Empirical Behavioral Models to Support Alternative Tools for the Analysis of Mixed-Priority Pedestrian-Vehicle Interaction in a Highway Capacity Context

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Abstract

This paper presents behavioral-based models for describing pedestrian gap acceptance at unsignalized crosswalks in a mixed-priority environment, where some drivers yield and some pedestrians cross in gaps. Logistic regression models are developed to predict the probability of pedestrian crossings as a function of vehicle dynamics, pedestrian assertiveness, and other factors. In combination with prior work on probabilistic yielding models, the results can be incorporated in a simulation environment, where they can more fully describe the interaction of these two modes. The approach is intended to supplement HCM analytical procedure for locations where significant interaction occurs between drivers and pedestrians, including modern roundabouts.

Keywords

Pedestrians; Alternative Tools; Simulation; Highway Capacity; Unsignalized

1. Introduction

Current traffic engineering analysis tools and capacity models are of limited use for evaluating the interaction of pedestrians and vehicles at unsignalized crossing facilities. Highway Capacity Manual (HCM) analysis methodologies for unsignalized intersections are limited to boundary cases, which assume strictly enforced right-of-way rules (TRB, 2000). In that sense, pedestrian operations are analyzed by either assuming pedestrian priority (100% driver yielding) or vehicle priority without yielding right-of-way to pedestrians. The traditional HCM methods typically ignore the more complex interaction of the two modes in which some drivers yield to pedestrians and some pedestrians accept gaps in traffic. This type of interaction will be referred to as a mixed-priority crossing (Schroeder and Rouphail, in press). While changes in the 2010 HCM (TRB, 2010) have made an attempt at combining pedestrian gap acceptance and driver yielding behavior for pedestrian delay analysis, the revised methodology is not based on empirical observations and has not been calibrated by field observations. In practice, alternative analysis tools in the form of microscopic simulations are frequently used to help overcome some of the limitations of the HCM. This paper describes an approach for adopting simulation-based tools for evaluating mixed-priority pedestrian crossings, based on empirical models of pedestrian and driver behavior at unsignalized crosswalks in the United States.
2. Literature Review

The greatest challenge in the analysis of unsignalized pedestrian crossings is the interplay between pedestrian gap acceptance and driver yielding behavior. Absent the appropriate data, pedestrian crossing behavior is oftentimes analyzed with the implication that it is analogous to vehicular gap acceptance. But can an unsignalized mid-block pedestrian crossing really be compared to minor street traffic operation at a two-way stop controlled intersection? In fact, yielding behavior at pedestrian crossings in the US varies greatly, which may be attributable to differences in geographic location, the type of crossing location, the time of day, and a range of other factors that are not well understood in current research practice. Current research gives evidence for the variability of driver yielding behavior across geographic locations (Fitzpatrick et al., 2005), and further indicates that some pedestrian treatments are effective in increasing the rate of yielding. But important questions remain: What are the operational impacts of an increased yielding rate? In the absence of yields, is pedestrian crossing behavior strictly governed by the availability of gaps in the traffic stream, or do other factors affect the pedestrian’s decision to step off the curb and into the street? In order to analyze the interaction of the pedestrian and vehicle modes it is important to gain better insight into both the yielding and the gap acceptance processes, and to identify ways that these behavioral characteristics can be related back to a measurable effect on operations.

2.1. Describing Driver Yielding Behavior

The likelihood of drivers to yield in a macroscopic sense has been linked empirically to vehicle speeds and the relative positioning of the pedestrian to the curb (Geruschat and Hassan, 2005), to pedestrian assertiveness and brightly-colored clothing (Harrel, 1993), and the presence of multiple pedestrians (Sun et al., 2002) at the crossing. In addition to these behavioral factors, geometric characteristics impact yielding, as higher yielding rates are for example observed at roundabout entry versus exit lanes, (Ashmead et al., 2005, and Rodegerdts et al., 2007). Yielding behavior can further be impacted by the presence of crossing treatments, including those associated with a red indication, which seem to generally illicit a high rate of yield compliance (Fitzpatrick et al., 2005).

More recently, the authors have linked yielding behavior to microscopic characteristics of driver and pedestrian behavior. Schroeder and Rouphail (in press) developed logistic-regression based models that predict the probability of driver yielding as a function of vehicle dynamics (speed and position relative to the crosswalk), pedestrian assertiveness, whether the vehicle is part of a platoon of vehicles, and the presence of pedestrian crossing treatments. This paper builds on the earlier-developed yield model results and adds companion behavioral models for pedestrian gap acceptance at unsignalized pedestrian crossings. Together, the yield and gap models represent the building blocks necessary to evaluate the mixed-priority interaction between the two modes in a simulation environment.

