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Fuzzy Logic for Improved Dilemma Zone Identification: A Driving Simulator Study

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ABSTRACT

Type-II dilemma zones are the segment of roadway approaching an intersection where drivers have difficulty deciding to stop or proceed at the onset of the circular yellow (CY) indication. Signalized intersection safety is improved when dilemma zones are correctly identified and steps are taken to reduce the likelihood that vehicles are caught in such zones. This research purports that using driving simulators as a means to collect driver response data at the onset of the CY indication is a valid methodology to augment our analysis of decisions and reactions made within the dilemma zone. The data obtained was compared against that from previous experiments documented in the literature and the evidence suggests that driving simulation is valid for describing driver behavior under the given conditions. After validating the data, fuzzy logic was proposed as a tool to model driver behavior in the dilemma zone, and three 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.

INTRODUCTION

Type-II dilemma zones (DZ) describe a segment of roadway approaching a signalized intersection where drivers have difficulty deciding to stop or proceed when presented with the circular yellow (CY) indication. The conflicts created in the Type-II DZ, or “indecision zone,” result in increased rear-end crashes caused by abrupt braking and right-angle or left-turn head-on collisions caused by 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, DZ conflicts have a significant negative effect on the overall safety at signalized intersections. Some researchers have even proposed the number of vehicles caught in the dilemma zone is a surrogate measure for safety performance (1). Despite the implications of these conflicts, there is no national standard to properly address this issue.

The Manual on Uniform Traffic Control Devices (MUTCD) provides a range of yellow change interval durations and information relating the meaning and sequence of the CY indication (2). In absence of a national standard, the Institute of Transportation Engineers (ITE) has developed a recommended equation for the length of the CY (3), and The Traffic Signal Timing Manual, which provides a comprehensive overview of signal timing practices, puts forth the same ITE equation (4). However, there are still agencies that apply alternative approaches to determining the length of the CY. Regardless of what approach is used, the initiation of the CY indication at the wrong time can contribute to DZ conflicts.

An accurate identification of where the DZ exists would 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 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 their success is based in part on the accuracy of that placement. Yet, there are multiple definitions that have been used to describe where the DZ occurs.

The most commonly applied definition is based on a driver’s decision to stop, identifying the downstream edge of the DZ as where 10 percent of drivers stop and the upstream edge where 10 percent of drivers continue (5). The other primary definition is based on a vehicle’s time-to-stop line (TTSL), describing the DZ as 2.5-5.5 seconds from the intersection (6). Recent research suggests that these two definitions result in different DZ locations on the same approach (7).

This research aims to improve the identification of dilemma zones as this is a critical factor to efficient and safe operations at 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 and reduce safety performance. Building on the work of Hurwitz et al. (8), 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 measure vehicle position and speed fifteen times per second to develop a more accurate model of DZs. Additionally, the probability-to-stop data is compared to the previous naturalistic experiments of Hurwitz et al. (8, 9) and test track experiments of Rakha et al. (10); while the deceleration data is compared to those reported by Gates et al. (11).

BACKGROUND

To appreciate the implications of modeling driver behavior in the DZ, it is critical to consider how drivers respond to the CY and how fuzzy logic can be used to model human decision making.

Driver Response to the CY

There have been several research efforts focused on improving the understanding of driver behavior in response to the CY indication. Rakha et al. (10) used data from test-track experiments to gain a better understanding of driver behavior at the onset of the CY. They found that the probability of stopping varied from 100 percent at a TTSL of 5.5 seconds to 9 percent at a TTSL of 1.6 seconds.

Gates et al. (11) performed field observations on over 1000 vehicles that were the first-to-stop or last-to-go at the termination of priority for that approach. The authors evaluated the effects of several variables on the decision to stop/go and reported 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 (11).

Liu et al. (12) 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 significant differences between the observed size and location of the DZ and theoretical estimates. The need to reduce or eliminate that difference shows the need for a new method, such as FL, to more accurately model DZs.

Fuzzy Logic

FL is 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" (13). 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 (14).

Research efforts (8,16) have focused on using FL to better model and understand the behavior of drivers as they interact with traffic control devices, such as traffic signals. As drivers approach 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 candidate for FL modeling.

