Title
Red-Light-Running Collision Avoidance

Authors
Grembek, Offer
Zhou, Kun
Zhang, Wei-Bin

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Offer Grembek, Kun Zhou, Wei-Bin Zhang

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Red-Light-Running Collision Avoidance

Task Order: 5210

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Final Report

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Abstract

Red light running (RLR) problem has been recognized as a significant safety problem in California as well as throughout the United States. This paper follows a two step process to develop enhanced signal timing models for possible reduction of RLR. In the first step, field data are collected with one-second resolution and discrete choice models are estimated to determine the significant influencing factors of RLR; in the second step, based on the findings from the first step, T7F software package as well as custom designed programs is used to find the enhanced signal timing plans that can potentially reduce RLR, while at the same time maintain the commonly used signal control objectives, such as intersection delay. Future research direction is also discussed.

Key words,

Red light running; Regression analysis; Traffic safety; Traffic signal intervals; Traffic signal timing; Yellow interval (Traffic signal cycle); Optimization;

Executive Summary

Red-light running (RLR) is defined as entering and proceeding through a signalized intersection after the signal has turned red. Over the years RLR has become a national safety problem. Based on data provided by the Federal Highway Administration (FHWA), in Year 2001, there were almost 218,000 RLR crashes, which result in as many as 181,000 injuries and 880 fatalities. The annual economic loss is estimated to be $14 billion.

The objectives of this study are two-fold: first to identify and evaluate potential modifications to the signal timing schemes so that they will provide more safety. The second objective is to develop "adaptive" red-light running collision avoidance algorithm which is able to react to the predicted RLR collision in real-time.

RLR is influenced by a variety of factors, including driver behavioral factors (human factors), intersection characteristics, policy and regulatory factors. This report focuses on the operational factors, partly because of scarce data and information regarding behavioral factors, but primarily because it holds the most convenient set of countermeasures.

The research team used detailed traffic and signal timing data to isolate significant and substantial traffic operations factors and to study the impact of a platoon arriving to an intersection within different phases of the traffic cycle. A discrete choice model was developed from loop detector and signal timing data collected from the intersection of El Camino Real and 28t h Avenue in San Mateo, CA.

The dependent variable used is an indicator variable. When the cycle has at least one RLR, the dependent variable takes the value of "1", otherwise, the variable equals to "0". The independent variables were selected based on the assumptions of this study and findings of previous studies.

Several variables were shown to be significant. Progression ratio was found to reduce the RLR probability by 9.3% for phase two (northbound direction) and by 8.1% reduction for phase six (southbound direction). The green arrival flow increases the RLR probability by 12% for phase two and by 9.3% for phase six. The arrival flow during yellow is found to be the most substantial variable and increases RLR probability by 32.7% for phase two and by 11.7% for phase six. The number of vehicles in a cluster before the onset of yellow has the least impact on RLR probability, which increases by less than 0.5% for both phases.

The cycle based data analysis suggests that the arrival flow during the yellow phase is a significant influencing factor of RLR. This finding motivated the next step of this study that aims at determining if shifting the signal offsets can produce reduced yellow flow without sacrificing significantly the intersection delay or efficiency.

To study the dynamics between signal timing offsets, intersection delay, and yellow arrival flow and platoons, we developed a TRANSYT-7F model. The TRANSYT-7F traffic network study software is chosen for this analysis, mostly for its ability to model platoon dispersion and to simulate traffic flow under predetermined signal timing plans

The main insight obtained from this analysis is that there are situations when shifting t he offsets can reduce yellow arrival with little change in intersection delay. Based on this insight a simple optimization algorithm to find the offset for an intersection that optimizes the whole route was developed. The algorithm is iterative and it finds the optimal offset for the first intersection while keeping all other offsets constant, and then performs the same at all other intersections iteratively.

A case study of a five intersection corridor was used to evaluate the performance of the proposed algorithm. The result shows that yellow arrival in the section decreased by 37.5%, delay increased by 1.8%, and the total cost (which is a weighted sum of yellow arrival and delay) for this section decreased by 21%.

To further validate the optimization model, we also evaluated its performance on an extended section along the same corridor that includes 10 intersections. The result for this extended corridor shows a 17.9% decrease in yellow arrival, a 1.2% increase in delay, and a 7.9% decrease in total cost.

Under this project, a signal-cycle-based data analysis was performed to study the contribution factors of red-light -running occurrences. This analysis used second-by-second signal phasing and timing data together with loop data. It identifies the yellow arrival flow, i.e., number of vehicles arrived at intersection during the yellow phase, as the most significant factor on RLR occurrences. The importance of this finding is that the yellow arrival is a controllable parameter of traffic operation and therefore it can be used as a safety measure in the design of signal timing. Inspired by this finding the research team has proposed a proactive signal timing optimization concept. The preliminary study demonstrated the potential of this timing optimization concept in significant reducing RLR occurrences without compromising intersection efficiency.

As a continuation of this project (TO5210), the research team is performing more detailed study, under Task Order 6210. The objectives are

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1 INTRODUCTION

Red-light running (RLR) is defined as entering and proceeding through a signalized intersection after the signal has turned red. Over the years RLR has become a national safety problem. Based on data provided by the Federal Highway Administration (FHWA), in Year 2001, there were almost 218,000 RLR crashes, which result in as many as 181,000 injuries and 880 fatalities. The annual economic loss is estimated to be $14 billion [1].

Intersections, which provide the environment where these incidents take place, are controlled by traffic signals, which are managed by signal timing schemes. Signal timing schemes are usually optimized to minimize traffic delay and the number of stops per vehicle, within a corridor. However, they don't always consider the safety aspect of traffic, such as cutting off a platoon with the onset of red.

The objectives of this study are two-fold: first to identify and evaluate potential modifications to the signal timing schemes so that they will provide more safety. The second objective is to develop "adaptive" red-light running collision avoidance algorithm which is able to react to the predicted RLR collision in real-time. Both objectives require significant data collections and analysis along with identifying surveillance, hardware/software, and communication requirements that will lead to develop and implement a field testing system.

This report serves as the final report for PATH Task Order 5210. This research project is continued under PATH Task Oder 6210, and the findings beyond TO5210 will be documented in the final report for TO6210.

