RED LIGHT RUNNING AND DRIVER BEHAVIOR AT SIGNALIZED INTERSECTIONS IN WESTERN PUERTO RICO

by

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ABSTRACT

Red Light Running (RLR) is a potentially severe safety issue at signalized intersections. To determine the driver reaction at the end of the green period at signalized intersections, a RLR study was performed using 32 approaches at nine signalized intersections located in the western region of Puerto Rico. The results indicate that, on average, a driver runs a red signal every 4 minutes. RLR events increased as the traffic flow rate or the ratio of traffic flow rate per cycle length increased at the intersection approaches. The study revealed the presence of aggressive RLR behavior at the observed intersections with an average violation rate of 12.8 RLR per hour and 18.8 RLR per 1,000 vehicles.

Driver behavior at the onset of the yellow signal was analyzed at one signalized intersection in Mayagüez using video data collected with three digital cameras. For passing vehicles at the intersection, the results of the yellow and red entry time of 3.00 and 2.46 seconds, respectively, show a high degree of driver aggressiveness at the intersection. Regression analysis indicated that the significant explanatory variables for the yellow entry time and the probability of the STOP/GO decision are the vehicle distance and speed at the moment of the yellow onset. A novel technique to determine the dilemma zone (DZ) parameters using field observations at an intersection was developed in this study. The calibrated parameters were compared against the DZ theoretical model demonstrating consistency with the values observed in the field and also with the values recommended for the design of a signal timing plan. The proposed technique can be extended to other intersections with similar

characteristics using the parameters suggested in this study, also can be used for other types of intersections to find the calibrated parameters. A practical manner to avoid involuntary RLR, through the elimination of DZ, is proposed by marking the pavement with a transverse line corresponding to the value of maximum passing distance (X_0) for the vehicle speed limit for that segment as calculated from field observations and the model. This marking will assist drivers to stop at the intersection if they approach this line during yellow onset. The Driver Aggressiveness Index (DAI) is proposed as an indirect way to measure the aggressiveness of drivers at a signalized intersection.

RESUMEN

La infracción a la indicación roja (RLR, por sus siglas en inglés) en un semáforo es un problema de seguridad potencialmente severo. Con el fin de determinar la reacción de los conductores al final de la indicación verde en una intersección, se observaron estos eventos en 32 accesos de nueve intersecciones con semáforo del área oeste de Puerto Rico. En promedio, se observó que un vehículo viola la indicación roja cada 4 minutos. Se observó que las infracciones RLR aumentaron según aumentaron la razón de flujo de vehículos o la razón de flujo de vehículos sobre la longitud del ciclo. Se encontró la presencia de una conducta agresiva en las intersecciones observadas con un promedio de 12.8 eventos RLR por hora y una razón de 18.8 eventos RLR por cada 1,000 vehículos.

El comportamiento de los conductores al inicio de la indicación amarilla en una intersección semaforizada se analizó a partir de datos recolectados en el campo, usando tres cámaras digitales de video. Para los vehículos que cruzaron la intersección, los resultados de tiempos de entrada en amarillo y rojo fueron de 3.00 segundos y 2.46 segundos, respectivamente, demostrando así un alto nivel de agresividad de los conductores en la intersección. Los análisis de regresión indicaron que las variables significativas para el tiempo de entrada en amarillo y para la probabilidad de que el vehículo siga o se detenga al inicio del periodo de amarillo, son la distancia y velocidad. Una técnica novedosa fue usada para determinar los parámetros relacionados con la zona de dilema (DZ, por sus siglas en inglés) haciendo una comparación de los modelos teóricos y las observaciones de campo en la intersección. Los

estimados demostraron consistencia con los valores observados en el campo y también con los valores recomendados para diseño del plan de tiempos del semáforo. La técnica propuesta se puede extender a otras intersecciones de características similares usando los parámetros sugeridos en este estudio o puede ser usada en otro tipo de intersecciones para calibrar los parámetros de la DZ. Se propone como una forma práctica de eliminar la DZ y así reducir el RLR involuntario el marcado en el pavimento de una línea transversal correspondiente al valor de distancia máxima de pasada (X_0) para el límite de velocidad del segmento calculado a partir de observaciones de campo, y educando a los conductores a detenerse en la intersección, si se acercan a esta línea durante el inicio del periodo de amarillo. También se propone el uso del Índice de Agresividad del Conductor (DAI, por sus siglas en inglés) como una forma indirecta de medir la agresividad de los conductores en una intersección con semáforo.

To God and my family

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List of Abbreviations and Symbols

AASHTO	American Association of State Highway and Transportation Officials
CPI	Crash Potential Index
DZ	Dilemma zone
DAI	Driver Aggressiveness Index
DRAC	Deceleration Rate to Avoid a Crash
DOT	Department of Transportation
FHWA	Federal Highway Administration
GHM	Gazis, Herman, and Maradudin
ITE	Institute of Transportation Engineers
MARD	Maximum Deceleration Rate Available
MUTCD	Manual on Uniform Traffic Control Devices
OZ	Option Zone
RLR	Red Light Running
SVDCS	Simultaneous Video Data Collector System
X_c	Minimum Stopping Distance
X_0	Maximum Passing Distance
YLR	Yellow Light Running

1 INTRODUCTION

Signalized intersections are among the most complex elements of a highway system. At intersections, vehicular flows have different interactions with converging, diverging, and crossing maneuvers, creating conflicts that may translate into potential crashes. At particular intersections, the right of way to specific movements is controlled through use of the traffic signal indications. In this manner, one can control the number and type of conflicts between vehicles and also in the interaction with pedestrians. However, since the right of way to a vehicle stream can cause delays to vehicles that are waiting, it is important that traffic signals are installed only when warranted. The most important factor that determines the need for traffic signals at a particular intersection is the intersection's approach traffic volume, although other factors such as pedestrians volume and crash experience also play a significant role (FHWA, 2003). The indications given by a traffic signal are green to give right of way to the movements, yellow to warn drivers of the change from green to red, indicating that the movement loses the right of way, and the red indication that prohibits the movement and indicates that the vehicle must stop. Driver compliance to these signals is a very important factor on which safety at the intersections has a heavy dependence.

1.1 Problem Statement

Every year, about 43,000 people are killed and more than 2.5 million people are injured in crashes occurring on roads in the United States (Bureau of Transportation Statistics, 2008).

According to the Bureau of Transportation Statistics (2008), the costs to society due to these crashes exceed $230 billion annually. In general, more than 45 percent of crashes and 25 percent of the reported highway fatalities occur at intersections. One of the major causes of severe crashes in the operation of a signalized intersection is the violation of the red indication. In 2003, 206 million crashes occurred in the United States related with vehicles passing the red signal (Red Light Running, RLR), in which nearly 1,000 people lost their lives and 176,000 were injured. These conflicts involve economical losses of approximately $14 billion annually (National Highway Traffic Safety Administration, 2005). Pant et al. (2005) reported that most conflicts at signalized intersections are caused by speeding vehicles during the yellow change period, vehicles running the red indication, and vehicles stopping abruptly.

In Puerto Rico, there were 5,323 reported motor vehicle crashes in 2003 related with RLR events. These crashes occurred as a result of drivers ignoring the red or the yellow indications without reducing their speed. In 2004, there were 4,407 crashes related with RLR, where 14 people lost their lives and 1,106 persons were injured, while in 2005 six people were reportedly killed by these types of events (Caro, 2006).

The number of people killed and injured in crashes at signalized intersections can be reduced by modifying the geometric design of the intersection, optimizing the programming of the traffic indications, improving the traffic control devices, implementing regulatory measures to comply with the laws and promoting educational campaigns for drivers and pedestrians.

To achieve these goals, it is necessary to conduct studies to evaluate safety and detect potential problems at intersections without having to wait to collect historical data of crashes. It is important to develop assessment methodologies and analysis of signalized intersections that address road safety during the design stage of new projects or redesigning existing intersections, or during the initial phase of the vehicle operation.

1.2 Research Objectives and Scope

Driver attitude or behavior is the most important factor in the decision-making process before the end of the green period in vehicular operation. This factor is not easy to measure because one would need to enter the mind of each driver to know his/her decision making process. Nevertheless, it is possible to study factors that serve as alternative measures and that in some way reflect driver behavior. There are other important factors such as environmental factors, vehicle type, geometry of the intersection, traffic control etc., that influence the decision making at the beginning of the yellow change period. The main objective of this research was to obtain a comprehensive understanding of vehicle behavior at the end of the green period at signalized intersections. In order to carry out this study, the analysis of a group of intersections was first taken into account, followed by the analysis of a single intersection, to assess the incorporation of other variables that may be contributing factors to this approach. The contribution of this study involves a method of data collection at intersections that capture data with reference to traffic control, speeds, traffic conditions and the characteristics of the trajectory of the vehicles. The potential variables that may be significant in the prediction of a stop or go model decision at the yellow onset were also explored.

The specific objectives of this study were the following:

- analyze the frequency and severity of crashes related with RLR events and the characteristics of roads, vehicles and drivers present in the databases of Puerto Rico,
- identify intersection, traffic flow, and individual vehicle factors associated with RLR events,
- develop and perform a field experiment to observe and measure variables of vehicle behavior reflected in the trajectory of vehicles and speed changes at the change of the yellow and red indications at signalized intersections,
- perform statistical analyses to determine the distributions of observed variables associated with vehicle operating behavior of drivers with yellow and red signals at signalized intersections, and
- develop a regression model for stop and go decision based on contributing factors accounting for the geometry, traffic control, and driver behavior at intersections.

The contributions of this dissertation to the state-of-the-art include the following aspects:

- the calibration of a stop and go decision model for signalized intersections in Puerto Rico using data observed locally,

- the development of a technique to determine the dilemma zone (DZ) parameters using field observations and video technology, and extending the approach influence zone to 480 feet upstream of the stop bar, and
- the proposal of an indirect way to measure the aggressiveness of drivers through the Driver Aggressiveness Index (DAI).

This research focused on studying and evaluating the reaction of drivers at the end of the green period at signalized intersections under daylight and dry weather conditions. Vehicular operation was observed outside of peak traffic periods so that factors associated with congestion do not influence the study.

1.3 Justification

Road safety is an important area within Transportation Engineering. Not only do the vehicle operation measures, such as delay and level of service, affect the process of evaluation and decision-making, but the safety level of an intersection should also have an impact on this process. For this reason, it is important to estimate the probability of the occurrence of events that represent potential crashes at the intersections (e.g. vehicles passing in red) and also, to study the impact of individual vehicle speeds, accelerations and decelerations, and the drivers reaction before signal change, among other measures, with the purpose of incorporating the direct effect of traffic in the level of safety at intersections.

Human behavior reflected in red light running events is associated with the attitude of the drivers, whether intentional or not. The literature indicates that intentional behavior can be changed through the establishment of surveillance strategies and law enforcement, while unintentional behavior can be modified through the implementation of engineering strategies. The Institute of Transportation Engineers (ITE, 2003) and the National Campaign to Stop Red Light Running (2002) suggest that research should be conducted to assess and identify intersections with a high potential for vehicles passing the red indication to analyze the cost-effectiveness of various measures of engineering education and surveillance.

There are different safety strategies that have the potential to reduce crashes due to vehicles passing the red signal, in problematic intersections, and in the study area. These strategies are changes in variables related to the operation of the intersection, the yellow and red periods, the sequence of phases and movements, the geometry of the intersection, the visibility, the presence of signs and other devices (Bonneson et. al, 2002). Also, the use of conventional and electronic surveillance and the establishment of information programs and public education are critical to improving safety. To implement these strategies it is necessary to identify intersections with a high probability of RLR-related crashes by analyzing the factors that influence the occurrence of such events and develop models to predict their frequency. Furthermore, an in-depth study and analysis of driver reaction at the end of the green period in a specific signalized intersection is an important step in understanding the factors that influence RLR events.

It must be emphasized that while a model which relates factors affecting RLR at a specific intersection is important, it is even more critical to analyze the driver reaction at the end of the green period in a signalized intersection which will lead to a greater understanding of the RLR phenomenon and possibly provide strategies to mitigate them. It must be emphasized that there is no record that a study of this nature has been performed in Puerto Rico in which continuous data of the trajectory of vehicles approaching a signalized intersection has been collected through the use of a digital video camera and later analyzed to understand the driver reaction at the end of the green period in a signalized intersection.

The main benefit of doing this study is to improve safety at signalized intersections because the costs to the society and loss of lives are sufficient reasons for developing and implementing strategies and cost-effective measures. An ancillary benefit is that this study will also be important for insurance agencies whose priority is a reduction in costs and liabilities associated with traffic accidents.

1.4 Organization of the Dissertation

Chapter 1 contains an introduction explaining the definition of Red Light Running (RLR), while presenting some facts related to RLR in United States and Puerto Rico, and mentioning the problem that exists because of RLR events. The objectives, scope and benefits of this study are also included. presents the study objectives, scope and benefits of this study. Chapter 2 explains the general methodology used for the preparation of this dissertation. Chapter 3 presents a detailed literature review and mentions the different studies that have been carried out and those that are important to safety at intersections. For the subsequent chapters, this study was divided in two parts: in the first part in Chapter 4, an analysis and evaluation of the RLR phenomenon in general was made, with reference to the approaches of a group of intersections. In the second part given in Chapter 5, a study of the driver reaction at the end of the green period was conducted in a more specific manner taking into account only one approach of an intersection located on a main artery. Conclusions are presented in Chapter 6 followed by recommendations for future work.

2 METHODOLOGY

The methodology used for this research is presented in Figure 2-1. The methodology consists of 21 tasks. The first task was the identification of the safety problem related to RLR events and an extensive literature review including the most important topics of safety at signalized intersections, starting from the definition of an intersection and including topics such as review of intersection safety studies, surrogates measures of safety at intersections, dilemma and option zones, prediction of RLR events and characteristics of driver behavior at signalized intersections.

To take into account all important aspects of the occurrences at the end of the green period, the work was divided into two parts: the first part includes an analysis of a group of intersections; and the second part consists of the analysis of a particular intersection. For the first part, the criteria for selection of intersections to be studied were based on literature review, analysis of historical crash data, and review of the RLR related crashes. The sites used for data collection required the availability of an appropriate safe area to install the equipment and the personnel making the observations.

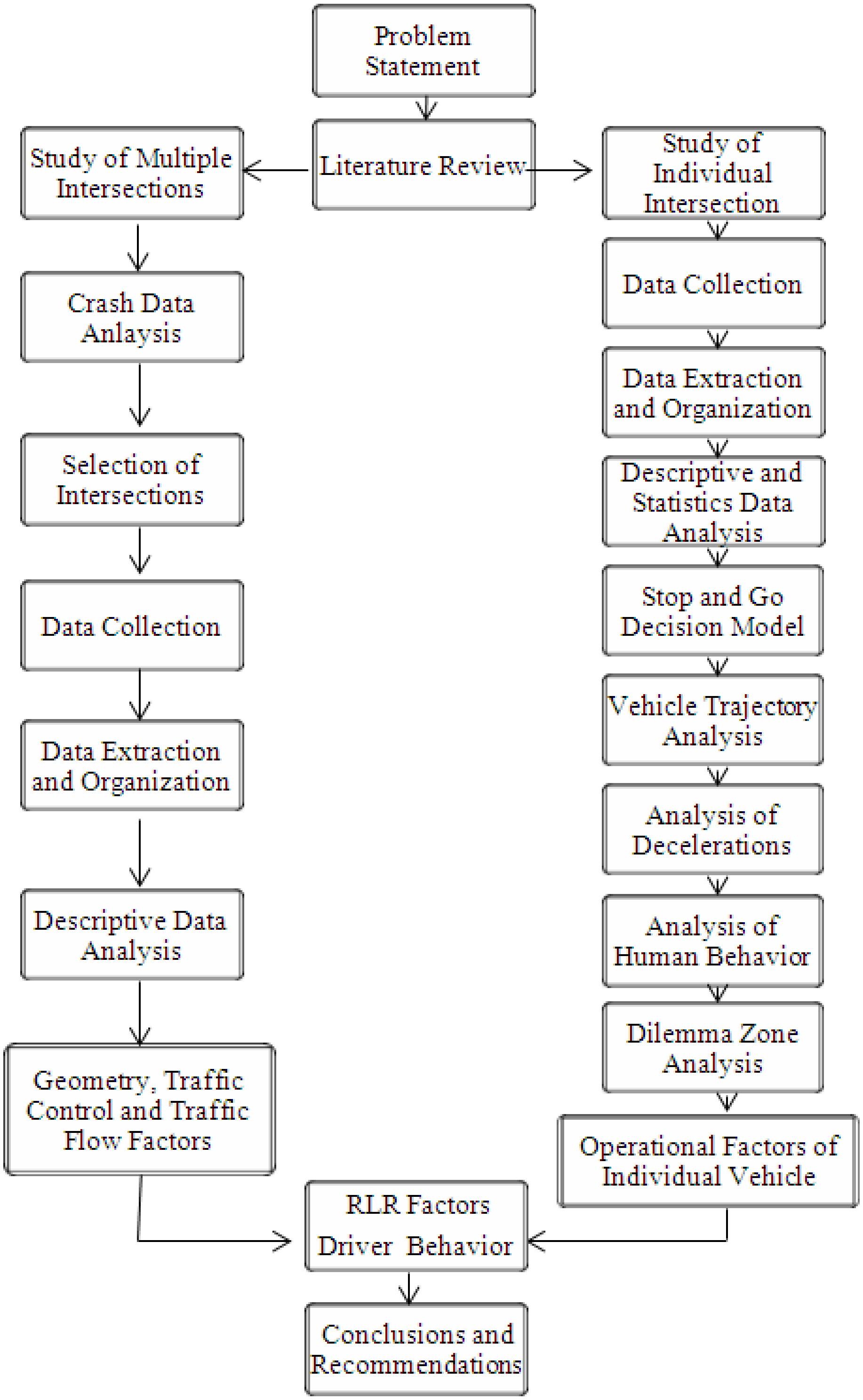


Figure 2-1: Research methodology

The objective of the data collection of the first study was to acquire information about the intersection geometry, the signal timing plan, traffic flow, percentage of heavy vehicles, vehicle speeds and number of RLR and YLR (yellow light running) events. Some data were registered manually, and other data were recorded in videos taken in the field to be later analyzed in the laboratory, and in this manner capture the features related to the reaction of drivers at the yellow onset in each intersection. With these data, a descriptive analysis of data and an analysis of RLR and related factors were carried out.

The second study required more detailed data about the trajectory of vehicles approaching the signalized intersection. The objective was to take into account factors related to individual vehicles. A set of digital video cameras was placed, focused on one approach of the intersection in order to collect data related to the vehicle deceleration, the vehicle speeds in the corresponding approach, vehicle type, the travel lane, the distance of the vehicles at the yellow onset from the stop bar, time periods of the traffic signal etc. With these data the trajectory of the vehicles and the reaction of the drivers at the end of the green period or the beginning of the yellow change could be analyzed.

With the data collected, statistical analysis and graphical representations such as frequency distribution curves and scatter plots to establish the distribution and characteristics of the data were made. Different analysis were performed including analysis of deceleration, analysis of the trajectories of the vehicles, analysis of human behavior and analysis of the dilemma zone.

A regression model was calibrated for the prediction of stop and go decision and an evaluation and analysis of the model was conducted. Finally conclusions including findings of the study and recommendations for future research are presented.

This chapter presented the methodology of the intersection in general. Chapters 4 and 5 will be dedicated to the specific methodologies of the studies for a group of intersections and individual study at a particular intersection respectively.

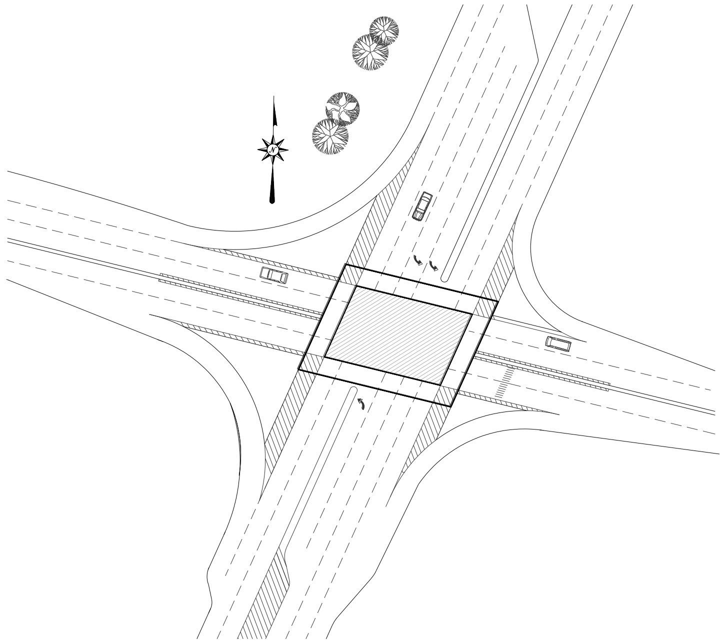
The following chapter presents an extensive literature review covering the aspects related to safety at intersections and presents an explanation of the topics that were considered during the development of this study.

3 LITERATURE REVIEW

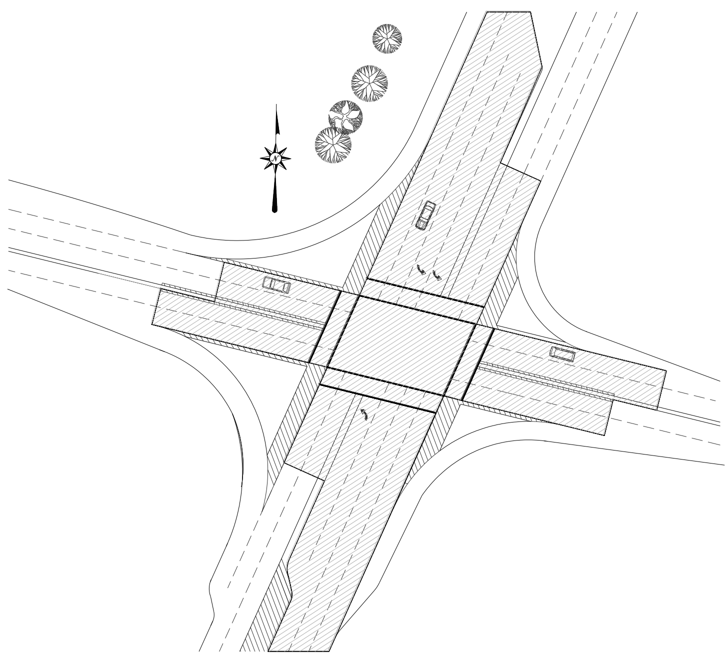
There are many factors that contribute to intersection safety, which have been studied from different points of view. First, there have been studies regarding the prediction of crashes taking into account the history of crashes and the characteristics of particular sites. Other studies have used surrogate measures, which represent factors contributing to crashes and allow the estimation of the safety in a reliable and faster manner. Some authors have studied the behavior of drivers at the end of the green period and the vehicle dynamics in the area before the intersection, driver indecision between going or stopping, while others have focused on developing models to predict RLR events.

3.1 Definition of an Intersection

An intersection is defined as "the general area where two or more roadways join or cross, including the roadway and roadside facilities for traffic movements within the area" (AASTHO, 2004). An at-grade intersection is defined "by both its physical and functional areas", as presented in Figure 3-1. The functional area "extends both upstream and downstream from the physical intersection area and includes any auxiliary lanes and their associated channelization" (AASTHO, 2004).



a) Intersection Physical Area



b) Intersection Functional Area

Figure 3-1: Illustration of physical and functional areas of the intersection

As shown in Figure 3-2, the functional area corresponding at each approach to an intersection consists of three basic elements:

- decision distance
- maneuver distance, and
- queue-storage distance.

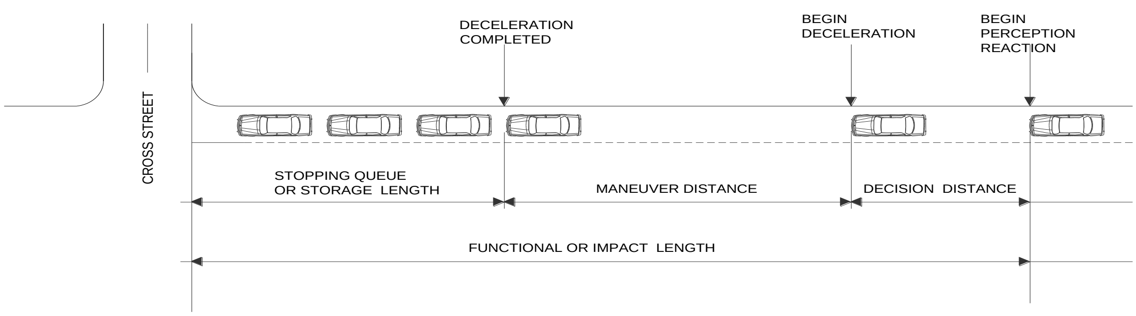


Figure 3-2: Elements of the functional area of an intersection

3.2 Review of Intersection Safety Studies

According to Hauer et al. (2003) the safety of an entity (road segments, intersections, drivers, vehicles, etc.) can be defined as the frequency of crashes by type and severity, which is expected to occur at an entity during a specific period time. The safety in a signalized intersection is commonly measured by the number of crashes that occur at the intersection or close to the intersection, and their consequences in terms of its severity. The typical approach to identify safety problems in a transportation facility is the use of historical data of crashes, which are not always available in the relevant government agencies. Also, in some cases the data reported has errors in data entry that makes this information not completely reliable, and collecting the data and entering it in the crash database takes several years.

Statistical models are deemed to be effective in describing safety at intersections since crashes are discrete and random events requiring a statistical analysis. Generally, Poisson regression or negative binomial models are used to predict the frequency of crashes, as the number of collisions is a positive integer. Linear regression models are not appropriate to model the frequency of crashes since in these models the dependent variables are assumed to be continuous and can take both positive and negative values (Figueroa, 2005).

Different statistical models have been developed to evaluate highway safety (Hauer et al., 1988; Persaud et al., 1988; Davis et al., 1995; Zhou et al., 1997; Bauer et al., 2000; Wong et al., 2007). These models have established relationships between the number of crashes or crash rate with independent variables of operational parameters (average speed, type of traffic control, etc.) and other non-operational variables such as those related to the geometry of the intersection. For example, one of the first models was developed by McDonald (1953) in California using 150 at grade intersections on divided highways. This model relates the expected number of crashes per intersection per year with the volume at the intersection. McDonald's model found that the intersections that had a low volume on the cross street had a higher rate of crashes than those with higher volumes. The safety performance model developed by Bauer et al. (2000) related traffic accidents and highway geometric elements for at-grade signalized intersections based on all collision types. The lognormal regression equation is as follows:

$$\boldsymbol{Y = e^{-3.428}(X_1)^{0.224}(X_2)^{0.503}\exp^{(0.063X_{19}+0.622X_{20}-0.2X_{21}-0.31X_5-0.13X_{22}-0.053X_{16}-0.115X_{11}-0.225X_3-0.13X_{17})}} \tag{3-1}$$

where:

Y = expected number of total multiple-vehicle accidents in a three year period,

X_1 and X_2 = average daily traffic (veh/day) on minor and major roads, respectively,

X_{19} = pre-timed signal timing design,

X_{20} = fully actuated signal timing design,

X_{21} = 1 if multiple (>2) signal timing, 0 otherwise,

X_5 = 1 if no access control on major road; 0 otherwise,

X_{22} = number of lanes on minor road,

X_3 = 1 if major road has ≤ 3 through lanes in both directions of travel combined; 0 otherwise,

X_{17} = 1 if major road has 4 or 5 through lanes in both directions of travel combined; 0 otherwise, and

X_4 = design speed on major road (mph).

The regression model between crashes and geometric design of intersections included traffic control variables and traffic volume. It was found that these models explain between 16 and 39 percent of the variability in crash data (Bauer et al., 2000). However, most of the variability is explained by the traffic volume from major road and minor road. The geometric design variables included in the model accounted for only a small additional portion of the variability.

David et al. (1975) considered factors of crashes for the Bay Area in San Francisco California, but only at intersections that reported at least two crashes in the period from 1971 to 1973. Crashes were classified by severity, by conflict, and by movements (typical and others). The study resulted in a regression model to predict the number of crashes per intersection for three years. Among the variables included in the model were the volume, restrictions of U-turns, the number of right turn lanes, the number of lanes on the main road, the number of left turn lanes, the number of divided streets, and whether the intersection control used stops sign versus traffic signals (0 versus 1). With this model it was found that the introduction of left turn lanes at signalized intersections (without changing the system of two phases) tended to increase the number of crashes.

From the nature of the data and the models the reason for the frequency of crashes is determined without taking into account the behavior of drivers and their response to different important conditions to evaluate the safety of a facility. Typically these models require large amounts of historical data of crashes to establish the significant variables and get valid statistical inferences. Some other studies have applied the Bayesian method and statistical techniques to estimate the safety in highways based on observations of vehicle operation (Higle et al., 1988; Persaud et al., 1999). In these studies, the frequency of crashes is calculated for each site as a weighted average of the expected frequency of crashes obtained from a safety performance function (SPF) and the count of expected crashes.

3.3 Surrogate Measures of Safety Intersections

Alternative measures to crashes have also been applied to measure and monitor safety in a site or a number of sites. These measures are known as surrogate safety measures, providing an indirect measure of safety without the need for crash data. These measures are important because they would not need to wait for a certain number of crashes to occur to recognize the problem and address it thus reducing the wait time for crash data to be available. Past practices have mostly used two basic types of surrogate measures in place of observed crash frequency (AASTHO, 2010). These are:

- surrogates based on events which are proximate to and usually precede the crash event. For example, at an intersection encroachment time, the time during which a turning vehicle infringes on the right of way of another vehicle may be used as surrogate estimate, and
- surrogates that presume existence of a causal link to expected crash frequency. For example, proportion of occupants wearing seatbelts may be used as a surrogate for estimation of crash severity.

The use of alternative surrogate measures to increase the reliability of estimates of the road safety has increased. The traffic conflict technique (Perkins et al., 1967; Glauz et al., 1980;

Parker et al., 1988; Archer, 2005) is a methodology in which observers can identify conflict events at intersections, such as abrupt braking and evasive maneuvers. These studies depend on the observer to detect whether or not a conflict exists, or if there are safety concerns at the facilities.

Other recent studies discuss the safety aspects based on alternative measures to motor vehicle crashes (Federal Highway Administration, 2003; Songchitruksa et al., 2006; Cunto el al., 2007). These measures could be used as a support in evaluation of safety alternatives without having to depend only on studies of crashes or reconstruction of a crash. Among the surrogate measures used are: time to crash, the deceleration rate to avoid a crash (DRAC), time during which the turning vehicle invades the space of the direct vehicle, the lapse of time between the end of the invasion of the turning vehicle and the instant the direct vehicle reaches the point of potential crash, among others.

DRAC considers the speed and decelerations differentials in the occurrence of crashes and is expressed as a function of time/space and deceleration profiles experienced by pairs of individual vehicles in the traffic flow (anterior and posterior vehicles). This measure reflects the deceleration which would require a posterior vehicle to avoid hitting the anterior vehicle.

Cunto et al. (2008) define the Crash Potential Index (CPI) in terms of the probability that the DRAC on a vehicle exceeds the ratio of maximum deceleration rate available (MARD) or ability to stop, for every 0.1 seconds a simulation. Using the CPI, the study evaluated the safety of intersections with different types of control (signalized versus unsignalized) and different geometric features by using microscopic simulation.

Other authors (Wang Y. et al., 2002; Wang X. et al., 2008) have investigated and modeled the occurrence of rear end crashes caused by different patterns of left turns at signalized intersections. The frequency of crashes of each pattern of left turns was modeled for each approach using generalized estimating equations with the Negative Binomial as the link function to find the correlation between crash data. The studies identified differences in the factors that cause crashes for different patterns of left turns.

3.4 Dilemma and Option Zones

A significant number of crashes, both rear and at an angle, is associated with the passing of vehicles during the red signal period and the existence of an area in which the driver of a vehicle arriving at an intersection must decide whether to accelerate to pass the intersection with the risk of passing in red and have a crash at an angle, or suddenly stop with the risk of a rear crash. This area is called the Dilemma Zone.