This research will build and expand upon the work of Hurwitz et al. (8), 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. (10), the authors argue that the FL model more effectively accounts for driver behavior in the DZ than previous models.

METHODOLOGY

Driving Simulator

The Oregon State driving simulator is a high-fidelity simulator, consisting of a full 2009 Ford Fusion cab mounted on top of a pitch motion system. The pitch motion system accurately models acceleration and braking events. Three projectors produce a 180 degree front view and a fourth projector displays a rear image for the driver's center mirror. The two side mirrors have 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 simulator software can record performance measures such as speed, position, brake, and acceleration at a sampling rate of 60Hz. The simulator is pictured in Figure 1.

Scenario Layout and Intersection Control

The experiment was designed to maximize the number of DZ conflicts while limiting the driving time 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. (10) and Hurwitz et al. (7). 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, while the observed speed for the 85th percentile 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.

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. This was accomplished by placing time-to-contact sensors at each signalized intersection that would terminate the green indication at the desired TTSL. A series of 22 approaches, each separated by roughly 2000 feet of roadway, were modeled forming a large figure-eight.

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 650 ft. away from the stop line until the vehicle cleared the intersection. The following parameters were recorded at 15 Hz (15 times a second).

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

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

A total of 30 drivers (17 male, 13 female) were used to develop and validate the FL model. There was an over-representation of college aged students in the experiment, resulting in a relatively young subject population (average age of 24.5 years). This over-representation may limit the application of these results to a wider driving population; however it is adequate to demonstrate the research methodology and model accuracy.

DATA ANALYSIS AND RESULTS

Vehicle Trajectory

Several time-space diagrams were developed to help understand driver responses to the CY indication. Figure 2 shows vehicle trajectories, with each line representing the path of a single vehicle approaching the intersection. In this figure, distance is mapped on the vertical axis and time on the horizontal axis, meaning that the slope of the line represents velocity and the curvature indicates acceleration/deceleration.

In Figure 2(a), 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 this figure, 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 2(a), it is observed 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.

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 TTSL threshold, one can gain insight into where inconsistent behaviors occur. Figures 2b, 2c, and 2d provide trajectory data for all subjects at three TTSL thresholds (1 second, 3.5 seconds, and 6 seconds).

In Figure 2(b), it can be seen that vehicles close to the intersection at the onset of the CY indication consistently proceed through well before presentation of the circular red. Figure 2(c) shows that drivers behave in a less consistent manner when they are 3.5 second away from the intersection, sometimes continuing 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 2(d) 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.

Driver Decision Making

A driver's decision to stop prior to or proceed through the intersection is the foundation for developing models to describe the DZ. 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). It was observed 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. (6) and Gates et al., (11) 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.

By changing the independent variable from TTSL to vehicle position, the driver's decision data can be compared to empirically observed data sets used by Rakha et al. (10) and Hurwitz et al. (7). Figure 3 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 (95% confidence level), and that the distribution from Rakha et al. did not share a continuous distribution with either study (95% confidence interval). The curve generated for this research is similar in spread to the curve generated by Hurwitz et al., (7), and similar in shape the curve generated by Rakha et al., (10). 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.

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 (3) 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 4 plots the cumulative distribution of deceleration rates for this study and several previous field studies. As shown, the deceleration rates from the simulated experiment are consistent with previous field research.

Table 1 provides summary statistics associated with the deceleration rates determined from this research as well as those displayed in Figure 4. Deceleration rates for this experiment appear to be slightly higher than those reported by Gates et al., (11); however, they appear to fall within the range of values reported by other studies. Table 1 demonstrates the comparability of this data to that obtained from field observations. The 95% confidence intervals calculated and included in Table 1 indicate no statistical difference in the mean deceleration rates from this research and the research by Gates et al. (11). This finding provides preliminary evidence to

support the validation of the driving simulator for research concerning driver response to traffic signals on tangent road segments.

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.

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 position or a combination of speed and position.

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 development process previously described results in the creation of a probability-to-stop curve, as shown in figure 5.

