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The Type-II dilemma zone refers to the segment of roadway approaching an intersection where drivers have difficulty deciding to stop or proceed through at the onset of the circular yellow (CY) indication. Signalized intersection safety can be improved when the dilemma zone is correctly identified and steps are taken to reduce the likelihood that vehicles are caught in it. This research employs driving simulation as a means to collect driver response data at the onset of the CY indication to better understand and describe the dilemma zone. The data obtained was compared against that from previous experiments documented in the literature and the evidence suggests that driving simulator data is valid for describing driver behavior under the given conditions. Fuzzy logic was proposed as a tool to model driver behavior in the dilemma zone, and three such models were developed to describe driver behavior as it relates to the speed and position of the vehicle. These models were shown to be consistent with previous research on this subject and were able to predict driver behavior with up to 90% accuracy.

Fuzzy Logic for Improved Dilemma Zone Identification: A Simulator Study

by
Derek Moore

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APPROVED:

Major Professor, representing Civil Engineering

Head of the School of Civil and Construction Engineering

Dean of the Graduate School

I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Derek Moore, Author

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TABLE OF CONTENTS

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

FUZZY LOGIC FOR IMPROVED DILEMMA ZONE IDENTIFICATION: A SIMULATOR STUDY

1 Introduction

The Type-II dilemma zone (DZ) describes a segment of roadway on the approach to a signalized intersection where drivers have difficulty deciding to stop before the intersection or proceed through it when presented with the circular yellow (CY) indication. The conflicts created in the Type-II DZ, also known as the ”indecision zone,“ result in increased rear-end crashes as the result of abrupt braking, and right-angle or left-turn head-on collisions as the result of poor estimates of intersection clearance time. While inadequate signal timing or driver failure to comply with signal operation (either disobedience or distraction) can result in collisions, it is thought that DZ conflicts contribute significantly to the overall safety of signalized intersections. Some researchers have even proposed the number of vehicles caught in the dilemma zone a surrogate measure for safety performance (Zimmerman & Bonneson, 2004). Despite the implications of these conflicts, there has yet to be a set of national standards to properly and consistently address this issue.

The Manual on Uniform Traffic Control Devices (MUTCD) provides guidance for the installation and application of many traffic control devices including signs, signals and pavement markings. This document provides a range of reasonable yellow change interval durations as well as information relating the meaning and sequence of the CY indication (MUTCD, 2009). In the absence of a national standard, the Institute of Transportation Engineers (ITE) has developed a recommended approach to determining the length of the CY indication based on several key factors, including approach grade, perception-reaction time of the driver, velocity and deceleration rate of the vehicle, length of the vehicle, and width of the intersection (ITE, 1999). The Traffic Signal Timing Manual, which provides a comprehensive overview of signal timing practices, puts forth the same ITE equation when discussing timing of the yellow change interval (FHWA, 2008). However, there are still agencies that apply any one of several alternative approaches to determining the appropriate length of the CY indication. Regardless of what approach is used, the initiation of the CY indication at the wrong time can contribute to the potential for DZ conflicts.

An accurate identification of where the DZ exists could allow engineers to reduce the frequency with which drivers are caught in the DZ. Numerous technologies have been developed to identify when a vehicle is in the DZ (defined in one way or another) and then to delay the presentation of the CY indication until there are no (or few) vehicles in the DZ. These DZ protection systems tend to operate with a predetermined description of where the DZ exists, and the success of their applications is based in part on the accuracy of that placement. With that said, there are multiple definitions that have been used to describe where the DZ occurs. One of the most commonly applied definitions is based on a driver's decision to stop, identifying the downstream edge of the DZ as the location where 10 percent of drivers stop and the upstream edge where 10 percent of drivers continue through the intersection (Zegeer and Deen, 1978). The other primary definition is based on a vehicle's time-to-stop line, describing a DZ that exists between 2.5-5.5 seconds from the intersection (Chang et al., 1985). Recent research has suggested, however, that these two definitions potentially result in different DZ locations on the same intersection approach (Hurwitz et al., 2011a).

This research aims to improve the identification of vehicles caught in the DZ as this is a critical factor to both the efficient and safe operation of signalized intersections. A DZ definition that is too broad can hinder signal operations, while a narrowly defined DZ can unnecessarily expose vehicles to DZ conflicts leading to reduced safety performance. Building on the work of Hurwitz et al. (2012a), this research uses Fuzzy Logic (FL) as an analytical tool to improve DZ identification. Hurwitz et al. proposed a model based strictly on vehicle position that demonstrated the potential for improved DZ identification. This research exploits the capabilities of a high-fidelity driving simulator to output measurements of vehicle position and speed fifteen times per second to develop a more accurate model of DZ location on intersection approaches with different speeds. Additionally, the probability to stop data is compared to the previous naturalistic experiments of Hurwitz et al. (2012) and the test track experiments of Rakha et al. (2007); while the deceleration data is compared to those reported by Gates et al., (2006).

2 Literature Review

This literature review covers a variety of topics that are central to the development of a FL model for driver behavior. It is critical to understand the basic definitions and models currently used to describe DZs. It is also important to understand the characteristics of the yellow change interval, including the laws governing how drivers should react to its presentation, the recommended applications and durations, and the level to which drivers understand the intended message communicated by the CY indication. The literature review also includes a basic orientation to FL, as well as the use of driving simulators for traffic control and driver behavior experimentation.

2.1 Definition of Dilemma Zones

It is essential that an accurate definition of the DZ problem be the first thing established. Literature has identified two forms of DZ that a driver can experience as they approach an intersection and are presented with a CY indication. The Type-I DZ was first referenced in 1960 by Gazis et al. They identified the possibility that the design parameters of an intersection (timing and phasing, detector layout and operation, and geometry) may make it impossible for a motorist to either safely stop before the stop line or safely pass through the intersection. This can be the result of poor signal timing (excessively short yellow change intervals) and/or detector placement (detector setbacks too short), while site-specific characteristics such as approach grade, speed, and available sight distance can also contribute to these errors. Since the identification of this issue in 1960, signal timing practices have changed to account for this possible conflict and, when applied correctly, eliminate the potential for a Type-I DZ to occur.

An second form of DZ conflict (termed a Type-II DZ) was identified and formally documented in a technical committee report produced by the Southern Section of ITE (Parsonson, 1974). This DZ refers to the area on an approach to a signalized intersection where drivers have difficulty making the stop/go decision when presented the CY indication. Literature has also termed this the “dilemma zone” or the “indecision zone” which reflects the dynamic and probabilistic nature of the Type-II DZ (Gates et al., 2006). Figure 1 illustrates both types of DZ.

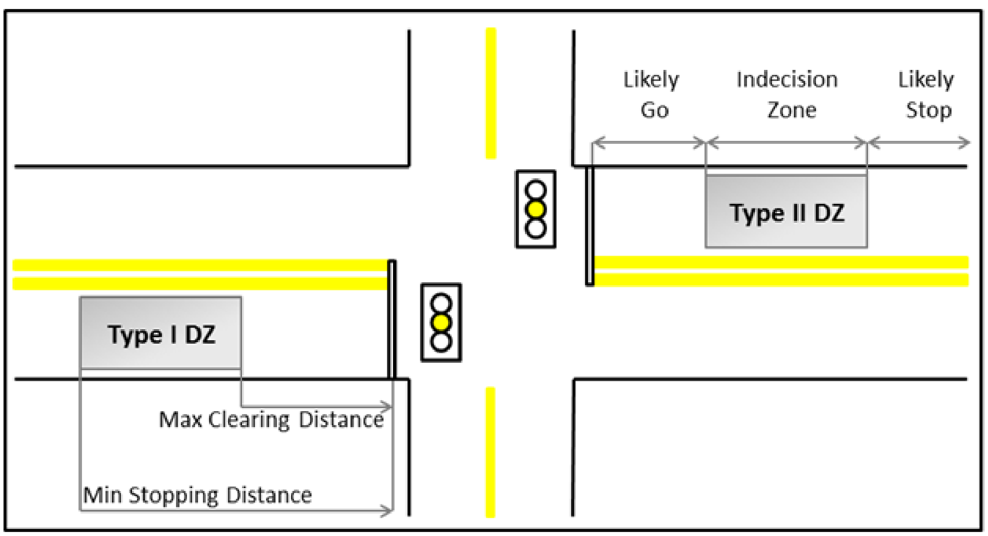

Figure 1: Type-I and Type-II DZ (Hurwitz et al., 2011)

DZ incursions are important to mitigate because they are associated with three potential crash scenarios: rapid deceleration leading to rear-end crashes, failure to stop resulting in right-angle crashes, and incorrect judgment of clearance distance leading to left-turn head-on crashes. Many research efforts focus on high-speed intersections because the increased speeds have the potential to result in more severe crashes (Zimmerman & Bonneson, 2004).

2.2 Guidance from Signal Timing Standards

The MUTCD describes the generally accepted standards used for the design and placement of traffic control devices such as signs, signals, and pavement markings. The MUTCD provides the accepted meaning of the circular CY indication as the following: "A yellow signal indication shall be displayed following every CIRCULAR GREEN or GREEN ARROW signal indication. The exclusive function of the yellow change interval shall be to warn traffic of an impending change in the right-of-way assignment. The duration of a yellow change interval shall be predetermined" (MUTCD, 2009).

The MUTCD clearly identifies the need for inclusion of the CY indication in the phasing sequence; however, it provides limited guidance when it comes to the timing of the yellow change interval, stating that "A yellow change interval should have a minimum duration of three seconds and a maximum duration of six seconds. The longer intervals should be reserved for use on approaches with higher speeds" (MUTCD, 2009). The MUTCD also notes that the duration of the yellow change interval should not change on a cycle-to-cycle basis.

The lack of design standards for the calculation of the yellow change interval has led to the adoption of numerous practices throughout the country. One of the most prominent approaches used to determine the duration of the CY indication was developed by the Institute of Transportation Engineers (ITE). The methodology, which accounts for many characteristics of the specific approach, is as follows (ITE, 1999):

$$y = t + \frac{V}{2a + 64.4g} \tag{1}$$

Where: y = length of the CY indication (s)

t = perception-reaction time (use 1.0 s)

V = 85th percentile speed (ft/s)

a = deceleration rate of vehicle (ft/s^2) (use 10.0 ft/s^2)

g = approach grade (decimal form)

The Traffic Signal Timing Manual (FHWA, 2008) provides the same equation and description when discussing timing of the CY. However, several other strategies have been adopted to determine the appropriate length of the yellow change interval. Some agencies simply set the yellow change interval equal to one tenth of the operating speed, while others simply use the same yellow change interval for similarly classified or closely spaced intersections (ITE, 1999). To complicate the issue further, the laws dictating how drivers should behave when presented with the CY indication also vary geographically.

2.3 Differing Laws

When discussing DZs, it is important to mention the different meanings and laws associated with the CY indications that are enforced throughout the country. Both the Uniform Vehicle Code (UVC) and the MUTCD support a permissive yellow law, meaning that a vehicle can legally occupy an intersection on red as long as it entered the intersection while the CY indication was being presented (NCUTLO, 1992). By 2009, at least half of the states were following this rule, while the remaining states follow one of two versions of a restrictive rule. The first version of a restrictive rule asserts that a vehicle must stop when presented with the CY indication unless it is unsafe to do so. The other version of a restrictive rule states that a vehicle must clear the intersection before it turns red (i.e. the vehicle may not enter or be in the intersection when the red indication is presented) (Brustlin, 2009).

One could hypothesize that the majority of drivers do not realize there are multiple definitions, or what specific language is used in their state. However, a traffic engineer should be aware of these subtle differences as they design and implement signal timing plans. Traffic engineers should also be aware of the various approaches used to identify the location of the DZ.