2 RED LIGHT RUNNING FACTORS

RLR is influenced by a variety of factors, including driver behavioral factors (human factors), intersection characteristics, policy and regulatory factors.

2.1 Human Factors

No specific category of red-light runners has been identified. However, the most frequent violators are likely to be young, and have previous traffic convictions and are usually alone in the car [2]. Studies have also shown that being in a rush typically results in drivers taking higher risks. According to a FWHA survey [3], 48% of red light runners said they ran lights because they were in a hurry.

Many researchers have investigated drivers' decision-making processes at signalized intersections. The probability of a driver stopping in response to the onset of a yellow indication was discussed in a variety of literature. For instance, a study by Olson and Rothery [4] indicates that a driver's probability of stopping is based on the speed and distance to the stop line, the driver's perception of his/her ability to stop and the degree of comfort associated with the stop.

2.2 Intersection Characteristics

Three major categories of environmental factors were studied in past studies: traffic flow, intersection geometry and signal visibility, and signal timing.

2.2.1 Traffic Flow

The most often studied parameter in the traffic flow category is average daily traffic (ADT). Several studies have shown that increased ADT on the through direction increases RLR and that increased ADT on the crossing approaches increases the probability for collision (e.g., [5], [6]). Kamyab *et al.* reported the relationship between the occurrence of RLR and traffic flow rates based on 1,242 hours of observation at 12 intersections in Iowa [7]. Their results indicate that RLR increases at a rate of about 3.0 violations per 1,000 vehicles per hour in urban areas.

2.2.2 Intersection Geometry and Signal Visibility

Studies have shown that every additional lane on the main approach to an intersection increases the probability of a vehicle running the red light on a minor street by 7% [5]. The grade of an intersection approach affects drivers' probability of stopping. Drivers on downgrades are less likely to stop than drivers on level or upgrade approaches (at a given travel time to the stopline) [8]. Poor signal visibility could also affect the RLR rate. According to a survey study [1], 40 percent of red-light violators claimed that they did not see the signal or its indication. Although it is not likely that all the claims are true, there probably are situations where a more visible signal would not have been violated.

2.2.3 Signal Timing

Signal timing is also a frequently studied factor in RLR research. Studies have shown that increased all-red intervals increase RLR while not necessarily increasing RLR collisions [9]. In addition, researchers have found that the violation frequency is positively correlated with the number of yellow signal presentations [10]. It has also been found that long cycle length reduces RLR [8]. Van der Horst and Wilmink [12] showed that yellow and all-red intervals have a direct effect on the frequency of RLR -- they suggest that setting the yellow interval longer than 3.5 seconds is of great significance in reducing RLR frequency and that setting all-red intervals close to values proposed by the Institute of Transportation Engineering (ITE) can reduce violation rates and potential right-angle conflicts.

Van der Horst and Wilmink [12] reported that drivers approaching an actuated intersection are less likely to stop than if they are approaching a fixed-timing intersection. This finding suggests that drivers learn which signals are actuated and then develop an expectation of service as they travel through the detection zone. The authors extrapolated this finding to drivers traveling within platoons through a series of coordinated signals. Drivers in a platoon seem to have an expectation that they can travel without interruption through successive signals. Their expectancy is that each signal they approach will remain green until after they pass through the intersection. Their desire to stay within the platoon makes them less willing to stop at the onset of the yellow indication.

2.3 Policy and Regulatory Factors

Policy and regulatory factors include legislation and education programs that aim to reduce RLR. Red-light photo enforcement has been shown to reduce RLR by 23 to 70 percent and RLR collisions by 22 to 40 percent [10]. Regarding legislation, it has been shown that compliance with the ITE formulation for calculating the yellow interval can reduce the RLR frequency [7].

3 STATISTICAL ANALYSIS OF RED-LIGHT RUNNING FACTORS

As described in the previous chapter the phenomenon of Red Light Running (RLR) is influenced by a variety of factors. This report focuses on the operational factors, partly because of scarce data and information regarding behavioral factors, but primarily because it holds the most convenient set of countermeasures. Therefore, the purpose of this task is to study what traffic related characteristics are significant to RLR and to estimate their impact.

Since RLR violations occur in a relatively small time-space region, a fruitful analysis of RLR would require detailed data of the relevant region. The data regularly collected by traffic agencies is at best aggregated over five-minute intervals and rarely possess the level of detail required. The aggregated information that is available can reveal important factors associated with RLR, such as average daily traffic (ADT) [5, 6]. However, it is often insufficient for in-depth analysis that leads to the development of advanced road safety measures.

The risk for RLR is not constant within a traffic signal cycle. Using detailed data we can break a traffic signal cycle up into three sections associated with different RLR probability. First is a section when there is no probability of RLR (most of the green phase), followed by a section with the highest probability of RLR (the yellow phase and a few seconds immediately before and after it), and finally is a section when the probability of RLR is relatively small (most of the red phase). Therefore, within every cycle there is only a short duration when risk for RLR is high. Since the risk of RLR is not constant within a traffic signal cycle, the time an approaching platoon is truncated can also influence RLR

The research team used detailed traffic and signal timing data to isolate significant and substantial traffic operations factors and to study the impact of a platoon arriving to an intersection within different sections of the traffic cycle. The benefits of understanding these relationships will be utilized to the development of appropriate RLR countermeasures.

Under this task, an in-depth analysis of contributing factors to RLR was performed. In the following of this Chapter, the field data collection effort is presented first, and then followed by a discrete choice model analysis of the data that results in the determination of the contributing factors to RLR as reflected in the collected data set.

3.1 Field Data Collection

The data for the analysis in this section is based on loop detector and signal timing data collected from the intersection of El Camino Real and 28t h Avenue in San Mateo, CA. This is a T-intersection, fitted with advance and departure loop detectors and a semi-actuated traffic signal controller and is shown in Figure 2-1 below. The data were collected between 7AM and 8PM over a period of one month in October, 2004, which consist of 7,357 signal cycles. The data are in one second increments, and include vehicle count and vehicle occupancy along with the corresponding signal phasing and timing data.