According to the literature, the DZ is the portion of the highway in which a driver is undecided about whether to stop or continue to cross the intersection (FHWA, 2006). The concept of dilemma zone was initially proposed by Gazis, Herman and Maradudin (1960), and their model is typically referred to as the GHM model. This model uses deterministic values, such as driver's reaction and perception time, deceleration rate, length of the yellow change period, etc., to determine the location of the dilemma zone. The distance from the stop line required for a driver to stop in a safe and comfortable way is defined as X_c (

Figure **3-3**). This is referred as the critical distance or the *minimum stopping distance* from the stop line. Up to the distance X_c from the stop line at the beginning of the yellow period, there exists a zone in which the vehicles cannot stop safely. The distance X_0 is usually referred to as the *maximum passing distance* from the stop line. The vehicles located at a distance shorter than X_0 from the stop line, also cannot stop safely before the stop line. The dilemma zone exists for $X_c > X_0$, i.e. when a vehicle which is approaching the intersection at a speed less than or equal to the speed limit cannot maneuver in a safe, legal, and convenient way. The dilemma zone is represented by $[X_c - X_0]$.

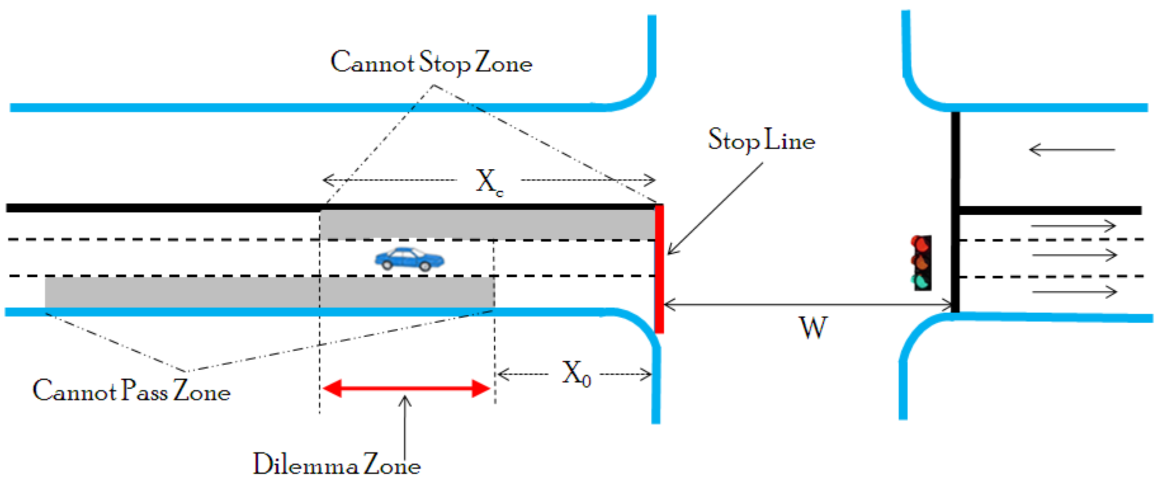


Figure 3-3: Schematic diagram of the Dilemma Zone

According to the GHM model, X_c and X_0 can be represented by the equations (3-2) and (3-3) (Gazis et al., 1960) as follows:

$$X_c = V_0 \delta_c + \frac{{V_0}^2}{2d_{\max}} \tag{3-2}$$

$$X_0 = V_0 \tau - (W + L) + \frac{1}{2} a_{\max} (\tau - \delta)^2 \tag{3-3}$$

where:

X_c = minimum stopping distance (ft),

X_0 = maximum passing distance (ft),

V_0 = initial vehicle speed when the yellow interval begins (ft/s),

τ = duration of the yellow phase (s),

δ = driver's perception-reaction time (s),

a_{max} = maximum acceleration rate of approaching vehicles (ft/s^2),

d_{max} = maximum deceleration rate of approaching vehicles (ft/s^2),

W = intersection width (ft), and

L = average vehicle length (ft).

When $X_0 > X_c$, the driver has the option to stop or continue (Figure 3-4). This area is known as the Option Zone (OZ). In this area the driver has two choices during the yellow change period, either to cross the intersection or slow down and stop before the line. If a vehicle arrives at the yellow onset and is located in this area, it can choose to pass the intersection or stop before the end of the yellow period in a safe manner.

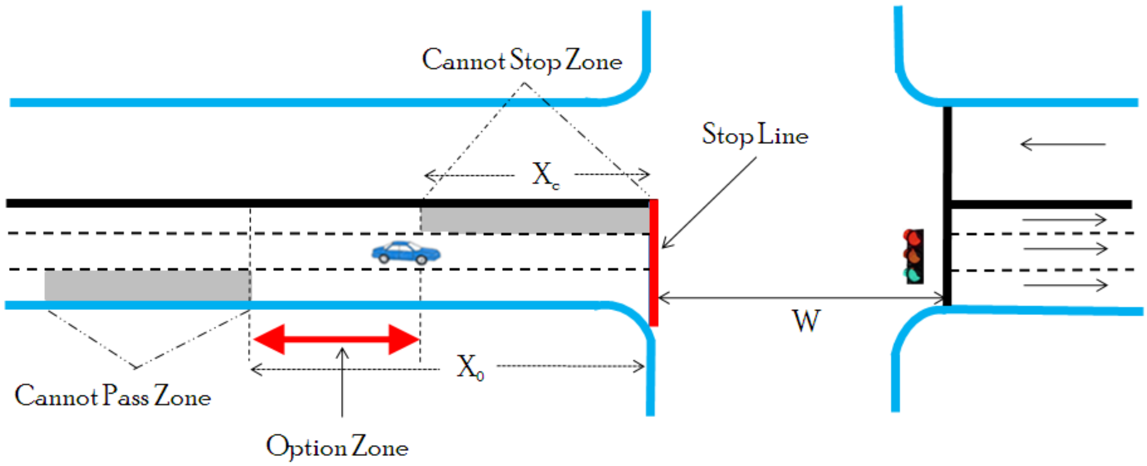


Figure 3-4: Schematic diagram of the Option Zone

One of the important measures to determine DZ at signalized intersections is the length of the yellow change period. According to the MUTCD (FHWA, 2003), "A yellow signal indication shall be displayed following every CIRCULAR GREEN or GREEN ARROW signal indication. The exclusive function of the yellow change interval shall be to warn traffic of an impending change in the right-of-way assignment. The duration of a yellow change interval shall be predetermined".

Usually the dilemma zone exists at intersections where the yellow period is not long enough. This causes a situation in which a vehicle cannot stop in time before the start of the red change period without having to accelerate uncomfortably or able to stop without applying a drastic deceleration and stop abruptly.

The ITE (2003) recommends the following equation for timing the yellow interval based on the kinematic model:

$$Y(\text{sec}) = T + \frac{V}{2d + 2Gg} \tag{3-4}$$

where:

d = deceleration rate (recommended 10 ft/s^2),

g = gravitational acceleration, 32.2 ft/ s^2,

G = approach grade (*ft/ft*),

T = perception-reaction time (recommended 1.0 second), and

V = speed of approaching vehicles (ft/s).

Equation 3-4 shows the yellow interval calculation when an all-red clearance interval is used. The all-red interval is a time period whose purpose is to allow additional time for motorists already in the intersection to clear the intersection on the red indication before conflicting traffic movements are released (FHWA, 2005). Typically, the duration of the all-red clearance interval is from 0.5 to 3.0 seconds. The general formula proposed by the ITE for the all red interval is as follows:

$$r(s) = \frac{W+L}{V} \tag{3-5}$$

where:

W = width of the intersection, in feet, measured from the near-side stop line to the far edge of the conflict traffic lane along the actual vehicle path,

L = length of vehicle, in feet (assumed to be 20 ft), and

V = speed of the vehicle through the intersection (ft/s).

The Traffic Detector Handbook (FHWA, 2006) provides a formula for determining the dilemma zone by adding the all-red time to the yellow period, and this is referred to as the clearance interval. The present study is based on the original model (GHM (1960)), since the dilemma zone study takes into account the vehicles that arrive during the yellow period and deems that all vehicles that pass in red (even during the all-red period) are in violation.

The dilemma zone has been studied to develop binary models related to the probability of stopping or crossing the intersection in terms of operational variables such as speed and driver-related variables such as gender, age, level of aggressiveness, etc. With these models, it has been determined that speed is an important factor in the decision of drivers either to pass or stop at the yellow onset and that larger intersections with high volumes of vehicles are more prone to RLR violations (Porter et al., 2000; Gates at al., 2007; Papaioannou et al., 2007). The dilemma zone has also been modeled taking into account the probability that drivers stop at the beginning of the yellow period. Zegeer (1977) defined this distance as that which corresponds to the zone upstream of the stop bar where more than 10% and less than 90% of drivers decide to stop. This area is clearly related to the approach speed.

3.5 Prediction of RLR events

According to statistics, RLR crashes have become a serious safety problem in the United States and Puerto Rico. Of the fatal crashes at intersections in the U.S., 16 to 20 percent is attributed to the passing of the vehicles in red (Mohamedshah, 2000). Retting et al. (1998) reported that drivers involved in crashes associated with RLR have a higher probability to be hurt (45%) in this type of crash than in others (35%). Retting et al. (1999) also identified the crashes due to RLR as those that occur in a signalized intersection and involve a driver who failed to obey the traffic signal. This action may cause rear end crashes when two successive drivers make conflicting decisions in response to the yellow signal and the leading vehicle decides to stop while the following vehicle wants to pass the intersection. On the other hand, an inappropriate action of the leading vehicle may result in a collision with vehicles of the conflicting movements at the intersection (Lum et al., 2003).

There are many studies focused on modeling the phenomenon of red light running and the strong relationship it has with different factors. Chang et al. (1985) used logistic regression to model the stop or go decision at the yellow onset as a function of speed and distance to the intersection. They concluded that the probability of stopping is higher when the yellow onset occurs at a greater distance to the intersection and for a lower approach speed.

Bonneson et al. (2002) developed a model to predict the expected frequency of RLR events by deriving an equation as an expected value of stops at the yellow onset using a probability distribution. The resulting calibration equation is the following:

$$E(R) = \frac{Q}{C}\frac{1}{b_1} ln\left[1 + e^{(b_0 - b_1 T + b_2 x_{2 \ldots\ldots} + b_n x_n)}\right] \tag{3-6}$$

where:

$E[R]$ = expected red-light-running frequency veh/h),

Q = approach flow rate (= $q \times 3600$) (veh/h),

C = cycle length (s),

$\ln[x]$ = natural log of x,

x_i = variables describing selected traffic and geometric characteristics,

b_i = regression coefficients, $i = 0, 1, 2, ..., n$, and

T = travel time before RLR can occur (s).

Bonneson et al. (2002, 2004) conclude that the frequency of RLR increases with flow rate, speed, dense platoons arriving at the end of the phases and decreases with long cycle lengths, intersection width, and when the traffic signal heads have back plates.

A binary logistic regression model was calibrated by Gates et al. (2006) to determine the factors influencing the occurrence of RLR. This model takes into account variables such as estimated travel time at the yellow onset, flow rate per lane, cycle length, yellow period, all red, gaps, the presence of vehicles, bicycles and pedestrians, turning left lanes in the adjacent lane and vehicle type. From this study, it was concluded that the most significant variable for the probability of stopping or passing the intersection at the yellow onset was the estimated travel time to the intersection in agreement with Chang et al. results. This study also reveals the importance of incorporating variables representing individual characteristics of drivers, which were not taken into account in the model.

In a method developed by Zhang et al. (2008) to predict RLR based on probabilistic models, an algorithm that uses statistics from the measurements obtained from historical data was utilized. The event was modeled using measurements of speeds from two discrete point sensors to stop at the yellow onset and to identify the RLR events. The decision itself was taken with the Neyman-Pearson criterion based on empirical statistics. With this method it was found that for the same intersection, but for different approaches, the mean and variance matrices of speed for stop or go were different. The authors concluded that the algorithm can be improved and as a result, the intentional RLR can be reduced with a combination of a dynamic system and the application of security cameras at the intersection.

Elmitiny et al. (2010) analyzed driver behavior at the start of the yellow change period and the driver decision to stop or cross the intersection. To determine the probability of the stop/go decision, classification tree diagram were used to associate RLR events with traffic parameters. According to their model, the stop/go decision depends on the speed and distance at which the vehicle is located at the beginning of the yellow signal indication and its relative position in the platoon of vehicles. These results agree with Chang et al. (1985) and Gates et al. (2007). The latter study reveals the importance of incorporating variables representing the individual characteristics of drivers. Bonneson et al. (2002) included factors such as short intervals due to the flow in the platoon, the type of signal control (actuated or fixed time), approach grade, yellow interval length, and the expected delay time to take the decision to stop or continue.

Although most previous studies mentioned provide acceptable results for the prediction of RLR events, these studies do not include a large enough group of variables based on the characteristics of traffic conditions at the intersection, such as driver behavior, to produce a more robust model. The current research seeks to undertake a comprehensive study of the vehicular trajectory from the yellow onset until they stop or cross the intersection; speed changes are assumed to reflect the behavior of drivers.

3.6 Characteristics of Driver Behavior at Signalized Intersections

Although there are different traffic operational factors that affect the response of the drivers at the yellow onset, the most important factor is the human factor. Human factors along with the type of vehicle and the characteristics of the road and traffic, determine the action that a driver should take.

Van der Horst et al. (1986), in their study indicated that such a response depends on many factors including the emotional state and attitude of the driver, the ability to cross the intersection before the end of the yellow phase, the interaction with other drivers and the vehicle's approaching speed, parameters that were also used in Milazo et al. (2001), Koppa (1992), Shultz et al. (1998), and AASTHO (2004).

Chang et al. (2004) investigated the characteristics of more than 700 drivers at 9 intersections of different counties in Maryland. They classified the drivers based on their responses to the onset of yellow into four types: "aggressive-pass", "conservative-stop", "normal-pass", and "normal-stop". They concluded that not only were individual characteristics important but also a series of factors such as traffic speed, yellow duration, congestion, and type of vehicle affected driver behavior. In contrast, in a much earlier study at five different intersections, Olson and Rotery (1961) concluded that the yellow time does not influence driver behavior since the yellow period is taken as an extension of the green.

Other factors that affect the driver behavior at the start of the yellow signal were studied by Shinar et al. (2004). The study observed that drivers who probably have a pattern of aggressiveness were men, youth, and the value that drivers give to travel time. They concluded that the response of drivers at the yellow onset varies with factors such as the use of cell phones while driving. Patten et al. (2004) investigated the impact of the use of cell phone from the perspective of attention to the road. According to their study, the reaction time of most drivers is significantly increased while using cell phones, regardless of the use of hands-free units.

Different authors have investigated the perception and reaction time and braking time at the yellow onset. Gazis et al. (1960) found in their study that the average braking reaction time was 1.14 seconds, while Wortman et al. (1983) observed a perception and reaction time of 1.3 seconds. According to Chang et al. (1985) drivers tend to react faster when the vehicles are closer to the intersection. When vehicles are farther from the intersection, perception time can be longer because there is no hurry to make a decision. The values they found were on an average of 1.3 seconds for perception and reaction time, in agreement with the value encountered by Wortman et al. (1983).

Diew et al. (2001) analyzed three intersections in Singapore and defined the perception and reaction time as the time from the onset of the yellow and the application of the brakes. They found an average of 0.86 seconds which is consistent with other studies. A lower value of reaction times was reported by Kai et al (2004) as 0.8 seconds.

El-Shawarby et al. (2008) studied the behavior of 60 drivers at the yellow onset at high-speed signalized intersections where the perception and reaction time and braking time were characterized. In their study, they concluded that the perception time is not affected by the time to stop line, driver's gender and age, while reaction time depends on the driver’s gender and the time to the stop line. In general, they identified an average perception and reaction time of 0.73 seconds.

3.7 Countermeasures to Decrease RLR

Driver behavior and attitude is related to RLR, whether it is an intentional act or not. It is understood that intentional behavior can be modified through conventional police enforcement or automated enforcement systems with sensors and video cameras at the intersections. The implementations of educational campaigns that provide safety information at all age levels further contribute to the reduction of RLR behavior.

Unintentional RLR behavior can be reduced through engineering strategies. The National Campaign to Stop RLR (2002) and the Institute of Transportation Engineers (ITE, 2003) suggest local studies are needed to evaluate the cost-effectiveness of engineering, enforcement, and educative solutions at signalized intersections with high RLR potential. The strategies could include removing unnecessary signals, replacing the intersection with a modern roundabout, improving the signal visibility and conspicuity by increasing the signal head size or by adding backplates, improving the intersection sight distance, increasing the likelihood of stopping by placing advanced warning signs, flashers or rumble strips, optimizing the signal phase sequence and cycle length, and modifying the yellow and all-red change intervals with respect to speeds and intersection geometry (Chang et al., 1985; Vander Horst et al., 1986; Retting et al., 1998; Polanis, 2002).

Numerous studies have found that extending the yellow period influences the reduction in the frequency of RLR. Retting et al. (2007) evaluated the effect of the extension of the length of the yellow period and the installation of red light cameras at six approaches of two intersections in Philadelphia, Pennsylvania. As a result they determined that the RLR events decreased by 36% due to the change in the yellow time and 96% (beyond the levels obtained with the change in yellow) due to the installation of RLR cameras. It was concluded that the combination of countermeasures is important to obtain a favorable result in the decrease of RLR.

It is known that RLR is not only a violation of the red indication, but is also a safety problem because it can result in crashes with injuries or deaths. Traditionally, police penalize this violation by observing the behavior and issuing a citation. However, this application can now be automated through the use of a red light camera system that can detect an offending driver, capture an image of the plate and issue a citation by mail (Hugh et al., 2003).

Automated red light cameras can have a significant impact on red light enforcement. The cameras work with speed and magnetic sensors in the pavement along with signal control circuitry to determine when a vehicle has run a red light (Figure 3-5). When the system detects a violation, a series of cameras take three pictures. One picture is taken with the vehicle entering the intersection clearly showing the vehicle and the color of the active signal indication, one with the vehicle exiting the intersection again showing the vehicle and the color of the light and a third showing a close up of the license plate. Red light runners are then sent a ticket in the mail with a copy of the pictures of the violation.

Figure 3-5: Red light camera system implemented in the state of Michigan (LTAP, 2004)

Red light camera enforcement programs involve more than the installation of the cameras and sending the tickets. These programs also include education and outreach, level of fines, adjudication, type of signaling, etc.

The automated camera system has been implemented in different countries with different outcomes. Maisey et al. (1981) reported in Australia that the camera system brought about a reduction in right angle crashes along with an increase in rear end crashes. The London Research Centre for Environment and Transport Studies (1997) reported a 69% reduction in Great Britain in the total number of red light violations. The violation rate (violations as percentage of number of opportunities for violation) fell from 6.1% to 2.2%, and a significant reduction in the number of violations that occurred for a longer period into the red-signal phase. Ng et al. (1997), studied the effect of the automated cameras on right-angle and total collisions in Singapore and found a reduction of 8% and 7%, respectively, with a slight increase of 5% in rear-end collisions. In the United States the results of this analysis seem to confirm positive benefits from the use of automated systems with a reduction of approximately 26% in both rear end and right angle crashes (Flanery et al. 2002).

The most important aspects related to safety at intersections that have been studied by different authors and are relevant to the development of this work have been reviewed in this chapter. The following chapter presents the study of a group of signalized intersections that are made with the aim of identifying factors regarding the geometrical characteristics of the intersection, traffic, and traffic light times which have some relation to the reaction of drivers at end of green period.

4 INTERSECTION CHARACTERISTICS, SIGNALS AND TRAFFIC FLOW FACTORS AFFECTING RLR

4.1 Introduction

This chapter focuses on identifying the effect of general roadway and intersection factors on the frequency of RLR events. One objective of the study is to identify factors that influence the reaction of drivers at the end of the green period at signalized intersections. At the end of the green period, depending on the decision of the driver, there may be situations that put at risk the safety of vehicles passing through the intersection. In the case of a high frequency of RLR, safety becomes extremely important as it is expected that the intersection will be prone to crashes, and hence the importance of identifying the contributing factors to the occurrence of these events.

4.2 Methodology

The first screening for candidate sites of signalized intersections was performed using the Crash Database of the Puerto Rico Department of Transportation and Public Works. Crash data from three consecutive years, from 2002 to 2004, were the latest available for the study. The database includes the categories from the Police crash reports to identify associated events and circumstances, and driver actions to crashes (Figure 4-1). The database does not identify directly that a crash was caused by a RLR event. Therefore, the first step was to filter the data including those categories of circumstances and driver actions that could be associated with a RLR event.

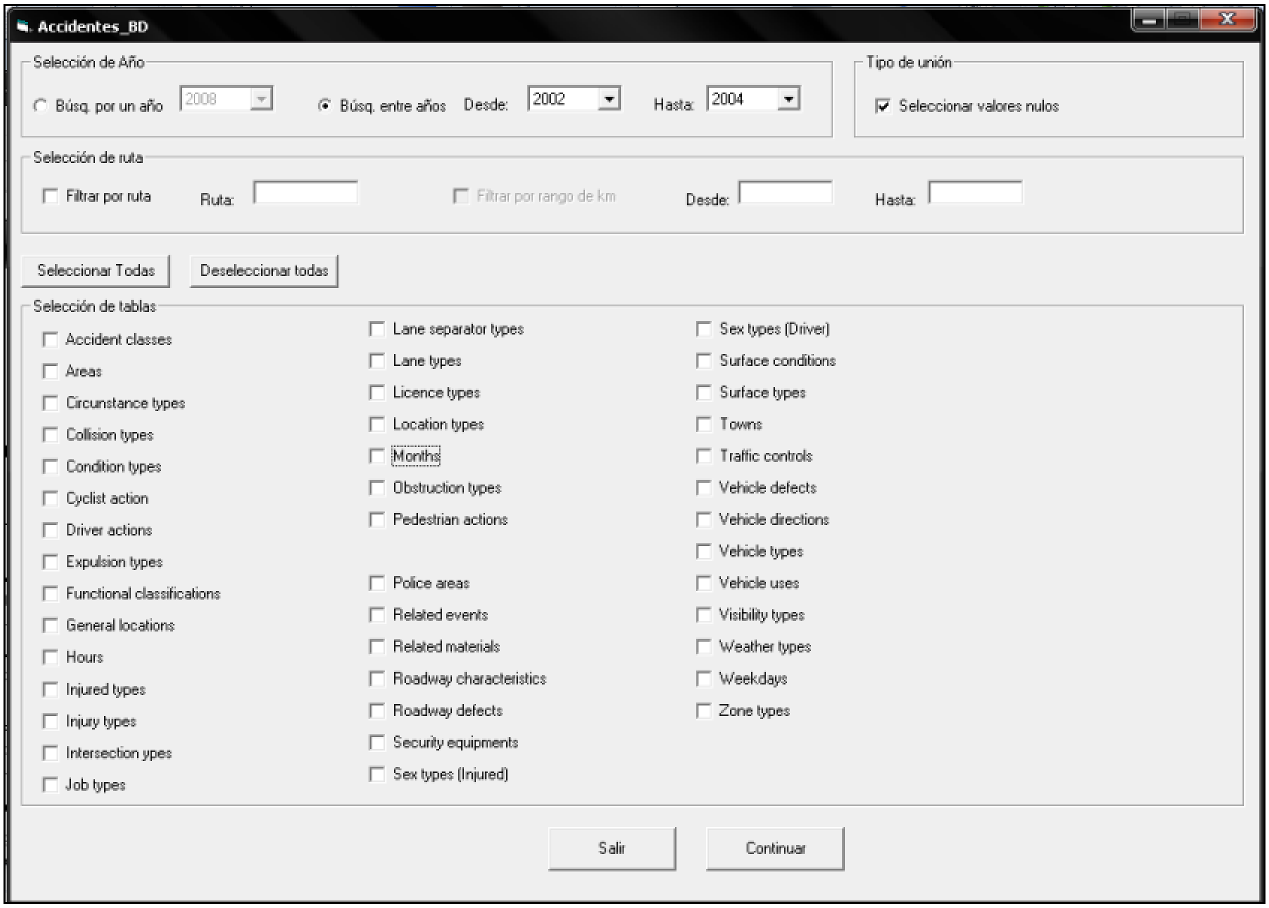


Figure 4-1: Major data categories of the crash database of Puerto Rico

The crash data categories shown in Figure 4-1 were used to select the circumstances and conditions under which a crash occurred. The study was conducted specifically for signalized intersections in urban areas, hence, the first filter was the selection of crashes which occurred at intersections and whose control type is a traffic signal. Crashes occurring in other facility type, such as highway segments or stop controlled intersections were discarded. The second filter was the associated circumstances of the crash. For example, once the intersections with traffic signals where crashes occurred were selected, crashes whose cause was a result of noncompliance to the signal by the driver were chosen. Thus, utilizing the different filters, the number of crashes that occurred due to RLR and the intersections where these crashes occurred were determined. The intersections selected were located in the western region of Puerto Rico. The municipalities of the western region of Puerto Rico are presented in Figure 4-2.

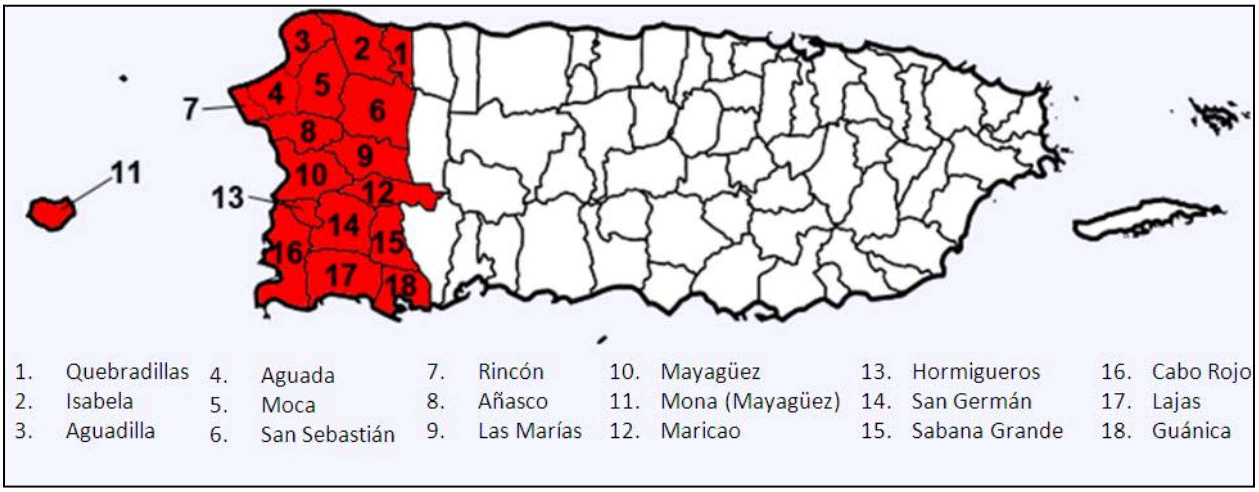
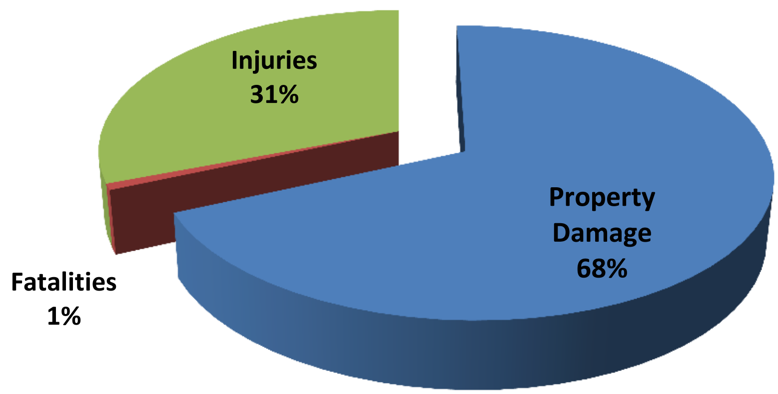


Figure 4-2: Municipalities in the western region of Puerto Rico

A total of 700 RLR-related crashes were identified from the crash database. Figure 4-3 shows the distribution of the crashes per severity in property damage only (PDO), injuries, and fatalities. Of the total crashes, 68 percent were registered as PDO. A total of five fatalities were registered, which occurred in the municipalities of Aguadilla (1), Mayaguez (3), and Hormigueros (1).

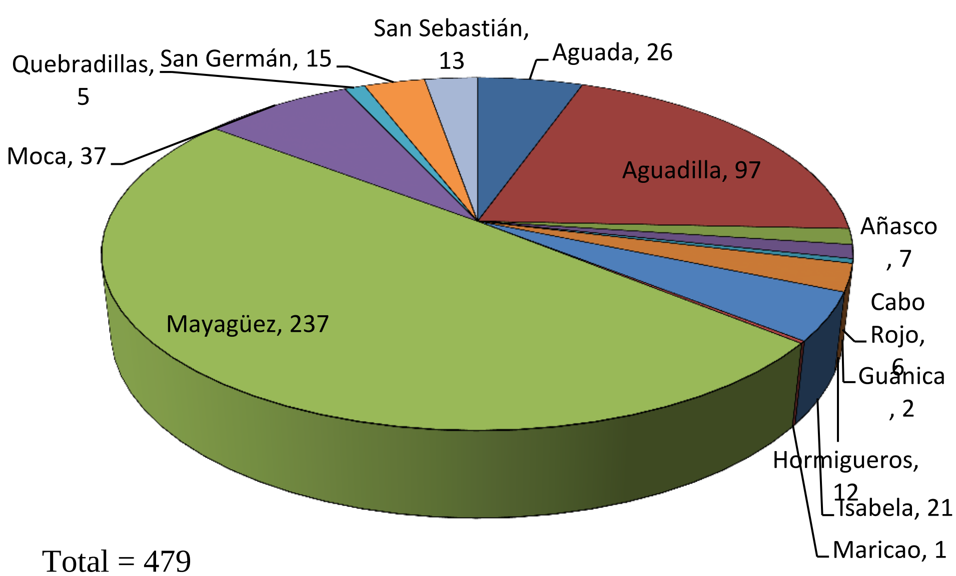
Figure 4-4 shows the total RLR-related crashes in which property damage was registered for the different municipalities of the western region. Mayaguez was the municipality with the highest percentage of RLR crashes with approximately 50%, followed by the Municipality of Aguadilla with 20%. Of the 17 municipalities, three did not record any RLR-related crashes. Figure 4-5 shows the crashes in which injuries were reported. The municipalities with the largest total of

RLR-related crashes were Mayaguez with 29%, followed by Aguadilla with 24%, and Moca with 9%.



Total = 700

Figure 4-3: Total of RLR related crashes western region of Puerto Rico



Total = 479

Figure 4-4: RLR related crashes with property damage by municipality

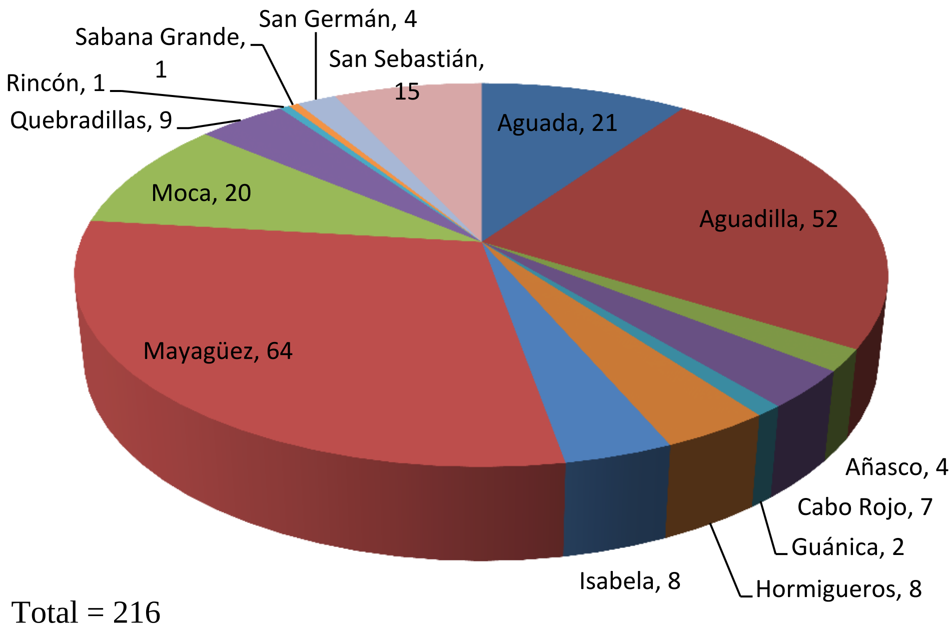


Figure 4-5: RLR related crashes with injuries by municipality

4.3 Selection of Intersections

Nine urban signalized intersections (eight four-leg and one T) from the municipalities of Aguadilla, Aguada, Moca, Mayagüez, and Hormigueros were selected. Thirty-two approaches were observed. Bonneson et al. (2002) suggest a minimum of 20 intersection approaches for RLR studies. Three minor approaches at those intersections were later discarded based on an extremely short green time assigned to those movements in relation to traffic.

