# Fuzzy Logic for Improved Dilemma Zone Identification

## Driving Simulator Study

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**A Type II dilemma zone (DZ) is the segment of roadway on the approach to an intersection at which drivers have difficulty deciding whether to stop or proceed at the onset of the circular yellow (CY) indication. The safety of signalized intersections is improved when DZs are correctly identified and steps are taken to reduce the likelihood that vehicles will be caught in such zones. This research purports that using driving simulators as a means of collecting driver response data at the onset of the CY indication is a valid methodology for augmenting analysis of decisions and reactions made within the DZ. The data obtained were compared with data from previous experiments documented in the literature, and the evidence suggested that driving simulation was valid for describing driver behavior under the given conditions. After the data were validated, fuzzy logic was proposed as a tool for modeling driver behavior in the DZ, 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.**

A Type II dilemma zone (DZ) is the segment of roadway on the approach to a signalized intersection at which drivers have difficulty deciding whether 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 in right-angle or left-turn head-on collisions caused by poor estimates of intersection clearance time. Although inadequate signal timing or driver failure to comply with signal operation (through 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 that the number of vehicles caught in the DZ 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* provides a range of durations for the yellow change interval and information relating the meaning and sequence of the CY indication (*2*). In the absence of a national standard, ITE has developed a recommended equation for the length of the CY (*3*); 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 the approach 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 vehicles, or few, 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; this definition identifies the downstream edge of the DZ as the place where 10% of drivers stop and the upstream edge as the place where 10% of drivers continue (*5*). The other primary definition is based on a vehicle's time to stop line (TTSL); this definition describes the DZ as 2.5 to 5.5 s from the intersection (*6*). Recent research suggests that these two definitions result in different DZ locations on the same approach (*7*).

This research aimed to improve the identification of the DZ, as it is a critical factor in 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 used fuzzy logic (FL) as an analytical tool for improving DZ identification. Hurwitz et al. proposed a model based strictly on vehicle position that demonstrated the potential for improved DZ identification. The present research exploited the capabilities of a high-fidelity driving simulator to measure vehicle position and speed 15 times per second to develop a more accurate model of the DZ. Additionally, the data on the probability of stopping were compared with data from the previous naturalistic experiments of Hurwitz et al. (*8, 9*) and the test-track experiments of Rakha et al. (*10*). The deceleration data were compared with 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.

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## Driver Response to the CY

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

Gates et al. performed field observations on more than 1,000 vehicles that were the first to stop or last to go at the termination of priority for that approach (*11*). These authors evaluated the effects of several variables on the decision to stop or 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. found that the length and location of the DZ varied with the speed of the vehicle, reaction time, and the operational tendencies of different driving populations (*12*). 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 the DZ.

## 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 on the basis of noisy and imprecise information inputs. Kaehler explains, "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 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 (*8, 15*). 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. Furthermore, drivers must continuously make these approximations during the approach to the intersection. These conditions make this form of driver behavior a candidate for FL modeling.

The research reported here builds and expands on 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 approaches to high-speed signalized intersections in Vermont to build an 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 University 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° front view, and a fourth projector displays a rear image for the driver's center mirror. The two side mirrors have liquid crystal 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 60 Hz. The simulator is pictured in Figure 1.

(a) (b)

FIGURE 1 Oregon State University driving simulator.

### 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 indication, 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 experiment by Rakha et al. required participants to drive along a test track at 45 mph; the observed speed for the 85th percentile in the study by Hurwitz et al. 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 with a posted speed of 55 mph.

Within each speed condition, drivers were exposed to the CY indication at various locations on their approach to the intersection. Because the prevailing DZ definition uses a measure of TTSL, the presentation of the CY indication was varied on the basis of 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 s 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 2,000 ft 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 caused by the order of exposures, each participant was exposed to a randomly generated order of TTSL CY indication triggers.

A data collection sensor placed on the approach to each intersection tracked 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 per second):

- Time,
- Speed (instantaneous),
- Position (instantaneous),
- Acceleration–deceleration (instantaneous), and
- Signal indication.