2.2. Overview of Gap Acceptance Models

Traditionally, literature on vehicle gap acceptance has used a constant value of critical gap (CG) that is calibrated for local conditions (Troutbeck and Brilon, 2002). The CG can differ depending on the type of movement and the type of vehicle. For example, the CG for left turns is likely to be larger than for right turns, and heavy vehicles tend to have longer CG because of slower acceleration profiles and longer vehicle lengths. In the following, this type of gap acceptance model will be referred to as the deterministic model.

By definition, the critical gap is the time between consecutive vehicles on the major road at which a vehicle waiting at the minor approach is equally likely to accept the gap or reject it.
Literature on gap acceptance oftentimes assumes that drivers are both homogeneous and consistent. In a homogeneous driver population, all drivers have the same critical gap. Under consistency assumption, the same gap acceptance situation will always cause a driver to make the same (consistent) decision. Although these assumptions are not necessarily realistic, Troutbeck and Brilon (2002) justify their use because inconsistencies in driver behavior tend to increase capacity, while a heterogeneous driver population will decrease capacity, thereby offsetting the previous effect.

The most common US application of deterministic gap acceptance is in the US Highway Capacity Manual (TRB, 2000) and the 2010 HCM update (TRB, 2010), where gap acceptance concepts are used to describe operational performance at two-way and all-way stop-controlled intersections, as well as modern roundabouts.

There are several ways for estimating CG from field data, including a graphical method (Troutbeck and Brilon, 2002), a regression method (Troutbeck and Brilon, 2002), a statistical method based on maximum likelihood estimation (Troutbeck, 2001), and the Ramsey-Routledge method (ITE, 2010). In application of these methods, the capacity of the minor street flow becomes a function of the CG on the minor approach tc, the follow-up time on the minor approach tf, and the conflicting major street flow qp, as shown in HCM2000 equation 17–70 adopted below:

\[
\text{Capacity} = \frac{3,600 \times q_p \times e^{-q_p \tau_c}}{1 - e^{-q_p \tau_f}} \quad \text{Equation 1: HCM Capacity Equation for Two-Way Stop Controlled Intersection (17–70)}
\]

The follow-up time describes the time needed for additional vehicles in a stored queue to accept the same gap. The size of tf is typically less than tc, because some of the decision and acceleration times for subsequent vehicles occur during the initial gap.

In addition to deterministic gap acceptance, a report compiled for the Federal Highway Administration (FHWA) Next Generation Microsimulation (NGSIM) research effort (Cambridge Systematics, 2004) discusses probabilistic gap acceptance models, for which the driver response for an identical event (same speed, same gap in conflicting traffic) can be drawn from a probabilistic distribution of possible responses. Using a probit or logit approach, these models assume a mean CG with a random variance term depending on the specific coefficients defined for a driver and/or situation. Logit gap acceptance models have been proposed by Ben-Akiva and Lerman (1985), and Cassidy (1995), and probit models were suggested by Mahmassani and Sheffi (1981) and Madanat (1994). Conceptually, these models could represent inconsistent driver behavior and a heterogeneous population by drawing gap acceptance decisions from random distributions. Some researchers have proposed even more complex algorithms for modeling gap acceptance. Kita (1993) used neural networks to describe the process, under the assumption that gap acceptance is not a linear sequence of events, but that multiple factors affect the decision making process. This modeling approach is capable of removing consistency assumptions, but the authors upheld the assumption of homogeneity.

Adopting gap acceptance concepts to pedestrian movements require a revisit of underlying assumptions. Pedestrians are not subject to the same first-in-first-out (FIFO) priority as queued vehicles on a single-lane approach and multiple pedestrians can generally accept the same gap simultaneously (Blue and Adler 2000). Arguably, the concept of follow-up time therefore has little application to pedestrian gap acceptance. The pedestrian population is further highly heterogeneous, as the risk-taking behavior of pedestrians differs widely. Further, pedestrian trip purpose varies from commuting to recreational trips, and this trip
purpose likely impacts pedestrian decision-making. The discussion suggests that pedestrian movements, pedestrian gap acceptance, and pedestrian-vehicle interaction are different enough from conventional vehicular traffic to warrant alternate models for pedestrian movements, gap acceptance, and capacity. The deterministic gap acceptance model in the HCM2000 Pedestrian Chapter offers a method for estimating critical gap $t_c$ as a function of crosswalk length $L$, Pedestrian Walking Speed $S_p$, and pedestrian start-up time $t_s$ (Equation 2).

$$t_c = \frac{L}{S_p} + t_s$$

Equation 2: Pedestrian Critical Gap after HCM (Equation 18-17)

Rouphail et al (2005) described pedestrian gap acceptance as the sum of latency and actual crossing times, an approach similar to the HCM2000 method discussed above. The authors used field estimates of the median latency time in place of the HCM2000 start-up time, measured from the time the previous car cleared the crosswalk to when the pedestrian decision was initiated.

