Modeling Integrated Lane-changing Behavior

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ABSTRACT

The lane-changing model is an important component within microscopic traffic simulation tools. Following the emergence of these tools in recent years, interest in the development of more reliable lane-changing models has increased. Lane-changing behavior is also important in several other applications such as capacity analysis and safety studies.

Lane-changing behavior is usually modeled in two steps: (i) the decision to consider a lane-change and (ii) the decision to execute the lane-change. In most models, lane-changes are classified as either mandatory (MLC) or discretionary (DLC). MLC are performed when the driver must leave the current lane. DLC are performed to improve driving conditions. Gap acceptance models are used to model the execution of lane-changes.

The classification of lane-changes as either mandatory or discretionary prohibits capturing trade-offs between these considerations. The result is a rigid behavioral structure that does not permit, for example, overtaking when mandatory considerations are active. Using these models within a micro-simulator may result in unrealistic traffic flow characteristics. In addition, little empirical work has been done to rigorously estimate the parameters of lane-changing models.

In this paper, an integrated lane-changing model, which allows drivers to jointly consider mandatory and discretionary considerations, is presented. Parameters of the model are estimated using detailed vehicle trajectory data.

1. INTRODUCTION

Lane-changing behavior has a significant effect on traffic flow. Therefore the understanding of lane-changing behavior is important in several application fields such as capacity analysis and safety studies. In particularly, lane-changing behavior is among the most important components of a microscopic traffic simulator. In recent years, following the emergence of these tools as a useful tool for the analysis of transportation systems, interest in the development of more reliable driving behavior models and in particular lane-changing models has increased.

Lane-changing is usually modeled in two steps: (i) the decision to consider a lane-change and (ii) the decision to execute the lane-change. In most models, lane-changes are classified as either mandatory or discretionary. Mandatory lane-changes (MLC) are performed when the driver must leave the current lane. Discretionary lane-changes (DLC) are performed to improve driving conditions. Gap acceptance models are used to model the execution of lane-changes.

The classification of lane-changes as either mandatory or discretionary prohibits capturing trade-offs between these considerations. The result is a rigid behavior structure that does not permit, for example, overtaking when mandatory considerations are active. Applying these models within micro-simulators may result in unrealistic traffic flow characteristics. In addition, little empirical work has been done to rigorously estimate the parameters of lane-changing models.

In this paper, an integrated lane-changing model, which allows joint evaluation of mandatory and discretionary considerations is presented. Parameters of the model are estimated with detailed vehicle trajectory data.

The rest of this paper is organized as follows: state-of-the-art lane-changing models and their limitations are discussed in the next section. The proposed model is presented in section 3. The data used to estimate the parameters of this model is described in section 4. Estimation results are presented and interpreted in section 5, followed by concluding remarks.

2. LANE-CHANGING MODELS

Gipps *[1]* introduced the first lane-changing model intended for micro-simulation tools. The model covers various urban driving situations, in which traffic signals, transit lanes, obstructions and presence of heavy vehicles affect drivers' lane selection. The model considers the necessity, desirability and safety of lane-changes. Drivers' behavior is governed by two basic considerations: maintaining a desired speed and being in the correct lane for an intended turning maneuver. The zone the driver is in, defined by the distance to the intended turn, determines which of these considerations is active. When the turn is far away it has no effect on the behavior and the driver concentrates on maintaining a desired speed. In the middle zone, lane-changes will only be considered to the turning lanes or lanes that are adjacent to them. Close to the turn, the driver focuses on keeping the correct lane and ignores other considerations. The zones are defined deterministically, ignoring variation between drivers and inconsistencies in the behavior of a driver over time. When more then one lane is acceptable the conflict is resolved deterministically by a priority system considering locations of obstructions, presence of heavy vehicles and potential speed gain. No framework for rigor estimation of the model's parameters was proposed.