### Texting as a Distraction

To reduce the likelihood that participants would deduce the primary research question of the study and thus potentially alter their behavior in response, they were asked to complete several texting tasks while traversing the route. As drivers 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

Thirty drivers (17 male and 13 female) were used to develop and validate the FL model. An overrepresentation of college-aged students in the experiment resulted in a relatively young subject population (average age of 24.5 years). Because of this overrepresentation, the applicability of the results of this study to a wider driving population may be limited; however, the data are adequate for demonstrating 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 farther 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 ft away from the intersection at the onset of the CY but then chose to proceed through the intersection when it was roughly 250 ft away at the onset of the CY. This inconsistency points toward 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 behavior occurs. Figure 2, *b*, *c*, and *d*, provides trajectory data for all subjects at three TTSL thresholds (1 s, 3.5 s, and 6 s, respectively).

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 indication. Figure 2*c* shows that drivers behave in a less consistent manner when they are 3.5 s away from the intersection, sometimes continuing and sometimes stopping. This figure also shows variability in the location at which vehicles completed their stop—some of which may be attributed to a poor selection of deceleration—but mostly shows differences in how drivers perceived their position relative to the stop line. Figure 2*d* shows that almost every driver stops when 6 s 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 before the intersection 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 proceeded when they were 2 s or less from the intersection at the onset of the CY indication. This finding is consistent with the findings of Chang et al. (*6*) and Gates et al. (*11*), who found that nearly all