In the application of any of these methods to pedestrians, the analyst generally needs to distinguish between gap and lag events. A gap describes the time difference between consecutive vehicle events. A lag corresponds to the time between a pedestrian’s arrival at the crosswalk and the next vehicle event. Just as a gap, the lag can either result in a GO decision (ped. arrival – crossing – vehicle event) or NOGO decision (ped. arrival – vehicle event). In field estimation, it needs to be clearly distinguished which type of observation is recorded. The following evaluation treats the two events separately, initially estimating the likelihood of crossing in a lag (the first event), and subsequently applying the gap acceptance model.

3. Objective

This research seeks to develop an analysis methodology for pedestrian-vehicle interaction that is applicable for inclusion in a microsimulation environment. The research is based on empirical observations of pedestrians and drivers at unsignalized crossings and takes into account the mixed-priority nature of the interaction. The principal objective then is to develop behavioral algorithms to predict the probability of drivers yielding and pedestrians accepting gaps in traffic. These algorithms should meet the following criteria:

- Account for vehicle dynamics and incorporate vehicle speed and relative distance to the crosswalk;
- Capture the behavioral characteristics of pedestrian and driver;
- Consider concurrent events at the crosswalk;
- Allow sensitivity to the installation of crosswalk treatments to aid pedestrians; and
- Assure compatibility with microsimulation models.

Following these criteria, the resulting models would go significantly beyond existing analytical gap acceptance approaches that rely principally on the temporal availability of gaps (Troutbeck and Brilon, 2002). Similarly, they go beyond most existing simulation models, which also tend to rely on just the available gap time (Cambridge Systematics, 2004), although some do allow for multiple “types” of drivers and pedestrians to be modeled with different characteristics.
4. Approach

This research is based on an analysis framework for unsignalized pedestrian crossings that utilizes both pedestrian crossing behavior and driver yielding behavior. The framework allows for the analysis of signalized and unsignalized pedestrian crossing facilities and a comparison among the two in a microsimulation environment. For unsignalized crossings, the authors proposed a framework for evaluating the interaction of pedestrians and vehicles in a microsimulation environment (Schroeder and Rouphail, 2007). The paper discusses modeling parameters for the interaction of pedestrian and vehicle traffic that should be included in a microscopic simulation analysis of unsignalized pedestrian crossing facilities, but fell short of presenting any empirical data to justify the behavioral parameters. Specifically, the interaction is characterized by four interaction processes that can be expressed in the form of probabilities:

- $P(G)$ - The probability of a gap occurring in the traffic stream
- $P(GU)$ - The probability of a gap being utilized by the pedestrian
- $P(Y)$ - The probability of a driver yielding
- $P(YU)$ - The probability that a yield is utilized by the pedestrian

The probability of gap occurrence, $P(G)$, is a function of vehicle arrivals and the headway distribution in the traffic stream. The behavioral characteristics of pedestrians and drivers are generally described by the probability of crossing in a gap, $P(GU)$, and the probability of a driver yielding to a waiting pedestrian, $P(Y)$. The fourth parameter typically has application to pedestrians with vision impairments or other special populations who tend to reject or miss a portion of the encountered yields (Schroeder et al., 2009). For the population of pedestrians observed in this research, the yield utilization rate, $P(YU)$, is 100%.

The gap acceptance concept is commonly applied in the analysis of driver behavior at yield- or stop-controlled intersections. For example, a driver waiting to enter a modern roundabout screens the circulating traffic for a large-enough gap between successive vehicles. Similarly, a driver waiting at the minor approach of a two-way stop controlled intersection looks for gaps in traffic on the major road. At an unsignalized pedestrian mid-block crossing, pedestrians have to make a similar decision before crossing the road: Is the gap in the traffic stream large enough to allow for a safe crossing?

With the potential of drivers yielding to pedestrians, the gap acceptance process is further complicated because there are now two alternative types of crossing opportunities: crossing in a gap or crossing in a yield. In previous research (Schroeder and Rouphail, in press), the authors described models for predicting the likelihood of a yield:

- A yield is defined as an obvious driver action that delayed the vehicle arrival at the crosswalk and thus creates a crossing opportunity for the pedestrian. The driver action can be deliberate or can be triggered by the pedestrian by stepping into the roadway.

