Proposed Safety Index Based on Risk-Taking Behavior of Drivers

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A new safety indicator 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 at which drivers are willing to take a higher risk is not as safe as one at which drivers are not willing to take high risks. Driver risk-taking behavior is modeled as a function of a driver's reaction to a possible collision scenario. 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 are presented from the perspective of permissive left turns; however, the concept of risk taking is universal; thus it is a feasible alternative for other maneuver types if appropriate data are obtained. Use of a safety index based on risk taking helps solve the engineer's dilemma of which of two intersections that have no crash history, or that have equal crash history, should be the target of a safety improvement program. The methodology presented can remove the subjective judgment that often takes place in such a scenario and provides the engineer with an objective alternative.

A basic principle in economic theory is the scarcity principle, by which the needs of the society are unlimited, whereas the resources are limited. The transportation system is not an exception to this principle. Although everyone wants to fix road congestion, only some of the projects that could reduce congestion will be funded. Improving the safety of the transportation system also is subject to this principle. Transportation engineers would like to make necessary improvements to the system to bring the fatality count to zero, but resources are limited, and engineers must select those elements for which the highest return on investment can be obtained.

If an agency can afford to improve only one of two intersections that, if treated, would experience an equal reduction in number of crashes, then the decision is purely monetary. The site selected for improvement is the one with the lowest ratio of cost per expected reduced crashes. Thus, when the expected number of crashes can be computed because a crash history is available, established procedures provide engineers with the guidance needed for decision making.

Unfortunately, the decision is not always straightforward. There is agreement among the transportation engineering community that an intersection with no crash history is not necessarily a safe intersection. Thus, transportation engineers are 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 instead of another be justified in this scenario? Such decisions are made largely on a subjective basis; political factors sometimes also have weight.

Various approaches have been suggested for measuring the safety of transportation system elements. The traffic conflicts technique, developed by General Motors (GM) research laboratories in the 1960s, uses a set of specific guidelines to count conflicts between vehicles at an intersection or other elements of the transportation system such as weaving sections. The observed conflicts are classified according to actions performed by 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. The methodology records conflicts by using a binary state: the conflict either happened or did not happen. No measurement of severity is made. Furthermore, the GM methodology gives the field observer latitude in what can be considered a conflict; therefore, ranking of the intersection with the conflict count as an index relies on the judgment of the field observer. An approach to conflict counting that can solve this problem is to define a conflict based on a particular value, such as the gap experienced or the headway maintained. The approach implies the use of surrogate safety measures (SSM). In this approach, a conflict is considered as such if the SSM value meets a specific threshold, for example, the gap accepted by a left-turning vehicle is smaller than a value believed to be safe and predefined by an analyst.

The SSM approach cannot distinguish which of two intersections is safer when they have a similar number of conflicts as defined by the scenarios exceeding the safe value. The approach presented in this research is to look at what drivers at an intersection perceive as unsafe. For example, given Intersections A and B, do drivers at Intersection A react in the same way as do drivers at Intersection B when a left-turning vehicle accepts a small gap in the opposing traffic? Knowing how drivers react to different scenarios allows the engineer to judge the level of risk taking occurring at both intersections. This approach can solve the problem determining which of two competing intersections having similar crash histories and volume conditions should be the target of improvement programs—the one with higher risk is chosen.

PROBLEM DEFINITION AND OBJECTIVES

Before risk-taking behavior is pursued as a safety ranking tool, the risk-taking behavior itself must be characterized. For example, in the interaction between a left-turning and an opposing vehicle, the risk-taking behavior of the left-turning driver can be easily characterized

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by the gap it accepts. A low gap value indicates high risk taking, whereas a high value indicates low risk taking. The opposing vehicle has no control over the gap accepted by the left-turning vehicle; therefore, its risk-taking behavior can be characterized only by 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, a higher level of risk taking is indicated than if the reaction is observed for high values of gap acceptance.