Various shapes were evaluated, and it was determined that trapezoidal input membership functions best describe this data. 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 lose predictive ability. With that in mind, three membership functions were used to describe the input variable of vehicle position (VP) in this model and are defined as equations 1, 2, and 3. This fuzzy subset is consistent with previously documented efforts by Hurwitz et al., (8) in which the three membership functions were described as "close, middle, and far distance."

$$f(VP) = \begin{cases} 1.0 & VP \leq 128.2 \\ 2.37 - \left(\frac{1}{93.8}\right)VP, & 128.2 < VP \leq 222 \\ 0 & 222 < VP \end{cases} \quad (1)$$

$$f(VP) = \begin{cases} 0 & VP \leq 128.4 \\ -1.37 + \left(\frac{1}{93.9}\right)VP, & 128.4 < VP \leq 222.3 \\ 1 & 222.3 < VP \leq 363.6 \\ 4.86 - \left(\frac{1}{94.1}\right)VP, & 363.6 < VP \leq 457.7 \\ 0 & 457.7 < VP \end{cases} \quad (2)$$

$$f(VP) = \begin{cases} 0 & VP \leq 364 \\ -3.87 + \left(\frac{1}{94}\right)VP, & 364 < VP \leq 458 \\ 1 & 458 < VP \end{cases} \quad (3)$$

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 was determined.

As shown, the position based FL model correctly 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. (8) for their position-based FL model. Raw data from the 2012 field study was obtained and evaluated according to this position-based model and the results were virtually 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 incorrectly predicted a vehicle would stop.

Vehicle Speed (VS) and Position (VP) 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-dimensional surface to describe a vehicle's probability to stop as shown in Figure 6. Similar to the position-based model, trapezoidal membership functions were used to describe the input variables vehicle position (VP) and vehicle speed (VS) and are described in Equations 4, 5, 6, and 7.

$$f(VP) = \begin{cases} 1.0 & VP \leq 198.7 \\ 2.05 - \left(\frac{1}{188.5}\right)VP, & 198.7 < VP \leq 387.2 \\ 0 & 387.2 < VP \end{cases} \quad (4)$$

$$f(VP) = \begin{cases} 0 & VP \leq 198.2 \\ -1.05 + \left(\frac{1}{188.7}\right)VP, & 198.2 < VP \leq 386.9 \\ 1 & 386.9 < VP \end{cases} \quad (5)$$

$$f(VS) = \begin{cases} 1.0 & VS \leq 43.39 \\ 3.99 - \left(\frac{1}{14.5}\right)VS, & 43.39 < VS \leq 57.89 \\ 0 & 57.89 < VS \end{cases} \quad (6)$$

$$f(VS) = \begin{cases} 0 & VS \leq 44.02 \\ -3.42 + \left(\frac{1}{12.89}\right)VS, & 44.02 < VS \leq 56.91 \\ 1 & 56.91 < VS \end{cases} \quad (7)$$

Again, data from 15 drivers was used to develop the model, which was then used to predict behavior for the remaining 15 drivers. The accuracy of this model (89%) 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.

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 equations 8, 9 and 10) and a similar process to that described for the other models. The probability-to-stop surface, shown in Figure 7, looks similar to that obtained by plotting the raw data.

$$f(TTSL) = \begin{cases} 1.0 & TTSL \leq 1.76 \\ 2.74 - \left(\frac{1}{1.01}\right) TTSL, & 1.76 < TTSL \leq 2.77 \\ 0 & 2.77 < TTSL \end{cases} \quad (8)$$

$$f(TTSL) = \begin{cases} 0 & TTSL \leq 1.77 \\ -1.79 + \left(\frac{1}{0.99}\right) TTSL, & 1.77 < TTSL \leq 2.76 \\ 1 & 2.76 < TTSL \leq 4.33 \\ 3.7 - \left(\frac{1}{1.17}\right) TTSL, & 4.33 < TTSL \leq 5.5 \\ 0 & 5.5 < TTSL \end{cases} \quad (9)$$

$$f(TTSL) = \begin{cases} 0 & TTSL \leq 4.13 \\ -3.44 + \left(\frac{1}{1.2}\right) TTSL, & 4.13 < TTSL \leq 5.33 \\ 1 & 5.33 < TTSL \end{cases} \quad (10)$$

This model provides the highest predictive power when attempting to predict the behavior of the remaining 15 drivers. This model is slightly more accurate than the previous ones (90%), and the errors tend to be related to preceding vehicles that were predicted to stop (78%).