2.4 Existing Dilemma Zone Boundary Definitions

There have been numerous efforts to accurately quantify the location of the DZ. One of the first approaches taken was to identify the DZ boundaries in terms of the driver's decision to stop or go. Supported by the work of May (1968) and Herman et al. (1963), Zegeer and Deen defined the upstream terminus of the DZ as the location where 90 percent of drivers stopped and downstream terminus of the DZ as the location where only 10 percent of drivers stopped (1978).

In 1985, Chang et al. (1985) proposed definition based on a vehicles travel time to the stop line (TTSL). The authors reported that 85 percent of drivers would stop if they were five or more seconds from the stop line, and that nearly all drivers continued through the intersection if they were less than two seconds from the stop line when presented with the CY indication. Other examples of defining DZ boundaries in terms of TTSL can be found in the efforts by Webster & Elison (1965) and Bonneson et al. (1994). Figure 2 provides a graphical representation of these two definitions from the Traffic Signal Timing Manual (FHWA, 2008).

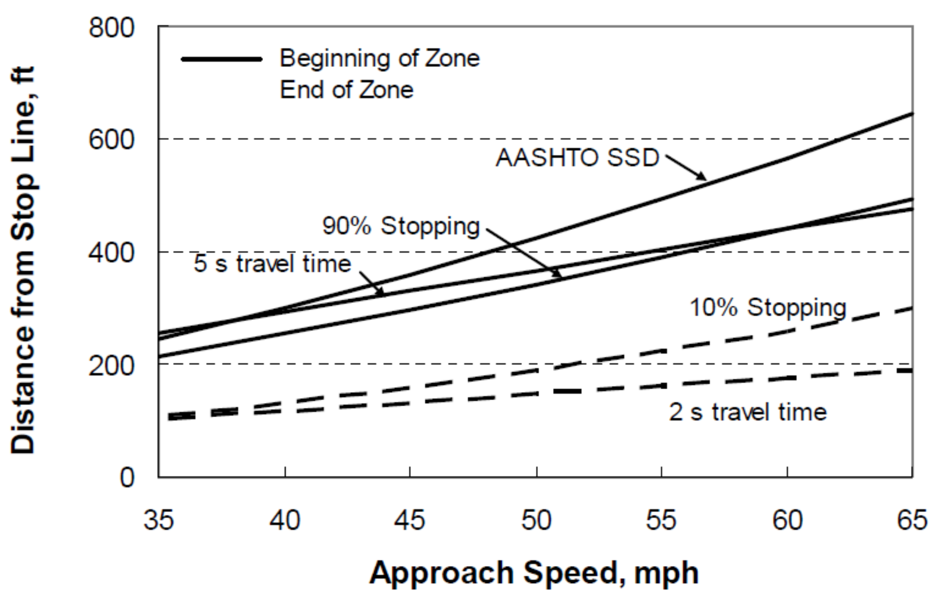

Figure 2: Type-II DZ Boundary Definitions

Hurwitz et al. (2011a) used field observations of over 1000 vehicles to perform a comparison of the two most common Type-II DZ definitions. The authors found that there was a statistically significant difference between the classification of vehicles as either downstream, within, or upstream of the DZ when using the two definitions. Specifically, it was found that the decision to stop definition classified far more vehicles as ‘within’ the DZ than the TTSL definition, which classified many more vehicles as ‘downstream’ of the DZ. This work illustrates the potential for a new model to more accurately and consistently identify the DZ for each individual approaching vehicle. Regardless of what definition is used, it is important to understand the natural tendencies of drivers being exposed to the CY indication.

2.5 Advanced Vehicle Detection

In an effort to reduce the number of vehicles that are presented with the CY indication while occupying the DZ, advanced vehicle detection systems have been developed. These systems detect an approaching vehicle, determine if it is in the DZ based on one of the previous definitions, and most commonly extend the green allowing the vehicle to pass through the DZ before calling for the CY indication to begin. These systems will continue to extend the green while vehicles occupy the DZ until it reaches a maximum green time, at which point the CY indication will be presented and vehicles caught in the DZ are forced to make the potentially difficult decision. This phase termination scenario is known as a “max-out” and is much less desirable than “gap-out” where the phase is terminated due to the expiration of the passage timer. Promoting the safer phase termination scenario of gap-out is a motivating need for an accurate definition of the DZ, so that acceptable gaps in the traffic stream are not missed, which increases the likelihood of a max-out occurring.

Many of these systems use in-pavement loop detectors operating in pulse mode placed in advance of the intersection to detect approaching vehicles. These systems vary in sophistication, with the simplest designs providing DZ protection based simply on the single point vehicle pulses. The more complex systems use sequential in-pavement loops and algorithms to estimate speed and length of vehicles, resulting in improved identification of a DZ conflict. An example of the latter can be found in the work of Zimmerman et al. (2012) in which a group of in-pavement loops are placed 1000 ft. upstream of the intersection. These in-pavement loops allowed for the determination of a vehicle's position, speed, length, and type. With this information, the associated software would compute a "dynamic DZ" which was unique to each approaching vehicle. If max-out was unavoidable, the system would activate in-pavement LEDs to warn each vehicle in the DZ of the impending shift of right-of-way (Zimmerman et al., 2012).

A relatively new vehicle sensor system is the Wavetronix Smartsensor, which is designed specifically for DZ protection. This system uses radar to detect approaching vehicles up to 500 ft. away from the sensor and measures their speed and position throughout their approach to the intersection. Hurwitz et al. (2012b) conducted a comparison between this radar-based sensor system and a typical in-pavement loop detector system. It was found that the radar-based system reduced the rate of drivers exposed to the CY indication while in the DZ by 20 percent and red-light running rates by nearly 70 percent (Hurwitz et al., 2012b).

2.6 Driver Comprehension and Behavior

The engineering community acts under the assumption that drivers understand the meaning of the CY indication as well as all other traffic control devices. The accuracy of this assumption was evaluated by Hurwitz et al. (2011b) in a survey-based research effort (130 participants) considering the following three questions:

1. <u>Can drivers correctly identify the meaning of the CY indication?</u> Results showed that comprehension rates ranged from 20 percent to 69 percent depending on the presentation.
2. <u>Do drivers know what signal indication follows the CY indication?</u> An average of over 80 percent answered correctly.
3. <u>Do drivers accurately estimate the duration of the CY indication?</u> It was found that only 57 percent of drivers estimated the duration of the CY to be within the MUTCD recommended three to six second range.

This research brings to light the fact that many drivers struggle to understand the simple message communicated by the CY indication. It is obvious that the signal presentation is important, but even under the best conditions, only 69 percent of drivers understand the meaning. The notion that just over half of drivers have an accurate mental model of yellow change interval duration could contribute to the difficulty of identifying the boundaries of the DZ.

Rakha et al. (2007) used data from test-track experiments to gain a better understanding of driver behavior at the onset of the CY indication. They found that the probability of stopping varied from 100 percent at a TSL of 5.5 seconds to 9 percent at a TTSL of 1.6 seconds Furthermore, Rakha et al. reported that male drivers are less likely to stop when compared to their female counterparts, and that drivers over the age of 65 are significantly less likely to pass through the intersection.

Gates et al. (2006) performed field observations on over 1000 vehicle that were either the first-to-stop or last-to-go at the termination of priority for that approach. In addition to making detailed measurements of brake-response time and deceleration rates, the authors evaluated the effects of several variables on the decision to stop/go, including: approach speed, distance to the stop line, vehicle type, headway, tailway, action of vehicles in adjacent lanes, presence of opposing vehicles/pedestrians/bicycles, presence of opposing left-turn vehicles, flow rate, and cycle length. The authors report that the factor with the most influence on driver decision making was the estimated TTSL, with the following conditions associated with a higher probability of stopping: shorter yellow interval, longer cycle lengths, vehicle type, presence of opposing roadway users, and absence of vehicles in adjacent through lanes (Gates et al., 2006).

Yet another research effort relying on empirically observed data focused on the dynamic nature of the DZ. Liu et al. (2006) found that the length and location of the DZ varies with the speed of the vehicle, reaction time, and the operational tendencies of different driving populations. The authors also found that there are significant differences between the observed size and location of the DZ and theoretical estimates for these values. The need to reduce or eliminate that difference contributes to the argument to utilize FL as a new method to more accurately model DZs.

2.7 Fuzzy Logic and Model Development

FL is a concept that was first described by Professor Lotfi Zadeh at the University of California Berkley. It was based on the idea that humans are capable of highly adaptive control even though the inputs used are not always precise. In an attempt to mimic the human decision making process, FL was developed to make decisions based on noisy and imprecise information inputs. “FL provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information” (Kaehler, 1998). Typically, fuzzy systems rely on a set of if/then rules paired with membership functions used to describe input and output variables. In short, the fuzzy rules work to ‘fuzzify’ and aggregate the input values, convert them into terms of output variables, and finally ‘defuzzify’ the values of the output functions (Celikyilmaz & Turksen, 2009).

Research efforts have focused on using FL to better model and understand driver behavior as they interact with traffic control devices, such as traffic signals. As drivers approaches a signalized intersection, they must base their actions on assumptions about their speed, deceleration/acceleration capabilities, distance from the intersection, and duration of the currently displayed indication. To further complicate things, a driver must continuously make these approximations during the approach to the intersection, making this form of driver behavior a viable candidate for FL modeling.

FL has been used as a tool for the development of an adaptive traffic signal controller based on its ability to qualitatively model complex systems (Yulianto, 2003). Yulianto took this approach a step further, using it to control signal operations under mixed traffic conditions (referring to traffic streams composed of vehicles with a wide range of operating characteristics; more commonly found in developing countries). Results showed a general decrease in delay under FL control when compared to fixed-timed control.

FL has also been proposed as a tool for calculating the yellow change and all-red clearance intervals for a traffic signal. Kuo et al. (1996) considered variable such as level of congestion, vehicle location, speed, approach grade, and intersection width as inputs to a FL model. This model was then used to determine the appropriate yellow change interval time, all-red time, and green extension time for that phase. The authors suggest that FL has many advantages over traditional timing practices as it provides dynamic values for the yellow change and all-red clearance intervals (Kuo et al., 1996).

It is important to note the uncertainty and anxiety associated with driver behavior in the DZ. Rakha et al. (2007) performed a field study on 60 participants and evaluated their behavior at the onset of the CY indication. They modeled the uncertainty in the decision-making process with an equation described by Yager (1982) as seen in Equation 2:

$$A = 1 - \int_{0}^{\alpha_{\max}} \frac{1}{|A_{\alpha}|} d\alpha \tag{2}$$

Where A is the level of uncertainty, and A_{α} is the number of alternative choices. Since there are only two alternatives a driver can choose from in reaction to the CY indication, the previous equation can be reduced to Equation 3:

$$A = 1 - \max(P_S, P_G) + \frac{1}{2}\min(P_S, P_G) \tag{3}$$

Where P_S and P_G are the possibility of stopping and going, respectively.

This research will build and expand upon the work of Hurwitz et al. (2012a), which focused on using fuzzy sets to better describe driver behavior in the DZ. The previous research effort used field data, specifically the distance to the stop line at the onset of the CY indication, from high speed signalized intersection approaches in Vermont to build a FL model. With results comparable to the previous efforts of Rakha et al. (2007), the authors argue that the FL model more effectively accounts for driver behavior in the DZ than previous models.

