A Proposed Safety Index Based on the Risk Taking Behavior of Drivers

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Submitted: July 31, 2009 (**Submitted with Revisions on November 15, 2009)**
Word Count: 5,576 words in text + (3 figures * 250 words) + (2 tables * 250 words) = 6,826

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ABSTRACT

This research presents a new safety indicator that takes into consideration the risk taking behavior of drivers as well as the prevailing traffic conditions at an intersection. The indicator is based on the idea that an intersection with drivers willing to take a higher risk is not as safe as one with drivers not willing to take high risks. The driver risk taking behavior is modeled as a function of a driver's reaction to a possible collision scenario. A binary logistic regression was used to understand how the probability of a driver reacting to a possible collision scenario changes as a function of the variables defining the scenario.

The data collection and safety index definition is presented from the perspective of permissive left turns; however, the concept of risk taking is a universal one thus making it a feasible alternative for other maneuver types provided that the appropriate data are obtained. Using a safety index based on risk taking helps solving the dilemma faced by engineers when trying to decide which of two intersections that have no crash history, or equal crash history, should be the target of a safety improvement program. A methodology like the one presented can take away the subjective judgment that often takes place in such a scenario and provides the engineer with an objective alternative.

INTRODUCTION

One of the basic principles in economic theory is the scarcity principle in which the needs of the society are unlimited while the resources are limited. Our transportation system is not an exception to this principle. There is no doubt that everyone wants to fix congestion on the road while, in reality, only some of the projects that are able to reduce congestion can be funded. The same situation applies when it comes to improving the safety of our transportation system. Although transportation engineers would like to make the improvements necessary in the system to bring fatalities to zero, they have to account for the limited resources available and select those elements where the highest return on investment can be obtained.

Assuming that an agency is faced with a decision in which it can only afford to improve one of two intersections that, if treated, will suffer an equal reduction in the number of crashes; then the decision is purely a monetary one. The site that will be selected for improvement is the one with the lowest cost per expected reduced crash ratio. Thus, when the expected number of crashes can be computed as a result of having a crash history, there are already established procedures that provide the engineers with guidance on how to make a decision.

Unfortunately, the decision is not always a straight forward one. There is an agreement among the transportation engineering community that an intersection with no crash history is not necessarily a safe one. Thus, transportation engineers are usually faced with a complicated challenge in which a certain amount of funds are available for improving intersections that have no crash history. How can spending the funds on one intersection over another be justified in this scenario? The fact is that decisions such as the aforementioned one are mostly made on a subjective basis; sometimes political factors also weight in too. From an engineering stand point, it should not be the desired practice.

There have been different approaches suggested as a measure of how safe transportation system elements are. For example, a methodology known as the Traffic Conflicts Technique was developed by the General Motors (GM) Research laboratories in the 1960s. The aforementioned methodology is based on counting, using a set of specific guidelines, the conflicts between vehicles that take place at an intersection or other elements of the transportation system such as weaving sections. The conflicts observed are classified in different types according to the actions performed by the drivers.

In the absence of a crash history for a location, the number of conflicts observed can be used as a measure of safety. However, the problem that arises is how a conflict is defined since in the methodology conflicts are recorded using a binary state, the conflict either happened or it did not; no measurement of severity is taken into consideration. Furthermore, the methodology developed by GM gives latitude to the field observer on what can be considered a conflict; therefore, the ranking of the intersection using the conflict count as an index becomes a function of the judgment of the field observer. One approach to counting conflicts that can solve this problem is to define a conflict based on a particular value such as the gap experienced and the headway maintained, among others. The aforementioned approach implies the use of surrogate safety measures (SSM). Under this approach, a conflict would be considered as such if the SSM value meets a specific threshold, e.g., the gap accepted by a left turning vehicle is smaller than a pre-defined value, believed to be safe, by an analyst.

Similar to the situation of two intersections with no crash history, the SSM approach cannot distinguish which intersection is safer when both a have similar number of conflicts defined by the scenarios exceeding the safe value. The approach presented in this research is to look at what the drivers of an intersection perceive as unsafe. For example, given intersections *A* and *B*, do the drivers from intersection *A* react in the same way as the drivers from intersection *B* when a left turning vehicle accepts a small gap in the opposing traffic? Knowing the way drivers react to different scenarios allows the engineer to judge the level of risk taking that is going on at both intersections. The aforementioned approach can solve the problem of having to decide which of two competing intersections with a similar crash history and volume conditions should be the target of improvement programs; the one with higher risk is selected.