Figure 2-1 Ariel Photo of El Camino Real and 28th Avenue

3.2 Data Analysis

3.2.1 Definition of a Sample

RLR occurs under specific momentary circumstances. Therefore, to capture the relevant factors, we need to analyze the smallest relevant time frame. We define the time around the yellow signal phase as the section with the highest probability for RLR. Cycle based analysis is appropriate since each cycle includes one high risk section. Furthermore we assume that characteristics within the phases prior to the onset of the red signal influence RLR more than those within cycles. Consequently, in this study every cycle represents a sample, and all variables are collected or averaged over a cycle. To evaluate the impact of the different phases of the traffic signal, each sample has data for the green, yellow and red signal phases. The analysis is performed separately for each of the main traffic directions along the corridor.

3.2.2 Dependent Variable

The dependent variable used is an indicator variable. When the cycle has at least one RLR, the dependent variable takes the value of "1", otherwise, the variable equals to "0". The data for the dependent variable is collected from departure loops which are located at the stop bar. The departure loops reflect the outcome of the cycle in terms of RLR and correspond to the legal definition of RLR.

3.2.3 Independent Variables

The independent variables were selected based on the assumptions of this study and findings of previous studies described before. The data for the independent variables is collected from the advance loops of the two center lanes which are located 60 meters upstream of the stop bar and reflect causal factors for the dependent variable. The independent variables include the arrival flows during the different signal phases and other additional variables previously shown to impact RLR, such as progression ratio, cross-traffic and termination of the green signal phase. Since second-by-second data is used, estimations of occupancy from the loop detectors have significant estimation errors; as a result, reliable estimations for speed are not obtainable and are not included as part of the analysis.

We also compiled variables that represent the platoons in a traffic flow. Vehicles following with headways of two seconds or less are defined as a cluster, and the proportion of clustered vehicles within the different signal phases is calculated. The percentage of clustered vehicles within the flow that arrived during the yellow phase was excluded from the analysis, since it is conceptually correlated with the yellow signal phase arrival flow. Furthermore, we calculated the number of clustered vehicles behind and ahead of the advance loop at the onset of the yellow signal. The definitions of the included variables are listed in Table 2-1.

Table 2-1 Independent Variables Included in the Analysis

Variable name	Variable ID	Variable Description
Progression Ratio	G_COUNT_R	Total arrivals to the advance loop, during the green phase, divided by the total arrivals to the advance loop during cycle.
Green Flow	GRN_FLOW	The number of vehicles crossing the advance loops, during the green phase.
Yellow Flow	YLW_FLOW	The number of vehicles crossing the advance loops, during the yellow phase.
Red Flow	RED_FLOW	The number of vehicles crossing the advance loops, during the red phase.
Termination of the Green	GRN_TER	Dummy variable indicating reason for termination of the green phase (gap-out, max-out, force-off).
Cross Traffic	CRS_EGRN	The proportion of green time provided to the cross traffic
Time of Day	TOD	Dummy variable indicating time of day, (AM, off peak, PM).
Green Clustering	GRN_CLUS	Percentage of clustered vehicles of the green flow
Red Clustering	RED_CLUS	Percentage of clustered vehicles of the red flow
Clustered Vehicles Before Yellow Onset	N_BF_O_Y	The number of clustered vehicles ahead of the advance loops when a cluster is present, at the onset of the yellow signal
Clustered Vehicles After Yellow Onset	N_AF_O_Y	The number of clustered vehicles behind the advance loops when a cluster is present, at the onset of the yellow signal

3.2.4 Statistical Analysis Method

Because of the binary nature of the dependent variable, a binary logistic regression model was used to estimate the parameters [13]. The probability for RLR (dependent variable) is given by:

$$\pi(x) = \frac{e^{g(x)}}{1 + e^{g(x)}} \qquad \text{2-1}$$

And the logit link function of the logistic regression which calculates the changes in the log-odds of the dependent variable is given by:

$$g(x) = \ln\left(\frac{\pi(x)}{1-\pi(x)}\right) = \beta_0 + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + \ldots + \beta_i \cdot X_i \qquad 2\text{-}2$$

where X_i are the independent variables and β_i are the estimated parameters, which are the logits of independent variables. A positive value of β_i means that higher values of the corresponding variable increases RLR, while a negative β_i means that higher values the variable decrease RLR.

To further interpret the logit of an independent variable we convert it to its odds-ratio using $\exp(\beta_i)$ which tells us what happens to the odds-ratio of the dependent variable when we increase X_i by one unit, keeping all other variables constant. Once we know how the odds-ratio for the dependent variable change, in response to one unit increase of an independent variable we define the changed odds-ratio as $Odds_{new}$. Now we can extract the new probability, $\pi_{new}(x)$, for the dependent variable in response to one unit increase of an independent variable by solving:

$$Odds_{new} = \frac{\pi_{new}(x)}{1-\pi_{new}(x)} \qquad 2\text{-}3$$

and obtain the change in probability as a result of one unit change in an independent variable. This way we can also estimate what impact the significant variables have on RLR and focus our study on the substantial ones.

3.3 Findings

3.3.1 Descriptive statistics

The analysis is performed separately for each of the main directions on the corridor, namely phase two (Northbound) and phase six (Southbound). Descriptive statistics for the data reveal the following characteristics about the studied intersection:

- RLR is observed in 12% of the signal cycles of phase two and in 5% of phase six;
- Both phases are characterized by relatively low traffic volume, average total flow is about 381 vph/lane for phase six and about 411 vph/lane for phase two;

- The maximum flow for phase six is about 1,800 vph/lane, while for phase two, it is only 1,044 vph/lane;
- The progression ratio for the synchronized phase two is 88% as opposed to a lower 75% for phase six;
- Both phases have about 69% of clustered vehicles during green;
- Regarding arrival flow during the yellow phase, some cycles are observed with as much as three vehicles per lane for four second of yellow on phase two and as much as four vehicles per lane on phase six.

3.3.2 Regression estimates for Phase two

The logistics regression analysis is preformed using the Statistical Package for the Social Sciences (SPSS) software [14]. The estimates obtained by the regression for phase two are shown in Table 2-2.