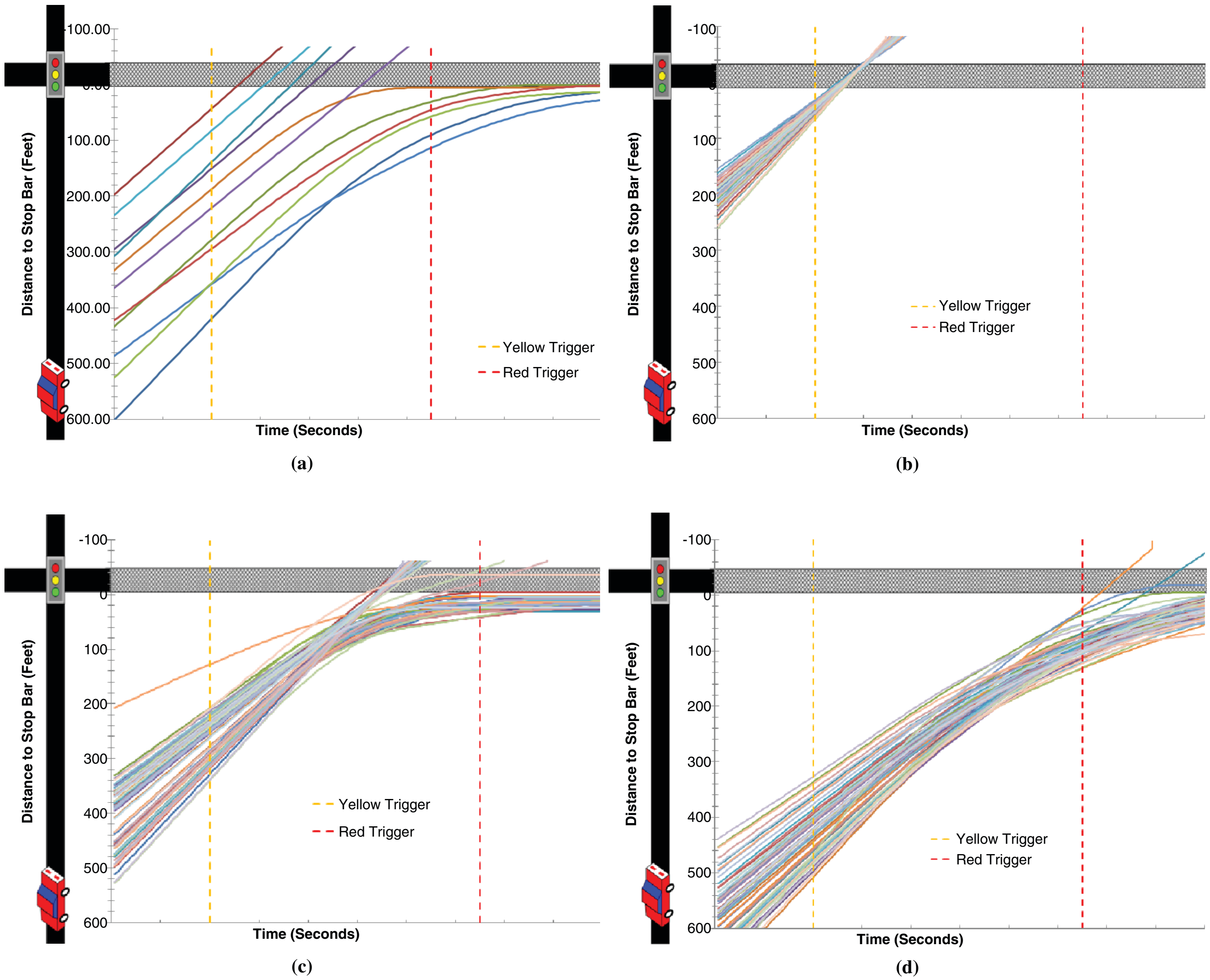


**FIGURE 2 Vehicle trajectories in response to CY: (*a*) single participant trajectories at 45 mph, (*b*) 30 vehicle trajectories for TTSL = 1 s, (*c*) 30 vehicle trajectories for TTSL = 3.5 s, and (*d*) 30 vehicle trajectories for TTSL = 6 s.**

vehicles proceeded through the intersection when they were 2 s or less from the intersection at the onset of the CY. At a TTSL of 4.5 or greater, most drivers (93%) stop before the intersection.

By changing the independent variable from TTSL to vehicle position, the driver's decision data can be compared with 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 were no statistical differences in the distributions from the research by Hurwitz et al. (*7*) and the present research (95% confidence level), and that the distribution from Rakha et al. (*10*) 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 to 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 in the evaluation of drivers' decisions to stop or go. The ITE equation for the timing of the change interval incorporates an assumption for a comfortable deceleration rate (10 ft/s$^2$) (*3*). To support the validity of using a driving simulator to evaluate driver behavior in this way, the observed deceleration rates must be comparable to that threshold as well as to 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 present simulated experiment are consistent with previous field research.