2.8 Simulator Validation and Standards of Practice

Several studies have focused on the validation of driving simulators to accurately reflect a driver's behavior as they interact with work zones (Godly et al., 2002; Bella, 2005: McAvoy et al., 2007; Bella, 2008; Mathur et al., 2010). These studies used the advantages associated with simulator experimentation, including the improved safety and efficiency of data acquisition and the control of extraneous variables. Simulator validation efforts will be discussed through the consideration of work zones experiments as these are more numerous and their evaluations are dependent on similar performance metrics, including speed across roadway segments of interests.

Studies concerned with the validation of simulators for speed related research is of particular interest to the DZ modeling effort. It has been repeatedly found (Godley et al., 2002, Bella, 2008) that drivers tend to travel at slightly higher speeds in simulated environments, which some have contributed to a difference in perceived risk. Hurwitz et al. (2007) determined the accuracy in which drivers could perceive their speed in both a real world environment and a driving simulator. It was found that drivers consistently travelled about 5 mph faster in the simulated environment compared to the real world, which was consistent with the findings of Godley (2002) and Bella (2008). The authors concluded that driving simulation could be an effective tool for speed-related research if the appropriate question was asked.

Bella (2005) tested the validity of the Inter-University Research Center for Road Safety (CRISS) simulator located at the European Interuniversity Research Center for Road Safety by recreating an existing work zone on Highway A1 in Italy. Over 600 speed observations were taken throughout the work zone and compared to the speed measurements from the simulated environment. The study found that there were no statistically significant differences between field-observed speeds and those from the simulated environment at any location throughout the work zone (Figure 3). Additionally, Bella hypothesized that the lack of inertial forces on the driver, since it was a fixed-base simulator, contributed to a decrease in speed reliability under simulated conditions as the maneuvers became more complex.

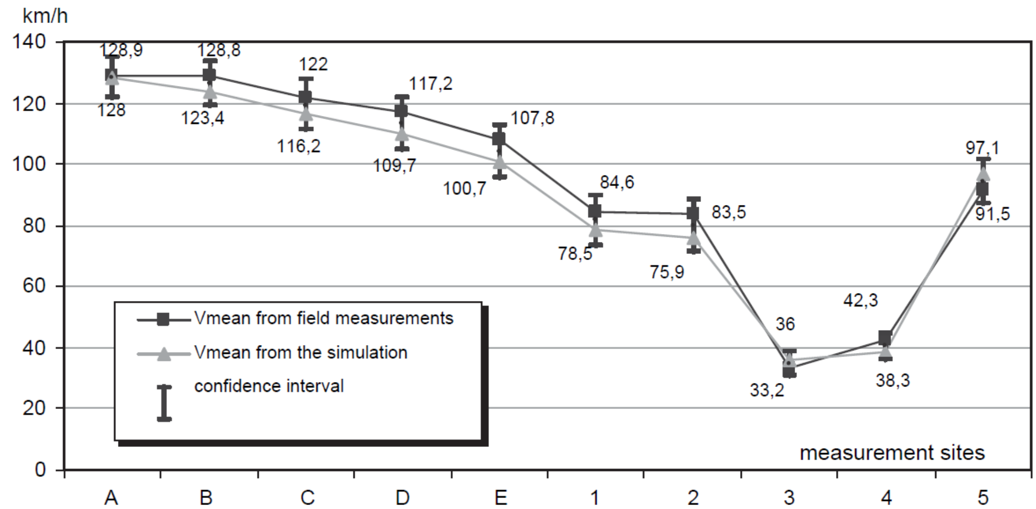

Figure 3: Results from simulator validation study (Bella, 2005)

In 2007, McAvoy et al. attempted to validate driving simulation as a tool to evaluate driver behavior under nighttime conditions. The validation process was part of a larger experiment, including field observations and the simulated experiment, looking at the effectiveness of temporary traffic control devices with nighttime applications. Spot speed data taken throughout a series of work zones was compared to similar speed data from 127 simulator participants, with results suggesting that driver's perception of risk was significantly different under simulated conditions and that driving simulation may not be an appropriate tool for evaluating driving behavior during nighttime conditions (McAvoy et al., 2007). As can be seen in Figure 4, drivers in the simulated environment did not slow down through the work zone like those in the field study.

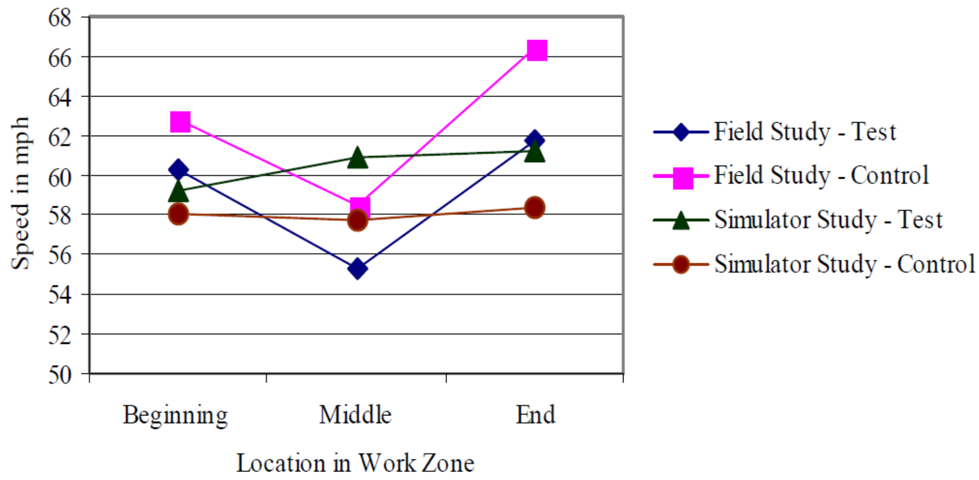

Figure 4: Speed comparison (McAvoy et al., 2007)

Mathur et al. (2010) developed a potential framework for validation of a driving simulator, which was demonstrated using a work zone scenario. In a similar fashion to the previously discussed studies, field observations were taken through a work zone on I-44 in Missouri which was then recreated in a simulated environment. Using the fixed-base simulator at Missouri S&T, 46 participants traversed the simulated work zone while speed data was being recorded. An objective evaluation was performed, beginning with a qualitative, or graphical, comparison of the speed data (Figure 5). Once it was confirmed that the data sets were similar, an extensive statistical quantitative evaluation was performed resulting in absolute and relative validation of the simulator.

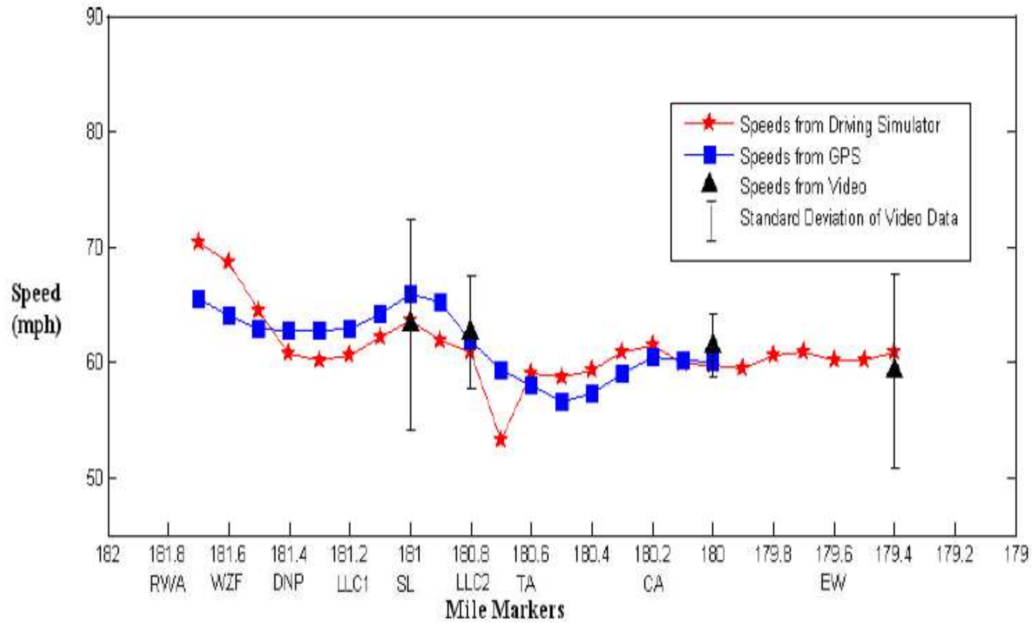

Figure 5: Speed comparison (Mathur et al., 2010)

Participants were also asked to complete a post-experimental survey in which they rated the realism of several aspects of the simulator, resulting in generally positive feedback (Mathur et al., 2010).

There is a persistent concern among researchers about the validity of using driving simulation to evaluate driver behavior, due primarily to differences in perceived risk between the simulated environment and the real world. Validation of a simulator can occur on one of two levels, either absolute or relative validation, based on observed differences in performance measures such as speed or acceleration (McAvoy et al., 2007; Bella, 2005). A simulator is relatively validated when the differences in performance observed in the simulated environment are of similar magnitude and in the same direction from those observed in the real world. A simulator becomes absolutely validated when the magnitude of these differences is not significantly different. For a simulator experiment to be useful, it is not required that absolute validity is obtained; however, it is necessary that relative validity is established (Tornos, 1998).

2.9 Summary

The literature has revealed that differences in DZ boundary definitions can result in deficient DZ zone protection. Various technologies have been used to reduce the number of vehicles caught in the DZ, but current practices may not correctly identify the location of the DZ, therefore, forcing drivers to make difficult stop/go decisions. FL is widely accepted as a tool for modeling systems with imperfect data, and the work by Hurwitz et al. (2012b) indicates it has the potential to improve the identification of vehicles that may be caught in a dynamic DZ. A limitation of that research effort, and many others, was the lack of high-fidelity measurements of vehicle speed and position. The work of Gates et al. (2006) and Rakha et al. (2007) identify speed as a critical factor affecting drivers' decisions. Results have shown that simulator studies are capable of efficiently providing detailed and reliable results without exposing drivers to potentially hazardous conditions. It is hypothesized that a carefully designed simulator experiment will contribute to existing gaps in knowledge relating to DZ identification and protection.

3 Methodology

This section reviews the specific research objectives as well as the experimental methods implemented to address them. It also provides information about the Oregon State University (OSU) driving simulator and the scenario control features used to develop the experimental scenarios.

3.1 Research Objectives

This research focuses on the following objectives to contribute to the understanding of driver behavior in DZs.

1) Analyze deceleration rates of stopping vehicles responding to the yellow light as measured in the driving simulator and compare them to previous measurements from the real-world to validate the simulator results.
2) Develop and validate multiple FL models based on either time to stop bar, position data, or speed data obtained from a driving simulator and compare the models.
3) Compare the probability to stop distributions from the driving simulator to previously observed results by Rakha et al., (2007) and Hurwitz et al., (2012a).

3.2 Driving Simulator

The Oregon State driving simulator is a high-fidelity motion base simulator. The simulator consists of a full 2009 Ford Fusion cab mounted on top of an electric pitch motion system. The vehicle cab is mounted on a pitch motion system with the driver's eye-point located at the center of the viewing volume. The pitch motion system allows for onset cues for acceleration and braking events. Three projectors are used to project a 180 degree front view and a fourth projector is used to display a rear image for the driver's center mirror. The two side mirrors also have embedded LCD displays. The vehicle cab instruments are fully functional and include a steering control loading system to accurately represent steering torques based on vehicle speed and steering angle. The computer system consists of a quad core host running Realtime Technologies SimCreator Software with an update rate for the graphics of 60 Hz. The simulator software is capable of capturing and outputting highly accurate values for performance measures such as speed, position, brake, and acceleration. The simulator is pictured in Figure 6.