Table 4-1 provides a list of the selected intersections for the observation study with their number of crashes related to RLR. Figure 4-6 shows the approximate location of these intersections in the Western Region. The selection of these intersections was based primarily for their location on a major urban road. All but two of the signalized intersections are located along Highway PR-2, which is the highway with the highest functional classification and has the highest amount of traffic in the Western Region of Puerto Rico. The selected intersections are expected to have a high number of crashes due to the high traffic exposure at the intersections.

Table 4-1: Selected signalized intersections for the RLR observation study

Municipality	Intersection	RLR related crashes
Mayagüez	PR2 & Nenadich Street	27
Aguadilla	PR2 & PR459	24
Hormigueros	PR2 & PR343	18
Moca	PR110 & PR111	16
Aguada	PR2 & PR417	14
Aguadilla	PR2 & PR107	14
Mayagüez	PR2 & PR114	10
Mayagüez	PR2 & Carolina Street	9
Mayagüez	PR65 & PR108	7

Figure 4-6: Approximate location of the intersections

The Hazard Index developed by Diaz et al. (2002) was used to review the safety condition of the selected intersections. The Hazard Index is a measure of the level of safety of an intersection. This index was determined in a study of the municipalities in the western region of Puerto Rico and took into account factors such as access with a significant approach grade; skewed angle or uneven topography, uneven flow and/or lanes in the secondary versus primary highway roads, presence of frontage roads with business and commercial access in the vicinity of the intersection.

Table 4-2 shows the ranking of the top 25 signalized intersections in the western region with the highest Hazard Index, as identified by Diaz et al. (2002). Six of the nine intersections selected for the present study were included in the top 25 list of potentially hazardous intersections (shown with arrows on the table).

Table 4-2: Ranking of intersections by Hazard Index

Ranking	Intersection	Municipality	*Hazard Index*
1	PR-2 con PR-343	Hormigueros	10.692
2	PR-2 con PR-107	Aguadilla	7.313
3	PR-2 con PR-402	Añasco	7.217
4	PR-2 con PR-199	Mayagüez	6.547
5	PR-110 con PR-111	Moca	6.371
6	PR-111 con PR-446	San Sebastián	6.263
7	PR-110 con PR-125	Moca	6.153
8	PR-111 con PR-445	San Sebastián	6.144
9	PR-2 con PR-114	Mayagüez	5.811
10	PR-2 con PR-485	Quebradillas	5.745
11	PR-2 con PR-186	Mayagüez	5.697
12	PR-2 con PR-474	Isabela	5.532
13	PR-2 con PR-725	Mayagüez	5.453
14	PR-2 con PR-329	Mayagüez	5.374
15	PR-111 con PR-420	Moca	4.985
16	PR-2 con PR-112	Isabela	4.904
17	PR-65 con PR-108	Mayagüez	4.903
18	PR-2 con PR-103	Hormigueros	4.773
19	PR-2 con PR-417	Aguada	4.729
20	PR-2 con PR-394	Mayagüez	4.422
21	PR-100 con PR-102	Cabo Rojo	4.263
22	PR-2 con PR-233	Mayagüez	4.173
23	PR-2 con PR-446	Isabela	4.06
24	PR-116 con PR-117	Lajas	4.045
25	PR-111 con PR-444	Moca	4.013

4.4 Data Collection

The data collected in the field for each approach include elements of the intersection geometry, traffic signal timings, traffic volumes, free-flow speeds, vehicle type, and RLR events. Table 4-3 shows a summary of the data collected at the approaches of the intersection of PR-2 with PR-343. Figure 4-7 shows a plan view of the intersection geometry and the available travel lane. Appendix A includes the data summary table and the plan view for the other intersections.

Table 4-3: Summary of data collected for intersection PR-2 with PR-343

Variable	Observed Approaches			
	Southbound	Northbound	Westbound	Eastbound
Flow rate (veh/h)	1116	1616	480	377
Heavy vehicles (%)	10.84	7.05	3.5	2.55
RLR (veh/h)	20	19	14	4
Speed limit (mph)	45	45	25	25
Yellow period duration (s)	3	3	3	3
Green period average (s)	109	105	31	21
Cycle length (s)	180			

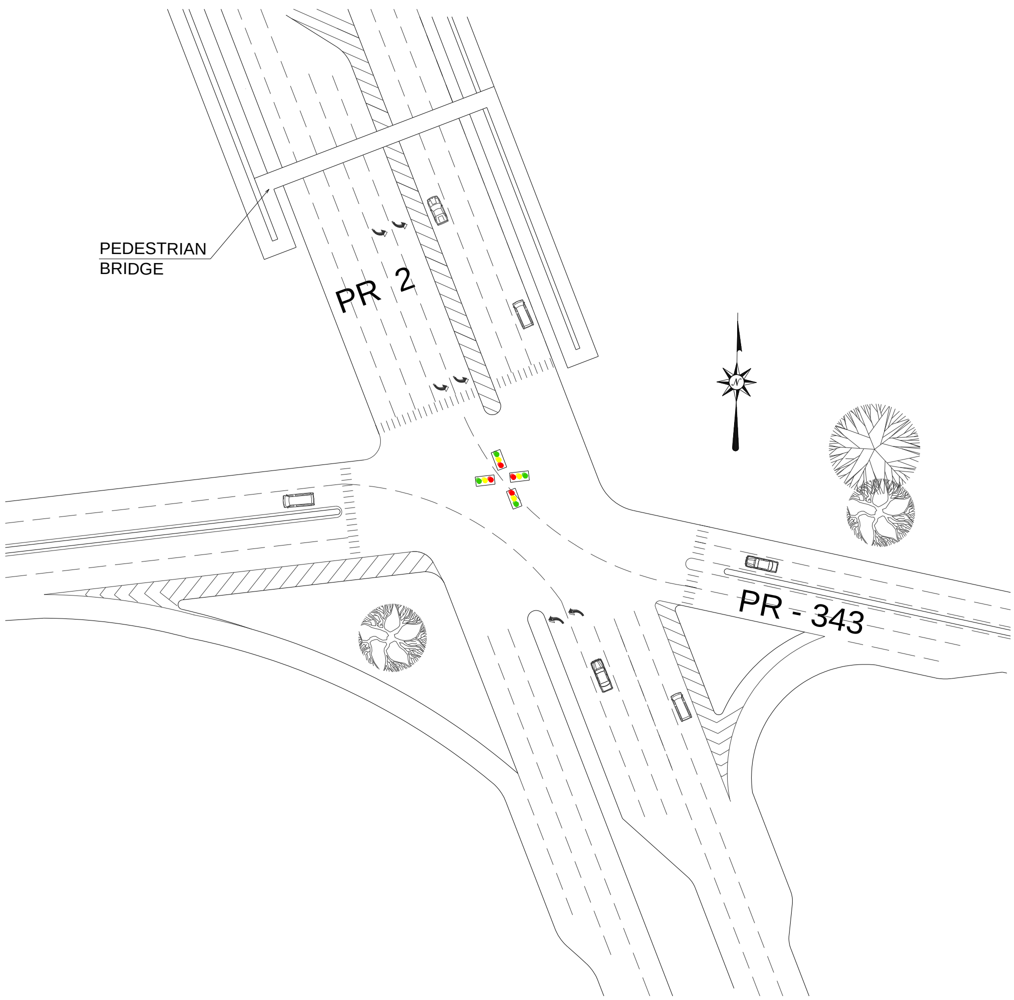


Figure 4-7: Plan view of intersection PR-2 with PR-343

Table 4-4 presents a summary of the data collected at the nine signalized intersections. Vehicle free-flow speeds were measured with a laser gun. The intersection cycle length and the signal timings for each approach were timed. The signal timings included the splits in seconds for the green, yellow, and red signal indications. Research shows that the yellow signal time can affect the frequency of RLR events. Most of the yellow signal indications timed in the study at the observed intersections was 3.0 seconds long. Video cameras were used for collecting the signal timing data, traffic volumes, and the RLR and YLR events. Traffic volumes were collected for one hour during non-peak periods, under daylight and dry pavement conditions. Data collection for this part of the study was conducted during the months of June and July 2009.

Table 4-4: Descriptive statistics for selected data elements

Data	Minimum	Maximum	Average	Standard Deviation
RLR, veh/hr	2	37	12.8	9.33
Number of lanes per approach	1	4	2.3	0.65
Lane width, feet	10	16	11.0	1.17
Approach flow rate, veh/hr	101	2,442	906.7	598.2
Heavy vehicle flow rate, veh/hr	1	128	47.4	42.6
Speed limit, mph	25	50	36.2	10.54
Operating speed, mph	18	53	38.2	9.71
Mean free-flow speed, mph	14	47	31.6	9.06
Cycle length, s	106	183	153.2	27.51
Green interval duration, s	15	115	56.0	34.26
Yellow interval duration, s	3	4	3.1	0.24

The RLR and YLR data was collected after reviewing the videos in the laboratory. Individual tallies of YLR and RLR number are totaled for each cycle. The overall total is also determined for the one hour video. An RLR event was identified when a vehicle travelling in the main (thru) lane crossed the approach stop line after the onset of the red signal indication and before the start of the next green signal indication. An YLR event was recorded when a vehicle crossed the approach stop line after the yellow signal onset.

4.5 Identification of RLR Factors

Table 4-5 shows the approach average RLR values. A total of 409 RLR events were observed, 399 from passenger cars and 10 from heavy vehicles. A total of 28,981 vehicles were observed. Heavy vehicles accounted for 1.4% of the sample. RLR events were observed in 40% of the 727 signal cycles. The data indicate that a vehicle runs a red signal an average of once every 4 minutes. Studies from Virginia and Rhode Island (Retting et al., 1999; Hunter, 2003) found that a RLR event happens, on average, every 12 minutes and 9.5 minutes, respectively.

Table 4-5: RLR frequency and ratios

	RLR	Vehicles	Signal cycles	RLR per 1,000 veh	RLR per 10,000 veh-cycle
Approach average	12.8 / hr	906 / hr	22.7 / hr	18.8	8.4

The RLR frequency was normalized in terms of 1,000 vehicles and 10,000 veh-cycle to account for the traffic effect and to compare them with values from Iowa, Texas, and the United Kingdom. The local average of 18.8 RLR per 1,000 vehicles is 3.5 to 6.2 times higher than the values of 3.0 observed in Iowa, 4.1 in Texas, and 5.3 in the United Kingdom (Kamyab et al., 2000; Bonneson et al., 2002; Baguley, 1988). The local average of 8.4 RLR per 10,000 veh-cycle is also much higher than the ratio of 1.0 observed in Texas, although it must be pointed out that Bonneson et al. (2002) collected data from typical intersections that were not previously identified as having a problem with RLR while Baguley (1988) used data from rural intersections typically associated with high speed operations. In the other studies urban intersections were targeted to study RLR.

To determine which factors affect the frequency of RLR at these intersections will use the linear regression (LR). This is a method used to model the linear relationship between a dependent variable and one or more independent variables. The dependent variable is sometimes also called the predictand, and the independent variables the predictors. LR is based on least squares: the model is fit such that the sum-of-squares of differences of observed and predicted values is minimized. The model expresses the value of a predictand variable as a linear function of one or more predictor variables and an error term:

$$Y_i = b_0 + b_1 x_1 + b_2 x_2 + \cdots . b_k x_k + e_i \tag{4-1}$$

where:

$x_{i,k}$ = value of k^{th} predictor,

b_o = regression constant,

b_k = coefficient on the k^{th} predictor, and

e_i = error term.

The goodness of fit of the model can be determined by the coefficient of determination R^2. In regression, R^2 is a statistical measure of how well the regression line approximates the real data points. An R^2 of 1.0 indicates that the regression line perfectly fits the data.

Figure 4-8 shows the RLR frequency as a function of flow rate. The positive trend is consistent with Kamyab et al. (2000) and Baguley (1988). Bonneson et al. (2002), as well as the two previous studies, barely observed 10 RLR events per hour, whereas RLR values of up to 37 events per hour were observed in the current study. The traffic flow rate should have a positive relation with RLR events as more drivers have the possibility of encountering a signal change period and finding themselves in the yellow signal dilemma zone, particularly at intersections without actuated signal control plans. The RLR data obtained in the current study has a wide range of flow rate values and RLR frequencies. Such variation depending on the intersection indicates that factors other than flow rate alone may possibly influence RLR events at these intersections.

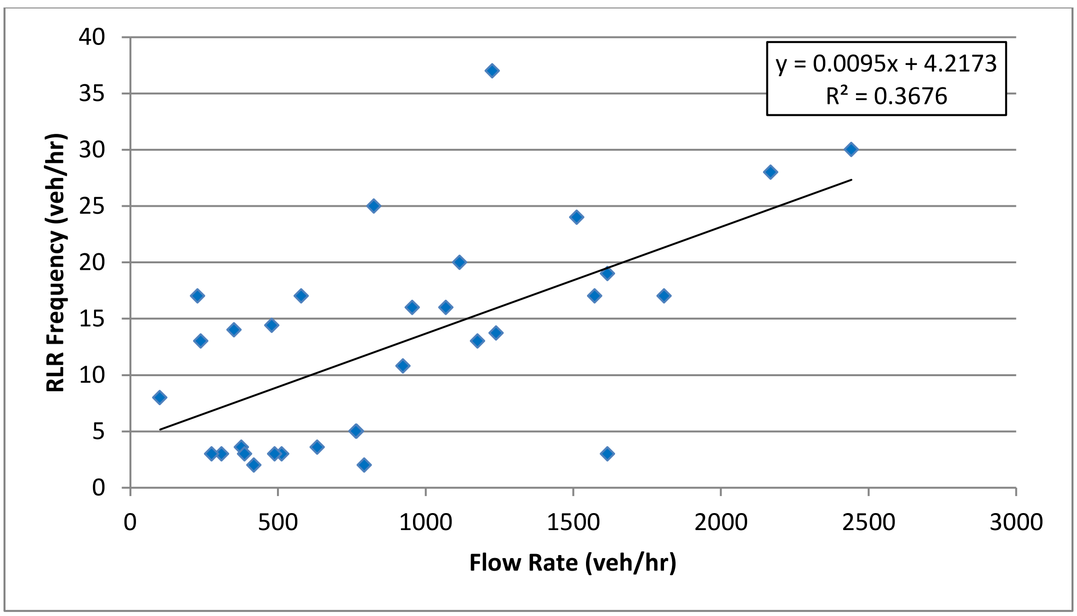


Figure 4-8: Relationship between flow rate and RLR frequency

Figure 4-9 shows the RLR frequency as a function of flow rate per cycle time (q/C). In this case the regression that best fits the observations is a second-order polynomial resulting in a quadratic equation. The data shows the effect of higher traffic volumes with respect to the signal timing. As either the flow rate increases and/or the cycle length decreases, more RLR events are present. The observations in the present study show that RLR was higher on those approaches where the green signal time was very short compared to the time the vehicles had to wait in red. This may be an indirect indication of driver behavior where such aggressiveness is adopted based on the short green cycle time.

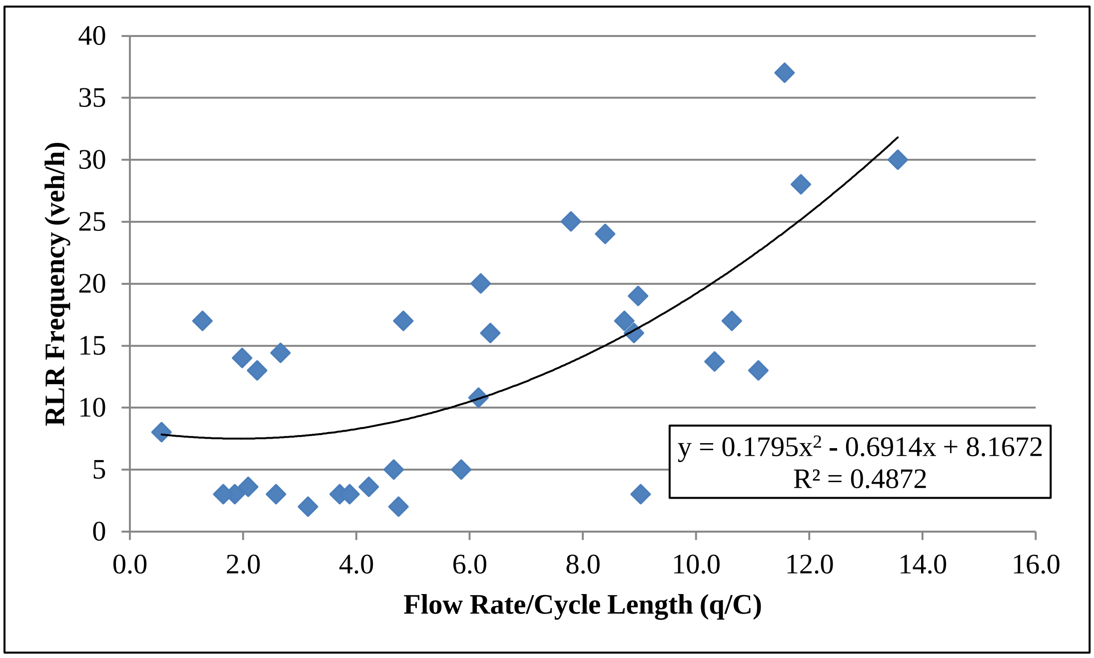


Figure 4-9: Relationship between q/C and RLR frequency

According to Bonneson et al. (2002) flow rate and cycle length are factors considered as "exposure factors", which are basic events that must occur or be present for the occurrence of RLR. It was determined from the vehicle data that the frequency of RLR as a function of flow rate has a positive trend, indicating that the greater the number of vehicles reaching the intersection greater is the possibility that more of these vehicles encounter the yellow period and consequently, greater the probability that many vehicles pass the intersection during the red period. Also, the relationship between the frequency of RLR and the ratio of flow rate to cycle length (q/C) has a positive trend. With increasing flow or decreasing cycle length the frequency of RLR will have a tendency to increase.

At the local intersections the yellow change interval was set at either 3 or 4 seconds. The Manual on Uniform Traffic Control Devices (FHWA, 2009) requires that the duration of the yellow change interval, and the red clearance interval if used, shall be determined using engineering practices, as shown by the ITE formulas in Equations 3-4 and 3-5. The difference between the observed and the computed yellow interval at the intersections varied from -2.3 to 0.5 seconds. Although before-after studies could be performed to clearly identify the effect of the change in the yellow change interval on RLR events, the observed data do show that as the difference between the observed and the computed yellow change interval at the observed intersections goes to zero, the observed RLR events tend to decrease.

Figure 4-10 shows the relation between RLR frequency and flow rate based on three mean speed ranges. The observed mean speeds were grouped in 10-30 mph, 31-39 mph, and 40-49 mph ranges to analyze the effect of speed on the RLR-flow rate relation. Increasing linear trends were obtained for all three ranges of speed; however, the slopes show that as the mean approach speed increases, the rate of RLR events with respect to flow rate decreases.

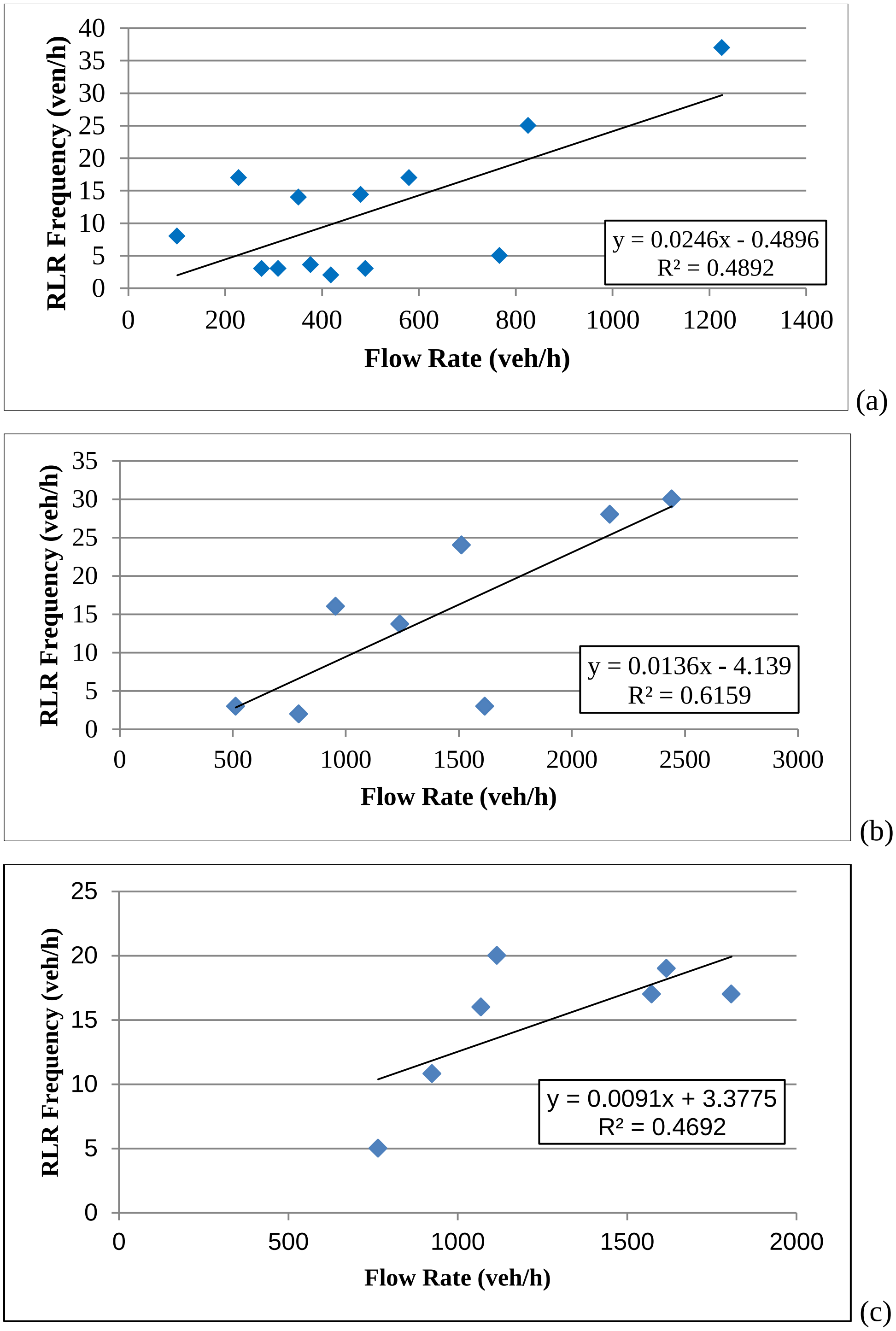


Figure 4-10: RLR frequency for mean vehicle speeds from (a) 10-30 mph, (b) 31-39 mph, and (c) 40-49 mph

On dividing the observed data into three different groups of vehicle speeds, a positive trend in all three speed ranges was observed. It was determined that at higher speeds, the trend of the frequency of RLR with respect to the flow is lower based on the lower slope in the observed data. In contrast, at lower speeds the tendency for RLR events appears to be higher. This may indicate a higher level of aggressiveness of drivers, since one would normally expect vehicles traveling at a low speed to see the yellow indication and stop at the intersection. Instead, these slower vehicles pass the intersection during the red period deliberately reflecting driver aggressiveness.

Driver reaction and behavior may be significant variables that would improve the predictability of this model. Thus, the information from this analysis will be used to focus on studying the driver reaction at the end of the green period at an individual intersection which may in the future be utilized to develop models to predict driver behavior for other intersections with similar characteristics. This type of analysis is performed in the following chapter for a single specific intersection.

Both intentional and unintentional RLR can be modified through conventional police enforcement or automated enforcement systems with sensors and video cameras at the intersections. Educational campaigns that provide safety information for all age levels will further contribute to the reduction of RLR behavior.

Unintentional RLR behavior can be reduced through engineering strategies. The National Campaign to Stop RLR (2002) and the Institute of Transportation Engineers (ITE) (2003) suggest local studies are needed to evaluate the cost-effectiveness of engineering, enforcement, and educative solutions at signalized intersections with high RLR potential. The strategies could include removing unnecessary signals, replacing the intersection with a modern roundabout, improving the signal visibility and conspicuity by increasing the signal head size or by adding backplates, improving the intersection sight distance, increasing the likelihood of stopping by placing advanced warning signs, flashers or rumble strips, optimizing the signal phase sequence and cycle length, and modifying the yellow and all-red change intervals with respect to speeds and intersection geometry (Chang et al., 1985; Van der Horst et al., 1986; Retting et al., 1998; Polanis, 2002).

In this chapter a group of intersections were studied to see the effect of factors such as the geometry of the intersection, the signals and flow rates on the reaction of drivers at the end of green period. Specifically it was determined that the flow rate is an important factor and that greater the flow the greater is the RLR. The trend is also positive for the frequency of RLR with respect to flow rate per cycle length. Intersection geometric and design factors such as approach grade, number of lanes, median width, and presence of left-turn and right-turn exclusive lanes, speed limit, did not show relationship with the frequency of RLR events.

The next chapter presents the study of one of the approaches of a signalized intersection located in a main road in the municipality of Mayaguez. This study is detailed and presents various analyses of different factors relating to individual vehicles arriving at the intersection.

5 STUDY OF DRIVER REACTION AT THE YELLOW ONSET AT AN INDIVIDUAL INTERSECTION

5.1 Introduction

In the first part of this work, by taking into consideration general factors that influence the incidence of RLR events, a group of intersections were first identified and taken as the sample for the study conducted. It was clearly observed that the intersections studied had high flow rates and high incidences of RLR events. It was also noted that at these intersections the frequency of RLR increases with flow rate and with the ratio of the flow rate to cycle length. On the other hand, the geometry of the intersection, speed and cycle length were not significant factors contributing to the RLR events. Based on the frequency of RLR observed at these intersections, the drivers demonstrated aggressive behavior. It is for this reason, that it was deemed necessary to consider factors related to individual vehicles and to study the driver behavior. Hence it was imperative to study and analyze the trajectory of the vehicles from the start of the yellow period, changes in speed, whether or not a dilemma zone was formed, as well as other variables. Since this study requires a more in-depth analysis and the recording of the trajectory of a large number of vehicles. Therefore, this part of the work focused on one of the approaches of a signalized intersection and the variables were measured using video cameras. Thus, continuity was achieved in the trajectory of the vehicles from the point of entry into the area of study until they pass the intersection during the yellow period, pass at the beginning of the red period, or decelerate and stop at the intersection.

5.2 Methodology

5.2.1 Selection of the Intersection

The signalized intersection located at Highway PR2 and Los Velez Street in the Municipality of Mayaguez (Figure 5-1), was selected for the in-depth study and analysis. This site is a four-leg intersection located in an urban area with frontage roads at the two sides. The PR-2 southbound approach was selected for the analysis. The southbound approach has five lanes: three for through movements, one exclusive lane for left turns, and one exclusive lane for right turns (Figure 5-2). The speed limit at the intersection for the northbound and southbound approaches is 45 mph and the yellow interval is set at 3.0 seconds.

Figure 5-1: Location of Highway PR-2 in the Municipality of Mayagüez, Puerto Rico

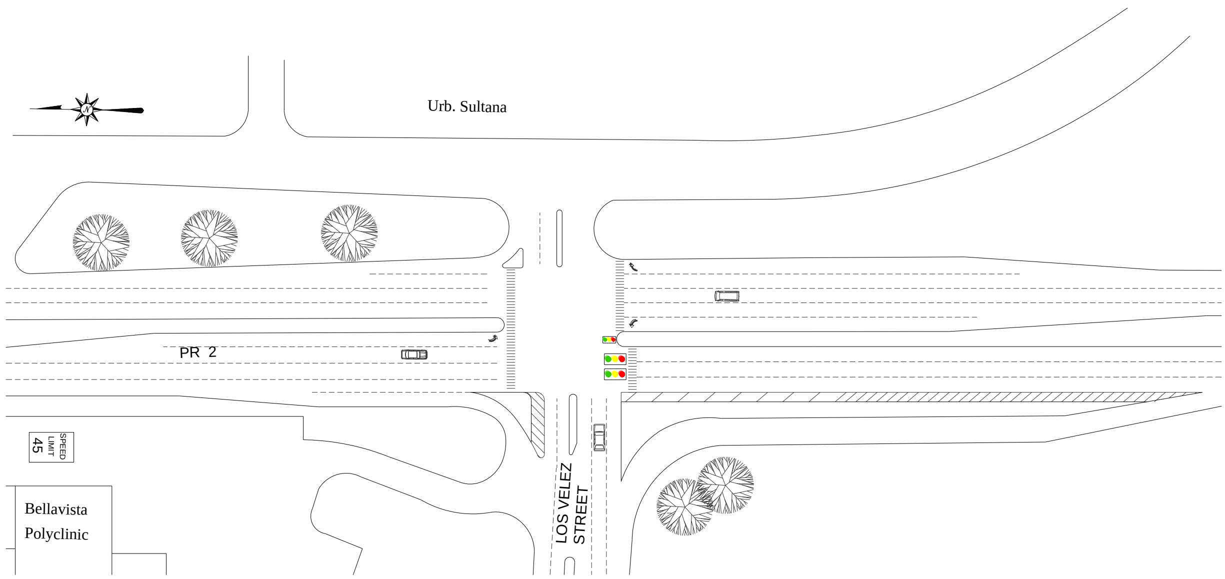


Figure 5-2: Plan view of the Intersection of PR-2 with Los Velez Street

The intersection of the PR-2 and the Los Velez Street was selected for the study taking into account the following criteria:

- it is an arterial highway located in an urban area,
- access to a tall structure where the entire intersection could be observed from within a reasonable distance,
- feasibility to conduct the study over several days,
- location in the western region of Puerto Rico,
- no influence from adjacent intersections, and
- location of the cameras outside of the point of view of the drivers.

5.2.2 Data Collection

Since the focus of this study is to record the behavior of drivers with regard to the end of green signal phase for the southbound approach, three digital camcorders were placed on the terrace of a three-story building located 300 feet upstream of the intersection, pointing at the southbound approach. This building is owned and operated by the Bella Vista Polyclinic and hence it was necessary to request authorization from the administration to place the cameras on the building.