In the yield analysis the inclusion of the triggered or forced yields was justified, because the logistic regression approach accounted for this category with a binary explanatory variable. The likelihood of a driver yielding was thus predicted both with and without a triggering behavior on the part of the pedestrian. The models for pedestrian crossing decisions discussed in this paper similarly predict the likelihood of a GO Decision:

- A GO decision is defined as a deliberate action by the pedestrian, evident by stepping off the sidewalk and into the roadway with intent to cross. This pedestrian action can further be characterized as being a function of the lag time to the next...
vehicle, or by the gap time between successive vehicles in the conflicting traffic stream. By definition, these events do not include crossings that occurred because of a vehicle yield event.

4.1. Data Collection and Site Description

The field data collection for this approach used a video camera positioned downstream of the studied crosswalk intended to capture yielding and gap acceptance events. The video record was synchronized with a laser speed gun, which was used to record the vehicle speed at each pedestrian event. The speed measurement equipment included a time-stamp of each observation and also recorded the distance between the speed gun and the vehicle. During the experiment, the analyst monitored the crosswalk and measured the speed and distance of the closest vehicle when a pedestrian arrived at the crosswalk. In many cases, the observer took multiple measurements of the same vehicle as the pedestrian walked towards the crosswalk. This allowed the analyst to selectively match speed observations to video events during post-processing in the lab. With the observer positioned at a known and constant distance from the crosswalk, it is possible to infer the distance between the vehicle and the crosswalk.

This data collection approach was applied to a total of four extended field studies, with two studies performed at each of two crosswalks. The two studies per crosswalks were timed to take place just before and approximately one month after the installation of a pedestrian crossing treatment. In addition to increasing the sample size of observations, this approach was intended to capture what impact the pedestrian crossing treatment had on pedestrian and driver behavior.

The first site (A) was located in Charlotte, NC at a mid-block crossing location at an urban two-lane road with wide 20-foot lanes. The measures average vehicle speed was 27.5 mph (44.3 km/h) and 67% of vehicles traveled in platoons discharged from upstream signalized intersections. Pedestrian behavior was classified as 14% assertive, defined by a pedestrian walking briskly and intensely in the approach to the crosswalk. The site was outfitted with in-pavement pedestrian flashing beacons between the two field studies. The treatment was activated by only 32.4% of pedestrians and resulted in a statistically significant, but marginal increase of driver yielding from 15.0% to 20.9%. Observations at the site resulted in a sample size of 551 gap acceptance events, 23% of which were accepted gaps by the pedestrians.

The second site (B) was located in Raleigh, NC also at a two-lane urban mid-block crossing, but with more standard 12-foot lanes. The mean vehicle speed was measured at 24 mph (38.6 km/h) with 38% platooning. A total of 9% of pedestrians were classified as assertive at this site, using the same definition as site A. This site was outfitted with an in-road pedestrian warning sign, which resulted in a significant increase in yielding from 27% to 42% between the two field studies. The sample at this site contains 768 gap selection events, with 60% of gaps accepted. Figure 1 shows close-up photographs of the two sites after treatment installation.

4.2. Variable Definitions

Table 1 defines the variables considered in the analysis of pedestrian gap acceptance. The dependent or response variable for all models is GO, which describes the binary decision of whether or not the pedestrian stepped into the roadway during a given lag or gap event. The explanatory variables include those describing vehicle dynamics (SPEED_FT, DIST, DECEL), which are converted to the expected lag and gap times experiences at the
5. Results

A total of 1319 pedestrian events were recorded at the two sites with a total of 584 accepted and 735 rejected gap or lag events. The data were initially analyzed using the traditional gap acceptance approaches to estimate the mean critical gap and lag of pedestrians crossing before and after treatment installation. The data were then evaluated using a logistic regression approach to estimate the microscopic models for describing pedestrian crossing behavior.

5.1. Traditional Gap Acceptance Approaches

The initial analysis applied three common methods for gap acceptance to the data collected at the two midblock crosswalks MB-RAL and MB-CLT. The analysis presents an important benchmark against which to measure the following logistic regression analysis of pedestrian crossing behavior. Table 2 presents summary statistics of the results from three methods: graphical method (Troutbeck and Brilon, 2002), maximum likelihood estimation (MLE, Troutbeck, 2001), and the Ramsey-Routledge (RR, ITE, 2000) method.

The table shows that the MLE and RR are relatively close in their estimation of the mean pedestrian critical gap times, where applicable. In one instance, the sample size for rejected gaps wasn’t sufficient to allow the MLE method to converge. Similarly, the MLE is not applicable to lag analysis, since it uses as input the accepted gap and largest rejected gap for the same pedestrian, and since each pedestrian by definition can only encounter one (initial) lag event. The graphical method predicts lower critical values in all cases. The methods are inconsistent in their prediction of how the treatments affect gap acceptance behavior, with some suggesting more assertive behavior, while others showing greater critical gaps after treatment installation. All critical gap times should be interpreted as applying to a single pedestrian (no pedestrian platooning) crossing the entire width of roadway (one-stage) crossing.

