MODELING DRIVER BEHAVIOR AND LEARNING IN DILEMMA ZONE USING AN ADAPTIVE DRIVING SIMULATOR DESIGN

Sahar Ghanipoor Machiani, Department of Civil, Construction, and Environmental Engineering, San Diego State University, 5500 Campanile Dr., San Diego, CA 92182, 619-594-1937, sghanipoor@mail.sdsu.edu
Montasir Abbas, Department of Civil and Environmental Engineering, Virginia Tech, 301-A Patton Hall, Blacksburg, VA 24061, abbas@vt.edu
Kaye Balfour-Kawasaki, Department of Civil, Construction, and Environmental Engineering, San Diego State University, 5500 Campanile Dr., San Diego, CA 92182, munchkin.kk@gmail.com

ABSTRACT

Many crashes at signalized intersections are attributed to Dilemma zone (DZ)-related conflicts at the onset of yellow indication. This study focuses on the learning aspects of the driver decision-making process, and investigates the effect of learning on the different approaches taken by DZ-protection algorithms and advanced signal settings. An Adaptive Randomized Incomplete Block Split-plot (ARIBS) plan was designed and executed in a driving simulator environment. Data were collected from 34 drivers and statistical analysis was conducted. The results of the analysis showed that drivers learn from their experience when exposed to longer or shorter yellow durations.
Keywords: *traffic safety; dilemma zone; driver behaviour modeling; driving simulator*

BACKGROUND

Several research efforts have been dedicated to modeling drivers' stop or go decision at the commence of the yellow indication at signalized intersections -widely known in the literature as dilemma zone. Researchers agree that drivers who are far from the signal at the onset of yellow are going to stop, while drivers who are too close to the signal are going to continue. However, researchers do not necessarily agree on the definition of the "too far" and "too close" boundaries, nor on the probability of stopping in between those two boundaries. Dilemma zone (DZ) conflicts remain to be an important area of interest because of the recognition that it is a major cause of accidents at high speed signalized intersections. The issue especially arises when the driver is not able to clear the intersection before the initiation of the red light phase leading to possibility of right-angle crashes or the driver decides to stop while the following vehicle made the decision to go leading to possibility of rear-end crashes [1–10].
Drivers' decision in dilemma zone along with the signal control strategies are the two main elements that play important roles in DZ conflict analysis. These two elements have attracted significant research interests over the years, resulting in major contributions in the development of DZ-protection algorithms. DZ-protection algorithms generally target two settings in the signal control system; (1) extension of the green time, and (2) extension of the clearance (yellow and/or all-red) interval to provide the driver with extra time to clear the intersection. The challenge here is that none of these DZ-protection setups have taken the drivers learning process (dynamic nature of drivers' decision making) into account. Learning reflects the evolving of choice behavior in decision making process from a one-shot event to a dynamic model influenced by practice and observation [11]. In this paper, the question that we would like to answer is that whether the drivers learn from their

experience at signalized intersections with different settings, and based on the result of this learning process, which one of the DZ-protection approaches (green extension and yellow or all-red extension) is more suitable?

DEVELOPMENT AND IMPLANTATION OF THE DRIVING SIMULATOR EXPERIMENT

The primary goal of this study is to investigate the drivers' learning process when driving through safe and unsafe intersections. This is done by designing adaptive settings in the simulator. In fact, the driver simulator in our research acts as an intelligent agent predicting and reacting to driver's decisions, and providing responsive scenarios based on each situation. Figure 1 summarizes the experiment adaptation and hypotheses testing. Basically, three scenarios are developed that extend green, shorten yellow, or lengthen yellow based on driver's behavior.