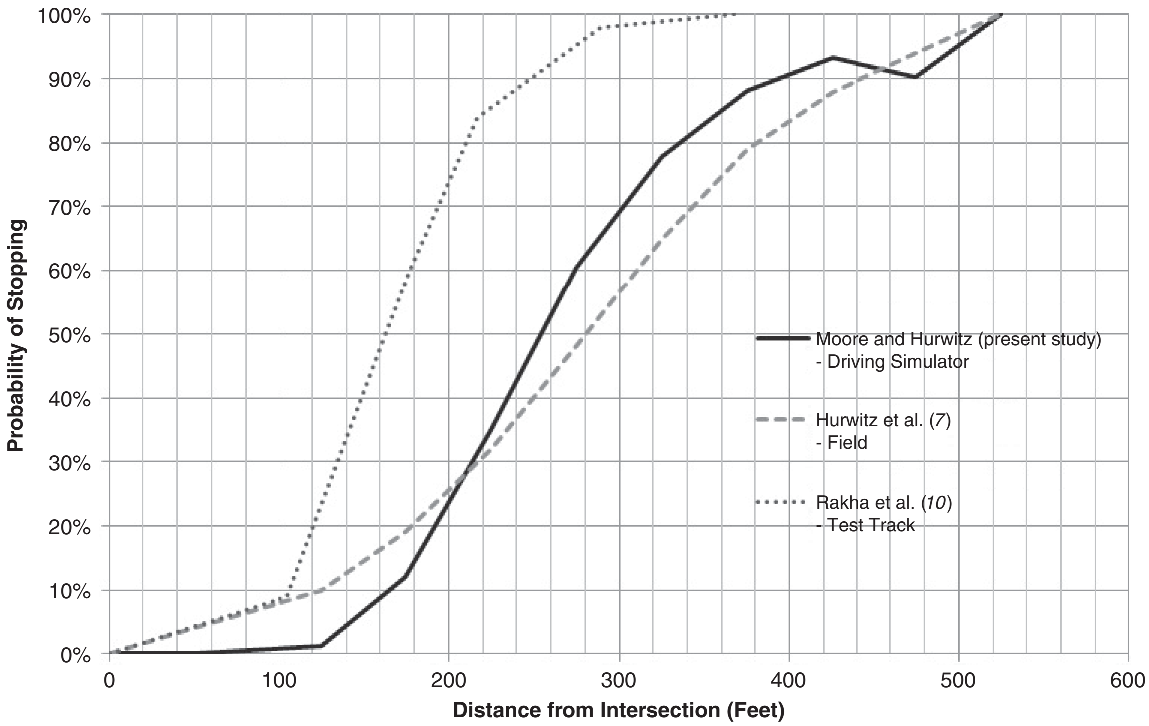


FIGURE 3 Probability of stopping.

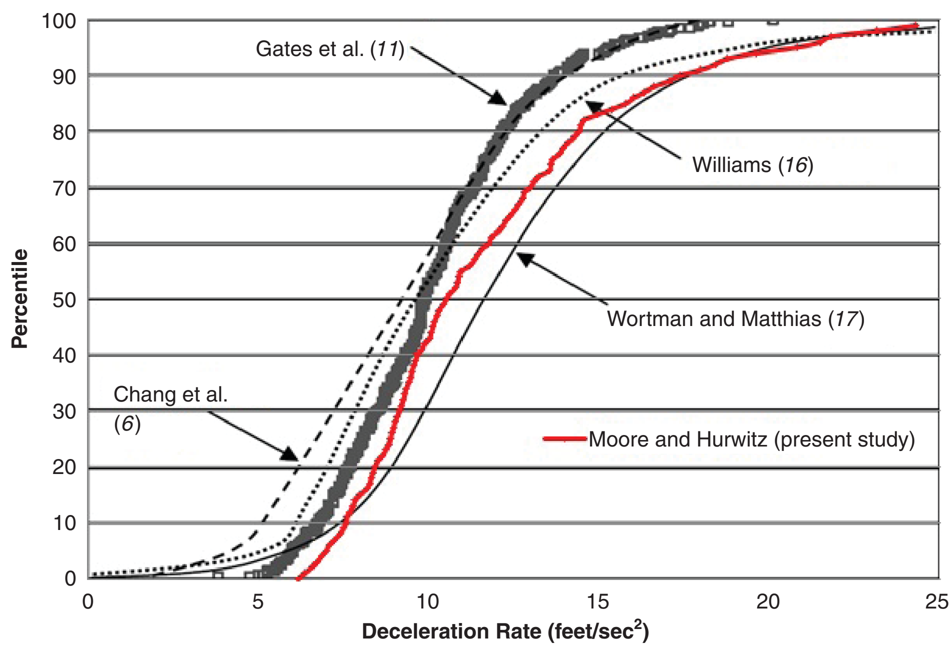


FIGURE 4 Average deceleration rates.

**TABLE 1 Deceleration parameters**

| Study | Year | Mean | SD | 95% CI Low | 95% CI High | Deceleration Rate 15% | Deceleration Rate 50% | Deceleration Rate 85% |
|---|---|---|---|---|---|---|---|---|
| Moore and Hurwitz (present study) | 2012 | 11.7 | 4.0 | 3.62 | 19.78 | 8.0 | 10.5 | 15.8 |
| Gates et al. (*11*) | 2006 | 10.1 | 2.8 | 4.44 | 15.76 | 7.2 | 9.9 | 12.9 |
| Chang et al. (*6*) | 1985 | 9.5 | — | — | — | 5.6 | 9.2 | 13.5 |
| Wortman and Matthias (*17*) | 1983 | 11.6 | — | — | — | 8.0 | 11.0 | 16.0 |

NOTE: SD = standard deviation; CI = confidence interval; — = data could not be acquired from published study.

Table 1 provides summary statistics associated with the deceleration rates determined from the present research as well as the studies displayed in Figure 4. Deceleration rates for the present 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 these data to those obtained from field observations. The 95% confidence intervals calculated and included in Table 1 indicate no statistical difference in the mean deceleration rates found in the present study and in 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 the DZ 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 on the basis of a training process. An adaptive neuro-fuzzy inference system is used to develop an FL model that is based on a set of training data. For this research, behavior data from 15 randomly selected drivers were used to train the creation of the FL model, and data from the remaining 15 drivers were used to validate the model and evaluate its predictive power.

