Modeling the Dynamics of Driver's Dilemma Zone Perception Using Machine Learning Methods for Safer Intersection Control

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16. Abstract

The "dilemma zone" is defined as the area where drivers approaching a signalized intersection must decide to either proceed or stop at the onset of the yellow indication. Drivers that might perceive themselves to be too close to an intersection for a safe stop, and too far to proceed without violating traffic regulations, are said to be caught in DZ. Despite the vast body of related literature, there is a critical gap in research related to the "dynamic nature of drivers' decision" in dilemma zones. In order to identify and capture all significant factors beyond existing research, a driver survey was administered in the three states of Virginia, Pennsylvania, and Maryland. State-of-the-art techniques in human psychology, experimental design, and statistical analysis were used to design the survey and interpret the results. A driving simulator study was conducted to investigate the dynamic nature of driver perception of the dilemma zone and to assess significant factors affecting a driver's decision at the onset of yellow. In addition, the use of machine learning methods to capture the effect of a driver's learning/dynamic perception of DZ was investigated. Findings from this research suggest that drivers do learn from their experience and also that agent-based models can be used for modeling driver behavior in the dilemma zone more accurately than models that currently exist in the literature. The research team therefore recommends that agent-based modeling and simulation techniques should be used for assessing the impacts of dilemma zone mitigation strategies.

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Disclaimer

INTRODUCTION AND PROBLEM STATEMENT

About 45 percent of all crashes in the United States take place at intersections, of which a majority are related to drivers decisions at the "dilemma zone" (DZ) [1-3]. Generally, the dilemma zone is defined as the area where drivers approaching a signalized intersection must decide to either proceed or stop at the onset of the yellow indication [4]. Drivers that might perceive themselves to be too close to an intersection for a safe stop, and too far to proceed without violating traffic regulations, are said to be caught in the DZ [5]. Avoiding improper decisions to brake hard in response to a yellow signal indication (leading to rear-end crashes) or to proceed into the intersection without being able to clear the stop bar before the beginning of red (leading to red-light running incidents and possibly right-angle crashes) can be achieved by operating the signal such that the number of drivers caught in the DZ is minimized. In addition to drivers' behavior and perception, there are other influencing factors such as traffic composition (i.e., cars versus trucks), pavement condition, and the grade of the roadway, which make it especially important to address DZ safety issues with better modeling of driver behavior. Building a drivers' behavior model in the dilemma zone that mimics the reality could contribute significantly to dilemma zone protection methods and crash prevention.

Calculation of the beginning and end of the DZ for two different vehicles is illustrated in Figure 1, where the beginning and end of the DZ are shown at 5.5 seconds and 2 seconds, respectively. Points B and F are the estimated arrival times of each vehicle to the stop bar, points C and G define the beginning of each vehicle's DZ, and points D and H define the end of each vehicle's DZ, respectively. The DZ for each individual vehicle is shown in bold in each vehicle trajectory. At the onset of yellow, vehicle 1 is about 1 second away from the stop bar, which means that vehicle 1 has exited its DZ and the driver will have no hesitation in continuing to cross the stop bar. Vehicle 2 is about 3 seconds away from the stop bar, which means that vehicle 2 is in its DZ and the driver will be caught in the DZ. Looking at the figure, one can immediately tell whether a vehicle is caught in its DZ (if the onset of yellow line passes through the bold DZ line), will continue (if the bold DZ line is to the left of the onset of yellow line), or will stop (if the bold DZ line is to the right of the onset of yellow line).

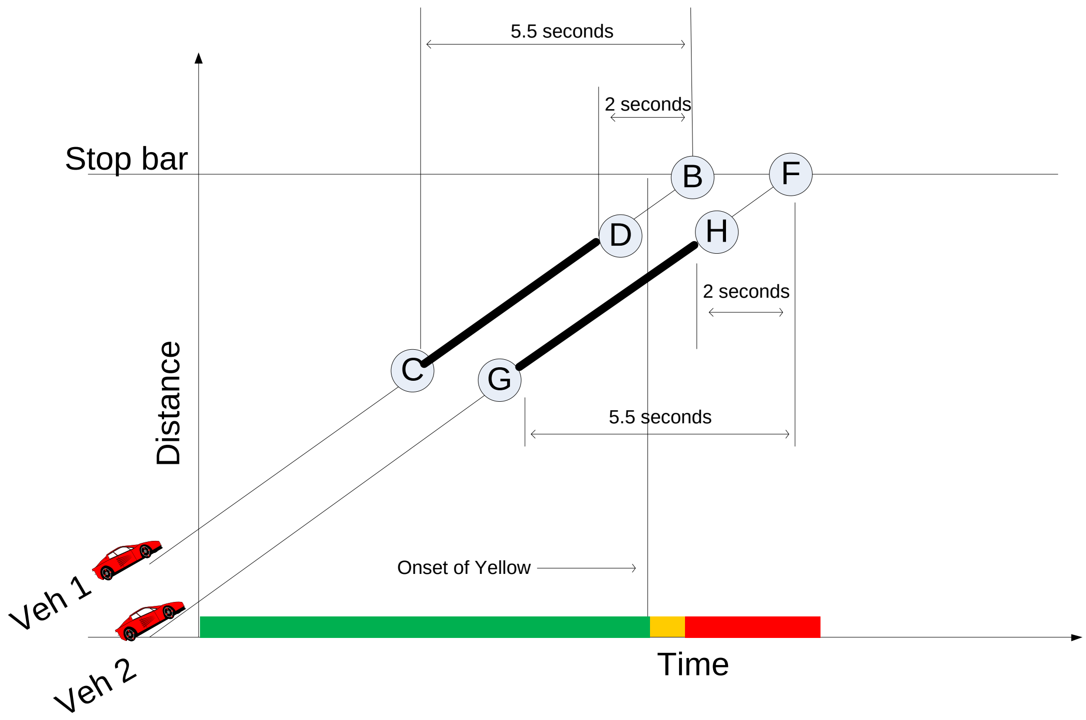


Figure 1: Illustration of the dynamic beginning and end of DZ for individual vehicles

Despite the vast body of related literature, there is a critical gap in research related to the "dynamic nature of drivers' decision." In other words, one important question that remains unanswered is whether the DZ definition changes individually as a function of experience. A major concern is whether driving through safer intersections could be reducing the alertness of drivers to possible DZ issues, and therefore setting them up for more severe crashes at other intersections. Alternatively, one would like to be able to model and quantify the changes in DZ definition in individual drivers as a function of their positive and negative experience, including the ability to quantify the benefits of training/educating drivers about DZ issues. It is of vital importance to investigate the effect of drivers' experience as it contributes to determining the benefits of training drivers about dilemma zone issues. This study fills a gap in the literature about the drivers' learning aspect of the dilemma zone by designing an adaptive experimental plan for a driving simulator study and investigating the use of machine learning and agent-based modeling methods in capturing the effect of drivers' dynamic perception of the DZ.

This report is divided into four main parts. In the first part, a complete literature review related to dilemma zone influential factors, modeling approaches, and agent-based modeling is provided. The second part is dedicated to investigating influential factors that affect drivers' decision at the onset of yellow. There are many factors contributing to the decision of drivers regarding how to proceed when they see the yellow light. These factors include drivers' attributes, intersection characteristics, signal control settings, vehicle characteristics, and traffic flow attributes. The purpose of this part of the research is to identify significant factors contributing to drivers' perception of the dilemma zone at the commencement of yellow, specifically from drivers' perspective. A driver survey was developed and administered in three states: Virginia, Maryland, and Pennsylvania. The responses obtained from the 1,213 participants were analyzed, and a descriptive statistical analysis was carried out. Significant factor analysis of the results recognized nine factors as the significant factors in these three states. They include speed, distance to intersection at the onset of yellow, presence of a red-light camera, presence of police, whether the pavement is wet or dry, presence of a vehicle in front of the subject car, presence of a vehicle behind the subject car, how well the driver knows the intersection, and whether the traffic is heavy. The results also showed that the difference between states' proportions (the percentage of responders who indicated that a given factor was influential in their decision at the onset of yellow) is significant.

The third part of the report focuses on developing a suitable experimental design in a driving simulator environment to investigate the learning aspect of drivers and evaluate the significance of influential factors in drivers' decision at the commencement of yellow. To achieve this goal, an Adaptive Randomized Incomplete Block Split-plot (ARIBS) design was developed and utilized in this research. The adaptive process of the design allows the treatment and examination of drivers based on their individual behavior and reaction. Learning hypotheses were developed and implemented in a driving simulator. Design verification was provided through preliminary results obtained from six drivers who drove through the scenarios. The preliminary results verified the experimental design, indicating that 97.3% of the time experimental procedure was able to predict drivers' decision correctly and adapt the experiment based on the prediction of drivers' behavior. Thirty-four participants volunteered to conduct the full experiment. The results also showed that for two out of three learning hypotheses, drivers' behavior did not remain the same after being exposed to the treatments related to the learning hypotheses.

The last part of the report presents an investigation of the use of machine learning methods in capturing the effect of driver's learning/dynamic perception of DZ. An actor-critic reinforcement learning algorithm was implemented to model the dynamic behavior of drivers in the dilemma zone using the driving simulator data. Fuzzy logic was used to partition traffic state variables and reinforcement learning was used for fuzzy rule policy calibration and update. The study results showed a close match between the driver's action from the driving simulator and the model output.

The research reported here contributes to improved modeling of driver definition and behavior in the dilemma zone, which will have a significant impact on the design of optimal control methods and the assessment of intersection safety. Moreover, it lays the groundwork for several subsequent simulator studies and scenario development in the driving simulator to investigate drivers' behavior at signalized intersections.

CHAPTER 1: LITERATURE REVIEW

Dilemma Zone

Dilemma zones have been the subject of intensive research in traffic signal literature for decades [6, 7]. It is an important subject due to the great number of incidents that occur at intersections due to issues related to dilemma zones. Two types of dilemma-zone-related crashes are recognized in intersections: namely, rear-end crashes (when a driver decides to stop while its follower decides to proceed) and right-angle crashes (when a driver ends up violating the red light and crashes with side-street traffic) [8].

Generally, dilemma zones are defined as the area where drivers approaching a signalized intersection must decide to either proceed or stop at the instance of yellow indication [4]. Drivers may find themselves too close to the intersection for a safe stop or too far to proceed without violating traffic regulations [5]. There are two types of dilemma zones that are recognized in the literature, related to vehicle dynamics and different decisions performed by drivers, respectively [9-14]. Type I dilemma zones are defined as an area where the driver can neither stop without a hard deceleration nor clear the intersection safely without running the red light. Type II dilemma zones are associated with drivers' "perception" of whether it is safe to stop or proceed at the onset of the yellow indication.

In the earliest studies of the dilemma zone [6, 7, 15, 16], the zone was mostly treated as a deterministic value [17]. However, eventually researchers started to investigate the stochastic nature of the dilemma zone [18-20]. A stochastic dilemma zone specifies the zone where more than 10% and less than 90% of drivers would choose to stop [20]. This area between 10 and 90 percentile is also called an "indecision zone" [10]. To specify the boundary of the dilemma zone, charts of "percent drivers stopping" versus "distance from stop bar at the onset of yellow" have been proposed by researchers (e.g., [16, 20, 21]). However, producing these kinds of curves requires a large number of observations [17]. To overcome this shortcoming, Sheffi and Mahmassani [17] proposed a Probit estimator to represent curves.

Several mitigation strategies and dilemma zone protection settings were introduced to increase the safety of signalized intersections, such as advanced options of modern traffic signal controllers [22, 23]. Advanced control algorithms for dynamic dilemma zone protection such as D-CS [3, 24, 25], Platoon Identification Algorithm (PIA)[26], signal control system of LHOVRA [27], MOVA [28, 29], SOS [30], Flashing Amber Signal Phasing [31, 32], and advanced warning flashers [33-37] are some of the systems developed for this purpose.

Contributing factors to driver behavior in dilemma zone

Drivers approaching an intersection may experience a state of indecision as they need to assess many parameters and decide on whether to pass through the intersection or stop at the onset of yellow [38]. Various factors influencing the dilemma zone, driver behavior, and the decision-making process at the onset of the yellow indication have been the subject of research in the literature [9, 39-42].

Figure 2 summarizes how the interaction of various factors contributes to dilemma zone location and decisions by the driver. Two groups of factors affect the dilemma zone and drivers' decision on proceeding or stopping at the instance of yellow indication. The first group, called internal factors, includes driver attributes such as age and gender. The second group specifies external factors, including the vehicle, traffic, intersection, and signal settings. These two groups directly influence dilemma zone location and the decision to stop or go. There are also an intermediate group of factors that influence dilemma zones directly, which are affected by external factors as well as internal ones. Perception-reaction time (PRT) and acceptable acceleration/deceleration rates constitute this group of factors. As shown in the figure, internal and external factors influence dilemma zones directly and indirectly. PRT and acceptable acceleration/deceleration rates are sometimes placed in the driver characteristics group, yet the authors believe the relationship diagram presented in Figure 2 indicates the interaction of different factors more clearly. Contributing factors are discussed in the following section.

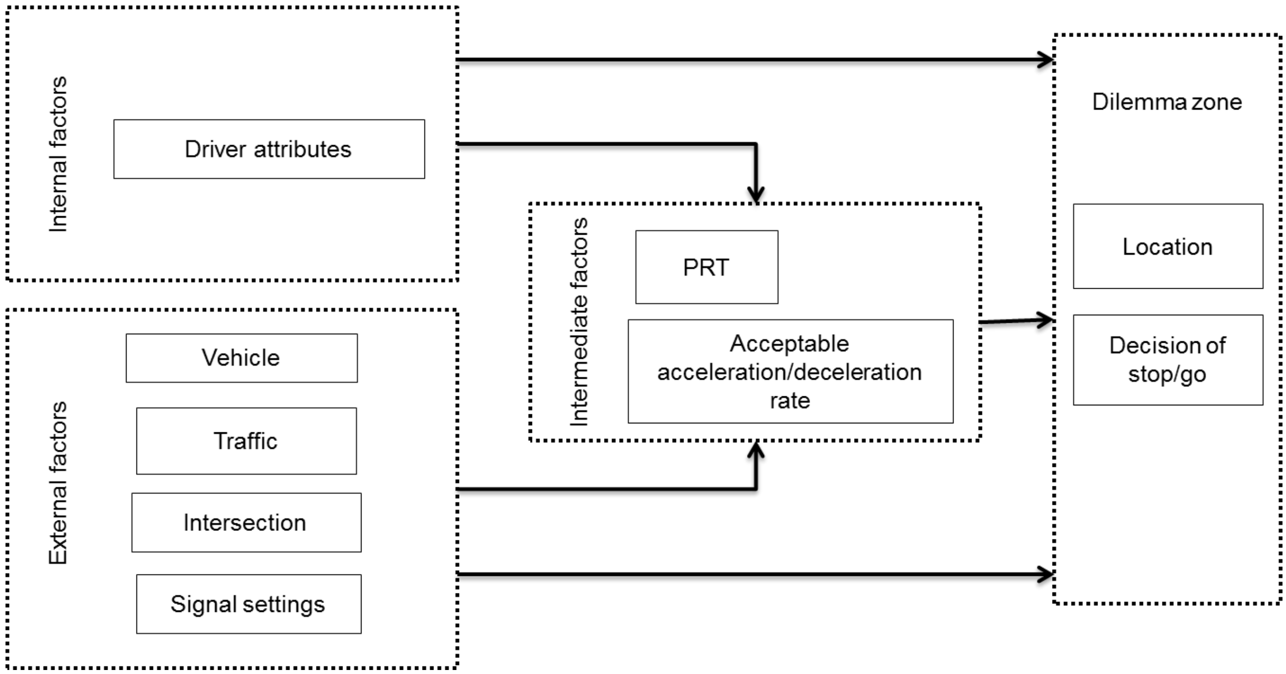


Figure 2: Dilemma zone contributing factors diagram

Driver's attributes and human factors

Driver error is cited as the main contributing factor in automobile crashes [43]. This emphasizes the importance of the driver's role in safety issues related to the dilemma zone. Driver characteristics are one of the factors affecting a driver's decision-making process [9, 44], especially by influencing perception reaction time (the time between the commencement of the yellow indication and the activation of the vehicle's brake lights [39]) and acceleration/deceleration rate. Although several researchers have studied PRT and acceleration/deceleration rate [7, 45-50], it is still not clear how they vary as a function of other factors such as drivers' age and gender [39].

In addition to age and gender, other factors such as experience, effects from drivers' safety/violation record, concentration level during driving [9], drivers' personality, and emotional states [51] are also influential on drivers' decisions. For instance, impulsive drivers are more likely to accelerate or violate traffic lights at intersections [52]. Concentration level itself is affected by other factors, such as talking on the phone. The reaction time of most drivers increases significantly when using phones [53].

Some studies have focused more on human factors and drivers' psychology in the decision-making process. Generally speaking, decisions are grouped into three types, namely: (1) certain decisions, (2) risky decisions, and (3) uncertain decisions. Decisions of drivers in a dilemma zone fall into the risky decision group, in which the occurrences of diverse future conditions can be suggested by probability [52]. Wu et al. [52] divided the decision-making process of drivers at intersections into six processes, including: observing problems, ensuring decision objectives, analyzing prepared plans and possible results, choosing a plan, implementing the plan, and giving feedback.