The objectives of this research are to develop a safety ranking measurement that takes into consideration the risk-taking behavior of drivers, as well as the prevailing field conditions, and to identify the means by which to obtain the required data for the methodology through the use of existing conflict-counting techniques and by considering the fundamental values that define the traffic flow.

Achieving these objectives could provide engineers with not only new guidance on accounting for driver risk-taking behavior when evaluating the safety of left turns at intersections but also the means with which to obtain the data from field observations. Although data gathering and the application of the methodology in this research are discussed regarding interaction of left-turning and opposing vehicles, the concepts of risk taking are universal and can be applied to any other field maneuver if similar data can be obtained and fed into the models.

LITERATURE REVIEW

There is considerable literature on the use of SSMs to rank intersections for safety performance, and how to collect conflict measurements, either by using simulation or from field observations, has been discussed. The literature review here presents a discussion of the basic methodologies for conflict counting, including their weaknesses, as well as two of the most fundamental SSMs.

A traffic conflict is defined by 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*). A traffic conflict can be considered part of the normal driving process since braking is not always done to avoid a collision. There is an apparent agreement among researchers that 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 conflict is as well as how to measure its severity, that is, severity is not considered in the methodology.

The traffic conflicts technique (TCT) was developed by GM for the former Bureau of Public Roads in 1967 (*3*). According to the manual, a traffic conflict takes place when "a driver takes evasive action, brakes or weaves, to avoid a collision" (*3*). A total of 24 types of conflicts are described in the document, along with the best methods for observing them in the field. The research was done to establish a procedure for counting traffic conflict for determining accident potential.

Baker was among the first to look at the relationship between conflicts and crashes at intersections (*4*); it was found that conflict counts obtained with the technique developed by GM can be used as a predictor of crashes at those intersections. Further research by Migletz et al. looked at the relationship between a group of crash types and the corresponding conflict types that lead to the type of crash (*5*). 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 on the attempt 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 to this point has been based on observing a driver's evasive actions, such as braking. It can be argued that an evasive action is conflict; however, not every conflict, per 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 fail at some point to take an evasive action. However, common sense suggests that in some situations an evasive action took place, but it was not sufficient to prevent a crash.

Surrogate safety measures, in addition to conflicts, have been proposed as an alternative to conflict counts for evaluating the safety of transportation-system elements. As the name suggest, these are measurements taken from traffic stream characteristics, such as gaps and headways. Surrogate safety measures can supplement conflict counts or act as substitutes because of their known capacity to act as indicators of conflict severity. The term "conflict severity measure" has been used in the literature to refer to the measurements such as time to collision (*8*).

Hayward introduced the time-to-collision (TTC) concept, originally called the time measured to collision, as a measure of the danger of near-miss situations (*9*). A near-miss situation is an event in which the danger to which a vehicle's occupants, the second vehicle's occupants, or pedestrians are exposed is greater than the danger under normal conditions. TTC is defined as the time required for two vehicles to collide if they continue at their current speeds and on the same path and is computed as follows:

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

where d is the distance between vehicles and V_i is the speed of the vehicles involved.

One would expect that values of TTC lower than the perception and reaction time should be considered dangerous; however, because of variance in drivers and other driving environment characteristics, it is possible that values of TTC higher than the driver's perception and reaction time can still be considered unsafe and could result in a collision. There appears to be an agreement in the literature that no value of TTC higher than 6 s is dangerous. Although it looks like an obvious indicator of safety, the measurement has the disadvantage that as it indicates a safer situation, that is, higher values, it starts losing reliability as a safety indicator (*10*), since a high value of TTC provides the driver with more time for avoiding a potential crash.

Since the introduction of the concept in 1972, it has become one of the most popular indicators of the safety of a particular scenario, despite its shortcomings (*9*). 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*) It appears that the only feasible method for obtaining field values of TTC is through video processing, which is an extremely time-consuming process.