Table 2-2 Parameter Estimates for the Selected Model (Southbound)

Variable name	B	S.E.	Wald	df	Sig.	Exp(B)
Phase two						
GCOUNT_R	-1.596	.591	7.304	1	.007	.203
GRN_FLOW	1.676	.371	20.403	1	.000	5.342
YLW_FLOW	3.556	.202	309.734	1	.000	35.009
RED_FLOW	-1.623	.829	3.831	1	.050	.197
CRS_EGR	-1.180	.655	3.250	1	.071	.307
N_BF_O_Y	.024	.011	4.831	1	.028	1.024
Constant	-1.273	.556	5.233	1	.022	.280

For phase two the log likelihood (-2LL) of the chosen model is 4937.6 as opposed to the 5502.3 original log likelihood. Six variables are found to be significant and the following is observed:

- Higher progression ratios correspond to lower probability of RLR;
- Higher flows during the green interval increase the probability of RLR;
- Higher flows during the yellow interval increase the probability of RLR;
- Higher flows during the red interval decrease the probability of RLR (This result makes sense if we remember that the flows are calculated roughly four seconds away from the stop bar. Therefore the red flows include vehicles arriving four seconds or more after the red and therefore are unlikely to run the light);
- Higher cross traffic corresponds to lower probability of RLR;
- Higher numbers of clustered vehicles ahead of the arrival loop at onset of yellow increase the probability of RLR.

3.3.3 Regression estimates for Phase six

The estimates obtained by the regression for phase six are shown in Table 2-3.

Table 2-3 Parameter Estimates for the Selected Model (Northbound)

Variable name	B	S.E.	Wald	df	Sig.	Exp(B)
Phase six						
GCOUNT_R	-1.199	.406	8.708	1	.003	.301
GRN_FLOW	1.369	.348	15.487	1	.000	3.931
YLW_FLOW	1.642	.134	149.528	1	.000	5.167
RED_CLUS	.508	.209	5.898	1	.015	1.662
N_BF_O_Y	.028	.012	5.228	1	.022	1.028
Constant	-3.180	.318	99.751	1	.000	.042

For phase six the log likelihood (-2LL) of the chosen model is 2885.8 as opposed to the 3124.5 original log likelihood. Five variables are found to be significant and the following is observed:

- Higher progression ratios correspond to lower probability of RLR;
- Higher flows during the green interval increase the probability of RLR;
- Higher flows during the yellow interval increase the probability of RLR;
- Higher numbers of clustered vehicles ahead of the arrival loop at onset of yellow increase the probability of RLR;
- Higher numbers of clustered vehicles during the red interval increase the probability of RLR.

Comparing both phases we observe that four of the five variables were found to be significant for phase six are the same as the ones for phase two (progression ratio, yellow flow, green flow and clustered vehicles ahead). Red flow and cross traffic are not significant. However, red clustering is significant for phase six.

3.3.4 Impact of significant variables

We assumed the variables found to be significant on both directions (phase two and phase six) represent characteristics which are less sensitive to individual intersection design and evaluated their impact on RLR probability. The changes of probability for RLR under different values of the variables are estimated using the odds ratio. To compare the impact among the significant variables, we calculated how the RLR probability changes when we change the variables from their average observed value to their maximum observed value. The first benefit of this technique is that the result is unrelated to the units of each variable and RLR probability is evaluated based on a range that represents reasonable values to the extreme values of each variable. Furthermore, we are predicting a change in the probability within the observed range for each variable.

The change in probabilities for the progression ratio is a 9.3% reduction in RLR probability for phase two, and an 8.1% reduction for phase six. The green arrival flow increases the RLR probability by 12% for phase two and by 9.3% for phase six. The arrival flow during yellow is found to be the most substantial variable and increases RLR probability by 32.7% for phase two and by 11.7% for phase six. The number of vehicles in a cluster before the onset of yellow has the least impact on RLR probability, which increases by less than 0.5% for both phases. These findings support our assumption about the high risk section for RLR around the yellow signal and that increased flows during the yellow have a greater influence on RLR than the flows during the green.

3.3.5 Divide the high risk to two sections

To further look into the area around the yellow interval we divided the time around the yellow interval to four sub-sections and collected the arrival flows for each of these sub-sections. The definitions of the included variables are listed in Table 2-4.

Table 2-4 Additional Variables Included in the Sub-Section Analysis

Variable name	Variable ID	Variable Description
Last two seconds of green	G_FLW_2	The number of vehicles crossing the advance loops, during the last two seconds of the green phase.
First two seconds of yellow	Y_FLW_02	The number of vehicles crossing the advance loops, during the first two seconds of the yellow phase.
Last two seconds of yellow	Y_FLW_24	The number of vehicles crossing the advance loops, during the last two seconds of the yellow phase.
First two seconds of red	R_FLW_02	The number of vehicles crossing the advance loops, during the first two seconds of the red phase.

We have to keep in mind that the data for these variables originates from the advance loops which are about four seconds of travel time from the stop bar. Therefore, a vehicle crossing the advance loop during the first two seconds of red would arrive to the stop bar about six seconds into the red.

We used SPSS to perform another logistics regression analysis for each phase and t he estimates obtained by the regression for phases two and six are shown in Table 2-5.

Table 2-5 Parameter Estimates for the Sub-Section Analysis

Variable name	B	S.E.	Wald	df	Sig.	Exp(B)
Phase six						
G_FLW_2	0.315	0.061	26.320	1	.000	1.371
Y_FLW_02	0.538	0.053	102.995	1	.000	1.713
Y_FLW_24	0.222	0.058	14.586	1	.000	1.249
RED_CLUS	0.910	0.181	25.184	1	.000	2.485
Constant	-3.814	0.118	1048.470	1	.000	0.022
Phase two						
G_FLW_2	0.460	0.055	69.719	1	.000	1.584
Y_FLW_02	1.135	0.062	331.455	1	.000	3.112
Y_FLW_24	0.527	0.084	39.378	1	.000	1.694
Constant	-2.529	0.048	2768.370	1	.000	0.080

Looking at the regression results we can see that for both phases the coefficient estimated for Y_FLW_02 was higher than its adjacent sub-sections (phase two-3.112, phase six-1.713). Furthermore, the coefficients estimated for the G_FLW_2 and Y_FLW_24 for each phase have similar values (1.584 vs. 1.694 and 1.371 vs. 1.249). The findings reveal that within the eight seconds around the yellow signal, the arrival flow during the 2nd two seconds of the yellow has the most substantial impact on RLR probability, while the adjacent sub-secti ons are somewhat symmetric around it.