FL Model Comparison

The overall predictive power of all three models is very similar, between 88% and 90% (Table 2). While they are very similar, the observed differences can be attributed to slight variations in parameter selection during the model development process. The aforementioned data shows that the introduction of speed as an additional measured variable did not significantly increase the accuracy of the predictive power of the model as one might expect. 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.

CONCLUSIONS

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.

Model Development and Comparison

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 predict the outcome of the driver's decision making process.

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. (7, 15), 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.

Future Work

This research has developed preliminary evidence to suggest the validity of driving simulators for accurately modeling driving response to traffic signals. Furthermore, it demonstrates the

predictive power of using fuzzy logic to model driver behavior. Additional work in this area should include:

- A larger, more diverse sample size.
- The consideration of other factors, such as varying speeds or proximally located vehicles, in the predictive models.
- The application of the developed models to signal timing and detector design.

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TABLE 1 Deceleration parameters

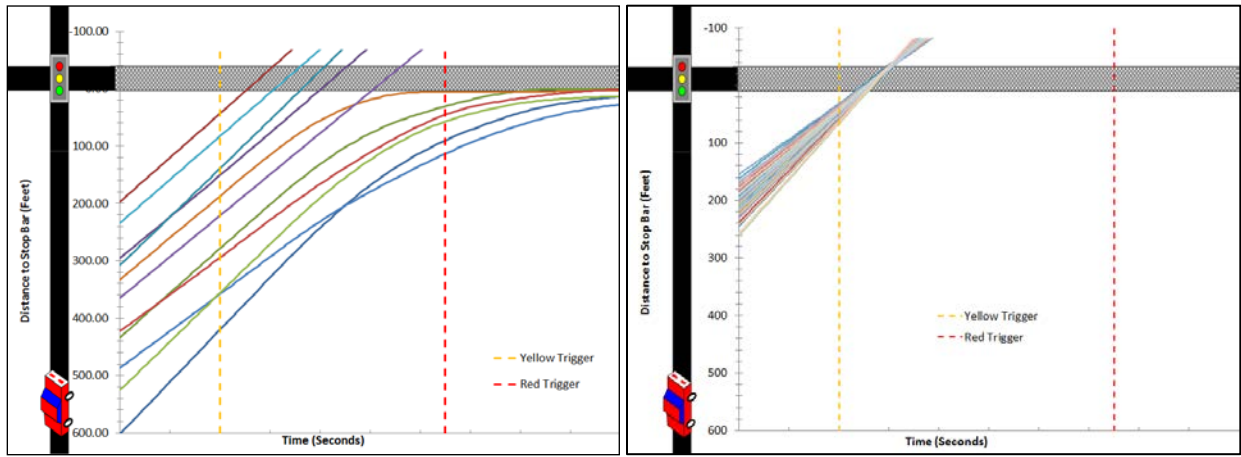
Authors	Year	Mean	SD	95% CI		Deceleration Rate		
				Low	High	15%	50%	85%
Moore, Hurwitz	2012	11.7	4.0	3.62	19.78	8.0	10.5	15.8
Gates et al.	2006	10.1	2.8	4.44	15.76	7.2	9.9	12.9
Chang et al.	1985	9.5	-	-	-	5.6	9.2	13.5
Wortman, Matthais	1983	11.6	-	-	-	8.0	11.0	16.0

TABLE 2 Predictive Power of FL Models

			Predicted		% Correct	Total
			Stop	Go		
Position-Based Model	(Observed)	Stop	145	11	93%	88%
		Go	27	137	84%	
Speed/Position-Based Model	(Observed)	Stop	132	24	85%	89%
		Go	12	152	93%	
TTSL-Based Model	(Observed)	Stop	149	7	96%	90%
		Go	25	139	85%	