The TTC measure is suited for measuring the severity of rear-end conflicts. A new severity measure has been proposed for conflicts between vehicles making a left turn and vehicles in the opposing traffic flow. The corresponding measure is called postencroachment time (PET) and is defined by Allen et al. as "the time from the end of encroachment to the time that the through vehicle arrives at the potential point of collision" (*11*). 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 toward the encroachment point. The computation of the measurement is shown in Equation 2:

$$\mathrm{PET} = \frac{d_{\mathrm{ov}}}{v_{\mathrm{ov}}} - \frac{d_{\mathrm{ltv}}}{v_{\mathrm{ltv}}} \qquad (2)$$

where

d_{ov} = distance from encroachment point to opposing vehicle (measured at the moment when encroachment by the left-turning vehicle starts),
d_{ltv} = distance traveled by the left-turning vehicle toward the encroachment point, and
$v_{\mathrm{ov,ltv}}$ = speeds of the opposing and left-turning vehicles.

Two concepts have been presented so far. A methodology for traffic conflicts has been successfully used as a predictor of the number of crashes. However, the methodology lacks a quantitative definition of the severity of the conflict. Surrogate safety measures are thus introduced to solve this problem. Two of the most fundamental surrogate safety measures are 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 is based on analyses performed by engineers without taking into consideration what a driver considers to be safe conditions.

RESEARCH APPROACH

One of the problems is that the current conflict count methodologies based on the use of surrogate safety measures are based largely on judgment. The field conflict identification methodology presented in this research considers 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, and any other indication of a reaction by the opposing driver. This type of action by the driver is known as a driver adverse reaction (DAR). Identification of the conditions at which a DAR is observed provides an idea of the level of risk taking by the driver population; for example, a DAR observed at a high gap value suggests that drivers are more conservative; the same observation at a low value suggests that drivers are willing to take a higher risk.

One of the problems in making DAR observations during a field study is that the real time and the speed at which everything happens can be contributing factors to errors in the data collection process, and missed observations or misjudgment may result. To avoid this, three intersections with similar geometric characteristics were videotaped for 2 h each. All the intersections have left-turn bays and 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, Wisconsin. Recording took place from the median, and the data were processed later in an office environment. Use of video for data collection allows review of the interaction among vehicles on a frame-by-frame basis, removing much of the guesswork associated with real-time field data collection and observation. The downside of this process is that it is labor intensive, because going through the video more than once in slow motion is necessary.

With the use of video to analyze data, time stamps of each vehicle that goes through the intersection can be obtained. DAR and non-DAR observations were assigned a corresponding time stamp from the video. When the video is processed, variables describing the microscopic conditions can be obtained for the vehicle interaction; for example, for every vehicle making a left turn, the time at which the vehicle arrives at the queue and the time at which it crosses the opposing traffic are known, as are the gaps that were rejected and accepted. Because of the data set characteristics, it is possible to determine the microscopic conditions that lead to a DAR.

From the observation of a DAR and the prevailing microscopic flow conditions, that is, the gap accepted at the moment, a new data set was assembled. The resulting data set follows the structure of a dichotomous response, that is, only two conditions are possible: a DAR was observed or was not observed, 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, this modeling approach would yield a 100% probability of observing a DAR when the gap accepted by the left-turning vehicle approaches zero as well as a 0% probability when the gap approaches infinity.

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

RESULTS

To prove the feasibility of obtaining an adequate data set for implementing the proposed methodology, this research analyzed 6 h of intersection recording while using the procedure described in the section on the research approach. During those hours of observation, 70 gaps below a threshold of 12.0 s were accepted by vehicles, a value identified in the literature as providing absolute certainty of acceptance (*12*). Furthermore, of those 70 accepted gaps, a DAR was observed during 18, representing 26% of the cases. A histogram for the groups of gaps producing a DAR and not producing a DAR is shown in Figure 1. Both data sets follow a normal distribution according to a Ryan–Joiner test with a null hypothesis of normality.