4 PROACTIVE SIGNAL TIMING

4.1 Background

The cycle based data analysis discussed in the previous Chapter suggests that the arrival flow during the yellow phase is a significant influencing factor of RLR. This finding prompts a study that aims at determining if shifting the signal offsets can produce reduced yellow flow without sacrificing significantly the intersection delay or efficiency.

Traffic signals are designed primarily to improve safety and efficiency of traffic. A study by Shinar et al. [12] shows that accommodating efficiency can many times also have safety benefits. The study showed that in synchronized corridors, the odds of running the red light are a 1/7 of the odds in non-synchronized corridors.

Advanced detection systems can also accommodate both safety and efficiency through the use of actuated signals [15]. However, during high volume conditions it is sometimes not possible to find large gaps so the green is extended until it is maxed out. The max-out termination compromises the safety benefits of the advanced detection system by ending the phase regardless of vehicles in the dilemma zone. Bonneson et al. [6] have studied this problem and have proposed and developed an alternative Detection Control System (D-CS) for providing dilemma zone protection. The system differs from the traditional advance detector system because it predicts the best time to end the major-road through phase using an external computer to process vehicle speed and length information.

In addition to providing drivers with additional dilemma zone protection, recent studies have developed algorithms to detect in real time a potential RLR related collisions. A study by White and Ferlis [14] has suggested an algorithm to identify inattentive violators. The model assumes that inattentive violators act identically to attentive drivers with a green signal. Therefore, the algorithm is based on comparing velocity and acceleration data of vehicles traveling at free-flow speeds through an intersection with data from alert motorists stopping for a red signal on the same approach.

4.2 An Enhanced Traffic Signal Optimization Model

4.2.1 The TRANSYT-7F Model

To study the dynamics between signal timing offsets, intersection delay, and yellow arrival flow and platoons, we developed a TRANSYT-7F model. The TRANSYT-7F traffic network study software is chosen for this analysis, mostly for its ability to model platoon dispersion and to simulate traffic flow under predetermined signal timing plans [17].

To construct the model, flows and intersection geometry from a five intersection section on El Camino Real in San Mateo, CA are collection. The section includes five intersections, Jordan (1), Showers (2), San Antonio (3), Del Medio (4) and Los Altos (5), as seen in Fi gure 3-1 below. The flows observed on the arterial range from 1,300vph to 1,800vph. San Antonio is a critical intersection for this section and demonstrates residual queues which enable us to study different traffic patterns.

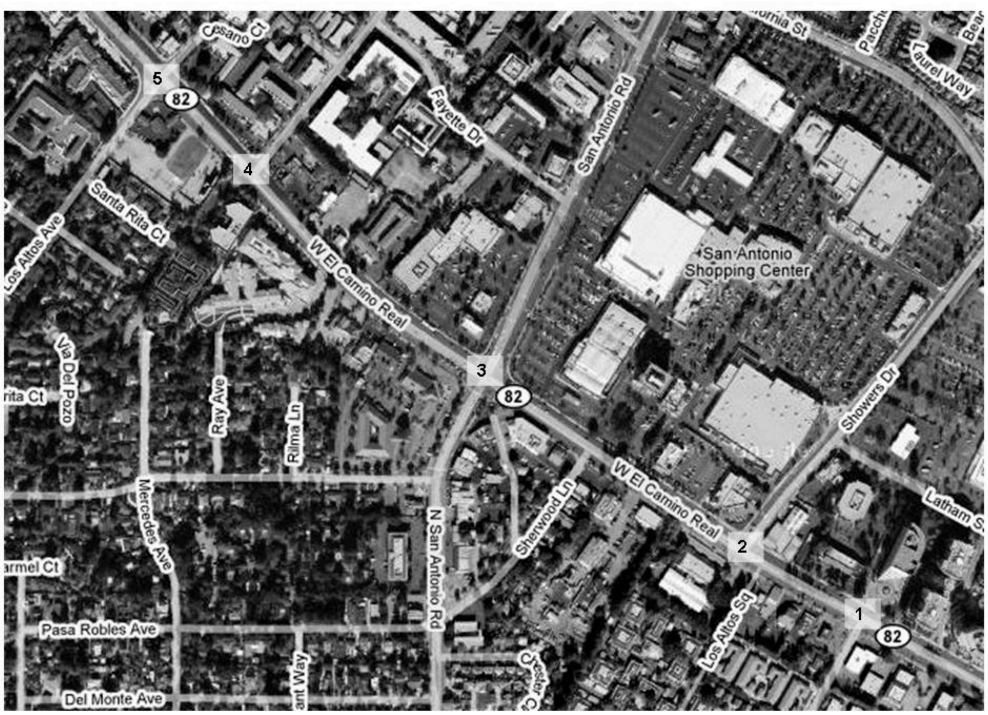


Figure 3-1 Ariel Photo of El Camino Real between del Medio and Jordan

Custom-designed software is also developed to evaluate the outcome of changing the offsets. The software modifies the offsets, generates batch runs of the TRANSYT-7F model, and calculates the delay and yellow arrival flow for individual intersections or for the whole section. The outputs and diagrams are generated as a spread sheet.

Each of the major directions of the corridor at each intersection is defined as a link and separate outputs were generated for each link. Figure 3-2 shows the delay and yellow arrival flow under different offsets for the northbound direction on node 4 (link 401).