One important psychological issue related to red-light-running and the dilemma zone is aggressive driving. Aggressive driving has been proven to correlate with gender and age. Men and older drivers are more likely to drive aggressively [54].

There are three categories of drivers recognized in the literature; namely, "aggressive," "conservative," and "normal," which are based on drivers' response to the yellow indication, the existence of a dilemma or option zone, and initial approaching speed. [9, 55]. Liu et al. [56] introduced an ordered probit model, the outcome of which is one of the following responses by drivers: conservative stop, normal, and aggressive-pass. Based on their study, approaching vehicle speed appears to be the best indicator to determine the aggressive level of a driver.

Intersection characteristics and condition

Driver decisions are also attributed to intersection characteristics such as intersection layout, clearing width, number of lanes, and number of intersection legs. The number of legs in the intersection could be representative of both the geometry and safety of an intersection, as the probability of accident occurrence at three-leg intersections is less than those occurring at four-leg intersections [4]. The existence of surveillance cameras, gradient, roadway surface condition, and pavement markings are also recognized as influential factors [4, 9, 57-59] .

Subject vehicle characteristics

The characteristics of an approaching vehicle to the intersection are noted as a significant factor in regard to the dilemma zone and drivers' decisions [9, 60-62]. Vehicle speed, distance to the intersection, position in the traffic flow (leading or following), and vehicle type are some of the studied factors in this field [9, 63].

Signal control settings

Signal settings and characteristics are one of the important factors affecting dilemma zones and drivers' decisions. Length of yellow interval, the ratio of the green time to the cycle length, signal phasing sequence, cycle length, control type (being fixed or actuated), and existence of countdown timers are factors noted in literature [5, 9, 52, 64-69]. Previous research [4] suggested that the probability of proceeding through an intersection increases as the yellow interval increases. Moreover, when the ratio of the green time to the cycle length decreases, drivers are more willing to proceed rather than waiting for another cycle.

Traffic flow characteristics

Traffic surrounding the approaching vehicle affects the driver's performance and decision while encountering the yellow indication. Subject street volume, opposing volume, presence of side-street vehicles/pedestrians/bicycles, and capacity are factors influencing driver behavior in a dilemma zone [56, 70, 71]. As a case in point, the ratio of secondary traffic flow to the main road flow is important, as right-angle accidents are more likely when this ratio increases [4].

Driver behavior modeling in the dilemma zone

In this section, the influencing factors mentioned above and their role in driver behavior modeling are investigated in detail.

The probability of stopping in earlier studies was usually determined based upon a limited number of factors, such as the distance to the intersection [16, 42, 72-74], time to intersection [51, 75], and approaching speed [17, 75]. Other factors started to be taken into account to better estimate the drivers' behavior at the onset of yellow indication. Research efforts in this regard fall into two main groups, statistical and fuzzy models, as described below. Table 1 summarizes the factors as well as the dependent variable considered in each study.

Statistical approach

A group of researchers examined the relationship between driver behavior and influencing parameters through the statistical approach. The prevailing method is to collect data and run the statistical analysis to characterize the relationship between variables. Various studies examined different factors considering their available datasets, and are all summarized in Table 1.

Table 1: Dilemma zone contributing factors considered in different studies

Study	Approach	Dep. Variables	Dilemma zone contributing factors															
			Driver							Intersection								
			Age	Gender	PRT	Acceleration/Deceleration rate	Drivers' safety/violation record	Concentration level during driving	Talking on phone or not	Speed limit	Number of lane (width)	Roadway grade	Light (day or night)	Clearing width	Number of arms	Surveillance by camera or police	Visibility of next signal	Dry or wet surface
(Olson and Rothery 1961)	Statistical	Probability of stopping																
(Amer, Rakha et al. 2012)	Statistical	PRT and Deceleration rate	x	x						x		x						
(Sheffi and Mahmassani 1981)	Statistical	Stop or go																
(Kikuchi, Perincherry et al. 1993)	Fuzzy	Stop and go rules								x								
(Allos and Al-Hadithi 1992)	Statistical	Likelihood of stopping or going													x	x		
(Chang, Messer et al. 1985)	Statistical	Yellow response time, deceleration rate, and probability of stopping								x		x	x					x
(Gates, Noyce et al. 2007)	Statistical	Brake response time (PRT), deceleration rate and probability of stopping			x					x				x				
(Elmitiny, Yan et al. 2010)	Statistical	Stop/go decision and red-light running																
(Wu, Juan et al. 2009)	Statistical	Decision behavior: accelerating", "decelerating", "maintaining speed", and "stopping"									x							

Table 1 (continued): Dilemma zone contributing factors considered in different studies

Study	Approach	Dep. Variables	Dilemma zone contributing factors															
			Driver							Intersection								
			Age	Gender	PRT	Acceleration/Deceleration rate	Drivers' safety/violation record	Concentration level during driving	Talking on phone or not	Speed limit	Number of lane (width)	Roadway grade	Light (day or night)	Clearing width	Number of arms	Surveillance by camera or police	Visibility of next signal	Dry or wet surface
(Papaioannou 2007)	Statistical	Probability of stopping	x	x														
(Liu, Chang et al. 2007)	Statistical	Drivers' group			x	x												
(Liu, Chang et al. 2011)	Statistical	Responses: conservative stop, normal, and aggressive-pass	x	x					x	x	x						x	
(Amer, Rakha et al. 2010)	Statistical	Probability of stop/go, PRT, accepted deceleration rate, and error in distance-to-intersection estimation.	x	x								x						
(El-Shawarby, Rakha et al. 2006; Rakha, El-Shawarby et al. 2007)	Statistical	Probability of stop/go	x	x	x													
(Lin and Kuo 2001)	Fuzzy	Determine yellow and clearance interval									x	x						
(Caird, Chisholm et al. 2007)	Statistical	Percentage of stop/go	x		x	x												
(Hurwitz, Wang et al. 2012)	Fuzzy	Probability of stop/go																
(El-Shawarby, Abdel-Salam et al. 2012)	Statistical	Stop or go decision	x	x								x						
(Sharma, Bullock et al. 2011)	Statistical	Probability of stop/go				x												

Table 1 (continued): Dilemma zone contributing factors considered in different studies

Study	Dilemma zone contributing factors												
	Vehicle												
	Distance	Approaching speed	Time to intersection	Type	Vehicle model (which country)	Headway (with leading veh)	Tailway (with following veh)	Lane position	Leading or following or alone	Lane changing	Degree of vehicle newness	Existence of DZ or option zone	Passenger in the car
(Olson and Rothery 1961)	x												
(Amer, Rakha et al. 2012)		x	x										
(Sheffi and Mahmassani 1981)	x	x											
(Kikuchi, Perincherry et al. 1993)	x	x											
(Allos and Al-Hadithi 1992)	x	x											
(Chang, Messer et al. 1985)	x	x		x									
(Gates, Noyce et al. 2007)	x	x		x		x	x						
(Elmitiny, Yan et al. 2010)	x	x		x				x	x				
(Wu, Juan et al. 2009)		x		x						x	x		
(Papaioannou 2007)	x	x										x	
(Liu, Chang et al. 2007)	x	x											
(Liu, Chang et al. 2011)	x	x	x	x	x			x	x				x
(Amer, Rakha et al. 2010)	x	x							x				
(El-Shawarby, Rakha et al. 2006)	x												
(Lin and Kuo 2001)	x	x											
(Caird, Chisholm et al. 2007)			x										
(Hurwitz, Wang et al. 2012)	x	x											
(El-Shawarby, Abdel-Salam et al. 2012)			x										
(Sharma, Bullock et al. 2011)	x	x	x										

Table 1 (continued): Dilemma zone contributing factors considered in different studies

Study	Dilemma zone contributing factors												
	Traffic						Signal setting						
	The ratio of secondary traffic flow to the main traffic	Presence side-street ped/bike/veh	Presence of opposing veh to turn left	Ave. speed	Flow	Capacity	Yellow time	Percentage of green time to the cycle time	Actuated or pretimed	Phase sequence	Cycle length	Coordinated	Countdown
(Olson and Rothery 1961)				x									
(Amer, Rakha et al. 2012)							x						
(Sheffi and Mahmassani 1981)							x						
(Kikuchi, Perincherry et al. 1993)							x						
(Allos and Al-Hadithi 1992)	x						x						
(Chang, Messer et al. 1985)									x				
(Gates, Noyce et al. 2007)		x	x		x		x		x	x	x		
(Wu, Juan et al. 2009)													x
(Liu, Chang et al. 2007)							x						
(Liu, Chang et al. 2011)				x	x		x	x			x	x	
(Amer, Rakha et al. 2010)							x						
(Lin and Kuo 2001)					x	x							

In one of the earliest efforts in this regard, Olson and Rothery [16] determined the probability of stopping as a function of distance to the intersection for five intersections with different speeds.

Chang et al. [72] conducted a study based on collected data on seven different sites and analyzed the relationship between yellow response time, deceleration rate, and probability of stopping. Allos and Al-Hadithi [4] developed a model of drivers' behavior by capturing the relationship between the likelihood of stopping and going and the influential factors. One interesting finding in their study is that police presence did not have a direct influence on the likelihood of stopping. On the other hand, it influenced the dependent variable indirectly, as a significant correlation was recognized between police presence and approaching speed [4].

Collecting data on first-to-go and last-to-go vehicles encountering the yellow time interval, Gates et al. [71] modeled deceleration rate and brake-response time statistically. The estimated travel time to the intersection at the onset of yellow indication turned out to be the most important influential factor on a driver's likelihood to stop or go.

Utilizing data collected by a driving simulator, Caird et al. [46] estimated drivers' stop or go decision based on time to the stop line. The main focus of their study was to evaluate the effect of age group on perception-reaction time. They observed no age differences in perception-reaction time.

Wu et al. [52] modeled drivers' behavioral decision-making at signalized intersections with countdown display units and compared it to intersections without countdown display units. In the case of having countdown displays, drivers' decision was found to be depended on their personalities and signal timing, whereas for intersections without countdown units, the most important factor was found to be vehicle speed.

Elmitiny et al. [10] conducted a statistical analysis, specifically tree-based classification analysis, on video-based system collected data and concluded that the most important predictors for both the stop/go decision and red-light running violation are the vehicle's distance from the intersection, operating speed, and position in the traffic flow.

El-Shawarby et al [76] examined drivers' stop or go decision by triggering the yellow phase at five different distances for vehicles approaching the intersection. Male and younger drivers showed a higher probability of running. Later, they added the analysis of perception-reaction time to their study [77]. Amer et al. [78] applied controlled field data to capture the relationship between perception-reaction time, accepted deceleration rate, and error in distance-to-intersection estimation with six explanatory variables using a stepwise regression technique. The three dependent variables are utilized in their Behavioral Model (BM) validation process [78]. They also developed a Statistical Model (SM) for the stop-run decision and compared its success rate to that of the Behavioral Model [78, 79]. Later, focusing on the stochastic nature of PRT and deceleration rate, Amer et al. [39] concluded that for drivers older than 60 years of age compared to younger drivers, PRT increases in the range of 0.1 s. Based on the findings, they developed lookup tables for computing yellow indication duration. Gathering data on the same research facility, El-Shawarby et al. [59] focused on the effect of rainy weather conditions and concluded that the probability of stopping decreases and location of dilemma zone starts 0.1 second farther from the stop line in the wet pavement condition as compared to clear weather.

Sharma et al. [80] tested five variables, including required acceleration and deceleration rates. According to their study, the acceleration required by the vehicle to cross the stop bar prior to onset of red turned out to be a significant factor in drivers' decision of stopping or going.

Fuzzy approach

There is a smaller group of studies that investigated drivers' behavior from the fuzzy aspect of making decisions to choose between the conflicting actions at the onset of the yellow indication. In this regard, as the perceived information is unclear and the driver has different interpretations of the decision parameters, his decision is coupled with uncertainty.

Applying field data, Kikuchi et al. [38] modeled the drivers' decision considering a set of fuzzy inference rules for stopping or passing through the intersection. They estimated the degree of anxiety for aggressive and conservative drivers using Yager's anxiety measure [81]. Anxiety level is the degree of uncertainty the driver experiences in making a correct decision to stop or go [70]. Based on a rule-based fuzzy logic system, Lin and Kuo [70] introduced a procedure to estimate the change and clearance intervals of a traffic signal.

Hurwitz et al. [14] developed a binary logistic regression model for drivers' probability of stopping or going. The input for the model is generated from a fuzzy subset while requiring fewer data compared to a similar model.

Despite the fact that the dilemma zone has generated significant research interest over the years, resulting in major contributions in the area, more research needs to be done. According to Table 1, approaching speed and distance to the intersection at the commencement of the yellow indication are by far the most studied factors. The research literature contains relatively little material on factors such as lane changing behavior, countdown units, coordinated signals, vehicle models, and concentration level.

Another shortcoming observed in the body of the literature is neglecting the "dynamic nature of drivers' decision." Looking at the dynamic behavior corresponds to how the dilemma zone definition changes as a function of drivers' positive and negative experience. It is of vital importance to investigate the effect of drivers' experience as it contributes to determining the long-term benefits or drawbacks of exposing drivers to dilemma zone mitigation strategies.

Agent-based machine learning modeling techniques

The concept of Agent Based Modeling (ABM) has historically been studied and researched by scientists for decades beginning in the early 1940s. ABM can be defined as a mathematical computational model that attempts to predict the behaviors of humans after simulating their behaviors in computer programs. It is a form of computational social science [82]. It is mainly used by sociologists and economists. ABM models consist of agents that interact within a given environment. Agents are either separate computer programs or distinct parts of a program that are used to represent social actors, individual people, organizations, or nations [82].The Phillips (Phillips 1950) hydraulic social science model is one of the well-known models used by social scientists in their industry. It modeled water flowing through interconnected glass pipes and vessels that represented the circulation of money [82].

The use of ABM has emerged as a modeling algorithm for modeling complex systems composed of interacting and autonomous units (i.e., agents) [83]. Civil engineers (more specifically hydrological civil engineers) have a long history of using ABM to model non-discrete and non-linear engineering behavior characteristics of water. Today, transportation/traffic engineers are attempting to adopt the use of agent-based models to model precise driver behavior on transportation networks. Specifically, they attempt to develop mathematical computational behavior problems in computer simulation programs (rather than the traditional regression models) to model the possible outcome of a driver or drivers (an agent or agents). One of the advantages of computational modeling is that it forces researchers to be precise; unlike mathematical theories and models developed in natural language, a computer program has to be exactly specified if it is to run [82]. The most important defining characteristic of an agent in a computer program is its capability to act autonomously; that is, to act on its own without external direction in response to situations it encounters during its decision-making process [84]. An agent's autonomous behavior within the dilemma zone at an intersection is critical to the development of the ABM at the onset of the yellow time (amber time).

Simulation programs have made major strides in incorporating autonomous behavior in the programs. Transportation simulation software programs such as VISSIM and CORSIM and others have developed autonomous agents to act on their own during operational analysis on transportation networks or at intersections. There are models that focus on specific aspects, such as the demographics of forecasting trips, car ownership, and trip mode choice. There are also macroscopic frameworks that link multiple sub-models to capture the interactions among subsystems [85]. Simulation modeling in transportation planning plays a major role in effectively making decisions based on the results of the model. Hoa et al. [85] explored candidate micro-simulation models by integrating an existing activity-based travel demand simulation model, TASHA, with a dynamic agent-based traffic simulation model, MATSim. The integration of both models was considered to model light-duty vehicle emissions. The results showed an advantage of using micro-simulation over the aggregation of spatial or temporal simulation. It should be noted that the authors wished the framework to be further improved by enhancing the sensitivity of TASHA to travel time [85].

The behavior of a driver at a signalized intersection dilemma zone is governed by four main characteristics: the characteristics of the driver, the characteristics of the vehicle, the characteristics of the signalized intersection's geometry, and the characteristics of the driver's trip. There is limited research on ABM at intersection dilemma zones. Recent notable research in this area includes:

- Combined Car-Following And Unsafe Event Trajectory Simulation using Agent Based Modeling Techniques [86].
- Agent-Based Reinforcement Learning Model for Simulating Driver Heterogeneous Behavior during Safety-Critical Events in Traffic [87].
- Agent-Based Framework for Modeling Driver Left-Turn Gap Acceptance Behavior at Signalized Intersections [83].
- Agent-based Evaluation of Driver Heterogeneous Behavior during Safety Critical Events [88].
- Integrating an Activity-Based Travel Demand Model with Dynamic Traffic Assignment and Emission Models Implementation in the Greater Toronto, Canada, Area [85].
- Neural Networks for Real-Time Traffic Signal Control [89].
- Evaluating Green-Extension Policies with Reinforcement Learning and Markovian Traffic State Estimation [90]
- Modeling the Complexity of Driving Behavior during Signal Yellow Interval using Reinforcement Learning Accession Number [91].
- Reactive-Driving Agent Based Approach for Modeling Gap Acceptance Behavior [92].
- Real-Time Coordinated Signal Control using Agents with Online Reinforcement Learning [93].

