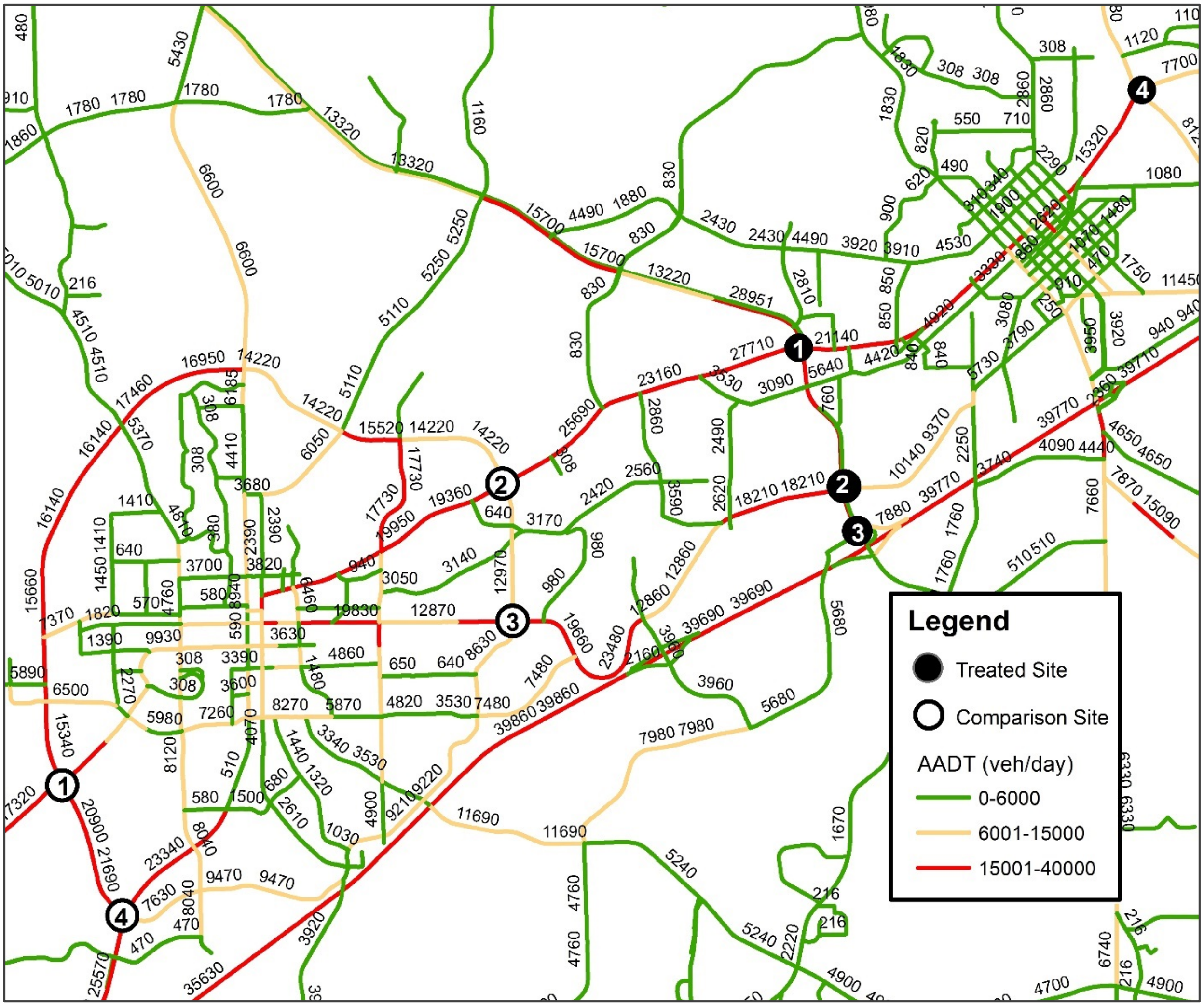

Figure 3.1 Locations of Study Intersections w/ and w/o RLCs

The following data were gathered from ALDOT website (ALDOT 2016), field survey, and Google Street View, to determine the similarity between RLC intersections and non-RLC intersections: Annual Average Daily Traffic (AADT) information, signal timing, speed limit, median type, channelization, and number of lanes.

The eight intersections identified are among the busiest intersections in the cities of Auburn and Opelika. The average posted speed limits for the intersection approaches are 45 mph. Intersection approaches have right- and left-turn lanes. The right turn lanes are separated by channelizing islands, thus right turning vehicles are not under signal control and do not affect the capacity and delay of the intersection. Traffic control signals are actuated at all the studied intersections, and no countdown timers are installed at the study intersection locations. Table 3.1 shows the number of lanes and posted speed limits for the intersection approaches. "1 or 2" for the number of through lanes at the intersection of S College St and Shug Jordan Pkwy indicates that two (major) approaches had two through lanes and the other two (minor) approaches had one thru lane.

Table 3.1 Speed Limit and Geometric Features of the Studied Locations

	No.	Intersection Name	Number of Lanes			Approach Speed Limits (mph)			
			Left	**Thru**	**Right**	**NB**	**SB**	**EB**	**WB**
RLC Intersection	1	Gateway Dr and Pepperell Pkwy	2	2	1	45	45	45	45
	2	Frederick Rd and Gateway Dr	1	2	1	45	45	35	45
	3	Gateway Dr and I-85 Off-ramp	1	2	1	45	45	45	45
	4	West Point Pkwy and Fox Run Pkwy	1	1	1	45	45	35	45
Non-RLC Intersection	1	Wire Rd and Shug Jordan Pkwy	1	2	1	50	40	55	55
	2	E University Dr and Opelika Rd	1	2	1	45	45	45	45
	3	E University Dr and E Glenn Ave	1	2	1	35	45	45	45
	4	S College St and Shug Jordan Pkwy	1	1 or 2	1	45	45	55	35

3.2.2 Crash Data

In the next step, RLR crash data for a 3-year period was compared between RLC and non-RLC intersections to determine if both groups had experienced similar RLR complications before the commencement of the photo enforcement. Crash data were sourced from the Critical Analysis Reporting Environment (CARE) software. CARE is a database that consists of traffic crash reports, designed for crash identification and countermeasure development. A discussion of the details of the data collection process will be described in Chapter 5. More information about this database can be found at studies conducted by Jalayer et al. (2015a) and Baratian-Ghorghi et al. (2016a).

Inspection of Tables 3.2 and 3.3 demonstrates that one intersection in each RLC and non-RLC groups experienced no crash; the other intersections experienced 5 to 8 crashes. Between groups, injury crashes were the same (0, 1, 3, and 3) as well as comparable number of crashes incurring property damage only (PDO). In summary, a total of 18 and 19 crashes occurred at the RLC and non-RLC intersections, respectively, wherein, 11 and 12 were PDO crashes, respectively. Also, a total of seven injury crashes and no fatal crashes were recorded at both sites before RLCs have been installed. This crash analysis supports that the two groups of intersections had similar RLR crash patterns.

Table 3.2 RLR Crashes at RLC Sites-Before Period (April 2010 –April 2013)

Intersection	**Severity**			**Number of crashes**
	PDO	**Injury**	**Fatal**	
Gateway Dr/ Pepperell Pkwy	5	3	0	8
Frederick Rd/Gateway Dr	2	3	0	5
Gateway Dr/I-85 Off-ramp	5	1	0	6
West Point Pkwy/Fox Run Pkwy	0	0	0	0
Total	**12**	**7**	**0**	**19**

Table 3.3 RLR Crashes at Non-RLC Sites-Before Period (April 2010 –April 2013)

Intersection	**Severity**			**Number of crashes**
	PDO	**Injury**	**Fatal**	
Wire Rd/Shug Jordan Pkwy	0	0	0	0
E University Dr/Opelika Rd	4	1	0	5
E University Dr/E Glenn Ave	3	3	0	6
S College St/Shug Jordan Pkwy	4	3	0	7
Total	**11**	**7**	**0**	**18**

3.2.3 Used Clearance Time

Weekday field observations were conducted over a continuous three-hour period from 3:30 p.m. to 6:30 p.m. at eight intersections in Lee County, Alabama. Data collection occurred after the RLCs had been operational for more than one year. The experimenters were positioned in locations hidden from the view of drivers approaching the intersection. Video cameras were placed at a distance from the intersections where both the stop line and signal indications were visible. The following variables: time at which vehicles crossed the stop line during the clearance interval, the number of vehicles crossed, and the number of vehicles stopped, were recorded in the field and after reviewing the videos.

Figure 3.2 provides a description of the data collected. Cases 1 through 4 represent examples of actual situations observed in the field. The x-axis represents the time upon the start of clearance interval, note that time intervals are not scaled. In this example, four vehicles approached an intersection in case 1, three of which crossed the line during the yellow time (denoted by an arrow), while the last one stopped before the light had turned to red (denoted by an X). Case 2 shows a situation wherein both vehicles approaching the intersection chose to stop rather than cross. In case 3, two vehicles reached the intersection; one went through it just after the light had turned red, during the all-red interval, and the other ran the red light after the termination of the clearance interval. In case 4, no vehicles arrived during the yellow and all-red times.

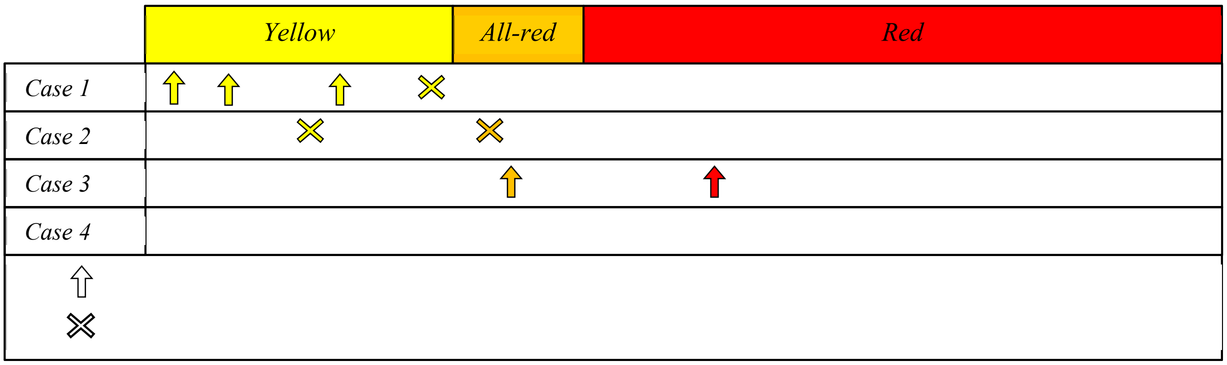

Figure 3.2 Data Collection Examples

Data were collected separately for each approach and each signal phase. For instance, the intersection of Gateway Drive at Pepperell Parkway has eight clearance intervals: four for the through traffic and four for the left turns. Table 3.4 presents the signal timing and number of crossings for all intersections. The yellow and all-red time duration did not change during data survey time periods. Time data was recorded to a hundredth of a second and then rounded to a tenth of a second.

Table 3.4 Signal Timing and Crossing Data at each Intersection

	Intersection Name	Number of Crossing	Number of usable phases	Yellow Time (s)	All-red Time (s)
RLC Intersections	Gateway Dr/Pepperell Pkwy	439 (174*)	285 (126*)	4.5 (3.0*)	1.5
	Frederick Rd /Gateway Dr	808	465	4.5	1.5
	Gateway Dr/I-85 Off-ramp	162	140	3.8	2.0
	West Point Pkwy/Fox Run Pkwy	218	164	4.5	1.5
Non-RLC Intersection	Wire Rd/Shug Jordan Pkwy	121	95	4.5	2.1
	E University Dr/Opelika Rd	317	210	4.6	1.7
	E University Dr/E Glenn Ave	64	51	4.2	1.5
	S College St/Shug Jordan Pkwy	88	77	4.9	1.3

Note: *Left-turn phase

No vehicles crossed the stop line during the clearance intervals for many phases. Approaches were monitored for 300 ft. away from the intersection to check if any vehicle was present during the yellow change interval. In this case, one of two following scenarios was possible:

1. At least one vehicle was approaching the intersection but stopped (as in phase 2 in Fig. 3.2), or
2. No vehicle was approaching (as represented in phase 4 of Fig. 3.2).

The first case was coded as UCT=0 indicating zero seconds of clearance interval was used whereas the second case was not analyzed because it constituted a non-event where the clearance interval had not been tested by any driver.

3.3 Data Analysis and Results

In the first step, the percentages of vehicles stopping or crossings for both intersection groups are found and a Chi-Square test is used to determine if there is a significant difference between the two samples. The level of significance is 0.05 and the degrees of freedom is 2. The null hypothesis assumes that there is no difference between RLC and non-RLC intersection. If the null hypothesis is accepted there would be no significant difference in drivers' behavior between two groups of intersections. Next, a cross-sectional analysis is conducted to compare the range of actual UCTs for both intersection groups.

3.3.1 Distribution of Driver Responses

Table 3.5 presents the percentages of vehicles stopping or crossings during each phase (i.e. yellow, all-red, and red). At RLC intersections, 32% of drivers chose to stop rather than to cross, 65% crossed the stop line while the signal was yellow, and 3% ran the red light. At non-RLC intersections, fewer drivers tended to stop (approximately 16%) as compared to the RLC sites

(32%). The majority (82%) of vehicles crossed the stop line during the yellow intervals, and only 2% of drivers entered the intersection after the red light came on.

Table 3.5 Drivers Population at Each Phase

	Percent of stops	**Percent of yellow crossings**	**Percent of red crossings**	**Total**
RLC	32.2 (855) *	64.7 (1,719) *	3.1 (82) *	100 (2,656) *
Non-RLC	15.9 (111) *	82.1 (575) *	2.1 (15) *	100 (701) *
X^2	**7.8**			

Note: * indicates the sample size

For two degree of freedoms the critical value from a Chi Square table is $X^2_{.05} = 5.991$. Since the calculated value (i.e., 7.8) is greater than the critical value, and the p-value is smaller than 0.01, the null hypothesis that there is no difference in driver's behavior between RLC and non-RLC intersections is rejected. These results indicate differences in driver behavior such that many drivers at non-RLC sites chose to proceed on the yellow signals and avoid waiting for another cycle.