The models presented in the following sections 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 vehicle's distance to the stop line at the onset of the yellow indication (position). The previously described process for developing the FL model results in the creation of a curve showing the probability of stopping, as shown in Figure 5.

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

$$f(\text{VP}) = \begin{cases} 1.0 & \text{VP} \le 128.2 \\ 2.37 - \left(\dfrac{1}{93.8}\right)\text{VP} & 128.2 < \text{VP} \le 222 \\ 0 & 222 < \text{VP} \end{cases} \qquad (1)$$

$$f(\text{VP}) = \begin{cases} 0 & \text{VP} \le 128.4 \\ -1.37 + \left(\dfrac{1}{93.9}\right)\text{VP} & 128.4 < \text{VP} \le 222.3 \\ 1 & 222.3 < \text{VP} \le 363.6 \\ 4.86 - \left(\dfrac{1}{94.1}\right)\text{VP} & 363.6 < \text{VP} \le 457.7 \\ 0 & 457.7 < \text{VP} \end{cases} \qquad (2)$$

$$f(\text{VP}) = \begin{cases} 0 & \text{VP} \le 364 \\ -3.87 + \left(\dfrac{1}{94}\right)\text{VP} & 364 < \text{VP} \le 458 \\ 1 & 458 < \text{VP} \end{cases} \qquad (3)$$

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 were input into the model, and for each interaction with the signal, the probability of stopping was reported. A probability of stopping greater than .5 was interpreted to identify a condition resulting in a vehicle stopping before the intersection, and a value less than .5 was interpreted as a condition in which the vehicle continued through the intersection. These values were compared with the actual observed behavior of the second 15 drivers, and the predictive power of this model was determined.

As shown in Table 2, 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. for their position-based FL model (*8*). Raw data from the 2012 field study were obtained and evaluated according to this position-based model, and the results were virtually identical