The methods described above are useful in evaluating average pedestrian behavior and are sufficient to determine inputs for deterministic delay models that are based on the gap acceptance concept. Further, the RR and MLE methods account for heterogeneity in the pedestrian population by estimating a distribution of critical gaps (not shown). In a microsimulation application, gap acceptance algorithms can ideally utilize these distributions directly. Alternatively, at least some currently available microsimulation tools allow the modeler to code multiple “types” of pedestrians (PTV, 2010). Given the distribution of critical gaps, the overall population can be subdivided into multiple groups, whose gap acceptance behavior and relative frequency match the calculated distributions (Schroeder and Rouphail, 2007). However, all the above methods fail to identify underlying contributions to the variability in gap acceptance behavior. The analyst may assume that variability can be attributed to population heterogeneity, with some pedestrians having inherently but consistently different gap selection attributes. The event-based approach suggested in this research can account for additional factors that contribute to the observed variability in the gap selection process explicitly.

5.2. Behavioral Gap Selection Models

In an effort to overcome the limitations associated with the mean critical gap estimate, the observed data were used to develop probabilistic models to predict pedestrian gap selection. Given the binary nature of the GO response variable, the analysis used a binary logit
estimation to predict the likelihood of a pedestrian accepting a gap given a set of attributes. Using logistic regression (Agresti, 2007), the log odds of a pedestrian GO decision are described by:

\[
\logit \left[ P(\text{GO}=1) \right] = \log \left( \frac{P(\text{GO}=1)}{1 - P(\text{GO}=1)} \right) = \alpha + \sum_{i=1}^{m} \beta_i x_i \quad \text{Equation 3}
\]

with intercept \(\alpha\) and parameters \(\beta_i\) describing the effects of \(m\) explanatory variables \(x_i\) on the GO response. Keeping all other effects fixed, a one-unit increase in the variable \(x_i\) has a multiplicative effect of \(e^{\beta_i}\) on the odds of GO. This is referred to as the odds ratio of the effect. The model parameters can be obtained through maximum likelihood estimation in statistical analysis software. The probability estimates for the GO response can be obtained using the exponential function as follows:

\[
P(\text{GO}=1) = \frac{e^{\alpha + \sum_{i=1}^{m} \beta_i x_i}}{1 + e^{\alpha + \sum_{i=1}^{m} \beta_i x_i}} \quad \text{Equation 4}
\]

The crossing probabilities calculated from equation 4 can be used to quantify the impact of a change in a binary variable on the likelihood of pedestrian accepting a gap, or to plot the change in \(P(\text{GO}|x)\) by varying a continuous variable. Additional insight on the absolute fit of a model to the data is given by the max-rescaled R-Square (max-R\(^2\)) statistic (SAS, 2007). It describes the amount of overall variability in the data explained by the model, similar to the \(R^2\) statistic commonly used in linear regression. Generally, a higher max-R\(^2\) indicates that more of the variability in the response variable is explained by the model.

Table 3 shows the selected logit models for predicting \(\logit[P(\text{GO}=1)]\) using the listed explanatory variables for Sites A and B. The full set of logit models considered (but found inferior) is given in Schroeder (2008). Separate models are presented for Sites A and B, as well as for lag and gap events.

The model results in table 3 generally show the expected trend of an increasing likelihood of a pedestrian GO decision with longer expected gap or lag times. The odds ratios for these temporal factors are around 3, which means that a one second increase in the available gap/lag size increases the odds of crossing by a factor of 3. Considering that the four models shown were obtained from different sites and describe gap and lag events separately, it is quite surprising that both the model intercepts and the parameter for \(E_{\text{LAG}}\) and \(E_{\text{GAP}}\) are fairly consistent across models.

In addition to these temporal factors, the remaining model parameters also show consistency across models. The odds of crossing in a gap or lag are both increased significantly for assertive pedestrians. A pedestrian was classified as assertive if they exhibited a fast walking pace in their approach of the crosswalk. This behavioral attribute appears to correlate well with a lower critical gap threshold, as supported by the high odds ratios for the AST term. The likelihood of a pedestrian GO decision is further increased if the gap acceptance decision is made relative to the vehicle in the near lane. The effect of \(\text{NEAR}\) is only significant for the gap models, but was retained for the lag models for consistency despite p-values slightly above the 90% confidence level at the given sample size.
Finally, the gap and lag acceptance model for Site A are described by the activation of the in-pavement flashing beacons, and the lag events at Site B are related to the presence of the in-road pedestrian warning sign. These findings are interesting, considering that both treatments are primarily intended to encourage driver yielding behavior. The presence of the FLASH and TRTMT variables in the gap selection models suggest that pedestrian gap selection thresholds have been lowered with the installations of the treatments.