Problem Definition and Objectives

The question that needs to be answered before pursuing a risk taking behavior approach as a safety ranking tool is how to characterize the risk taking behavior itself. For example, in the case of the interaction between a left turning and an opposing vehicle, the risk taking behavior of the left turning driver can be easily characterized by the gap it accepts. A low gap value indicates high risk taking while a high value indicates low risk taking. On the other hand, the opposing vehicle has no control over the gap accepted by the left turning vehicle; therefore, its risk taking behavior can only be characterized based on the reaction to low and high values of gap acceptance. If the opposing vehicle reacts by taking evasive action only when faced with low values of gap acceptance that indicates a higher level of risk taking than if the reaction is observed for high values of gap acceptance.

The objectives of this research are:

- Develop a safety ranking measurement that takes into consideration the risk taking behavior of the drivers, as well as the prevailing field conditions, and
- Identify the means to obtain the required data for the methodology through the use of existing conflict counting techniques and taking into consideration the fundamental values that define the traffic flow.

By achieving these objectives, not only will engineers have new guidance on how to account for the drivers risk taking behavior when evaluating the safety of left turns at intersections but also have the means to obtain the data from field observations. Although the data gathering and the application of the methodology in this research is discussed from the case of left turning and opposing vehicle interaction, the concepts of risk taking are universal and can be applied to any other field maneuver type, provided that similar data can be obtained and fed into the models.

LITERATURE REVIEW

There are plenty of works in the literature related to the use of SSM to rank intersection in terms of their safety performance. Furthermore, the means to collect the conflict measurements, either from simulation or from actual field observations has also been discussed. This literature review is focused on presenting the reader with a discussion of the basic conflict counting methodologies, including their weaknesses, as well as two of the most fundamental SSM.

A traffic conflict is defined by the Federal Highway Administration (FHWA) as “an event involving the interaction of two or more road users, usually motor vehicles, where one or both drivers take evasive action such as braking or swerving to avoid a collision” (1). From the definition, a traffic conflict can be considered part of the normal driving process since braking is not always done to avoid a collision. There seems to be an agreement among researchers that the existence of a high number of conflicts can be considered an indicator of lower levels of safety at an intersection (2). Unfortunately, there is the question of how severe a particular conflict is as well as how to measure its severity, i.e., severity is not considered in the methodology.

In 1967, a procedure known as the Traffic Conflicts Technique (TCT) was developed by the General Motors (GM) Research Laboratories for the former Bureau of Public Roads under the FHWA (3). According to this publication, a traffic conflict takes place when “a driver takes evasive action, brakes or weaves, to avoid a collision”. A total of 24 types of conflicts are described in the document along with the best methods to observe them in the field. The intention of the aforementioned research was to establish a procedure of traffic conflict counts as a means for determining accident potential.

Baker (4) was one of the first authors who looked at the relationship between conflicts and crashes at intersections; it was found that conflicts counts obtained using the technique developed by GM can be used as a predictor of crashes at those intersections. Further research by Migletz (5) looked at the relationship between a group of crash types and the corresponding conflict types that lead to the type of crash. The procedures developed were used to obtain the expected number of crashes as a function of the number of conflicts occurring and a crash-to-conflict ratio for the system in question. At the time, it was argued that the limitations of such methodology were not a result of the limitations of the TCT but instead of the time constraints that exists when trying to obtain an accurate count of conflicts for the site studies as well as the variability of the conflict process itself. For example, Hauer found that conflict counts performed along different weekdays for the same site can have a variance-to-mean ratio of 1.4 and 2.2 depending on whether the conflicts considered are of the same class or if an aggregate value is used which shows the variability of the methodology results (6).