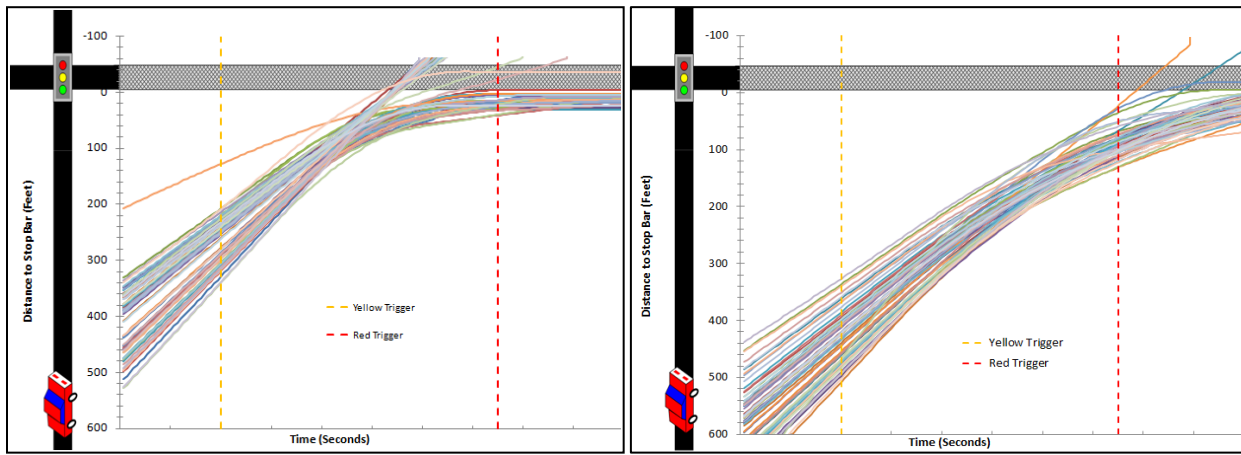


FIGURE 1 Oregon state driving simulator.



(a) Single participant trajectories @ 45 mph

(b) 30 Vehicle trajectories for TTSL=1 sec



(c) 30 Vehicle trajectories for TTSL=3.5 sec

(d) 30 Vehicle trajectories for TTSL=6 sec

FIGURE 2 Vehicle trajectories in response to the CY.