In addition, a multi-agent systems approach was developed to distributed unsupervised traffic responsive signal control models. In this system each agent acted as a local traffic signal controller for one intersection in the network [89]. A fuzzy neural network was integrated into the multi-agent model; more specifically, into the simultaneous perturbation stochastic approximation theorem found in the fuzzy neural networks. The results of the fuzzy neural network showed that the mean delay of each vehicle declined by 78% and the mean stoppage time declined by 85%. This was contrary to the existing traffic signal control algorithm that showed varying results [89]. Choy et al. [93] developed a multi-agent architecture for real-time unsupervised coordinated signals using online reinforcement learning techniques. The multi-agent architecture consisted of three hierarchical layers of controller agents: intersection, zone, and regional controllers [93]. The fuzzy logic, neural network, and evolutionary algorithm were implemented to the layers of the multi-agent architecture developed. Performance of the multi-agent architecture was evaluated with an actual traffic model network. Results of the research showed lower average delay per vehicle and total stoppage.

Researchers have studied the behavior of drivers at signalized intersections and on transportation networks by looking into the various patterns they exhibit during green time and yellow time and at intersections with red-light cameras. The traditional concept of using simulation autonomous computer programs and the logistic regression method without the use of the ABM concept is often used to model the behavior of drivers on a network. Whereas other engineering disciplines incorporate the concept of ABM, transportation engineers, researchers, and planners have lacked an in-depth study on this concept of modeling driver behavior on their transportation networks. Adam et al. [91] modeled the behaviors of drivers at signalized intersections during the yellow interval using reinforcement learning techniques. Vehicle headways and the number of vehicles trapped in dilemma zones were used as proxy to driver aggression and traffic volume conditions, respectively. The results showed that the reinforcement learning technique was superior at recognizing the different traffic patterns and eventually generating human class performance for the traffic control system [91]. In a different study conducted on "Evaluating Green-Extension Policies with Reinforcement Learning and Markovian Traffic State Estimation" [90], a novel approach was presented to control traffic signals for the number of vehicles trapped in the dilemma zone to reduce its optimal state due to the changes in traffic patterns [90]. "A comparison between the proposed optimal policy and the emerging detection-control system two-stage policy was conducted, and it was found that the policy based on reinforcement learning reduced the number of vehicles caught in the dilemma zone by up to 32%." [90]. The algorithm developed in this research was able to adapt to changes in traffic patterns. It also produced an optimized methodology to terminate or extend signal phasing in real time, compared to the traditional method of phase extension and termination at signalized intersections.

The concept of ABM has been used in traffic/transportation engineering applications to include traffic control systems and management, alternative route planning and choices, intelligent transportation systems (ITS), and traffic operation simulation. However, little has been done on the dilemma zone at signalized intersections on the onset of the yellow light due to its complexity, the unpredictable behavior of drivers, and the varying duration of the yellow time.

CHAPTER 2: DRIVERS SURVEY

As mentioned in the previous sections, contributing factors to drivers' perception of dilemma zones, studied by researchers to date, do not cover the wide spectrum of factors that could significantly affect the driver's decision. In order to identify and capture all significant factors beyond existing research, a driver survey was administered in the three states of Virginia, Pennsylvania, and Maryland. State-of-the-art techniques in human psychology and experimental design and statistical analysis were used to design the survey and interpret the results. The results of this survey provide useful information on potential factors for further study and to develop proper scenarios in the driver simulator experience.

Survey design

The survey questionnaire was designed to address significant factors affecting driver's decision at the onset of dilemma zones and cater to the future task needs. A sample of the survey questionnaire is provided in Appendix A. The questionnaire consisted of three groups of questions. The first group of questions obtains personal information on participants' age, gender, education level, race, and living location. The second group focuses on general driving questions. Participants are asked to specify their car type and how often they drive. Questions about the number of times they have been pulled over (ticketed and non-ticketed) and their incident involvements are also in this part of the questionnaire. Moreover, there was a question asking participants if they considered themselves safe drivers or not. The third group mainly intended to capture information on what drivers believe influences their decisions while encountering yellow lights. Twenty-three factors were listed for recipients to choose as influencing factors. In this part, drivers were also asked about the duration of yellow lights and different yellow light lengths at different intersections. At the end of the questionnaire, an open answer question was included so that participants could specify their comments, experience, and suggestions.

Survey distribution

The survey questionnaire was prepared through a free online tool, Google Docs, offered by Google to create and manage surveys documents. The questionnaire was accessible on a webpage for participants to submit their answers. The survey results were also stored online and were saved in various formats (.xlsx, .csv, etc.).

A pilot survey was conducted to ensure that the questions were logical and understandable, and that they conveyed the intended concepts. Twenty people participated in the pilot survey; they were asked to specify any vagueness or ambiguity in the questions. Based on the result of the pilot survey, the questions were altered to ensure the delivery of the right messages in each question.

The survey was distributed at Virginia Tech, Morgan State University, and Penn State through LISTSERVs and news webpages. Participants were asked, in an email, to complete the online survey that takes approximately 5 minutes. They were also informed that participation in this study is completely voluntary and their responses are anonymous and confidential. It should be noted that all participants were at least 18 years old.

Survey results analysis

General questions

Responses to the online survey were stored in excel worksheets. In total, 1,213 people participated, among which 57% were females. Age distribution is shown in Figure 3, with means and standard deviation equal to 31.59 and 12.76, respectively.

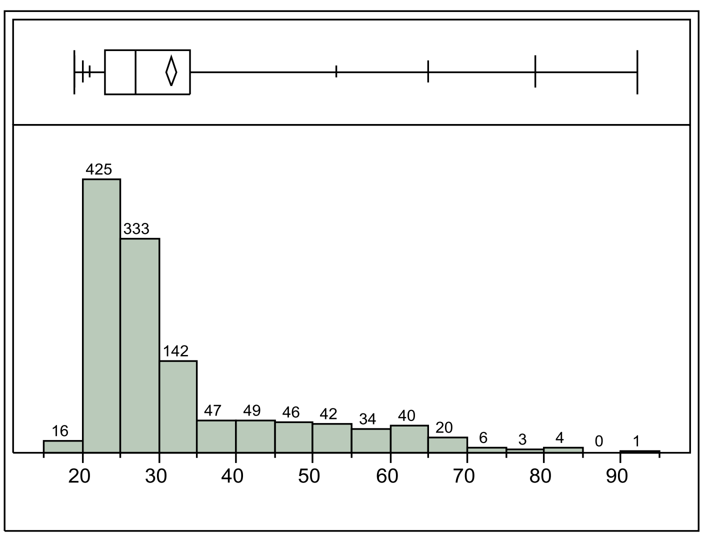


Figure 3: Age distribution

Figure 4 and Figure 5 depict, via pie charts, survey participants' highest level of education and race distribution. As the survey was conducted at universities, it was expected that the majority of respondents would be graduate or undergraduate students. According to Figure 5, whites are the majority racial group among the participants. The second largest ethnic group belongs to Blacks or African Americans. In both figures, some of the responses with negligible counts are excluded from the legend.

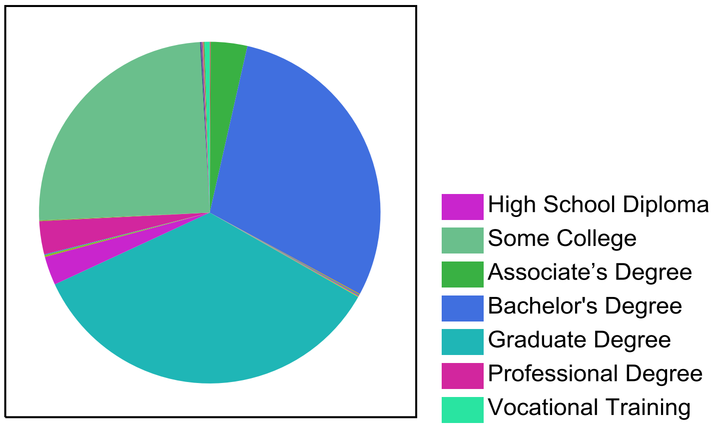


Figure 4: Distribution of highest level of education

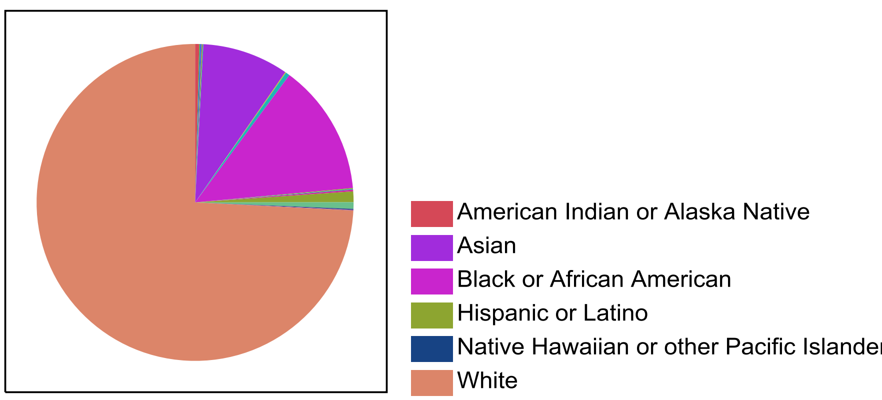


Figure 5: Distribution of race

Figure 6, Figure 7 and Figure 8 show, in bar charts, respondents' answers to three questions: "How often you drive a motor vehicle?", " What kind of vehicle do you usually drive?", and "How many times have you been pulled over by the police in the past year?", respectively. Numbers shown on top of the bars indicate the count of corresponding categories.

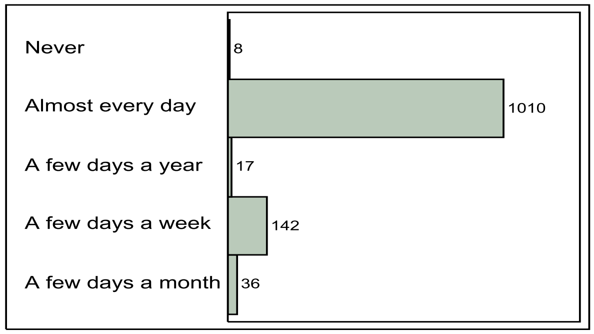


Figure 6: Distribution of how often participants drive

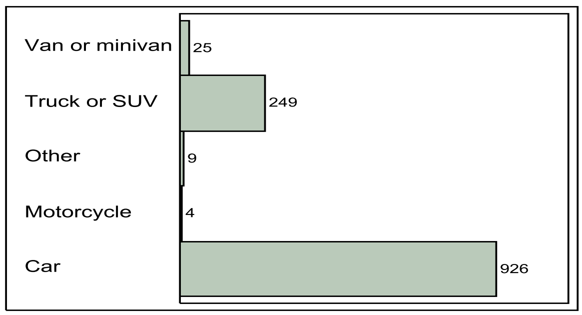


Figure 7: Distribution of vehicle type

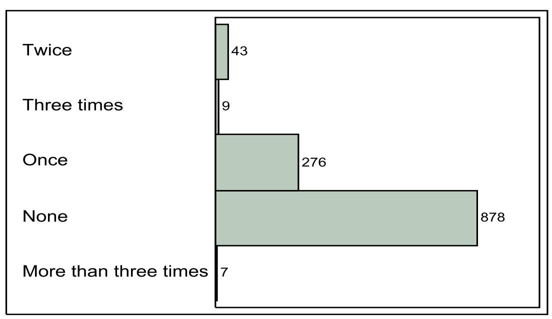


Figure 8: Distribution of being pulled over by the police

According to the results of one of the questions, 22% have been involved in an accident at an intersection. Note that this does not mean they were at fault, or not at fault, in the accident.

In answering the "safe driver" question, it is interesting that 94% of drivers consider themselves safe drivers, and there is a small group, 4%, who do not know if they are safe drivers or not.

As mentioned earlier, the last part of the questionnaire includes questions directly related to the yellow light dilemma zone.

Figure 9 shows how many people chose each choice for the question asking "How often do you try to catch a yellow light and end up running a red light?" According to this figure, the majority of drivers rarely do this, yet there is a large group, 30%, who sometimes try to catch the yellow light and end up running a red light. Pie charts in Figure 10 show gender disparities in answering this question. The most apparent difference is related to the percentage of males who answered "never," which is higher than the female group. Figure 11 summarizes the answers by states. According to this figure, Penn State drivers show riskier behavior since the "never" portion is smaller while the "sometimes" and "very often" portions are larger as compared to the other states.

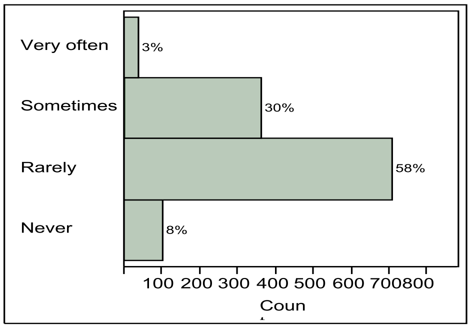


Figure 9: Bar chart of yellow light catching frequency

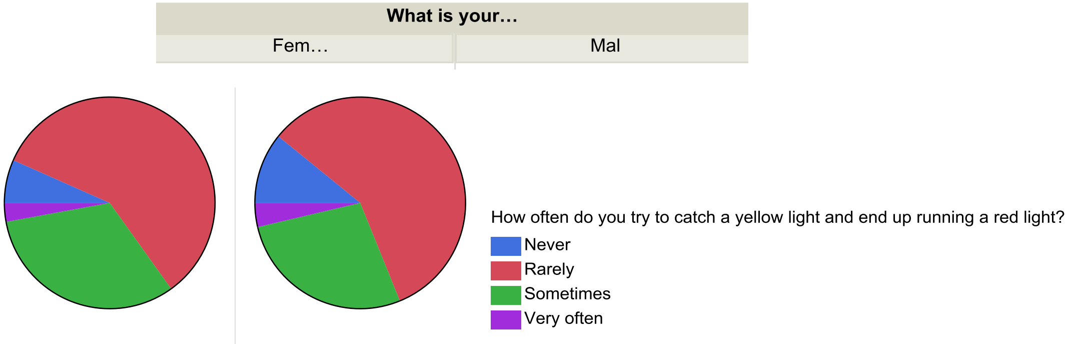


Figure 10: Gender disparities in how often drivers try to catch a yellow and end up running a red light.

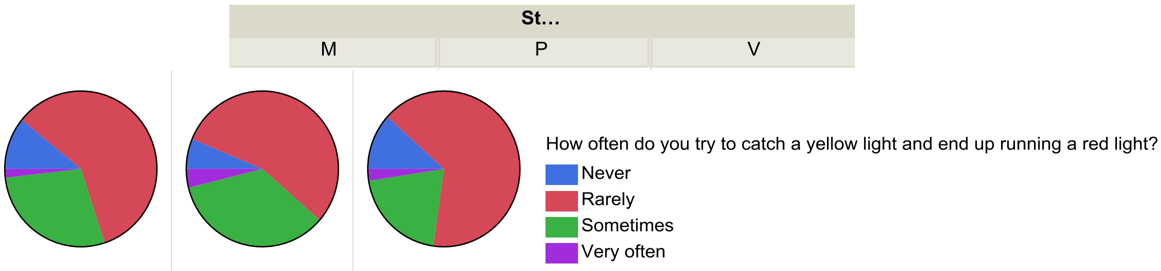


Figure 11: State disparities in how often drivers try to catch a yellow and end up running a red light.

Figure 12 depicts the distribution of the normal actions of participants when they see a yellow light. According to this figure, the decision of most drivers depends on other conditions, and 20% of them slow down.

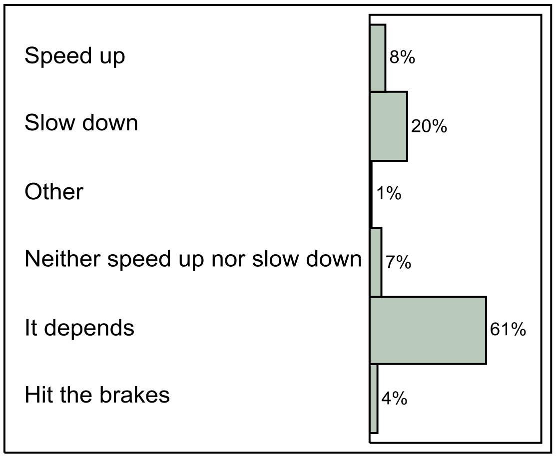


Figure 12: Distribution of responder's reaction while encountering a yellow light.

Figure 13 shows a bar chart of how long participants think yellow lights usually last. As shown in the figure, most participants assume that the yellow light duration is 3 seconds. However, looking at the next question, results indicate that 78% of participants have noticed that some yellow lights are longer or shorter than others.