The definition of a traffic conflict up to this point has been based on observing a driver’s evasive action such as braking. It can be argued that an evasive action is conflict however not every conflict, using the TCT, can be defined as an evasive action. Thus, if conflicts measured according to the TCT are used as a surrogate measure of crashes it is assumed that an evasive action took place before the accident. Crashes, and near miss situations, according to Chin and Quek (7) take place because drivers failed, at some point, to take an evasive action. However, common sense tells us that there are indeed crashes were an evasive action took place but it was not sufficient to prevent it.

Surrogate safety measures, in addition to conflicts, have been proposed as an alternative to conflict counts to evaluate the safety of transportation system elements. As the name suggest, these are, in fact, measurements taken from the traffic stream characteristics, e.g., gaps, headways, among others. Surrogate safety measures can supplement conflict counts, or act as substitutes, due to their known capacity to act as indicators of conflict severity. In fact, the term Conflict Severity Measure has been used in the literature (8) to refer to the measurements such as time to collision.

Hayward (9) introduced the time to collision (TTC) concept, originally named time-measured-to-collision (TMCT) as a measure of the danger of near-miss situations. A near-miss situation can be considered an event where the danger to which the vehicle occupants, the second vehicle occupants, and/or pedestrians are exposed is higher than the danger under normal conditions. TTC is defined as "the time required for two vehicles to collide if they continue at their present speeds and on the same path". The equation used to compute TTC is shown below in Equation 1.

$$TTC_i = \frac{d}{V_i - V_{i-1}} = \frac{1}{\frac{V_i}{\mathrm{d}} - \frac{V_{i-1}}{\mathrm{d}}} \tag{1}$$

Where,

d = distance between the vehicles, and

V_i = speed of the vehicles involved.

One would expect that values of TTC lower than the perception and reaction time (PRT) should be considered dangerous; however, due to variance in drivers and other driving environment characteristics, it's possible that values of TTC higher than the driver's perception and reaction time can still be considered unsafe and can potentially result in a collision. Among the literature there appears to be an agreement that no value of TTC higher than six seconds is dangerous. Although it looks like an obvious indicator of safety, the measurement has the disadvantage that as it indicates a safer situation, i.e., higher values, it starts losing reliability as a safety indicator (10) since a high value of TTC actually provides the driver with more time for avoiding what could be a potential crash.

Besides the shortcomings associated with the use of this indicator, since the introduction of the concept in 1972, (9) it has become one of the most popular indicators of how safe a particular scenario is. An additional problem with the measurement is obtaining the value itself. As Equation 1 indicates, it is necessary to obtain the speed of both, the leading and the following vehicle in addition to the distance between them which is a difficult process. (11) In fact, it appears that the only feasible method to obtain field values of TTC is through video processing which is an extremely time-consuming process.

As it can be seen, the TTC measure is one that is suited for measuring the severity of rear end conflicts. In the case of conflicts between vehicles making a left turn and vehicles on the opposing traffic flow, a new severity measure has been proposed. The corresponding measure is called post-encroachment time (PET) and is defined by Allen (11) as “the time from the end of encroachment to the time that the through vehicle arrives at the potential point of collision”. The PET is a function of the gap accepted by the left turning vehicles as well as the speeds of both vehicles and the distance traveled towards the encroach point. The computation of the measurement is shown below in Equation 2.

$$\mathrm{PET} = \frac{d_{\mathrm{ov}}}{v_{\mathrm{ov}}} - \frac{d_{ltv}}{v_{ltv}} \tag{2}$$

Where,

d_{ov} = distance from encroachment point (EP) to opposing vehicle (its measured at the instance that encroachment by the left turning vehicle starts),
d_{ltv} = distance traveled by the left turning vehicle toward the EP, and
$v_{ov,ltv}$ = speeds of the opposing and left turning vehicle.

Two concepts have been presented so far; first, the existence of a methodology to document what is known as traffic conflicts. The methodology has been successfully used as a predictor of the number of crashes. However, the methodology lacks a quantitative definition of what is the severity of the conflict. Therefore, surrogate safety measures are introduced to solve the aforementioned problem. A discussion was presented on two of the most fundamental surrogate safety measures, that is the TTC and the PET. There is no disagreement that as the value of these two measurements approaches zero the situation becomes more dangerous; however, the threshold for defining the safe region has been selected based on analyses performed by engineers without taking into consideration what a driver considers safe conditions.