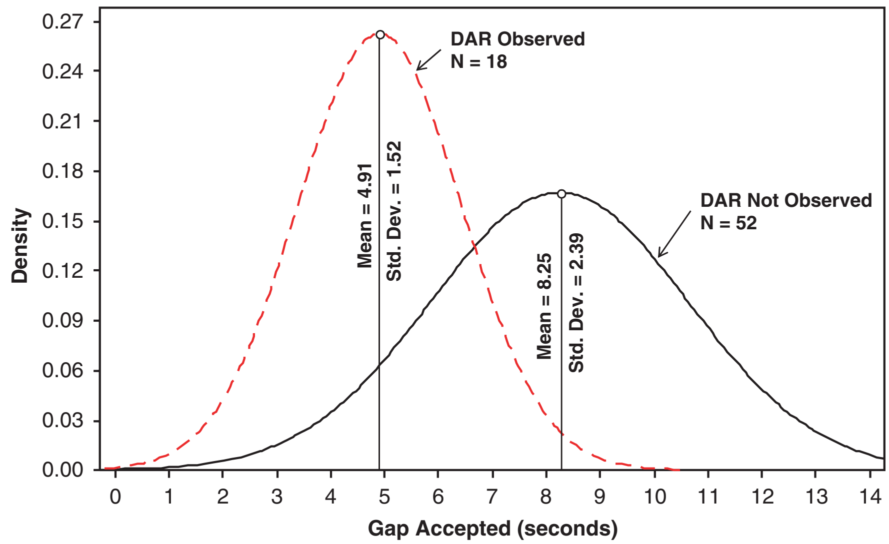

FIGURE 1 Distribution of gaps with DAR observed and DAR not observed.

From the data collected, it was possible to generate a binary logistic regression model that 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 in Table 1, and a visual representation 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.

The odds ratio value of 0.47 indicates that an increase of 1.0 s in the gap accepted by the driver reduces the odds of observing a conflict by almost half. Figure 2 shows that an increase of 6.0 s in the gap accepted by the left-turn driver reduces the probability of observation of a DAR from 0.9 to 0.1. The change in the predictor variable responsible for the 0.8 change in probability can be considered a measure of the gray area between gaps accepted that cause a DAR and those that do not cause a DAR.

Another model that explains the process of gap acceptance was created as part of this research. The model specification is shown in Table 2. 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, use of this form of the model is necessary so that the results can be used as part of a proposed safety indicator, discussed in the next section. 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.

As the model specification shows, the gap to which the driver is exposed is a significant factor, *p*-value lower than .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 1 s longer than the alternative. Figure 3 is a visual representation of the model shown in Table 2. As can be seen, the model is not only mathematically sound but logical, since it indicates nearly a 0% probability of accepting a gap of around 1 s and an almost 100% probability of accepting a gap near 10 s.

ANALYSIS OF RESULTS

The preceding section presented an important finding: the observation of a DAR can be modeled through the use of binary logistic regression by using gap accepted by a driver as the predictor variable. 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, $P_D = f(r_{gap})$. A model that returns the probability of gap

TABLE 1 Disaggregate Model Specification for Observation of DAR

Predictor	Coefficient	Standard Error of Coefficient	Z	P	Odds Ratio	95% CI Lower	95% CI Upper
Constant	3.71305	1.19708	3.10	.002			
Gap	−0.746383	0.20080	−3.72	.000	0.47	0.32	0.70

NOTE: Hosmer–Lemeshow = 0.354.