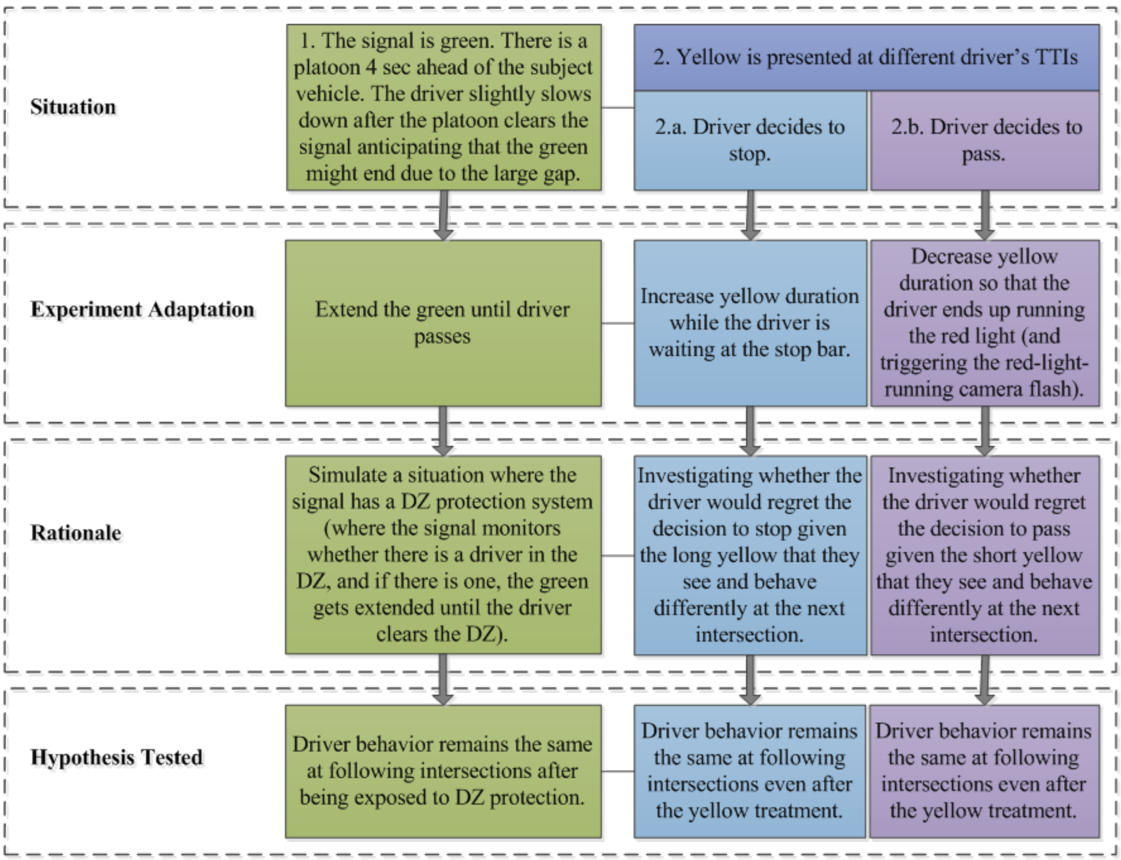

FIG. 1. Experiment Adaption Situations and Rationale

To account for the experiment adaptation, the "experiment adaptation factor" is introduced with two levels of "Do nothing" and "Do something." "Do nothing" refers to the condition that no "experiment adaptation factor" is tested on an intersection; meaning that normal yellow indication and duration is followed. In this situation, when driver slows down anticipating that the green will end due to the large gap, the signal turns yellow at 1.5 sec ahead of the intersection as expected by the driver, and the yellow lasts for 4.5 sec (appropriate yellow time for 55 mph speed). However, if the driver does not slow down, the yellow will be provided at 2.5, 3.5, and 4.5 sec ahead, and lasts for 4.5 sec. In contrast, "Do something" indicates one of the experiment adaptation approach is considered based on the situation presented by drivers' behavior.