Figure 6: Oregon State Driving Simulator

3.3 Scenario Layout and Intersection Control

The experiment was designed to maximize the number of DZ conflicts while limiting the driving time participants spent in the simulator. To validate the measurements of driver response to the CY, the roadway cross-section and adjacent land use were designed to be consistent with the previous work by Rakha et al. (2007) and Hurwitz et al. (2011a). In both cases, roadway cross-sections consisted of two lanes in the direction of travel, a substantial clear zone and minimal development of adjacent land. The Rakha experiment required participants to drive along a test track at 45 mph, and the observed 85th percentile speed in the Hurwitz study was 57.5 mph. With those speeds in mind, the experiment was divided into two parts: one with a posted speed of 45 mph and one posted at 55 mph. The higher posted speed was reinforced by a slightly wider clear zone and less surrounding development. Figure 7 illustrates the typical road environment used in this experiment.

Figure 7: Typical Roadway

Within each speed condition, drivers were exposed to the CY indication at various locations on their approach to the intersection. Since the prevailing DZ definition uses a measure of TTSL, the presentation of the CY indication was varied base on the TTSL of the vehicle. To adequately cover the range of potential DZ conflicts, each driver was presented with the CY indication at 11 different TTSL values ranging from 1 to 6 seconds at half-second intervals. A series of 22 approaches, each separated by roughly 2000 feet of roadway, were modeled forming a large figure-eight as shown in Figure 8.

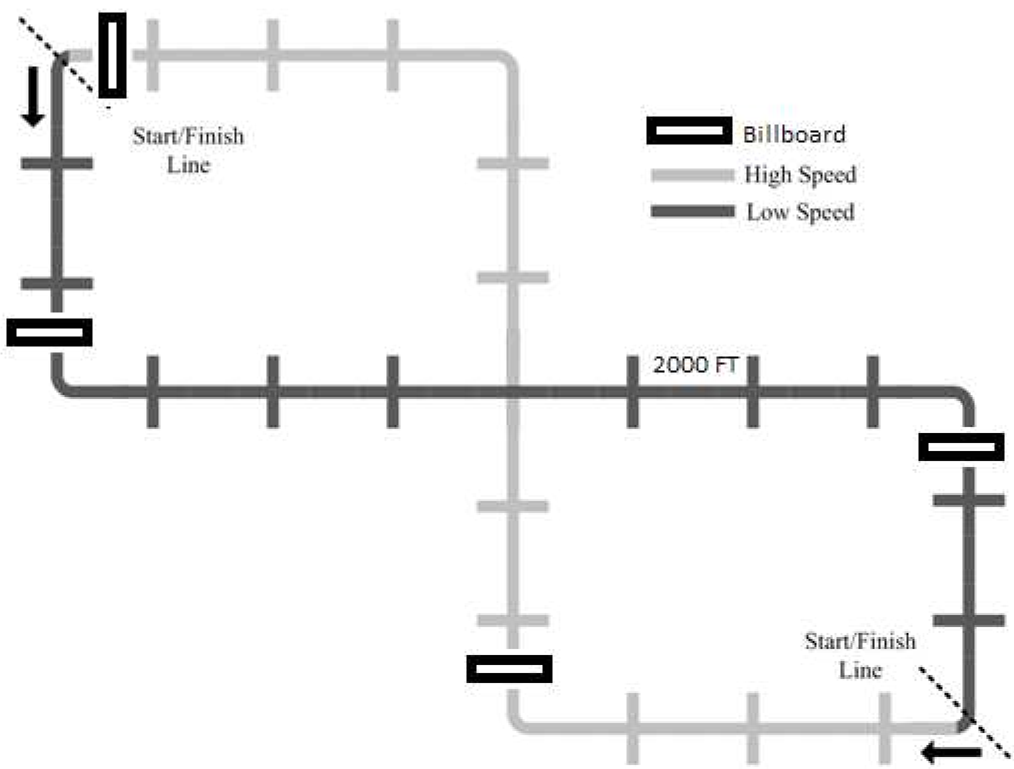

Figure 8: Intersection Layout

The duration of the CY indication was determined using the ITE change interval equation described in Equation 1, resulting in a CY duration of 4.5 seconds for the 45 mph intersections and 5.5 seconds for the 55 mph intersections. The number of participants assigned to traverse the high-speed or the low-speed portion of the track first was counterbalanced. To further eliminate confounding effects due to the order of exposures, each participant was exposed to a randomly generated order of TTSL CY indication triggers.

A data collection sensor was placed on the approach to each intersection, tracking specified parameters from about 650 ft. away from the stop line until the vehicle cleared the intersection. The following parameters were recorded at roughly 15 Hz (15 times a second).

- Time
- Speed (instantaneous)
- Position (instantaneous)
- Acceleration/Deceleration (instantaneous)
- Signal Indication

A new text file was created each time the test vehicle entered a sensor on the approach to the next intersection. This allowed for an organized and efficient transfer of data to a spreadsheet application for further analysis.

3.4 Texting as a Distractor

To reduce the likelihood that participants deduced the primary research question of the study, thereby potentially altering their behavior in response, they were asked to complete several texting tasks while traversing the route. As driver's approached the horizontal curves, they were presented with a message on a billboard. Each message was a phrase or movie title in which one of the key words was left out, and the participants were asked to send a text message containing the missing word to a phone number they were given prior to experimentation. Participants navigated a total of six corners (three high speed and three low speed), two of which were controls with no texting task, two of which required a short (three character) response, and two of which required a longer (9 or 10 character) response (Table 1).

Table 1: Text Message Prompts

Curve #	Speed	Condition	Sign	Response
Curve 1	High Speed	Control	None	N/A
Curve 2		Texting Illegal	___ Ventura: Pet Detective	Ace (3)
Curve 3		Texting Allowed	___Forest, Run!	Run (3)
Curve 4	Low Speed	Control	None	N/A
Curve 5		Texting Illegal	Pirates of the _____: Dead Man's Chest	Caribbean (9)
Curve 6		Texting Allowed	Life is Like a Box of _____	Chocolates (10)

Participants were instructed that the background color of the sign denoted the laws governing texting while driving, with blue indicating it is illegal and green indicating it is legal. The data associated with driver glance patterns and vehicle control parameters was not analyzed as a part of this research, however it is hoped to serve as a starting point for future research efforts. Anecdotally, in post experiment debriefing, nearly every driver supposed that the experiment was concerned with texting while driving.

3.4 Procedure

Interested participants were asked to meet a student researcher in Graf Hall at the driving simulator laboratory. They were briefly introduced to the facility before being escorted to a nearby office where the informed consent process was completed. Upon returning to the lab, each participant was equipped with the eyetracking device and seated in the driver's seat of the driving simulator. A student researcher informed the participants about driving in the simulated environment, and then each participant was allowed three minutes to drive in a practice environment to calibrate their driving in the simulator and assess the potential for simulator sickness.

Upon completion of the practice drive, participants were given additional instruction on how to drive in the experimental scenario. Each driver was instructed to behave as they normally would and to react to all traffic control devices in a manner consistent with their typical driving behavior. They were given instructions on how to perform the texting task and then they were allowed to begin the experiment. Upon completion of the experiment, drivers were escorted back the nearby office where they completed a post-test questionnaire, received a $20 cash compensation for participating, and were debriefed on the purpose of the experiment.

3.5 Participants

A total of 30 drivers were used to develop and validate the FL model. To acquire 30 drivers, 38 drivers actually participated in the experiment where five withdrew due to simulator sickness, and an additional three more were deemed unreliable due to highly questionable behavior by the driver. In all three cases, the drivers focused completely on the texting task and failed to respond in any way to the intersections. Conversation following the experiment revealed that they did not understand how to respond to traffic control devices in the scenario and that they would not normally drive in that fashion.

Table 2 provides the basic demographic information describing the driver population used in this experiment. There was an over-representation of college aged students in the experiment, resulting in a relatively young subject population. This is not atypical for a study of this type (simulator experiment taking place on a university campus).

Table 2: Subject Demographics

How many years have you been a licensed driver?		
Possible Responses	*Number of Participants*	*Percent of Participants*
0-5	9	30%
6-10	13	43%
11-15	6	20%
16-20	1	3%
20+	1	3%
How many miles did you drive last year?		
Possible Responses	*Number of Participants*	*Percent of Participants*
0-5,000	8	27%
6,000-10,000	10	33%
11,000-20,000	8	27%
20,000+	4	13%
What type of vehicle do you typically drive?		
Possible Responses	*Number of Participants*	*Percent of Participants*
Passenger Car	21	70%
SUV	4	13%
Pickup Truck	5	17%
Van	0	0%
Gender		
Possible Responses	*Number of Participants*	*Percent of Participants*
Male	17	56%
Female	13	44%
Age		
Minimum	*Average*	*Maximum*
19	24.5	37

4 Results and Discussion

This chapter presents the findings from the evaluation of driver behavior conducted in the OSU driving simulator. It explores responses to the post-experiment survey as well as considers various aspects of the observed driver response to the CY indication, including vehicle trajectory, decision to stop/go, and deceleration rates. It also proposes and evaluates a FL model to help describe the boundaries of a Type-II DZ.

4.1 Driver Behavior

4.1.1 Questionnaire and Driver Understanding

In the post-experiment questionnaire, drivers were asked questions related to traffic signal operation and the CY indication, the results can be found in Table 3. The aggregate response to the first question indicates that drivers think the CY has a mean value of 3.6 seconds with a standard deviation of 1.0 seconds.

The second question reveals that the majority of drivers understand the Oregon laws relating to the CY indication, which is best described by the last option. This finding is consistent with the research by Hurwitz et al., which found that 69% of drivers correctly understood the meaning of the CY indication (2011b).

Nearly all subjects agreed that their decision to stop/go is influenced by both speed and distance to the intersection, which supports the development of a FL model based on these parameters. Roughly half of the drivers felt that presence of law enforcement and the action of nearby vehicles would also affect their behavior.

Table 3: Driver Response to Questionnaire

How long do you think the typical yellow indication duration is?		
Possible Responses	*Number of Participants*	*Percent of Participants*
2 seconds	1	3%
3 seconds	17	57%
4 seconds	9	30%
5 seconds	1	3%
6 seconds	1	3%
7 seconds	1	3%

Which of the following best describes the traffic laws relating to the yellow indication in Oregon?		
Possible Responses	*Number of Participants*	*Percent of Participants*
A vehicle can occupy the intersection on red as long as it enters the intersection while the yellow indication is being presented.	4	13%
A vehicle must clear the intersection before it turns red.	5	17%
A vehicle must stop when presented the yellow indication unless it is unsafe to do so.	21	70%

What factors do you feel are critical when deciding to stop or go when presented with the yellow indication (circle all that apply):		
Possible Responses	*Number of Participants*	*Percent of Participants*
Intersection width	6	20%
Grade of approach	11	37%
Speed	30	100%
Distance to intersection	29	97%
Presence of law enforcement	16	53%
Action of nearby vehicles	14	47%

4.1.1 Vehicle Trajectory

Time-space diagrams can prove a valuable tool to help visualize the trajectory of a vehicle approaching an intersection. Due to the robustness and accuracy of this data set, several time-space diagrams were developed to help understand driver responses to the CY indication. Each line on the figures represent the path of a single vehicle approaching the intersection. Figures 9 and 10 show the vehicle trajectories for a single participant under both the posted 45 mph (9) and posted 55 mph (10) conditions. In these figures, the slope of the line represents the speed of travel, and curvature indicates acceleration/deceleration.

In both figures, the vehicles positioned closest to the stop line at the onset of the CY indication are more likely to proceed through the intersection, while those further back are more likely to stop. For vehicles that stop, the degree of curvature of the line is an indication of the deceleration rate that was experienced to bring the vehicle to a complete stop. In Figure 10, it can be seen that some vehicles decelerated at a higher rate than others in order to stop before the stop line.