Several micro-simulators implement lane-changing behaviors based on Gipps' model. CORSIM (*[2]*, *[3]*) classifies lane-changes as either mandatory (MLC) or discretionary(DLC). MLC are performed when the driver must leave the current lane (e.g. in order to use an off-ramp or avoid a lane blockage). DLC is performed when the driver perceives that driving conditions in the target lane are better, but a lane-change is not required. In MITSIM *[4]*, drivers perform MLC to connect to the next link on their path, bypass a downstream lane blockage, obey lane-use regulations and respond to lane-use signs and variable message signs. Conflicting goals are resolved probabilistically using utility maximization models. DLC is considered when the speed of the leader is below a desired speed. The driver then checks the opportunity to increase speed by moving to a neighbor lane. In SITRAS *[5]* downstream turning movements and lane blockages may trigger either MLC or DLC, depending on the distance to the point where the lane-change must be completed. MLC are also performed in order to obey lane-use regulations. DLC are performed in an attempt to obtain speed or queue advantage, defined as the adjacent lane allowing faster traveling speed or having a shorter queue. A similar model is used in MRS *[6]*.

Ahmed et al *[7]* and Ahmed *[8]* developed and estimated the parameters of a lane-changing model that captures both MLC and DLC situations. A discrete choice framework is used to model three lane-changing steps: decision to consider a lane-change, choice of a target lane and acceptance of gaps in the target lane. When an MLC situation applies, the decision whether or not to respond to it depends on the time delay since the MLC situation arose. DLC is considered when MLC conditions do not apply or the driver chooses not to respond to them. The driver's satisfaction with conditions in the current lane depends on the difference between the current and desired speeds. The model also captures differences in the behavior of heavy vehicles and the effect of the presence of a tailgating vehicle. If the driver is not satisfied with driving conditions in the current lane, neighboring lanes are compared to the current one and the driver selects a target lane. Lane utilities are affected by the speeds of the lead and lag vehicles in these lanes relative to the current and desired speeds of the subject vehicle. A gap acceptance model is used to represent the execution of lane-changes. Ahmed estimated the parameters of this model using second-by-second vehicle trajectory data. The model does not explain the conditions that trigger MLC situations. Therefore, parameters of the MLC and DLC components of the model were estimated separately. The MLC model was estimated for the special case of vehicles merging to a freeway, under the assumption that all vehicles are in MLC state. Gap acceptance models were estimated jointly with the target lane model in each case.

Wei et al *[9]* developed a model for drivers' lane selection when turning into two-lane urban arterials. The model captures the effect of the driver's path plan on the lane choice. Arterial lanes are classified according to the following criteria:

- Target (non-target) lane: a lane (not) connecting to the turn the driver wishes to perform at the next intersection.
- Preemptive (non-preemptive) lane: a lane (not) connecting to the turn the driver wishes to perform at an intersection further downstream.
- Closest (farther) lane: the lane closest to (farther away from) the curb on the side the driver is turning into the arterial from.

Using observations made in Kansas City they identified a set of deterministic lane selection rules:

- Drivers wishing to turn at the next intersection choose the target lane.
- Drivers wishing to turn farther downstream choose the preemptive lane if it is the closest. If the preemptive lane is the farthest, the choice is based on the aggressiveness of the driver.
- Drivers already traveling on the arterial remain on their lane.

Gap acceptance is an important element in most lane-changing models. In order to execute a lane-change, the driver assesses the positions and speeds of the lead and lag vehicles in the target lane (see Figure 1) and decides whether the gap between them is sufficient to execute the lane-change.

Gap acceptance models are formulated as binary choice problems, in which drivers decide whether to accept or reject the available gap by comparing it to the critical gap (minimum acceptable gap). Critical gaps are modeled as random variables to capture the variation in the behaviors of different drivers and for the same driver over time.

In CORSIM, critical gaps are defined through risk factors. The risk factor is defined by the deceleration a driver will have to apply if his leader brakes to a stop. The risk factors to the subject vehicle with respect to the intended leader and to the intended follower with respect to the subject vehicle are calculated for every lane-change. The risk is compared to an acceptable risk factor, which depends on the type of lane-change to be performed and its urgency.