In addition to the learning aspect of drivers embedded in the experiment adaptation factor, some influencing factors on DZ are included in the design. These factors are extracted from the result of a survey study designed by authors, and administered in Maryland, Virginia, and Pennsylvania [12]. Based on the result of the survey, the following five factors were included in the in the driving simulator study. These factors include (1) Presence of police with two levels of Yes and No, (2) Time to intersection (TTI) at the commence of yellow with three levels of 2.5, 3.5, and 4.5 sec, (3) Other vehicles around with two levels of No Vehicle and Back, (4) Pavement condition with two levels of Wet and Dry, and (5) Presence of side street queue with two levels of Yes and No.

The experimental design of this study was an Adaptive Randomized Incomplete Block Split-plot design. This experimental design was implemented using custom design capability in SAS JMP Pro 10.0.0 software. Considering main effect and two-way interactions of factors, the minimum number of runs was found to be 28, but this minimum was driven by the degrees of freedom required to define the model, and there were no degrees of freedom left to use for the error term. The minimum number of runs needed to also consider the error term was found to be 35. Split-plot design was used to account for the factors that were hard to change ("pavement condition" and "other vehicles around"). Consecutive intersections on a road corridor were considered whole plots with intersections in the corridor playing the subplot (split plot) role. Randomization was also conducted among the whole plots. It was found that at least 5 whole plots are required to estimate the whole plot variance. This leads to 5 corridors (whole plots) including 7 (35/5) consecutive intersections (split plots). The number of split plots was decided to be 10 out of which 3 were randomly chosen to always show green signal indications.

The Driving simulator used in this study was a DriveSafety DS-250 model including main software components of Vection™, HyperDrive, and Dashboard. HyperDrive was used to design and implement custom driving environment models including traffic conditions, environmental states and events occurring during the simulation. Specific events and scenarios are implemented by scripting using Tool Command Language (TCL). The simulator is fixed-based and provides no motion cues (Figure 2). The basis of the driving environment was constructed using drag and drop assembly of database elements called tiles. Then, static objects such as speed signs, side street traffic, and police cars are placed according to the experimental design. Signal status changes are mostly handled using an external TCL file. Location and time triggers were created and programmed appropriately to specify events occurrence.

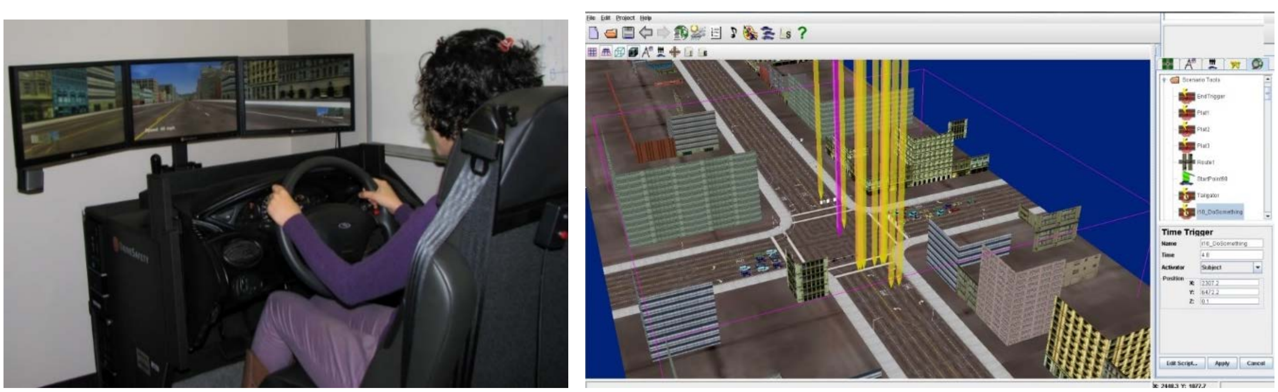

FIG. 2. DriveSafety DS-250 Driving simulator and HyperDrive layout of triggers.