RESEARCH APPROACH

One of the problems is that the current conflict count methodologies based on the use of surrogate safety measures are mostly based on judgment. The field conflict identification methodology presented in this research takes into consideration the behavior of drivers as they approach the conflict point. The action that the observer looks for when performing the field study are a diving of the vehicle nose, sudden changes in the speed of the opposing vehicle, as well as any other indication suggesting a reaction by the opposing driver. This type of action by the driver will henceforth be known as a driver adverse reaction (DAR). Identifying the conditions at which a DAR is observed provides an idea of the level of risk-taking by the driver population; for example, if a DAR is observed at a high gap value that suggests that drivers are on the conservative side; on the other hand, the same observation at a low value suggests drivers are willing to take a higher risk than conservative ones.

One of the problems of making DAR observations during a field study is that the real time and the speed at which everything happens can be a contributing factor to errors in the data collection process since it might result in missed observations or misjudgment. Thus, in order to avoid the aforementioned situation, three intersections, with similar geometric characteristics, were videotaped, for a period of two hours each. All of the intersections have left turns bays, two lanes of opposing traffic and operate under a permitted-only left turn phase scheme with no pedestrian-vehicle interaction. Data were collected in the city of Madison. Recording took place from the median and data processed later in an office environment. Using video for the data collection process allows reviewing the interaction among vehicles on a frame-by-frame basis thus removing much of the guesswork associated with real-time field data collection an observation. The downside to this process is the overhead, in terms of labor, that video analysis introduces since going through the video more than one time in slow motion is required.

Furthermore, an advantage of using video to analyze data is that it allows obtaining the timestamps of each vehicle that goes through the intersection. DAR and non-DAR observations were assigned a corresponding timestamp from the video. After processing the video, variables describing the microscopic conditions can be obtained for the vehicle interaction; for example, for every vehicle making a left turn, the time that the vehicle arrives to the queue, and the time it crosses the opposing traffic are known, as well as the gaps that were rejected and accepted. Because of the dataset characteristics, it’s possible to determine the microscopic conditions which lead to a DAR.

Based on the observation of a DAR and the prevailing microscopic flow conditions, i.e., the gap accepted at the moment, a new dataset was assembled. The resulting dataset follows the structure of a dichotomous response, i.e., only two conditions are possible, a DAR was observed or not given the value of the predictor variables such as gap accepted by the left turning vehicle. In the case of a dichotomous response with continuous predictor variables a binary logistic regression can be used to fit a model to the corresponding data. The resulting model computes the probability of a DAR being observed given a value of gap accepted by the left turning vehicle. Theoretically, the aforementioned modeling approach would yield a 100 percent probability of observing a DAR when the gap accepted by the left turning vehicle approaches zero as well as a zero percent probability when the gap approaches infinity.

As mentioned in the objective sections, the reaction of the opposing driver to a gap acceptance situation is not the only consideration in the safety for a left turn scenario. Therefore, a binary logistic regression model was created to understand the probability of a particular left turning vehicle accepting a gap when exposed to it. With these two regression models, both of the elements that provide an indication of the risk taking behavior of the vehicles involved in a gap acceptance process are described mathematically. When both of these models are combined in the way shown in the following analysis section, a newly proposed safety ranking measurement able to account for the risk taking behavior of drivers is presented.

RESULTS

In order to prove the feasibility of obtaining an adequate dataset to implement the proposed methodology, six hours of intersection recording were analyzed as part of this research using the procedure described in the research approach section. During those hours of observation there were 70 gaps accepted by vehicles that are below a threshold of 12.0 seconds identified in the literature as a value that provides absolute certainty of acceptance (12). Furthermore, for those 70 gaps accepted, a DAR was observed during 18 of those instances, representing 26% of the cases. The histogram for the groups of gaps producing a DAR as well as not producing a DAR is shown below in Figure 1. Both datasets follow a normal distribution according to a Ryan-Joiner test with a null-hypothesis of normality.