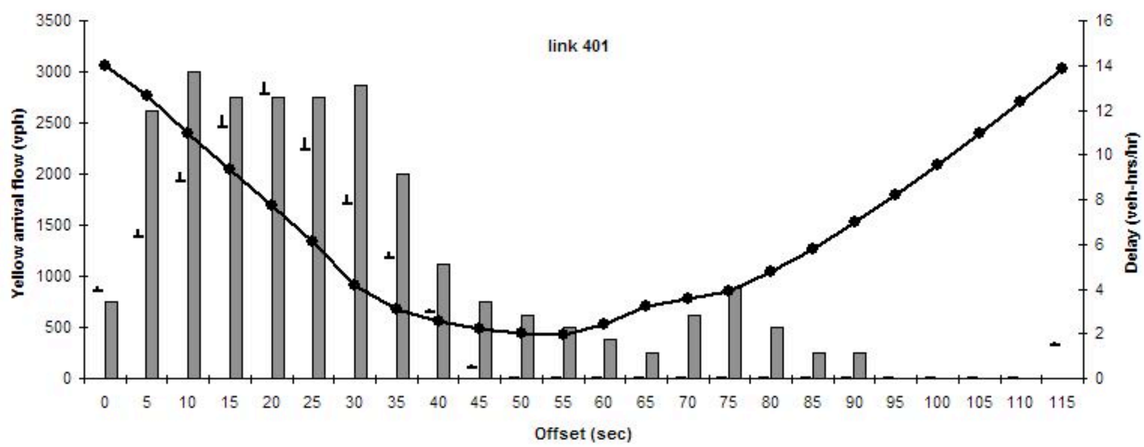


Figure 3-2 Delay and Yellow Arrival Flow as a Function of Offset

In Figure 3-2, the horizontal axis represents the offsets, in seconds, for the current link. Since the cycle length is 120 seconds, the offsets range between 0 and 115 in 5 second increments. Each offset represents the outcome of a separate TRANSYT-7F analysis and the values associated with it are on the vertical axis.

The bars that correspond to the left-hand-side vertical axis represent the flow during the yellow phase. The units for this axis are vehicles per hour over all lanes. We can observe that different yellow flows are obtained for different offsets. The line corresponds to the right-hand- side vertical axis and represents the link delay. The units for the delay are vehicle-hours per hour. "⊥" signs in the figure are a coarse outline representing when the through-flow platoon is truncated by the yellow signal. The "⊥" sign to the right of each offset represent s the through-flow vehicles that are truncated and t he "⊥" sign to the left represents the through flow vehicles that are let through by the signal. For link 401 about half of the platoon is truncated wit h an offset of 20 seconds, while only about 20% is cut off with an offset of 40 seconds.

Figure 3-3 provides an intuitive explanation of the changes shown in Figure 3-2 and a demonstration of the potential benefits of shifting offsets. Each of the diagrams in Figure 3-3 (a-d) has below it a time-space diagram corresponding to the offset marked by the vertical gray band. The time-space diagram shows on the time axis the red signal (black stripe) and the green signal (empty spaces between black stripes) for all nodes marked 1 to 5 on the vertical axis. This example is again for link 401. Two thin lines on each time-space diagram roughly represent the through-flow platoon traveling from node 3 to node 4. The line on the left represents the first vehicles in the platoon while the line on the right represents the last vehicles of the platoon. In each of the figures, we increase offset of node 4 and observe how it affects the platoon coming from node 3.

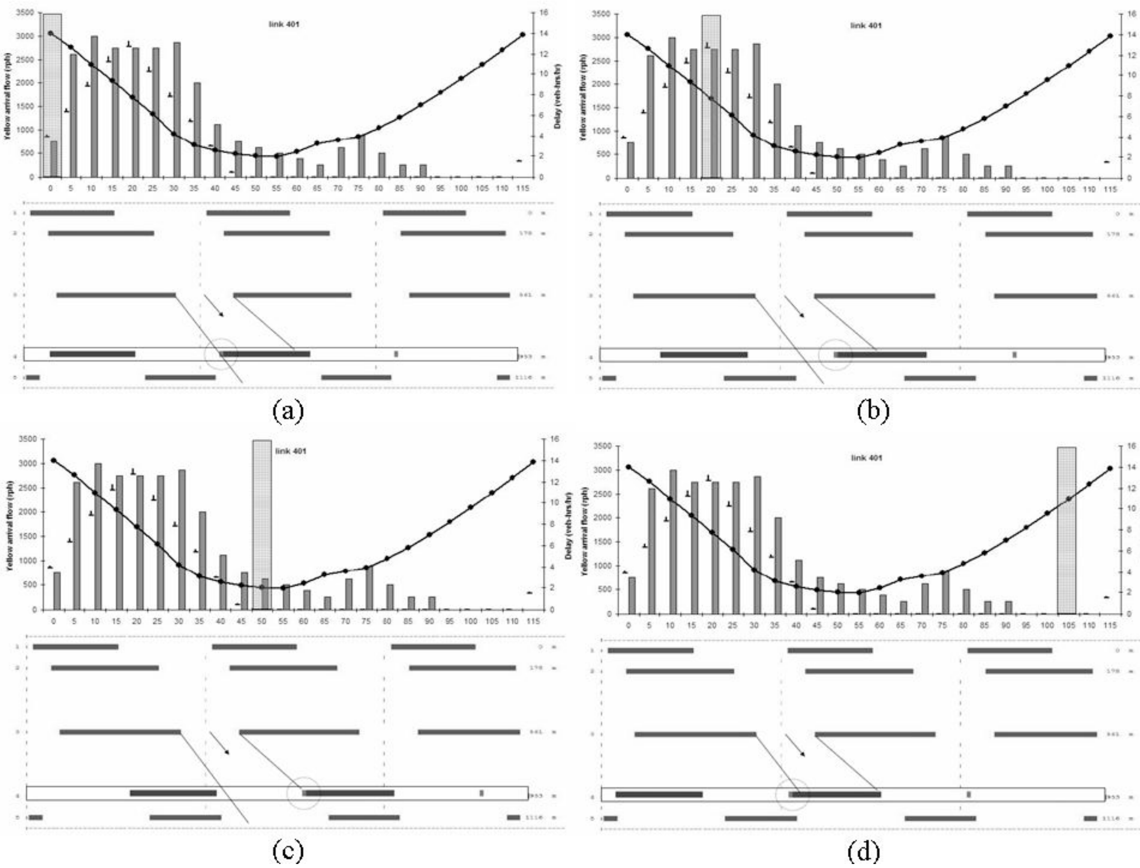


Figure 3-3 Delay and Yellow Arrival Flow along with Time-Space Diagrams

In Figure 3-3(a) with an offset of zero, we can see that only the very first vehicles in the platoon pass through the intersection, thus relatively low yellow flow is observed. Furthermore, since most of the platoon is stopped at this link, all vehicles have to wait during the red interval and the corresponding delay observed is high. In Figure 3-3(b), with an offset of 20 seconds, we can see that the truncation is around the middle of the platoon which is dense and therefore corresponds to a high value of yellow flow. However, the delay is now reduced since fewer vehicles are required to wait at the intersection. Figure 3-3(c) and (d) demonstrate the same mechanism. Reviewing all intersections, we observe that delays are usually minimal when only the very last part of the platoon is truncated and the corresponding yellow arrival is also relatively low.