The predicted likelihood of a pedestrian GO decision can be plotted graphically by applying the logit models using equation 3. For illustration purposes, the relationship is shown for the probability of crossing in a gap at Site A (Figure 2). The resulting logit equation is as follows:

\[
\text{logit}\left[P(\text{GO}=1)\right] = -8.511 + 4.360 \text{AST} + 1.726 \text{FLASH} + 1.454 \text{NEAR} + 0.974 \text{T \_ GAP}
\]

Equation 5: \(P(\text{GO}) - \text{Site A} - \text{Gaps}\)

The plots in Figure 2 visually show the impact of the underlying model parameters and the odds ratio associated with the effects. The probability curves generally increase with increasing gap time. Further, gap acceptance probability for a near-side gap (a) is shifted to the left towards lower gap times relative to a far-side gap crossing in (b). For both figures, a change in the variables FLASH and AST from zero to one, similarly results in a shift towards the left and lower gap times. As described above, assertive pedestrians and those activating the flashing beacon system consequently are more likely to accept an equal length gap compared to non-assertive pedestrians and those not activating the treatment.

6. Synthesis of Prior Yielding Research

Previous work by the authors describes probabilistic models for driver yielding at unsignalized crosswalks (Schroeder and Rouphail, in press). This section synthesizes the highlights of that prior research, as it represents the necessary counterpart to the gap selection models presented in this paper. The model data sets in this and the prior research were collected at the same crosswalks, but from the respective perspectives of the two different modes. Events resulting in a pedestrian crossing decision were mutually exclusive, meaning that each pedestrian either crossed in a gap or a yield. Non-yield events are also associated with a pedestrian rejecting a gap in traffic, as both events are recorded if a vehicle proceeds through the crosswalk while a pedestrian is waiting to cross. Through the combination of both models, it is feasible to fully describe the microscopic interaction of pedestrians and drivers in a simulation environment, which is discussed further below. Table 4 summarizes the selected yield models from the previous research effort.

7. Conclusion

The 2010 Highway Capacity Manual recognizes that the analytical procedures have limitations and that in some cases alternative tools may be the more appropriate analysis approach. This paper argues that for the analysis of pedestrian-vehicle interaction at unsignalized crosswalks, alternative tools may be more appropriate than current HCM procedures, particularly if the pedestrian population is heterogeneous. The pedestrian population commonly includes various sub-groups that differ in their behavioral attributes, including students, children, elderly pedestrians, or persons with disabilities. The assumption that all these pedestrians act the same at a mid-block, two-way stop controlled, or roundabout crosswalk is unreasonable, as the delay (and risk) experienced by these different groups is highly variable. Many modern microsimulation tools have the ability to code multiple pedestrian types to capture this heterogeneity, as well as multiple driver types to capture those more and less likely to yield. The challenge remains that the underlying
behavioral algorithms for pedestrian-vehicle interaction are not based on empirical research. The Next Generation Microsimulation (NGSIM) effort by the Federal Highway Administration recognizes the need to enhance pedestrian models and ranks this area 7th in a top 10 list of modeling stakeholder requirements (FHWA, 2004). The six higher ranked problem statements are lane selection on arterials, oversaturated freeway flow, freeway lane distribution, weaving sections, two-way left-turn lanes, and response to variable message signs. However, while NGSIM is sponsoring the development of new core algorithms for simulation it will take time before limited resources become available to address aspects of pedestrian-vehicle interaction.

The behavioral models for pedestrian gap acceptance developed in this research along with those for driver yielding from Schroeder and Rouphail (in press) can be used to enhance the microscopic models for pedestrian and driver behavior. The logistic regression models are sensitive to the dynamic state of the simulated vehicles and are thus compatible with a simulated environment. But rather than conventional simulation algorithms, they take into account other attributes of the pedestrian and driver modes, such as pedestrian assertiveness, vehicle platooning, and notably the presence of pedestrian crossing treatment. The proposed implementation in simulation is in the form of new core model algorithms (FHWA, 2004), which are dynamically updated every simulation time step. The algorithms would in turn refer to some global attributes (e.g. pedestrian assertiveness, presence of treatment, etc.) and some dynamic attributes, including vehicle speed, relative position, and platooning. The likelihoods of pedestrian gap acceptance and of drivers yielding are therefore recomputed as the state of the simulation changes. The crossing decision or yield is initiated if the computed probability exceeds a predetermined threshold (such as 0.5). Some additional assumptions are necessary to assure consistency in decision-making, in that a driver committed to yielding remains in that state for some period of time.