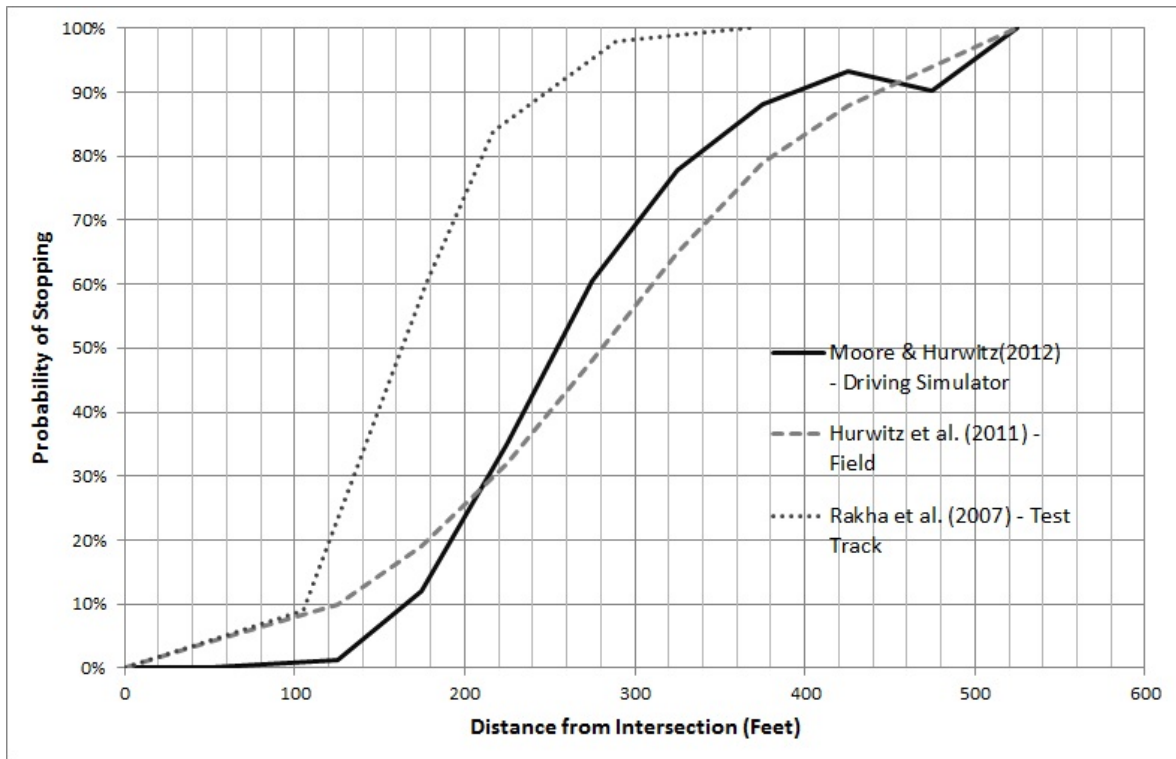


FIGURE 3 Probability of stopping.

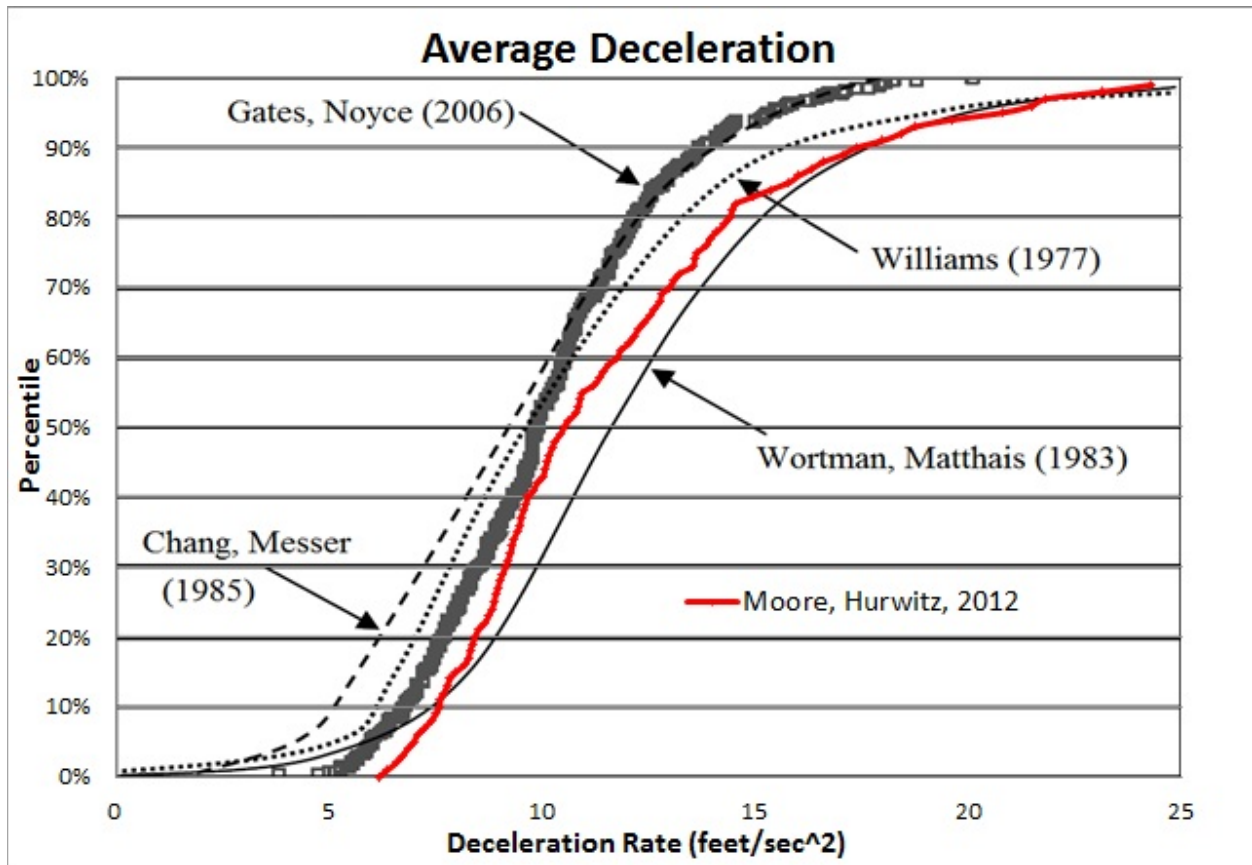


FIGURE 4 Average deceleration rates.