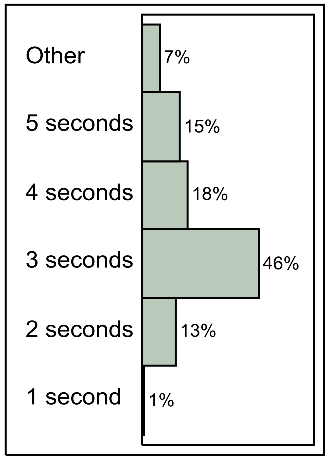


Figure 13: Distribution of drivers' understanding of yellow lights duration.

Open-ended question

In the last question, driver survey participants were asked to specify any experience or suggestions that they may have on the subject of "drivers' decision to stop or go at the onset of yellow light." The responses cover a wide spectrum of the recipients' points of view and experiences regarding this issue. General remarks are summarized below:

- Based on drivers' perception of yellow time duration and how long it has been since the light turned yellow, drivers estimate how much time they have to the end of yellow to pass through. Some drivers indicated that if they do not see the light turn from green to yellow (attentive drivers), they usually stop.
- Countdown units appear to be useful in assisting drivers with their prediction process. It has also been mentioned that pedestrian timers for the cross streets is used to anticipate whether a yellow light is likely. However, the effectiveness of countdown units is debatable as drivers may change their behavior based on this extra information, and try to use the yellow light as much as possible to proceed through and end up running red lights more.
- The dynamic nature of drivers' decisions is indicated in the responses. How well the drivers know the intersection (familiarity) (e.g., knowing that the intersection is set to have an all-red phase) and what they have experienced before affect their decisions. Drivers' awareness of different timing in various states or countries and specifying that

they follow cultural cues mentioned by participants emphasizes this dynamic nature. There are interesting responses in this regard, such as “If you don't know the intersection, and you see a yellow light, stop the first time and see how long the yellow is on for” and “If the light’s turned red by the time I'm under it, I take note so as to improve my gauge if faced with the same yellow light again.”

- Three types of flashing yellow lights were mentioned in the responses. The first one is the flashing yellow light located before the intersection to warn the approaching drivers that the light is going to turn yellow. Most drivers mentioned that they slow down and get ready to stop when they see it flashing. Although the majority of drivers found it helpful, some people believed it was confusing. The second flashing yellow light refers to the traffic light indicator flashing before (this one could also be flashing green instead) or after the solid yellow. Most people mentioned they prefer flashing yellow before terminal yellow. The third type is a flashing yellow phase which is set after red in some European countries.
- Some drivers are so cautious that they pause for a little or look both ways before proceeding when their light turns green due to the tendency of side street drivers to run red lights.
- One critical factor some drivers consider when deciding whether to stop or go is the amount of time they will need to wait until the next green, especially based on the degree of urgency, how much of a rush the drivers are in, and the value of time for them. This indicates how important it is to time the signals well, especially in a string of traffic lights. Long wait times in consecutive intersections and stopping at multiple red lights can make drivers impatient. Regarding this, one person stated that “If I have already stopped at a yellow light once in the last five minutes, I will be less likely to do so. Not sure why that happens, I just think it is unfair to have to stop at every consecutive light.”
- Although all lights’ red clearance time is considered helpful to avoid accidents, and it gives time to clear the intersection, there is an argument that it could tempt drivers to attempt to run the yellow more. It is because they think they are less likely to have problems and if they end up in the intersection for additional time, it is OK.

- Drivers try to make distance rules for themselves in order to ease the decision-making process. For example, some drivers tend to pick a “point of no return” when approaching intersections. That is, if they pass a certain point and the light turns yellow they decide not to stop. This point is determined based on their speed and perception of a safe stop. Apparently learned in driver education, for some drivers this point is the start of solid white line in the middle of two lanes. Another example of rulemaking is a response saying that “If you're more than 2-3 car lengths away from the light, you should stop instead of try to speed through.”
- It could also be helpful if there is a sign or roadway marking to show when it is safe to stop.
- The existence of a car behind, size and type of vehicle behind, decision made by the driver behind (being the same as the car in front or not), and how much attention the driver in back is devoting, is of concern to many drivers about a safe stop or going through without making problems for the followers.
- Hesitation in the decision of stopping or going through is as dangerous as the wrong decision. When a decision is made, some drivers believe it is better to not change your mind probably due to a small amount of time for the action.
- There are some other factors in addition to the ones in the survey that seem to be important, based on the responses. These include:
    - Presence of tractor trailers
    - Amount and type of cargo (heavy or fragile cargo like cake or sleeping baby)
    - If the oncoming vehicles are turning left crossing the through traffic
    - Personal knowledge of the driver on the car maintenance situation and tires (new or wearing)
    - Weather conditions affecting visibility
    - Time of day
    - Traffic patterns
    - Type of car (e.g., SUVs are harder to brake)
    - Driving a long vehicle (e.g., bus)
    - Driving behind a large truck that blocks vision

- Yellow catching for left turn increases if there is not a protected left-turn phase.
- An interesting strategy was indicated by one person, who stated: “I always slow down going into an intersection when the green is ‘stale’.” He gets ready for yellow even before its arrival.
- The importance of the training process and where it occurs is notable, since different states have different laws in the driving manual regarding proper action while encountering a yellow light. It could be helpful if this skill were tested during the licensing procedure. In addition to the training process, behavior at a yellow light could be country/culture related.
- Slamming on the brakes to avoid red light running causes such concerns as rear-end collision, loss of vehicle control (skidding), and stopping in the middle of the intersection.
- Although the survey results show that most drivers slow down or act dependent on the situation when they see yellow, the general belief by many people is that “other drivers speed up.”

Differences in timing plans in different states and countries and the necessity of mind adjustment are mentioned in the responses. Some drivers are interested in the existence of a standard timing plan that would be implemented everywhere.

Significant Factor Analysis

The most important question in the survey, in relation to this study, is the one inquiring about the factors that affect drivers’ decision at the onset of a yellow light. Contributing factors are numbered from 1 to 23 and described in

Table 2.

Table 2: Description of the factors

Factor number	**Factor description**
F1	Your speed
F2	Your distance to intersection
F3	Presence of passengers in the car
F4	Existence of yellow flashing traffic light
F5	Model (e.g., Toyota Camry, Ford Fusion) of the car you are driving
F6	Whether you are talking on the phone
F7	Whether it is night or day time
F8	Presence of a red light camera
F9	Presence of police
F10	Whether the pavement is wet or dry
F11	Presence of a vehicle in front of you
F12	Presence of a vehicle behind you
F13	Presence of a vehicle in the lane next to you
F14	Presence of a bicycle, pedestrian or vehicle in the side-street
F15	Whether the next traffic light is timed
F16	Whether the traffic is bad
F17	Existence of a countdown display to show the time of each traffic light color
F18	Whether you are tired, angry, or sad
F19	How well you know the intersection
F20	Whether it is a safe intersection
F21	Whether the intersection is at the bottom of a hill
F22	Whether the intersection is at the top of a hill
F23	Whether you've successfully beaten that red light in the past

The survey results summarized in

Table 3 show the percentage of participants who indicated that a given factor was influential in their decision at the onset of yellow. The factors are sorted in descending order based on overall selection percentage and are listed by state.

Table 3: Percentage of each factor selection by states

VA		PA		MD		All	
Factor	**Selection percentage**	**Factor**	**Selection percentage**	**Factor**	**Selection percentage**	**Factor**	**Selection percentage**
F2	97.15	F2	98.03	F2	86.82	F2	95.7955
F1	87.19	F1	93.26	F1	81.82	F1	89.7774
F11	69.40	F11	73.31	F10	64.09	F11	70.6513
F10	61.21	F10	60.25	F11	63.64	F10	61.1707
F12	48.04	F9	57.44	F8	47.27	F9	51.8549
F19	44.84	F19	49.86	F12	47.27	F12	47.4856
F9	43.42	F12	47.33	F9	44.55	F19	45.0124
F16	36.3	F16	45.37	F16	33.64	F16	41.1377
F14	23.84	F8	30.48	F19	29.55	F8	31.7395
F8	22.78	F14	29.35	F17	27.73	F14	27.2877
F17	21.00	F20	28.51	F14	25.00	F20	24.8969
F4	19.93	F21	26.4	F21	21.82	F21	22.8359
F20	19.93	F3	24.3	F3	19.55	F3	21.5993
F3	16.37	F7	22.61	F20	19.55	F4	20.3627
F21	14.59	F4	21.21	F4	18.18	F17	18.5491
F22	13.17	F18	20.37	F7	12.27	F7	18.3017
F18	12.81	F22	17.56	F22	11.36	F18	16.6529
F7	12.10	F15	16.15	F13	9.545	F22	15.4163
F15	11.03	F17	14.75	F15	9.545	F15	13.7675
F5	9.964	F23	12.92	F18	9.545	F23	11.4592
F23	9.964	F13	8.006	F23	8.636	F13	8.49134
F13	8.897	F5	6.882	F5	4.545	F5	7.1723
F6	4.982	F6	5.056	F6	3.182	F6	4.69909

Figure 14 shows the results of

Table 3 in bar chart format. In each bar chart, a dropping point can be recognized that indicates where there is a significant change in drivers' perception of factors being influential to their decision. These points are shown by circles in Figure 14. Factors located below the dropping points are considered significant.

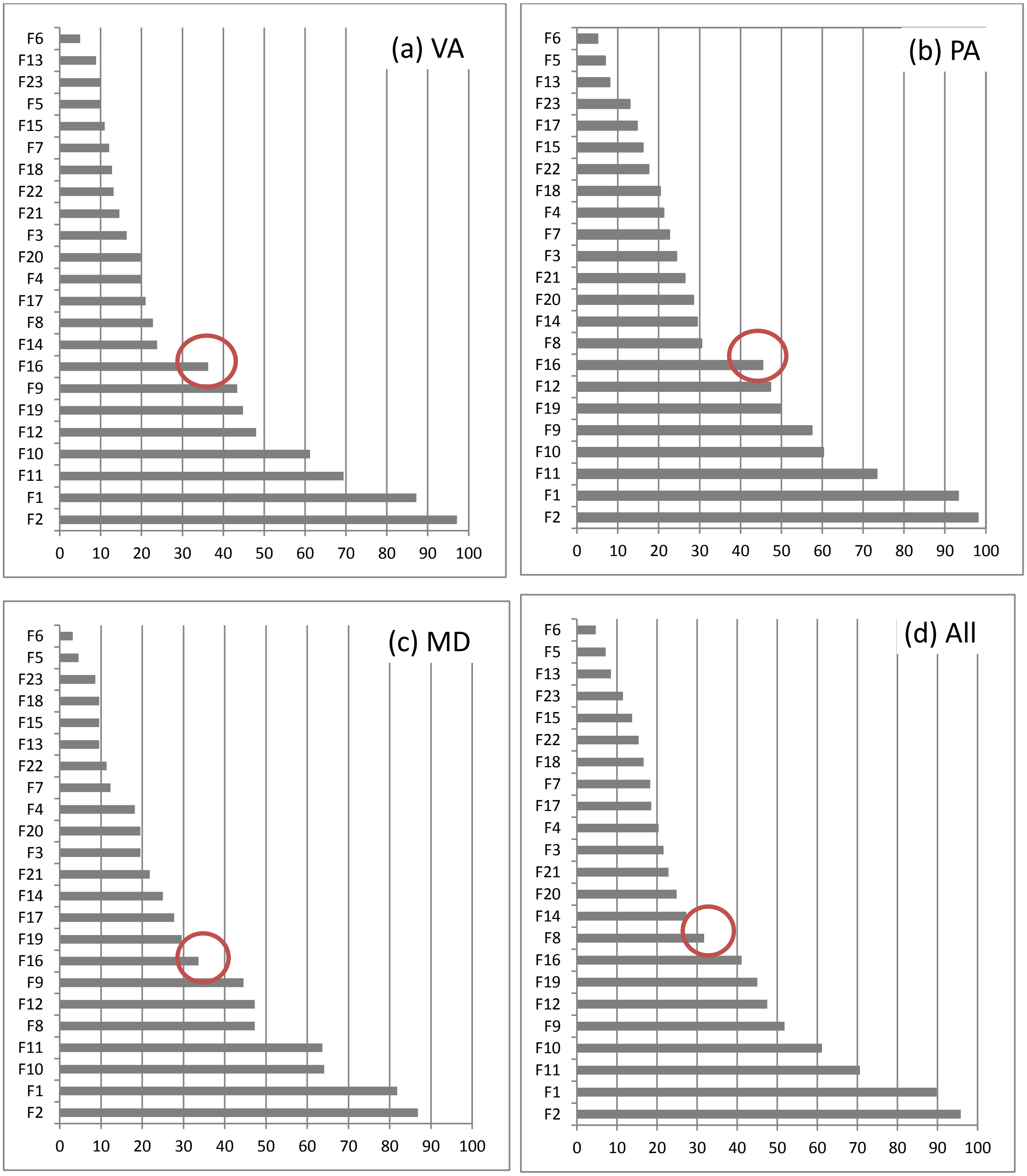


Figure 14: Bar chart of factor selection by states.

Table 4 summarizes the results of the significant factor recognition process described above. Among nine significant factors, seven are overlapped in all states. Factor number 8 is considered significant for Maryland as opposed to factor number 19, which does not show a high selection percentage for this state as it does in other two states.

Table 4: Significant factors

Factor	Factor Description	States			
		All	VA	PA	MD
F1	Your speed	x	x	x	x
F2	Your distance to intersection	x	x	x	x
F8	Presence of a red light camera	x			x
F9	Presence of police	x	x	x	x
F10	Whether the pavement is wet or dry	x	x	x	x
F11	Presence of a vehicle in front of you	x	x	x	x
F12	Presence of a vehicle behind you	x	x	x	x
F19	How well you know the intersection	x	x	x	
F16	Whether the traffic is bad	x	x	x	x

A hypothesis, two-proportion z-test was conducted to determine whether the difference between two states' proportions is significant. If P_1 and P_2 are two population proportions, then the null and alternative hypotheses are the following:

H_0: $P_1 = P_2$ (there is no difference in proportions)

H_a: $P_1 \neq P_2$ (there is a difference in the proportions)

The significance level of 0.05 was chosen. Pooled sample proportion was calculated as $p = (p_1 * n_1 + p_2 * n_2) / (n_1 + n_2)$ where n_1 and n_2 are sample sizes. Standard error is also computed using the equation $SE = \sqrt{p * (1 - p) * [(1/n_1) + (1/n_2)]}$. Then, Z-score is equal to $z = (p_1 - p_2) / SE$. Corresponding p-value is compared to the significant level to reject the null hypothesis when the P-value is less than the significance level.

Table 5 summarizes the results of two-proportion z-tests for significant factors among different states. P-values less than the significance level are highlighted, indicating that the null hypothesis (P1 = P2) is rejected. As shown in the table, only the proportion of factors number 10 and 12 are not significantly different among the three states.

Table 5: Result of two-proportion z-test

Factor	**Factor descriptions**	**State pairs**					
		VA & PA		**VA & MD**		**MD & PA**	
		z-score	**p-value**	**z-score**	**p-value**	**z-score**	**p-value**
F1	Your speed	-3.1	0.0019	1.663	0.0963	-5.07	0.0001
F2	Your distance to intersection	-0.85	0.3953	4.39	0.0001	-6.93	0.0001
F8	Presence of a red light camera	-2.43	0.0151	-5.76	0.0001	4.582	0.0001
F9	Presence of police	-3.99	0.0001	-0.25	0.8026	-3.36	0.0008
F10	Whether the pavement is wet or dry	0.278	0.7810	-0.66	0.5093	1.021	0.3073
F11	Presence of a vehicle in front of you	-1.24	0.2150	1.356	0.1751	-2.77	0.0056
F12	Presence of a vehicle behind you	0.202	0.8399	0.171	0.8642	-0.02	0.9840
F19	How well you know the intersection	-1.43	0.1527	3.498	0.0005	-5.29	0.0001
F16	Whether the traffic is bad	-2.6	0.0093	0.62	0.5353	-3.07	0.0021

Based on the above-mentioned analysis, the following nine factors are considered to be significant factors in drivers' perception and decision at the onset of yellow indication:

1. Speed
2. Distance to intersection
3. Presence of a red light camera
4. Presence of police
5. Whether the pavement is wet or dry
6. Presence of a vehicle in front of the subject car
7. Presence of a vehicle behind the subject car
8. How well the driver knows the intersection
9. Whether the traffic is heavy

In addition to these factors, the scenario development could benefit from some additional factor considerations mentioned by survey participants in the “comments and recommendations” section of the questionnaire. These factors include:

- How much of a rush the drivers are in
- The amount of time they should wait until the next green
- If the driver sees the yellow light turning moment or not
- Presence of tractor trailers or large trucks

It should be noted that pairwise correlations were also conducted to investigate the correlation between each pair of factors for different states. The purpose of this was to analyze if any two factors are likely to be selected together by survey respondents. The results show a correlation between factor numbers 21 (whether the intersection is at the bottom of a hill) and 22 (whether the intersection is at the top of a hill) in all three states. Moreover, for Maryland and Virginia, factor numbers 8 (presence of a red light camera) and 9 (presence of police) are correlated. These two latter factors are recognized as significant, as mentioned above. Therefore, the correlation of these factors should be taken into account in the design of scenarios. It is also notable that none of the factors located below the dropping points shown in Figure 14 is correlated with the factors above the dropping points.