These figures assist in identifying inconsistent behavior for an individual driver. In Figure 9, you can see that the driver chose to stop the vehicle when it was roughly 200 feet away from the intersection on the onset of the CY, but then chose to proceed through the intersection when it was roughly 250 feet away at the onset of the CY. This inconsistency points towards some degree of indecision for the driver in this region on the approach to the intersection. It is difficult to draw statistical conclusions based on data presented exclusively in this fashion, but it provides a meaningful visualization of the driver response to the CY indication.

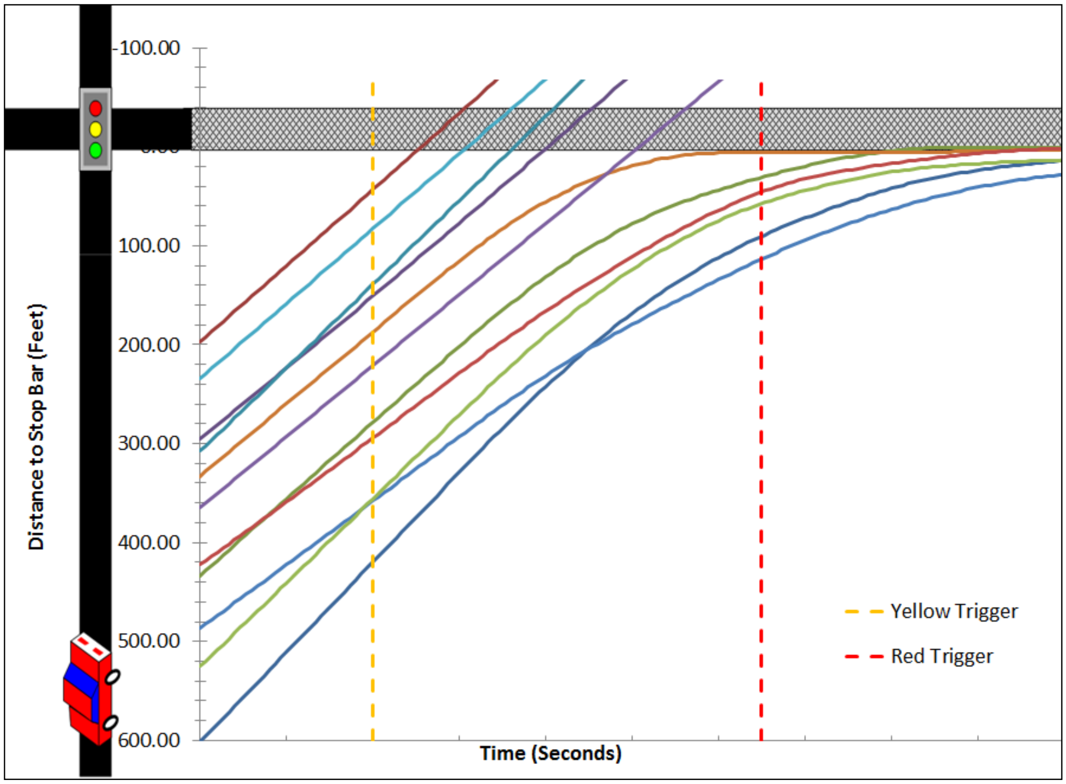

Figure 9: Lower Speed (45 mph)

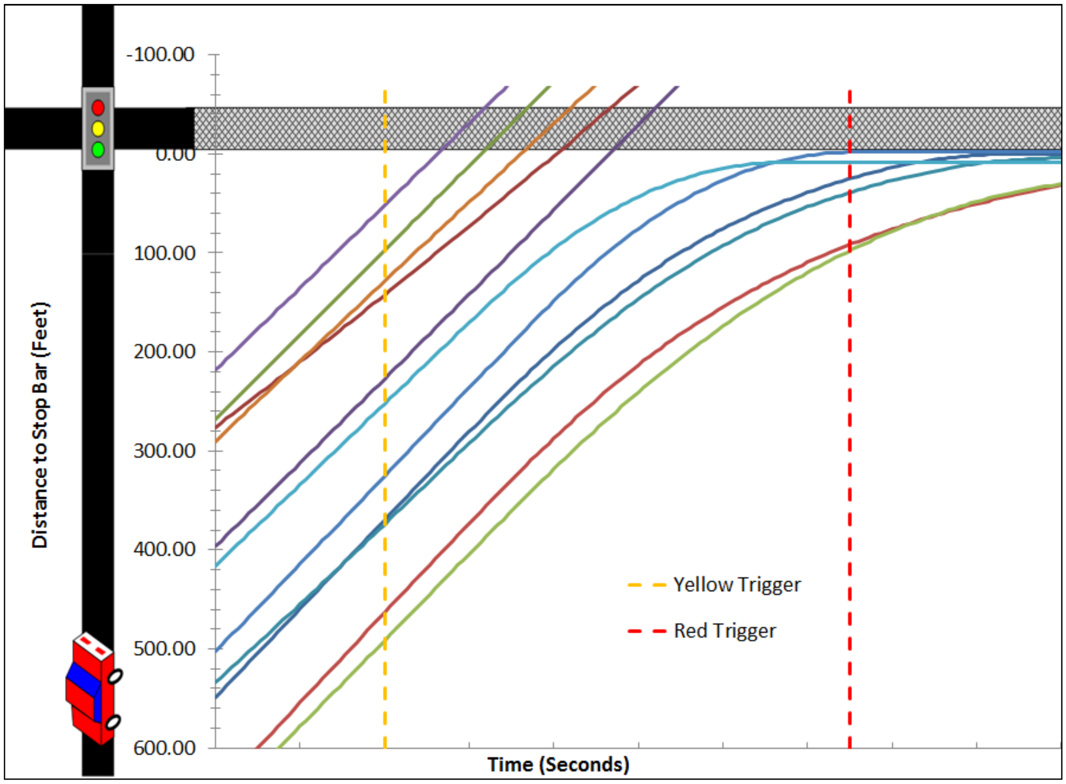

Figure 10: Higher Speed (55 mph)

Another way to visualize this type of data is to display the trajectories for all of the drivers on a single plot. By making each figure represent a single time-to-stop line threshold, insight can be gained into where the most inconsistent behavior occurs. Figures 11, 12, and 13 provide trajectory data for all thirty drivers.

In Figure 11, it can be seen that vehicles are close to the intersection at the onset of the CY indication, and they consistently proceed through the intersection well before the CR. Figure 12 shows that drivers behave in a less consistent manner when they are 3.5 second away from the intersection, sometimes continuing through and sometimes stopping. This figure also shows variability in the location where vehicles completed their stop, some of which may be attributed to a poor selection of deceleration, but mostly differences in how drivers perceived their position relative to the stop line. Figure 13 shows that almost every driver stops when they are 6 seconds away from the intersection at the onset of the CY indication. It can be seen that there were two instances of red light running.