Matters start to complicate when both directions are included in the analysis of an intersection. Figure 3-4 displays diagrams for three intersections. In each diagram the optimal offset used in the field is marked with a vertical gray band. Figure 3-4(a) shows what happens when the offset is included from the current value of 5 seconds to 10 seconds. It is clearly observed that the delay and yellow arrival on link 201 remain about the same, while on the opposing link 203 both delay and yellow arrival are reduced. Further shifting the offsets to 15 seconds continues to reduce the yellow arrival on link 203, while increases the delay on link 201. Thus the benefits of changing offset may need to be evaluated by applying weights on delay and yellow arrival and an optimization mechanism that locates the optimal offset for an intersection could be established. Figure 3-4(b) and (c) demonstrate different patterns due to the residual queues in node 3 and a different pattern of side street platoons on node 4, but the same optimization concept still applies.

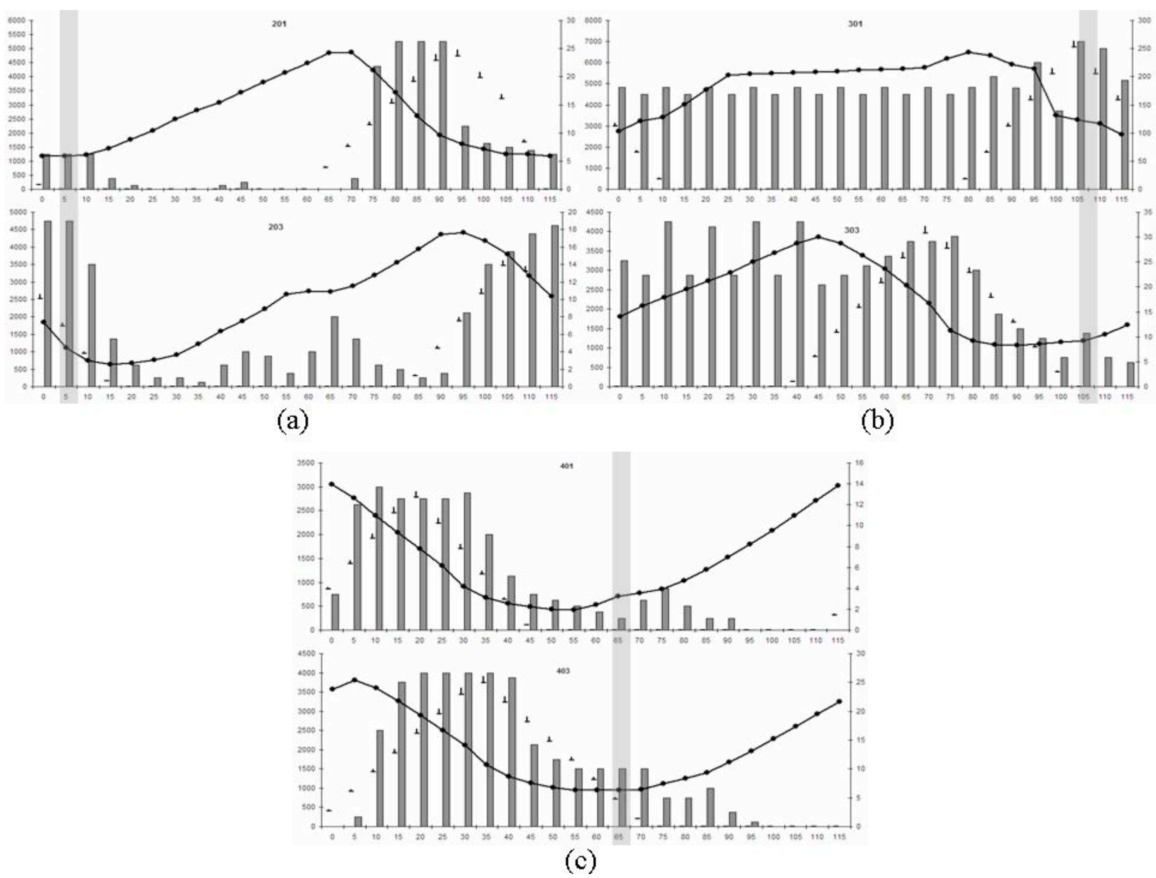


Figure 3-4 Delay and Yellow Arrival Flow Diagrams for all Links

The main insight obtained from this analysis is t hat t here are situations when shifting t he offsets can reduce yellow arrival with little change in intersection delay. Furthermore, we have established a framework for optimizing an isolated intersection with respect to delay and yellow arrival.

4.2.2 The Optimization Model

Utilizing the insights from the previous section, a simple optimization algorithm is developed. The algorithm generates diagrams similar to the ones used in the previous section, but instead of calculating delay and yellow arrival for the link, it calculates delay and yellow arrival for the whole route. Thus it is possible to find the offset for an intersection that optimizes the whole route. The algorithm is iterative and it finds the optimal offset for the first intersection while keeping all other offsets constant, and then performs the same at all other intersections iteratively.

This simple algorithm has several drawbacks which and often results in finding a local minimum rather than a global optimum. The setbacks are primarily a result of sensitivity to the starting point of the algorithm and to the order of nodes to be optimized. To reduce the sensitivity, following an exhaustive analysis of possible outcomes, the algorithm shown in Figure 3-5 is proposed.