CHAPTER 3: DRIVING SIMULATOR STUDY

This part of the report presents the development of an experimental design of a driving simulator study. The objective is twofold: to investigate the dynamic nature of drivers' perception of the dilemma zone and to assess significant factors affecting driver's decision at the onset of yellow using the results of the survey study explained in the previous part.

Experimental design of driving simulator experiment

Experimental units

An experimental unit is the unit of experimental material to which the experimental factor is applied. In our driving simulator study, experimental units are intersections. Factors that are assigned to intersections are explained in the following section.

Driving simulator factors

<u>Intersection factors</u>

Five significant factors were used in the scenario development of the driving simulator. These factors, referred as intersection factors, and their associated levels are shown below:

- Time to intersection (TTI) at the onset of yellow (s)
    - Levels: 2.5, 3.5, 4.5
- Presence of police
    - Levels: Yes, No
- Pavement condition
    - Levels: Wet, Dry
- Other vehicle around
    - Levels: No Vehicle, Back
- Presence of side-street queue
    - Levels: Yes, No

<u>Experiment adaptation factor</u>

To investigate the drivers' learning process, three hypotheses were tested according to Table 6. The experiment situation and rationale behind the hypotheses are also explained in the table.

Table 6: Experiment adaption situations and rationale

Situation	Experiment Adaptation	Rationale	Hypothesis Tested
1. The signal is green. There is a platoon 4 sec ahead of the subject vehicle. The driver slightly slows down after the platoon clears the signal anticipating that the green might end due to the large gap.	Extend the green until driver passes	Simulate a situation where the signal has a DZ protection system (where the signal monitors whether there is a driver in the DZ, and if there is one, the green gets extended until the driver clears the DZ).	Driver behavior remains the same at following intersections after being exposed to DZ protection.
2. Yellow is presented at different driver's TTIs			
2.a. Driver decides to stop.	Increase yellow duration while the driver is waiting at the stop bar.	Investigating whether the driver would regret the decision to stop given the long yellow that they see and behave differently at the next intersection.	Driver behavior remains the same at following intersections even after the yellow treatment.
2.b. Driver decides to pass.	Decrease yellow duration so that the driver ends up running the red light (and triggering the red-light-running camera flash).	Investigating whether the driver would regret the decision to pass given the short yellow that they see and behave differently at the next intersection.	Driver behavior remains the same at following intersections even after the yellow treatment.

These hypotheses are introduced as "experiment adaptation factor" in the experimental design. Two levels of "do nothing" and "do something" are assigned to this factor with the following explanation:

- Do nothing: means that no experiment adaptation is implemented and normal yellow duration is followed (4.5 seconds).
- Do something: means that one of the experiment adaptations (shown in Table 6) is implemented depending upon driver's action.

Figure 15 illustrates the flowchart of the "experiment adaptation factor" and associated signal settings based on driver's behavior.

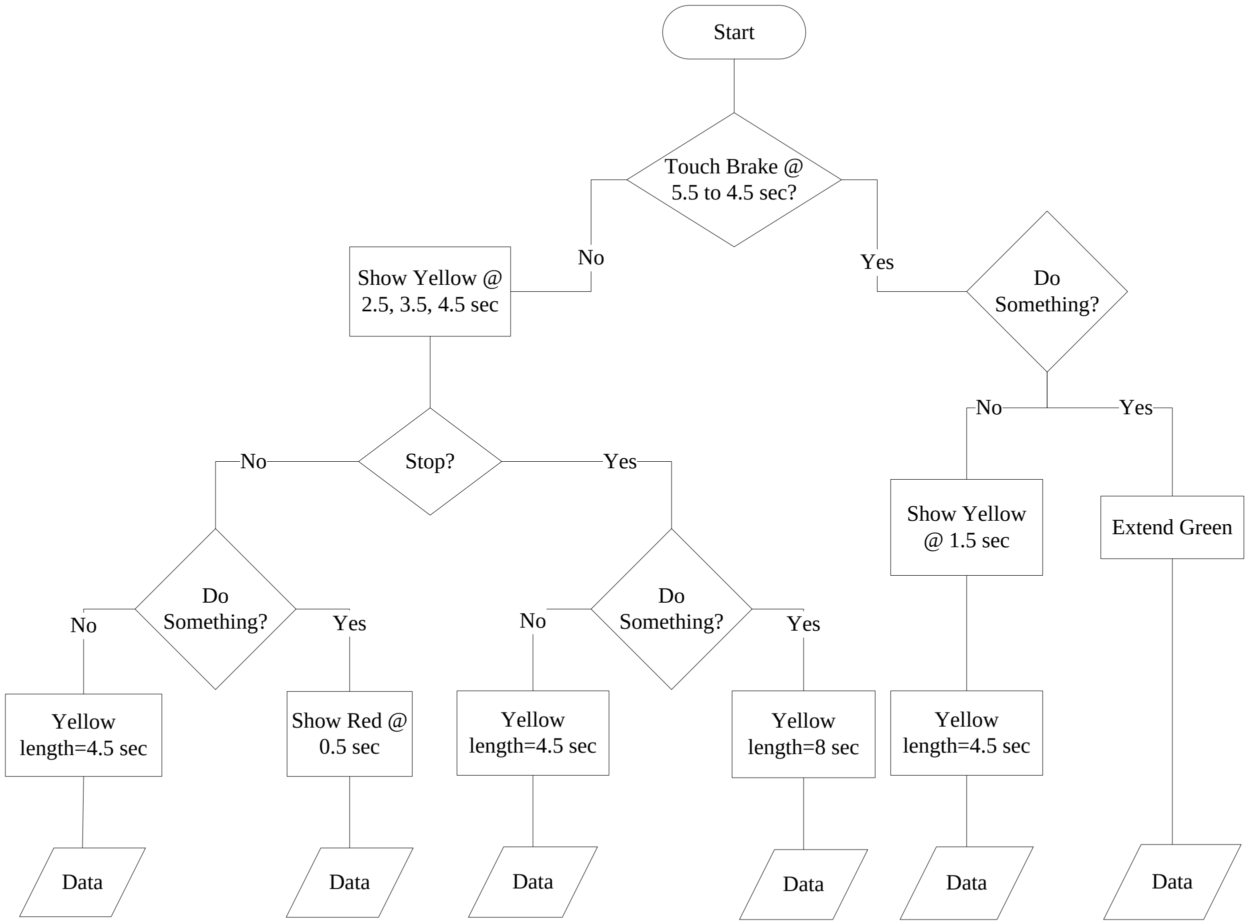


Figure 15: Flowchart of the experiment adaptation.

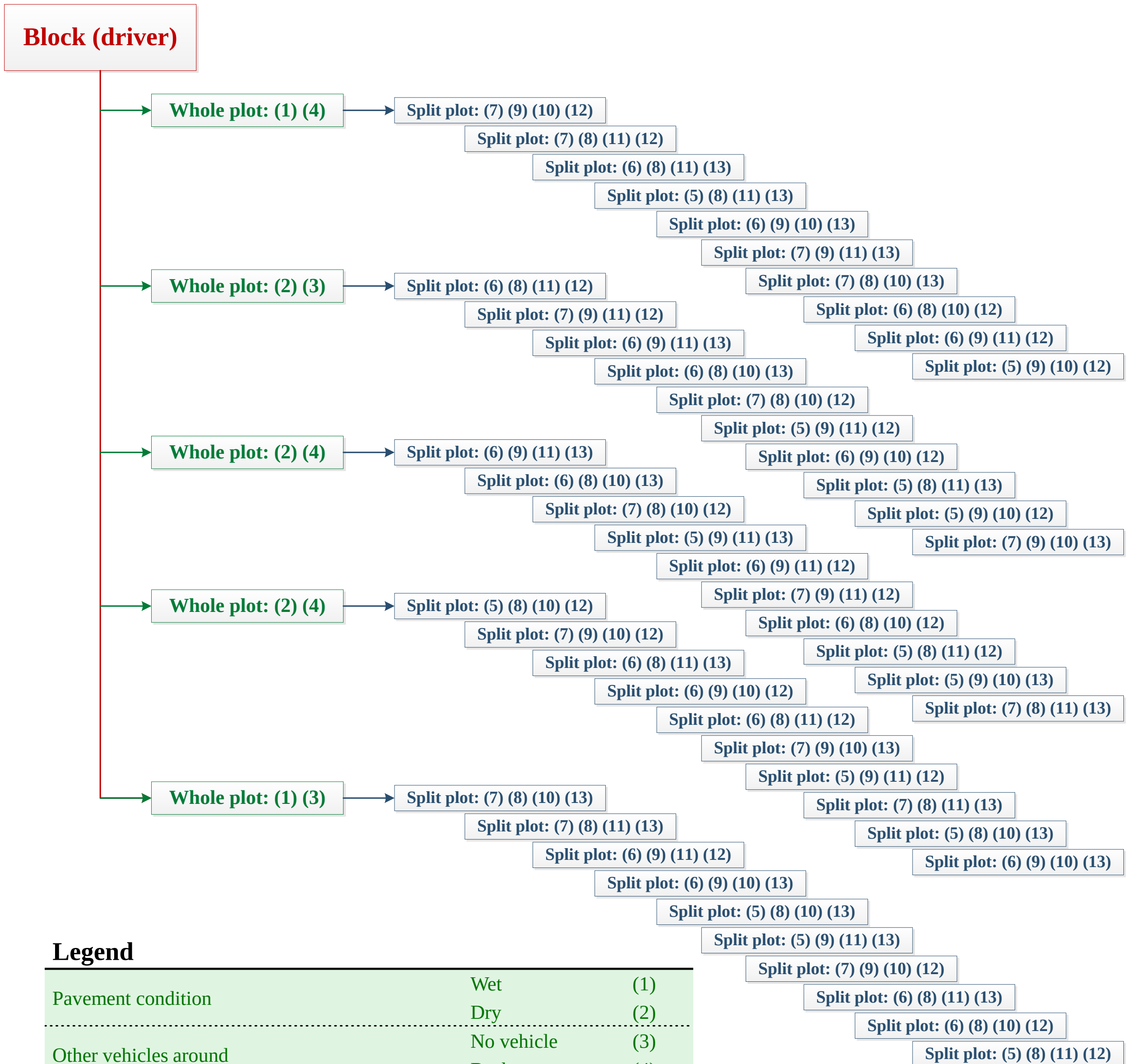
Adaptive Randomized Incomplete Block Split-plot Design

The experimental design of this study is complex due to “the high number of factors and levels,” “several drivers to run the experiment as oppose to one experimenter,” and “factors that are hard to change through one session of driving.” To account for these complexity issues, the following design specifications are considered.

“Fractional factorial design**”** is considered to account for the high number of factors and levels (combinations). In fractional factorial design, only a fraction of the possible combinations are actually used in the experiment. In this study, the main effects and second-order interactions are taken into account in determining the number of runs.

The second challenge is to have several drivers run the experiment instead of one experimenter. Since each driver has a specific driving behavior, it is expected that the driver might have a significant effect on the hypotheses testing. To account for this, a **"**randomized block design**"** is considered having drivers as blocking factors.

To overcome the issue related to the factors that are hard to change during one session of driving ("pavement condition" and "other vehicle around"), a "split-plot design" was used. Two groups of factors were considered in this kind of design: whole-plot factors associated to hard-to-change factors and split-plot factors corresponding to other factors. In this driving simulator study, whole plots were sequential intersections forming a signalized corridor, whereas each intersection was considered as a split plot. It was impossible to randomize in every block (for each driver) since that would have required specific driving simulation settings of scenarios for every driver, so randomization was carried out among the whole plots. This Adaptive Randomized Incomplete Block Split-plot design was implemented using JMP Pro 10.0.0 software from SAS [94]. The minimum number of runs and whole plots were found to be 35 and 5, respectively. Based on that, seven intersections are needed in each corridor (35/5=7). The research team decided to increase it to 10 to increase the power in the statistical analysis. Figure 16 illustrates the experimental design structure including level of the factors to be implemented at each intersection.



Legend

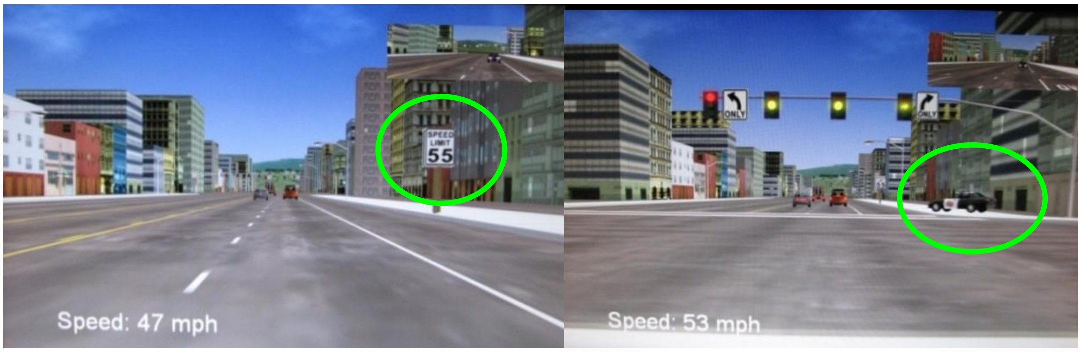
Pavement condition	Wet	(1)
	Dry	(2)
Other vehicles around	No vehicle	(3)
	Back	(4)
Time to intersection (TTI) at the onset of yellow (s)	2.5	(5)
	3.5	(6)
	4.5	(7)
Presence of police	Yes	(8)
	No	(9)
Presence of side street queue	Yes	(10)
	No	(11)
Experiment Adaptation Factor	Do nothing	(12)
	Do something	(13)

Figure 16: Structure of the experimental design.

Scenario implementation in the driving simulator

A DriveSafety DS-250 model driving simulator (fixed-based with no motion cues) was employed in the study (see Figure 17). The simulator contains three major components, namely Vection™ (high-fidelity, real-time driving simulation software), HyperDrive (advanced scene and scenario authoring tool set), and Dashboard (software that interfaces with Vection™ and HyperDrive). Running scenarios were carried out by the main software component of the simulator (Vection™). Scenario development was implemented using the HyperDrive component of the simulator. HyperDrive includes some database elements such as signage, pedestrian, street items, and road tiles that constitute the basic environment of the design. Figure 18 illustrates how different factors and events were implemented in the simulator environment. More complex settings and elements such as signal status setting and driver's behavior monitoring were implemented by scripting using TCL (Tool Command Language).

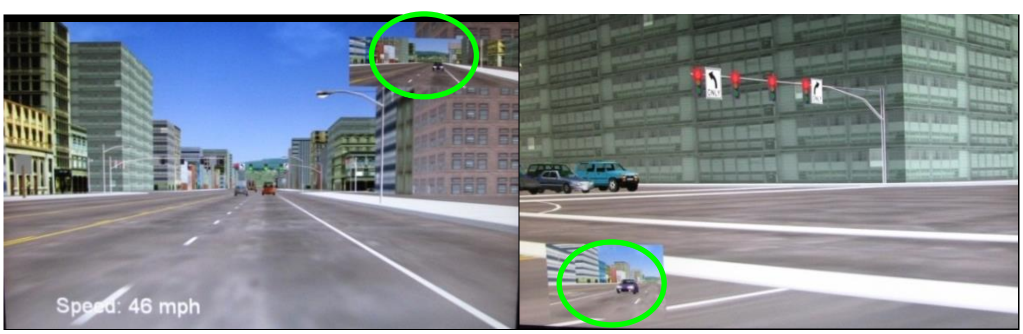
Figure 17: Driving simulator.



a) Speed limit b) Police car

c) Signal status

d) Other vehicles

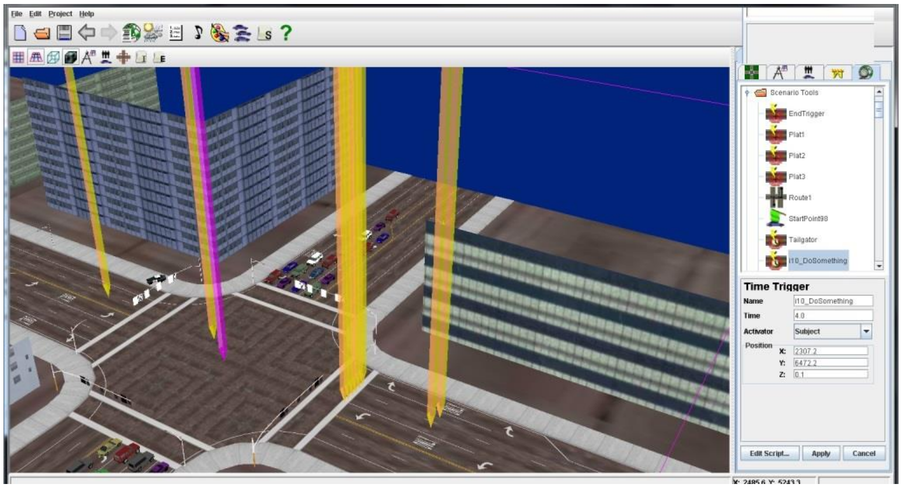


e) Vehicle in the back

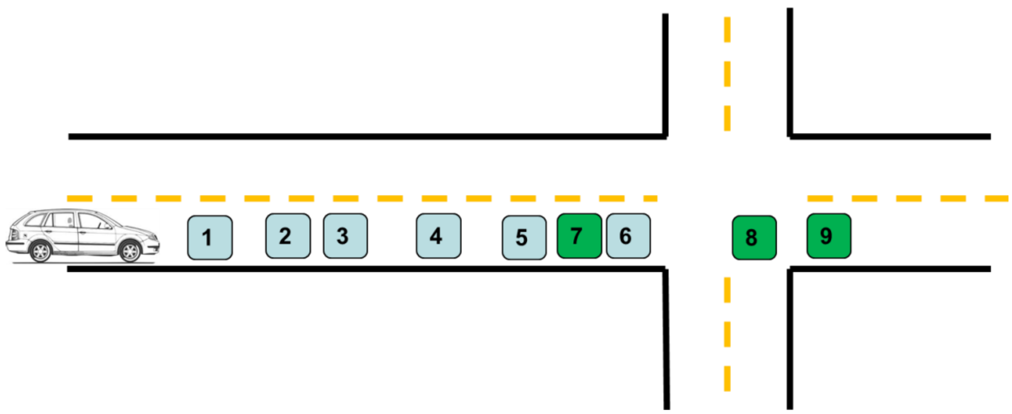
Figure 18: Simulator environment and scenario specification.