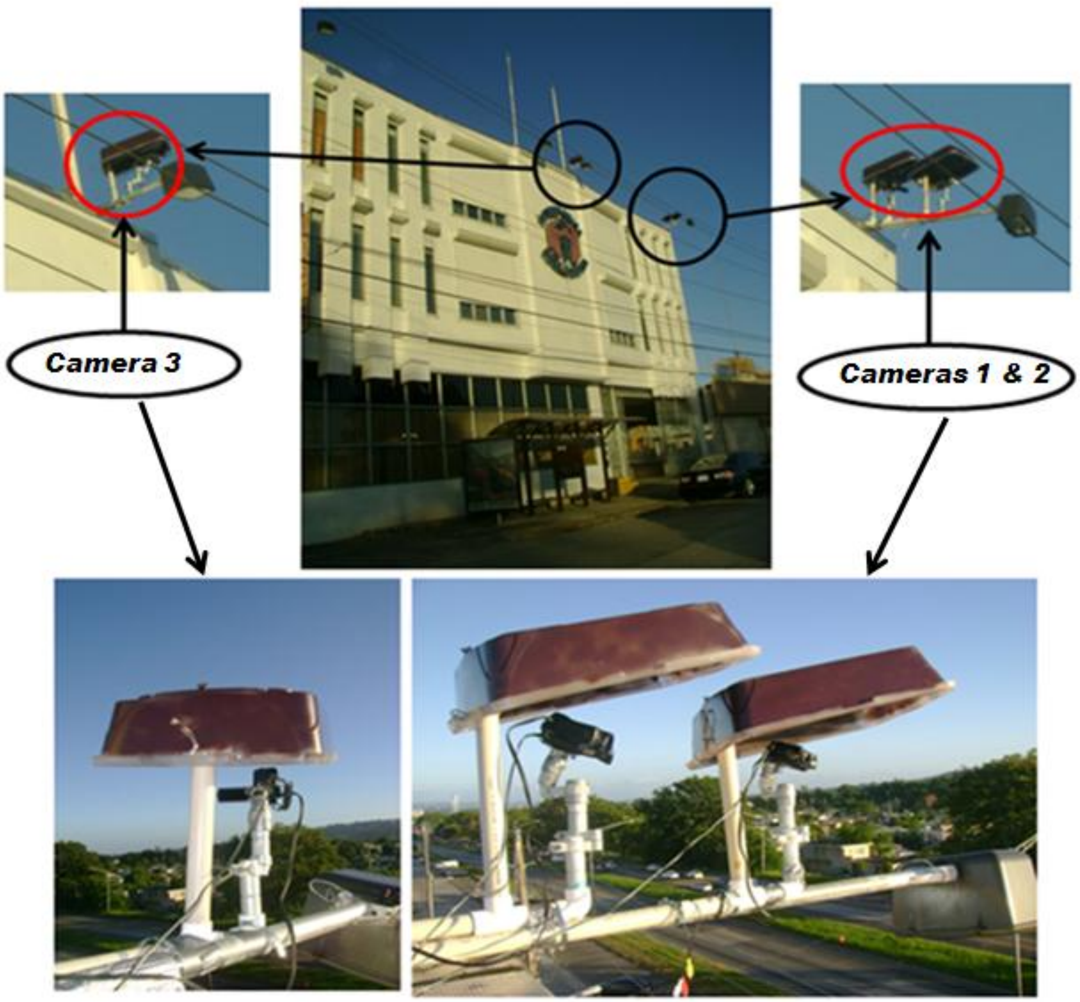


Figure 5-3: Position and setup of the digital video cameras

From the building rooftop it was possible to view the segment approach to the intersection, including the stop bar and the signal changes. As presented in Figure 5-3, the video cameras were installed using PVC supports in custom made mounts, including a plastic cover to protect the cameras from the sun.

A marking system was used as a reference in the field for the video recording. Markers were placed on both sides of the roadway at intervals of 80 feet along the approach starting at the stop bar, which was set as a “zero” and ending at 480 feet upstream. These markers were used to create coordinates for the video screen that permit measurement of the moment in time at which a vehicle passes each point in order to calculate vehicle speeds over the different study sections of the approach.

Figure 5-4 shows the top view of the data collection site. Camera 1 was placed facing the intersection and was utilized for capturing traffic moving across markers 1 (80 feet), 2 (160 feet) and 3 (240 feet). Camera 2 overlapped the first segment to about 340 feet from the stop bar and covered markers 3 and 4 (320 feet). Camera 3 covered the last segment which is at a distance of 480 feet from the stop bar and included marker 5 (400 feet) and marker 6 (480 feet). The custom mounts were fixed on the roof terrace and the cameras were placed on the mounts using the same viewing points.

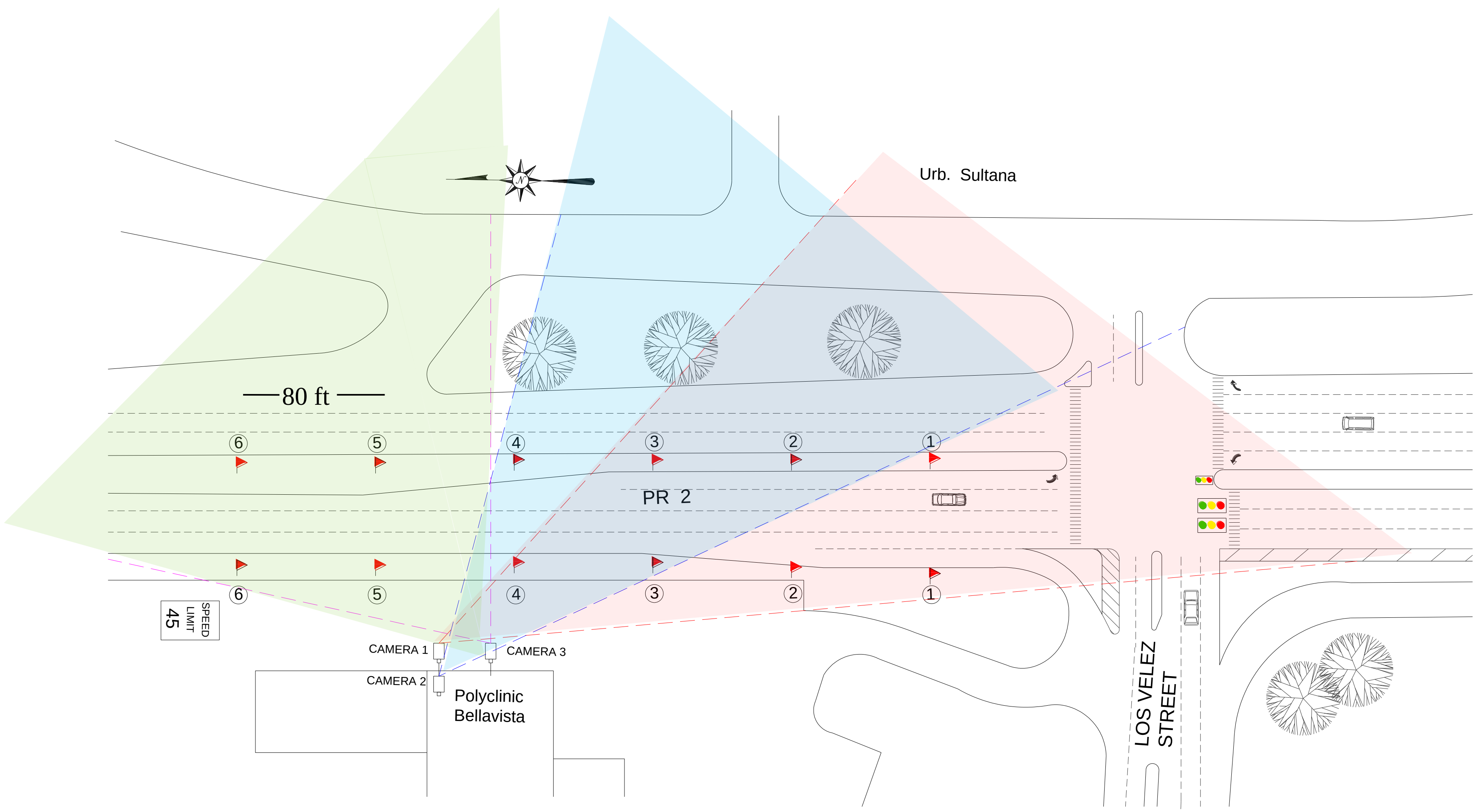


Figure 5-4: Video data collection setup with distance markers

Vehicular traffic operation and the traffic signal indications were recorded for a total of 10 hours during four weekdays (November 22, December 1, December 2, and December 6, 2010) and off peak periods. The videos were synchronized using the commercial software Boilsoft Video Splitter v5.16 by taking into account the overlap between the video tracks. In this manner, continuity in the trajectory of the vehicles was ascertained. A video rate of 30 frames per second with an estimated error of 0.03 seconds ensured a high degree of accuracy of the time-related events in the study.

Figure 5-5 indicates four speed-related variables that were recorded and computed using the video cameras and the markings on the field. These are:

- vehicle entry speed at the approach,
- vehicle initial speed at the yellow onset,
- distance to stop line at the yellow onset, and
- vehicle speed at the stop bar of the intersection.

Vehicle speed at the entry approach was used to determine the average speed at which the vehicle reached the intersection before the yellow onset. The initial speed of the vehicle at the yellow onset and the distance to stop line at the yellow onset were used to determine the distribution of vehicles at the beginning of the yellow period and to determine the dilemma zone. The deceleration/acceleration of the vehicles was determined using the vehicle speed at the stop bar. All the speeds were used to determine the vehicle trajectories.

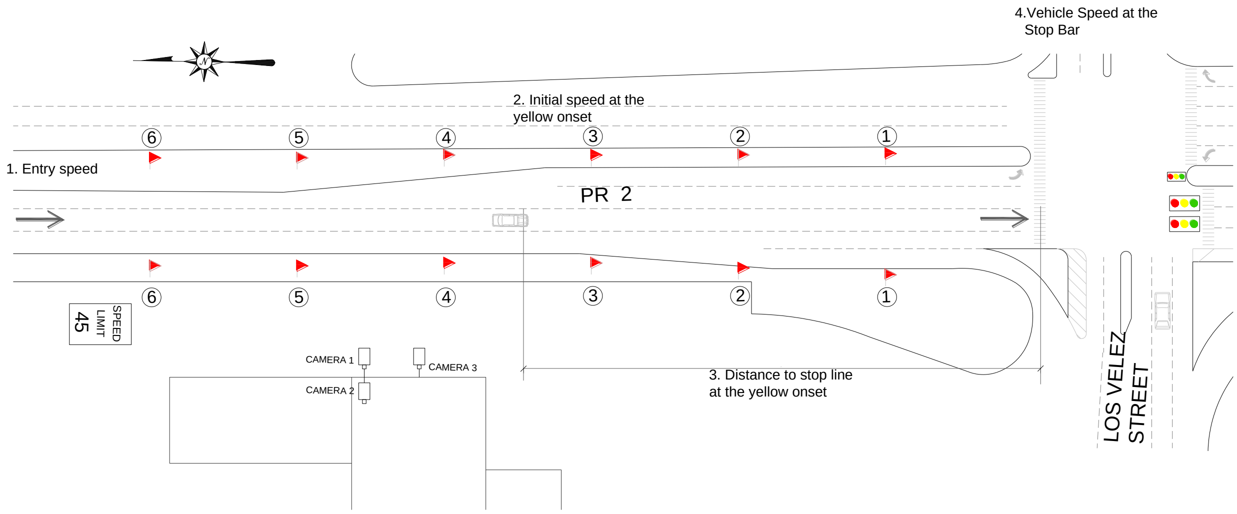


Figure 5-5: Variables related to individual vehicles speeds

5.2.3 Data Extraction

To extract the data from the digital videos, an in-house program SVDCS (Simultaneous Video Data Collector System), which permits uploading and handling of the videos corresponding to the three segments mentioned above on a single computer was developed, as shown in Figure 5-6. Thus, it is possible to record events continuously from 480 feet until the stop bar. The SVDCS program can run the video in slow motion at a speed of 3 frames per second. This ensures that the data collected is very accurate.

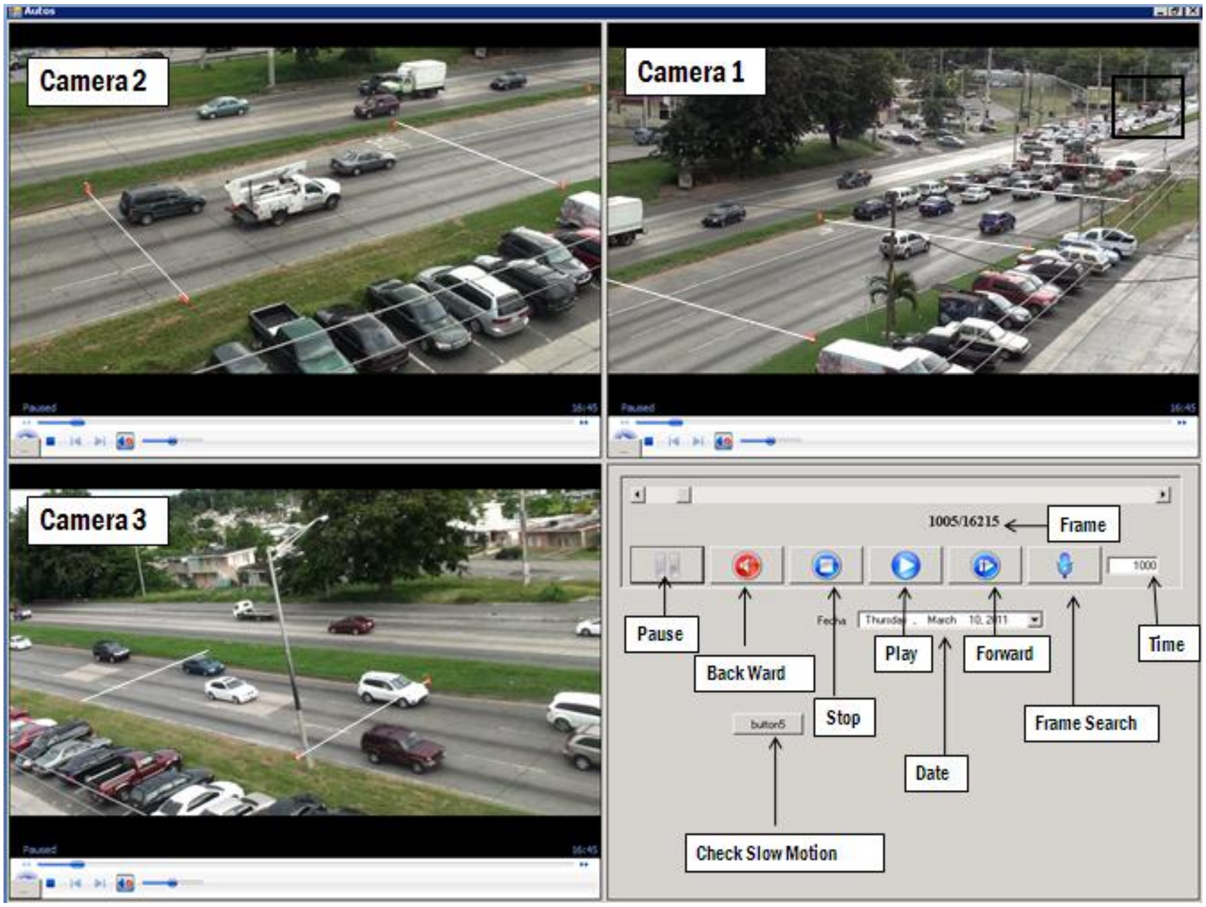


Figure 5-6: Data screen shots from videos using SVDCS program

The SVDCS software was developed using a custom made Visual Basic program. The conceptual idea is from the author, while the program was written with external assistance. The SVDCS software was used to help manual data collection from the videos. Data collection functions were programmed for events with 3 subprograms that record different types of data: volume data, timing data (green, yellow, and red signal changes) and traffic flow characteristics. Figure 5-7 shows an example of the registered data with reference to the traffic flow characteristics in the Access 2007 database that SVDCS uses for this purpose. In this table, the data registered are:

- vehicle identification,

- observation date,
- timestamp when a vehicle passed each marker,
- stop/go decision: whether the vehicle stopped or not at the stop bar,
- leader vehicle,
- vehicle type.
- travel lane,
- RLR or YLR: If the vehicle passed the stop bar after the start of the red or yellow period, respectively, and
- stop: If the vehicle stopped at the stop bar during the yellow period.

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IdVehic	Fecha	Tipo	Carri	Lider	Punto1	Punto2	Punto3	Punto4	Punto5	Punto6	Punto7	Paso
312	5/16/2011 3:34:59 PM	L	1	1	3305.0331985	3306.7999985	3308.5567985	3310.3135985	3311.9350985	3313.5798985	3315.3142985	1
313	5/16/2011 3:34:59 PM	L	2	1	3306.9674982	3308.2886982	3309.5998982	3310.9839982	3312.3007982	3313.6750982	3314.9342982	1
314	5/16/2011 3:34:59 PM	L	2	0	3309.8733982	3311.1154982	3312.3475982	3313.6866982	3315.0290982	3316.7602982	3319.4987982	0
315	5/16/2011 3:34:59 PM	L	3	1	3308.6522983	3310.2142983	3311.7662983	3313.2926983	3314.8215983	3316.7030983	3319.9695983	0
316	5/16/2011 3:34:59 PM	L	1	0	3454.8981988	3457.1769988	3459.4457988	3461.3001988	3462.9561988	3464.6177988	3466.2240988	1
317	5/16/2011 3:34:59 PM	P	3	0	3454.6644985	3456.1712985	3457.6680985	3459.2904985	3460.8577985	3462.3785985	3463.7633985	1
318	5/16/2011 3:34:59 PM	L	2	0	3457.8066985	3459.2862985	3460.7558985	3462.3590985	3463.7871985	3465.4359985	3468.2662985	0
319	5/16/2011 3:34:59 PM	L	1	0	3608.2492983	3609.5880983	3608.2454986	3609.9887986	3611.4871986	3612.9247986	3614.2182986	1
320	5/16/2011 3:34:59 PM	L	1	0	3606.5341982	3608.2809982	3610.0177982	3611.7953982	3613.2969982	3614.7225982	3616.1512982	1
321	5/16/2011 3:34:59 PM	L	2	0	3605.9957982	3607.7354982	3609.4651982	3610.9963982	3612.4123982	3613.8074982	3614.9970982	1
322	5/16/2011 3:34:59 PM	L	2	0	3607.5213985	3609.3833985	3611.2353985	3612.8833985	3614.3592985	3615.7160985	3617.0585985	1
323	5/16/2011 3:34:59 PM	L	3	0	3608.2492983	3609.5880983	3610.9168983	3612.1312983	3613.4121983	3614.6921983	3615.8768983	1
324	5/16/2011 3:34:59 PM	L	1	0	3756.3219984	3757.8591984	3608.2368984	3609.9416984	3611.4040984	3612.8248984	3614.1599984	1
325	5/17/2011 10:18:09 AM	L	1	0	3760.7293985	3762.2217985	3759.3863984	3760.7943984	3762.1631984	3763.5023984	3764.7351984	1
326	5/17/2011 10:18:09 AM	L	1	0	3758.7855986	3759.9706986	3763.7041985	3765.0833985	3766.6153985	3768.7248985	3772.3801985	0
327	5/17/2011 10:18:09 AM	L	2	0	3760.7191985	3761.8003985	3761.1457986	3762.2937986	3763.4185986	3764.5529986	3765.6209986	1
328	5/17/2011 10:18:09 AM	P	3	1	3906.5836985	3908.2416985	3762.8715985	3763.9835985	3765.0595985	3766.0643985	3767.0531985	1
329	5/17/2011 10:18:09 AM	L	1	0	3908.8365986	3910.4665986	3909.8896985	3911.3624985	3912.7352985	3914.0984985	3915.4008985	1
330	5/17/2011 10:18:09 AM	L	1	0	3907.3701987	3908.6889987	3912.0865986	3913.6145986	3914.9745986	3916.2137986	3917.4089986	1
331	5/17/2011 10:18:09 AM	L	2	0	3908.7804986	3910.1112986	3909.9977987	3911.3377987	3912.6393987	3913.9065987	3915.1073987	1
332	5/17/2011 10:18:09 AM	L	2	0	3910.4069989	3911.9185989	3911.4320986	3912.7144986	3913.9696986	3915.1816986	3916.3048986	1
333	5/17/2011 10:18:09 AM	L	2	0	3905.0948985	3906.8472985	3913.4201989	3914.9121989	3916.4321989	3918.4666989	3921.9897989	0
334	5/17/2011 10:18:09 AM	L	3	0	3907.1613985	3908.7368985	3908.5896985	3910.0440985	3911.3440985	3912.6016985	3913.7136985	1
335	5/17/2011 10:18:09 AM	L	3	0	3908.468599	3910.128999	3910.3023985	3911.8839985	3913.3183985	3914.6687985	3915.8751985	1
336	5/17/2011 10:18:09 AM	L	3	0	4056.0486985	4057.8362985	3911.779399	3913.252999	3914.713799	3916.625799	3919.445799	0

Figure 5-7: Screenshot of the Access 2007 database created by SVDCS

5.3 Data Collected with SVDCS software

The following variables of the vehicle operation at the intersection were calculated or determined from the videos using the SVDCS program:

- Distance (feet): vehicle distance from the stop line at yellow onset,
- Speed (mph): approaching vehicle operating speed,
- Speed at yellow (mph): vehicle speed at yellow onset,
- Stop or go: whether vehicle stopped or not (Stop = 1, Go = 0),
- RLR: if the vehicle passed the intersection during the red period (No = 0, Yes = 1),
- Leader or not: (No = 0, Yes = 1),
- Lane_1: (Left (through) Lane = 1, Other = 0),
- Lane_2: (Middle (through) lane = 1, Other = 0), and
- Vehicle Type: (Passenger car = 1, Heavy vehicle = 0).

The variables Lane_1 and Lane_2 were coded as binary variables. For example, if variable Lane_1 is coded as one (1), it indicates that the vehicle is using the left through lane, while if the vehicle is traveling in one of the other lanes, the variable was coded as zero (0). It is implicit that the condition corresponding to Lane 3, which is the right through lane, is the case in which both Lane_1 and Lane_2 variables are coded as zero.

This study focused on drivers who approached an intersection during the yellow signal phase. Data for each vehicle approaching the intersection at the signal change from green to yellow and to red was collected. The leader vehicle was identified as a vehicle that did not have another in front to prevent it from accelerating to pass through the intersection. This vacant distance to the other vehicle was taken to be approximately 350 feet, representing headways of 5.3 seconds.

The sample size of observations needed for the study was calculated using the following formula:

$$N = \frac{pqZ^2}{E^2} \tag{5-1}$$

where:

- N = sample size,
- p = proportion of vehicles arriving in the yellow indication and crossing the stop bar,
- q = proportion of vehicles arriving in yellow and although having the opportunity to cross, stop at the intersection,
- Z = corresponding constant of the desired confidence level (1.96 for a confidence level of 95%), and
- E = absolute permitted error in the estimated proportion (assumed as 5%).

A total of 750 vehicles were observed, with 550 vehicles crossing the intersection and 200 vehicles stopping at the intersection. The proportion of passing vehicles involved was set as p = 73% and the proportion of stopping vehicles was set as q = 27%. With these proportions, a sample of 303 vehicles should pass once they reach the intersection at the yellow signal and 112 vehicles should stop at the intersection. In total, 415 vehicles would be needed for the analysis. The obtained data set included 750 vehicles.

5.4 Results from observed driver behavior

Of the total number of 750 vehicles observed, 113 were RLR events and 437 YLR events; 202 vehicles were leaders and 548 were followers. There were a total of 28 heavy vehicles approaching the intersection at the yellow onset, which is 4.02% of the total.

5.4.1 Distribution of vehicles at the yellow onset

The distribution of vehicles and their respective speeds in the segment under study at the time the signal turned yellow are shown in Figure 5-8. The color coding and corresponding symbols enable the easy visualization of the number of vehicles which passed during yellow and during red, and those vehicles which stopped at the intersection.

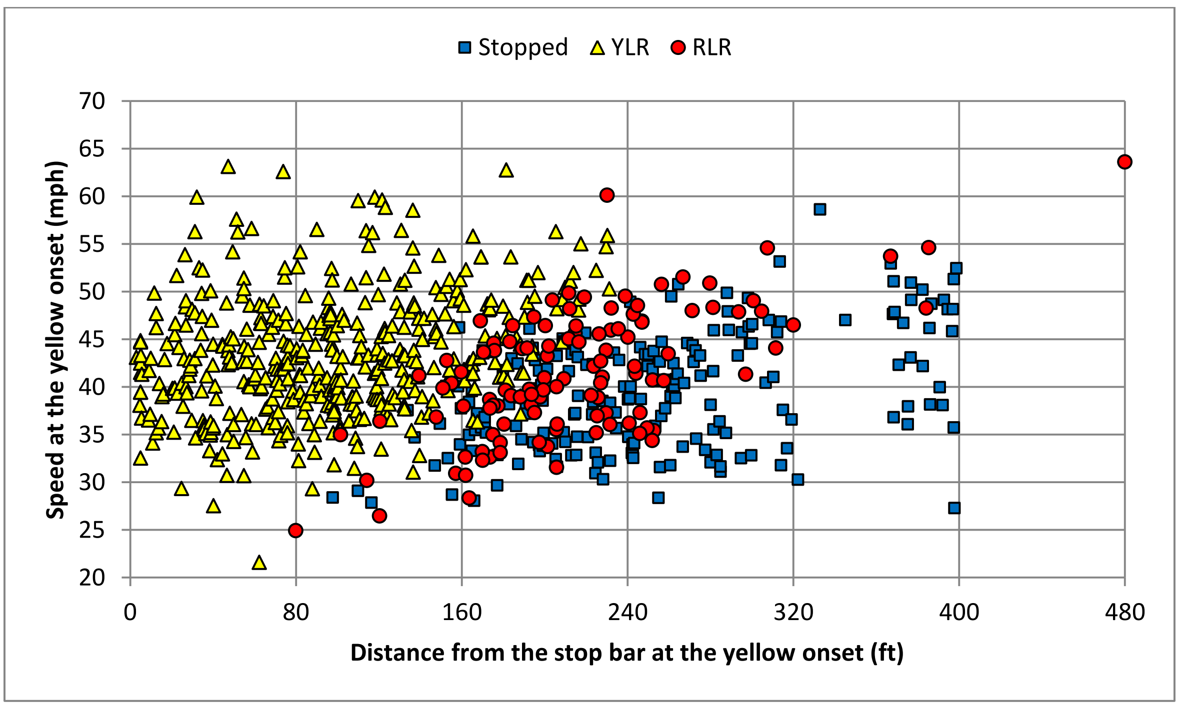

Figure 5-8: Distance from the stop bar and corresponding speeds of individual vehicles at onset of yellow signal

Figure 5-8 shows the distance at which the vehicles were from the stop bar at the yellow onset. At this moment, the driver must perceive and react to decide either to stop at or cross the intersection. All the vehicles that were located at less than 80 feet from the stop bar crossed the intersection during the yellow onset. From 80 to 160 feet, only a few vehicles (13.12%) either stopped or passed in red. Speeds for vehicles in this section ranged from 25 to 62 mph. For the distance spanning 160 to 240 feet, it can be seen that the majority of vehicles (68.6%) either stopped at the intersection or ran the red light. From this section the vehicles had to accelerate to be able to pass the intersection during the yellow phase. When the yellow signal turned on and the vehicles were in the section from 240 to 320 feet, none of the vehicles had any yellow time left to pass the stop bar; therefore most of the vehicles (73.08%) made the decision to stop, while 26.92% passed on red.

5.4.2 Red Entry Time

Another important analysis to study the reaction of drivers at the end of the green period is the red entry time. This is the time spent by vehicles that cross the intersection during the red period. The RLR events occurred in a time period ranging from 0.02 to 2.46 seconds after the red onset. While it may be acceptable that a high percentage of vehicles in the 0-160 ft segment pass the intersection on yellow, it is rather intriguing that a large number of vehicles farther away from the stop bar decide to go through the intersection on red (Figure 5-8). Such high RLR frequency is a clear indication of aggressive driver behavior at this intersection. Also, the 15th, 50th, and 85th

percentile entry times for these vehicles were 0.21, 0.55 and 1.21 seconds respectively, after the red onset.

Figure 5-9 presents the distribution of red entry time. This variable indicates the time period that passed after the start of the red signal when the vehicles crossed the stop bar. The majority (79%) of vehicles involved in RLR events crossed the intersection in the first second after the termination of the yellow period. A rather large fraction of vehicles (21%) passed after the first second, increasing the probability of risking a crash at an angle because the conflicting vehicles already have the right of way.

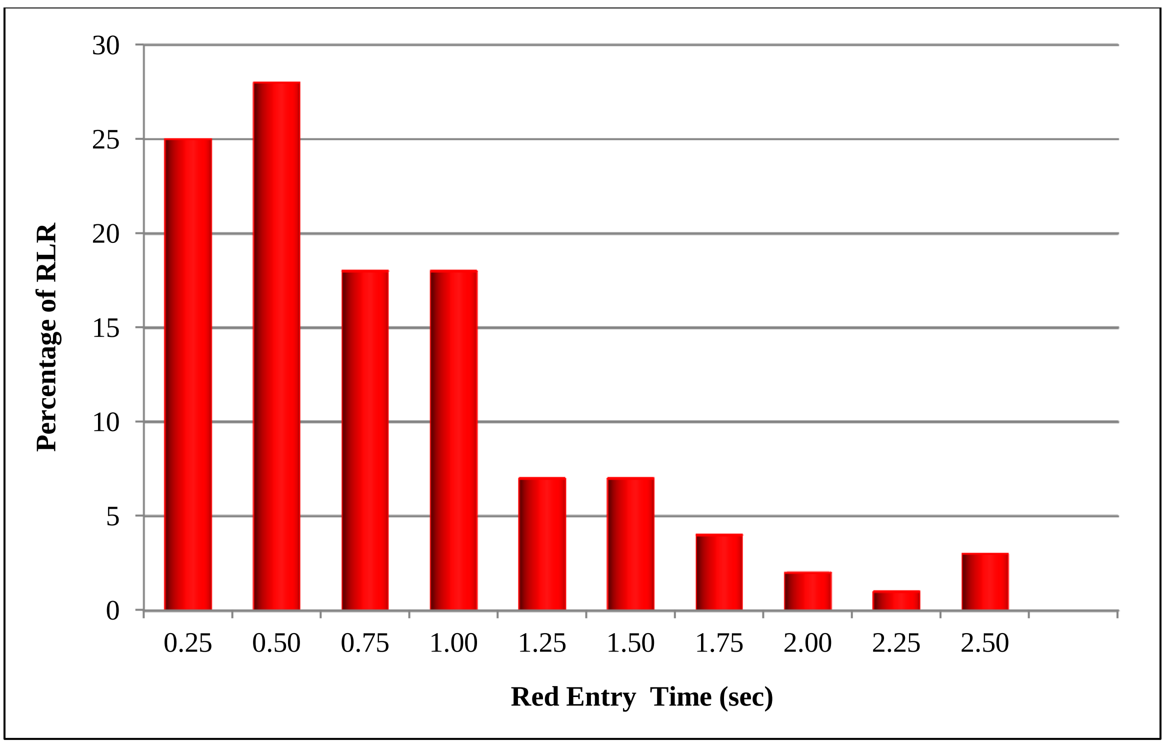

Figure 5-9: Distribution of red entry time

Bonneson et al. (2002; 2004) observed 50th and 80th percentile entry times of 0.5 and 1.0 seconds, respectively. Gates et al. (2007) observed 15th, 50th, and 85th percentile entry times of 0.02, 0.30 and 0.84 seconds, respectively. Comparing these results with those observed in Mayaguez further underscores the fact that, drivers at this intersection are more aggressive based on the larger values of red entry times. This is clearly likely to create more conflicting movements and increases the likelihood of RLR crashes.

5.4.3 Yellow Entry Time

Another important measure in a RLR event analysis is the duration of time from the moment at which the yellow turns on until the vehicle crosses the intersection. Figure 5-10 shows the relationship of yellow entry time and the distance from the stop bar at which the vehicle was located at that particular moment. A linear regression model shows the direct relationship of these two variables, with a coefficient of determination of 0.82.