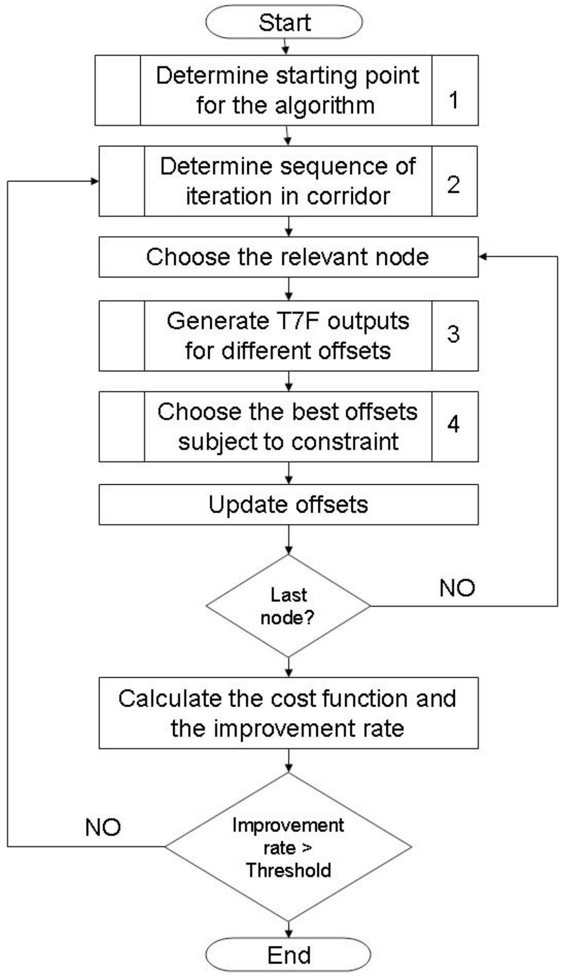


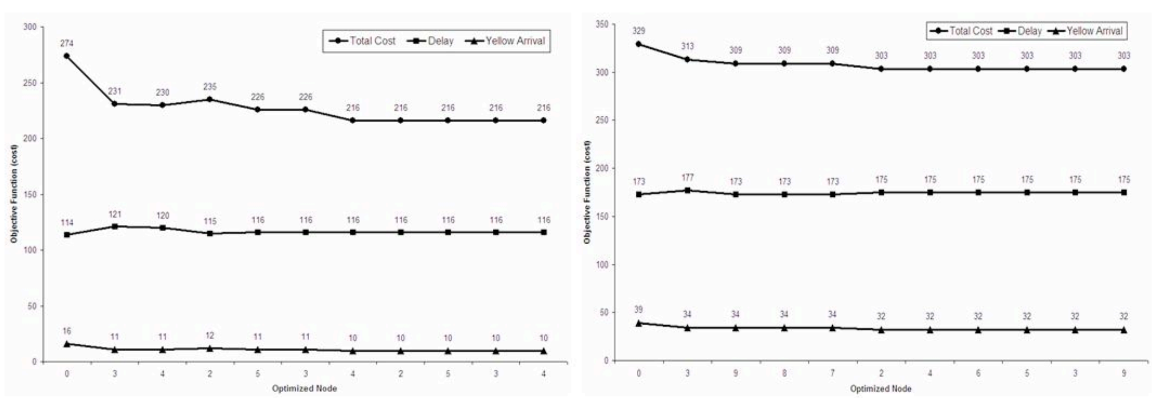
Figure 3-5 Algorithm for Proactive Signal Timing Optimization

The algorithm requires as an input a TRANSYT-7F model of several adjacent intersections. Sub-process 1 (shown in Figure 3-5) determines the initial values of the offsets for the process. The initial values found to produce the best results are the optimal offsets calculated using TRANSYT-7F that minimizes intersection delay, thus Sub-process 1 performs a standard TRANSYT-7F offset optimization. The second sub-process determines the sequence in which the nodes will be optimized. The sequence is decided based on descending weighted value of delay and yellow arrival. This sub-process ensures that the critical nodes will be optimized first. Next, the algorithm goes into a loop of optimizing each node with respect to the corridor, while keeping all other nodes constant. Sub-processes 3 and 4 perform the simple optimization process described earlier in this section with an additional constraint on the maximum increase in corridor delay. The new optimal offset for each node is used for the consecutive optimization of the next node. The process is terminated when the improvement rate is lower than a predetermined threshold.

4.3 A Case Study

The five intersection corridor described previously is initially used to evaluate the performance of the proposed algorithm. The result shows that yellow arrival in the section decreased by 37.5%, delay increased by 1.8%, and the total cost (which is a weighted sum of yellow arrival and delay) for this section decreased by 21%.

To further validate the optimization model, we also evaluated its performance on an extended section along the same corridor that includes 10 intersections from Jordan to Curtner. The result for this extended corridor shows a 17.9% decrease in yellow arrival, a 1.2% increase in delay, and a 7.9% decrease in total cost. Figure 3-6(a) shows the outcome produced by the algorithm for the five intersection case and Figure 3-6(b) for the 10 intersection case.



(a) (b)

Figure 3-6 Performance of Optimization Algorithm

5 CONCLUSIONS AND NEXT STEPS

Under this project, a signal-cycle-based data analysis was performed to study the contribution factors of red-light -running occurrences. This analysis used second-by-second signal phasing and timing data together with loop data. It identifies the yellow arrival flow, i.e., number of vehicles arrived at intersection during the yellow phase, as the most significant factor on RLR occurrences. The importance of this finding is that the yellow arrival is a controllable parameter of traffic operation and therefore it can be used as a safety measure in the design of signal timing. Inspired by this finding the research team has proposed a proactive signal timing optimization concept. The preliminary study demonstrated the potential of this timing optimization concept in significant reducing RLR occurrences without compromising intersection efficiency.

As a continuation of this project (TO5210), the research team is performing more detailed study, under Task Order 6210. The objectives are

- Further looking into the concept of proactive signal timing optimization, to validate the effective via microscopic and macroscopic simulation, and to develop a user-friendly software tool for traffic engineers.

- Investigate on-line countermeasures that aim at avoiding crashes caused by RLR.

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