Figure 3.3 presents the time of entry for 2,391 vehicles with a summary of a set of bivariate data (percentage of crossings vs. the time into clearance interval) at intersections with and without RLCs. The horizontal axis shows half-second time increments following the onset of the yellow light.

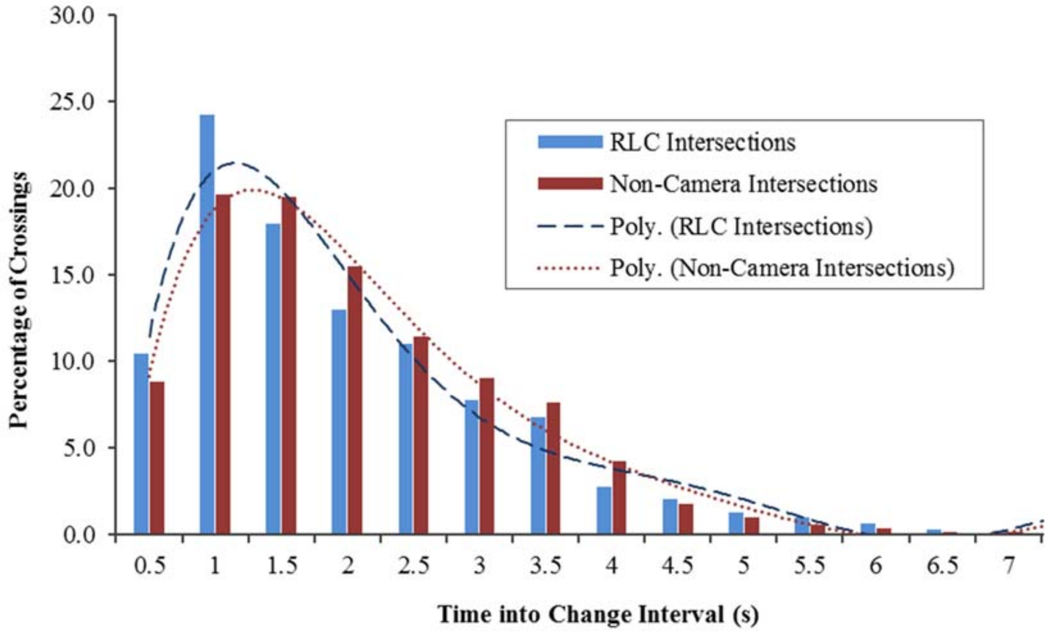

Figure 3.3 Percentage of Crossings vs. Time into Yellow/Red Interval[2]

Figure 3.3 indicates that both RLC and non-RLC intersections are positively skewed resulting in a decrease in crossing as time increases. However, at the shortest intervals, there are more crossings at RLC intersections compared to the non-RLC intersections. Specifically, 35% of drivers entered the intersection within 1 second after the start of yellow at RLC intersections, while less than 30% of drivers used this time at non-RLC intersections. The tendency of the observations falls within the first second of yellow time at RLC intersections, which might be attributed to avoiding RLR violation where drivers are monitored by a RLC. Thereafter, this trend reverses such that non-RLC intersections have a higher percentage than RLC intersections as time change interval increases in the yellow indication time. As can be noted from Figure 3.3, the

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[2] Equation for RLC intersections is: y = -0.0003x6 + 0.015x5 - 0.3301x4 + 3.605x3 - 20.054x2 + 49.065x - 20.863, and for non-RLC intersections is: y = -0.0002x6 + 0.0095x5 - 0.2154x4 + 2.4773x3 - 14.834x2 + 39.804x - 18.077

median and mean of crossing time at RLC intersections are smaller than non-RLC intersections. Furthermore, descriptive analyses showed that the median crossing time is 1.40 seconds at RLC intersections and less than 1.58 seconds at non-RLC intersections, meaning that 50% of drivers will use 1.58 seconds of yellow if no RLC is present, while they will use only 1.40 seconds or less of yellow if a RLC is monitoring them.

In the next step, the statistical significance (p-value) was reported. A between-groups t-test examined whether or not there was a statistically significant difference between RLC intersections and non-RLC intersections. To this end, 1,801 UCTs recorded for camera intersections and 590 for non-RLC intersections were used. The mean crossing time was found to be only 0.07 second shorter as a result of RLC installation (i.e., 1.74 seconds at RLC intersections and 1.81 seconds at non-RLC intersections). This difference, however, is not statistically significant as the two-tailed p-value equals 0.29 ($df = 2389$, $t = 1.0482$).

3.3.2 Used Clearance Time Estimation

The usage of yellow change interval during each phase (i.e. time into yellow/red for the last vehicle) was recorded in the field. A cross-sectional analysis compared the range of actual UCTs for both intersection groups. To do so, first, a descriptive analysis provided the minimum and maximum UCT values, as well as the means and the standard deviations for each intersection. Table 3.6 shows the detailed UCT results. As can be noted from the results, the minimum time of zero indicates that the yellow time was not used by drivers in at least one phase. As such, a maximum UCT value greater than the yellow intervals indicate that at least one vehicle ran the red light at each intersection.

Note that left turns and through movements have different clearance interval times at the first RLC intersection (i.e., 4.5 seconds for left turns and 6 seconds for through movements) as was shown in Table 3.4. In Table 3.6, the average clearance interval (i.e., 5.5 seconds) was calculated based on a weighted average method ((285×6.0+126×4.5)/ (285+126) ≈ 5.5 seconds).

Table 3.6 UCT at each Intersection

	Intersection	Clearance Interval	UCT (s)			
			Mean	**Min**	**Max**	**Std.**
Camera Intersections	Gateway Dr and Pepperell Pkwy	5.5	1.1	0	6.0	1.3
	Frederick Rd and Gateway Dr	6.0	1.5	0	6.0	1.6
	Gateway Dr and I-85 Off-ramp	5.8	0.9	0	5.8	1.3
	West Point Pkwy and Fox Run Pkwy	6.0	1.1	0	5.1	1.2
	Overall	**5.8**	**1.1**	**0**	**6.0**	**1.4**
Non-camera Intersections	Wire Rd and Shug Jordan Pkwy	6.6	1. 7	0	5.9	1.4
	E University Dr and Opelika Rd	6.3	1.7	0	6.3	1.4
	E University Dr and E Glenn Ave	5.7	1.5	0	4.7	1.1
	S College St and Shug Jordan Pkwy	6.2	1.6	0	5.6	1.3
	Overall	**6.2**	**1.6**	**0**	**6.3**	**1.4**
	***p*-value**		**<0.001**	**-**	**-**	**-**

In the next step, both the statistical significance (*p*-value) and substantive significance (effect size) were reported. A between-groups *t*-test examined whether or not there was a statistically significant difference between RLC intersections and non-RLC intersections. To this end, 1,180 UCTs recorded for camera intersections and 433 for non-RLC intersections were used. The *t*-test results revealed a statistically significant difference between the UCT values of the two groups (df = 1,611, t = -5.499, and p-value $\leq$ 0.001), indicating that the driver stopping behavior changes in the presence of RLCs. Furthermore, the data in Table 3.6 reveal that the average UCT is 1.1 seconds at RLC intersections, compared to an average of 1.6 seconds at non-RLC intersections. Therefore, the UCT is 0.5 seconds longer for non-camera intersections than for RLC intersections.

Additionally, the effect size calculation expresses the magnitude of the difference between groups (Sullivan and Feinn 2012). For two independent groups, effect size was measured by the standardized difference between two means from Equations 1 and 2.

$$\text{Cohen's } d = (M_1 - M_2) / \sigma_{pooled} \tag{1}$$

$$\sigma_{pooled} = \sqrt{[(\sigma_1^2 + \sigma_2^2) / 2]} \tag{2}$$

Where Cohen's d is the effect size index, M is the mean, and σ is the standard deviation. In this study, Cohen's term d was 0.36 indicating a moderate effect size. Cohen (1992) classified effect sizes as small ($d < 0.2$), medium ($d = 0.5$), and large ($d \geq 0.8$). For an effect size of 0.36, the mean of group 2 (Non-RLC intersections) is at the 64th percentile of group 1 (RLC intersections); thus, a vehicle at non-RLC intersections with the average UCT would have a higher UCT than 64% of the vehicles at RLC intersections (Sullivan and Feinn 2012). As such, it can be concluded that the difference between the groups is statistically and practically significant.

3.4 Summary and Discussions

As demonstrated from past studies, RLCs influence driver behavior, generally leading to fewer crashes. To avoid RLR violations, some drivers may stop abruptly, even though they might have had sufficient opportunity to cross the stop line before the onset of red light. The awareness of being monitored by RLC impacts driver behavior such that drivers are more likely to brake during clearance intervals. This change in behavior results in the reduction of the usable amount of yellow time and a decline in intersection capacity. This study introduced a method for quantifying the impact of RLCs on the UCT by applying a cross-sectional comparison of two groups with RLCs and without them.

Data were collected during the busiest hours of the day, so that, the maximum possible intersection traffic volume was used during the field study. The results of this study also support previous findings that fewer drivers (here is 16%) run yellow/red lights at RLC intersections than at non-RLC intersections.

The results obtained in this study revealed the following: the likelihood of a driver stopping increased at double in the presence of a RLC; drivers took half a second less to cross RLC intersections; drivers behaved in a less risky manner at RLC sites and entered within the first second of the yellow interval; and the number of vehicles passing through intersections decreases as the time elapsed increased after the yellow indication.

Note that the effect on the UCT may vary in different jurisdictions, depending on intersection characteristics or the RLC program implemented. Although efforts were made to identify and compare intersections with similar characteristics (e.g. signal timing; traffic volume; number of thru, left, and right lanes; type and number of crashes), the average clearance interval duration at non-camera intersections was 0.4 longer than that at RLC intersections. Hence, it is recommended to further investigate the possible effect of clearance interval duration on UCT. Furthermore, the RLC intersections and non-RLC intersections were located in two different cities (i.e., Opelika and Auburn, respectively). Since the city of Auburn is a college town, most drivers in this city are young students. Therefore, driver type might be considered when studying driver behavior in response to the light change. In conclusion, in order to make the best estimation of the UCT change resulting from photo enforcement programs, a before-and-after study is recommended to be conducted at intersections targeted for RLC installation. A comparison of UCT values before and after RLC program implementation will clarify the actual effect of the RLC on driver stopping behavior.

Furthermore, similar and ongoing studies should be conducted after the camera installation date, as it is expected that as the time passes, the program will be more publicized and driver behavior will continue to change in response to the newness or familiarity of the equipment. As a potential consequence, a greater number of drivers may exercise caution when approaching well-established RLC intersections—especially those who have received a previous citation—which will potentially reduce the UCT in the future.

CHAPTER 4 EFFECT OF CAMERA ON INTERSECTION OPERATION

4.1 Introduction

RLCs can influence the operational aspects of the intersection by potentially reducing the amount of usable yellow time, which in turn, may increase intersection delay and lost time, and reduce the capacity. This issue is not addressed in the HCM (2010), and no separate model is provided to estimate the capacity of intersections with RLC. Using conventional methods for estimating the capacity without considering the effect of potential lost times would result in overestimation of the capacity.

Field observations, conducted at eight intersections described in Chapter 3, provided data to investigate the impact of RLCs on the operation of signalized intersections. In the following sections the definition of clearance lost time (CLT) in HCM and the data required to estimate its value are identified. CLT for each intersection with and without RLC was ascertained and compared with the default values specified in past studies. Recommendations were developed based on the analysis results on adjustment to the default value of CLTs. In the next phase of this study, change in delay, resulting from a change in driver behavior, was estimated using the Highway Capacity Software (HCS).

4.2 Methodology

4.2.1 Clearance Lost Time

Every signalized intersection is not used by traffic during two time periods of each phase: a portion of the beginning of the green period and a portion of the yellow change interval plus the all-red interval. The first is called the start-up lost time and the latter is the CLT. The sum of these lost times for each movement is used to estimate the capacity and delay for each movement and the overall intersection. In HCM, signalized intersection capacity (c_i) is determined by Equation (1):

$$c_i = S_i \frac{g_i}{C} \tag{1}$$

Where; *i* represents the movement number, g_i denotes the effective green for the movement *i*, S_i represents the saturation flow rate, and *C* is the cycle length. To find the effective green, the following equations are provided in HCM (2010):

$$g_i = G_i + Y_i - (l_1 + l_2) \tag{2}$$

$$Y_i = y_i + ar_i \tag{3}$$

$$l_2 = y + ar - e \tag{4}$$

Where; G_i is the green time, Y_i denotes the clearance interval, y_i is yellow change interval, l_1 is the start-up lost time, l_2 denotes clearance lost time (CLT), *ar* denotes all-red time, and *e* represents extension of green or the UCT. Figure 4.1 demonstrates each of these parameters.

Figure 4.1 UCT and CLT in One Cycle

The longer CLT results in less effective green time and the lower capacity (*c* from Equation 1). The HCM defines CLT as "*The time, in seconds, between signal phases during which an* *intersection is not used by any critical movements*" and a default value of 2 seconds CLT for each phase. ALDOT's Traffic Signal Design Guide and Timing Manual (UTCA 2007), on the other hand, determines CLT to be half of the yellow interval plus the entire all-red interval.

In this chapter, the term CLT is used to compare the real-world data with the CLTs proposed by ALDOT's manual and the HCM.

4.2.2 Intersection delay

Delay at signalized intersections is associated with the lost time for road users. Delay in the HCM is defined as the difference between the travel time actually experienced and the time it would take the vehicle if traveling at the maximum permitted speed.

To quantify the impact of RLC on intersection delay, HCS was used. Traffic demand also plays an important role in the amount of delay. Ten test scenarios were developed for each site. Each scenario represents a different degree of traffic saturation with or without treatment. The volume to capacity (v/c) ratio, derived from the simulation output, was also used to refer to the degree of saturation. Based on the Institute of Transportation Engineers Signal Timing Manual (ITE 2009): "*A v/c ratio less than 0.85 generally indicates that adequate capacity is available and vehicles are not expected to experience significant queues and delays. As the v/c ratio approaches 1.0, traffic flow may become unstable, and delay and queuing conditions may occur. Once the demand exceeds the capacity (a v/c ratio greater than 1.0), traffic flow is unstable and excessive delay and queuing is expected. Under these conditions, vehicles may require more than one signal cycle to pass through the intersection*."

4.3 Data Analysis and Results

In the following sections, the effect of RLC on intersection operation in terms of clearance lost time and delay is quantified.