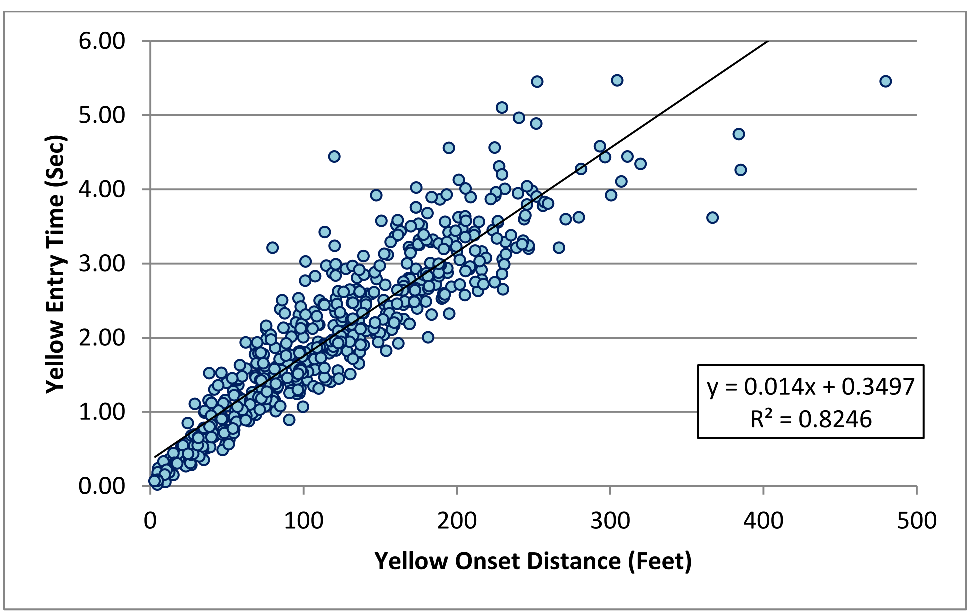

Figure 5-10: Relationship between yellow entry time and yellow onset distance

Since the yellow period for the intersection in this study is 3.0 seconds, values of yellow entry time above this period translate to a RLR violation. It should be noted, that the greater this time, the greater the chance of RLR crash.

Table 5-1: Descriptive statistics for yellow entry time

Factor	Sub-level	N	Mean	Standard Dev.	Min	Max
Vehicle type	Heavy vehicles	24	2.06	0.27	0.31	4.88
	Passenger cars	526	2.05	0.04	0.02	5.46
LD/FL	Follower	406	2.04	0.05	0.02	5.45
	Leader	144	2.10	0.09	0.14	5.46
Lane	Left	180	2.11	0.08	0.06	5.46
	Middle	228	1.99	0.07	0.02	4.74
	Right	142	2.08	0.09	0.15	5.10

Table 5-1 summarizes the descriptive analysis of the yellow entry times and Table 5-2 presents the analysis of variance and the coefficients. On average, the yellow entry time is 2.06 seconds, and the highest value was 5.46 seconds, indicating a time of 2.46 seconds after the red period turned on. The average of yellow entry time was greater for the leader vehicle (2.10 seconds) than for follower vehicles (2.04 seconds), while for vehicle type (heavy or not) the values of mean entry time were similar (2.05 seconds and 2.06 seconds, respectively).

A multiple regression model for the yellow entry time indicated that the significant variables were the distance and the speed at the yellow onset (both variables with p-value = 0.000). These two variables can explain 89 percent of the variability of the model. The other variables of vehicle type (p-value = 0.642), if the vehicle was leader or not (p-value =0.328), and lane (p-value = 0.071) were found to be not significant in the model.

Table 5-2: Analysis of variance for yellow entry time

Source	Sum of Squares	DF	Mean Square	F	Sig.
Regression	616.52	2	308.26	2208.26	0.000
Residual	76.35	547	0.140		
Total	692.87	549			
Predictors: Constant, Distance and Speed. R Squared = 0.890					

Coefficients[a]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
	B	Std. Error	Beta			Lower Bound	Upper Bound
Constant	2.210	.108		20.496	.000	1.998	2.422
Distance	.015	.000	.954	66.140	.000	.014	.015
Speed	-.045	.003	-.259	-17.996	.000	-.050	-.040
a. Dependent Variable: Yellow_Entry_time							

5.4.4 Yellow Onset Speed Analysis

Table 5-3 summarizes the descriptive analysis of the vehicle speeds at the beginning of the yellow period. The average approach speed is 42.03 mph (Standard Deviation = 6.50), which is slower than the speed limit of this road (45 mph). This value has been obtained with all the speed data of the vehicles at the start of yellow. These values have a range from 21.6 mph to 63.6 mph. The yellow onset speed data is normally distributed with an 85^{th} percentile of 48 mph. The higher mean speeds correspond to those vehicles who are leaders (44.18 mph) versus the vehicles which are followers (41.24 mph). The vehicles which decided to cross the intersection had a higher mean speed (43.00 mph) than the vehicles that stopped (38.6 mph). These results are consistent with traffic patterns that would be expected.

The mean speeds depending on vehicle type appear to be not significantly different (passenger car mean speed = 42.08 mph compared to heavy vehicle mean speed = 40.84 mph). The same is true for the RLR vehicles (41.4 mph) and the non RLR vehicles (42.11 mph) while these are slightly different for vehicles traveling in different lanes (right lane = 42.76 mph, middle lane = 43.17 mph, left lane = 40.08 mph). The results of vehicle speed based on lane type are slightly different from the typical characteristics of the traffic operating speeds at intersections since it is expected that the fastest vehicles generally use the left travel lane.

Table 5-3: Descriptive statistics for the speed at the yellow onset

Factor	Sub-level	N	Mean (mph)	Standard Dev. (mph)	Min (mph)	Max (mph)
Vehicle Type	Heavy vehicles	28	40.84	1.15	28.70	56.30
	Passenger cars	722	42.08	0.24	21.62	63.60
LD/FL	Follower	548	44.18	0.26	21.62	63.13
	Leader	202	43.95	0.49	24.91	63.60
Stop/go	Stop	200	38.36	0.41	27.26	53.14
	Go	550	43.00	0.27	21.62	63.60
RLR	Non RLR	637	42.11	0.25	21.62	63.13
	RLR	113	41.54	0.63	24.91	63.60
Lane	Left	248	40.08	0.40	21.62	63.60
	Middle	302	43.17	0.34	31.10	63.13
	Right	200	42.76	0.49	26.48	62.60

5.4.5 Stop and go decision

One of the most important variables in the analysis of RLR is the driver's decision to stop or continue to cross the intersection at the onset of the yellow period. The safety at signalized intersections depends to a large extent on this variable. In this study, 200 drivers took the decision to stop and 550 decided to cross the intersection after the signal had changed from green to yellow. Figure 5-11 and Figure 5-12 show the distribution of vehicles based on the decision to stop or go and distribution of RLR at the start of yellow, depending on the distance that they were from the intersection. Figure 5-11 shows that as the distance from the intersection increases, the probability to stop also increases and the probability of go decreases, until a distance of 280 feet from the intersection. In this section from 280 to 340 feet, the probability of stopping decreases while the probability to go increases up to 50%.

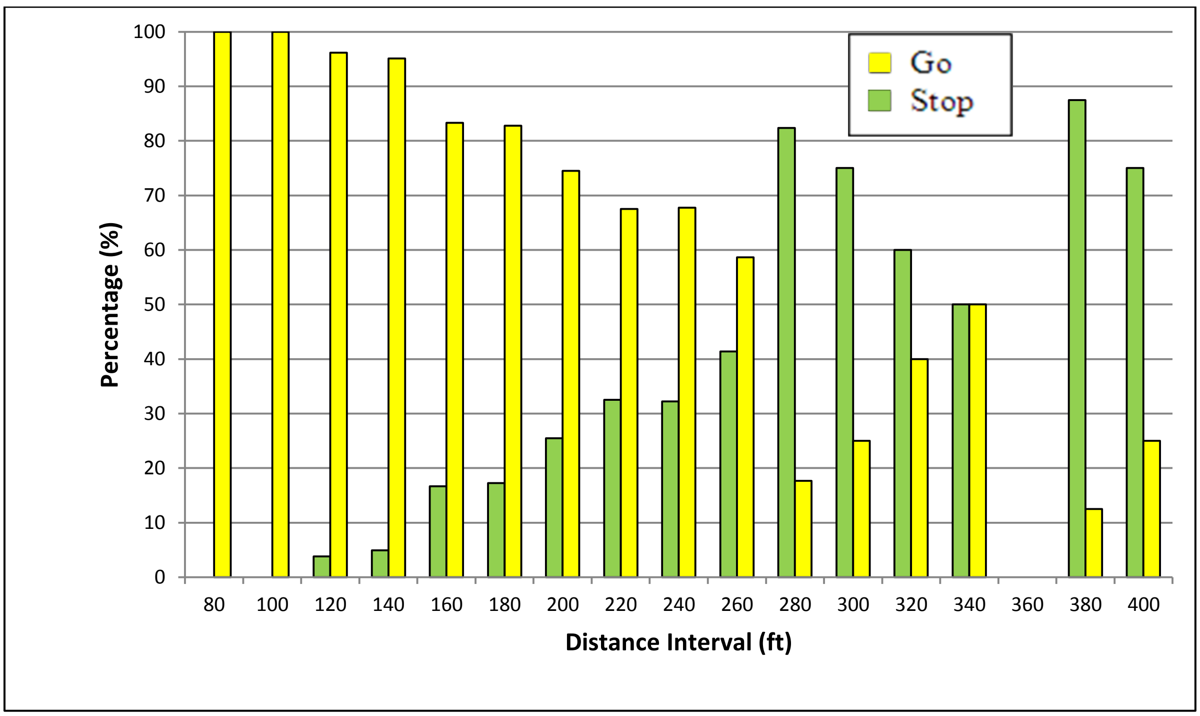

Figure 5-11: Distribution of stop and go decision by distance to the stop bar

It is in this section where the greatest variability in the decision to stop or go is found. Figure 5-12 shows that the largest number of RLR is observed in the segment from 180 to 260 feet from the intersection and reaches about 40%. The RLR then decreases and in the section of 320 to 340 increases again, up to 33% indicating a high level of aggressiveness of the drivers. It would be expected that the drivers would follow the tendency and after a certain distance (which in this case is 300 feet, as shown in the Figure 5-12) would stop at the intersection.

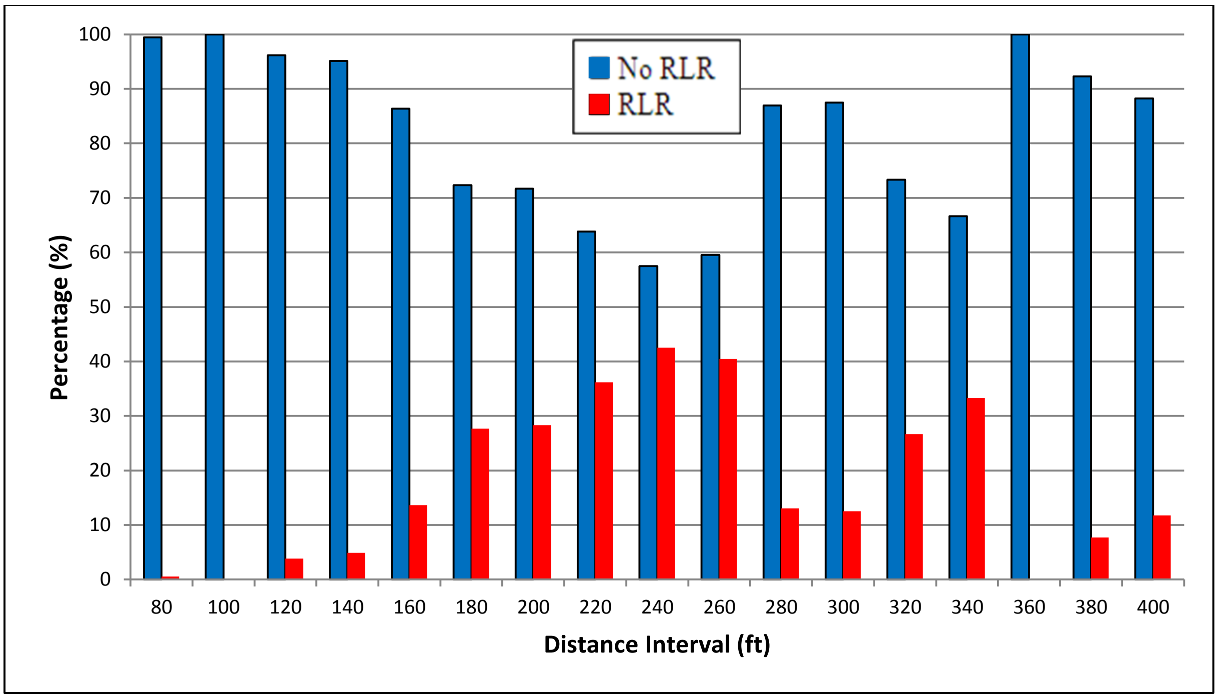

Figure 5-12: Distribution of RLR events by distance to stop bar

5.5 Stop and Go Decision Model

A binary logistic regression model was used to determine the probability that a vehicle arriving at the intersection at the start of the yellow would stop or continue crossing the intersection. This statistical analysis was performed using the computer program SPSS 17®.

A binary logistic regression is a statistical tool similar to a linear regression model, that is adapted to models where the dependent variable is dichotomous (only takes two possible values). This type of regression is used to predict the probability of a dichotomous outcome, taking into account a set of predictor variables (continuous or categorical) and their characteristics. The form of the model is:

$$P_i = \frac{1}{1+e^{-z_i}} \tag{5-2}$$

where:

P_i = the probability of the i^{th} vehicle to stop, and

z_i = the result of a linear function of the various factors (explanatory variables), with the form:

$$z_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \dots \dots + \beta_k x_k \tag{5-3}$$

where:

β_0 = the constant of the model or the independent term, and

β_i = the coefficients of the covariates and x_i are the covariates that are part of the model.

The variables considered for the model are the following:

- distance of the vehicles from the stop line at yellow onset (ft),
- vehicle speed at yellow onset (mph),
- whether vehicle stops or not (stop = 1, go = 0),

- leader or not: (No = 0, Yes = 1),
- lane 1: (left (through) lane = 1, other = 0),
- lane 2: (middle (through) lane = 1, other = 0), and
- vehicle Type: (passenger car = 1, heavy vehicle = 0).

Table 5-4 presents the statistically significant factors that impact the stop probability at a confidence level of 95%. These variables include the distance of the vehicles from the stop line at yellow onset and the corresponding vehicle speed at the yellow onset. The complete results of this model are presented in Appendix B1.

Table 5-4: Calibration results for the stop/go decision binary logistic model

Factors	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
							Lower	Upper
Distance	.030	.002	158.456	1	.000	1.030	1.026	1.035
Speed	-.226	.025	79.793	1	.000	.798	.759	.838
Constant	2.541	.856	8.817	1	.003	12.687		

The model is described as follows:

$$P_{(Stop)} = \frac{1}{1+e^{-(2.541+0.030(\text{Distance})-0.226(\text{Speed}))}} \qquad (5\text{-}4)$$

The Nagelkerke R Square is 0.66 which indicates that the model performs well and can give reasonable values. The variable speed has a negative coefficient of -0.226, which means drivers traveling at a higher speed at the yellow onset are more likely to make a pass decision. The odds ratio (EXP (B)) for the speed is 0.798 (CI = 0.759–0.838) indicating that vehicles which travel more than 1 mph faster than the mean speed are on average 0.798 times less likely to stop.

The yellow-onset distance has a positive coefficient of 0.030 indicating that drivers located at a farther distance from the stop line at the yellow onset are more likely to make a stop decision. The odds ratio value for the distance from the stop line at the yellow onset is 1.030 (CI = 1.026–1.035). This indicates that a driver who is 1 foot farther than the average distance is 1.030 times more likely to stop at the intersection.

The model calculates the probability that a vehicle stops depending on its speed and distance from the stop bar at the beginning of the yellow period. The number of correctly classified cases from the sample is 86% (Table 5-5) which indicates that the model is indeed useful for prediction, since if the classification is applied to the observations already known, the success rate will be of 86%. This suggests that future classifications will remain at the same percentage.

The model does a better job in correctly identifying individual vehicles in the go decision with 92% of correct classification. The model provides inferior results for the stop decision (70%) indicating that the model lacks other variables in addition of speed and distance that refer to those observations in the sample.

Table 5-5: Classification table for the stop and go model

Observed		Predicted		
		Stop	Go	Percentage
		.00	1.00	Correct
Go	.00	505	45	91.8
Stop	1.00	60	141	70.0
Overall Percentage				86.0

Overall, from equation 5-4 one can conclude that for a vehicle, the farther the distance and the slower the speed, the larger the probability of stopping at the yellow onset, and drivers travelling at a higher speed at the yellow onset are more likely to make a pass decision. Thus, a vehicle that is located 250 feet from the intersection and travels at a speed of 40 mph has a probability to stop of 73%, while for the same distance but, at 55 mph, the probability of stopping is reduced to 8.4%.

5.6 Vehicle Trajectory Analysis

To analyze the trajectories of the vehicles the average speed in each segment was calculated from 480 feet to 80 feet from the stop line, taking into account three segments: vehicles that encountered the yellow in the segment (i) 80 to 160 ft, (ii) 160 to 240 ft and (iii) 240 to 320 feet. Figure 5-13, Figure 5-14 and Figure 5-15, show the trajectories of the vehicles per group of a sample of 250 vehicles, depending on the segment in which they were positioned at the yellow onset.

Figure 5-13 shows the trajectories of the speed of the vehicles that were in the 320-240 ft segment at yellow onset. In this segment between 320 to 240 feet, there was an increase in the speeds of the vehicles that ran the red and a decrease in the speeds of the vehicles that stopped. In this case the vehicles did not pass the intersection in yellow because they were far enough from the intersection to make a decision. Of the total number of vehicles that encountered the yellow onset in this segment 28.1% were RLR events, whereas 71.9% stopped at the intersection.

When the vehicles were traveling in the 240-160 feet segment (Figure 5-14) at yellow onset, the percentages of vehicles that passed in red and those which stopped were 44.44% and 41.27%, respectively, whereas only 14.29% of the vehicles were YLR. In this case, the vehicles who wanted to pass in yellow had to increase speed. In this segment, those who took the decision to stop began to decelerate.

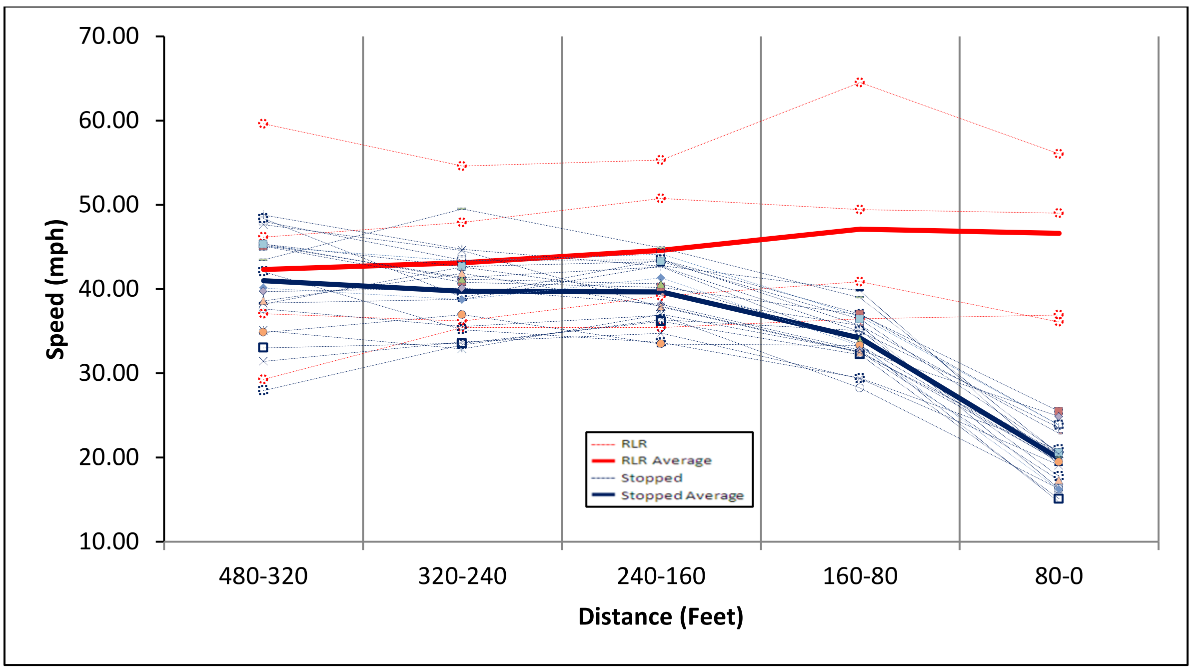

Figure 5-13: Speed trajectories for corresponding vehicle positions at yellow onset in the 320-240 feet segment

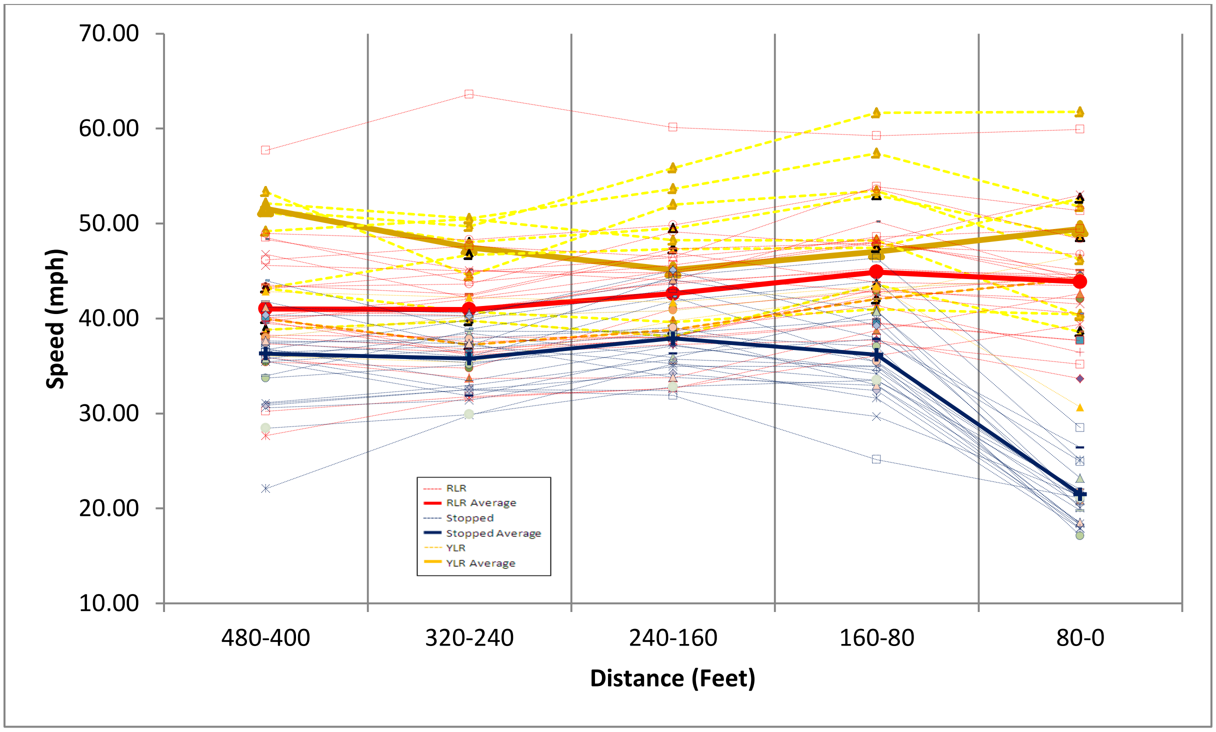

Figure 5-14: Speed trajectories for corresponding vehicle positions at yellow onset in the 240-160 feet segment

When the signal turns yellow for vehicles located in the segment from 160 to 80 feet (Figure 5-15) significant changes of speed are not observed and the vast majority crossed the intersection in the yellow period (80%). Vehicles which decide to stop or pass in red were 7.06% and 12.94% respectively.

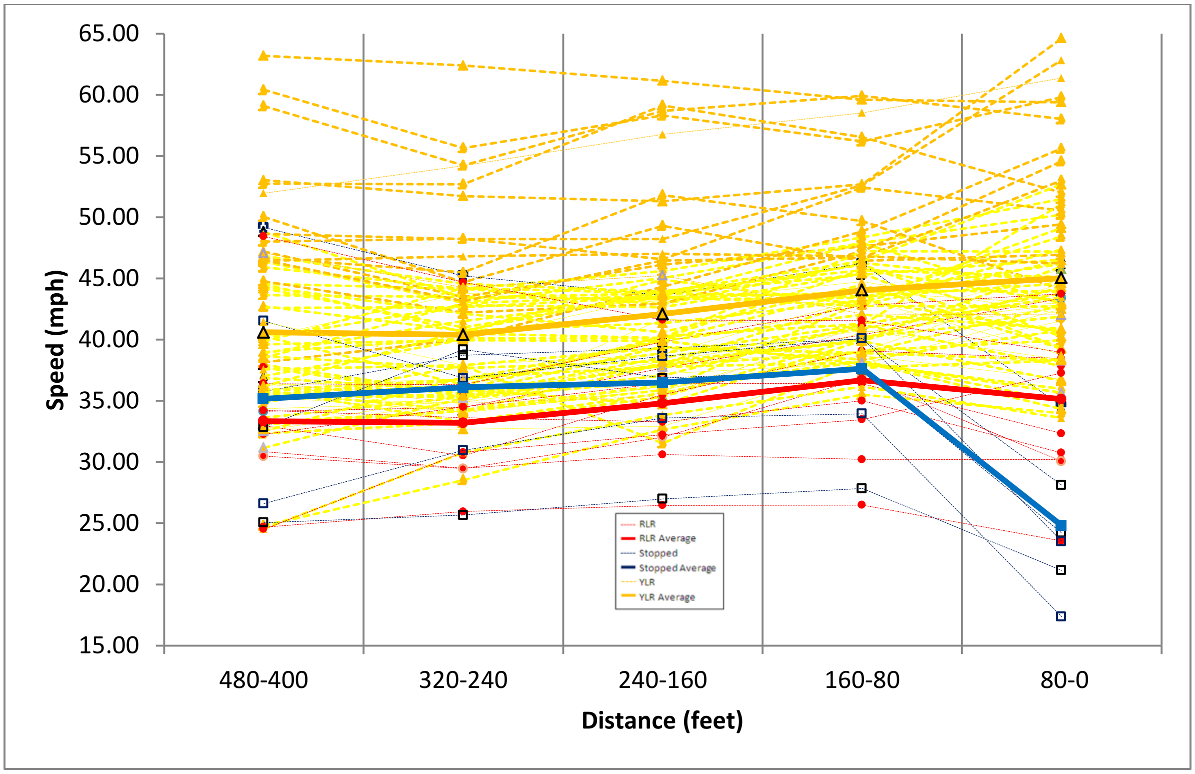

Figure 5-15: Speed trajectories for corresponding vehicle positions at yellow onset in the 160-80 feet segment

Generally, vehicles which cross the intersection during the yellow or red change periods tend to move at constant speed or to accelerate while stopping vehicles exhibit deceleration while approaching the intersection.

5.7 Vehicle Decelerations

From the analysis of the trajectories of the vehicles and according to the field observations, once the yellow change period starts, three groups of vehicles can be seen:

- the vehicles that begin to decelerate at the yellow onset,

- the vehicles that accelerate during a segment and realizing that they have no time to cross, slow and stop at the intersection, and
- the vehicles that accelerate and cross the intersection although they do not have enough time and are at a higher risk of crash.

Only the vehicles that stopped at the intersection once the yellow change period started were taken into account to determine the deceleration. The data of speeds and distances from the stop bar at the yellow onset were analyzed by following the trajectory of these vehicles.

The analysis of the deceleration rate was carried out by using a multiple linear regression approach to identify the effect of different variables on changes in speed of the vehicles approaching the intersection after the yellow onset. The potential independent variables in this study included the continuous variables of distance and speed of vehicles at the beginning of the yellow, and categorical variables of vehicle type, lane (Lane_1 (through left lane), Lane_2 (through middle lane), and if the vehicle was a leader or not. The regression analysis was performed using the program SPSS 17® and the results are presented in Table 5-6. The calibration results of the linear regression equation for the deceleration of first to stop vehicles are the following:

$$Deceleration\ (ft/s^2) = 5.798 - 0.030\ (Dist) + 0.340\ (Speed) - 0.993\ (Lane\_1) - 0.861\ (LD\_FL) \qquad (5\text{-}5)$$

Table 5-6: Analysis of variance for the deceleration model

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
	B	Std. Error	Beta			Lower Bound	Upper Bound
(Constant)	5.798	1.235		4.695	.000	3.362	8.233
Dist	-.030	.003	-.636	-10.791	.000	-.036	-.025
Speed	.340	.034	.598	10.020	.000	.273	.407
Lane_1	-.993	.378	-.140	-2.630	.009	-1.738	-.248
LD_FL	-.861	.396	-.117	-2.176	.031	-1.641	-.081

a. Dependent Variable: Deceleration

The results indicate that the variables that had the strongest effect on the dependent variable deceleration rate were the speed and the distance at the yellow onset (p-value=0.000). The model considered these variables significant at a 95% confidence level. Equation 5-5 shows that the variable that increases the deceleration is speed (i.e., faster vehicles require higher decelerations). The distance variable, on the other hand, has the effect of reducing the deceleration. Drivers who are farthest from the intersection at the yellow onset use a lower deceleration. The effect on deceleration rate is the same for the other two variables, Lane_1 and LD_FL (leader or follower vehicle), where vehicles in lane 1 (through left lane) and leader vehicles used lower decelerations. The complete results of this model are presented in Appendix B2.

5.7.1 Deceleration Model Verification

To verify the model, an analysis of residuals was performed to see if the assumptions of linear regression were met. Figure 5-16 shows the results which indicate that the residuals do not follow a normal distribution because as seen in the histogram there is a small bias towards the left. Also in the normality plot shown, the points that are found in the middle fall slightly away from the normal line. In the scatter plot, the points form a cone-shaped pattern of the residuals against the estimated value of y which indicates that the residuals do not have a constant variance.

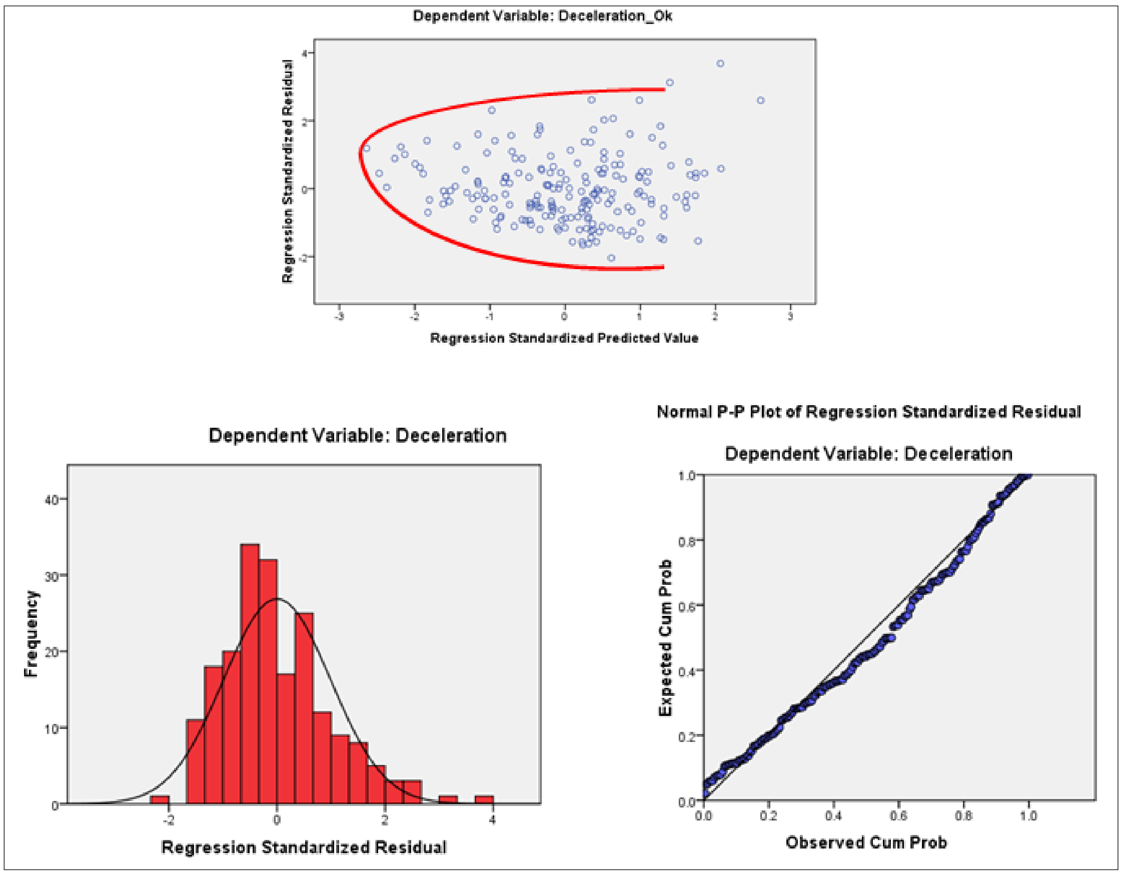

Figure 5-16: Residual analysis of the deceleration regression model

In such a case, it is recommended that transformations are made to the data starting with the dependent variable to see if the lack of normality can be corrected and the variance can be made constant, failing which the independent variables are transformed. The transformation that worked best for this case was the natural logarithm of the dependent variable. Figure 5-17 presents the residual analysis after transformation of the dependent variable.