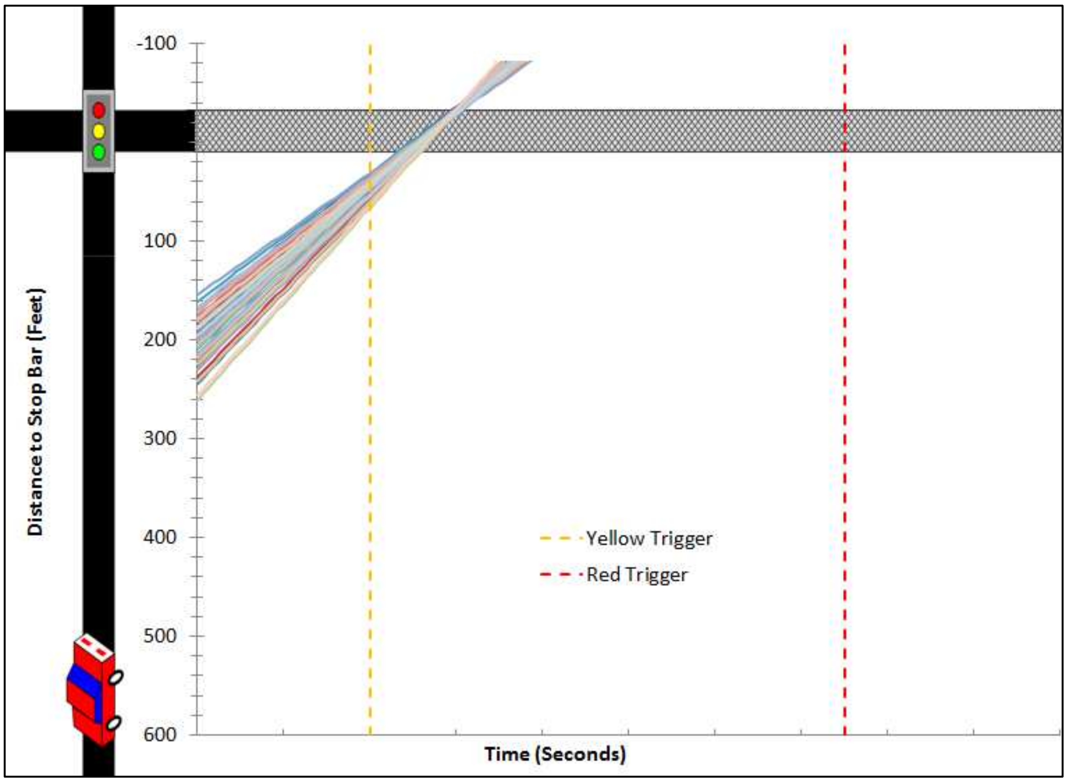

Figure 11: Vehicle trajectories for TTSL=1 sec

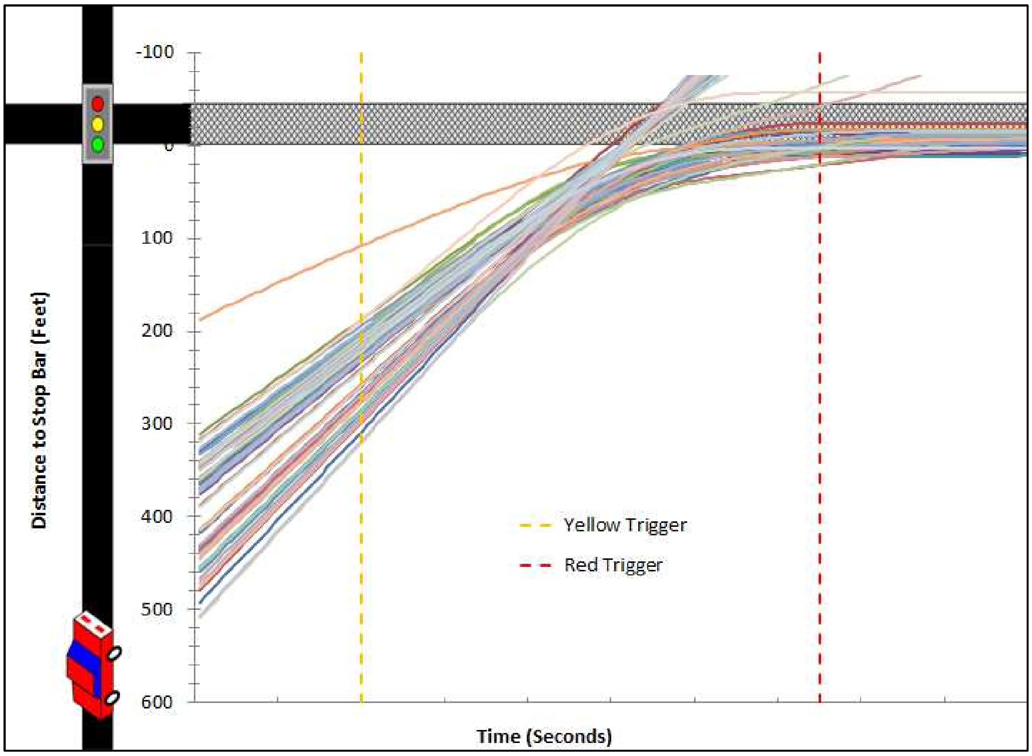

Figure 12: Vehicle trajectories for TTSL=3.5 sec

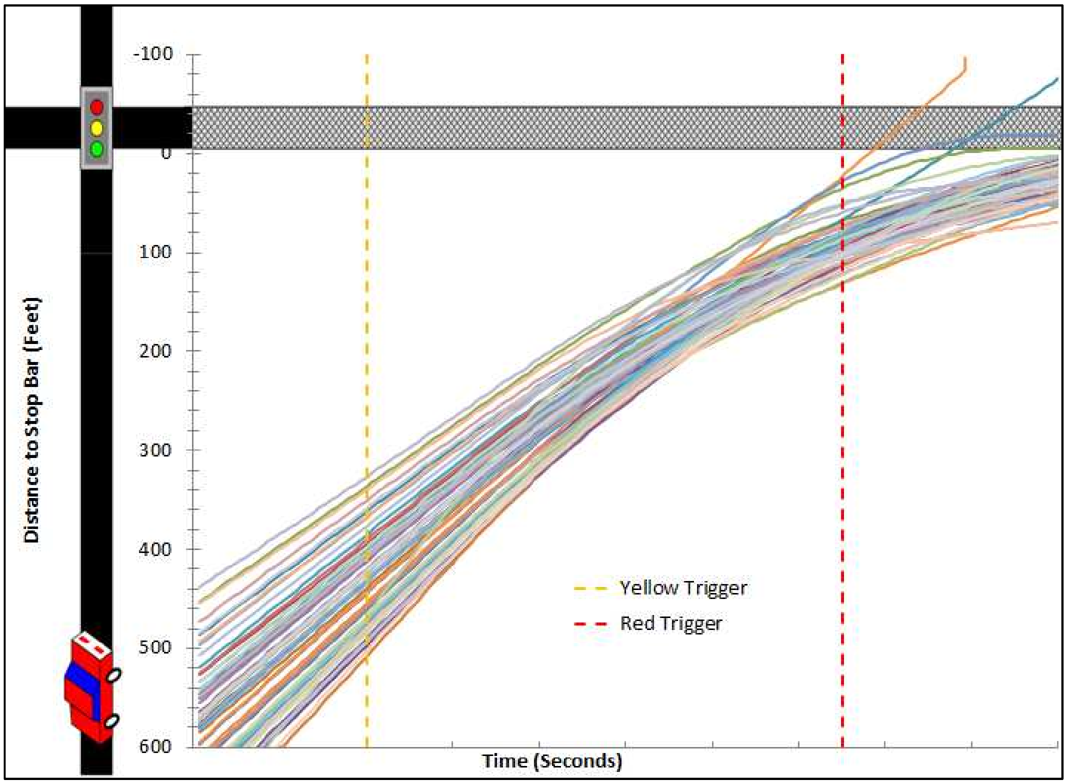

Figure 13: Vehicle trajectories for TTSL=6 sec

4.1.2 Decision Making

A driver's decision to stop before or proceed through the intersection is the foundation for developing models to describe the DZ. It is postulated that both speed and position are highly influential to a driver's decision; therefore driver behavior is presented in relation to the TTSL (which includes both factors). Table 4 and Figure 14 show that all drivers went when they were 2 seconds or less from the intersection at the onset of the CY indication. This finding is consistent with the finding of Chang et al. (1985) and Gates et al., (2006) who found that nearly all vehicles proceeded through the intersection when they were two seconds or less away at the onset of the CY. At a TTSL of 4.5 or greater, most drivers (93%) stop before the intersection and red-light running starts to occur.

Table 4: Driver Decision

TTSL	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5	6
Go	100%	100%	100%	93%	76%	41%	28%	10%	3%	7%	0%
Stop	0%	0%	0%	7%	24%	59%	72%	88%	93%	88%	97%
Run Red	0%	0%	0%	0%	0%	0%	0%	2%	3%	5%	3%

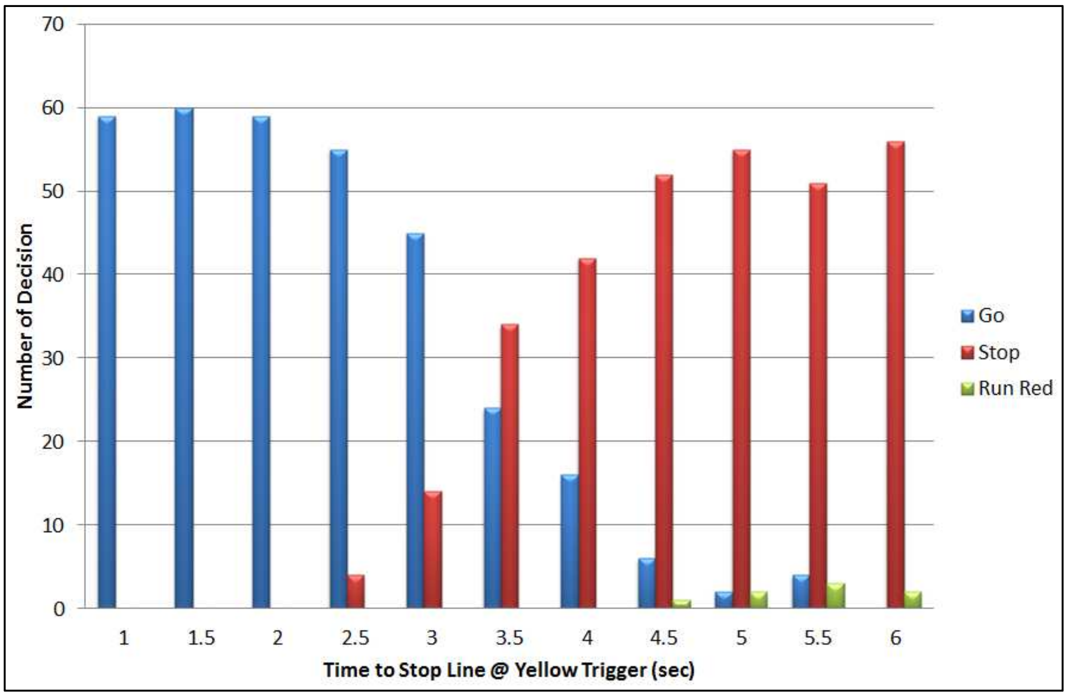

Figure 14: Driver Decision

By changing the horizontal axis from TTSL to vehicle position, the driver's decision data can be compared to empirically observed data sets used by Rakha et al. (2007) and Hurwitz et al. (2011a). Figure 15 shows the probability of stopping for all three experiments, one of which was conducted in the field, one on a test track, and one in a driving simulator.

A two-sample Kolmogorov-Smirnov test was used to compare the three distributions. It was found that there are no statistical differences in the distributions from research by Hurwitz et al. and this research at the 95% confidence level, and that the distribution from Rakha et al. did not share a continuous distribution with either study at the 95% confidence interval. The curve generated for this research is similar in spread to the curve generated by Hurwitz et al., (2011a), and similar in shape the curve generated by Rakha et al., (2007). The shift to the left associated with the Rakha et al. curve could be attributed to a lower operating speed and a reduced distance range during data collection.

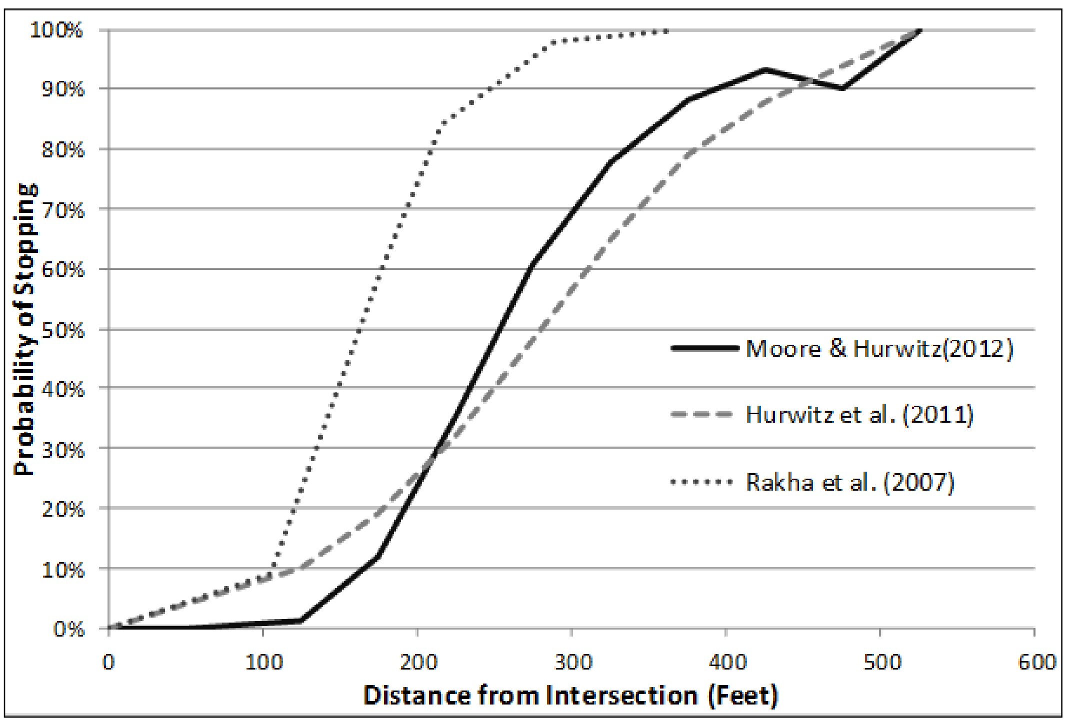

Figure 15: Probability of Stopping

4.2 Deceleration Rates

Deceleration rates are of critical importance when evaluating drivers' decisions to stop or go. The ITE equation for the timing of the change interval (Equation 1) incorporates an assumption for a comfortable deceleration rate (10 ft/s^2). To support the validity of using a driving simulator to evaluate driver behavior in this way, it is important that the observed deceleration rates are comparable to that threshold as well as other studies of this nature. Average deceleration rates were calculated as the speed at initial brake application divided by the time it took to come to a complete stop. Figure 16 plots the cumulative distribution of deceleration rates for this study and several previous field studies. As shown, the deceleration rates observed from the simulated experiment are consistent with previous field research.