4.3.1 Effect of RLC on CLT

It was found from the previous Chapter's results that installing RLC can reduce the UCT by 0.5 second, in other words:

$$UCT_{rlc} = UCT_{non-rlc} - 0.5 \tag{5}$$

The sum of UCT and CLT is constant and equal to the clearance interval, meaning that CLT has an opposite effect on the intersection operation than UCT. Using Equations (4) and (5) it can be concluded that:

$$CLT_{rlc} = y + ar - UCT_{rlc} = y + ar - UCT_{non-rlc} + 0.5 = CLT_{non-rlc} + 0.5 \tag{6}$$

Equation (6) indicates that RLC installation at an intersection has the potential to increase the lost time by 0.5 second. CLT is also used to calculate the capacity of the intersection, as was shown in Equations (1) through (3). As the CLT becomes longer after the treatment being applied, the effective green (g_i) becomes shorter by the same amount.

4.3.2 Clearance Lost Time Values

A total of 1,613 cycles and a total of 2,391 drivers' responses to clearance intervals, from the previous chapter, were used to estimate the CLT at both intersection groups. Table 4.1 presents the comparison results among CLTs calculated by the HCM 2010, ALDOT method (UTCA 2007), and the actual CLT measured in the field. The results indicate that there is a 2.7 seconds difference between HCM default CLT and field data, and an average 1.0 second difference between ALDOT method and the field data at intersections with RLCs. With regards to the intersections without cameras, the deviations from the default values in HCM and ALDOT manual are 2.6 seconds and 0.7 seconds, respectively.

Table 4.1 Relative Changes in Clearance Lost Times

Intersection	Ave. Yellow Interval	Ave. ar Interval	Ave. CLT			Deviation from HCM	Deviation from ALDOT
			Field	HCM	ALDOT		
RLC	4.2	1.6	4.7	2	3.7	2.7	1.0
Non-RLC	4.6	1.7	4.6	2	4.0	2.6	0.7

4.3.3 Intersection Delay Increase

HCS was used to simulate RLCs in two situations (1) with considering the treatment and (2) without considering the treatment. Also, five different degree of traffic saturation have been modeled for each intersection. Finally, forty scenarios have been tested (4 intersections, 2 treatment type, and 5 saturation condition) to measure the intersection delays in seconds per vehicle. In simulating intersections with and without RLCs, the value for the "extension of green", the same as UCT in this study, was derived from Table 3.6 and entered into the software. Table 4.2 shows the values of UTC used in HCS.

Table 4.2 Extension of Green at RLC Intersections

Intersection	Extension of Green (s)	
	with considering RLC	without considering RLC
Gateway Dr and Pepperell Pkwy	1.1	0.6
Frederick Rd and Gateway Dr	1.5	1.0
Gateway Dr and I-85 Off-ramp	0.9	0.4
West Point Pkwy and Fox Run Pkwy	1.1	0.6

Figure 4.2 illustrates the final results derived from the HCS outputs. The vertical axis is the change in delay time and the horizontal axis is v/c ratio. As indicated by this figure, the

presence of RLCs increases the delay. This increase is 0.5 second per vehicle for undersaturated conditions and can be as much as 12 seconds for oversaturated conditions.

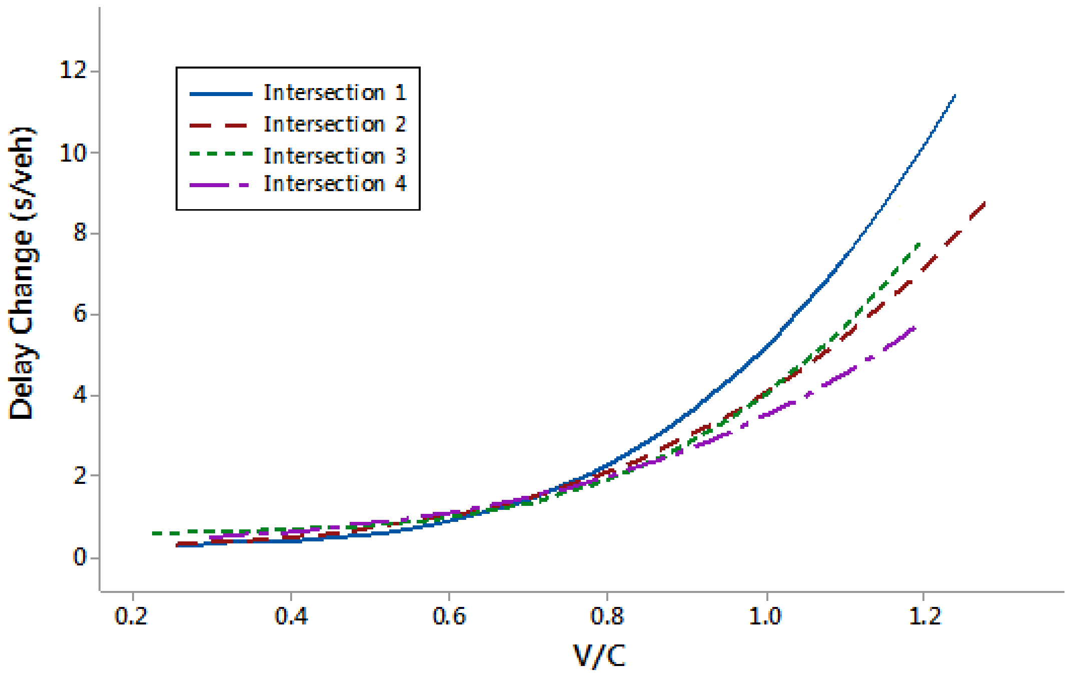

Figure 4.2 Intersection Delay Increase3

4.4 Conclusion

This study examined the effect of behavioral changes on the utilization of yellow intervals resulting in a possible reduction in intersection service capacity. A method was presented to quantify the impact of RLCs on CLT by a cross-section comparison for two groups of intersections with and without RLCs.

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[3] Int.1 fitted line: Delay Change = 2.927 v/c – 9.48 v/c^2 + 11.76 v/c^3 , R-Sq= 99.1%
Int.2 fitted line: Delay Change = 4.544 v/c – 11.41 v/c^2 + 10.92 v/c^3 , R-Sq= 99.4%
Int.3 fitted line: Delay Change = 1.773 v/c – 3.75 v/c^2 + 6.043 v/c^3 , R-Sq= 98.4%
Int.4 fitted line: Delay Change = 2.131 v/c – 3.178 v/c^2 + 4.544 v/c^3 , R-Sq= 99.7%

As the HCM and the ALDOT Traffic Signal Design Guide and Timing Manual take different approaches to estimate the CLT for capacity analysis of signalized intersections, an adjustment factor was found to be necessary for considering the impact of RLCs. The results showed that the actual mean CLT at camera-equipped intersections is about 2.7 seconds longer than the default value specified in the HCM and about 1.0 second longer than one estimated by ALDOT method. With regards to the intersections without cameras, the deviations from the default values in HCM and ALDOT manual are 2.6 seconds and 0.7 seconds, respectively. The analysis results reveal that both the HCM and ALDOT Manual methods estimated a shorter CLT and thus may overestimate the intersection's capacity if using the default values. The ALDOT Method gives a better estimate of the CLT as it took the specific signal timing plan at each intersection into consideration.

In the second step, the concurrent effect of traffic conditions and RLC treatment was investigated using HCS software to simulate all treated sites under different saturation conditions, assuming treatment was/was not implemented. The findings suggested that the more saturated the conditions, the greater the delay incurred by RLCs. This is logical, as the saturation rate increases the number of vehicles reaching the intersection during the light change interval increases as well, and because each of these vehicles experience an additional delay, imposed by RLC, the total intersection delay increases. In addition, as the condition is more saturated, queues on the approaches keep growing. A vehicle which stops during the light change at the RLC intersection, adds the length of the queue and imposes additional delay to other vehicles in queue too. The effect of saturation flow rate on the intersection delay has also been studied by Dion et al. (2004) and found the same results.

CHAPTER 5 EFFECT OF CAMERA ON CRASH EXPERIENCE

5.1 Introduction

RLR violations and RLR crashes are two general measures that could be used to quantify the effect that RLC have on safety (McGee and Eccles 2003). Safety consequences of RLCs are known to be significant. RA crashes, the principal type of crash associated with RLR, are expected to decrease, while additional RE crashes might occur due to changes in driver behavior (Retting and Kyrychenko 2002). In this chapter, a complete process of collecting RLR crash data is explained. Crashes were analyzed for 36 months preceding camera enforcement (April 2010- March 2013) and for 30 months of enforcement (April 2013- September 2015). A before-and-after analysis and an Equivalent Property Damage Only (EPDO) method was applied in order to verify if treatment was effective to reduce crashes and severities.

5.2 Data Collection

Crash data were collected using Critical Analysis Reporting Environment (CARE). CARE electronic format and hardcopies of target crashes were collected for 66-month period from the ALDOT crash database. Link-node maps were also reviewed in order to link the crash data to the given intersections. Other information was collected on field including geometric elements, signal timing, and signs.

Research on evaluating the safety effectiveness of RLC showed its favorable (i.e. prevention of RLR) and unfavorable (i.e. sharp braking maneuvers) effects. The consequence of these effects could be a decrease in RLR crashes occurring in the physical area of intersection, and an increase in RE crashes which occur on the approach queue. In this research, both types of crashes are taken into account. Figure 5.1 shows the situations when a RLR crash or a RE crash might occur. Figures 5.1 (a) to 5.1 (c) illustrate possible RLR crashes at a signalized intersection with different manners of crash: RE, RA, and angled, respectively, where the crash involves a violating vehicle (shown in red) and an adjacent vehicle proceeding through the intersection legally on a green signal display (shown in green). Figure 5.1 (d) illustrates a RE crash occurring in the queue, when the lead vehicle (green) suddenly stopped due to a light change and was then rear ended by another vehicle.

5.2.1 RLR Crash

A crash has to meet a set of criteria to be considered as a RLR crash. For example, the at-fault vehicle has to run a red light before a crash occurs and the crash location has to be recorded as "at intersection." CARE 10 makes it possible to generate and use filters to reduce the range of data to be analyzed. After inspecting all the variables in the database eight relevant variables were identified:

1. The "Ran Traffic Signal" variable from the "Primary Contributing Circumstance" category.
2. The "Ran Traffic Signal" variable from the "CU Contributing Circumstance" category.
3. The "Traffic Signals" variable from the "CU Traffic Control" category.
4. The "No" variable excluded from the "CU Traffic Control Functioning" category.
5. The "Under the Influence of Alcohol/Drugs" variable excluded from the "CU Driver Condition" category.
6. The "On an Emergency Call" variable excluded from the "CU Emergency Status" category.
7. The "In Police Pursuit" variable excluded from the "CU Emergency Status" category.

8. The “Yes, Crash Occurred at an Intersection” variable from the “At Intersection” category.

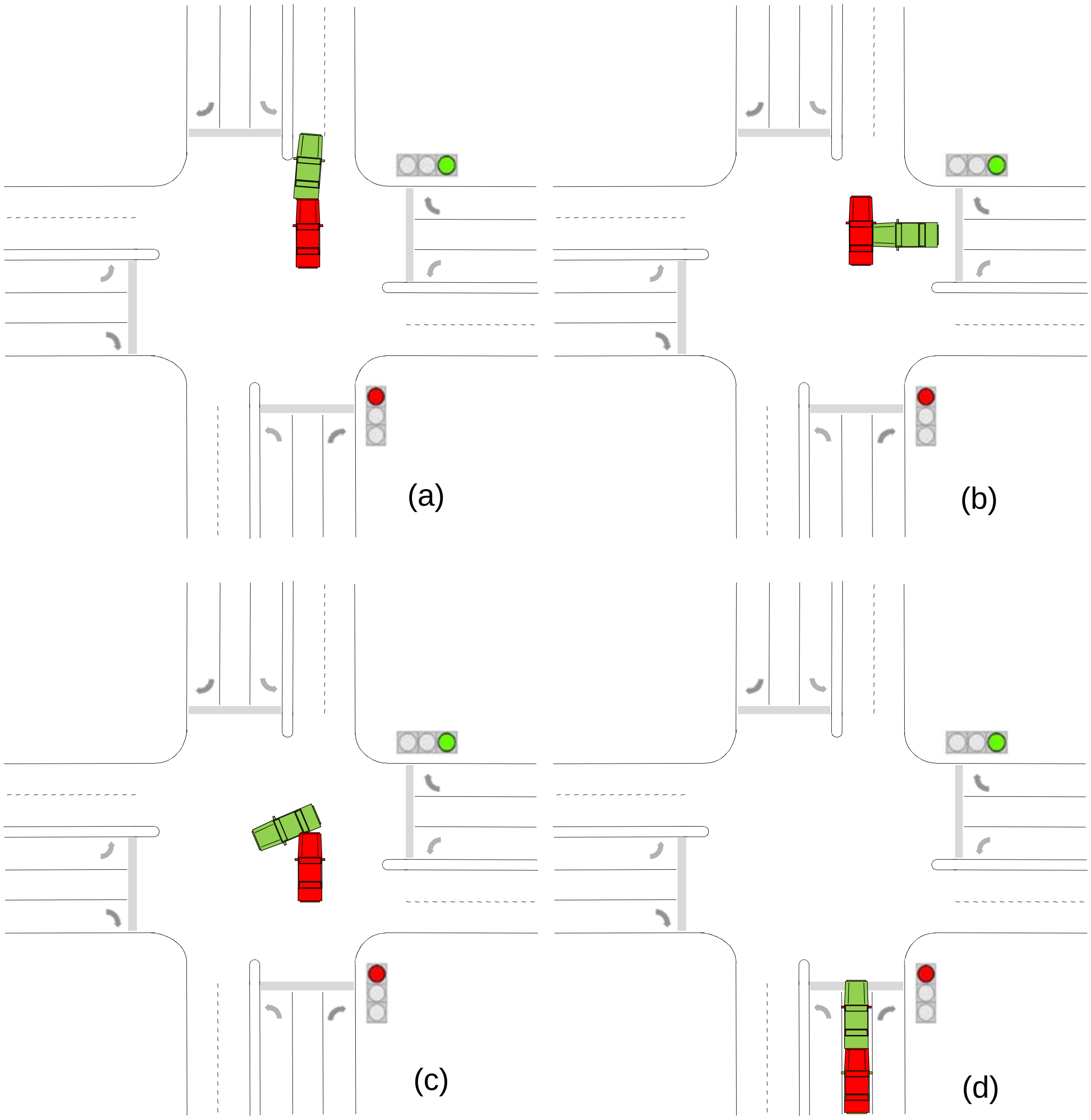

Figure 5.1 Crash Occurance at Signalized intersection
a) RLR crash-RE type b) RLR crash-RA type c) RLR crash-angled type d) RE crash in queue

Causal Unit (CU) denotes the at-fault vehicle in a crash. Crash identification in CARE requires creating filters using AND/OR logic. Variables in steps 1 and 2 were combined by OR logic. The result was then merged with the combination of variables defined in steps 3 through 8 by AND logic. In order to confirm that the crashes were caused due to a vehicle running the red light, those crashes that occurred due to driving under the influence of drugs or alcohol and crashes related to emergency vehicles or in police pursuit were filtered out. This was done through steps 6 and 7. The CARE "create filter" work screen is shown in Figure 5.2. More information about how to create a filter is provided in the Care Filter Catalog (2010).