Six participants participated in the pilot study, and 36 additional drivers participated in the main study. Two participants discontinued in the middle of the run because of simulator sickness and feeling discomfort. In total, 34 drivers completed the experiment consisting of 12 females and 22 males with their ages ranging from 18 to 68 (mean: 31.75, SD: 13.68). The pilot data were used to verify the experimental design, and were excluded from the analysis. Participants were recruited by email announcement. Before beginning the experimental session, participants were asked to read and sign a consent form, and to complete a questionnaire regarding demographic and driving information. Then, they drove through an acclimation drive. Participants were allowed to continue with the adaptation drive until they felt comfortable enough with driving in the simulator. The experiment lasted no more than 45 minutes.

RESULTS AND DISCUSSION

The simulator program was configured to record data including speed, acceleration, time, and activated triggers with the precision of 60 Hz. Data manipulations and reduction was conducted using a script, and statistical analysis was performed using SAS JMP Pro. The response variable considered in this study was the "mean speed" as the surrogate measure for "stop/go" decision. This variable was calculated by averaging vehicles speed from the onset of yellow until the end of decision implementation point. Three variables were constructed to test the effect of learning for the three learning related scenarios described in Figure 1 (Learning_green extension, Learning_long yellow, and Learning_ red light running). Variables were constructed starting from zero and adding up by one unit after experiencing each associated scenario. In addition to these three variables, presence of police, time to intersection at the commence of yellow, other vehicles around, pavement condition, driver number, and presence of side street queue are considered as model effects to determine the significance of each one of these factors. Moreover, "Do something" and "Do nothing" levels explained before, were included in the model by a binary variable named "DoSomething".

Given the specifications of the design of this study, drivers are deemed as blocking factor. Therefore, in constructing the model characteristics of the driver (e.g., age, state, and gender) were considered to be embedded in each "driver number" variable. "Driver number" was assumed a random effect to increase the generalization capability of the results. In line with this decision, all interactions of other independent variables and "driver number" were random effects as well. Also, second order interactions between split plot and whole plot factors were accounted for. Another consideration of the model development was that the learning variables were considered nested in the "DoSomething" variable.

To fit a linear mixed model capable of including both fixed and random effects, Restricted Maximum Likelihood (REML) was applied. Summary of the fit of the model is shown in Table 1. RSquare of the model was 0.48, and Root Mean Square Error was 4.09. The fixed effect tests are summarized in Table 2. The first and second columns show the fixed effects and their associated degrees of freedom, respectively. The last two columns show the computed F ratio and the p-value for the effect test. Based on the p-values, "Time to intersection", "Pavement condition" "Presence of side street queue* Time to intersection", "Presence of police* Time to intersection", "Learning_red light running", and "Learning_long yellow" are statistically significant at the p=0.05 rate. Table 3 summarizes the REML variance component estimates. The first column includes the random effects. The estimated variance component of the random effects and the percentage ratio of the random effect variance component to the total variance component are shown in the second and third columns, respectively. The forth column indicates the ratio of the variance component for the effect to the variance component for the residual, comparing the effects' estimated variance to the model's estimated error variance. The highest variance ratio was found to belong to the interaction of the "Driver number" and "Time to intersection" variable. The forth column was calculated by dividing the values from the second column for each effect over variance component for the residual. Columns 5 and 6 provide the lower and upper 95% confidence limit for the variance component, respectively. The last column shows the standard error for the variance component estimate. The highest error is related to "Driver number" effect.

Based on the result of the learning factors, drivers' behaviors change significantly after exposure to "short yellow durations (red light running)" and "long yellow" scenarios, but not for the green extension scenario. The feedback from the participants revealed that drivers usually do not notice the passing platoon in front of them and its relationship to the green extension treatment at the intersections. For the other two learning scenarios (red light running and long yellow), looking closer to the changes in driver behavior reveals that drivers act more cautiously after being exposed to these learning scenarios, and tend to stop more. The reason for this could be drivers losing their confidence in their own judgment. This leads to two main conclusions that “drivers learn from their experience,” and “they are more risk-averse when the likelihood of predicting the correct outcome of their actions decreases.” This finding implies that in designing mitigation strategies, for the DZ-protection algorithms that focus on green extension there is no need to consider any learning effect (no learning is involved). In DZ-protection algorithms that focus on yellow or all-red extension, drivers learning will result in more stopping actions by drivers after they learn. Intension to stop more doesn’t have a negative effect on the safety of the intersection. Therefore, no safety concerns should be considered in DZ-protection algorithms in regard to drivers learning process.