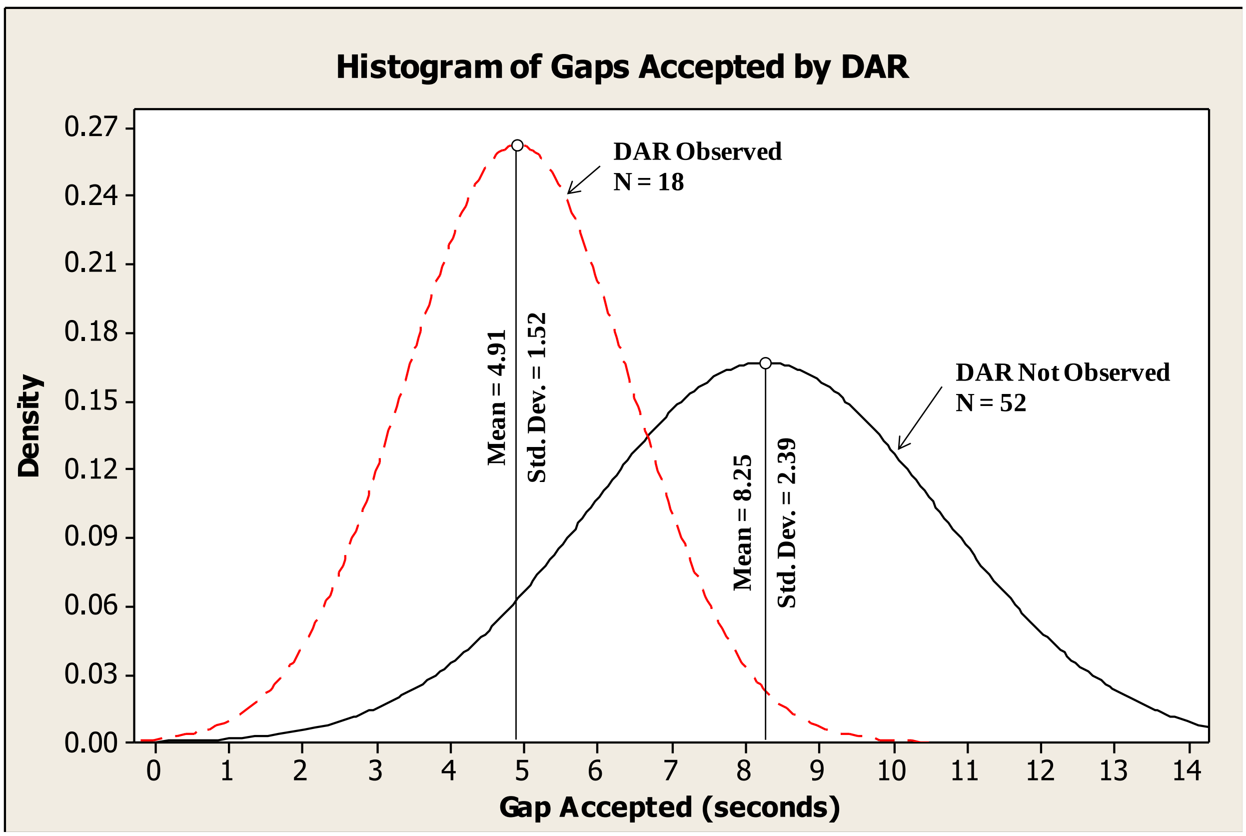

FIGURE 1 Distribution of gaps with DAR observed and DAR not observed.

Based on the data collected it was possible to generate a binary logistic regression model which returns the probability of observing a DAR as a function of the gap accepted by the driver of the left turning vehicle. The result of the model is shown below in Table 1 and a visual representation of it is shown in Figure 2. As the Hosmer-Lemeshow test suggests, the hypothesis of an adequate fit cannot be rejected for the model at a 95% level of confidence.

TABLE 1 Disaggregate Model Specification for Observation of DAR

Predictor	Coefficient	Standard Error of Coefficient	Z	P	Odds Ratio	95% CI	
						Lower	Upper
Constant	3.71305	1.19708	3.10	0.002			
Gap	-0.746383	0.20080	-3.72	0.000	0.47	0.32	0.70

Hosmer-Lemeshow = 0.354

The odds-ratio value of 0.47 indicates that an increase of 1.0 second in the gap accepted by the driver reduces the odds of observing a conflict almost by half. From the visual representation of the model, shown below in Figure 2, it can be seen that an increase of 6.0 seconds in the gap accepted by the left turn driver reduces the probability of observing a DAR from 0.9 to 0.1. The change in the predictor variable being responsible for the 0.8 change in probability can be considered a measure of the gray area that exist between gaps accepted causing a DAR and those not causing a DAR.