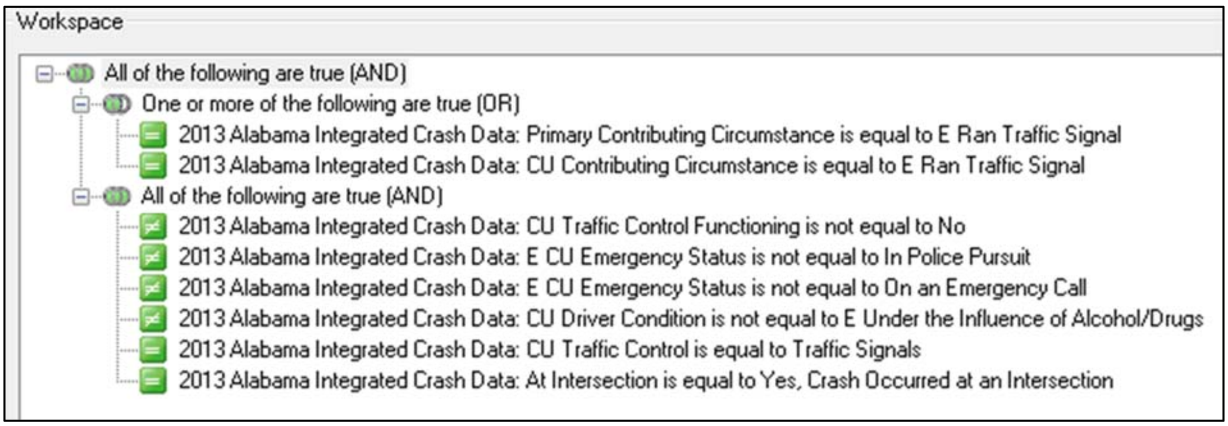

Figure 5.2 Red-Light-Running Crash Filter

To properly establish the relationship between crashes and enforcement program, efforts were made to assign at-fault vehicles to the given approach. This was done by controlling direction of travel and the approach street for every crash. The monitored approaches at RLC intersections are as follows:

Site 1: At the intersection of Gateway Drive and Pepperell Parkway, there are three RLCs facing northbound lanes of Gateway Drive, eastbound lanes of Pepperell Parkway, and westbound lanes of Pepperell Parkway.

Site 2: Traffic on the northbound lanes of Gateway Drive and the eastbound lanes of Frederick Road are subject to being monitored by two RLCs located at the intersection of Gateway Drive and Frederick Road.

Site 3: There are two RLCs located at the intersection of Gateway Drive and Interstate Drive, focused on the northbound and the southbound lanes of Gateway Drive.

Site 4: There is only one RLC at the intersection of Fox Run Parkway and Samford Avenue facing the westbound lane of Samford Avenue.

Figure 5.3 shows the monitored approaches at four RLC intersections.

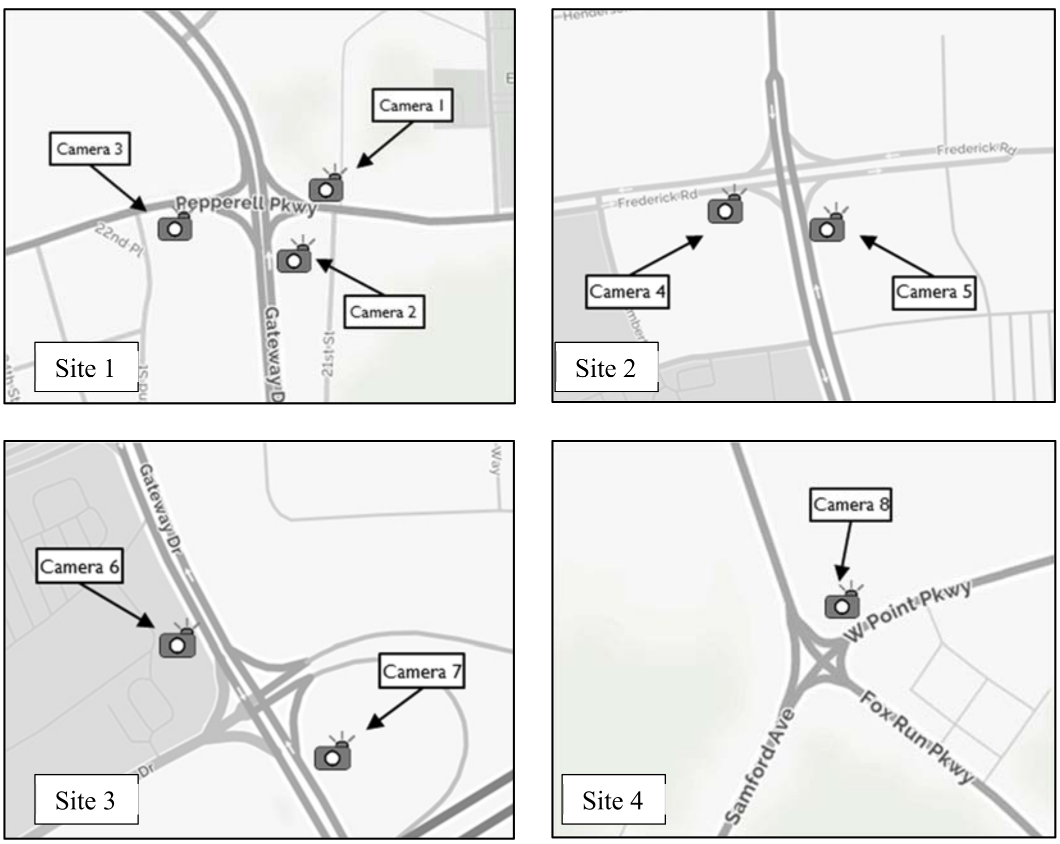

Figure 5.3 Positions of the RLCs at Treated Intersections

Regarding the RE crashes, many studies have considered all RE crash types at a signalized intersections assuming that they had occurred due to changes in driver behavior with regard to stopping for red lights. However, this assumption is not acceptable for two reasons: (1) not every RE crash is due to stopping for red light, and (2) not every approach is monitored at RLC intersections.

5.2.2 RE Crash

There is a concern that RE crashes between vehicles approaching the intersection will increase after the treatment being implemented. These crashes involve a cautious motorist who stops on seeing the yellow/all-red display, causing the following vehicle, not anticipating the stop, to hit the lead vehicle from behind. In order to identify RE crashes related to the light change, the following steps were taken. First, all RE crashes were defined by means of CARE variables, as the "Rear end (front to rear)" variable was selected from the "Manner of Crash" category. Next, each of the crash reports were manually reviewed to determine which crashes were truly the light-change related. The RE crash hardcopies were collected from the Opelika Police Department. Finally, the direction of travel was controlled to consider crashes on monitored approaches only. 530 crash records were identified as not being light-change related or not on the monitored approach, even though the manner of crash was classified as RE. The crash records that were not true target crashes were removed from the sample, leaving 17 crash records for use in the investigation.

Figure 5.4 shows an example of diagram and narrative for a RE crash occurred on the south-bound approach at the intersection of Frederick Road and Gateway Drive.

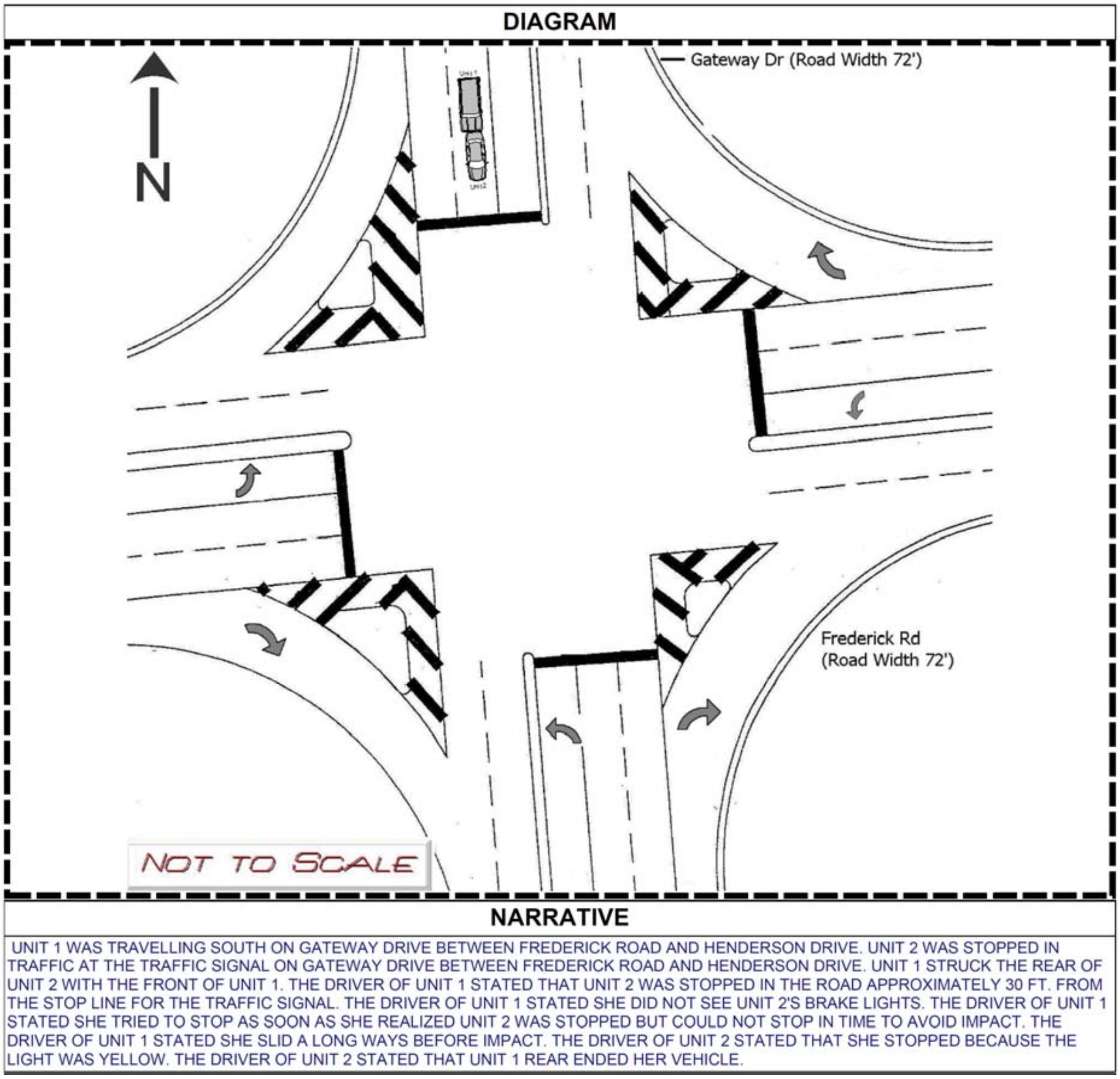

Figure 5.4 A Sample of Diagram and Narrative for a RE Crash

A review of the narrative revealed that the front vehicle has stopped due to the light change, then was rear-ended by a following vehicle. This action might be seen more frequently at RLC intersections. In the last step, the direction of travel and the approach street were controlled for every crash to make sure the crash occurred on a monitored approach.

5.2.3 Accuracy of Database

The quality of crash data will directly affect the quality of any findings of the evaluation. Errors can occur in transferring data from the police report into a computer database (McGee and Eccles 2003). To confirm the accuracy of data, a sample of 100 RLR crash hardcopies of seven months were reviewed. One hundred percent of these crashes were then confirmed to be correctly coded in CARE with respect to crash characteristics (severity, manner, type, contributing circumstance, location, and time).

5.3 Methodology

5.3.1 Before-and-After Analysis

The before-and-after method is a widely used approach by State DOTs for investigating the safety effects of a countermeasure. It is based on the assumption that if no improvement has been made, the expected number of the crashes would remain the same as in the before period (Gan et al. 2005). To apply this method, two pieces of information are needed: crash data before and after a treatment implementation, and the date that the treatment was implemented.

Assume that K(j) is the number of observed crashes in before period for site j, and L(j) is the number of observed crashes in after period for that site. A ratio between the time after and the time before a treatment is calculated as $r_d(j)$ for each site. The number of expected crashes in the after period given there was no RLC for that site would be $r_d(j) \times K(j)$. The variance of the expected crashes would be $r_d(j)^2 \times K(j)$. The effect of the RLC on safety is calculated using the expected and actual number of crashes, or π and λ, respectively (Hauer 1997). These are calculated as:

$$\hat{\lambda} = \sum L(j) \tag{1}$$

$$\hat{\pi} = \sum r_d(j) \times K(j) \tag{2}$$

$$VAR\{\hat{\lambda}\} = \sum L(j) \tag{3}$$

$$VAR\{\hat{\pi}\} = \sum r_d(j)^2 \times K(j) \tag{4}$$

Where $\hat{\lambda}$ is the number of crashes in the after period with RLC; $\hat{\pi}$ is the number of crashes in the after period given there was no RLC installed; and $VAR\{\hat{\lambda}\}$, $VAR\{\hat{\pi}\}$ are the variances, respectively. Two measures of effectiveness for RLCs on safety used in this analysis are δ, the reduction in the expected number of crashes, and θ, the index of effectiveness. θ is a ratio of what safety was with RLC to what it would have been without RLC. The estimates for effectiveness can be calculated using the following equations:

$$\hat{\delta} = \hat{\pi} - \hat{\lambda} \tag{5}$$

$$VAR\{\hat{\delta}\} = VAR\{\hat{\pi}\} + VAR\{\hat{\lambda}\} \tag{6}$$

$$\hat{\theta} = (\hat{\lambda}/\hat{\pi})/[1 + VAR\{\hat{\pi}\}/\hat{\pi}^2] \tag{7}$$

$$VAR\{\hat{\theta}\} = \hat{\theta}^2[(VAR\{\widehat{\lambda}\}/\widehat{\lambda}^2) + (VAR\{\widehat{\pi}\}/\widehat{\pi}^2)]/[1 + (VAR\{\widehat{\pi}\}/\widehat{\pi}^2)]^2 \tag{8}$$

Where; $\hat{\theta}$ is the index of effectiveness and $VAR\{\hat{\theta}\}$ is the variance of $\hat{\theta}$. Values of less than one ($\hat{\theta} < 1$) indicate a reduction in crashes, while values greater than one indicate an increase in crashes.