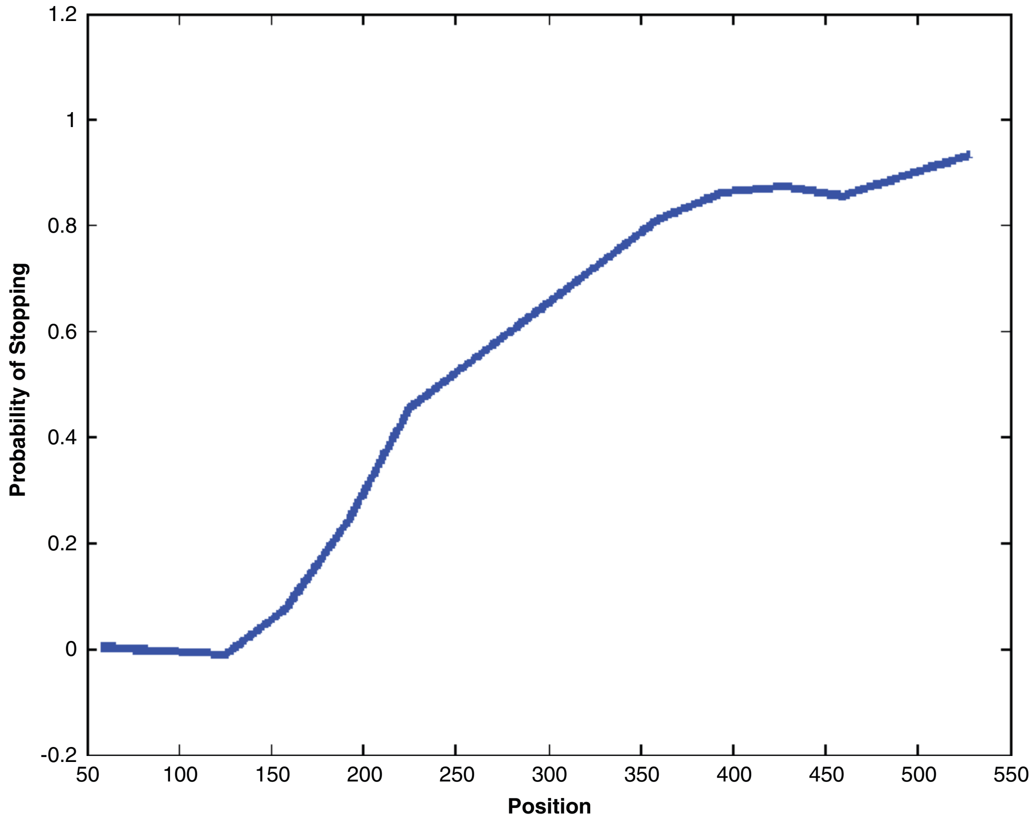


**FIGURE 5** Position-based FL model surface.

to those reported by Hurwitz et al. Table 2 also provides insight as to where the model is more prone to generating errors; in this case, the majority of the errors (71%) occurred when the model incorrectly predicted a vehicle would stop.

### *Vehicle 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 three-dimensional surface to describe a vehicle's probability of stopping, as shown in Figure 6. As in the position-based model, trapezoidal membership functions were used to describe the input variables VP and vehicle speed (VS); these functions are described in Equations 4 through 7.

**TABLE 2** Predictive Power of FL Models

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

$$f(\mathrm{VP}) = \begin{cases} 1.0 & \mathrm{VP} \le 198.7 \\ 2.05 - \left(\dfrac{1}{188.5}\right)\mathrm{VP} & 198.7 < \mathrm{VP} \le 387.2 \\ 0 & 387.2 < \mathrm{VP} \end{cases} \tag{4}$$

$$f(\mathrm{VP}) = \begin{cases} 0 & \mathrm{VP} \le 198.2 \\ -1.05 + \left(\dfrac{1}{188.7}\right)\mathrm{VP} & 198.2 < \mathrm{VP} \le 386.9 \\ 1 & 386.9 < \mathrm{VP} \end{cases} \tag{5}$$

$$f(\mathrm{VS}) = \begin{cases} 1.0 & \mathrm{VS} \le 43.39 \\ 3.99 - \left(\dfrac{1}{14.5}\right)\mathrm{VS} & 43.39 < \mathrm{VS} \le 57.89 \\ 0 & 57.89 < \mathrm{VS} \end{cases} \tag{6}$$

$$f(\mathrm{VS}) = \begin{cases} 0 & \mathrm{VS} \le 44.02 \\ -3.42 + \left(\dfrac{1}{12.89}\right)\mathrm{VS} & 44.02 < \mathrm{VS} \le 56.91 \\ 1 & 56.91 < \mathrm{VS} \end{cases} \tag{7}$$

Again, data from 15 drivers were 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 that of the