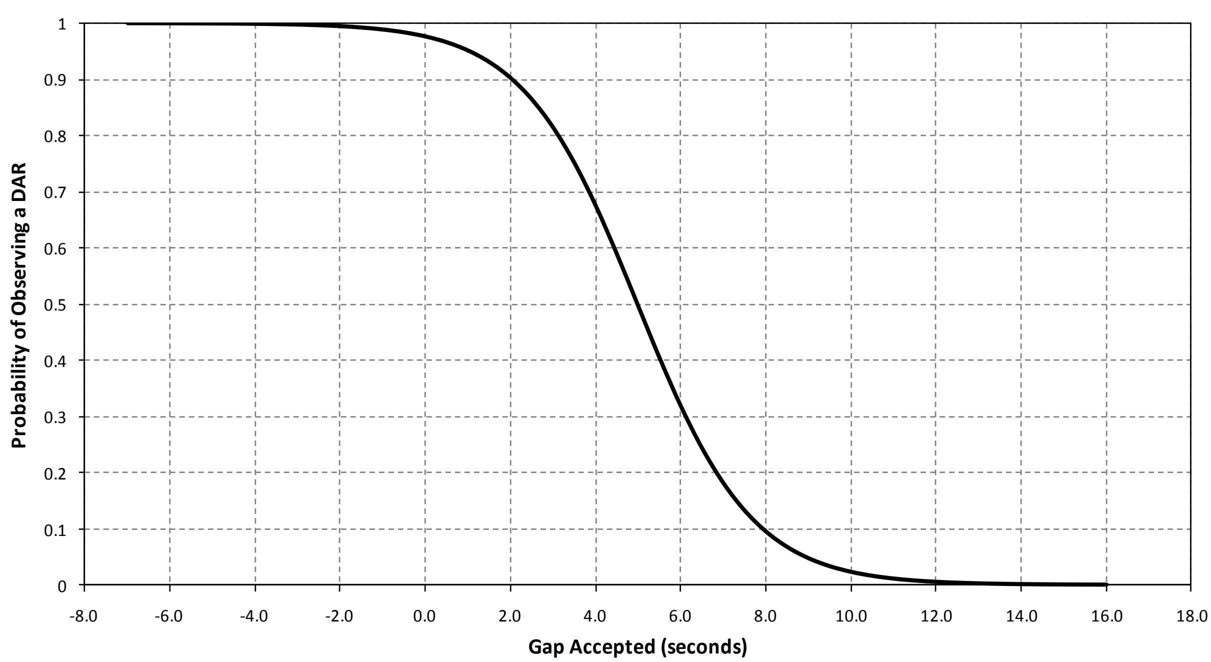

FIGURE 2 Probability of observing a DAR as a function of the gap accepted.

Another model that explains the process of gap acceptance was created as part of this research. The model specification is shown below in Table 2 and it returns the probability of accepting a gap as a function of the gap that the left turning vehicle is exposed to. Although it violates the common practice of performing gap acceptance studies, using this form of the model is necessary in order to use the results as part of a proposed safety indicator that is discussed in the section ahead. Table 2 shows that the predictor variables are significant at a 95% confidence interval and the 0.756 Hosmer-Lemeshow statistic value does not allow rejecting the null hypothesis of an adequate fit.

TABLE 2 Disaggregate Model Specification for Gap Acceptance

Predictor	Coefficient	Standard Error of Coefficient	Z	P	Odds Ratio	95% CI	
						Lower	Upper
Constant	-6.16528	0.493245	-12.5	<0.000			
Gap	1.06713	0.107683	9.91	<0.000	2.91	2.35	3.59

Hosmer-Lemeshow = 0.756

As the model specification shows, the gap to which the driver is exposed is a significant factor, p-value lower than 0.001, thus indicating it is at least significant at a 95% confidence level. The odds-ratio for the gap parameter, 2.91, indicates that the odds of accepting a gap almost triple when the gap to which the driver is exposed is one second longer than the alternative. A visual representation of the model shown above in Table 2 is shown below in Figure 3. As it can be seen, the model is not only mathematically sound, but also logically, since it indicates nearly a zero percent probability of accepting a gap around one second while almost a 100 percent probability of accepting a gap near ten seconds.