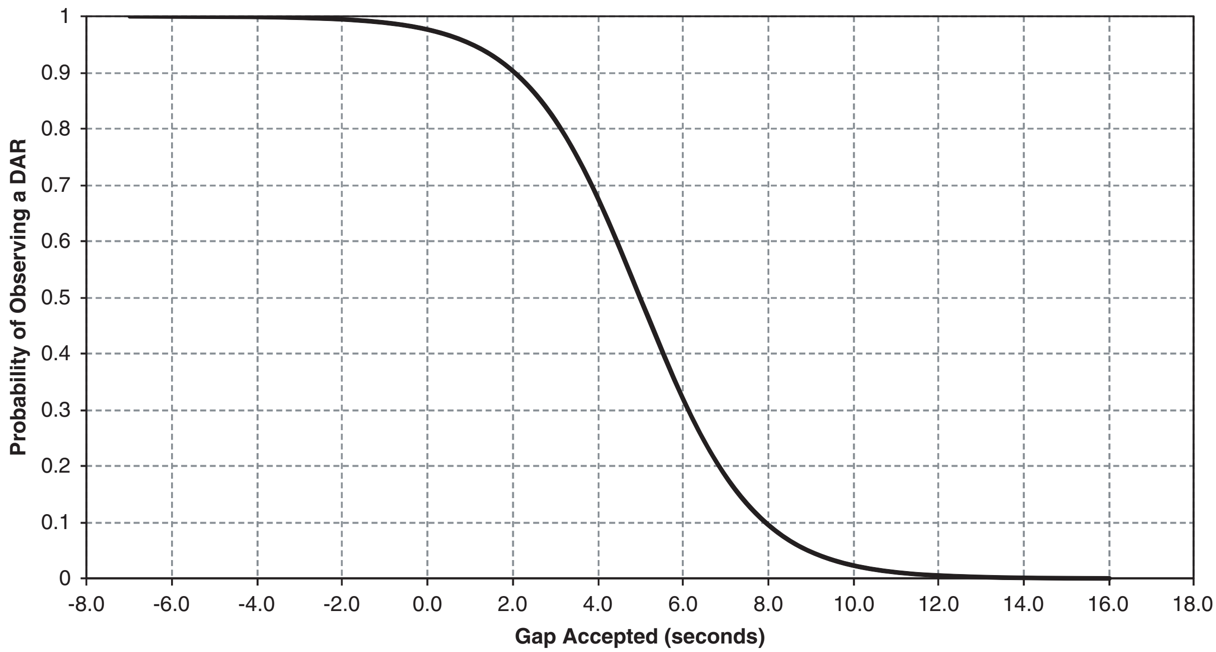

FIGURE 2 Probability of observing DAR as function of accepted gap.

acceptance as a function of the r_{gap} to which the driver is exposed 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. This 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 higher P_D 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, that is, the joint area of the Venn diagrams for those two probabilities, can act as a safety index that accounts for driver behavior at intersections. However, there remains one missing piece of information that should be considered: the distribution of gaps at an intersection. Although two intersections may have the same result of $P_D(r_{gap}) \times P_A(r_{gap})$, one could have a lower probability of observing gaps equal to the r_{gap}, that is, $P_G(r_{gap})$.

Thus, a newly proposed left-turn driver safety index (LTDS) is computed as shown 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 the left turn at that intersection can be argued to be. Therefore, high values of LTDS indicate a lower safety performance, that is, a safety concern, whereas lower values indicate the opposite.

$$\text{LTDS} = P_D\left(r_{gap}\right) \times P_A\left(r_{gap}\right) \times P_G\left(r_{gap}\right) \qquad (3)$$

where

P_D = probability of observing a DAR given that a gap is accepted,
P_A = probability of accepting a gap given that one is 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 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

TABLE 2 Disaggregate Model Specification for Gap Acceptance

Predictor	Coefficient	Standard Error of Coefficient	Z	P	Odds Ratio	95% CI Lower	95% CI Upper
Constant	–6.16528	0.493245	–12.5	<.000			
Gap	1.06713	0.107683	9.91	<.000	2.91	2.35	3.59

NOTE: Hosmer–Lemeshow = 0.756.