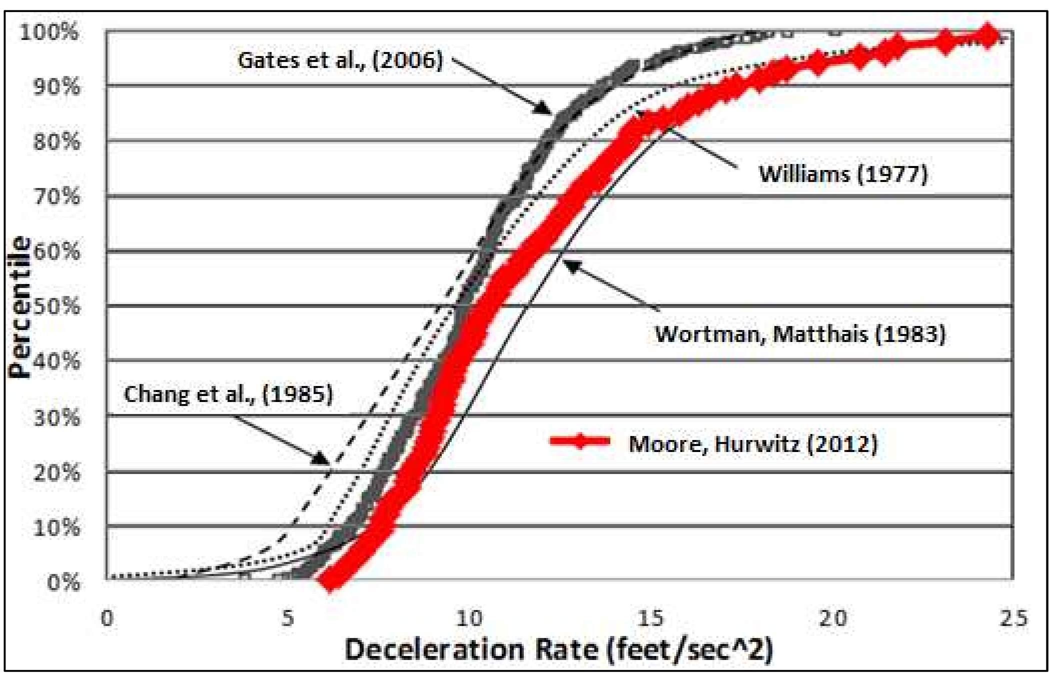

Figure 16: Average Deceleration Rates

Table 5 provides summary statistics associated with the deceleration rates determined from this research as well as those displayed in Figure 16. Deceleration rates for this experiment appear to be slightly higher than those reported by Gates et al., (2006); however, they appear to fall within the range of values reported by other studies. Figure 16 and Table 5 demonstrate the comparability of this data to that obtained from field observations. The 95% confidence intervals calculated and included in Table 5 indicate no statistical difference in the mean deceleration rates from this research and the research by Gates et al., (2006). This finding provides preliminary evidence to support the validation of the driving simulator for research concerning driver response to traffic signals on tangent road.

Table 5: Deceleration Parameters

Authors	Year	Mean	SD	95% CI		Deceleration Rate		
				Low	High	15%	50%	85%
Moore, Hurwitz	2012	11.7	4.0	3.62	19.78	8.0	10.5	15.8
Gates et al.	2006	10.1	2.8	4.44	15.76	7.2	9.9	12.9
Chang et al.	1985	9.5	-	-	-	5.6	9.2	13.5
Wortman, Matthais	1983	11.6	-	-	-	8.0	11.0	16.0

To aid in the visualization of the comparison, Figure 17 displays the means and 95% confidence intervals for both studies.

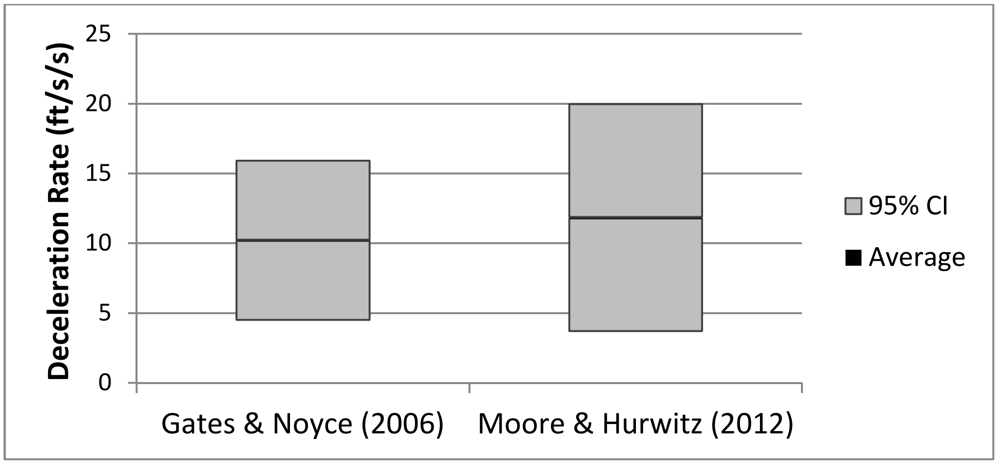

Figure 17: Comparison of mean and 95% CI

4.3 Fuzzy Logic Model

This section presents the use of FL to model DZs and the model's ability to predict a driver's behavior given certain parameters. The FL models were created and validated with the use of the FL toolbox available in MATLAB. As previously described, the general FL process involves using predictor variable data (i.e. speed and/or position) to create membership functions, a process which is referred to as "fuzzification." Inference is then used to relate the input variables to a specified output function, and finally "defuzzification" is used to relate the output to expected outcomes. Typically, visual inspection of input variable data is used to estimate the shape and parameters associated with input membership functions.

The MATLAB toolbox allows the software to determine specific membership function parameters for both input and output variables (and the rules relating them) to be selected based on a "training" process. It uses an Adaptive Neuro-Fuzzy Inference System (ANFIS) to develop a FL model based on a set of training data. For this research, behavior data from 15 randomly selected drivers was used to “train” the creation of the FL model, and data from the remaining 15 drivers was used to validate the model and evaluate its predictive power.

The models presented in this section are founded on either position (distance to stop bar), or a combination of speed and position.

4.3.1 Position Based FL Model

The first FL Model developed was based exclusively on a vehicles distance to the stop line at the onset of the yellow indication (position). The FL model was developed in MATLAB by determining the shape and number of membership functions that should be used to describe each input variable. The FL model development process previously described (Section 4.3) results in the creation of a probability to stop curve, as shown in Figure 18.

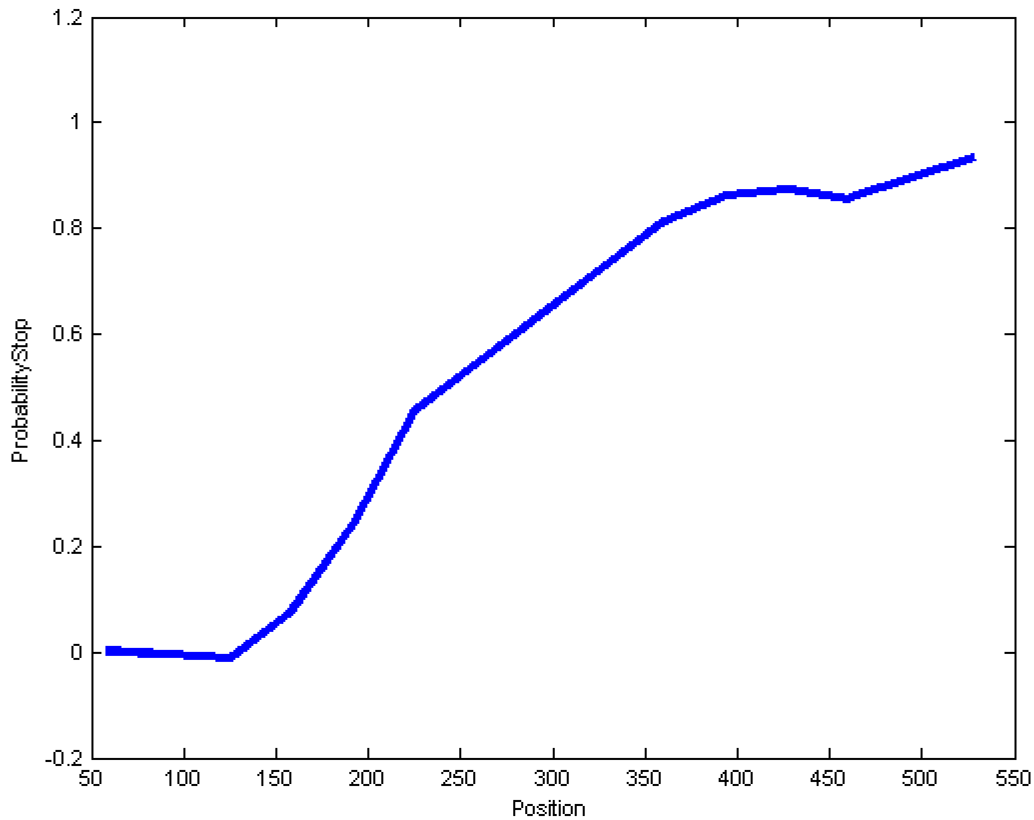

Figure 18: Position-Based FL Model Surface

Various shapes were evaluated, and it was determined that trapezoidal input membership functions best describe this data. Previous research on DZs has utilized triangular membership functions, which are similar to trapezoidal membership functions in that they consist of only straight lines, but they lack the horizontal surface at the peak. The more membership functions that are included to describe each input variable, the more closely this surface will resemble the shape of the raw data. However, if too many membership functions are used, the model will be over fit to the data and its predictive ability will deteriorate. With that in mind, three membership functions were used to describe the input variable of position in this model and are defined in Table 6. This is consistent with previously documented efforts by Hurwitz et al., (2012a) in which the three membership functions were described as “close, middle, and far distance.”

Table 6: Input Membership Functions for Vehicle Position (VP)

Fuzzy Subsets	Membership Function
Membership Function 1	$f(VP) = \begin{cases} 1.0 & VP \leq 128.2 \\ 2.37 - \left(\frac{1}{93.8}\right)VP, & 128.2 < VP \leq 222 \\ 0 & 222 < VP \end{cases}$
Membership Function 2	$f(VP) = \begin{cases} 0 & VP \leq 128.4 \\ -1.37 + \left(\frac{1}{93.9}\right)VP, & 128.4 < VP \leq 222.3 \\ 1 & 222.3 < VP \leq 363.6 \\ 4.86 - \left(\frac{1}{94.1}\right)VP, & 363.6 < VP \leq 457.7 \\ 0 & 457.7 < VP \end{cases}$
Membership Function 3	$f(VP) = \begin{cases} 0 & VP \leq 364 \\ -3.87 + \left(\frac{1}{94}\right)VP, & 364 < VP \leq 458 \\ 1 & 458 < VP \end{cases}$

After creating and training the FL model, MATLAB can evaluate new input data and provide the output value determined by the model. Position data from the second 15 drivers was input into the model and for each interaction with the signal, a probability to stop was reported. A probability to stop greater than 0.5 was interpreted to identify a condition resulting with a vehicle stopping before the intersection, and a value less than 0.5 was interpreted as a condition where the vehicle continued through the intersection.

These values were compared to the actual observed behavior of the second 15 drivers and the predictive power of this model is described in Table 7.

Table 7: Accuracy of Position-Based Model

		Predicted		
		Stop	Go	% Correct
Observed	Stop	145	11	93%
	Go	27	137	84%
			Total	**88%**

As shown, the position based FL model correclty predicted the behavior for the remaining 15 drivers with an accuracy of 88%. This result is slightly better than the 85% accuracy presented by Hurwitz et al. (2012a) for their position-based FL model. Raw data from the 2012 research was obtained and evaluated according this position-based model and the results were identical to those reported by Hurwitz et al. This table also provides insight as to where the model is more prone to generating errors, and in this case the majority of the errors (71%) occurred when the model predicted a vehicle would stop when in was observed going.

4.3.2 Speed and Position FL Model

A new FL model was then created by adding speed as a second input variable. The addition of a second input variable creates a 3-dimentional surface to describe a vehicle's probability to stop as shown in Figure 19. Similar to the position-based model, trapezoidal membership functions were used to describe the input variables and are described in Table 8 and 9.