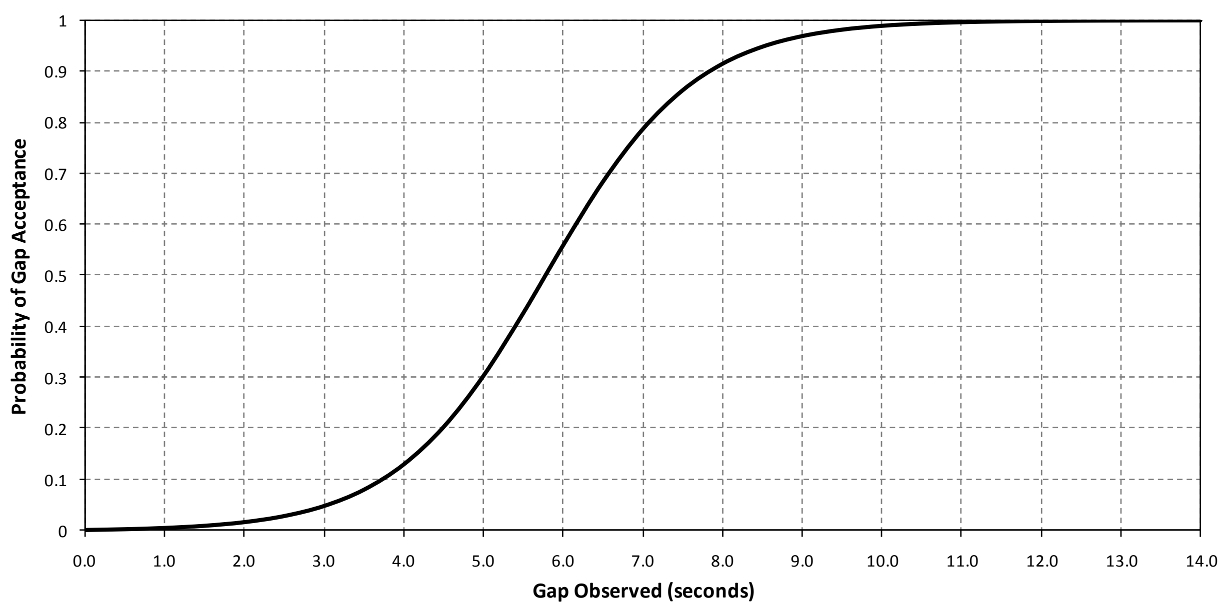

FIGURE 3 Gap acceptance model as a function of the gap the driver is exposed.

ANALYSIS OF RESULTS

The section above presented one important finding; that is, the observation of a DAR can be modeled through the use of binary logistic regression using gap accepted by a driver as the predictor variable. As a result of this it can be said that given a gap value, known as the reference gap, r_{gap}, the probability of observing a DAR can be computed; that is, $P_D = f(r_{gap})$. Furthermore, a model which returns the probability of gap acceptance as a function of the r_{gap} that the driver is exposed to was also presented; that is, $P_A = f(r_{gap})$. Given the scenario in which the value of P_A is similar for two intersections, the value that can be used to indicate whether one intersection should be considered safer than the other is based on the value of P_D. The aforementioned statement is based on the assumption that for a given r_{gap} a low value of P_D suggests that the drivers at that intersection believe the gap is safer than what other drivers, at an intersection with a higher PD values, believe.

The joint probability of gap acceptance and DAR observation for an intersection can then be computed by multiplying $P_D(r_{gap}) \times P_A(r_{gap})$. Thus, for a given r_{gap}, the lower the value of P_D is the lower value of the joint probability. Intuitively the result of the multiplication, i.e., the joint area of the Ben diagrams for those two probabilities, can act as safety index that accounts for driver behavior at intersections. However, there is still one missing piece of information that should be taken into consideration which is the distribution of gaps at an intersection. The reason for consideration lies in that, although two intersections might have the same result of $P_D(r_{gap}) \times P_A(r_{gap})$, one might have a lower probability of observing gaps equal to the r_{gap}, i.e., $P_G(r_{gap})$.