5.3.2 Equivalent Property Damage Only (EPDO) Analysis

One measure used in determining the effectiveness of safety programs involves calculating costs associated with KABCO injury severity scale found on police crash reports. Police reports in almost every State use KABCO to classify crash victims as K–killed, A–incapacitating injury, B–non-incapacitating injury, C–possible injury, or O–property damage only. The dollar value reflects both economic costs as well as costs associated with a lessor quality of life. To address the safety effectiveness of treatment implementation in Opelika, an Equivalent Property Damage Only (EPDO) analysis is used to express changes in crash severity. This method assigns greater importance, or weight, to serious injury or fatality crash and lesser importance to moderate or slight injury crash. PDO crashes are so given the least importance.

5.4 Data Analysis and Results

5.4.1 Data Description

A study of intersection crash data in CARE indicated that the total number of traffic crashes at 41 signalized intersections[4] in the City of Opelika between 2010 and 2014 was 1,354, of which 234 crashes (17.3%) were caused by RLR. Table 5.1 and 5.2 documents crashes at signalized intersections and crashes involving RLR, with the number of intersections shown in parentheses.

Table 5.1 Crash Frequency at Signalized Intersections in Opelika, AL

Year	All Types	RLR	Percent
2010	240 (38) *	55 (31)	22.9
2011	263 (39)	42 (26)	16.0
2012	248 (35)	42 (23)	16.9
2013	295 (40)	54 (29)	18.3
2014	308 (38)	41 (22)	13.3
Total	1,354	234	17.3

[4] New traffic signals were installed at two intersections of Jeter Avenue/Fox Run Parkway and Opelika Road/Commerce Drive in the following years of 2015 and 2016, respectively.

* The numbers in parentheses indicates the number of signalized intersections where the crashes have occurred.

Table 5.2 Crash Severity at Signalized Intersections in Opelika, AL

Year	All Types	RLR
Fatal	1 (~0%)	0 (0%)
Injury	329 (24%)	95 (41%)
PDO	1,024 (76%)	139 (59%)
Total	1,354 (100%)	234 (100%)

Every year over 85% of intersections have experienced crash, of which 60%-80% have experienced at least one RLR crash. Table 5.2 also indicates that RLR crashes were more likely than other crashes to produce some degree of injury. 24% of all intersection crashes are injury type, while 41% of RLR crashes involve injuries. Such crashes tend to be more severe than the typical crashes at signalized intersections. PDO crashes represent 59% of all RLR crashes in Opelika. Another study by Bonneson et al. (2003) has also indicated that PDO crashes account for about 50 percent of all red-light running related crashes.

5.4.2 Before-and-After Analysis

To investigate the effect of RLC program on the intersection safety, the crash counts at treated intersections were found by their type and severity. Tables A.1 to A.4 in the appendix show crash counts before and after RLC installation at each site on monitored approaches. A total of seven RE crashes occurred during the three years before the RLCs have been installed, while ten crashes have been recorded after the program was initiated. No fatal crash was recorded due to RLR at treated intersections. Although crashes are mostly PDO type (82% of RE crashes and 57% of RLR crashes), RLR crashes results in more severe crashes than RE type crashes (see tables A.1 through

A.4). It is worth mentioning that the total number of RLR crashes can be defined as a criterion to select potential sites for enforcement program implementation.

Tables A.5 through A.9 show the results of simple before-and-after analyses. The number of observed and expected crashes at each intersection are listed in terms of crash type (i.e. RLR and RE) and crash severity (i.e. PDO and Injury). Using equations (1) through (8), the same steps were performed to calculate the safety effectiveness of RLCs for RLR, RE, injury, and PDO crashes. Table 5.3 summarizes changes in the numbers of crashes from the baseline period through the enforcement period.

Table 5.3 Safety Effectiveness of RLCs

Parameter	RLR Crash	RE Crash	Injury Crash	PDO Crash
$\hat{\boldsymbol{\lambda}}$	9	10	8	11
$\hat{\pi}$	12	6	4	13
$\boldsymbol{VAR}\{\hat{\boldsymbol{\lambda}}\}$	9	10	8	11
$\boldsymbol{VAR}\{\hat{\pi}\}$	9.72	4.86	3.47	11.11
$\hat{\boldsymbol{\delta}}$	3	-4	-4	2
$\hat{\boldsymbol{\theta}}$	0.72	1.50	1.60	0.78
$\boldsymbol{VAR}\{\hat{\boldsymbol{\delta}}\}$	18.72	14.86	11.47	22.11
$\boldsymbol{VAR}\{\hat{\boldsymbol{\theta}}\}$	0.11	0.74	1.30	0.11

Based upon the simple method, RLR crashes decreased, while RE crashes increased. This was expected as most of the past research indicated a reduction in RLR crashes and an increase in RE crashes. Intersection of Gateway Drive and I-85 Off-ramp had the most significant increase in injury and RE crashes (one crash before and four crashes after) and the most significant decrease in RLR crashes (four crashes before and no crash after) and PDO crashes (four crashes before and one crash after) were observed at the intersection of Frederick Road and Gateway Drive since getting RLCs. Although the results indicate an increase in the injury crashes and a reduction in

PDO crashes, the effect of treatment on the severity of crashes needs further investigation as it is inconsistent with those found in past studies. To this end, the EPDO analysis have been used.

5.4.3 EPDO Analysis

To calculate the EPDO score for each site, crash costs from the National Highway Traffic Safety Administration (NHTSA) study were used (Blincoe et al. 2015) and the ratio of the cost of crashes over the cost of PDO crashes were selected as weighting factors. The monetary values of crashes in NHTSA study are in 2010 dollar values. Table 5.4 shows the comprehensive crash cost and human capital cost, which is a portion of comprehensive cost, as found in NHTSA report.

Table 5.4 Comprehensive Crash Cost and Human Capital Cost (Blincoe et al. 2015)

Injury Severity Level	**Comprehensive Crash Cost (2010 value)**	**Human Capital Cost (2010 value)**
K	$9,145,998	$1,381,984
A	$1,001,206	$77,145
B	$276,010	$20,282
C	$127,768	$16,078
O	$42,298	$7,789

The consumer price index (CPI) (United States Department of Labor 2015a) was used to adjust human costs to 2015 dollar values and the employment cost index (ECI) (United States Department of Labor 2015b) was applied to adjust the comprehensive costs, other than human costs, to 2015 dollar values (HSM 2010, Ozelim and Turochy 2016). In doing so, the human costs were multiplied by a ratio of the CPI for the year 2015 (237.017) divided by the CPI for 2010 (218.056). The difference between the comprehensive cost and the human cost was also multiplied by a ratio of the ECI for the year 2015 (123.1) divided by the ECI for the year 2010 (111.7). These costs are developed based on the KABCO scale as shown in Table 5.5.

Table 5.5 Crash Cost Estimates by Crash Severity (2015 Dollar Values)

Injury Severity Level	NHTSA Costs (2015 Values)			EPDO Factor
	2015 CPI Adjusted Costs	2015 ECI Adjusted Costs	2015 Adjusted Costs	
K	$ 1,502,154	$ 8,556,402	$ 10,058,556	216
A	$ 83,853	$ 1,018,370	$ 1,102,223	24
B	$ 22,046	$ 281,827	$ 303,873	7
C	$ 17,476	$ 123,089	$ 140,565	3
O	$ 8,466	$ 38,031	$ 46,497	1

The crash counts by severity for the periods before and after camera installation, provided in table A.1 through A.4, are multiplied by the EPDO factor. For example, three RE crash (Table A.1) and four RLR crash (Table A.3) has been recorded at the intersection of Pepperell Parkway& Gateway Drive before the RLC installation, of which six crashes were PDO and one other crash was non-incapacitating injury crash. Since the EPDO factor for each PDO crash is 1 and for each non-incapacitating injury crash is 7, then the total EPDO factor for the intersection of Pepperell Parkway& Gateway Drive before the RLC installation would be 13 (i.e., 6×1+1×7=13). Table 5.6 summarizes the results after crash data was weighted by EPDO factors.

Table 5.6 EPDO Scores

Intersection	EPDO - NHTSA 2015 Weights		
	Before	After	Percent Change (%)
Pepperell Parkway& Gateway Drive	13.0	18.0	+38
Frederick Rd & Gateway Drive	14.0	4.0	-71
Interstate Dr & Gateway Drive	29.0	22.0	-24
Fox Run Pkwy & W Point Ave	4.0	3.0	-25
Total	**60.0**	**47.0**	**-22**

The comparison between the two numbers gives an overview of the safety effectiveness of the camera with respect to the crash severity. RLC had improvements in the safety condition, with 22 percent reduction in EPDO.

5.5 Conclusion

What has been presented in this chapter is a process for determining if a RLR problem exists and if the RLC program could have any effects on that. Past studies have used the data for all RE crashes at signalized intersections assuming that they had occurred due to changes in driver behavior with regard to stopping for red lights. However, this assumption is not acceptable as not every RE crash is due to stopping for light change. In an attempt to remove this assumption, efforts were made to determine which crashes were truly the light-change related by manually reviewing the crash reports. Results indicated a reduction in RLR crashes and an increase in RE crashes. Since it was found that RLR crashes are more likely than other crashes to produce some degree of injury, an improvement in the safety condition in terms of crash severity, after RLC installation was also found.

Due to the limited number of sites, the simple before-and-after method and EPDO method were selected for the analysis. The EPDO method does not account for regression-to-the-mean bias, does not account for traffic volume, and may overemphasize intersections with a small number of severe crashes. However, the EPDO method is still useful and recommended to the agencies when there is a lack of available data. The simple before-and-after method, on the other side, is based on the assumption that if no improvement has been made, the expected number of the crashes would remain the same as in the before period. In this approach, sites are tested before the treatment and then again after the treatment and there is no external comparison group. The number of RLC-intersections has not been enough to perform a technically and statistically significant comparison of before and after crashes at intersections with RLCs. Future research should be undertaken to test RLC safety effects more extensively than was possible in this study. Evaluation of safety effectiveness of RLCs at more number of signalized intersections in Alabama is recommended by following the steps provided in this study.

CHAPTER 6 DETERMINING A FINE STRUCTURE

6.1 Introduction

Enforcement countermeasures are intended to encourage drivers to obey traffic laws via the threat of a citation and a possible fine (Egbendewe-Mondzozo et al. 2010). In 2016, the monetary fine for a RLR traffic violation varies widely in the U.S., with a fine of $50 in North Carolina and as much as $490 in California. Currently, a scientific method for determining the monetary fine based on the safety impacts associated with such violations does not exist, therefore causing disparities in fine structures. The fine is generally predetermined, based on the traffic violation that has been committed. The RLR drivers pay a predetermined monetary fine and/or accept a predetermined number of violation points, or challenges the citation by making an appeal (Sharma et al. 2007).

Table 6.1 lists the RLR fine amounts in six states, which were obtained from the Roadway Information Database (RID) that is maintained by Iowa State University's Center for Transportation Research and Education (CTRE 2015). The table shows that the monetary fine for a RLR traffic violation varies widely in the U.S. From Table 6.1, it appears that no points are assessed when traffic violations are captured by RLCs. It is because holding the driver of a vehicle accountable for a RLR traffic violation typically requires a frontal photograph to help with driver identification for a trial. Capturing high-quality facial images of the violator is often difficult for many reasons such as angled windshield, window tinting, and sun glare. Besides, the frontal photograph increases privacy concerns that often are raised in opposition to automated traffic law enforcement legislation (Eccles et al. 2012).

Table 6.1 RLR Fine Amount in Six U.S. States (CTRE 2015)

Enforcement Type	Florida	New York	North Carolina	Pennsylvania	Washington	Alabama
RLC	\$158	\$50	\$50	\$100 max	\$250 max	\$100 max
Traditional	\$125 / 3 points	\$100 / 3 points	\$100 max / 3 points	\$25 max / 3 points	\$250 max	\$150 max / 3 points

The National Highway Traffic Safety Administration (NHTSA) sponsored a national survey in 2002 that showed the majority of drivers in communities with and without cameras support this program (Royal 2004). In spite of these results, opponents claim that this system is a tool to generate revenue for state, city, and local municipalities. Considering the controversial nature of RLCs and the increased use of cameras, developing a fine structure that closely reflects the risk a RLR vehicle poses to society is needed.

RLCs have the ability to determine the exact time a violation occurs, thus making it possible to quantify the risk imposed on other road users by the violator. The exact time and date of a violation along with vehicle speed and traffic signal timing at the time of the violation are continuously being collected by the company operating and maintaining the RLC system. In this study, a mathematical model is developed to predict the probability that a RLR vehicle may collide with crossing traffic. Next, a method is suggested to quantify the cost of traffic delay if the all-red time was not provided, with the application of HCS. Finally, a novel fine structure is suggested to calculate the dollar value of RLR fines for various intervals based on the expected crash occurrence at an intersection as a result of the RLR traffic violation and estimated delay cost, caused by providing all-red intervals to prevent potential conflicts. The proposed approach is then applied to the case study of Opelika, AL as an example.

6.2 Methodology

A fine can be computed on the basis of the impact that resulted from a traffic violation. The impact may include the risk of potential crashes or delay incurred by road users. In this study, a mathematical model is developed to predict the probability that a RLR vehicle will collide with crossing traffic. Another method is also presented to quantify the cost of traffic delay resulting from a RLR traffic violation.