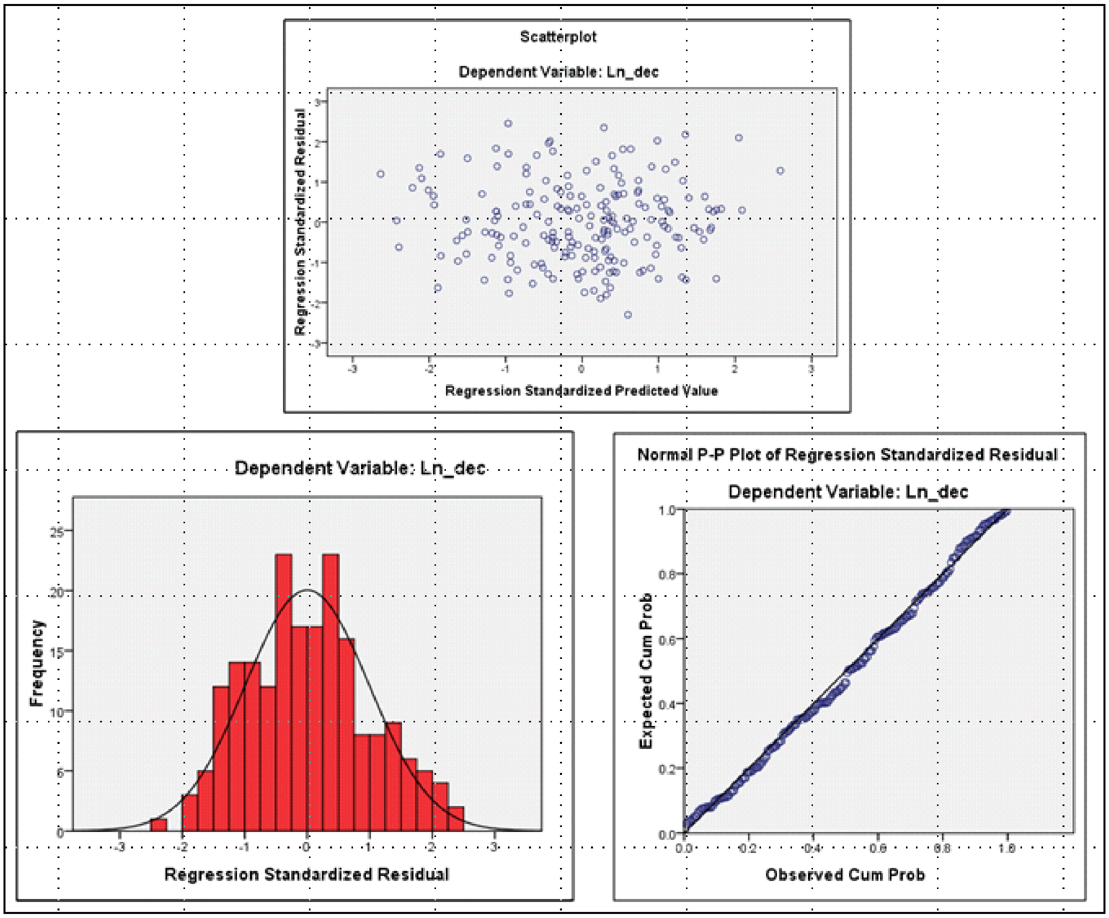

Figure 5-17: Residual analysis of the deceleration regression model after the transformation

Figure 5-17 shows that the residuals indeed follow a normal distribution after transformation and the variance is now constant. The new equation for this model is:

$$Ln\ (Dec) = 1.807 - 0.003\ (Dist) + 0.033\ (Speed) - 0.08\ (Lane\_1) - 0.07\ (LD\_FL) \qquad \text{(5-6)}$$

For example, if a leader vehicle is traveling in the through left lane (Lane_1 = 1) at a distance of 250 feet from the stop line and is travelling at 40 mph at the yellow onset, it is determined that this vehicle will require a deceleration of approximately 10.8 ft/s^2 to stop. However, under the same conditions, but at a speed of 55 mph, the vehicle will require a deceleration of 17.7 ft/s^2. These results agree with the field observations. The results of the residual analysis and the transformation of the dependent variable, deceleration rate (*Y*), are found in Appendix B3.

Chang et al. (1985) and Gates et al. (2007) also encountered correlation between the deceleration rate and the approach speed and the distance from the intersection, although they also considered additional variables such as the brake-response time.

The 15th, 50th, and 85th percentiles deceleration rates for the data observed in this study are 7.73, 10.54 and 14.33 ft/s^2, respectively. Figure 5-18 presents the distribution of deceleration rates for vehicles which were first to stop in this study and others found in the literature.

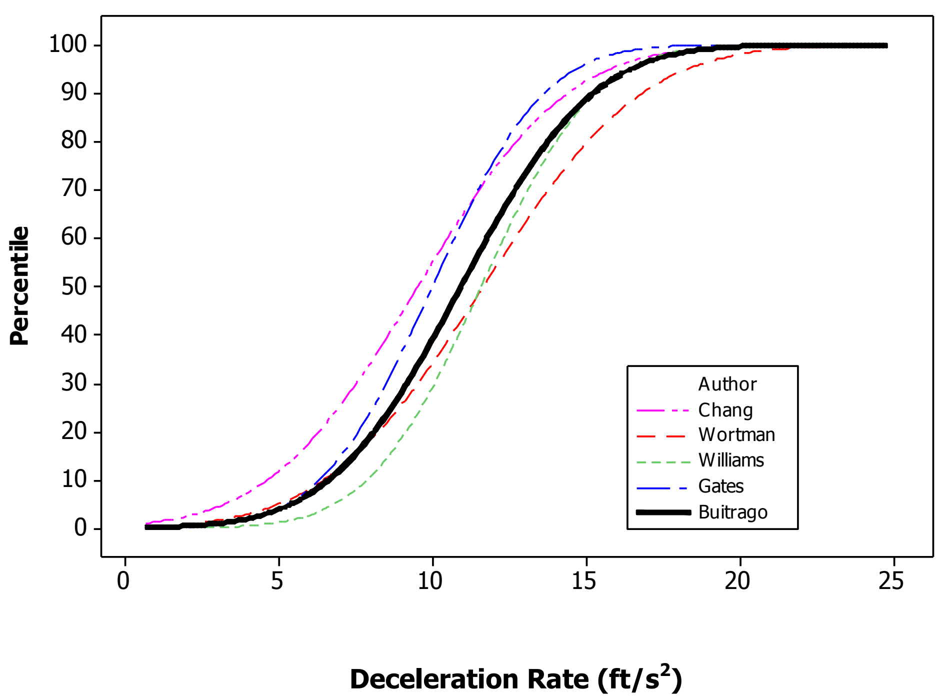

Figure 5-18: Distribution of deceleration rates

The tendency of the distribution of deceleration rates in this study are in agreement with the data presented in previous studies. The deceleration rates are very similar to those encountered by Wortman et al. (1983) until the twentieth percentile, after which the trend is similar to that observed by Chang et al. (1985), which is parallel to the data found by Gates et al. (2004), with the difference of 1 ft/s^2 approximately. It appears that the distribution of decelerations in the current study represents an average value for the other studies in that it lays approximately in the middle of the distribution S-functions. The values for the deceleration rate recommended by ITE (1989) of 10 ft/s^2 and AASTHO (2004) of 11.2 ft/s^2 correspond to the 38.9 and 53.1 percentiles, respectively, of the data in this study.

Figure 5-19 shows the cumulative distribution of the deceleration rates divided in two groups of speeds: the first group is for speeds less than or equal to 40 mph and the second group is for speeds greater than 40 mph. The distribution takes into account that vehicle speeds above 40 mph are considered high speed.

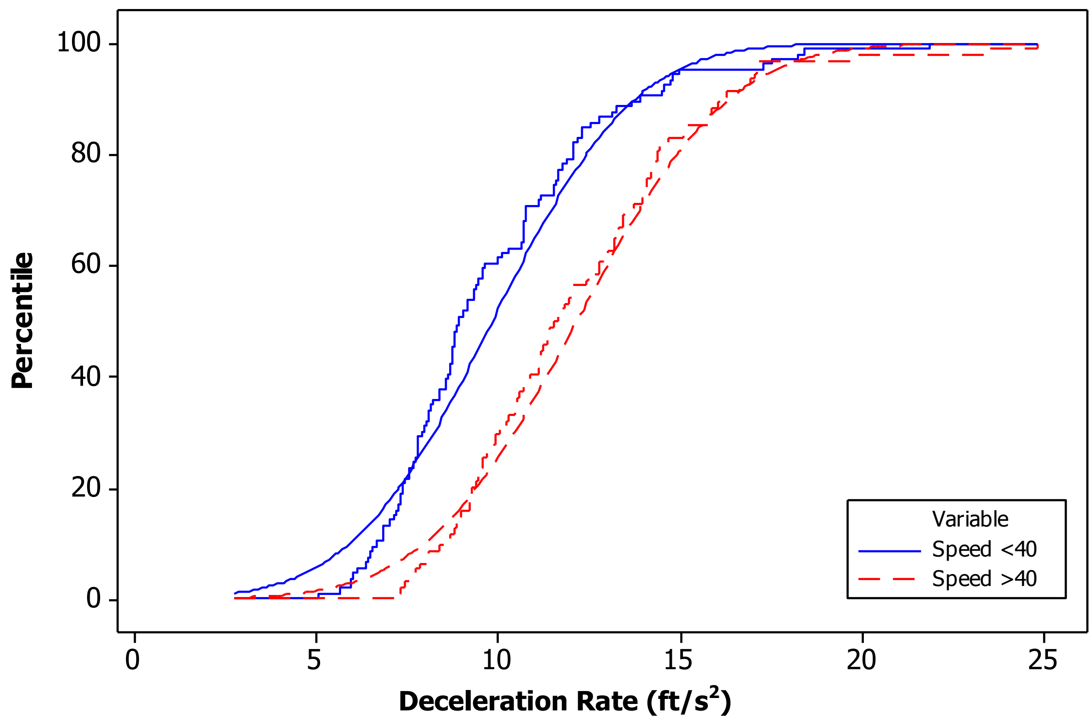

Figure 5-19: Cumulative distribution of deceleration rates classified by speed

It is observed that for vehicles traveling at speeds below or equal to 40 mph the decelerations are smaller, as expected, since these do not have to change the speed abruptly to stop. For vehicles that travel at higher speeds, the decelerations rates are higher varying from 5.01 ft/s^2 to the maximum value of 24.81 ft/s^2.

The 15th, 50th, and 85th percentile deceleration rates for drivers approaching at speeds of less than 40 mph were 7.20, 8.96 and 12.39 ft/s^2, respectively. The 15th, 50th, and 85th percentile deceleration rates for drivers approaching at speeds greater than 40 mph were 9.01, 11.59 and 15.21 ft/s^2 respectively.

The recommended value for comfortable deceleration of 10 ft/s^2 proposed by ITE (1989) corresponded to the 61.3th percentile for speeds which are over 40 mph and 25.4th percentile for speeds equal to or below 40 mph. This signifies that approximately 40% of the vehicles that stop after traveling at a speed greater than the speed of 40 mph have to decelerate at rates higher than that recommended for design by ITE. Even among those vehicles that stop at the beginning of the yellow signal phase and have approach speeds lower than or equal to 40 mph, 75% approximately use decelerations greater than 10 ft/s^2. According to Gates et al. (2007) this implies that it is important to evaluate the speeds and decelerations before using design default values to determine the length of the yellow period in a particular intersection. This requires the use of real time vehicular speed data at the intersection to determine the yellow times instead of using a fixed value.

5.8 Driver Reaction

The total sample for the analysis was 750 vehicles which approached the intersection at the yellow onset. As mentioned before, of these, 200 vehicles stopped at the intersection during the yellow period whereas 550 vehicles crossed the intersection. To perform an analysis of driver reaction the following methodology was utilized. The time that vehicles had to reach the intersection from the onset of yellow was calculated. The vehicles were then distributed in different categories based on various time periods such as less than 1 second, between 1 and 2 seconds, between 2 and 3 seconds and so on, until periods where vehicles had more than 10 seconds of time available to reach the intersection after the yellow onset were identified. Table 5-7 presents the results of this approach.

Table 5-7: Distribution of drivers by time to stop line

Time to the stop line (s)	Stopping Vehicles			Passing Vehicles		
	Sample	Percent	Cumulative %	Sample	Percent	Cumulative %
0-1	0	0.00%	0.00%	104	18.91%	18.91%
1-2	0	0.00%	0.00%	174	31.64%	50.55%
2-3	2	1.00%	1.00%	159	28.73%	79.45%
3-4	12	6.00%	7.00%	90	16.36%	95.64%
4-5	37	18.50%	25.50%	19	3.64%	99.27%
5-6	38	19.00%	44.50%	4	0.73%	100.00%
6-7	64	32.00%	76.50%	0	0.00%	100.00%
7-8	27	13.50%	90.00%	0	0.00%	100.00%
8-9	14	7.00%	97.00%	0	0.00%	100.00%
9-10	4	2.00%	99.00%	0	0.00%	100.00%
>10	2	1.00%	100.00%	0	0.00%	100.00%
Total Samples	200			550		

The data was divided in two groups depending on the action taken by the driver. The first group consists of drivers who decided to stop at the intersection at the beginning of yellow while the second group decided to accelerate to cross the intersection.

Table 5-7 shows the percent of vehicles in each category or interval of time and their respective cumulative percent. As shown in the group of "passing vehicles", about 79% of drivers decided to continue through the intersection before the end of the yellow period. The remaining 21% of drivers in this group needed more than 3.0 seconds to reach the intersection. These drivers decided to accelerate although the yellow phase had ended. These drivers, as shown in the table, can be classified as "aggressive drivers." In the group of “stopping vehicles” a similar pattern is observed, but only 1.0 % of drivers in this group could have passed the intersection during the

3.0 seconds of the yellow period, but decided to stop. These drivers can be categorized as "conservative drivers" (Maryland DOT, 2004). It is difficult in such a study to evaluate driver behavior and correlate it with an index of aggression. This is an indirect indication of the level of aggressiveness among drivers.

Figure 5-20 shows the relationship between the time periods that vehicles have to reach the intersection and the decision to stop or cross the intersection at the beginning of the yellow change period. It is observed that most of the vehicles that stopped took 5 seconds or more to reach the intersection and most of the passing vehicles took 4.0 seconds or less to cross the intersection. These times are longer than the assigned period of yellow for this approach which is 3.0 seconds. So, as expected, the vehicles that stop, since they do not have enough time to pass the intersection, decided to stop at the intersection. On the other hand, passing vehicles, even though they do not have time to go, decided do so indicating an aggressive attitude in terms of driver behavior.

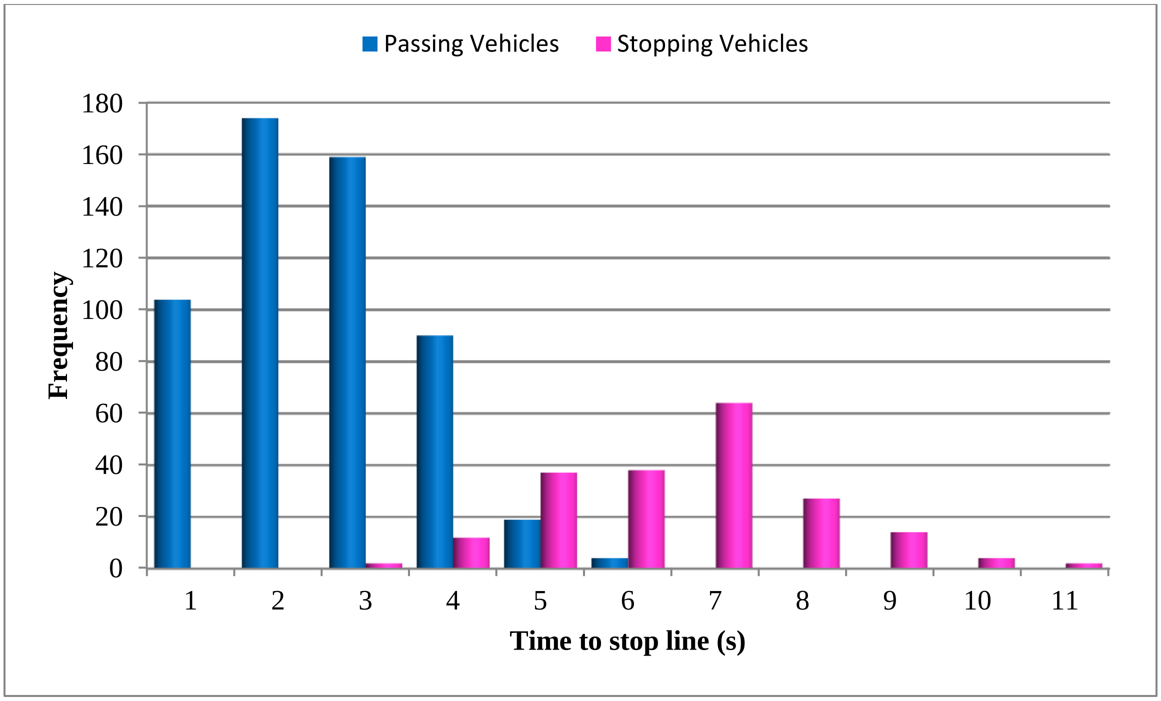

Figure 5-20: Distribution of passing and stopping vehicles depending on the time to stop line

5.9 Determination of Dilemma Zone

The dilemma zone (DZ) is determined from the data observed in the field which were plotted in a coordinate system presented earlier in Figure 5-8. In this figure, the distribution of the location of vehicles represented by the distance in feet at the yellow onset plotted on the horizontal axis, and the speed at the yellow onset in miles per hour plotted on the vertical axis are observed. The observed data are again presented in Figure 5-21. Figure 5-21 shows that at the beginning of the yellow change period a region with a number of overlapping points are noted which are classified as yellow light running (YLR), red light running (RLR) and stopped vehicles. A dilemma zone can be practically attributed to this region, or in some cases an option zone (OZ) may be found. The dashed oval has been superposed over the data in Figure 5-21 to indicate the probable dilemma zone.

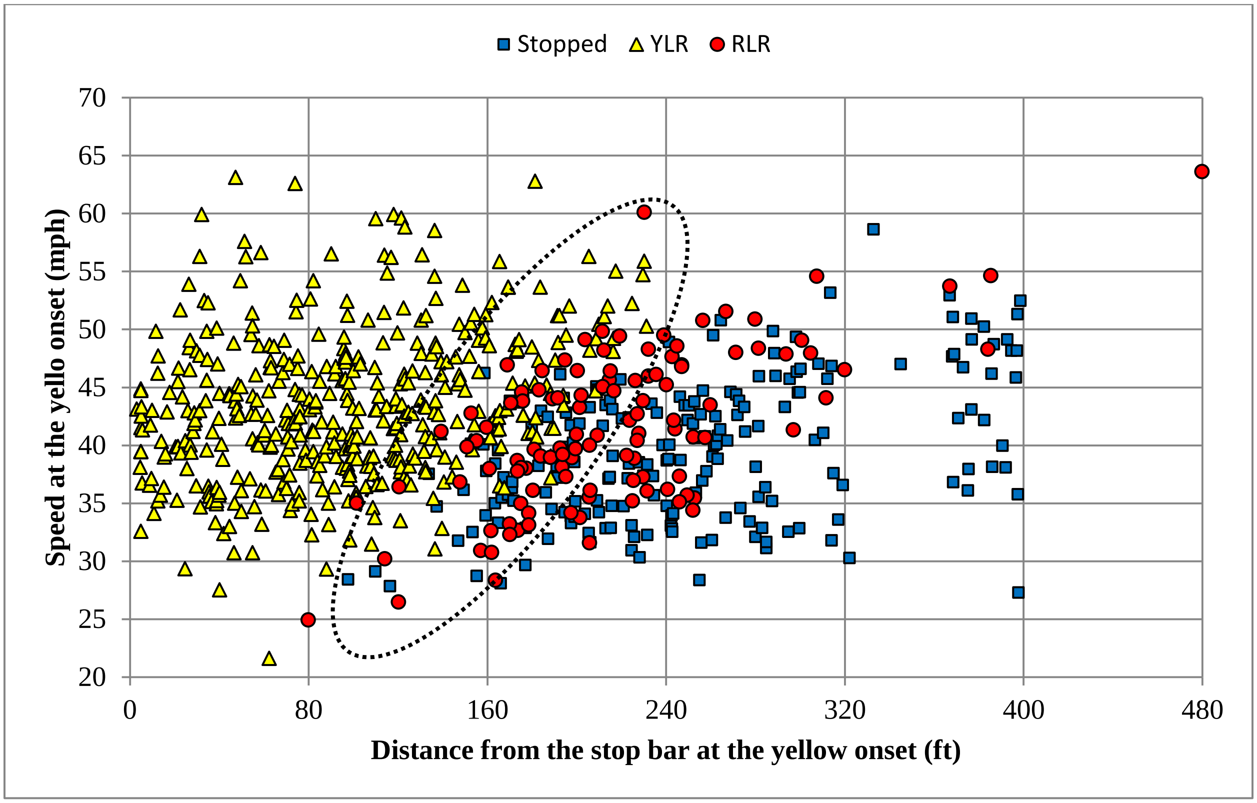

Figure 5-21: Distribution of vehicles at the yellow onset and the hypothetical boundaries of DZ

The dilemma zone is the portion of the highway in which a driver is undecided about whether to stop or continue to cross the intersection in a safe manner. If a vehicle is located in the DZ area at the yellow onset, it cannot stop safely before reaching the stop line, or cannot cross the intersection safely without speeding before the red signal starts. If the vehicle stops, there is a risk of a rear end crash, and if the vehicle crosses also there is a risk of an angle crash. It is important to conduct studies of this particular area to improve the safety at intersections. A considerable number of vehicles can be observed to be located in the dilemma zone shown in Figure 5-21.

To determine and further analyze the dilemma zone in the current study, a technique that utilizes the distribution of the vehicle positions in the observed data and relates these to theoretical concepts was developed. The dilemma zone is formed by two theoretical distances, defined as X_c *(minimum stopping distance* from the stop line), and X_0 (*maximum passing distance* from the stop line). The dilemma zone is represented by [X_c - X_0]. If $X_c > X_0$, the dilemma zone exists, while for the case of $X_c < X_0$, an option zone is established in which vehicles may safely stop or cross the intersection before the end of the yellow period. According to the GHM model, X_c can be represented by equation (3-2) (Gazis et al., 1960) as follows:

$$X_c = V_0\delta + \frac{{V_0}^2}{2d_{max}}$$

where:

X_c = minimum stopping distance (ft),

V_0 = initial speed when the yellow interval begins (ft/s),

δ = driver's perception-reaction (s), and

d_{max} = maximum deceleration rate of approaching vehicles (ft/s^2).

As observed in the Equation 3-2, X_c depends on the initial speed at the yellow onset (V_0), the perception and reaction time of drivers at the start of the yellow (δ) and the maximum deceleration that the vehicles may apply (d_{max}).

X_0 can be represented by equation 3-3 (Gazis, 1960) as follows:

$$X_0 = V_0\tau - (W+L) + \frac{1}{2}a_{\max}(\tau-\delta)^2$$

where:

X_0 = maximum passing distance (ft),

τ = duration of the yellow period (s),

δ = driver's perception-reaction (s),

a_{max} = maximum acceleration rate of the approaching vehicles (ft/s^2),

W = intersection width (ft), and

L = average vehicle length (ft).

As shown in equation 3-3, X_0 depends on the initial speed at the yellow onset, the length of the yellow period, the maximum acceleration, the width of the intersection or the distance that vehicles have to cross to be out of risk, and the average length of the vehicle.

Normally, these distances (X_c, X_0) are determined in a practical manner by using default values for the model parameters, such as perception and reaction time, acceleration and deceleration rates. The deceleration rate value recommended by ITE is 10 ft/s^2 (ITE, 2004) represents the 38.9 percentile of the drivers in this study, whereas the default value recommended by AASTHO of 11.2 ft/ s^2, represents the 53.1 percentile of drivers in this study. The default value used for the acceleration rate is usually 16 ft/s^2 (Maryland DOT). For the perception and reaction time, the value usually assumed is 1.0 second. While the recommended values of acceleration rate and deceleration rate are general values that can be applied to any intersection, the corresponding values for these parameters obtained from the field data is much more representative of the situation at each specific intersection. So also, the values of the perception and reactions times reflect a more real response from the vehicles studied at this particular intersection. This would enable one to determine the dimensions of the dilemma zone and other associated parameters much more accurately for each specific intersection.

Considering that each intersection is different and the characteristics and behavior of each driver are different, individual studies should take into account values specific to each intersection to determine both the dilemma and the option zones at the most dangerous intersections in terms of RLR and in terms of analysis of crashes caused by this type of violation. It must be emphasized that this study has established for the first time a novel and practical technique to determine these parameters bearing in mind the actual field observations collected for parameters such as speeds and distances at the yellow onset, the analysis of the trajectories of vehicles and the actions that the drivers take at the yellow onset.

In this technique, the region where there is an overlap of the different points representing the vehicles that passed the intersection when the signal was still yellow (YLR), the vehicles that stopped during the yellow period and the vehicles that passed in red (RLR) is determined as shown in Figure 5-21. It is expected that once the yellow period starts, depending on the distance from the stop line and the speed, vehicles that are close to the intersection and that cannot stop safely will cross the intersection, while vehicles which are farther away from the stop line at yellow onset will make the decision to stop. Figure 5-21 shows that even though some vehicles are far from the intersection and travel at a speed slower than the speed limit (45 mph), they indeed decide to pass the intersection demonstrating an attitude of aggressiveness. In the same figure, the overlapping of different points corresponding to YLR, RLR, and stopped vehicles over the marked zone, indicates the degree of indecisiveness of the driver and although it appears to be clearly marked in the figure, it is generally not easy to determine quantitatively.

The proposed technique initially identifies the points of minimum stopping distance and maximum passing distance in Figure 5-21, to corroborate the existence of this overlap area. According to the observations made in the field, the existence of very conservative drivers was noted. These are the drivers who stop at the intersection at the yellow onset even if there is sufficient time to cross the intersection in a safe manner. On the other hand, the existence of very aggressive drivers who cross the intersection even though there is insufficient time to do so in a safe manner is also clearly noted. The latter cross the intersection in the final seconds of the yellow signal or run the red indication risking an angle crash with the vehicles that have the right of way from other approaches.

In order to estimate the parameters of perception and reaction times, and acceleration and deceleration rates that apply to most cases, and thus to obtain an appropriate picture of the dilemma zone, only the vehicles that passed in yellow (YLR) and those which stopped were taken into account. The RLR vehicles were not considered for the calibration of parameters since these are already in violation of the traffic rules. Of the total of YLR data, only the 90^{th} percentile was taken to avoid the most aggressive drivers and in a similar manner, the 10^{th}

percentile of the total vehicles that are stopped are discarded to avoid the most conservative drivers. It is considered that discarding 10 percent of data both at the end of YLR (taking the 90th percentile of YLR) as well as discounting the 10 percentile of stopped vehicles gives a confidence level of 90%, and that avoiding the extremes will enable an accurate determination of the dilemma zone based on the observed data.

To identify the 90th percentile of the passing vehicles, the observations were divided into different groups each having a 5 mph range, from 20 to < 25 mph, from 25 to < 30 mph, etc., up to a maximum speed of 60 mph. Once the grouping was performed for the different speeds, the data of distances from the set of observations of YLR was organized from lowest to highest, and the 90th percentile determined for these observations. This was carried out using the cumulative frequency curve, from which a new set of data was obtained, which excludes the extreme values representing the most aggressive vehicles. An example of the speed classification from 30 to 35 mph is presented in Figure 5-22.

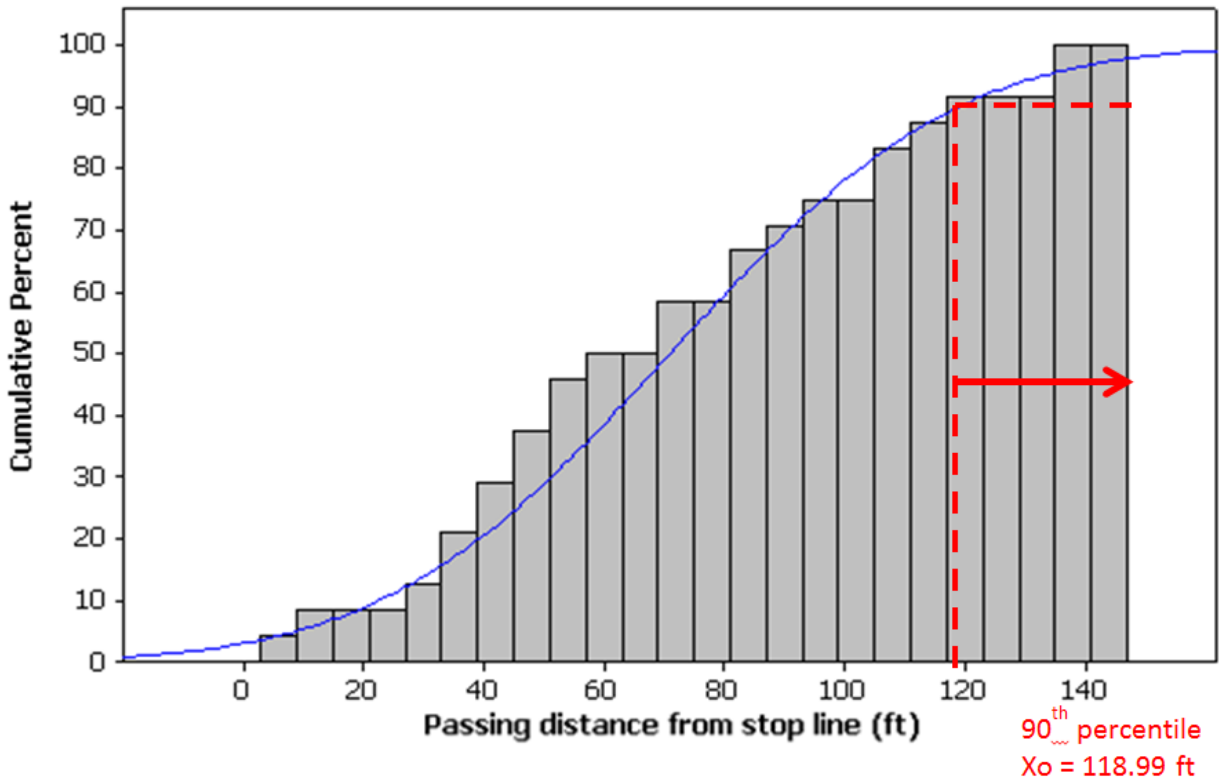

Figure 5-22: Determination of the 90th percentile of *Xo* for the 30-35 mph speed group

The same method was used to determine the 10th percentile of the stopped vehicles. An example of the speed classification 30 – 35 mph is presented in Figure 5-23. This percentage of data was discarded from the original data set, thus obtaining an adjusted set of data that does not consider the most conservative of the drivers in the estimation of the dilemma zone.