Specific events happening at a certain time or location were modeled using time and location triggers. Time triggers and location triggers were created and programmed appropriately to account for these events. In total, three location triggers and one time trigger were created at the start of each scenario, and six time triggers and three location triggers were implemented at each intersection. Triggers at each intersection are shown in Figure 19. Figure 19-a shows what the layout looks like in HyperDrive environment, and Figure 19-b provides a plan of triggers' sequence (time triggers and location triggers are colored differently; green shows location triggers and light blue is associated with time triggers). Applications of these triggers are summarized below.

1. DoSomething time trigger: 6 sec ahead of the intersection to set up initial values of the variable for each intersection
2. TouchBrakeStart time trigger: 5.5 sec ahead of the intersection to start tracking the vehicle for brake touching
3. TouchBrakeEnd time trigger: 4 sec ahead of the intersection to stop tracking the vehicle for brake touching
4. YellowSignal time trigger: 4.5, 3.5, or 2.5 sec ahead of the intersection to alter the signal status from green to yellow.
5. YellowSignalTouchBrake time trigger: 1.5 sec ahead of the intersection to alter the signal status from green to yellow
6. RedLightRunner time trigger: 0.5 sec ahead of the intersection to alter the signal status from yellow to red
7. StopGoDecision location trigger: 17 meters ahead of the intersection to identify driver's decision of stopping or going
8. CameraFlash location trigger: a short distance beyond the middle of the intersection to show camera flash and sound
9. AfterIntersection location trigger: immediately after the intersection to stop monitoring procedures



a) HyperDrive Layout



b) Trigger Sequence

Figure 19: Triggers layout.

To adapt the experiment based on drivers' behavior, one needs to know the decision going to be made by the driver sometime between the onset of yellow and the RedLightRunner time trigger. Based on initial analysis and experimentation, the research team came up with a combination of two mechanisms to identify drivers' decision to stop or go:

- A timer procedure was activated between the yellow indication time and the minimum yellow time duration (4.5 seconds). If the amount of time lost or gained by drivers compared to time associated with constant speed is less than a threshold (-0.2 sec in this study), the driver is stopping.

- A location trigger was activated before the stop line (17 meters upstream). A vehicle is considered to be stopping if the time lost or gained is less than -0.2 sec, or both speed and deceleration are respectively less than 25 m/s and 0 m/s^2.

Driving simulator data were obtained from two sources: built-in data (i.e., variables are selected from a predefined list) and user-defined data (i.e., variables are defined by user in the script).

Experiment procedure

To verify the design of the experiment, a pilot study was conducted first. Six volunteer participants performed the pilot study. All were licensed drivers older than 18. Upon arrival, participants read and signed an informed consent form. The information in the consent form was very general to avoid biasing the participants. A sample of the consent form is provided in Appendix B. They were then given a short questionnaire asking about their age, gender, race, and driving experience. Then they were led to the driving simulator, and progressed to the adaptation drive session lasting for 5 minutes. The adaptation and training drive was a world consisting of roadways similar to the experimental worlds. It was employed so that the participants were familiarized with the driving simulator and became comfortable with handling the car. They were asked to drive as they normally would in the real world. The study included 5 scenarios (each one contains 10 intersections) and lasted no more than 45 minutes. Of the 300 intersections driven by the participants, 5 attempts to slow down happened between 5.5 and 4.5 seconds upstream of the intersections. Experiment adaptation factor for four of these five had the "do something" setting resulting in green extension. Therefore, 296 intersections turned yellow at the driver's arrival. The location trigger to check for a stopping or going decision was activated 222 times, leaving the remaining 74 for the timer procedure to recognize the decision. The real decisions of the drivers at the intersections were compared to the recognized decision by these two mechanisms. It appeared that they were successful in recognizing the correct decision 97.3% of the time (only 8 out of 296 were incorrect).

Based on the feedback received from pilot drivers, the number of signals changed to yellow at each corridor, including 10 intersections, was reduced to 7 instead of all 10 so that drivers don't predict signal change at every intersection.

For the main study, thirty six drivers volunteered to participate. Generally, in simulator studies, simulator sickness is an important issue, with 5% to 80% of participants experiencing some level of discomfort, dizziness, or nausea [95]. In this study, two participants withdrew from the study due to this issue.

Data were recorded with the precision of 60 Hz and included speed, longitudinal acceleration, vehicle x and y coordinates, time, signal status, and active triggers. A Matlab script was written to manipulate the recorded data and analyze it. Similar to the design of the experiment, JMP Pro 10.0.0 software from SAS was used for the statistical analysis.

Results

In many dilemma zone studies, drivers' decision to stop or go is treated as a binary variable and statistical models are constructed based on that. In addition to drivers' decision to stop or go, drivers' change in behavior is also important to consider. For example, do drivers stop by hitting the brake hard or choose to stop very smoothly? Do they pass through the intersection while speeding up, or does the presence of police make them keep their speed under the speed limit? Do they pass through with a constant speed rather than accelerating after getting exposed to a long yellow treatment? Mean speed was used as a surrogate measure to reflect the process of stopping or going and to capture any behavioral change of driver beyond just stopping and going. This measure is calculated from the speed profile starting at the onset of yellow and finishing at the end of the decision termination point (stopping point for stopping vehicles and right after intersection for passing ones). Figure 20 shows the relationship between "mean speed" and drivers' stop/go decision. As the figure illustrates, drivers' stop/go decision is distinguishable with mean speed, verifying that mean speed is an appropriate representative for stop/go decisions.

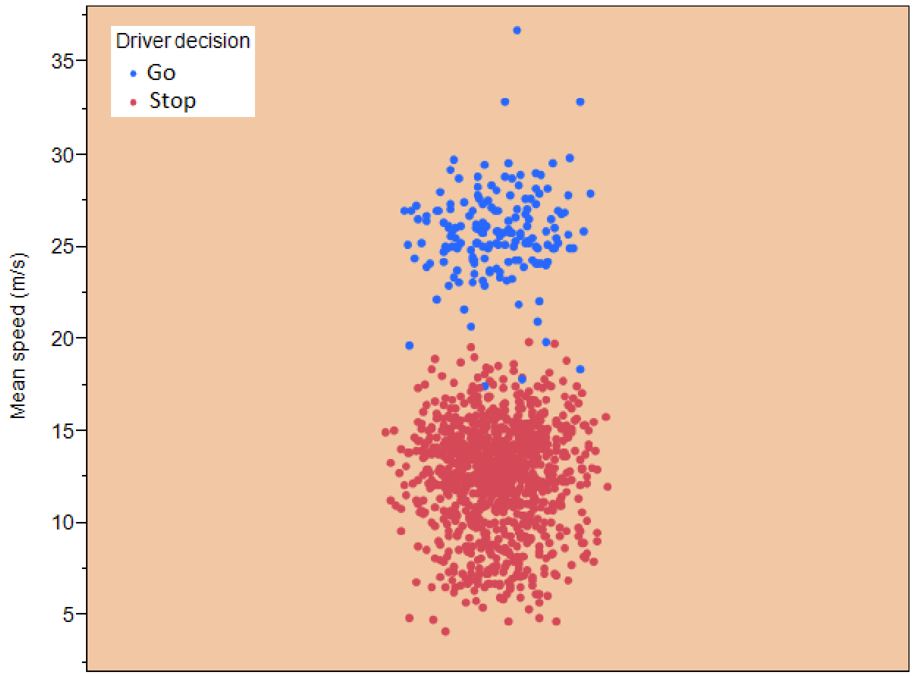


Figure 20: mean speed color-coded with stop/go decision

The mean speed variable was used as the response variable in the statistical model construction. Model effects are driver number, time to intersection (TTI) at the onset of yellow, presence of police, pavement condition, other vehicle around, and presence of side street queue, and variables associated with learning hypothesis explained in Table 6. The hypotheses were as following:

- Hypothesis 1: Driver behavior remains the same at following intersections after being exposed to DZ protection.
- Hypothesis 2: Driver behavior remains the same at following intersections even after the yellow treatment (increased yellow duration).
- Hypothesis 3: Driver behavior remains the same at following intersections even after the yellow treatment (decreased yellow duration).

Associated with each hypothesis, an independent variable was generated starting from 0 for each driver. The value of the variable was incremented by 1 unit each time the driver went under the treatment related to that hypothesis (to capture the effect of reinforced learning, if any). Also, a binary variable called “DoSomething” was included in the model corresponding to “Do something” and “Do nothing” as explained before.

The significance of these factors is examined through the constructed model presented later in this section, but to understand the relationship between response variable and these factors, some examples are discussed here. Figure 21 shows the correlation between TTI and mean speed in that as TTI goes down, drivers are more likely to proceed through, and mean speed increases. Figure 22 and Figure 23 both show learning (long yellow treatment) correlation with mean speed (Figure 23 is by TTI). According to these figures, as drivers are more exposed to the long yellow they are more likely to stop. The reason could be they lose their trust to their own judgment and act more cautiously. However, that’s a generalized result considering all drivers together. The results of individual drivers are shown in Figure 24, depicting the decision to stop and go in relation to learning (long yellow) for different drivers. For example, drivers numbered 11, 16, and 21 exhibited behaviors in line with the general result deriving from all drivers, in that as the learning variable goes up on the y-axis, the decision to go reduces. In contrast, driver number 25 shows a reverse trend to the general result, meaning that as this driver is more exposed to a long yellow, he/she tends to pass through the intersection more. Some of the drivers like number 13 seem not to change their behavior as they experience the learning scenario.

As explained before, to avoid having the comparison of factors distorted by the differences in drivers, they are considered as blocking factors. In line with this specification, driver characteristics such as state, age, and gender are assumed to be embedded inside the driver number variable. Figure 25 and Figure 26, respectively, illustrate the relationship between age and gender with mean speed. It seems that age has a correlation with mean speed in that as age goes up, the decision to go reduces, indicating that older drivers are willing to stop more than younger ones. Unlike age, no obvious relationship is observed between gender and mean speed. Figure 27 shows the difference between various states. No difference is recognized among states in choosing stop and go alternatives.

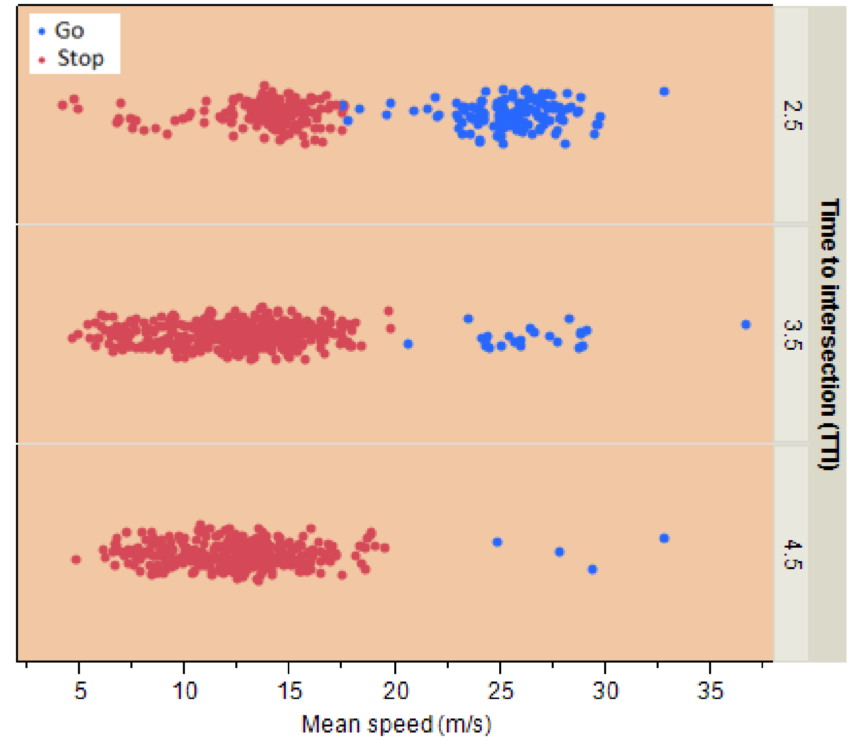


Figure 21: Mean speed versus TTI, color-coded by stop/go decision

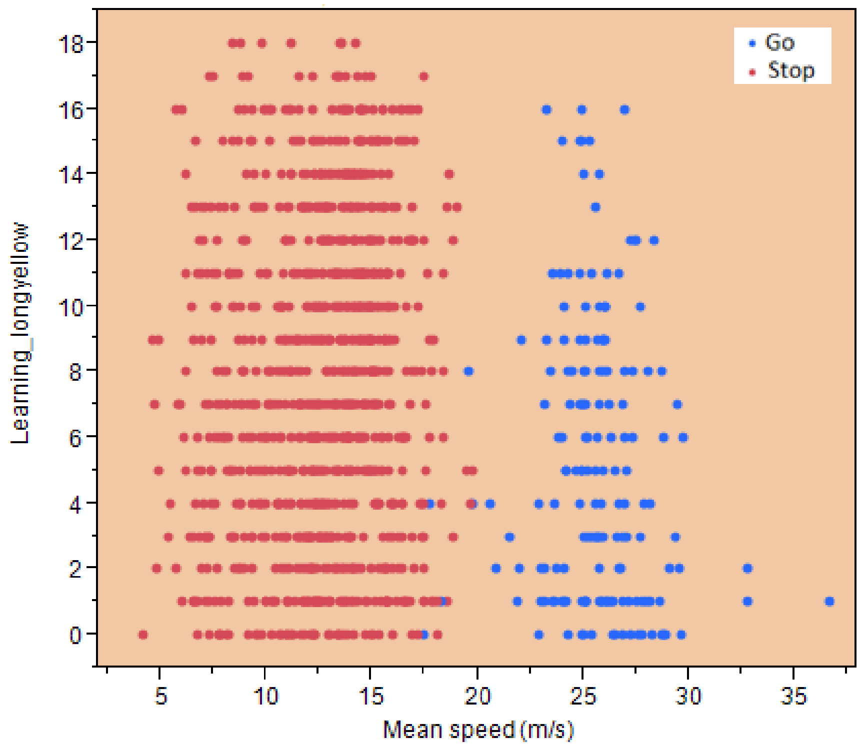


Figure 22: Mean speed versus learning_long yellow, color-coded by stop/go decision

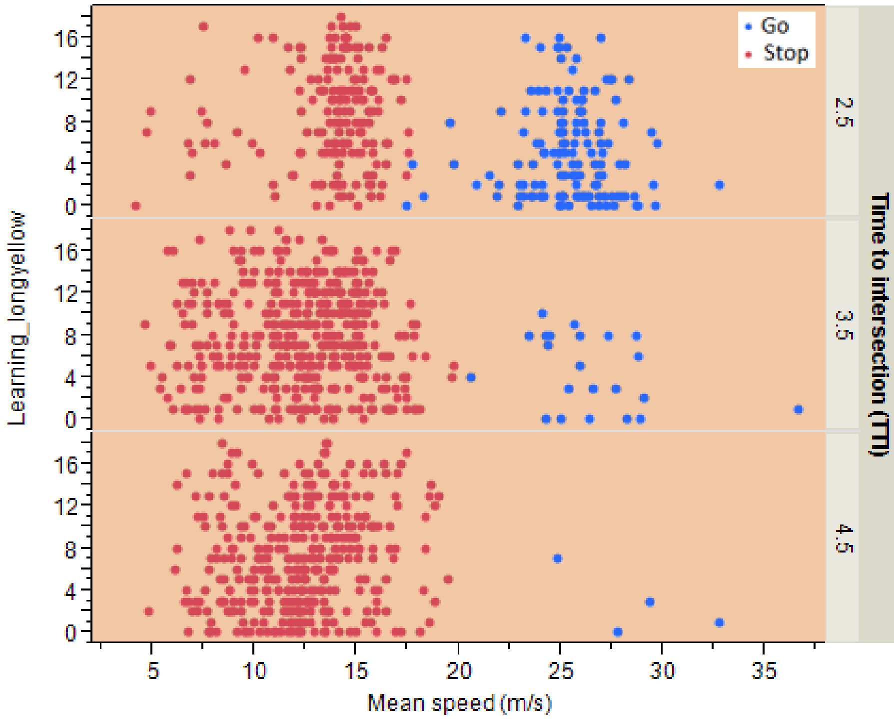


Figure 23: Mean speed versus learning_long yellow, color-coded by stop/go decision and categorized by TTI