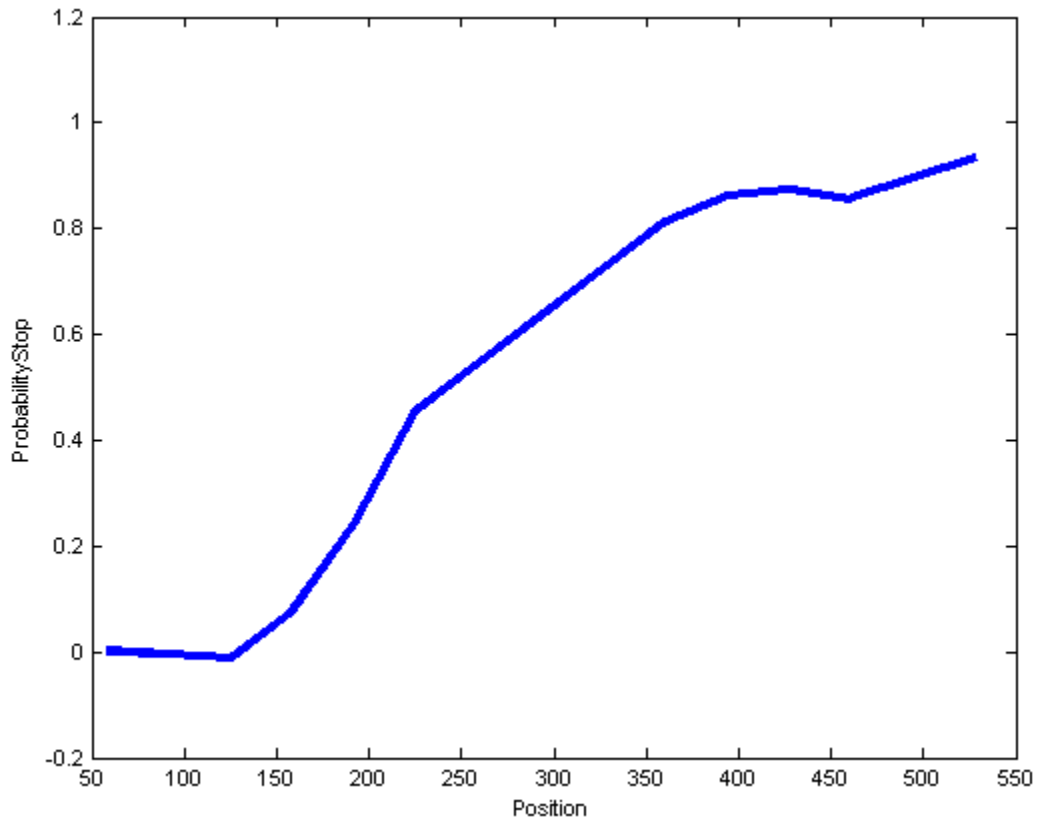


FIGURE 5 Position-based FL model surface.