Acknowledgments

The research leading up to this document was partially sponsored by the NCHRP 3-78 project, ‘Crossing Solutions at Roundabouts and Channelized Turn Lanes for Pedestrians with Visual Disabilities’ and NIH Bioengineering Research Partnership NIH Grant R01 EY12894-03, ‘Pedestrian Access to Complex Intersections’. The authors would like to acknowledge the National Academies for their support and the members of the project team, who have provided continuous feedback to the research efforts. This research was part of the doctoral dissertation by Dr. Bastian Schroeder that is available through North Carolina State University. The project described was partially supported by Grant Number R01EY12894 from the National Eye Institute. This content is solely the responsibility of the authors and does not necessarily represent the official views of the National Eye Institute or the National Institutes of Health.

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Figure 1.
Photographs of Data Collection Sites
Figure 2.
Model Probability Plot for Gaps – Restricted Model 3 - MB-CLT
### Table 1

#### Variable Definitions

| Code | Variable Definition                                                                 | Units          |
|------|-------------------------------------------------------------------------------------|----------------|
| GO   | Dependent Variable. Pedestrian Event is GO (crossing was initiated). Also the binary outcome of the pedestrian event (GO=1, NOGO=0) |                |
| ADY  | Presence of an adjacent yield in the opposite direction; ADY=1 if a vehicle in the opposite lane has already yielded for the pedestrian at the crosswalk | Bin            |
| AST  | The pedestrian is ‘assertive‘; AST=1 if the pedestrian exhibits assertive behavior in the approach of the crosswalk, indicated for example through fast walking pace | Bin            |
| D_WAIT | The duration of pedestrian waiting time at the decision point. The waiting time is zero for all initial lag events. For all subsequent gaps, the waiting time is calculated from the duration between the initial arrival at the crosswalk and the passing of the previous vehicle | Sec            |
| E_LAG | Expected lag time between pedestrian arrival and time vehicle would have arrived given its instantaneous speed and distance to the crosswalk | Sec.           |
| E_GAP | Expected gap time between two successive vehicles at the crosswalk calculated from the instantaneous speeds and position when the pedestrian arrives at crosswalk | Sec.           |
| FLASH | Indication whether the flashing beacon was actuated by the pedestrian; FLASH=1 if beacon was flashing during the yield event (SITE A Only) | Bin            |
| FOLL | Approaching vehicle has close follower; FOLL=1 if the vehicle has a follower at a short headway of approximately 2–4 seconds | Bin            |
| HEV  | Approaching vehicle is a heavy vehicle; HEV=1 if the vehicle is anything larger than the equivalent of a 15-passenger van (dump truck, TTST, bus) | Bin            |
| MUP  | There are multiple pedestrians present in the CIA; MUP=1 if the number of pedestrians waiting at the curb is greater than 1 | Bin            |
| NEAR | Pedestrian is waiting on the near-side of the approaching vehicle; NEAR=1 if the pedestrian waits on the same side of the road that the vehicle is traveling on | Bin            |
| PLT  | Approaching vehicle is part of a platoon of vehicles; PLT=1 if the headway to the following or the previous vehicle was short (approximately 2–4 seconds) | Bin            |
| PREV | The previous vehicle passed without yielding; PREV=1 if the previous vehicle failed to yield to the same pedestrian waiting at the crosswalk | Bin            |
| PXW  | A pedestrian from a previous event is still present in the crosswalk; PXW=1 if the driver has to account for a pedestrian who is still in the roadway from a previous event | Bin            |
| TRIG | The pedestrian triggered the yield by stepping into roadway; TRIG=1 if the pedestrian actively seized the roadway before the driver action indicated a yield | Bin            |
| TRTMT | Presence of the ‘in-pavement flasher’ crossing treatment; TRTMT=1 if the treatment was installed and so is equivalent to the ‘after’ case | Bin            |
| DECEL | Deceleration rate necessary to come to a full stop prior to crosswalk; DECEL is calculated from measured speed and distance; DECEL=(SPEED_FT*SPEED_FT)/(2*DIST1) | feet/sec²      |
| DIST | Vehicle position at the time of pedestrian arrival in crosswalk influence area measured in feet using a LIDAR speed measurement device | Feet           |
| SPEED_FT | Vehicle speed at the time of pedestrian arrival in crosswalk influence area measured in ft/sec using a LIDAR speed measurement device | Feet/sec
### Table 2