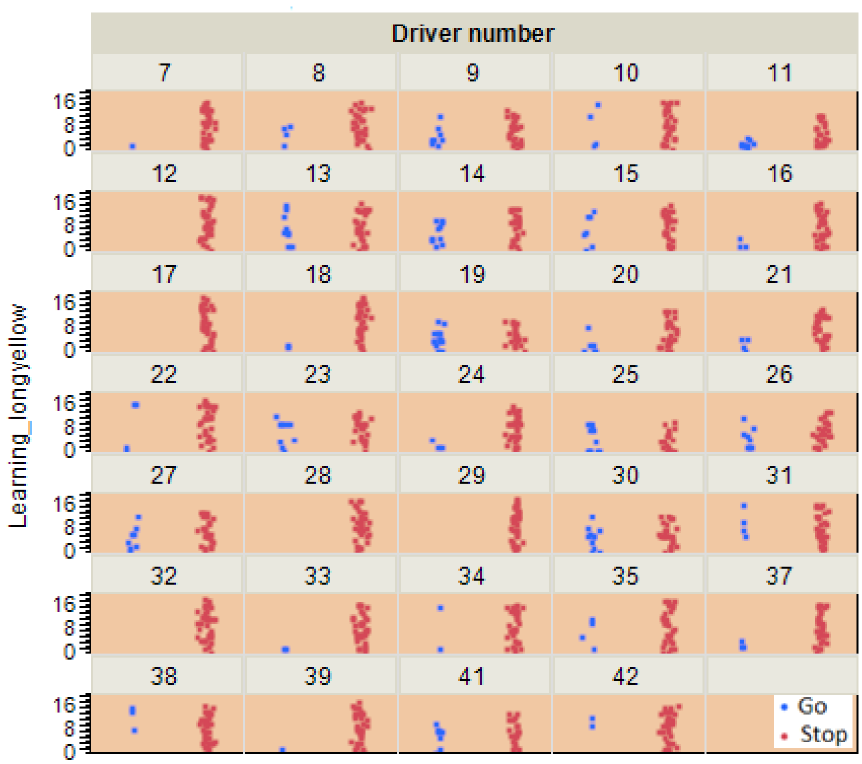


Figure 24: Learning_long yellow versus driver's decision for individual drivers

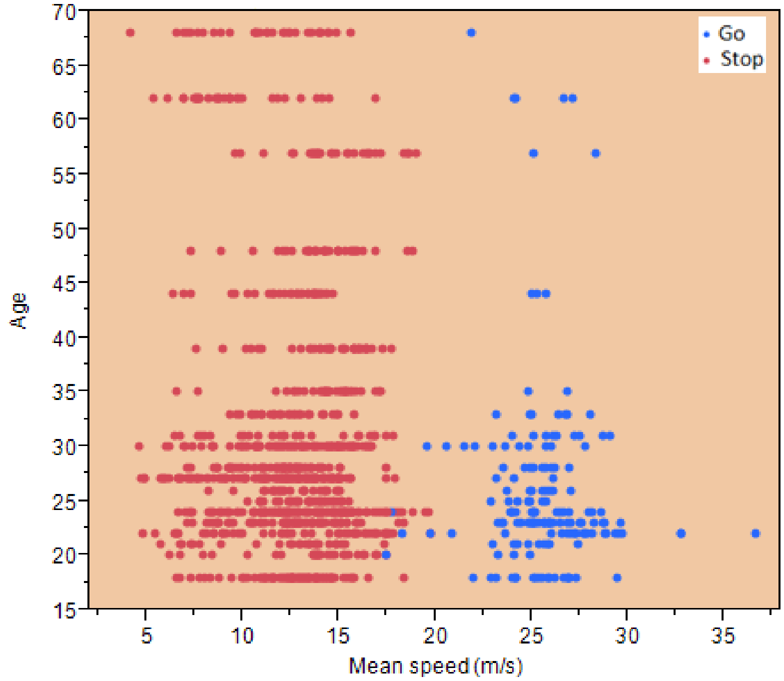


Figure 25: Mean speed versus age, color-coded by stop/go decision

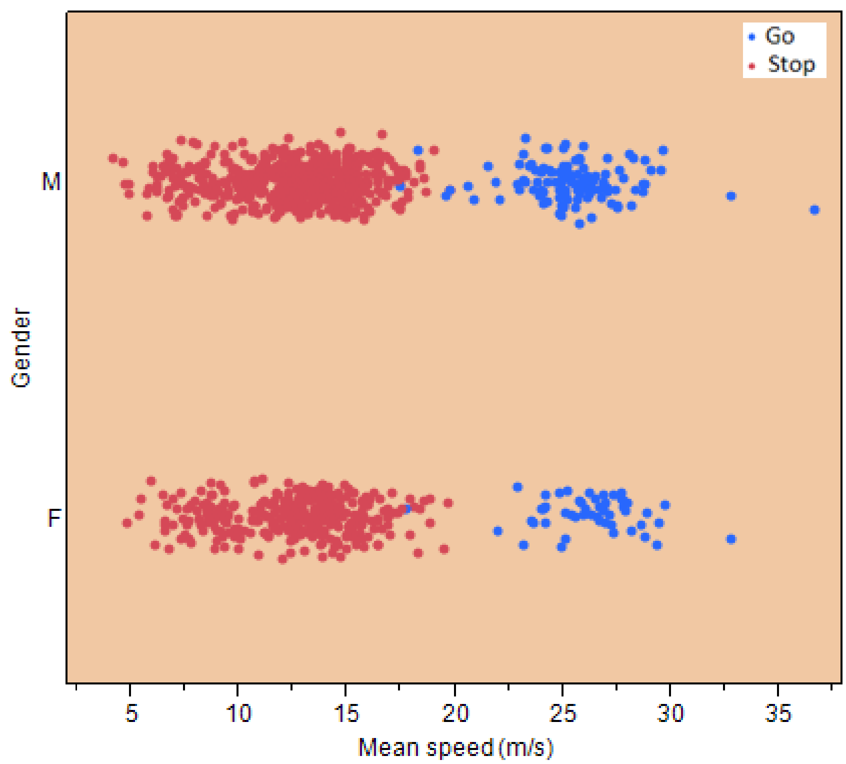


Figure 26: Mean speed versus gender, color-coded by stop/go decision

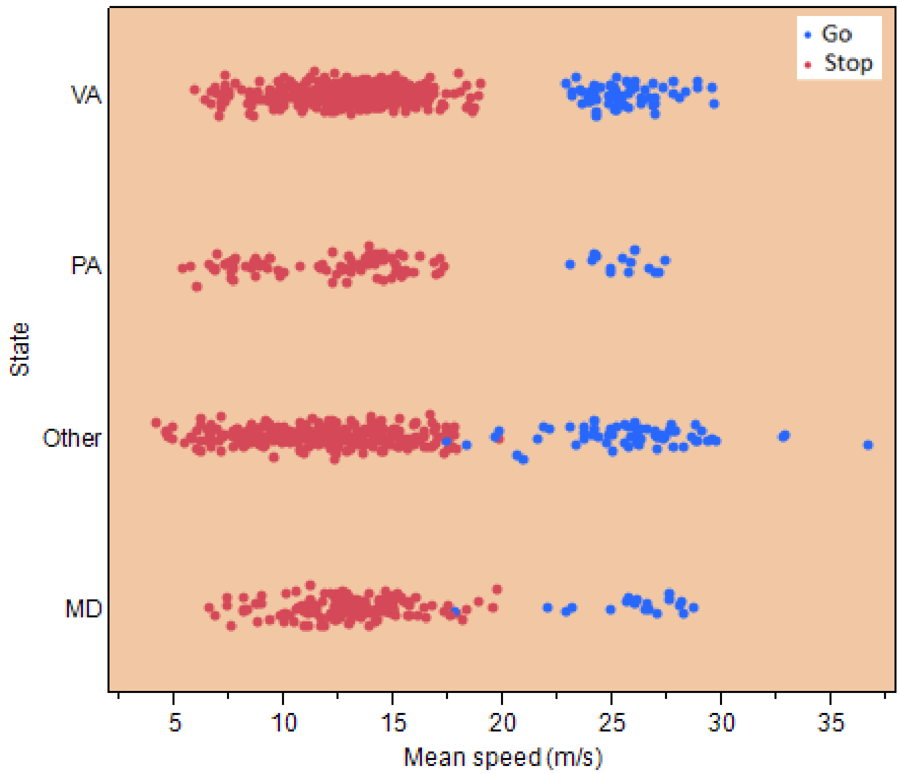


Figure 27: Mean speed versus state, color-coded by stop/go decision

Driver number is considered a random effect, meaning that the effect of the driver is regarded as a random sample of the effects of all the drivers in the full population of drivers. In this study, drivers are representative of a whole population of drivers and the results of the analysis must generalize to them. Therefore, any interaction between driver number and other variables are also random effect. To comply with the design of the experiment, a second-order interaction between whole plot and split plot factors were considered. Learning variables were also regarded as nested in the "do something" variable.

Restricted Maximum Likelihood (REML) analysis was used in this study for fitting linear mixed models (containing both random and fixed effects). REML Variance Component Estimates are shown in Table 7**Error! Reference source not found.**. Random effects are listed in the first column. The second column indicates the ratio of the variance component for the effect to the variance component for the residual, comparing the effects' estimated variance to the model's estimated error variance. The highest variance ratio belongs to the interaction of the driver number and TTI variable.

The fixed-effect test is summarized in Table 8. Looking at the p-value in the last column of this table, Pavement condition, TTI, Presence of police*TTI, Presence of side street queue*TTI, Learning (RLR), and Learning_long yellow have significant effects on the response variable at the p=0.05 rate. Based on the learning factor significance result, drivers' behavior was found to significantly change after being exposed to red light running and long yellow treatments.

Table 7: REML variance component estimates

REML Variance Component Estimates

Random Effect	Var Ratio	Var Component	Std Error	95% Lower	95% Upper	Pct of Total
Driver number	0.1127187	1.8815599	1.0110349	-0.100032	3.8631519	8.266
Driver number*Presence of police	0.0343886	0.5740331	0.3886098	-0.187628	1.3356943	2.522
Driver number*Presence of side street queue	0.0207026	0.3455783	0.3413003	-0.323358	1.0145146	1.518
Driver number*Pavement condition	0.0231175	0.3858903	0.3519337	-0.303887	1.0756675	1.695
Driver number*Time to intersection (TTI)	0.152042	2.5379663	0.828681	0.9137814	4.1621512	11.150
Driver number*Other vehicle around	0.0206223	0.3442381	0.3592466	-0.359872	1.0483484	1.512
Residual		16.69253	0.762682	15.293043	18.294335	73.336
Total		22.761796	1.4088532	20.234509	25.796632	100.000

-2 LogLikelihood = 6810.2225052

Note: Total is the sum of the positive variance components.

Total including negative estimates = 22.761796

Table 8: Fixed effect tests

Fixed Effect Tests

Source	Nparm	DF	DFDen	F Ratio	Prob > F
Presence of police	1	1	40.86	2.1964	0.1460
Presence of side street queue	1	1	78.28	3.6999	0.0581
Pavement condition	1	1	48.16	14.0955	0.0005*
Time to intersection (TTI)	1	1	48.63	62.1816	<.0001*
Other vehicle around	1	1	38.53	3.8203	0.0579
Presence of police*Presence of side street queue	1	1	968.4	0.0222	0.8815
Presence of police*Pavement condition	1	1	960.7	1.1171	0.2908
Presence of police*Time to intersection (TTI)	1	1	962.6	5.3229	0.0213*
Presence of police*Other vehicle around	1	1	962.2	1.8053	0.1794
Presence of side street queue*Pavement condition	1	1	962.7	2.4756	0.1160
Presence of side street queue*Time to intersection (TTI)	1	1	965.3	21.7667	<.0001*
Presence of side street queue*Other vehicle around	1	1	961	0.5183	0.4717
Pavement condition*Time to intersection (TTI)	1	1	962.7	3.6258	0.0572
Pavement condition*Other vehicle around	1	1	963.7	0.0560	0.8131
Time to intersection (TTI)*Other vehicle around	1	1	962.2	0.2728	0.6016
Learning_green extension[DoSomething]	2	2	790	0.1858	0.8305
Learning_RLR[DoSomething]	2	2	408.5	4.9088	0.0078*
Learning_long yellow[DoSomething]	2	2	695.3	3.1594	0.0431*
DoSomething	1	1	963.2	0.0366	0.8484

CHAPTER 4: DYNAMIC DRIVER MODELING USING AGENT-BASED MODELING TECHNIQUES

This part of the report investigates the use of machine learning methods in capturing the effect of driver's learning/dynamic perception of DZ. Data for the analysis were obtained from the driver simulator, which is used to investigate the potential of using a reinforcement learning model to model the driver decision in DZ.

Machine learning model

Since statistical learning models do not take into account future resulting states if a certain action was taken, they are not usually sufficient to model the dynamic aspect of a driver's perception of the DZ. Reinforcement Learning (RL) was considered in this research, as it captures the value of a given state taking into account its Makovian characteristics and transition probabilities [96]. The objective of reinforcement learning algorithms is to find an optimal policy that maps drivers' states to their corresponding actions. In our research scope, when an agent is following the optimal policy, it should act close enough to the represented driver's actions. Reinforcement learning is therefore used to train agents to mimic the behavior of a target driver, by reinforcing agent actions when they perform approximately close to the target driver's actions, and penalizing actions that significantly differ from the target actions. The only information available for learning is the system feedback, which describes in terms of rewards and penalties the task the agent must realize. In this sense, RL optimizes not only the direct action, but also the total reward the agent can receive in the future.

Reinforcement learning has been applied in driver behavior modelling, network route choice analysis and real time traffic signal control. Neuro-Fuzzy Actor-Critic Reinforcement Learning (NFACRL) approach was used by the authors' research group to combine safety and operation aspects of driver behavior in traffic to model naturalistic driver characteristic and following models [86, 88, 97-105]. Other researchers used feedback reinforcement learning mechanism to model route-choice decision-making under uncertainty [106, 107]. In traffic signal optimization research, Abdulhai proposed a Q-learning algorithm in an isolated intersection and then a corridor with coordinated intersections to find the optimal timing plans in a dynamic traffic environment [108, 109].

A major limitation of RL is dealing with continuous data. In this work, we use Actor-Critic RL with a fuzzy input layer to map each encountered state to the training set. We use a continuous output (average acceleration) rather than a binary stop or go decision variable. This modelling structure allows us to simulate the driver decision at a microscopic level when needed.

The structure of the actor-critic RL model is shown in Figure 28. Each node in the input (first) layer represents a continuous state variable. We model the driver's decision in the DZ as a function of a driver state ahead of the traffic signal. This state is represented in a multi-dimensional space using the driver's data as obtained from the driver's simulator. The second layer is the fuzzy membership layer. States are fuzzified in this layer to relate different states to maximum values in the data set. The third layer is the fuzzy rules layer. Each rule is connected with a number of antecedents (discrete fuzzy sets) from the second layer. The fourth layer is the discrete action layer including a set of discrete actions for neural network to choose. The output simulated action is the weighted average of the selected actions where fuzzy rule strengths are the associated weights. For a comprehensive description of the method we refer the reader to [102].