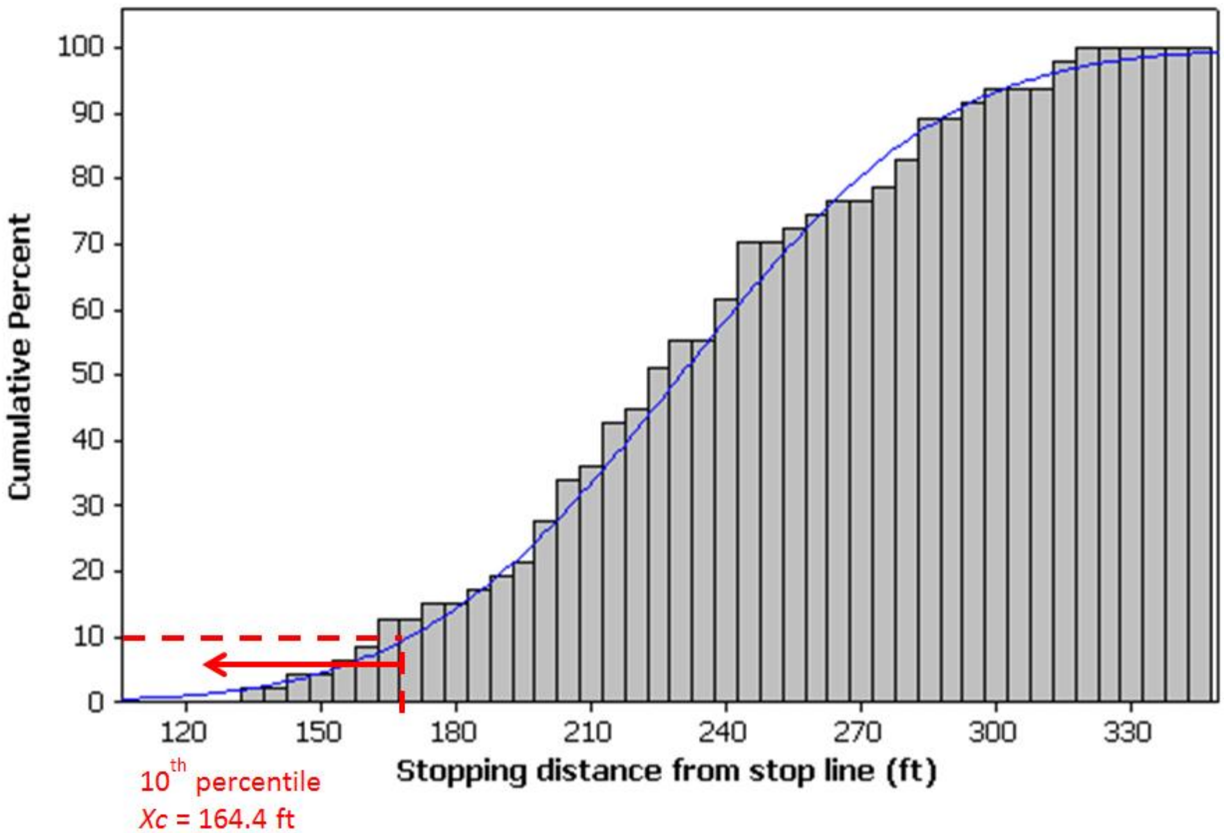

Figure 5-23: Determination of the 10th percentile X_c for the 30-35 mph speed group

With these two groups with the adjusted data plotted again in Figure 5-24, the points of minimum stopping distance and maximum passing distance from the stop line were determined. It should be noted that this chart presents the vehicle speed in ft/s on the horizontal axis and the distance data in feet on the vertical axis. The reason for representing the data in this manner is to compare the observed data with the available theoretical models proposed in the literature (Gazis et. al., 1960) and extract the data related to the traffic parameters. By comparing the parameters extracted from this data with the corresponding information from other studies the validity of the suggested approach will be corroborated. With these two sets of points, two mathematical equations were fitted correspondingly, one for passing vehicles (YLR) and one for stopping vehicles based on the equations proposed by Gazis et al. (1960). Figure 5-24 shows the data points and the two models obtained.

Excellent correlation for the observed data was obtained for the stopping vehicles with a second order polynomial (r^2 =0.978) and for passing vehicles with a linear fit (r^2=0.986). The second order and linear fits were chosen accordingly to comply with the theoretical equations proposed by the GHM model to directly extract parameters to characterize the driver behavior at the intersection and those that were the best fit for the observations. Table 5-8 and Table 5-9 show the results of the model calibration and the analysis of variance for $Y\ (X_c)$ and for $Y\ (X_0)$, respectively.

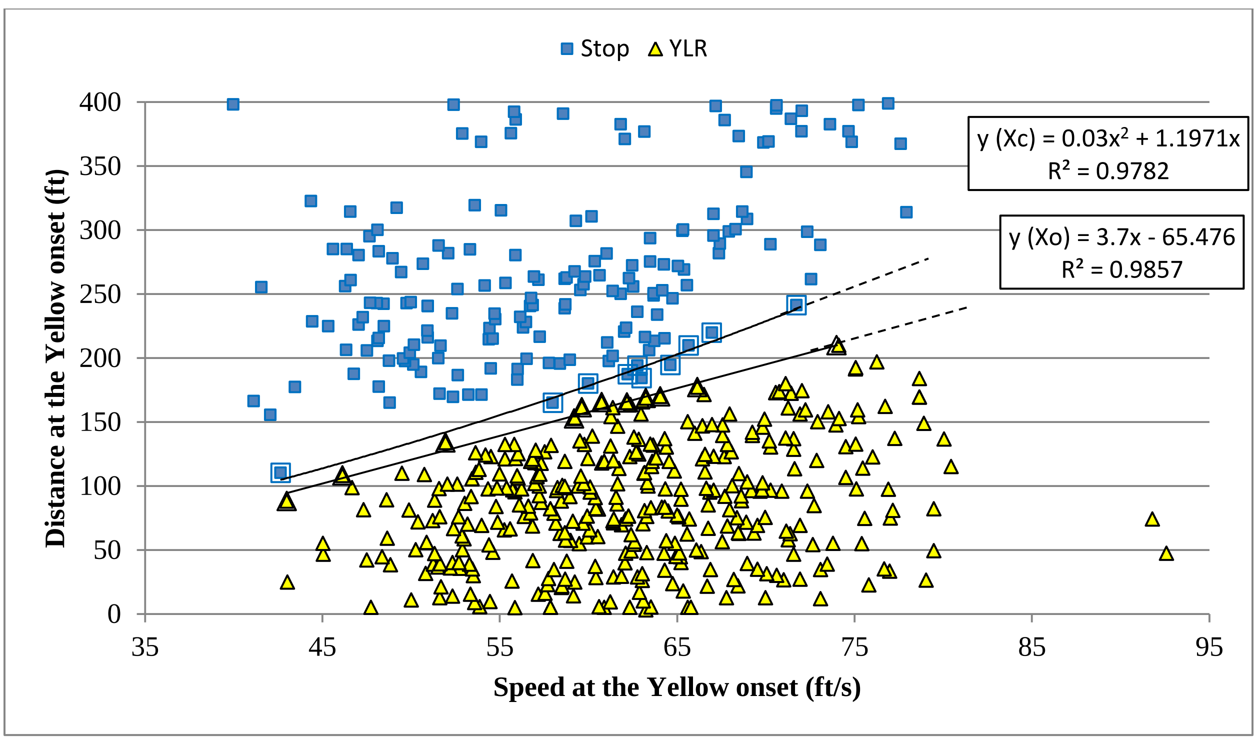

Figure 5-24: Distribution of vehicles at the yellow onset after considering the 10th and 90th percentiles of the data

Table 5-8: Regression summary and parameters estimates for X_c model

ANOVA[a]					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	366170.963	2	183085.481	6062.968	.000
Residual	241.579	8	30.197		
Total	366412.542	10			

Coefficients					
	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Speed	1.197	.298	.389	4.010	.004
Speed* 2	.030	.005	.612	6.311	.000
The independent variable is Speed					

Table 5-9: Analysis of variance for X_0 model

ANOVA[b]					
Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	11142.687	1	11142.687	619.805	.000[a]
Residual	161.800	9	17.978		
Total	11304.486	10			
a. Predictors: (Constant), Speed					
b. Dependent Variable: Distance					

Coefficients								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-65.470	8.931		-7.331	.000	-85.673	-45.268
	Speed	3.722	.150	.993	24.896	.000	3.384	4.060
a. Dependent Variable: Distance								

Figure 5-25 shows the dilemma zone formed by the lines drawn by the two mathematical fits representing X_c and X_o. Vehicles that passed the intersection in red are the only ones observed in this region because of the operation performed in removing the last 10[th] percentile of yellow light passing vehicles and the first 10[th] percentile of vehicles that stopped at the intersection.

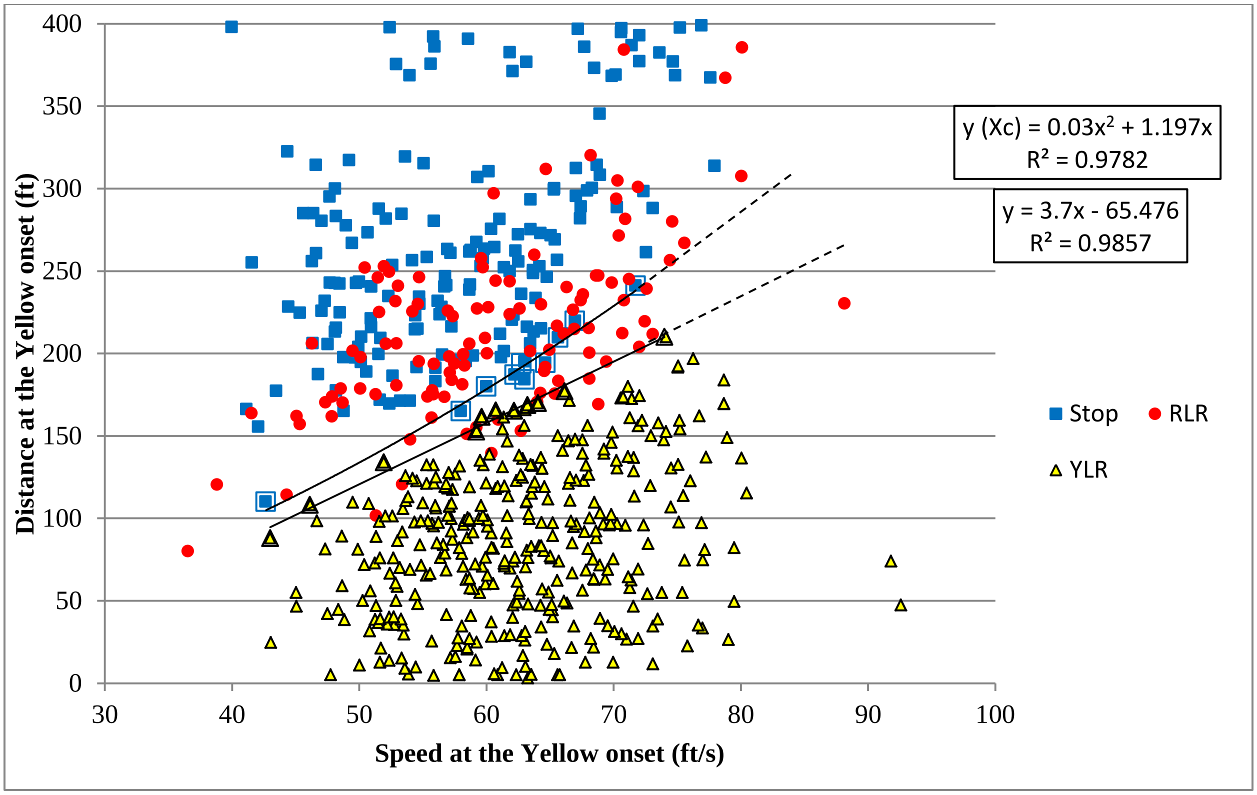

Figure 5-25: Determination of the dilemma zone using mathematical fits

With these two equations, a comparison of field observations for this particular intersection with the GHM theory was made and it was determined that the theoretical model fits the observed data fairly well based on the regression coefficients. The mathematical fit obtained from the field observations is as follows:

$$X_{cm} = 0.03V^2 + 1.197V \tag{5-7}$$

where:

X_{cm} = distance at the yellow onset from experimental data (ft), and

V = speed at the yellow onset (ft/s).

The theoretical model for X_c was shown in the equation 3-2. The two equations have the same form of a quadratic equation:

$$Y = \alpha X^2 + \beta X + C \tag{5-8}$$

In this manner, it becomes possible to compare the theoretical model with the empirical model, as follows:

$$(0.03)\ X^2 = (\frac{1}{2d_{max}})V^2$$

It can be then concluded that:

$$0.03 = \frac{1}{2d} \rightarrow \mathrm{d}_{max} = \frac{1}{2 \times 0.03} = 16.67\ \frac{ft}{s^2}$$

$$\beta\ X = \delta c \times V\ ,$$

$$\delta = 1.1971\ \approx 1.2\ s \text{ , and}$$

$$C = 0.$$

Similarly if we compare the models for maximum yellow passing distance:

$$X_{0m} = 3.7V - 65.476 \tag{5-9}$$

Where:

X_{0m} = Distance at the yellow onset from experimental data (ft), and

V = Speed at the yellow onset (ft/s).

The theoretical model for X_0 was shown in equation 3-3. From the theoretical model:

$$X_0 = V_0\tau - (W+L) + \frac{1}{2}a_{\max}(\tau-\delta) = V_0 \times (3) - (76+20) + \frac{1}{2}a_{\max}(3-\delta)^2$$

$$X_0 = 3 \times V - 96 + \frac{1}{2}a_{\max}(3-\delta)^2$$

From the observed data (equation 5-8):

$$X_{0m} = 3.7 \times V - 65.476$$

Comparing the two equations it can be concluded that:

$$-65.476 = -96 + \frac{1}{2}a_{\max}(3-\delta)^2.$$

Taking from the model of X_c, the value of perception and reaction time as:

$$\delta = 1.1971\ s$$

$$a_{\max} = \frac{(-65.476+96) \times 2}{(3-1.1971)^2} \to a_{\max} = 18.78\frac{ft}{s^2}$$

Table 5-10 presents the estimated parameters, comparing the GHM model with the empirical data.

Table 5-10: Calibrated parameters for X_c and X_0 models

Driver's perception-reaction time δ	Maximum deceleration rate d_{max}	Maximum acceleration rate a_{max}
1.2 s	16.67 (ft/s^2)	18.78 (ft/s^2)

The driver perception reaction time obtained from the experimentally observed data is 1.2 seconds and compares well with driver reaction time of 1.0 second from Gates (2007) and the 1.14 seconds from Chang et al. (2004).

The maximum deceleration rate of 16.67 ft/s^2 is lower than the maximum individual vehicle deceleration value of 24.81 ft/s^2 encountered in the field data which indicates that this field data is possibly an extreme value. The maximum acceleration rate of 18.78 ft/s^2, determined from the mathematical fit correlates well with the maximum vehicle acceleration rate (15.4 ft/s^2) found in the experimental observations. These estimates are also consistent with the value recommended for design of 16 ft/s^2 from Gazis (1960) and Chang et al. (2004). In the comparison of the theoretical model and the mathematical fit of X_0, there is a value of 3.7 which is the coefficient of the speed variable. This coefficient is expected to be 3.0 and the difference in the expected and estimated values is probably due to implicit human errors in the measurements of vehicle speeds and the distances from the digital video, which are generally expected in these manual data collection processes. Based on the literature review, it must be emphasized that the present study is the first to attempt to estimate the dilemma zone parameters based on field observations and extract acceptable values for reaction time, deceleration rate, and acceleration rate which affect the dilemma zone. Earlier attempts to estimate and characterize the DZ by Gates et al. (2004), Chang et al. (2004), and Wei (2008) can be found in literature. However, the method proposed in the present study and the good correlation obtained between the estimated data and the corresponding values for these parameters found in literature lend validity to the method. The proposed technique to determine the DZ at this intersection can be extended to other intersections with similar characteristics using the parameters suggested in this study to determine the dilemma zone. It is proposed that dilemma zones with similar features will be encountered at other intersections with the same characteristics as the one analyzed in this study. Wei et al. (2008) have highlighted the difficulty in observing the DZ in the field in their report.

The present study, on the other hand, clearly shows the presence of a dilemma zone and an effective manner to estimate it.

A practical manner to avoid involuntary RLR is to eliminate the DZ. This can be accomplished by marking the pavement with a line corresponding to the value of X_c for the vehicle speed limit for that segment as calculated from field observations. The drivers should be educated to stop at the intersection if they approach this line during yellow onset. This is suggested as a topic for further study.

One can also indirectly measure the aggressiveness of the drivers for the particular intersection under study based on field observations. Referring back to Figure 5-25, the number of RLR events for vehicles located behind X_c can be observed. These correspond to drivers who voluntarily violated the red signal and can be taken as an indication of the aggressiveness of these drivers. It is proposed that this aggressive behavior be quantified by means of the Driver Aggressiveness Index (DAI). For this purpose, the DAI is defined as the ratio of the number of drivers running the red signal and whose locations are behind X_c to the total number of drivers who are located behind X_c at the onset of yellow (RLR and the vehicles who decide to stop at the intersection).

$$DAI = \frac{RLR' + YLR'}{RLR' + YLR' + Stop\ veh'} \quad (5\text{-}10)$$

where:

RLR' = red light running for vehicles located behind X_c at the yellow onset, *YLR'* = yellow light running for vehicles located behind X_c at the yellow onset, and

Stop veh' = stopping vehicles for vehicles located behind X_c at the yellow onset.

For the approach at the intersection under study the DAI is calculated as 0.36. Driver aggressiveness at an intersection has never been quantified in literature. Considering that beyond the distance X_c all vehicles are expected to stop at the intersection and because there is no time to cross in a safe manner at a constant speed, this index should ideally be zero at an intersection. However, a DAI of 36% could be taken to reflect a higher degree of aggressiveness at this intersection. Therefore, we can deduce that the proposed index is a fairly good estimate which reflects the aggressive behavior of drivers. It is suggested that each intersection would have a specific value of DAI based on its characteristics and traffic operational parameters. The DAI of each intersection should be compared with the history of crash data to determine if a correlation exists between these two parameters as a future study. Based on the theoretical model proposed by Gazis et al. (1960), and utilizing the parameters estimated from the field data, X_c and X_o are plotted in Figure 5-26.

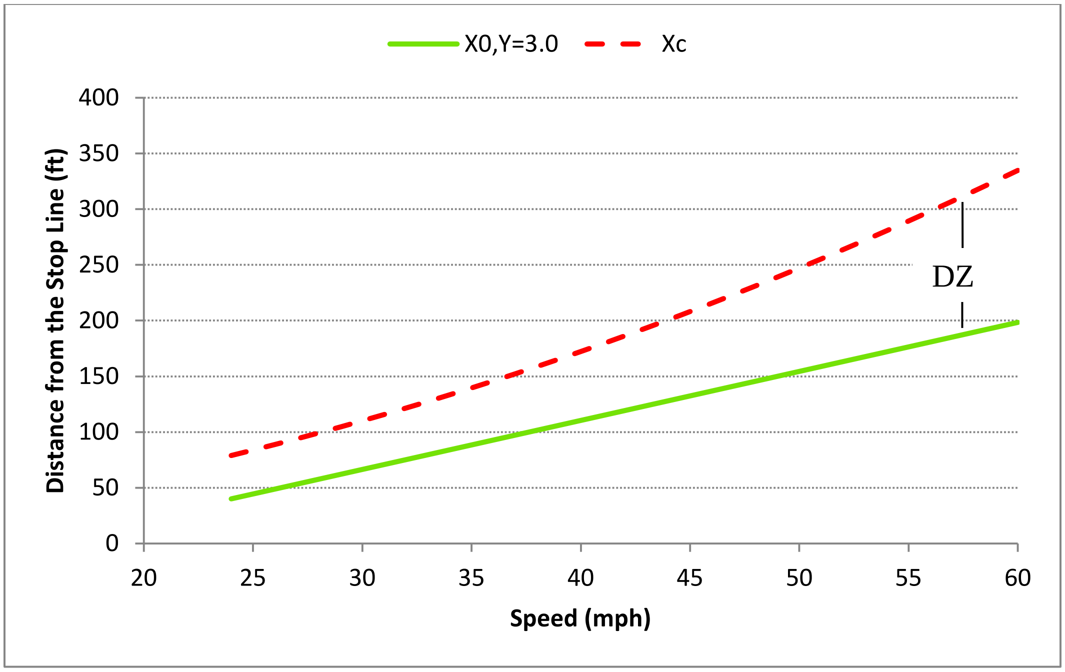

Figure 5-26: Dilemma zone for the present condition based on vehicles speed and location

It is observed that for all speeds X_c is always greater than X_0 which means that there is a dilemma zone at the intersection. The length of this zone ($X_c - X_0$) goes from 39 feet for lower speeds, up to a length of 136 feet at the highest speed (60 mph).

The value of X_0 varies with the speed and the length of the yellow period. Figure 5-27 shows the variation in the location and length of the dilemma zone for different speeds, as a function of the specific duration of the yellow period. To plot this figure the parameters of reaction time of drivers and deceleration and acceleration rates estimated earlier were used, for the same range of speeds (from 24 mph to 60 mph) and different periods of yellow (from 2.5 seconds to 5.0 seconds). Note that there is only one X_c profile, because the value of X_c does not change with the yellow duration.

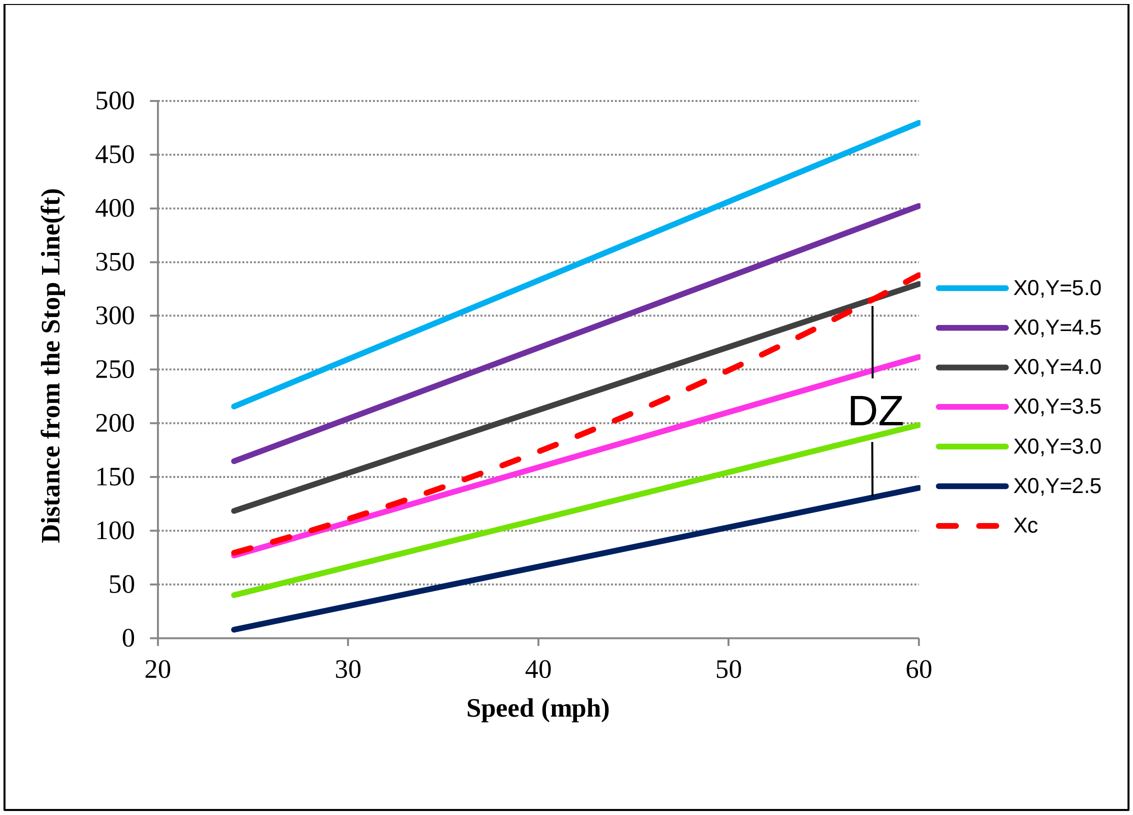

Figure 5-27: Variation of the dilemma zone with the yellow period

However, it can be seen that as the yellow period increases, the distance X_o on the graph is displaced vertically (X_c-X_o decreases), resulting in the formation of a dilemma zone with the lines X_0 corresponding to 2.5 and 3.5 seconds of yellow, and then forming an option zone, partially for a yellow period of 3.5 seconds and complete option zone for a yellow time of 4.0 seconds for all speed ranges. The duration of the yellow period should be recalculated based on the observed data at the intersection and increased to eliminate the dilemma zone.

In this chapter, different analyses were performed considering the arrival of vehicles at the intersection at the yellow onset by taking into account the trajectory of individual vehicles. Analyses of deceleration rates, the time of entry during the yellow period, the time of entry during the red period, or stopping of the vehicle before the stop bar were carried out. A prediction model for the stop and go decision was also determined along with a dilemma zone. From all these analyses some conclusions can be drawn indicating that the drivers at this intersection show a level of aggressiveness reflected in the red entry time. Red entry times were observed after the end of yellow for 2.46 seconds.

The significant variables for a binary logistic model of stop and go decision were the distance from the stop bar at the beginning of the yellow and speed. The greater the value of this distance, the higher the probability for a vehicle stop at the intersection, although the likelihood to stop decreases for faster vehicles. The dilemma zone for this intersection is clearly observed from plotting the actual data of speed and distance from the stop bar at the yellow onset collected in the field. The parameters of deceleration rate, acceleration rate, and reaction time to calculate the dilemma zone were determined based on the field observations. These parameters can be used at other intersections with similar characteristics. It was also concluded that while the intersection has a small yellow change period, the dilemma zone will be wider as the vehicle speed increases. With the technique proposed in this study, one can also determine the DAI (Driver Aggressiveness Index), which gives an idea of the level of aggressiveness of drivers at this particular intersection.

The following chapter presents the relevant conclusions as a result of the studies performed on the group of intersections and the approach at a single intersection. It also offers some recommendations for future work.

6 CONCLUSIONS AND RECOMMENDATIONS

The present study performed an analysis of RLR events and the driver reaction at the end of the green signal period in signalized intersections. To perform this extensive study, the work was divided into two parts. The first part took into account several intersections and traffic parameters associated, while for the second part of the study, a single intersection was considered with the purpose of performing an in-depth analysis from data of individual vehicles.

The local data demonstrates a much more aggressive RLR behavior with the potential for severe conflicts. In clear agreement with other studies, the RLR frequency increases with increasing traffic flow rate and increasing ratio of volume over cycle length. Nevertheless, the decreasing slope of RLR frequency as the mean vehicle speed increases gives an impression that as the flow rate increases, the RLR events may taper off to some specific value depending on the capacity of each particular approach of the intersection.

Although the results show some tendencies in the relations between RLR and the above factors, it is clear that there is a need to include other factors that better explain the variation in the models, such as those that take into account vehicle trajectory, changes in the vehicle speeds (accelerations and decelerations) and the reactions of individual vehicles at the end of the green period.

The second part of the study focused on a specific intersection. Data from a total number of 750 vehicles was recorded at a signalized intersection approach. Of those vehicles, 113 were involved in RLR events and 437 were YLR events; 202 vehicles were platoon leaders and 548 were followers. In total there were only 28 heavy vehicles approaching the intersection at the yellow onset, representing just 4.02% of the total.

The results of this study provided good agreement with results found in previous studies. However, it clearly shows that drivers on the local intersections reflect a more aggressive behavior based on the long duration of entry into the intersection on red. The RLR events occurred in a range varying from 0.02 to 2.46 seconds after the start of the red signal indication which creates more conflicting movements and resulting in a greater likelihood of RLR crashes.

Generally, the vehicles with higher speeds correspond to those traveling in the through middle and right lanes, whereas the mean speed of the vehicles traveling in the through left lane is lower. These results are different from the typical highway operating speeds, since is normally expected that the fastest vehicles use the left lane. From field observations it was noted that some vehicles choose to change lanes to ensure that they cross the intersection, showing aggressive driving.

This study found the stop and go decision to be well correlated with the speed and the distance at the yellow onset. Drivers located farther away from the stop line are more likely to make a stop decision and drivers travelling at a higher speed are more likely to make a pass decision.

This study also found that, as expected, speed and deceleration have a strong relationship and indicates that the faster vehicles need to apply greater deceleration to stop at the intersection. The distance variable has the effect of reducing the deceleration. Drivers who are farthest from the intersection at yellow onset use a lower deceleration. From the data it was observed that the 53 percentile of the deceleration rate is in agreement with the value recommended by AASTHO (2004), although some deceleration rates are higher, varying from 5.07 ft/s^2 to the maximum value of 24.81 ft/s^2 for vehicles that travel at higher speeds.

Based on the time to stop line data at the yellow onset, it was observed that there are two groups of drivers. The first group consists of aggressive drivers (risk-prone drivers), who decided to accelerate even though the yellow phase had ended, and the second group is composed of conservative drivers (risk-averse drivers), who could have passed the intersection during the 3.0 seconds of the yellow period, but decided to stop. It is observed that most of the vehicles that stopped took 5.0 seconds or more to reach the intersection and most of the passing vehicles took 4.0 seconds or less to cross the intersection. These times are longer than the assigned period of yellow for this approach which is 3.0 seconds.

For the first time, a novel technique to determine the parameters related to the dilemma zone was developed in this study. The proposed technique identified the minimum stopping distance and maximum passing distance field observations that were used to perform a comparison of the theoretical model. The parameters estimates for the driver perception reaction time, the maximum deceleration rate, and the maximum acceleration rate are consistent with the values observed in literature and also with the values recommended for road design processes. The proposed technique can be extended to other intersections with similar characteristics using the parameters suggested in this study.

This study proposes a practical manner to avoid involuntary RLR through the elimination of the DZ by marking the pavement with a transverse line corresponding to the value of X_0 for the vehicle speed limit for that segment as calculated from field observations while educating drivers to stop at the intersection if they approach this line during yellow onset. This is suggested as a topic for further study. An alternate way to reduce involuntary RLR could be to establish an intelligent detection and vehicle communication infrastructure system using the parameters estimated in this study and performing real-time monitoring of each vehicle.

This work also proposes an indirect way to measure the aggressiveness of drivers. Driver Aggressiveness Index (DAI) was proposed for the particular intersection under study based on field observations by counting the drivers who voluntarily violated the red signal or passed the intersection during the yellow indication. The DAI for the intersection under study was calculated as 0.36, which is assumed to represent a high degree of aggressiveness. Therefore, it is suggested that the proposed index is a fairly good estimate of the aggressive behavior of drivers. It is theorized that each intersection has a specific value of DAI based on its characteristics and traffic operational parameters. The DAI of each intersection should be compared with the history of crash data to determine if a correlation exists between these two parameters as a future study.

Driver behavior and attitude is related to RLR events, whether it is an intentional act or not. It is understood that intentional behavior can be modified through conventional police enforcement or automated enforcement systems with sensors and video cameras at the intersections. The use of educational campaigns that provide safety information for all age levels will further contribute to the reduction of RLR behavior. Unintentional RLR behavior can be reduced through engineering strategies such as determining the DZ from traffic data and marking the corresponding minimum stopping distance (X_c) on the pavement. An educative campaign can be further adopted to reinforce this important parameter to decrease RLR events and hence enhance the safety at each intersection.