Comparison of Traditional Gap Acceptance Approaches

|                   | Site A |          |          | Site B |          |          |
|-------------------|--------|----------|----------|--------|----------|----------|
|                   | All    | Before   | After    | All    | Before   | After    |
| **Mean Gap (sec.)** |        |          |          |        |          |          |
| Graphical Method  | 4.1    | 3.6      | 3.2      | 4.8    | 5.1      | 4.8      |
| MLE Method        | 5.7    | 5.6      | 6.0      | 6.6    | 6.3      | .        |
| RR Method         | 5.7    | 5.9      | 6.0      | 6.2    | 5.9      | 5.8      |
| **Mean Lag (sec.)** |        |          |          |        |          |          |
| Graphical Method  | 6.5    | 7.4      | 4.9      | 6.4    | 6.7      | 6.5      |
| MLE Method        | .      | .        | .        | .      | .        | .        |
| RR Method         | 8.6    | 9.2      | 8.0      | 7.4    | 7.1      | 7.8      |
Table 3

Results of Logistic Regression for Pedestrian Gap Acceptance

|                      | P(GO) – Site A - Lags | P(GO) – Site A - Gaps | P(GO) – Site B - Lags | P(GO) – Site B - Gaps |
|----------------------|------------------------|-----------------------|-----------------------|-----------------------|
|                      | Estimate   | Odds Ratio | Estimate   | Odds Ratio | Estimate   | Odds Ratio | Estimate   | Odds Ratio |
| Intercept            | −12.9***   | ~8.5***    | −10.2***   | ···         | −10.9***   | ···         |           |           |
| AST                  | 3.1**      | 22.0       | 4.4***     | 78.3        | 6.0***     | 411.3      | 5.3***     | 193.9     |
| FLASH                | 3.2**      | 25.5       | 1.7***     | 5.6         |           |           |           |           |
| NEAR                 | 1.9        | 7.0        | 1.5**      | 4.3         | 0.6        | 1.9        | 2.8**      | 15.8      |
| E_LAG                | 1.3***     | 3.5        |           |             | 1.1***     | 2.9        |           |           |
| E_GAP                | 1.0***     | 2.6        |           |             | 1.3***     | 3.8        |           |           |
| TRTMT                |           |            | 0.8        | 2.2         |           |            |           |           |
| AIC+                 | 34.874     | 101.337    | 121.727    | 55.096     |
| −2 Log L+            | 24.874     | 91.337     | 111.727    | 47.096     |
| R-Square             | 0.6229     | 0.5510     | 0.6787     | 0.6838     |
| Max-res. R-2         | 0.9292     | 0.8475     | 0.9198     | 0.9175     |
| # Data Points        | 185        | 366        | 219        | 549        |

*** p<0.001, ** p<0.01, * p<0.05

+ Fit Statistics Akaike Information Criterion (AIC), and Log Likelihood Criterion (~2 Log L) are shown for Intercept and Covariates.
Table 4

Results of Logistic Regression for Driver Yielding (Source: Schroeder and Rouphail, in press)

|                | P(Y) – Site A | P(HY|Y) – Site A | P(Y) – Site B | P(HY|Y) – Site B |
|----------------|---------------|-----------------|---------------|-----------------|
|                | Estimate      | Odds Ratio      | Estimate      | Odds Ratio      |
| Intercept      | −0.38         | 1.11*           | −0.12         | 0.10            |
| AST            | 1.72***       | 5.59            | −1.22**       | 0.72            |
| FLASH          | 1.19***       | 3.28            | −1.12*        | 0.85            |
| NEAR           | .             | .               | 0.62*         | 1.85            |
| PLT            | −0.96***      | 0.39            | −0.49*        | 0.61            |
| TRTMT          | .             | .               | 0.65**        | 1.91            |
| DECEL          | −0.38***      | 0.68            | −0.34***      | 0.71            |

|                | Estimate      | Odds Ratio      | Estimate      | Odds Ratio      |
|----------------|---------------|-----------------|---------------|-----------------|
| AIC            | 443.4         | 128.3           | 491.6         | 204.3           |
| −2 Log L+      | 433.4         | 120.3           | 479.6         | 198.3           |
| R-Square       | 0.1673        | 0.1193          | 0.1769        | 0.1073          |
| Max-res. R-2   | 0.2671        | 0.1656          | 0.2442        | 0.1431          |
| # Data Points  | 604           | 105             | 470           | 158             |

*** p<0.001, ** p<0.01, * p<0.05

+ Model Fit Statistics Akaike Information Criterion (AIC), and Log Likelihood Criterion (−2 Log L) are shown for Intercept and Covariates.