6.2.1 Modeling a RLR Crash Occurrence

The "probability" of a RLR crash for a given violation, in this paper, is a scenario defined as follows: A RLR vehicle that moves straight toward the intersection from the entering street and a vehicle coming from a crossroad exist in the same physical space at the same time. Figure 6.1 illustrates the scheme of a four-legged signalized intersection with the potential RLR conflict area at the onset of a conflicting green signal. The vehicle shown in grey represents a RLR vehicle, while the white colored vehicle shows the crossing vehicle (CV) with the right-of-way (ROW).

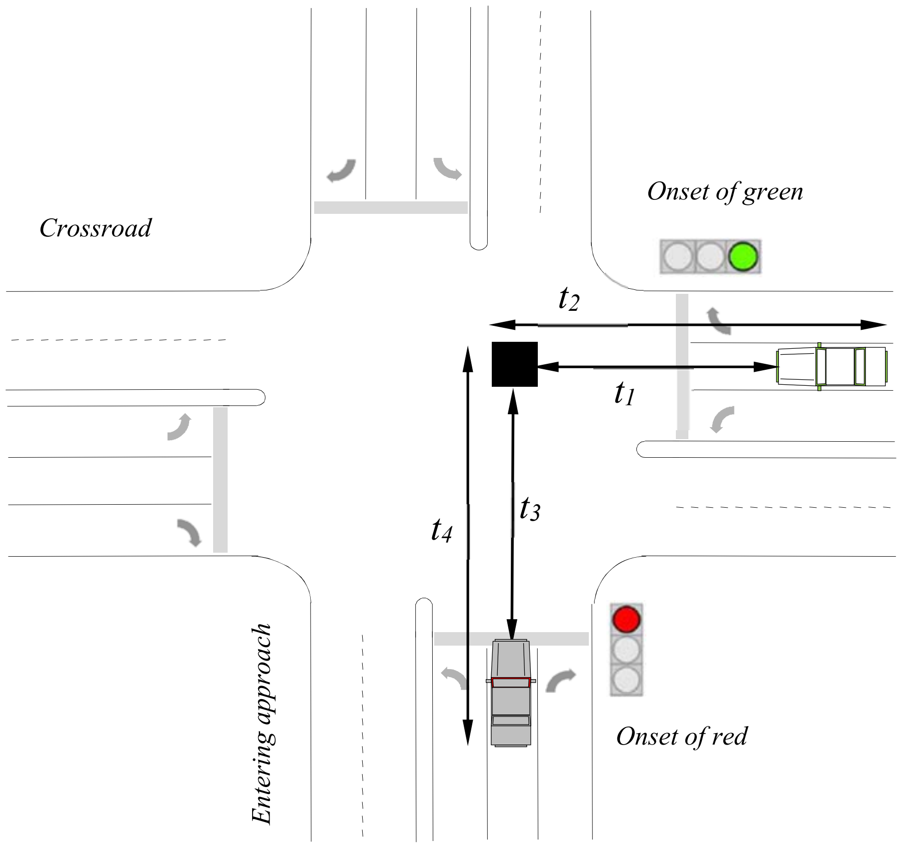

Figure 6.1 Schematic of a potential RLR conflict area at the onset of red

The travel times (t_1 through t_4) are defined as follows:

- t_1: the time interval from the onset of a green signal to the instant when the front bumper of a CV enters the conflict area. A t_1 is assigned to each CV,
- t_2: the time a CV needs to clear the conflict area after the onset of the green signal,
- t_3: the time a RLR vehicle needs to cross the stop line and to reach the conflict area, and
- t_4: the time a RLR vehicle needs to cross the stop line until its rear bumper leaves the conflict area. t_4 is computed as:

$$t_4 = t_3 + \frac{Length\ of\ vehicle\ (ft) + Lane\ width\ (ft)}{Speed\ of\ RLR\ vehicle\ (\frac{ft}{s})} \quad (1)$$

As long as the conflict area is occupied by a CV, there is a probability of a RLR crash. The important factor affecting the crash between a CV and RLR vehicle is the time into red. This is the time when the RLR vehicle crosses the line after the onset of red signal. When the CV crosses through the conflict area, it is exposed to a RLR crash for a period of time. For a given CV, assume that the minimum and the maximum time into red that can result in a RLR crash are t_{min} and t_{max}, respectively. These times are calculated as:

$$t_{min} = t_{ar} + t_1 - t_4 \tag{2}$$

$$t_{max} = t_{ar} + t_2 - t_3 \tag{3}$$

Where, t_{ar} stands for the length of all-red time, a brief phase when all signals are red. Figure 6.2 (a) depicts the positions of a RLR vehicle and CV when the time into red was equal to t_{min}, and Figure 6.2 (b) shows t_{max}.

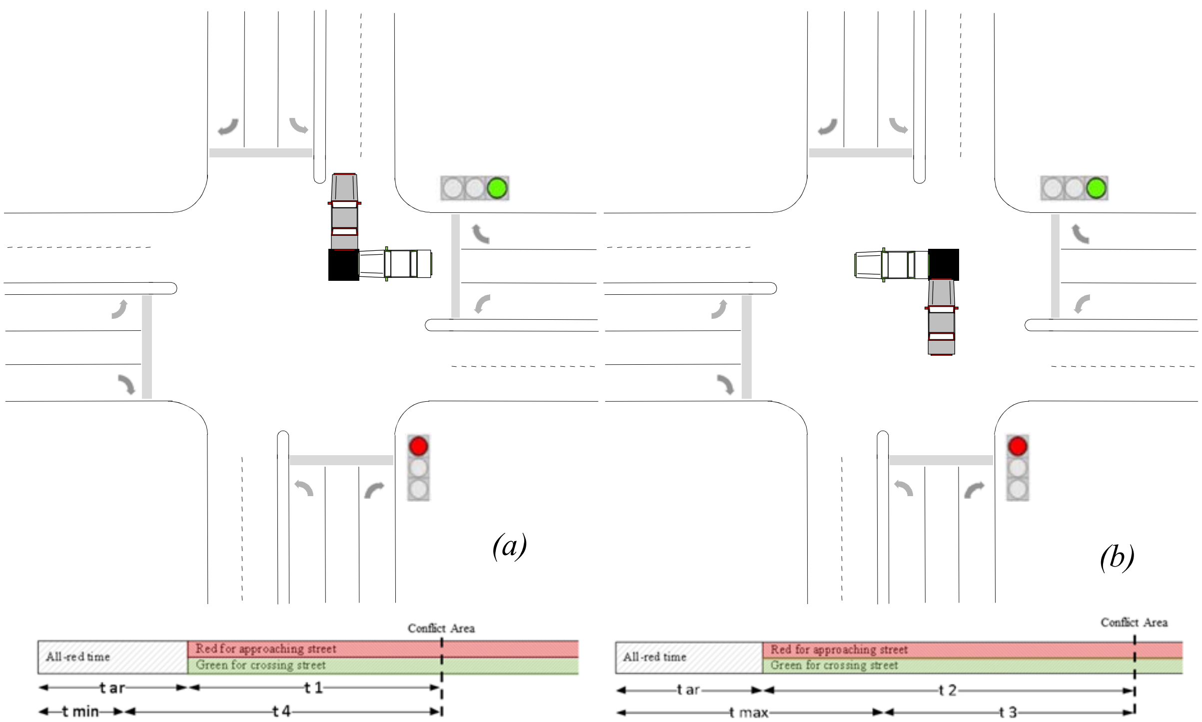

Figure 6.2 Minimum (a) and maximum (b) time into red for a RLR crash occurrence

The probability of a crash for j^{th} CV is computed as:

$$Pr_{crash}(T_i, j) = \begin{cases} t_{min}^{j} < T_i < t_{max}^{j} & , \ 1 \\ else & , \ 0 \end{cases} \quad , \quad j = 1, 2, \dots, N_{cv} \tag{4}$$

Where; T_i denotes a given time into red; and N_{cv} represents the number of CVs. The potential that a RLR crash would occur at T_i can be rewritten as follows:

$$Pr_{crash}(T_i) = \frac{\sum_{1}^{N_c} \sum_{j=1}^{N_{cv}} Pr(T_i, j)}{N_c} \tag{5}$$

Where N_c represents the number of cycles for which T_i is tested.

Variable N_{cv}, in Equation 5, is an indication of traffic volume. It is clear from the equation that a decrease/increase in N_{cv} will reduce/increase the probability of crash ($Pr_{crash}(T_i, j)$).

6.2.2 Road User Delay Cost

Providing an all-red clearance interval has been a treatment option to significantly decrease the likelihood of a RLR crash and to improve intersection safety (FHWA 2009). However, the all-red time at signalized intersections increases road users' costs through delay and the resultant congestion, especially during peak periods of travel (Souleyrette et al. 2004). Therefore, the cost of excess delay is a factor to consider when determining an appropriate fine.

The cost of providing an all-red phase is calculated by estimating the additional delay incurred by road users, considering the traffic volume and value of time. As the volume increases, more vehicles will stop in a queue, waiting for extended periods of time due to an all-red interval.

6.2.3 Fine Structure

In summary, the information above indicates that the monetary fine amount for each RLR vehicle could be calculated as:

$$\text{Fine }(T_i) = \text{Probability of RLR crash }(T_i) \times \text{Crash cost} + \text{Delay Cost} \tag{6}$$

Where Fine (T_i) is the monetary fine amount and T_i denotes the time increment after red.

6.3 A Case Study

In an effort to apply the developed model, a crash cost analysis and a delay cost analysis will be performed on the RLC program administered and implemented by the City of Opelika, AL as a case study. The current fine structure in the City of Opelika is $60 per RLR traffic violations, regardless of violation time.

6.3.1 Probability of a RLR Crash

Equations 1 through 5 were used to calculate the probability of crash occurrence for a given violation. The variables t_3 and t_4 were constants and were calculated by taking into account the geometric design of the intersection (i.e. lane width, median width, intersection width, the number of lanes) and the speed of the RLR vehicle (Lu et al. 2015). The variables t_1 and t_2 were derived from the VISSIM simulation output data. VISSIM traffic simulation models are used to predict the presence of vehicles at the intersection. The procedure was applied to a four-leg perpendicular intersection with an actuated traffic signal. Other characteristics of the site include 4-lane roadways, one left-turn lane per direction, 12-ft lanes, 45-mph speed limit, 4.5 seconds yellow time, and 1.5 seconds all-red time. All of these features were incorporated into the model. In this model RLR speed is assumed equal to the posted speed limit. The number of CVs and their respective times of entering and exiting the conflict area was archived from data collection points in VISSIM. The traffic simulation softwares are found to be applicable for determining a variety of traffic problems, such as predicting crash counts by severity (Ma et al. 2008), the effect of changing the number of lanes on crash rates (Li and Carriquiry 2005), the frequency of traffic crashes (Tamayo 2009), and the effect of intersection volume on crash probability (Zhou et al. 2014, Baratian-Ghorghi et al. 2015c, Zhou et al. 2016). VISSIM is also capable of simulating the situations where no CV was present in the queue. The intersection was modeled and was run for a total number of 300 cycles (10 different random seeds were used). Figure 6.3 represents the RLR crash probability computed by the VISSIM model over the 0.1 second aggregation intervals.

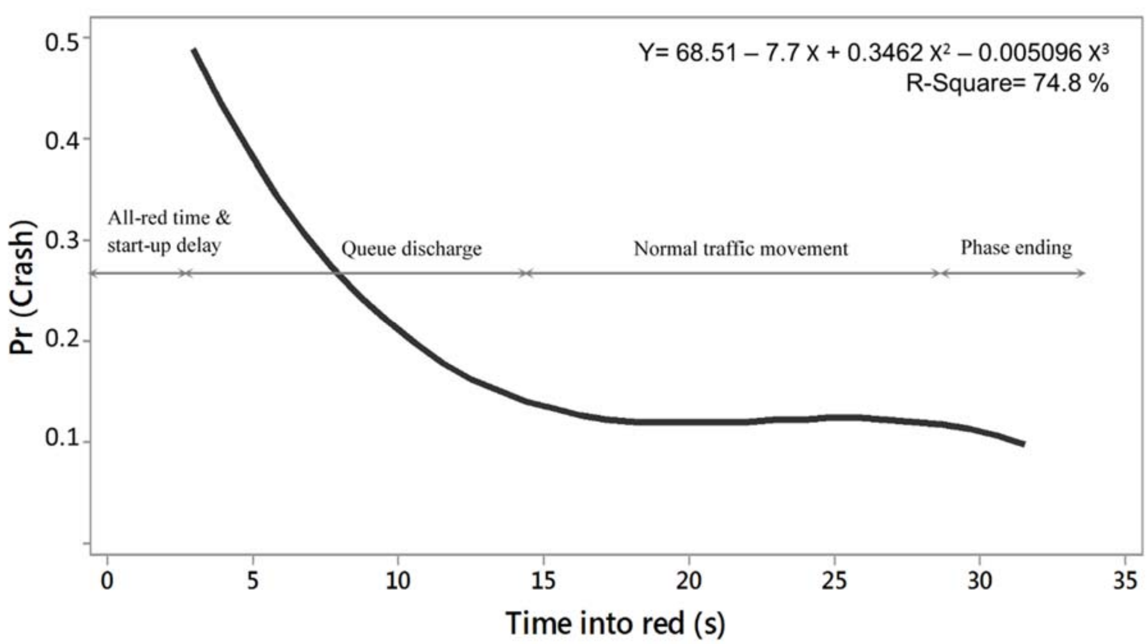

Figure 6.3 Probability of RLR crash

The data show that no RLR crashes will happen in the conflict area for up to 2.9 seconds after the onset of the red signal. This is consistent with that previously found in two other studies. Cunningham and Hummer (2004) have shown that RLR crashes are taking place two or more seconds after the onset of red. Milazzo et al. (2001) have found that RA red-light related crashes do not occur before 2.9 seconds of red light. From Figure 6.3, it is clear that the probability of a RLR crash is equal to zero during the all-red time of the signal phase. That means a RLR vehicle travelling at the speed limit could pass through the intersection without any risk of a crash because CVs are not released by the onset of the crossroad green signal yet. Thereafter, the light turns to green on the crossroad and a start-up delay is imposed to CVs, since it takes longer to accelerate from a stopped position stop and travel to the conflict area. Figure 6.3 shows a decreased risk of crash over time after the end of the queue for the crossroad. Also, since the speed of CVs increases, the traffic input reduces, and the gaps between vehicles become longer, the period of time the conflict area is occupied becomes shorter. Thus, the probability of a RLR crash occurring reduces over time, as can be seen in Figure 6.3.