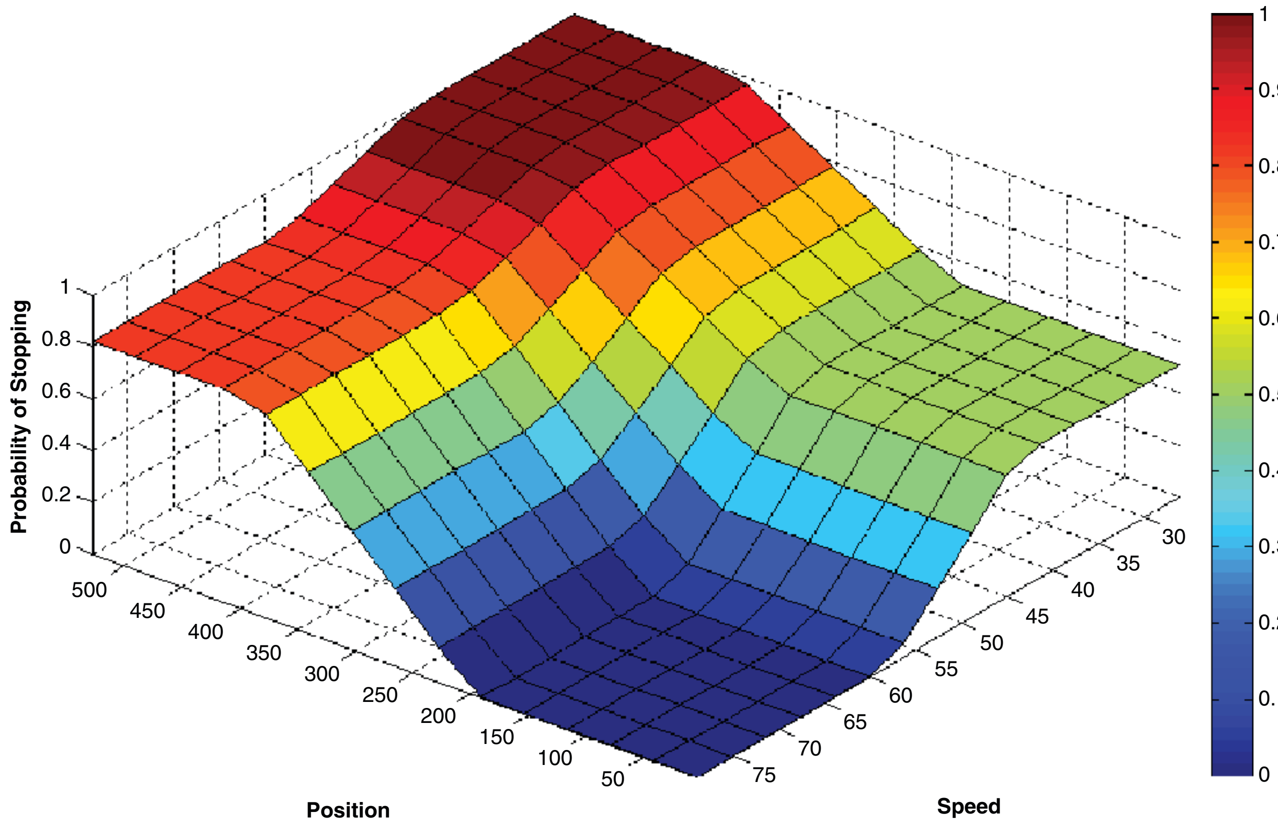


FIGURE 6 Speed and position–based FL model surface.

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

The previous model was taken one step further by combining speed and position into a single variable, TTSL, prior to its use in an FL model. Trapezoidal functions (described in Equations 8 through 10) and a process similar to that described for the other models were used to develop this model. The probability-of-stopping surface, shown in Figure 7, looks similar to that obtained by plotting the raw data.

$$f(\text{TTSL}) = \begin{cases} 1.0 & \text{TTSL} \le 1.76 \\ 2.74 - \left(\dfrac{1}{1.01}\right)\text{TTSL} & 1.76 < \text{TTSL} \le 2.77 \\ 0 & 2.77 < \text{TTSL} \end{cases} \tag{8}$$

$$f(\text{TTSL}) = \begin{cases} 0 & \text{TTSL} \le 1.77 \\ -1.79 + \left(\dfrac{1}{0.99}\right)\text{TTSL} & 1.77 < \text{TTSL} \le 2.76 \\ 1 & 2.76 < \text{TTSL} \le 4.33 \\ 3.7 - \left(\dfrac{1}{1.17}\right)\text{TTSL} & 4.33 < \text{TTSL} \le 5.5 \\ 0 & 5.5 < \text{TTSL} \end{cases} \tag{9}$$

$$f(\text{TTSL}) = \begin{cases} 0 & \text{TTSL} \le 4.13 \\ -3.44 + \left(\dfrac{1}{1.2}\right)\text{TTSL} & 4.13 < \text{TTSL} \le 5.33 \\ 1 & 5.33 < \text{TTSL} \end{cases} \tag{10}$$

This model provided the highest predictive power with regard to the behavior of the remaining 15 drivers. This model was slightly more accurate than the previous ones (90%), and the errors tended to be related to proceeding vehicles that were predicted to stop (78%).

### Comparison of FL Models

The overall predictive power of all three models was very similar, ranging from 88% to 90% (Table 2). Although the results of the models were very similar, the observed differences can be attributed to slight variations in parameter selection during the model development process. The data discussed earlier show that the introduction of speed as an additional measured variable did not significantly increase the accuracy of the predictive power of the model as might have been expected. 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 variability in speed is present in the traffic stream (as a result of congestion or other factors), individual speeds may become more important in predicting driver behavior accurately.