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APPENDICES

APPENDIX A: DATA COLLECTED

Table 1A: Data collected for intersection PR2 and PR417

Variable	Observed Approaches			
	Southbound	Northbound	Westbound	Eastbound
Flow rate (veh/h)	956	924	388	634
Heavy vehicles (%)	10.77	8.7	5.26	9.82
RLR (veh/h)	16	11	3	4
Speed limit (mph)	50	50	25	25
Yellow period duration (s)	3	3	3	3
Green period average (s)	75	73	22	30
Cycle length (s)	150			

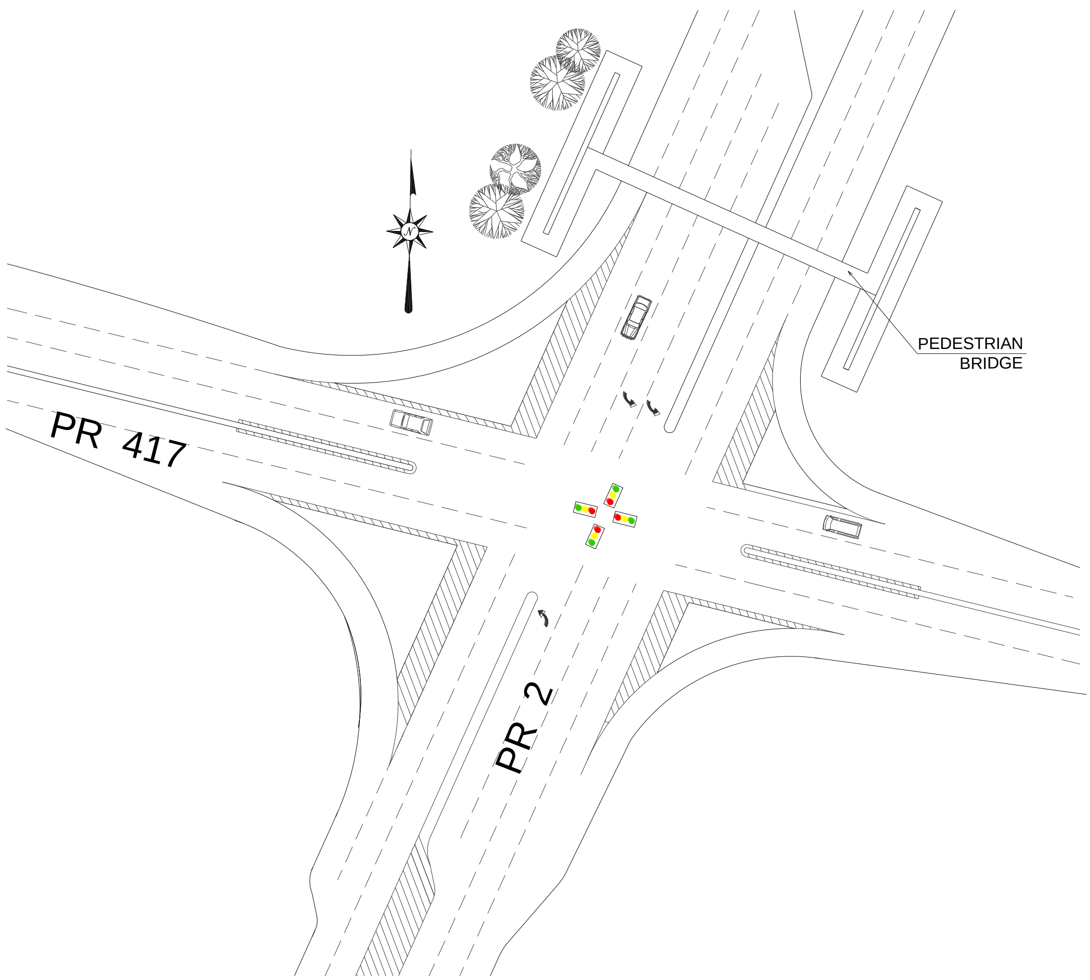

Figure 1A: Plan view of the intersection PR2 and PR417

Table 2A: Data collected for intersection PR2 and PR107

Variable	Observed Approaches		
	Southbound	Westbound	Eastbound
Flow rate (veh/h)	580	1239	1069
Heavy vehicles (%)	6.2	5.5	9.25
RLR (veh/h)	17	14	16
Speed limit (mph)	25	50	50
Yellow period duration (s)	3	4	4
Green period average (s)	25	55	84
Cycle length (s)	120		

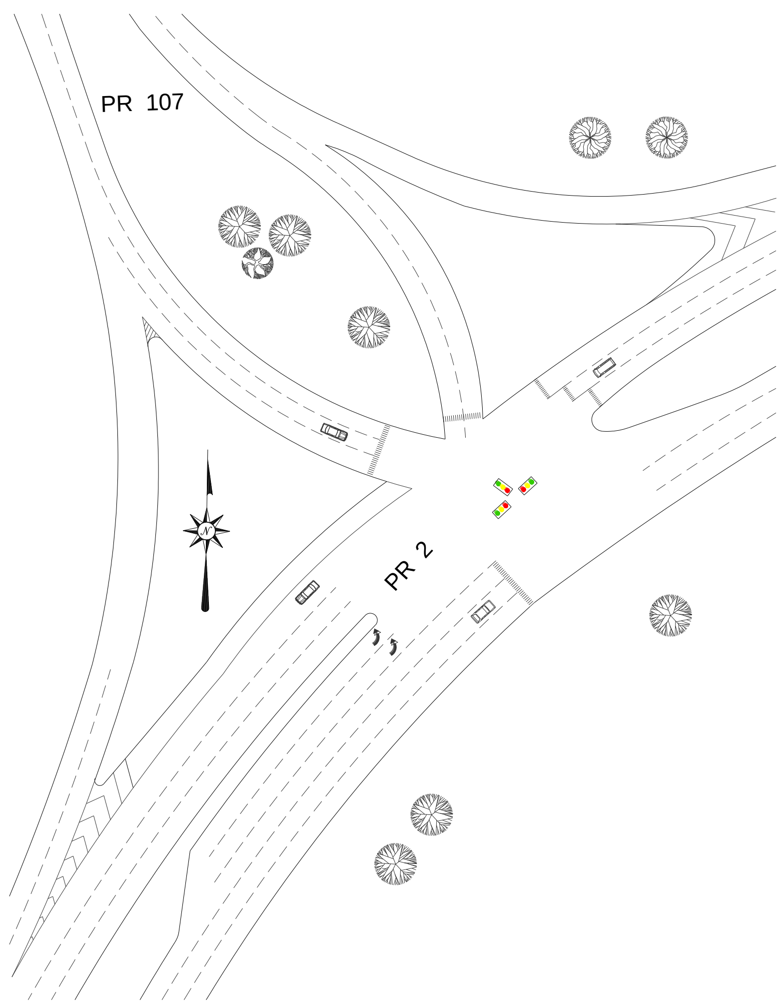

Figure 2A: Plan view of the intersection PR2 and PR107

Table 3A: Data collected for intersection PR2 and PR114

Variable	Observed Approaches	
	Southbound	Northbound
Flow rate (veh/h)	1512	573
Heavy vehicles (%)	7.21	2.67
RLR (veh/h)	24	17
Speed limit (mph)	45	45
Yellow period duration (s)	3	3
Green period average (s)	99	109
Cycle length (s)	180	

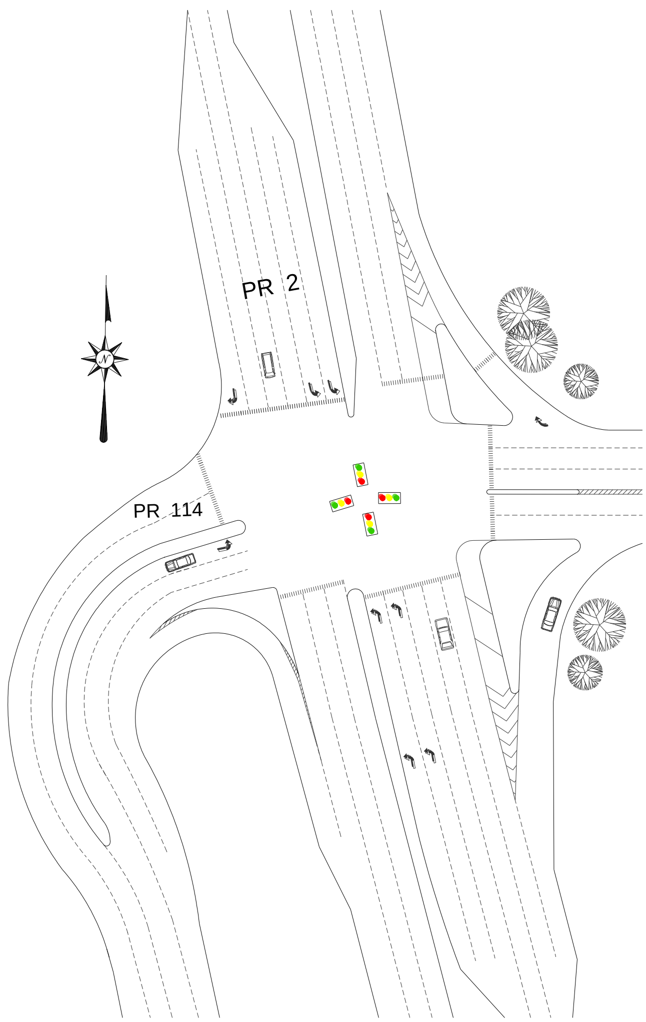

Figure 3A: Plan view of the intersection PR2 and PR114

Table 4A: Data collected for intersection PR2 and PR459

Variable	Observed Approaches			
	Southbound	Northbound	Westbound	Eastbound
Flow rate (veh/h)	826	239	1226	1177
Heavy vehicles (%)	5.69	0.84	10.44	5.44
RLR (veh/h)	25	13	37	13
Speed limit (mph)	25	25	50	50
Yellow period duration (s)	3	3	3	3
Green period average (s)	15	15	40	52
Cycle length (s)	106			

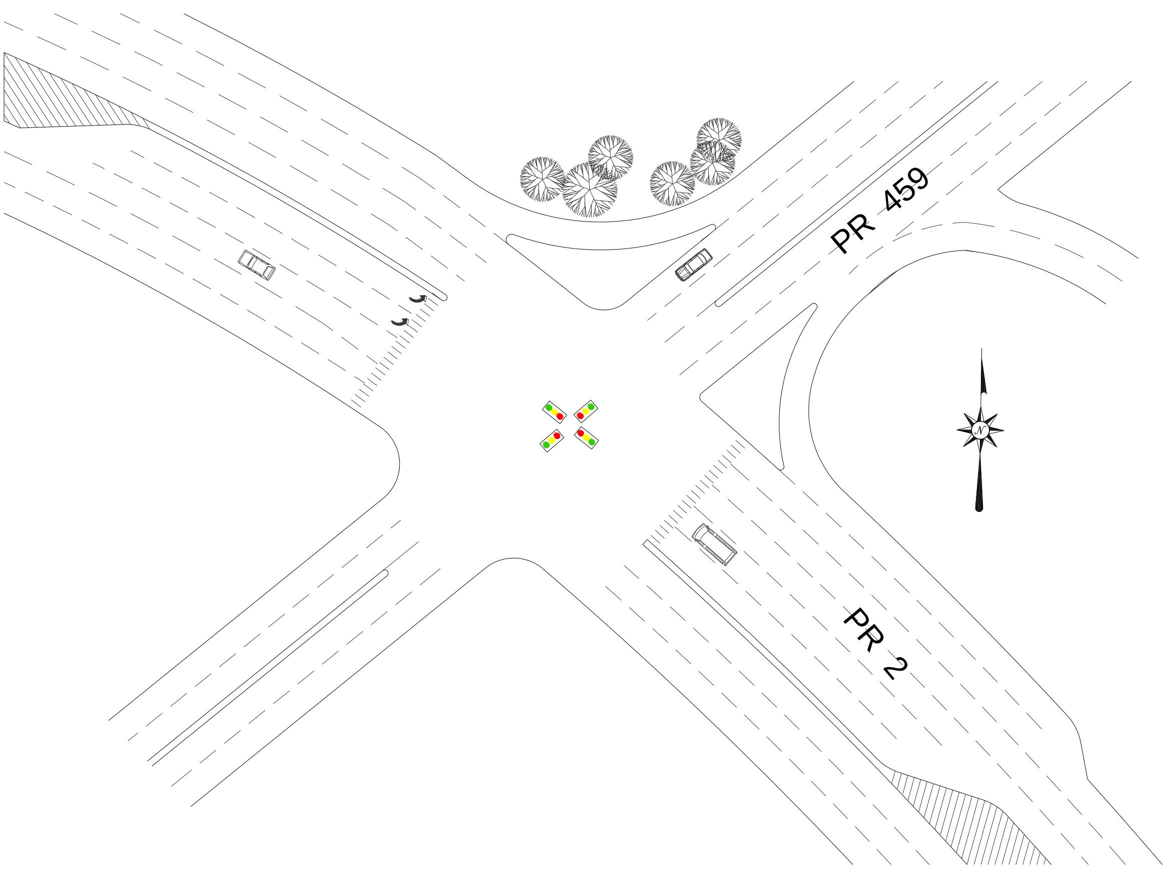

Figure 4A: Plan view of the intersection PR2 and PR459

Table 5A: Data collected for intersection PR2 and Nenadich street

Variable	Observed Approaches			
	Southbound	Northbound	Westbound	Eastbound
Flow rate (veh/h)	1616	1808	352	228
Heavy vehicles (%)	3.8	3.7	1.1	2.2
RLR (veh/h)	3	17	14	17
Speed limit (mph)	40	40	25	25
Yellow period duration (s)	3	3	3	3
Green period average (s)	115	104	24	16
Cycle length (s)	177			

Figure 5A: Plan view of the intersection PR2 and Nenadich Street

Table 6A: Data collected for intersection PR 65 and PR108

Variable	Observed Approaches			
	Southbound	Northbound	Westbound	Eastbound
Flow rate (veh/h)	490	419	513	767
Heavy vehicles (%)	0.6	0.2	1.8	1.4
RLR (veh/h)	3	2	3	5
Speed limit (mph)	25	25	40	40
Yellow period duration (s)	3	3	3	3
Green period average (s)	32	22	47	49
Cycle length (s)	132			

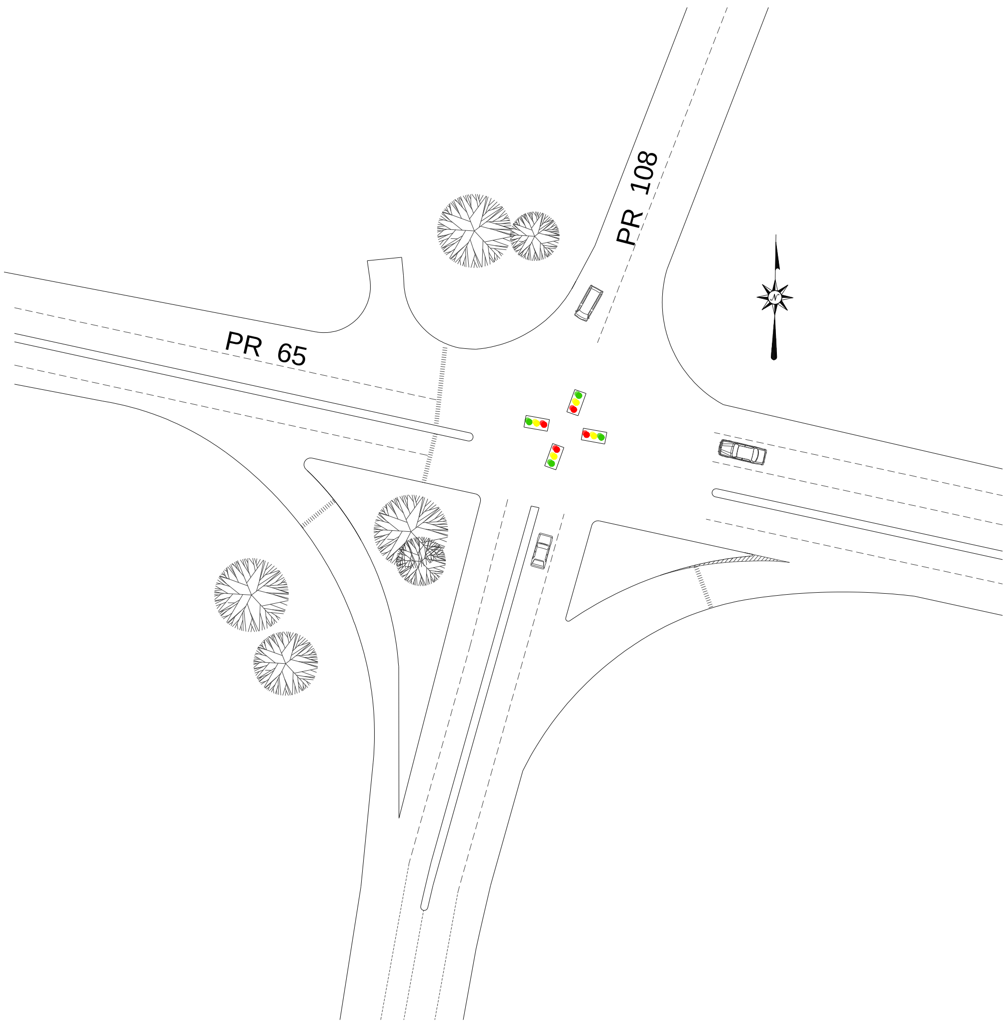

Figure 6A: Plan view of the intersection PR 65 and PR108

Table 7A: Data collected for intersection PR2 and Carolina Street

Variable	Observed Approaches		
	Southbound	Northbound	Eastbound
Flow rate (veh/h)	2442	2169	101
Heavy vehicles (%)	4.0	4.2	2.0
RLR (veh/h)	30	28	8
Speed limit (mph)	45	45	25
Yellow period duration (s)	3	3	3
Green period average (s)	91	107	25
Cycle length (s)	180		

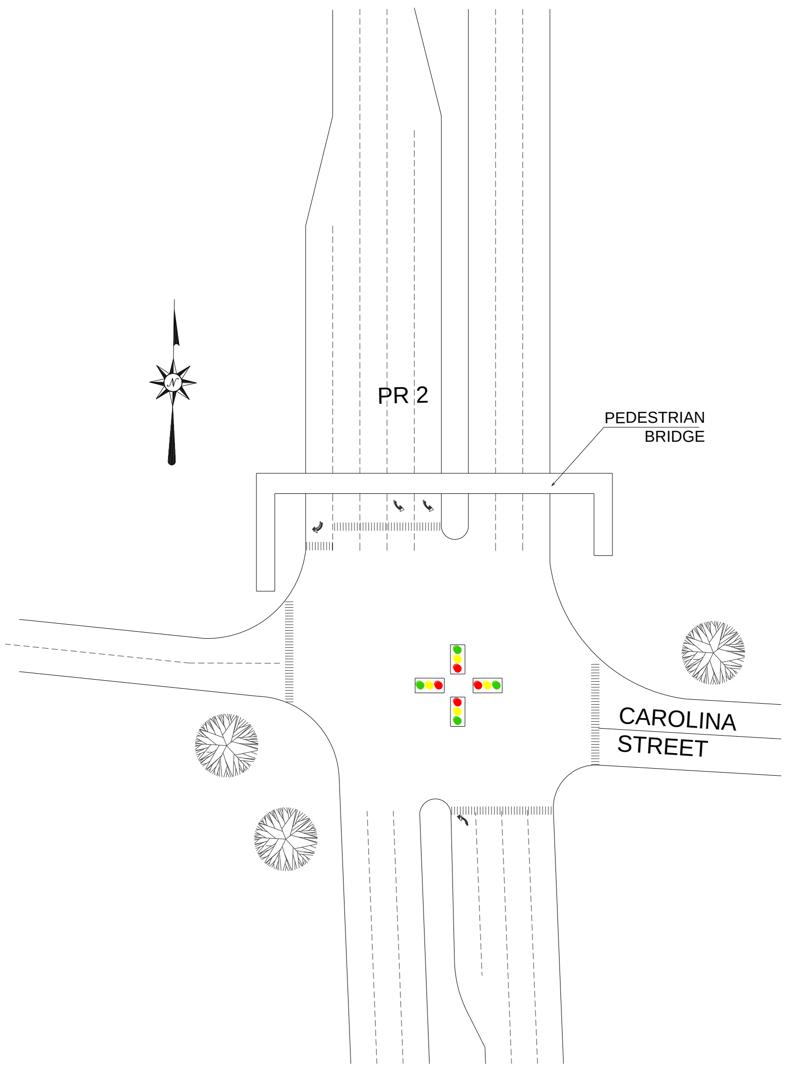

Figure 7A: Plan view of the intersection PR2 and Carolina Street

Table 8A: Data collected for intersection PR 110 and PR 111

Variable	Observed Approaches			
	Southbound	Northbound	Westbound	Eastbound
Flow rate (veh/h)	310	276	765	793
Heavy vehicles (%)	1.0	1.0	1.7	3.5
RLR (veh/h)	3	3	5	2
Speed limit (mph)	40	40	25	25
Yellow period duration (s)	3	3	3	3
Green period average (s)	30	30	69	71
Cycle length (s)	167			

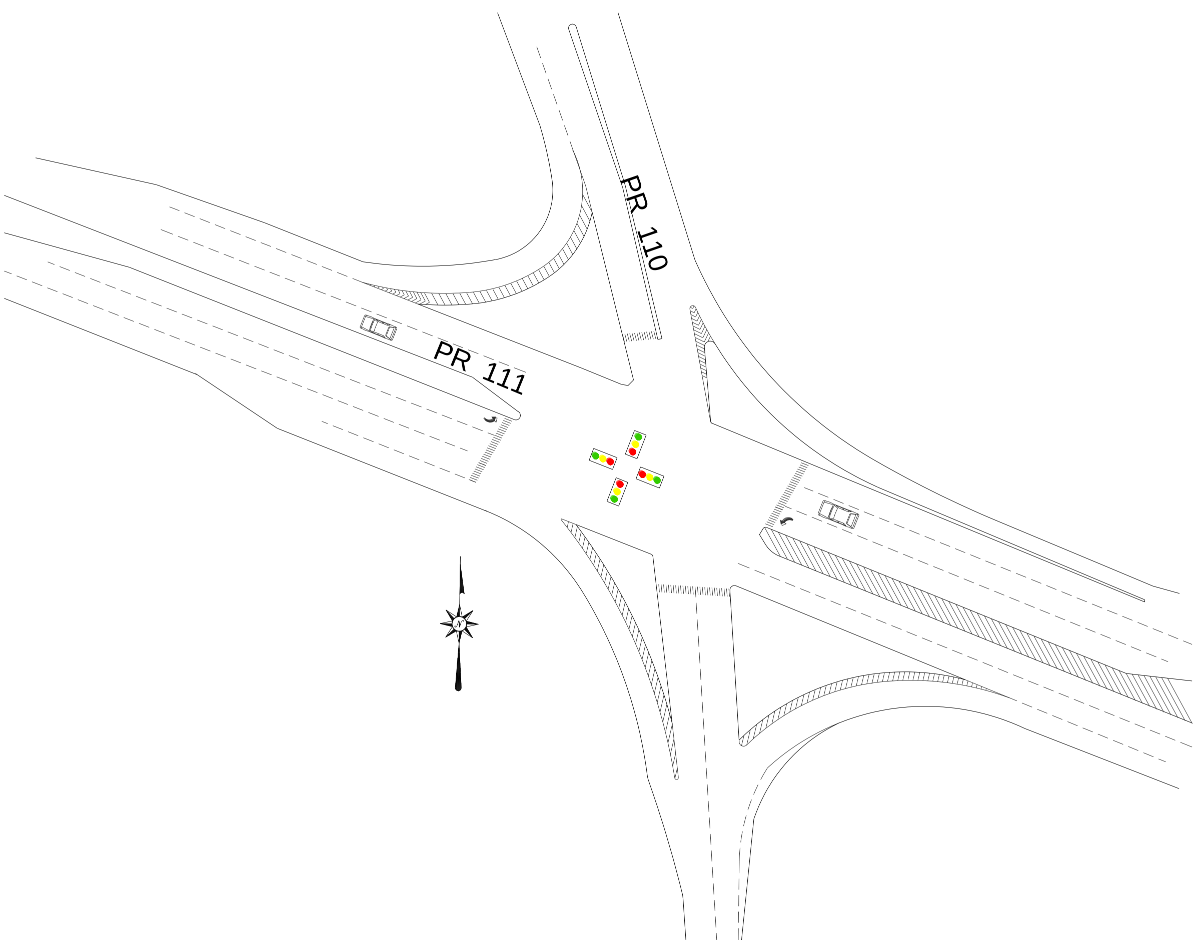

Figure 8A: Plan view of the intersection PR 110 and PR 111

APPENDIX B. CALIBRATION RESULTS FOR DEVELOPED MODELS

Appendix B1: Binary Logistic Model for Stop and Go Decision

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	750	100.0
	Missing Cases	0	.0
	Total	750	100.0
Unselected Cases		0	.0
Total		750	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
.00	0
1.00	1

Categorical Variables Coding

		Frequency	Parameter coding (1)
LD_FL	.00	548	1.000
	1.00	202	.000
Lane_1	.00	503	1.000
	1.00	247	.000
Lane_2	.00	448	1.000
	1.00	302	.000
Veh_Type	.00	28	1.000
	1.00	722	.000

Block 0: Beginning Block

Classification Table[a,b]

Observed			Predicted Stop_Go .00	Predicted Stop_Go 1.00	Predicted Percentage Correct
Step 0	Stop_Go	.00	550	0	100.0
		1.00	200	0	.0
	Overall Percentage				73.3

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-1.012	.083	150.089	1	.000	.364

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	Distance	292.177	1	.000
		Speed	45.829	1	.000
		Veh_Type(1)	2.280	1	.131
		Lane_1(1)	.040	1	.842
		Lane_2(1)	1.609	1	.205
		LD_FL(1)	.592	1	.442
	Overall Statistics		348.905	6	.000

Block 1: Method = Forward Stepwise (Wald)

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	340.808	1	.000
	Block	340.808	1	.000
	Model	340.808	1	.000
Step 2	Step	112.355	1	.000
	Block	453.163	2	.000
	Model	453.163	2	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	529.065[a]	.365	.532
2	416.710[b]	.453	.661

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

b. Estimation terminated at iteration number 7 because parameter estimates changed by less than .001.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Distance	.024	.002	160.792	1	.000	1.024	1.020	1.028
	Constant	-5.373	.387	192.597	1	.000	.005		
Step 2[b]	Distance	.030	.002	158.456	1	.000	1.030	1.026	1.035
	Speed	-.226	.025	79.793	1	.000	.798	.759	.838
	Constant	2.541	.856	8.817	1	.003	12.687		

a. Variable(s) entered on step 1: Distance.

b. Variable(s) entered on step 2: Speed.

Variables not in the Equation

			Score	df	Sig.
Step 1	Variables	Speed	96.692	1	.000
		Veh_Type(1)	.670	1	.413
		Lane_1(1)	1.310	1	.252
		Lane_2(1)	1.307	1	.253
		LD_FL(1)	1.345	1	.246
	Overall Statistics		100.731	5	.000
Step 2	Variables	Veh_Type(1)	2.954	1	.086
		Lane_1(1)	.236	1	.627
		Lane_2(1)	.418	1	.518
		LD_FL(1)	1.153	1	.283
	Overall Statistics		5.274	4	.260

Appendix B2. Linear Regression Model for Deceleration

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Distance	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	Speed	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
3	Lane_1	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
4	LD_FL	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).

a. Dependent Variable: Deceleration

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.372[a]	.138	.134	3.12473
2	.650[b]	.423	.417	2.56442
3	.666[c]	.444	.435	2.52337
4	.676[d]	.457	.446	2.49966

a. Predictors: (Constant), Distance

b. Predictors: (Constant), Distance, Speed

c. Predictors: (Constant), Distance, Speed, Lane_1

d. Predictors: (Constant), Distance, Speed, Lane_1, LD_FL

ANOVA[e]

Model		Sum of Squares	df	Mean Square	F	Sig.
4	Regression	1025.313	4	256.328	41.024	.000[d]
	Residual	1218.418	195	6.248		
	Total	2243.732	199			

d. Predictors: (Constant), Distance, Speed, Lane_1, LD_FL

e. Dependent Variable: Deceleration

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
4	(Constant)	5.798	1.235		4.695	.000	3.362	8.233
	Distance	-.030	.003	-.636	-10.791	.000	-.036	-.025
	Speed	.340	.034	.598	10.020	.000	.273	.407
	Lane_1	-.993	.378	-.140	-2.630	.009	-1.738	-.248
	LD_FL	-.861	.396	-.117	-2.176	.031	-1.641	-.081

a. Dependent Variable: Deceleration

Excluded Variables[e]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
4	Veh_Type	-.034[d]	-.635	.526	-.046	.962
	Lane_2	-.045[d]	-.703	.483	-.050	.685

a. Predictors in the Model: (Constant), Distance

b. Predictors in the Model: (Constant), Distance, Speed

c. Predictors in the Model: (Constant), Distance, Speed, Lane_1

d. Predictors in the Model: (Constant), Distance, Speed, Lane_1, LD_FL

e. Dependent Variable: Deceleration

Appendix B3. Linear Regression Model for the deceleration model Transformation

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Distance	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	Speed	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
3	Lane_1	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
4	LD_FL	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).

a. Dependent Variable: LN_Dece

Model Summary[e]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.357[a]	.127	.123	.11864
2	.678[b]	.459	.454	.09360
3	.691[c]	.478	.470	.09224
4	.700[d]	.489	.479	.09144

a. Predictors: (Constant), Distance

b. Predictors: (Constant), Distance, Speed

c. Predictors: (Constant), Distance, Speed, Lane_1

d. Predictors: (Constant), Distance, Speed, Lane_1, LD_FL

e. Dependent Variable: LN_Dece

ANOVA[e]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.404	1	.404	28.699	.000[a]
	Residual	2.773	197	.014		
	Total	3.177	198			
2	Regression	1.460	2	.730	83.301	.000[b]
	Residual	1.717	196	.009		
	Total	3.177	198			
3	Regression	1.518	3	.506	59.464	.000[c]
	Residual	1.659	195	.009		
	Total	3.177	198			
4	Regression	1.555	4	.389	46.496	.000[d]
	Residual	1.622	194	.008		
	Total	3.177	198			

a. Predictors: (Constant), Distance

b. Predictors: (Constant), Distance, Speed

c. Predictors: (Constant), Distance, Speed, Lane_1

d. Predictors: (Constant), Distance, Speed, Lane_1, LD_FL

e. Dependent Variable: LN_Dece

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
Model		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1	(Constant)	1.185	.032		37.442	.000	1.122	1.247
	Distance	.000	.000	-.357	-5.357	.000	.000	.000
2	(Constant)	.768	.045		16.896	.000	.678	.857
	Distance	-.001	.000	-.668	-11.190	.000	-.001	-.001
	Speed	.014	.001	.655	10.977	.000	.012	.017
3	(Constant)	.792	.046		17.321	.000	.702	.882
	Distance	-.001	.000	-.675	-11.463	.000	-.001	-.001
	Speed	.014	.001	.645	10.943	.000	.011	.016
	Lane_1	-.037	.014	-.136	-2.614	.010	-.064	-.009
4	(Constant)	.785	.045		17.265	.000	.695	.874
	Distance	-.001	.000	-.670	-11.479	.000	-.001	-.001
	Speed	.014	.001	.661	11.218	.000	.012	.017
	Lane_1	-.035	.014	-.130	-2.507	.013	-.062	-.007
	LD_FL	-.031	.014	-.110	-2.108	.036	-.059	-.002

a. Dependent Variable: LN_Dece

Excluded Variables[e]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Veh_Type	.026[a]	.383	.702	.027	.979
	Lane_1	-.174[a]	-2.636	.009	-.185	.992
	Lane_2	.104[a]	1.568	.119	.111	1.000
	LD_FL	-.044[a]	-.663	.508	-.047	.989
	Speed	.655[a]	10.977	.000	.617	.774
2	Veh_Type	-.006[b]	-.105	.917	-.007	.976
	Lane_1	-.136[b]	-2.614	.010	-.184	.988
	Lane_2	.029[b]	.553	.581	.040	.983
	LD_FL	-.118[b]	-2.231	.027	-.158	.974
3	Veh_Type	.011[c]	.206	.837	.015	.963
	Lane_2	-.063[c]	-1.015	.311	-.073	.695
	LD_FL	-.110[c]	-2.108	.036	-.150	.971
4	Veh_Type	.009[d]	.174	.862	.013	.962
	Lane_2	-.078[d]	-1.261	.209	-.090	.687

a. Predictors in the Model: (Constant), Distance

b. Predictors in the Model: (Constant), Distance, Speed

c. Predictors in the Model: (Constant), Distance, Speed, Lane_1

d. Predictors in the Model: (Constant), Distance, Speed, Lane_1, LD_FL

e. Dependent Variable: LN_Dece

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.7878	1.2509	1.0213	.08862	199
Residual	-.21033	.22499	.00000	.09051	199
Std. Predicted Value	-2.635	2.591	.000	1.000	199
Std. Residual	-2.300	2.461	.000	.990	199

a. Dependent Variable: LN_Dece