Considering the different types of movement for RLR vehicles and CVs, the location of the conflict area can shift. Thus, the probability of a crash occurring between two vehicles may change. After running additional models for near-side conflict areas (i.e. conflict between CVs coming from the other crossing street and right-turning/straight-through RLR vehicles), it was determined that the earliest time that a crash can happen is 3.9 seconds after the onset of a red signal. Since the far-side conflict area records the crash probability at 2.9 seconds and because only one crash can occur at a time, the crash probability on the far-side conflict area was chosen for further analysis.

6.3.2 Crash Cost

The cost of any crash is a function of the injury severity level. Table 6.2 presents the comprehensive cost of crashes that can result from a RLR event. The second column shows the comprehensive crash cost as was presented in Table 5.5. Understanding the RLR crash costs provides the economic incentive for municipalities to charge fines based on the likelihood of crashes to disincentivize an intentional RLR. The third column of Table 6.2 presents the frequency of each crash severity over a two-year period after RLC installation (Baratian-Ghorghi and Zhou 2016). These crash frequencies were used to estimate the cost of potential crashes. Lastly, the proportion of crashes within each severity category is multiplied by the crash cost resulting in a weighted average RLR crash cost.

Table 6.2 Cost of RLR Crashes at Opelika, AL Intersection

Injury Severity Level	**Comprehensive Cost**	**Frequency of Crashes (2 years)**	**Freq.× Cost**
K	$ 10,058,556	0	$0
A	$ 1,102,223	1	$1,102,223
B	$ 303,873	1	$303,873
C	$ 140,565	7	$983,955
O	$ 46,497	6	$278,982
Weighted average cost per RLR crash =			$177,935

Based on this analysis, the weighted average comprehensive cost per RLR crash was estimated as $177,935. To distribute this cost between all violators equally, Equation 6 was used:

$$\text{Crash cost per RLR} = \frac{\text{NO. RLR Crash} \times \text{Weighted average cost per RLR crash}}{\text{NO. RLR violations}} \qquad (6)$$

The violation data were provided by the City of Opelika Police Department. Considering that 8 out of 12,111 RLR violations resulted in a crash on monitored approaches during a two year after-installation period, an average amount of $118 is the cost that each violator caused, regardless of the time into red when the violation occurred. Figure 6.4 shows this cost as a dashed line. To distribute this cost based on the risk of a crash, a probability distribution was used.

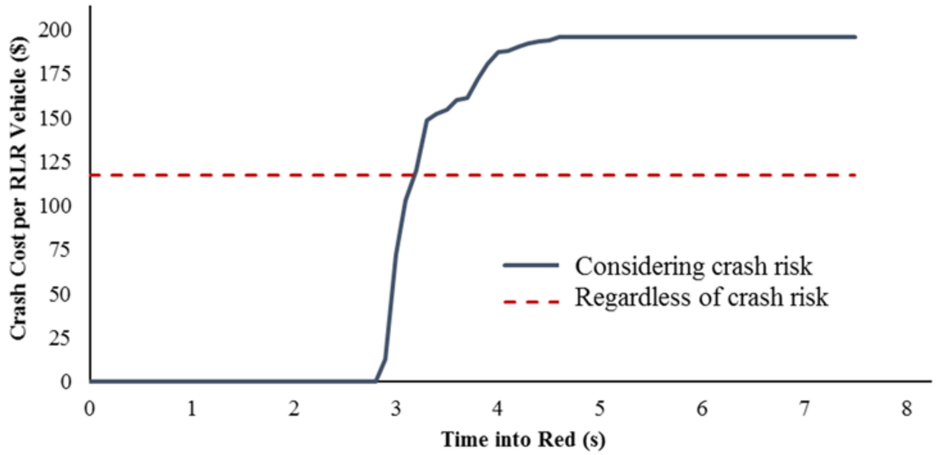

Figure 6.4 Crash Cost Based on the Crash Probability

The solid line in Figure 6.4 represents the new distribution of crash cost. No cost was assigned to the time between onset of all-red to 2.9 seconds after because the probability of a crash at this interval is zero. A $196 fine was computed as the greatest amount of drivers who intentionally ran the red signal after 7.5 seconds. This is the time when the second CV in a queue crosses the conflict area. The lower probability of crash after 7.5 seconds was not taken into account because as the time passes, a queue forms in each lane of the entering approach and the possibility of a RLR traffic violation decreases. This was also found in the partner study conducted in 2015 (Baratian-Ghorghi et al. 2015b) that the probability of RLR after 7.5 seconds is zero.

6.3.3 User Delay Cost

It was found in the previous section that during all-red time, the intersection is safe and no RLR crash may happen. However, in its absence, drivers who enter an intersection during the red signal run an extremely high risk of being struck by a CV. The all-red time increases road users' delay, which needs to be estimated. The HCS was used for this purpose. For various volume to capacity (v/c) ratios, the modeled intersection was simulated in two scenarios: (1) with and (2) without all-red time. The increase in intersection delay (seconds per vehicle) was then determined (Figure 6.5). Results indicate that the influence of all-red time is more and more significant as traffic volumes increase. When the facility is operating at 25% of its capacity, the expected delay per vehicle is equal to all-red time. By increasing the v/c ratio, the amount of delay as a result of all-red time increases, as well.

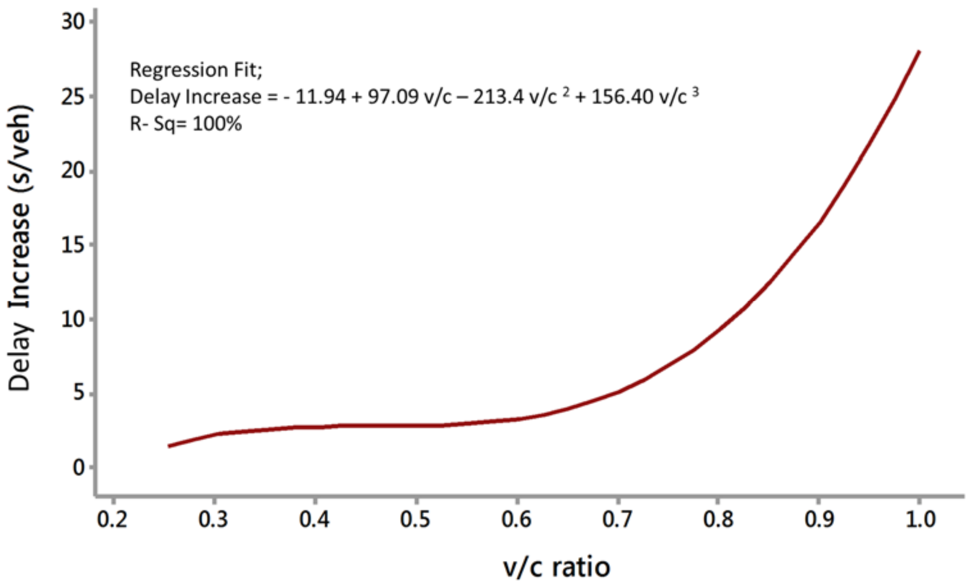

Figure 6.5 Intersection Delay Increase vs. v/c Ratio

Once the time delays have been calculated, the cost associated with this delay can be determined. Table 6.3 shows the steps taken to find delay costs that result from all-red time. The number of RLR violations came from annual traffic offenses recorded by the police.

Table 6.3 Cost of Delay

Variables	Off-peak hours	Peak hours
Excess Delay (s/veh)	1.5	3.25
Traffic Volume (veh/day)	103,499	52,614
Vehicle Occupancy (person/veh)	1.25	
Total delay (s/day)	194,061	213,744
Travel time value ($/hr)	2.74	8.23
Delay cost ($/year)	53,944	178,246
Number of RLR (2013-2014)	12,111	
Delay cost per violation ($/RLR vehicle)	$38	

In the case of the Opelika RLC program, treated intersections have a v/c ratio of 0.6 during the peak-hour time periods. In this condition, a 1.5 seconds all-red time can cause a delay of 3.25 seconds to the motorists. The volume at treated intersections for evening peak hours (4:00 PM to 6:00 PM), is 26,307 vehicles. Assuming the same volume for morning peak hours, a total of 52,614 vehicles use these intersections during the rush hours. Whereas the AADT is 156,113 vehicles per day, then 103,499 vehicles use the intersections during other times of the day. This would translate to 213,744- and 194,061-second cumulative delays during the peak and off-peak periods, respectively, using the 1.25 passenger per vehicle assumed in the 2011 Annual Urban Mobility Report (Lomax et al. 2011). The amount of traffic flow has been found to play an important role in the value of travel time and consequently in the cost of delay time (Soltani-Sobh et al. 2015b, 2016c, Sharifi et al. 2015, Sharifi and Shabaniverki 2016). Litman (2009) estimated that under peak conditions, drivers' time is valued at 50% of the average wage and under off-peak conditions it is valued at 17% of the average wage. The average hourly wage was $16.45 for Opelika in 2015 (ALDOT 2016). Therefore, the travel time value was calculated to be $8.23 and $2.74 for peak hours and off-peak hours, respectively. This would translate to $53,944 and $178,246 delay cost per year for peak hours and off-peak hours, respectively. Considering the total number of citations for the years after RLC installation, a cost of $38 per RLR violation is the result of the imposed delay.

6.3.4 Fine Structure

Combining costs of delay and crashes as a result of RLR violation, a basis for determining the fine will be achieved, as shown in Figure 6.6.

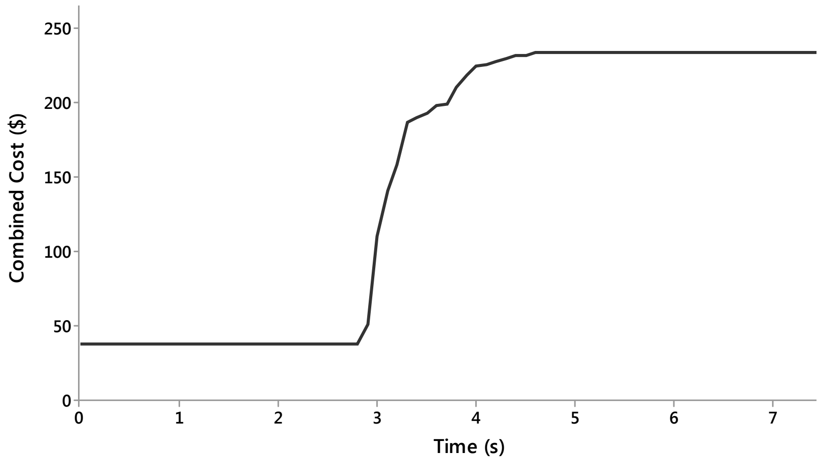

Figure 6.6 Expected Cost by Time

Figure 6.6 indicates that in the case of Opelika program, a $38 traffic ticket may be issued for drivers who ran a red light within 2.9 seconds. The amount of RLR fine, however, increases up to $234 at 4.6 seconds into the onset of the red signal and thereafter. To better represent the monetary fine for a red-light running traffic violation based upon the time into the red signal, Table 6.4 was created.

Table 6.4 Time-based RLR Fine

Time (s)	Crash Cost	Cost of Delay	Total Cost of RLR Violation
0-2.8	$0	$38	$38
2.9-3.5	$155	$38	$193
3.6-4.0	$187	$38	$225
> 4.0	$196	$38	$234

This table can be used as a sample for determining the monetary fine based on the safety impacts associated with RLR violations and additional road user delays caused by providing all-red intervals. It must be noted that if the local authority does not implement the all-red strategy, the length of all-red interval (here is 1.5 seconds) will be deducted from the time intervals, shown in the first column of Table 6.4. Also, the amount of fine will be reduced by $38 since no delay will be incurred due to providing all-red time. In this case, vehicles running red before 1.4 seconds (=2.9-1.5) will not be fined.

6.4 Conclusion

Currently, the fine associated with RLR has no relationship to its negative impacts and, as a result, may have less of a deterrent effect. Moreover, the use of RLCs across the nation is increasing even though it continues to receive criticism since the public perceives it as a revenue generating mechanism. As observed by Walden et al. (2011) and Porter et al. (2013), terminating the RLC enforcement program could revert and increase RLR violation rates over time. From this perspective, developing a fine structure that closely reflects the risk a RLR vehicle poses to society would be of great interest in supporting photo enforcement cameras.

This chapter presented a comprehensive probabilistic framework for devising a RLR traffic violation fine structure. The method described in this study is the first of its kind reported in the literature. The proposed method considered the estimated economic impact of potential crashes by RLR violations and additional motorist delays caused by providing all-red intervals to prevent potential conflicts. In the first step, VISSIM traffic simulation models were employed to predict the presence of vehicles at the intersection and a physical model was developed to determine a crash probability for a violator entering an intersection at a discrete time after the traffic signal changes to red. Although a quantitative approach to predict the number of expected crashes is presented in the Highway Safety Manual (HSM 2010), its only inputs are the cross-sectional geometrics and traffic volumes (Jalayer et al. 2014, Jalayer et al. 2015b). However, in the case of red-light running crashes, time into red plays an important role which has not been considered in the past studies.

The results indicated that the intersection remains safe during the all-red time and up to 1.4 seconds after the termination of this interval. The study demonstrates a sharp increase in the probability of a crash thereafter.

In the next step, The HCS was also employed to estimate the delay incurred by road users. The study then suggested methods to enable decision-makers to consider total costs to devise an appropriate fine structure, including crash costs and user delay costs associated with providing all-red time. The case study of Opelika, AL was used to show how the associated cost of RLR violation can be computed. The equations presented in this study enable researchers or decision-makers to:

- determine the probability of a RLR crash over time after the onset of the red interval,
- determine the RLR crash cost associated with the probability (or likelihood of occurrence) of a crash,
- determine the delays associated with all-red time at signalized intersections for a given traffic condition (v/c ratio), and
- determine the cost associated with delay incurred as a result of all-red time.

Devising a fine structure for RLR violations is important as it can enhance the RLC efficiency. Assigning a lower amount of fine for unintentional drivers (compared to intentional drivers), but not exempting them from the fine, can have an influence on their behaviors, as they would not be willing to stop unsafely. This alleviates the capacity reducing the effect of RLC, as well as the frequency of RE crashes.