Table 8: Input Membership Functions for Vehicle Position (VP)

Fuzzy Subsets	Membership Function
Membership Function 1	$f(VP) = \begin{cases} 1.0 & VP \leq 198.7 \\ 2.05 - \left(\frac{1}{188.5}\right)VP, & 198.7 < VP \leq 387.2 \\ 0 & 387.2 < VP \end{cases}$
Membership Function 2	$f(VP) = \begin{cases} 0 & VP \leq 198.2 \\ -1.05 + \left(\frac{1}{188.7}\right)VP, & 198.2 < VP \leq 386.9 \\ 1 & 386.9 < VP \end{cases}$

Table 9: Input Membership Functions for Vehicle Speed (VS)

Fuzzy Subsets	Membership Function
Membership Function 1	$f(VS) = \begin{cases} 1.0 & VS \leq 43.39 \\ 3.99 - \left(\frac{1}{14.5}\right)VS, & 43.39 < VS \leq 57.89 \\ 0 & 57.89 < VS \end{cases}$
Membership Function 2	$f(VS) = \begin{cases} 0 & VS \leq 44.02 \\ -3.42 + \left(\frac{1}{12.89}\right)VS, & 44.02 < VS \leq 56.91 \\ 1 & 56.91 < VS \end{cases}$

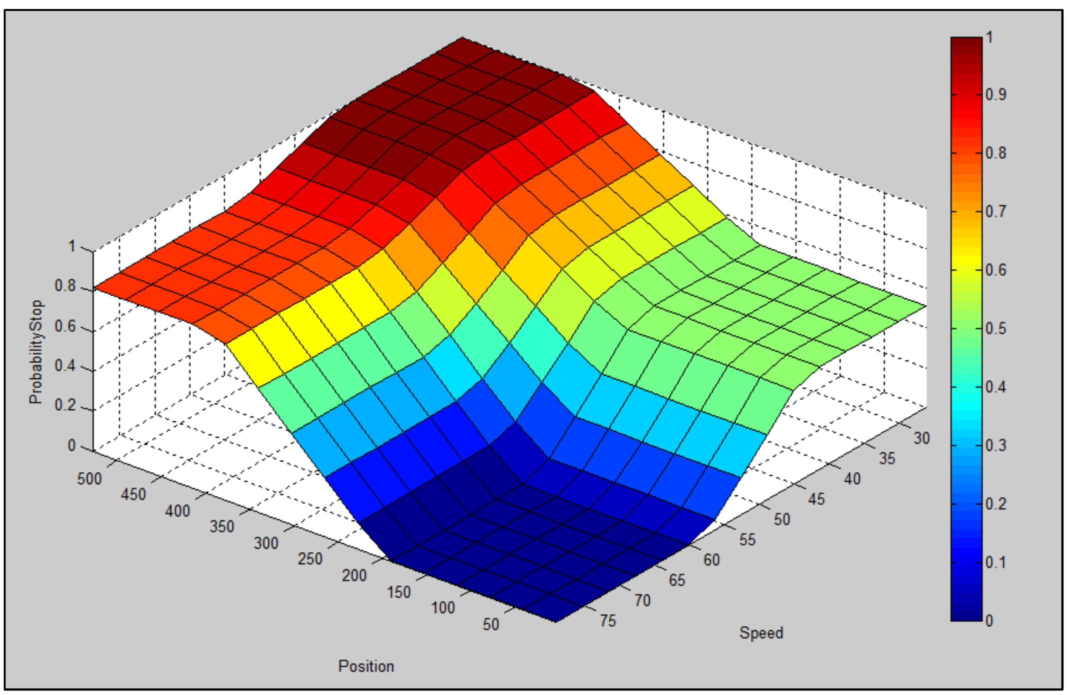

Figure 19: Speed & Position-Based FL Model Surface

Again, data from 15 drivers was used to develop the model, which was then used to predict behavior for the remaining 15 drivers. As shown in Table 10, the accuracy of this model was slightly better than the model based on position alone; however the pattern of errors shifted so that 66% of the errors were associated with a vehicle observed stopping when it was predicted to go.

Table 10: Accuracy of Speed/Position-Based Model

		Predicted		
		Stop	Go	% Correct
Observed	Stop	132	24	85%
	Go	12	152	93%
			Total	**89%**

4.3.3 TTSL FL Model

Taking the previous model one step further, speed and position was combined into a single variable (TTSL) prior to its use in a FL model. This model was developed using trapezoidal functions (described in Table 11) and a similar process to that described for the other models. The probability-to-stop surface, shown in Figure 20, looks similar to that obtained by plotting the raw data.

Table 11: Input Membership Functions for Time-To-Stop-Line (TTSL)

Fuzzy Subsets	Membership Function
Membership Function 1	$f(TTSL) = \begin{cases} 1.0 & TTSL \leq 1.76 \\ 2.74 - \left(\frac{1}{1.01}\right) TTSL, & 1.76 < TTSL \leq 2.77 \\ 0 & 2.77 < TTSL \end{cases}$
Membership Function 2	$f(TTSL) = \begin{cases} 0 & TTSL \leq 1.77 \\ -1.79 + \left(\frac{1}{0.99}\right) TTSL, & 1.77 < TTSL \leq 2.76 \\ 1 & 2.76 < TTSL \leq 4.33 \\ 3.7 - \left(\frac{1}{1.17}\right) TTSL, & 4.33 < TTSL \leq 5.5 \\ 0 & 5.5 < TTSL \end{cases}$
Membership Function 3	$f(TTSL) = \begin{cases} 0 & TTSL \leq 4.13 \\ -3.44 + \left(\frac{1}{1.2}\right) TTSL, & 4.13 < TTSL \leq 5.33 \\ 1 & 5.33 < TTSL \end{cases}$

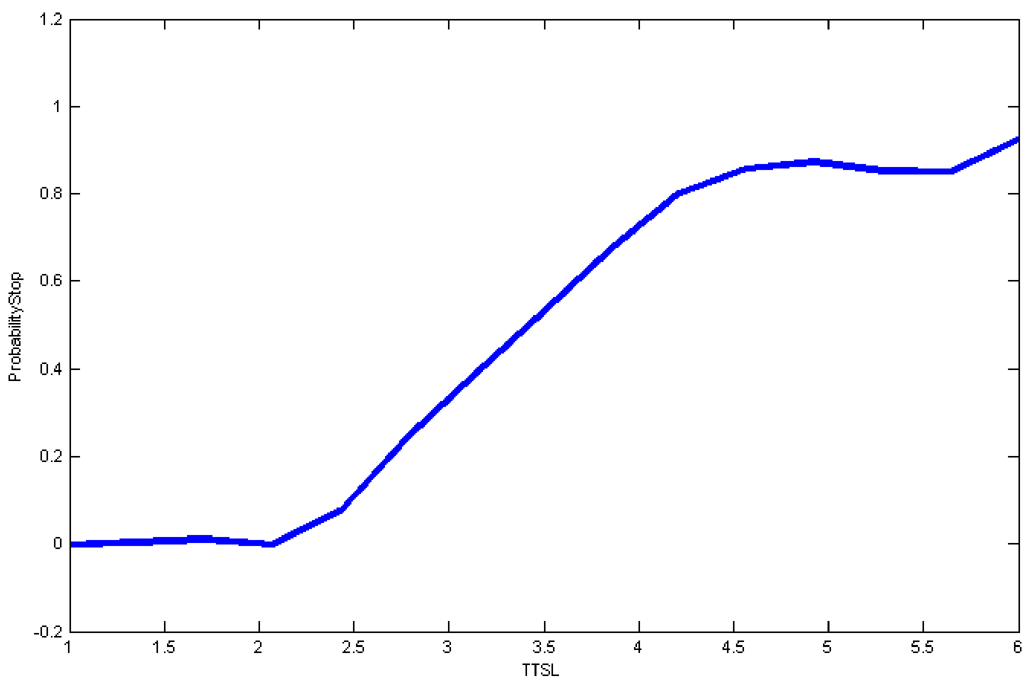

Figure 20: TTSL-Based FL Model Surface

This model provides the highest predictive power when attempting to predict the behavior of the remaining 15 drivers. Table 12 shows that this model is slightly more accurate than the previous ones, and that the errors tend be related to proceeding vehicles that were predicted to stop (78%).

Table 12: Accuracy of TTSL Model

		Predicted		
		Stop	Go	% Correct
Observed	Stop	149	7	96%
	Go	25	139	85%
			Total	**90%**

4.3.4 Model Comparison

The overall predictive power of all three models is very similar, between 88% and 90%. One might expect that the speed/position model and the TTSL model would produce the same result. While they are very similar, the observed differences can be attributed to slight variations in parameter selection during the model development process. It was expected that the addition of speed would significantly increase the accuracy of the model. It should also be noted that speeds were relatively consistent throughout the experiment and there was little interference from other vehicles. This finding can be interpreted to suggest that under similar conditions, distance to the intersection alone provides much of the predictive power of the model. If greater speed variability is present in the traffic stream (due to congestion or other factors), individual speeds may become more important to accurately predict driver behavior.

It is interesting to consider the shift in the type of behavior that was most often predicted falsely. Both the position-based and TTSL-based models tended to predict a vehicle would stop at the intersection, when in fact it proceeded through it. The speed/position-based model seemed to reverse that trend, predicting a vehicle would proceed through the intersection when it stopped. This suggests that an increased sample size and refinement of the models may lead to increased accuracy.

5 Conclusions

5.1 Simulator Validation

Driving simulation has been recognized as a safe, efficient, and effective method to evaluate driver behavior under various conditions. However, it is critically important to scope research questions appropriately in a driving simulator, and there is a need for extensive validation of the results obtained in laboratories of this type. As such, efforts should be made to compare results from simulator experiments with those obtained from alternative experimental mediums (surveys, test-tracks, field study, etc.).

Driver decision making and vehicle deceleration rates are important factors when attempting to evaluate and model driver behavior in DZs. Data collected as part of this research to describe these two factors was compared to several previous research studies conducted in different experimental mediums on this topic. The comparison provides evidence that driver response to traffic signals on tangent segments of roadway can be effectively evaluated and modeled in a driving simulator of a similar configuration to the one operated by the OSU Driving and Bicycling Research Lab.

5.2 Model Development and Comparison

FL is a widely accepted and applied strategy for modeling systems with imprecise input data. In one sense, it enables a computer to “reason” more like a person would, making it a viable option for modeling driver behavior. In the moment a driver identifies that the traffic signal has turned yellow, they must make rough estimates about their position, speed, and other factors to arrive at a decision to stop or proceed. When applied to this type of problem, FL essentially enables a computerized model to replicate that decision making process with a similar consideration of factors.

The FL models proposed in this research demonstrate their ability to predict driver behavior with a reasonably high degree of accuracy (88% - 90%). Due to similar accuracy thresholds, vehicle speed does not appear to be as influential as expected for the scenario described in this research. As previously mentioned, it is suspected that this might not be the case when there is more variability in the speed of the traffic stream.

When the position-based FL model was applied to the data used by Hurwitz et al. (2011), the predicted behavior was exactly the same as that reported by the authors. Since the previous work was founded on field observations, this strongly supports the validity of data collected in the driving simulator as well as the procedure used to develop the FL models.

5.3 Future Work

This research has developed preliminary evidence to suggest the validity of driving simulators for modeling driving response to traffic signals. With that said, there is the potential for the following additional work in this area:

- A larger, more diverse sample size would allow for further refinement of the parameters used to develop the membership functions, and ultimately the predictive power of the model.
- The models developed in this research focused on speed and position. While these are thought to be the most influential factors, literature has identified other factors (e.g. action of nearby vehicles) that could also help explain driver behavior.
- These models have demonstrated their ability to predict driver behavior based on speed and position. One of the most important questions still remaining is how these models can be applied to traffic signal design and operations practice. This research contributes to the understanding of driver behavior within the DZ, and the ultimate goal is the application of this information to improve DZ protection.

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