Thus, a newly proposed left turn driver safety index (LTDS) is computed as shown below in Equation 3. By taking into account what is known about gap distributions at an intersection approach; the lower the probability of observing a gap with a relatively high probability of acceptance, and low probability of conflict observation, the safer it can be argued that the left turn at that intersection is. Therefore, high values of LTDS indicate a lower safety performance, i.e., a safety concern, while lower values indicate the complete opposite.

$$LTDS = P_D(r_{gap}) \times P_A(r_{gap}) \times P_G(r_{gap}) \quad (3)$$

Where,

P_D = Probability of observing a DAR given that gap is accepted,

P_A = Probability of accepting a gap given that exposed to it, and

P_G = Probability of observing a certain gap on the traffic stream.

Equation 3 is technically an infinitesimal value which means that in order to obtain a more practical index, the summation of the Equation 3 values should be done from zero up to a selected value of r_{gap} as it is shown in Equation 4. Such an approach allows the LTDS index value to take into account the shape of the gap distribution curve at an intersection approach.

$$LTDS\ (r_{gap}) = \int_0^{r_{gap}} P_D(r_{gap}) \cdot P_A(r_{gap}) \cdot P_G(r_{gap}) dr_{gap} \quad (4)$$

The challenge for the engineer that performs the safety analysis using the proposed methodology is selecting the appropriate r_{gap} value. As a matter of guidance, it can be suggested that the r_{gap} value be equal to the gap with the highest probability of being observed, the median gap, the 85th percentile gap or any other gap with a mathematical meaning. When comparing the safety of different intersections, the index should not be computed for simply a fix r_{gap} value. Instead, it should be computed over a certain range of values to take into account variations that might result from the shape of the curves involved in the analysis and thus evaluate the sensitivity before making a decision as to which intersection is safer.

CONCLUSIONS

Two main findings are derived from this research. The first one is that through the use of field data collection and video techniques it is possible to obtain a model that describes the probability of observing an adverse reaction from a driver, given that the driver is faced with a set of conditions in the field. In the absence of any other information, given the characteristics of gap acceptance which yields a certain probability of observing an adverse driver reaction, that value alone can act as a safety index. A low value indicates that the corresponding driver population is a higher risk taker than a population with higher value. An approach like this one would be sufficient to rank two intersections with similar volume and gap distribution conditions. However, when two similar driver populations are considered the distribution of gaps needs to be taken into consideration.

The second finding of this research involves the use of a gap acceptance probability curve along with a gap distribution curve; when combined with the driver adverse reaction probability curve, it acts as the safety index measurement proposed. The index is based on the concept of joint probability. The newly proposed safety index takes into account not only the driver's behavior at an intersection but also the prevailing traffic conditions as described from a microscopic flow theory perspective. An approach like the one presented is able to solve the problem engineers face when deciding what intersections should be the target of safety improvement when no crash history exist. Furthermore, by having the knowledge about the shape of the adverse driver reaction as well as the gap acceptance probability curves, an engineer can select a timing plan that can influence the shape of the gap distribution curve in order to effectively increase the safety index at the intersection.

FUTURE WORK AND PRACTICAL APPLICATION

The field methodology used in this research is based on the observation of a DAR from video. Following this procedure is a step on the right direction since it reduces the error introduced as a result of real time data collection; however, there is still a level of judgment involved in the process. Thus, one alternative to consider as part of future research is to use radar equipment capable of tracking the positions of the vehicles as they approach the intersection as well as image processing techniques to determine when DAR's take place. Image processing techniques have successfully being used by Saunier and Sayed (13, 14) to perform conflict analyses. The application of the techniques presented in the aforementioned works as means for obtaining the data required in the proposed LTDS index allows engineers to break the wall between theory and practice. Furthermore, the data obtained from such technologies will allow observing drivers reactions, using a quantifiable change in the speed profile as opposed to a qualitative indicators, when exposed to a scenario such as a left turning vehicle crossing the opposing vehicle path.

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