Although there are additional items that need further investigation, this study generates important findings in the field of traffic safety and policy. It should be noted that in the case of having access to the data gathered by RLC, further researches is needed to establish a more accurate model for intersections in other cities. Considering that the use of RLCs is increasing in the nation, policymakers need to develop an objective fine structure that closely reflects the risk a RLR vehicle poses to other road users.

6.5 Limitations of Study

There has been no prior research and documentation on deterrent effects of fines on RLR violations or predicting the risk of such crashes. Lack of available data also required the researchers to offer new methodologies to determine the likelihood of a crash and an associated fine structure based on risk. To identify the crash potential of RLR vehicles, detailed crash and violation data occurring within a jurisdiction are needed. In this study, simulation models were developed to resemble the existing traffic conditions. There are some limitations associated with the model since it does not take into account avoidance maneuvers that normal drivers would perform if faced with an impending collision (i.e. change in speed or the direction of travel). Also, the model presented assumes that the RLR vehicle is traveling the posted speed limit, will not reduce speed, and the most severe crash may occur. These can be acceptable as the fine is determined based on the worst possible case. Note that with access to violation data, researchers will be able to overcome some of these limitations.

In the case of having access to the RLR violation data (e.g. time and occurrence of crash) researchers will be able to validate simulation-based findings based upon data obtained in a real-world environment. It is recommended that the real probability of crashes be used and then the steps presented in this research be followed for developing a fine structure.

The method used in this research has spatial transferability for any municipality or jurisdiction. The steps provided in this research can be used as a guide for finding a basis for RLR fines. However, some differences between jurisdictions have to be taken into account, in order to localize the method. For example, data must be collected under various traffic conditions and time periods at the different locations. This is because traffic condition, geometric design of intersection, and speed limit play important roles in probability of crash, which need to be used in the model. The crash cost and the value of time should also be determined for each municipality and jurisdiction, and applied using the proposed method.

CHAPTER 7 SUMMARY AND FUTURE WORK

7.1 Research Summary

The objectives of this research were to: 1) analyze the effect of the program on drivers' behavior, 2) investigate the operational impacts of this system, 3) evaluate the effectiveness of RLC systems on increasing intersection safety, and 4) develop a RLR fine structure.

Chapter 2 described RLC program and reviewed the past studies relevant to the objectives of this research. To date, numerous studies have been conducted to evaluate the safety effects of RLCs and several researchers examined drivers' behavior, however, still there is limited research examining drivers' stopping behavior in the presence of RLCs without a pre-post study. The literature review revealed that relatively little is known about the impacts of RLCs on the operation of signalized intersections. Also, no effort has been made to link results, costs, and fines that violators should pay.

Chapter 3 accomplished the first objective, quantifying the impact of RLCs on driver behavior by performing a cross-section comparison for two groups of intersections: with RLCs and without them. The results can be summarized as follows: the likelihood of a driver stopping during a light change interval increased at double when an RLC was present; at RLC intersections, drivers crossed intersections in one half second less time; most drivers took a lower level of risk at treated sites by entering within the first second of the yellow light; and a decreasing number of vehicles passed through the intersections as the time elapsed increased after the yellow signal indication. Based on these findings, RLCs appear to have a positive effect on driver behavior.

Chapter 4 used the collected data from Chapter 3 to achieve the second objective. In this chapter the actual mean CLT observed in the field was calculated and then compared with the default values presented in HCM and the ALDOT's manual. The analysis results revealed the following changes after the RLC installation: (1) a half second was added to the clearance lost time; (2) intersection delay increased directly related to the saturation condition, and for at least 0.5 seconds per vehicle. The findings also suggested that both of the HCM and ALDOT Manual methods estimated a shorter CLT and thus overestimate the intersection's capacity.

The third objective was accomplished as described in details in Chapter 5. This chapter presented a method to evaluate the safety effects of RLCs at signalized intersections. In this chapter, a complete process of collecting RLR crash data was explained. A before-and-after analysis and an EPDO method was applied in order to verify if treatment has been effective to reduce crashes and severities. It was found that the RLR crashes were more likely than other crashes to produce some degree of injury. Results showed a reduction in RLR crashes, an increase in RE crash, and an improvement in safety conditions in terms of crash severity, after RLC installation.

Chapter 6 examined a new facet of RLCs by developing a basis for RLR fines. To this end, an empirical model was proposed. The model described in this study is the first of its kind reported in the literature. An economic evaluation approach was used to devise a fine structure by considering the problem in terms of cost of a potential RLR crash and induced delay. The delay cost accrued on cross traffic, associated with providing all-red time. RLR crash potential, on the other side, was estimated as a probabilistic measure based on the analysis of vehicular movements. VISSIM traffic simulation models were utilized to predict the presence of vehicles at the intersection, and a physical model was developed in order to determine a crash probability for a violator entering an intersection at a discrete time after the light changes to red. The fine structure proposed in this study could have an added benefit of reducing the frequency of RLR vehicles, because the penalties upon conviction will not be the same, regardless of the risk of crash. The proposed method will consider higher fines for the drivers who intentionally run the red light, as opposed to those who unintentionally run the red light.

7.2 Recommendations

Due to limited number of study intersections, the safety evaluation based on four case studies in Opelika may not give a whole picture of safety effectiveness of RLCs in the whole state of Alabama. A more comprehensive statewide safety evaluation is recommended for further study. Future work should continue to investigate and develop a method that can accurately quantify the magnitude of crash/violation change by a RLC. Future research should include a before-after analysis of crashes using a control group. It is recommended that it be completed using the Empirical Bayes (EB) technique, which appears to be the most widely accepted method to date. It could also be used to determine if a spillover effect is seen at other intersections. Developing crash modification factors (CMFs) for different RLR crash types, such as total crashes, rear-end, and right angle crashes would be of great interest to the safety researchers. CMF is a multiplicative factor that indicates the proportion of crashes that would be expected after implementing countermeasure at target locations (Jalayer et al. 2015c). To date, no studies of this type have been conducted in Alabama. In order to estimate the effect of RLC on RE crashes, it is recommended to follow a similar approach as described in this study to gather crash data and obtain more accurate results.

Since the effect of RLC on driver behavior in terms of UCT may vary in different jurisdictions depending on intersection characteristics or the RLC program implemented, it is recommended that a before-after study be conducted at intersections targeted for RLC installation. Although in this study, efforts were made to identify and compare intersections with similar characteristics (e.g. signal timing; traffic volume; number of thru, left, and right lanes; type and number of crashes), the average clearance interval duration at non-camera intersections was 0.4 longer than that at RLC intersections. Hence, it is recommended to further investigate the possible effect of clearance interval duration on UCT. Furthermore, the RLC intersections and non-RLC intersections were located in two different cities (i.e., Opelika and Auburn, respectively). Since the city of Auburn is a college town, most drivers in this city are young students. Therefore, driver type might be considered when studying driver behavior in response to the light change. In conclusion, a comparison of UCT values before and after RLC program implementation is recommended to clarify the actual effect of the camera on driver stopping behavior. We also recommend that similar and ongoing studies be conducted after the camera installation date, as we expect that as the time passes, the program will be more publicized and driver behavior will continue to change in response to the newness or familiarity of the equipment. As a consequence, a larger number of drivers will exercise caution when approaching these intersections—especially those who have received a previous citation—which will potentially reduce the UCT in the future.

Due to the limitations associated with the use of video cameras in field data collection, it was not possible to measure the speed and acceleration of the crossing vehicles or the distance from stop-line during onset of yellow change interval. Having access to such information, one can determine whether a stopping vehicle would run the yellow or red light if proceeding through the intersection. This could help in identifying the impact of RLCs on reducing yellow running behavior as well as RLR violations. With the advances in technology, we recommend the use of additional methods in future studies such as video image processing techniques or the induction loops to examine finer-grain data and address additional research questions.

Further research needs to emphasize fairness in program design and operations. In case of having access to the RLR violation data (e.g. time and occurrence of crash) researchers can validate simulation-based findings based upon data obtained in a real-world environment. It is recommended that the real probability of crashes be used and then the steps presented in this research be followed for developing a fine structure. The steps provided in this research can be used as a guide for finding a basis for RLR fines for other case studies. However, some differences between jurisdictions have to be taken into account, in order to localize the method. For example, data must be collected under various traffic conditions and time periods at the different locations. This is because traffic condition, geometric design of intersection, and speed limit play important roles in probability of crash, which need to be used in the model. The crash cost and the value of time should also be determined for each municipality and jurisdiction, and applied using the proposed method.

To help ensure that the public perceives the RLC program as fair, the state or local agency should consider that the penalty assigned to each violation is proportionate to its negative impacts. This will help to gain more public support for installing RLCs, a policy that would result in safer intersections and communities by applying more fines to those intentional RLR violators.

It must be noted that RLC is not the first, nor the only way to combat RLR problem and resulting crashes. Engineering countermeasures are recommended and should be implemented before considering the use of enforcement countermeasures (Bonneson et al. 2002 and 2003, UTCA 2007, Tay and De Barros 2009, Cunningham and Hummer 2010, Baratian-Ghorghi et al. 2015b, Baratian-Ghorghi and Zhou 2016).

Hopefully, the ideas in this dissertation will be useful in the implementation of RLC programs in future, and they will encourage further research on the behavioral and operational impacts of the system, as well as applying a fair fine structure for RLR traffic violations.

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APPENDIX

Table A.1 RE Crash before Treatment

Intersection	Severity					Number of crash
	PDO	Possible Injury	Non-Incapacitating Injury	Incapacitating Injury	Fatal	
Pepperell Prkwy & Gateway Dr	2	0	1	0	0	3
Frederick Rd & Gateway Dr	2	0	0	0	0	2
Interstate Dr & Gateway Dr	1	0	0	0	0	1
Fox Run Pkwy & W Point Ave	1	0	0	0	0	1
Total	**6**	**0**	**1**	**0**	**0**	**7**

Table A.2 RE Crash after Treatment

Intersection	Severity					Number of crash
	PDO	Possible Injury	Non-Incapacitating Injury	Incapacitating Injury	Fatal	
Pepperell Prkwy & Gateway Dr	3	0	1	0	0	4
Frederick Rd & Gateway Dr	1	1	0	0	0	2
Interstate Dr & Gateway Dr	4	0	0	0	0	4
Fox Run Pkwy & W Point Ave	0	0	0	0	0	0
Total	**8**	**1**	**1**	**0**	**0**	**10**

Table A.3 RLR Crash before Treatment

Intersection	Severity					Manner of crash		Number of crash
	PDO	Possible Injury	Non-Incapacitating Injury	Incapacitating Injury	Fatal	RA	Other	
Pepperell Prkwy & Gateway Dr	4	0	0	0	0	1	3	**4**
Frederick Rd & Gateway Dr	2	1	1	0	0	0	4	**4**
Interstate Dr & Gateway Dr	4	0	0	1	0	4	1	**5**
Fox Run Pkwy & W Point Ave	0	1	0	0	0	1	0	**1**
Total	**10**	**2**	**1**	**1**	**0**	**6**	**8**	**14**

Table A.4 RLR Crash after Treatment

Intersection	Severity					Manner of crash		Number of crash
	PDO	Possible Injury	Non-Incapacitating Injury	Incapacitating Injury	Fatal	RA	Other	
Pepperell Prkwy & Gateway Dr	1	0	1	0	0	1	1	**2**
Frederick Rd & Gateway Dr	0	0	0	0	0	0	0	**0**
Interstate Dr & Gateway Dr	2	3	1	0	0	4	2	**6**
Fox Run Pkwy & W Point Ave	0	1	0	0	0	1	0	**1**
Total	**3**	**4**	**2**	**0**	**0**	**6**	**3**	**9**

Table A.5 Simple Method Input Data –RLR Crashes

Intersection	Years Before	Years After	Crashes before K(j)	Crashes After L(j)	$r_d(j)$	$r_d(j)\times K(j)$	$r_d(j)^2\times K(j)$
Pepperell Prkwy & Gateway Dr	3	2.5	4	2	0.83	3.33	2.78
Frederick Rd & Gateway Dr	3	2.5	4	0	0.83	3.33	2.78
Interstate Dr & Gateway Dr	3	2.5	5	6	0.83	4.17	3.47
Fox Run Pkwy & W Point Ave	3	2.5	1	1	0.83	0.83	0.69
Sum			14	9		11.67	9.72

Table A.6 Simple Method Input Data –RE Crashes

Intersection	Years Before	Years After	Crashes before K(j)	Crashes After L(j)	$r_d(j)$	$r_d(j)\times K(j)$	$r_d(j)^2\times K(j)$
Pepperell Prkwy & Gateway Dr	3	2.5	3	4	0.83	2.50	2.08
Frederick Rd & Gateway Dr	3	2.5	2	2	0.83	1.67	1.39
Interstate Dr & Gateway Dr	3	2.5	1	4	0.83	0.83	0.69
Fox Run Pkwy & W Point Ave	3	2.5	1	0	0.83	0.83	0.69
Sum			7	10		5.83	4.86

Table A.7 Simple Method Input Data –Injury Crashes

Intersection	Years Before	Years After	Crashes before K(j)	Crashes After L(j)	$r_d(j)$	$r_d(j)\times K(j)$	$r_d(j)^2\times K(j)$
Pepperell Prkwy & Gateway Dr	3	2.5	1	2	0.83	0.83	0.69
Frederick Rd & Gateway Dr	3	2.5	2	1	0.83	1.67	1.39
Interstate Dr & Gateway Dr	3	2.5	1	4	0.83	0.83	0.69
Fox Run Pkwy & W Point Ave	3	2.5	1	1	0.83	0.83	0.69
Sum			5	8		4.17	3.47

Table A.8 Simple Method Input Data –PDO Crashes

Intersection	Years Before	Years After	Crashes before K(j)	Crashes After L(j)	$r_d(j)$	$r_d(j)\times K(j)$	$r_d(j)^2\times K(j)$
Pepperell Prkwy & Gateway Dr	3	2.5	6	4	0.83	5.00	4.17
Frederick Rd & Gateway Dr	3	2.5	4	1	0.83	3.33	2.78
Interstate Dr & Gateway Dr	3	2.5	5	6	0.83	4.17	3.47
Fox Run Pkwy & W Point Ave	3	2.5	1	0	0.83	0.83	0.69
Sum			16	11		13.33	11.11