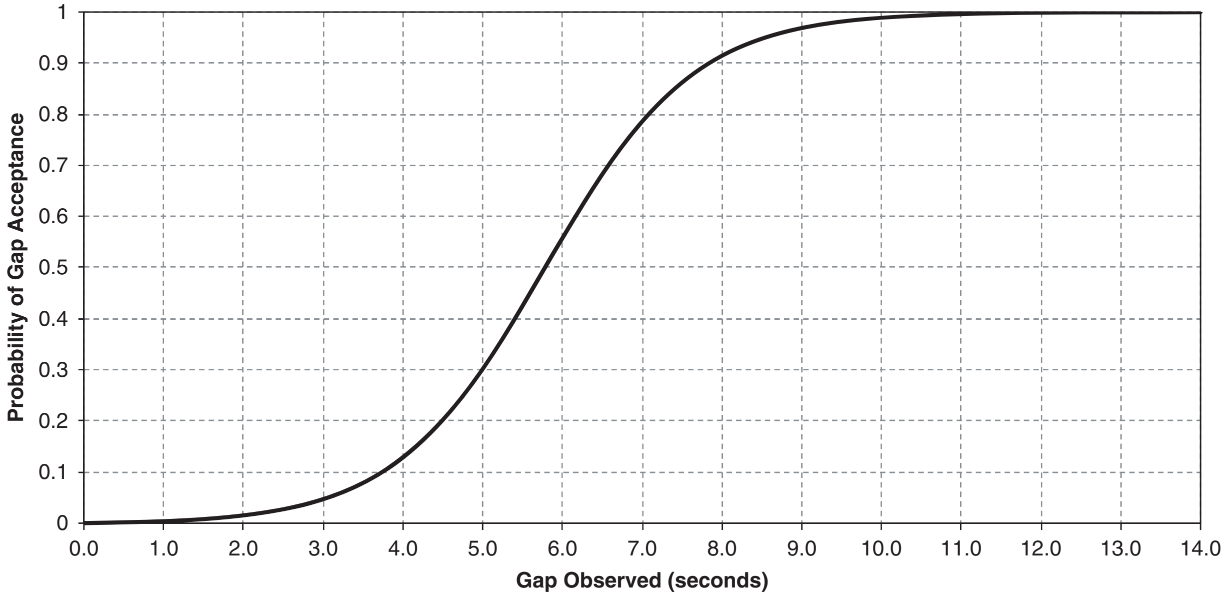

FIGURE 3 Gap acceptance model as function of gap to which driver is exposed.

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.

$$\mathrm{LTDS}\left(r_{\mathrm{gap}}\right) = \int_0^{r_{\mathrm{gap}}} P_D\left(r_{\mathrm{gap}}\right) \cdot P_A\left(r_{\mathrm{gap}}\right) \cdot P_G\left(r_{\mathrm{gap}}\right) dr_{\mathrm{gap}} \tag{4}$$

The challenge for the engineer who performs the safety analysis by using the proposed methodology is to select the appropriate r_{gap} value. The r_{gap} value will 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. In a comparison of the safety of various intersections, the index should not be computed for a fixed r_{gap} value. Instead, it should be computed over a range of values to take into account variations that might result from the shape of the curves involved in the analysis; thus the sensitivity can be evaluated before a decision is made about which intersection is safer.

CONCLUSIONS

Two main findings are derived from this research. First, 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 that yield 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 takes greater risks than does a population with a higher value. An approach like this one would be sufficient for ranking two intersections with similar volume and gap distribution conditions. However, when two similar driver populations are considered, the distribution of gaps must 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 probability curve for driver adverse reaction, 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 can solve the problem engineers face when deciding which intersections to target for safety improvement when no crash history exists. With knowledge of 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 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. This procedure reduces error introduced by real-time data collection; however, a level of judgment remains in the process. Thus, an alternative to consider as part of future research is the use of radar equipment capable of tracking the positions of vehicles as they approach the intersection as well as image-processing techniques to determine when DARs take place. Image-processing techniques were successfully used by Saunier and Sayed to perform conflict analyses (*13, 14*). Application of the presented techniques to 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 allows observation of driver reactions by using a quantifiable change in the speed profile rather than qualitative indicators, when exposed to a scenario such as a left-turning vehicle crossing the path of the opposing vehicle.

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