The shift in the type of behavior that was most often predicted falsely bears consideration. Both the position-based and TTSL-based

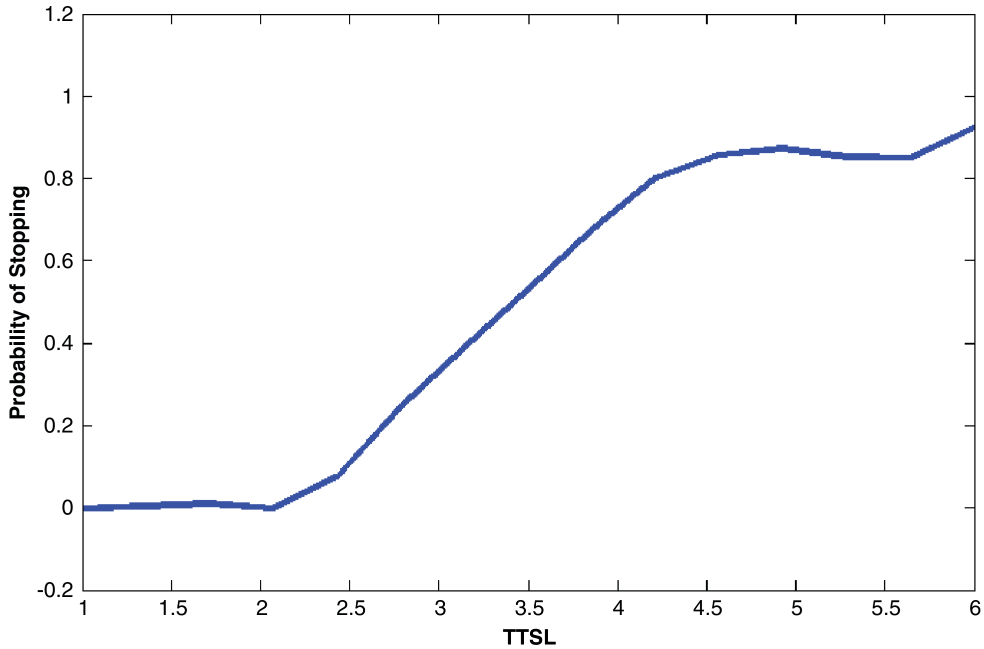


FIGURE 7 TTSL-based FL model surface.

models tended to predict that a vehicle would stop at the intersection when in fact it proceeded through the intersection. The speed and position–based model seemed to reverse that trend, predicting that a vehicle would proceed through the intersection when it stopped. This finding 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 of evaluating driver behavior under various conditions. However, it is critically important to set the scope of research questions appropriately when a driving simulator is used, and the results obtained in laboratories of this type need to be extensively validated. Therefore, efforts should be made to compare results from simulator experiments with those obtained from alternative experimental mediums, such as surveys, test tracks, and field studies.

Driver decision making and vehicle deceleration rates are important factors when one attempts to evaluate and model driver behavior in the DZ. Data collected as part of this research to describe these two factors were compared with data from several previous research studies on this topic that were conducted in different experimental mediums. 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 configuration similar to the one operated by the Oregon State University Driving and Bicycling Research Laboratory.

### Model Development and Comparison

In the moment when drivers identify 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 demonstrated their ability to predict driver behavior with a reasonably high degree of accuracy (88% to 90%). Because of similar accuracy thresholds, vehicle speed did not appear to be as influential as expected for the scenario described in this research. As previously mentioned, it is suspected that such 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, 18*), the predicted behavior was exactly the same as that reported in the present study. Given that the previous work was founded on field observations, this finding strongly supports the validity of both the data collected in the driving simulator and the procedure used to develop the FL models.

### Future Work

This research developed preliminary evidence to suggest the validity of driving simulators for accurately modeling driving response to traffic signals. Furthermore, it demonstrated 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 (e.g., varying speeds, proximally located vehicles) in the predictive models; and
- The application of the developed models to signal timing and detector design.

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