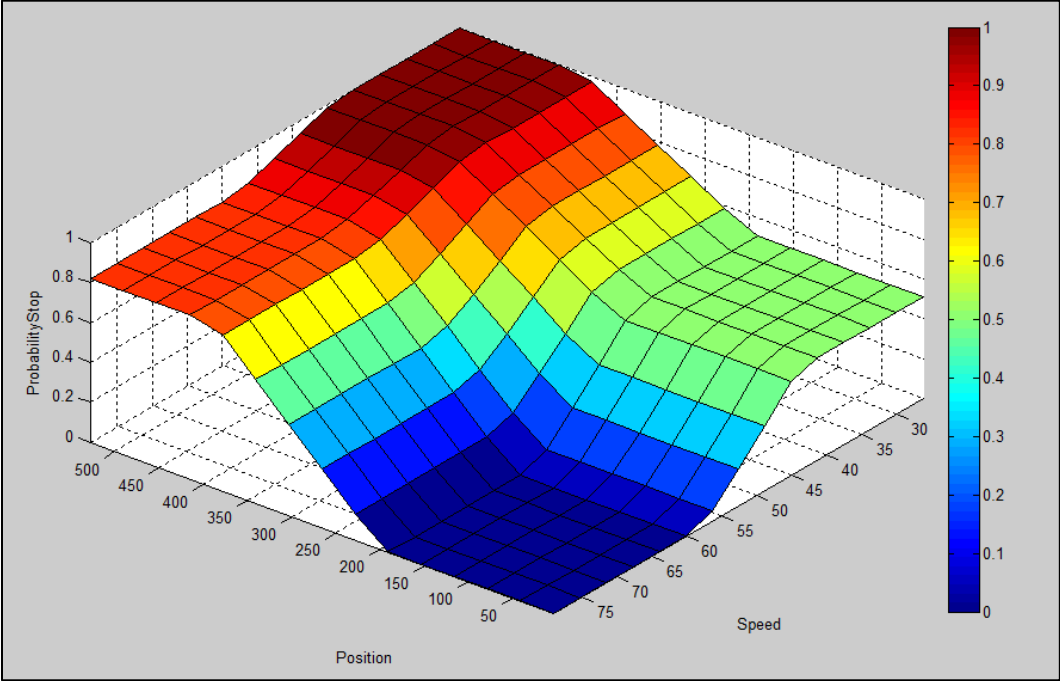


FIGURE 6 Speed & position-based FL model surface.

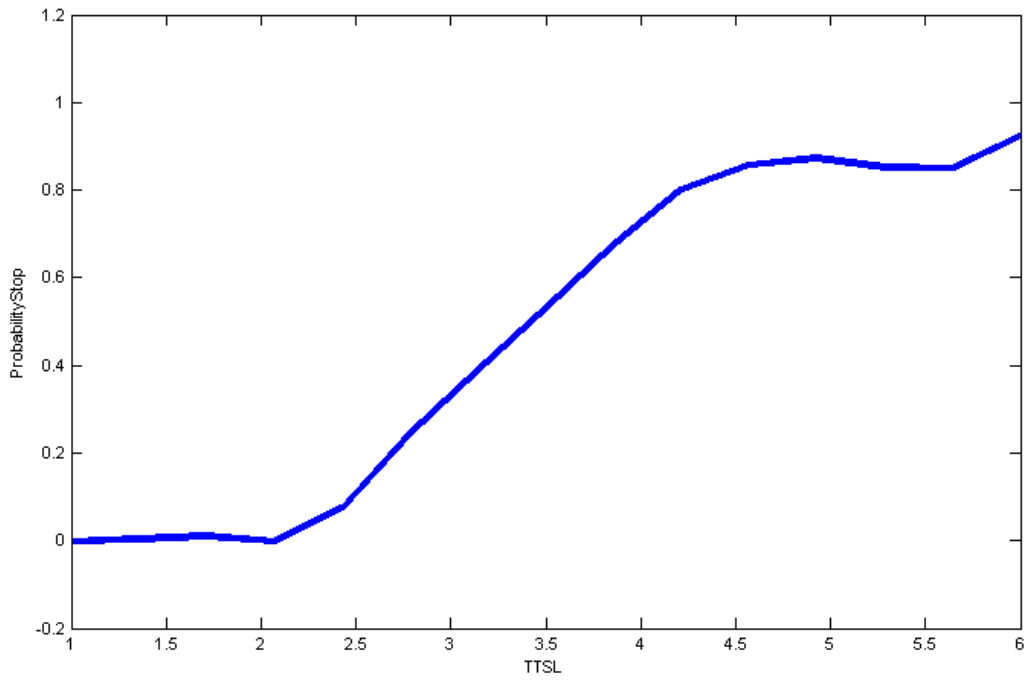


FIGURE 7 TTSL-based FL model surface.