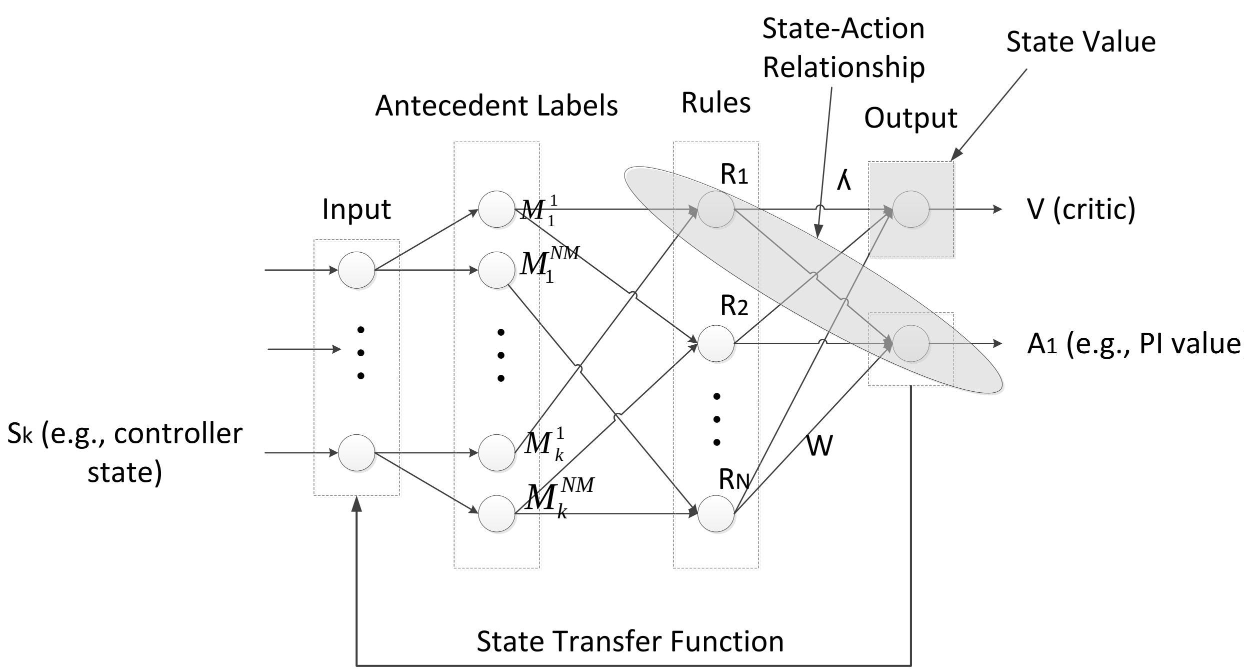


Figure 28: Actor-Critic Neuro-Fuzzy RL Structure.

As explained earlier, in addition to drivers' decision to stop or go, drivers' change in behavior is also important. Alternatively, one would like to know whether the driver stops by hitting the brake hard or chooses to stop very smoothly, or whether the driver passes through the intersection while speeding up or the presence of police makes them keep their speed under the speed limit. To be able to address these issues, a "mean acceleration" value was used as an action in this part to capture any behavioral change of the driver beyond just stopping and going.

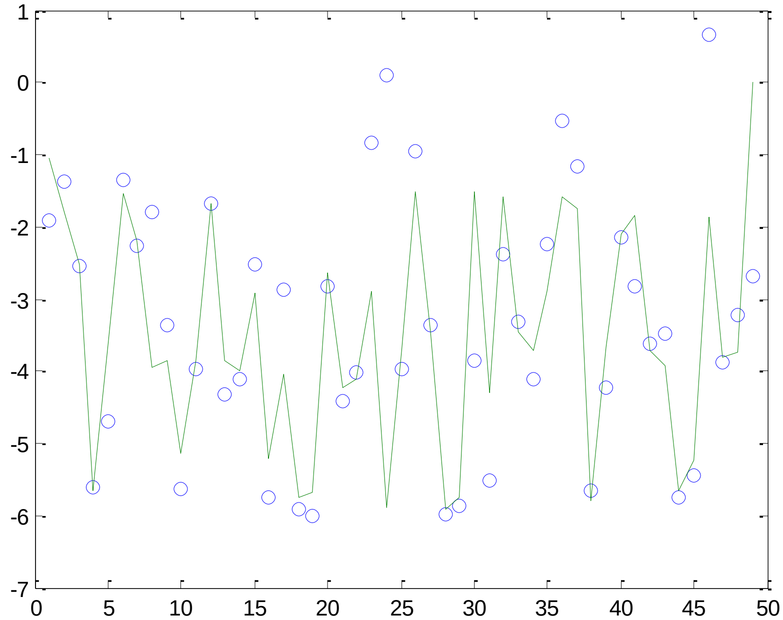
The driver's state is represented in this study by six variables as follows:

- S_1: Yellow extension learning variable: this variable keeps track of how many times a driver went through an extended yellow,
- S_2: Red-light running variable: this variable keeps track of how many times a driver ran a red light,
- S_3: Time to intersection (TTI): time to intersection based on driver's instantaneous speed,
- S_4: Time-lost-gained: cumulative time lost or gained starting from six second TTI until the onset of yellow in comparison to constant speed travel time,
- S_5: Mean speed: average speed calculated started from six second TTI until the onset of yellow,
- S_6: Mean acceleration: same as above, but for acceleration.

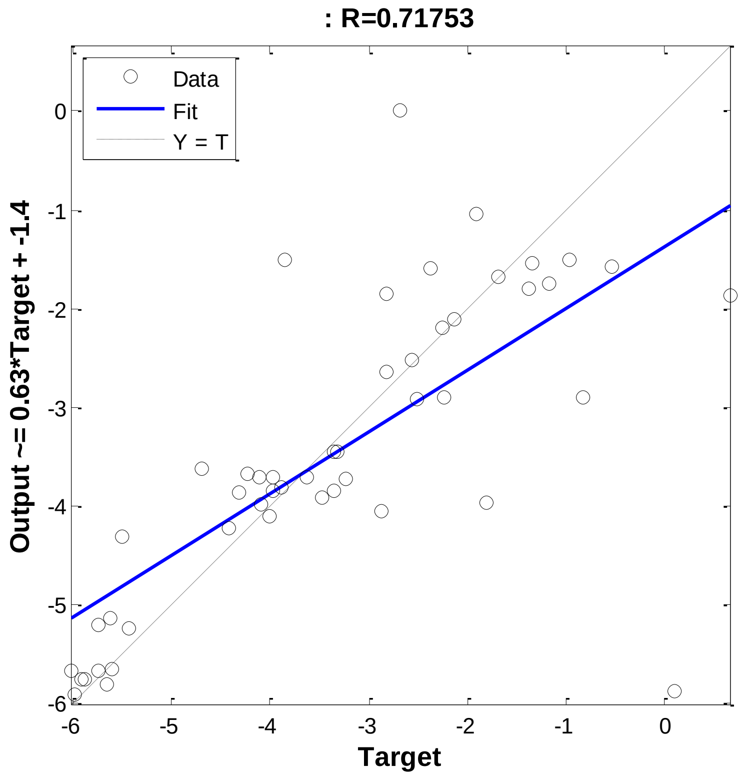
Analysis and results

Four hundreds iterations were run in the training process. Learning speed control of the NFACRL model was handled using three factors, namely memory discount factor γ, learning factor β and reward function scaling factor α. The γ factor controls the memory fade speed, where the value of recently occurring states is weighted more. The β factor controls how fast the agent gets the new information. The α factor controls the magnitude of the reward function and weights, and e_{th} controls the sign of the reward function. In our experiment, we used $\beta = 0.6$, $\gamma = 0.9$, $\alpha = 10$, and $e_{th} = 0.2$.

Figure 29 shows the results of the actor-critic agent model. Figure 29-shows the mean acceleration value for both raw data (circles) and the model's output (solid line). Figure 29-b shows a linear fit between the model's output and actual data with an R^2 of 0.72. The figure shows the output of the model to capture the driver's decision and trace it up and down in a temporal fashion and therefore illustrates the model's capabilities. This was deemed very satisfactory, as it illustrates the ability of the model to capture the driver's experience and to net only outputting mean values for the acceleration as found in the literature.



a. Model versus data for mean driver's acceleration



b. Model's accuracy

Figure 29: Driver's Actions Results

CHAPTER 5: SUMMARY AND CONCLUSIONS

The *dilemma zone*, or DZ, is an area ahead of signalized intersections in which drivers encounter a dilemma and must decide whether to stop or pass through the intersection at the onset of yellow indication. Driver behavior in dilemma zones is known as a major cause of rear-end and right-angle crashes. To reduce the occurrence of DZ-related safety problems, numerous researchers have published studies discussing the issues associated with dilemma zone modeling. Nevertheless, more research needs to be put into answering how drivers' behavior changes as a result of experience gained from driving through safe and unsafe intersections.

To investigate the driver learning aspect, a driver survey was designed and administered in the States of Virginia, Maryland, and Pennsylvania to identify significant factors affecting drivers' perception and decision at the onset of yellow. The results identified nine factors to be significant in these states, namely: (1) speed, (2) distance to intersection, (3) presence of a red light camera, (4) presence of police, (5) whether the pavement is wet or dry, (6) presence of a vehicle in front of the subject car, (7) presence of a vehicle behind the subject car, (8) how well the driver knows the intersection, and (9) whether the traffic is heavy. The results also revealed that the difference between states' proportions (the percentage of responders who indicated that a given factor was influential in their decision at the onset of yellow) is significant. The results of this survey were used for further study and to develop proper scenarios in a driver simulator experience. The authors designed an experimental plan for a driving simulator environment to investigate this learning aspect as well as exploring the significance of a group of influential factors. An Adaptive Randomized Incomplete Block Split-plot design was developed and implemented in a driving simulator. Preliminary results verified 97.3% accuracy in the stopping or going decision prediction mechanism. Learning hypothesis results also revealed that drivers' behavior significantly changes after being exposed to 2 out of 3 treatments related to the learning hypotheses developed in this study. The authors also implemented an actor-critic reinforcement learning algorithm to model the dynamic behavior of the driver in a dilemma zone. Fuzzy logic was used to partition traffic state variables and a reinforcement learning technique was used for the fuzzy rule policy calibration and update. The built model showed a close matching to the data from the simulator (R^2 of 0.72).

Recommendations and Future Research

The findings of this research can be summarized in the following points:

1- Drivers identified nine factors to be significant considering their behavior in dilemma zones. These factors were: (1) speed, (2) distance to intersection, (3) presence of a red light camera, (4) presence of police, (5) whether the pavement is wet or dry, (6) presence of a vehicle in front of the subject car, (7) presence of a vehicle behind the subject car, (8) how well the driver knows the intersection, and (9) whether the traffic is heavy.

2- A detailed experimental design and a driving simulator study further corroborated the significance of these factors. In addition, it was found that drivers do change their behavior based on their experience and exposure to dilemma zone mitigation strategies. Generally, drivers tend to drive more conservatively as a result of previous experience.

3- A reinforcement learning technique was attempted to examine the potential for using agent-based methods to capture the findings of this research. Findings from this research suggest that agent-based models can be used for modeling driver behavior in dilemma zone more accurately than models that currently exist in the literature.

It is therefore recommended that future research should look into a complete agent-based approach to evaluate the effect of driver experience on intersection safety. A larger research effort should be undertaken to utilize real data for building multiple agents. These agents should then be used in a full-scale, agent-based simulation platform to quantify the impact of control strategies on future driver decisions and safety implications.

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APPENDICES

Appendix A: Survey questionnaire

Driver survey

Thank you for taking the time to fill out this survey! Your responses are completely anonymous and confidential. This information will be used for research purposes only and will help us learn more about what drivers do when they get to a yellow traffic light. The survey should take you approximately 5 minutes.

PERSONAL QUESTIONS

1) In what year were you born:

2) What is your gender?

- o Male
- o Female

3) What is your highest education?

- o Some High School
- o High School Diploma
- o Some College
- o Associate’s Degree
- o Bachelor's Degree
- o Graduate Degree
- o Professional Degree
- o Vocational Training
- o Other:………. (please specify)

4) Which of the following racial categories best describes you? You may select more than one.

- o American Indian or Alaska Native
- o Asian
- o Black or African American

- Hispanic or Latino
- Native Hawaiian or other Pacific Islander
- White

5) Which town/city and state do you live in?

Town/City:…………..   State……………

GENERAL DRIVING QUESTIONS

6) How often do you drive a motor vehicle?

- Never
- Almost every day
- A few days a week
- A few days a month
- A few days a year

7) What kind of vehicle do you usually drive?

- Car
- Van or minivan
- Motorcycle
- Truck or SUV
- Other: …………… (please specify)

8) How many times have you been pulled over by the police in the past year?

- None
- Once
- Twice
- Three times
- More than three times

9) Have you ever been in an accident at an intersection?

- Yes

- No

10) Do you consider yourself a safe driver?

- Yes
- No
- Do not know

YELLOW TRAFFIC LIGHT QUESTIONS:

11) How often do you try to catch a yellow light and end up running a red light?

- Very often
- Sometimes
- Rarely
- Never

12) What do you **normally** do when you see a yellow traffic light?

- Speed up
- Slow down
- Neither speed up nor slow down
- Hit the brakes
- It depends
- Other:…………..(please explain)

13) Which of the following conditions affects what you do when you see a yellow light?

Your speed	
Your distance to intersection	
Presence of passengers in the car	
Existence of yellow flashing traffic light	
Model (e.g., Toyota Camry, Ford Fusion) of the car you are driving	

Whether you are talking on the phone	
Whether it is night or day time	
Presence of a red light camera	
Presence of police	
Whether the pavement is wet or dry	
Presence of a vehicle in front of you	
Presence of a vehicle behind you	
Presence of a vehicle in the lane next to you	
Presence of a bicycle, pedestrian or vehicle in the side-street	
Whether the next traffic light is timed	
Whether the traffic is bad	
Existence of a countdown display to show the time of each traffic light color	
Whether you are tired, angry, or sad	
How well you know the intersection	
Whether it is a **safe** intersection	
Whether the intersection is at the bottom of a hill	
Whether the intersection is at the top of a hill	
Whether you've successfully beaten that red light in the past	

14) About how long you think yellow lights **usually** last?

- 1 second
- 2 seconds
- 3 seconds
- 4 seconds
- 5 seconds…
- Other: ……… …(please specify)

15) Have you noticed that some yellow lights are longer or shorter than others?

- Yes
- No
- I do not know

16) Please specify any experience or suggestion that you may have on the subject of “drivers’ decision to stop or go at the onset of yellow light”

Thank you very much for your time and cooperation

Appendix B: Consent form

Project Title: **Modeling the Dynamics of Driver's Dilemma Zone Perception using Machine Learning Methods for Safer Intersection Control**

I. Purpose of this Research/Project

Rural, high-speed signalized intersections are associated with vehicle crashes due to dilemma zone problems. Dilemma zones (DZ) are defined in either time or space, as zones where some drivers may decide to proceed, and some may decide to stop at the onset of yellow. This disagreement among drivers can lead to rear-end crashes (when a driver decides to stop while their follower decides to proceed) and/or right-angle crashes (when drivers end up violating the red light and crash with side street traffic).

One important question that remains unanswered is whether the DZ definition changes individually as a function of experience. To answer this question, we conduct a driver simulation study in which subject drivers will drive through selected scenarios. Driving simulator is used to monitor driver behavior, performance, and attention when encountering the yellow light at a signalized intersection. Twenty to thirty gender and age balanced participants will be selected for the study. Subjects must be licensed drivers over 18 years old. Subjects originally from Virginia, Maryland, and Pennsylvania will be sought particularly.

II. Procedures

As a participant, you are invited to participate in a research study using the DriveSafety DS-250 model driving simulator located in Patton Hall, on the campus of Virginia Tech. First you will be asked some questions regarding your age and relevant driving experience for proper data collection. Then, you'll be sitting behind the steering wheel and a review of the experiment will be explained to you. The driving simulator includes steering wheel, gas and brake pedals, and on three screens. After a 5 – 6 minute practice session in order to familiarize you with the simulated driving environment, you’ll drive through the simulator. In each session of driving, comprising of a virtual driving course developed by the researchers, you may encounter different graphical environments on the screen. Examples of different graphical environments are driving on a straight road section in rainy weather and driving through an intersection in presence of a police car. You are expected to appear one time, and the total amount of time required of you as a participant is around two hours. The result of the simulated driving experience would provide us with data regarding the influence of different factors on driver behavior at the onset of yellow light.

III. Risks

The only potential risk to you associated with this experiment could be slight motion sickness (slight car sickness or slight light headedness) due to the conflicting body cues of visual movement without actual body movement. You can quit the experiment anytime without penalty if you feel uncomfortable or simply do not wish to continue. All activities during the study will be carefully monitored and actions will be taken to stop the study in case it is considered unsafe for any reason or if a participant seems to experience abnormal behavior.

IV. Benefits

The study results are used to develop a new model of dilemma zone behavior that incorporates the aspects of driver experience. This will ultimately lead to safer intersection designs. No promise or guarantee of benefits has been made to encourage you to participate.

V. Extent of Anonymity and Confidentiality

All the study records will be kept confidential. Data will be stored securely and will be available only to the research team. No reference will be made in oral or written reports which could link participants to the study.

It is possible that the Institutional Review Board (IRB) may view this study's collected data for auditing purposes. The IRB is responsible for the oversight of the protection of human subjects involved in research.

VI. Compensation

Participation is voluntary and there will be no compensation.

VII. Freedom to Withdraw

You are free to withdraw from the study at any time without penalty. You are free not to answer any questions or respond to experimental situations that you choose without penalty.

VIII. Subject's Responsibilities

I voluntarily agree to participate in this study.

IX. Subject's Permission

I have read the Consent Form and conditions of this project. I have had all my questions answered. I hereby acknowledge the above and give my voluntary consent:

Subject signature______________________________________ Date __________

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