TBL 1: Summary of fit

RSquare	0.48
RSquare Adj	0.47
Root Mean Square Error	4.09
Mean of Response	14.49
Observations	1173

TBL 2: Fixed effect tests

Source	DF	F Ratio	p-value
Presence of police	1	2.20	0.1460
Presence of side street queue	1	3.70	0.0581
Pavement condition	1	14.10	0.0005*
Time to intersection	1	62.18	<.0001*
Other vehicles around	1	3.82	0.0579
Presence of police*Presence of side street queue	1	0.02	0.8815
Presence of police*Pavement condition	1	1.12	0.2908
Presence of police*Time to intersection	1	5.32	0.0213*
Presence of police*Other vehicles around	1	1.81	0.1794
Presence of side street queue*Pavement condition	1	2.48	0.1160
Presence of side street queue*Time to intersection	1	21.77	<.0001*
Presence of side street queue*Other vehicles around	1	0.52	0.4717
Pavement condition*Time to intersection	1	3.63	0.0572
Pavement condition*Other vehicles around	1	0.06	0.8131
Time to intersection*Other vehicles around	1	0.27	0.6016
Learning_green extension [DoSomething]	2	0.19	0.8305
Learning_red light running [DoSomething]	2	4.91	0.0078*
Learning_long yellow [DoSomething]	2	3.16	0.0431*
DoSomething	1	0.04	0.8484

TBL 3: REML Variance component estimates

Random Effect	Var. Component	percentage of Total	Var. Ratio	95% Lower	95% Upper	Std. Error
Driver number	1.88	8.26	0.11	-0.10	3.86	1.01
Driver number*Presence of police	0.57	2.52	0.03	-0.19	1.34	0.39
Driver number*Presence of side street queue	0.35	1.52	0.02	-0.32	1.01	0.34
Driver number*Pavement condition	0.39	1.70	0.02	-0.30	1.08	0.35
Driver number*Time to intersection	2.54	11.15	0.15	0.91	4.16	0.83
Driver number*Other vehicles around	0.34	1.51	0.02	-0.36	1.05	0.36
Residual	16.69	73.33		15.29	18.29	0.76
Total	22.76	100.00		20.23	25.80	1.41

CONCLUSION AND FUTURE RESEARCH

Dilemma zones are of vital importance since they can lead to many accidents at signalized intersections. When the signal turns yellow, drivers approaching the intersection find themselves in a dilemma of deciding whether to stop or proceed through. The focus of this study is on investigating the learning aspect of drivers in DZ in addition to other influential factors. We investigated how drivers’ behaviors change in response to their positive and negative experience. The effect of drivers' learning process on DZ-protection algorithms was one of the main motivations of this study. DZ-protection algorithms and strategies include extending green, yellow, or all-red indications to provide drivers with a safer operation when they are in DZ. Here, we examine how the drivers learning relates to these strategies, and what safety concerns needs to be taken to account considering drivers learning. This goal has been accomplished by introducing an Adaptive Randomized Incomplete Block Split-plot (ARIBS) design in a simulator experiment. The data were collected from 34 volunteered participants. The result showed that Pavement condition, Time to intersection, and the interaction of Time to intersection with Presence of side street queue and Presence of police significantly affect drivers' decision significantly. Regarding learning hypotheses, the results revealed that drivers learn from what they experience; more specifically, 2 out of 3 learning hypotheses (long yellow and short yellow-red light running) turned out to have significant effects on drivers' decision in DZ. This significant effect is coupled with a higher intention of drivers to stop at the onset of yellow as they learn. In another word, drivers were found to be more risk-averse when the likelihood of predicting the correct outcome of their actions decreases. According to the results, there is no safety concerns in any of the approaches by DZ-protection algorithms whether they use green extension which is involved with no learning, or whether they use yellow or all-red extension which results in more stopping decision after the learning occurs.

In the future, a real time field-data assessment of DZ-protection algorithms will be conducted to quantify the changes in drivers' behavior when exposed to these protection strategies.

ACKNOWLEDGEMENT

The authors wish to thank the Mid-Atlantic Universities Transportation Center and the Virginia Center for Transportation Innovation and Research (VCTIR) for sponsoring this study. The contents of this paper reflect the views of the authors, and the views are not necessarily those of the supporting agencies.

REFERENCES

[1] Amer, A., H. Rakha, and I. El-Shawarby. Novel Stochastic Procedure for Designing Yellow Intervals at Signalized Intersections. Journal of Transportation Engineering, Vol. 138, No. 6, 2012, pp. 751–759.

[2] Chiou, Y.-C., and C.-H. Chang. Driver Responses to Green and Red Vehicular Signal Countdown Displays: Safety and Efficiency Aspects. Accident; Analysis and Prevention, Vol. 42, No. 4, 2010, pp. 1057–1065.

[3] Hurwitz, D. S., H. Wang, M. A. Knodler Jr., D. Ni, and D. Moore. Fuzzy Sets to Describe Driver Behavior in the Dilemma Zone of High-Speed Signalized Intersections. Transportation Research Part F: Traffic Psychology and Behaviour, Vol. 15, No. 2, 2012, pp. 132–143.

[4] Jahangiri, A., H. Rakha, and T. A. Dingus. Red-Light Running Violation Prediction Using Observational and Simulator Data. Accident Analysis & Prevention, 2016.

[5] Papaioannou, P. Driver Behaviour, Dilemma Zone and Safety Effects at Urban Signalised Intersections in Greece. Accident Analysis & Prevention, Vol. 39, No. 1, 2007, pp. 147–158.

[6] Sharma, A., D. Bullock, and S. Peeta. Estimating Dilemma Zone Hazard Function at High Speed Isolated Intersection. Transportation Research Part C: Emerging Technologies, Vol. 19, No. 3, 2011, pp. 400–412.

[7] Wei, H., Z. Li, P. Yi, and K. Duemmel. Quantifying Dynamic Factors Contributing to Dilemma Zone at High-Speed Signalized Intersections. Transportation Research Record: Journal of the Transportation Research Board, Vol. 2259, 2011, pp. 202–212.

[8] Ghanipoor Machiani, S., and M. Abbas. Assessment of Driver Stopping Prediction Models before and after the Onset of Yellow Using Two Driving Simulator Datasets. Accident Analysis & Prevention, Vol. 96, 2016, pp. 308–315.

[9] Ghanipoor Machiani, S., and M. Abbas. Modeling Human Learning and Cognition Structure: Application to Driver Behavior in Dilemma Zone. ASCE Journal of Transportation Engineering, Vol. 142, No. 11, 2016, p. 04016057.

[10] Ghanipoor Machiani, S., and M. Abbas. Safety Surrogate Histograms (SSH): A Novel Real-Time Safety Assessment of Dilemma Zone Related Conflicts at Signalized Intersections. Accident Analysis & Prevention, Vol. 96, 2016, pp. 361–370.

[11] Roth, A. E., and I. Erev. Learning in Extensive-Form Games: Experimental Data and Simple Dynamic Models in the Intermediate Term. Games and Economic Behavior, Vol. 8, No. 1, 1995, pp. 164–212.

[12] Abbas, M., S. Ghanipoor Machiani, P. M. Garvey, A. Farkas, and R. Lord-Attivor. Modeling the Dynamics of Driver's Dilemma Zone Perception Using Machine Learning Methods for Safer Intersection Control. Publication MAUTC-2012-04. US Department of Transportation, Washington, DC, 2014.