Kita *[10]* used a logit model to estimate a gap acceptance model for the case of vehicles merging from a freeway ramp. He found that important factors are the length of the available gap, the relative speed of the subject with respect to mainline vehicles and the remaining distance to the end of the acceleration lane.

Ahmed *[8]*, within the framework of the lane-changing model described above, assumed that the driver considers the lead gap and the lag gap separately. Both gaps must be acceptable in order to execute the lane-change. Critical gaps are assumed to follow a lognormal distribution in order to guarantee that they are non-negative. Ahmed jointly estimated the parameters of the target lane and gap acceptance models. He found that lead and lag critical gaps in MLC situations are smaller than those in DLC situations.

In summary, a number of lane-changing models have been proposed in the literature. However, there has been very little rigorous estimation of the parameters of these models. Most models either ignore the issue of calibration completely or assume values for some parameters and use ad-hoc procedures to determine values for others. Moreover, existing models are based on a rigid separation between MLC and DLC and therefore suffer from two important weaknesses:

1. They do not capture trade-offs between mandatory and discretionary considerations.
2. These models assume that the existence (or non-existence) of an MLC situation is known (i.e. drivers start responding to the MLC situation at a certain point, often defined by the distance from the point where they have to be in a specific lane). However, except for very special cases, such as on-ramp merging traffic, the emergence of MLC situations is unobservable. Therefore, the conditions that trigger MLC have not been estimated. Instead, micro-simulators use simple rules to determine whether MLC conditions apply. The parameters of these rules are usually based on the modelers' judgment.

The model proposed in this paper overcomes these limitations of existing models by integrating mandatory and discretionary considerations into a single utility model. The relative importance of these considerations varies depending on explanatory variables such as the distance to the off-ramp. This way the awareness to the MLC situation is more realistically represented as a continuously increasing function rather than a step function. To illustrate the advantage of the integrated utility approach, consider the situation shown in Figure 2. Suppose that vehicle A is planning to use the off-ramp, and that vehicle B is a slow-moving heavy vehicle. In existing models, once vehicle A enters an MLC state it will change to the right lane and stay in it until the off-ramp. The presence of vehicle B does not affect this behavior. The proposed model captures the trade-off between the utility of being in the correct lane (mandatory consideration) and the speed advantage offered by the left lane (discretionary consideration). Hence, the driver may choose to stay in the left lane until he passes vehicle B.

3. AN INTEGRATED LANE-CHANGING MODEL

In this section an integrated lane-changing model, in which the driver jointly evaluates mandatory and discretionary considerations is presented. The lane-changing process consists of two steps: choice of target lane and gap acceptance decisions. This decision process is latent since the target lane choice is unobservable, only the driver's lane-changing actions are observed. The structure of the model is shown in Figure 3. Latent choices variables are shown as ovals, observed ones are shown as rectangles.

The target lane is the lane the driver perceives as best to be in. The CURRENT branch corresponds to a situation in which the driver decides not to pursue a lane-change. In the RIGHT and LEFT branches the driver perceives that moving to these lanes, respectively, would improve his condition. In these cases, the driver evaluates the adjacent gap in the target lane and decides whether the lane-change can be executed or not. Only if the driver perceives that the gap is acceptable the lane-change is executed (CHANGE RIGHT or CHANGE LEFT), otherwise the driver does not execute the lane-change (NO CHANGE). This decision process is repeated at every time step.

Explanatory variables for lane-changing behavior can be classified into the following types of considerations:

1. Neighborhood variables - The vehicle's surroundings strongly affect the behavior. Most importantly, the presence of other vehicles and their actions directly influence drivers' decisions. Both the target lane and gap acceptance decisions depend on the relative positions and speeds of the subject vehicle with respect to vehicles surrounding it. Other elements in the vehicle's surroundings that may affect the behavior include geometry elements, signals and signs and police presence.
2. Path plan variables - Drivers are assumed to have already selected a destination, path and desired arrival time for their trip. These decisions affect driving behavior since drivers change lanes in order to follow their paths. Variables in this group may include the distance to a point when the driver needs to be in a specific lane to follow his path and the number of lane changes required to be in the correct lane.
3. Network knowledge and experience - Variables that capture drivers' considerations and preferences based on their knowledge and experience with the transportation system. For example, freeway lane choices may be affected by a preference to avoid using the right-most lane to avoid interacting with merging traffic. The knowledge that determines such behaviors is built over time. Commuters repeatedly travel the same parts of the network and thus learn the specific attributes of their paths. With experience, drivers also develop a more general knowledge that they use when traveling in networks they are not familiar with. Knowledge considerations may influence the behavior before the situation actually arises. For example, the presence of an on-ramp merging lane may affect lane

choices long before the vehicle actually arrives at the merging point and regardless of the presence of traffic on the ramp. Other examples of situations in which such behaviors may occur include urban arterials with permissive left-turning movements, bus stops, bus traffic and toll plazas.

4. Driving style and capabilities - Individual driver/vehicle characteristics, such as the aggressiveness of the driver and performance capabilities of the vehicle.

3.1 The target lane model

The target lane (*TL*) choice set includes up to three alternatives: the driver may stay in the current lane (*CL*) or target either the right lane (*RL*) or the left lane (*LL*). The utilities of these lanes are given by:

$$U_n^{lane\ i}(t) = X_n^{lane\ i}(t)\beta^{lane\ i} + \alpha^{lane\ i}\upsilon_n + \varepsilon_n^{lane\ i}(t) \qquad lane\ i = CL, RL, LL \tag{1}$$

$U_n^{lane\ i}(t)$ is the utility of lane *i* to driver *n* at time *t*, $X_n^{lane\ i}(t)$ is a vector of explanatory variables. $\beta^{lane\ i}$ is the corresponding vector of parameters. $\varepsilon_n^{lane\ i}(t)$ is the random term associated with the lane utility. υ_n is a driver specific random term that represents unobservable characteristics of the driver/vehicle, thus capturing correlations between observations of the same driver over time. υ_n is assumed to be normally distributed in the drivers' population. $\alpha^{lane\ i}$ are the parameters of υ_n. In model estimation, not all the α values can be identified. Instead, one of these parameters must be normalized to zero.

Assuming that the random terms $\varepsilon_n^{CL}(t)$, $\varepsilon_n^{RL}(t)$ and $\varepsilon_n^{LL}(t)$ are independently and identically Gumbel distributed, the choice probabilities of target lanes, conditional on the individual specific error term (υ_n) are given by:

$$P_n\left(lane\ i_t \mid \upsilon_n\right) = \frac{\exp\left(V_n^{lane\ i}(t) \mid \upsilon_n\right)}{\sum_{j \in I} \exp\left(V_n^{lane\ j}(t) \mid \upsilon_n\right)} \qquad lane\ i \in I = \left\{CL, RL, LL\right\} \tag{2}$$

$V_n^{lane\ i}(t) \mid \upsilon_n$ are the conditional systematic utilities of the alternatives, given by:

$$V_n^{lane\ i}(t) \mid \upsilon_n = X_n^{lane\ i}(t)\beta^{lane\ i} + \alpha^{lane\ i}\upsilon_n \qquad lane\ i = CL, RL, LL \tag{3}$$

Lane utility functions may depend on explanatory variables from the four categories discussed above. Variables should reflect the conditions in the immediate neighborhood in each lane (e.g. relative leader speed in each lane, presence of heavy vehicles and tailgating) path plan considerations (e.g. the distance to a point where the driver must be in specific lanes and the number of lane-changes needed in order to be in these lanes) and knowledge of the system (e.g. avoiding the left lane before permissive left-turns or avoiding on-ramp merging lanes). In most cases, information about the driver's style and characteristics is not available. Nevertheless, these characteristics are captured by the individual specific error term υ_n.

3.2 The gap acceptance model

The gap acceptance model captures drivers' decisions to execute the lane-change. The driver evaluates the adjacent gap in the target lane, which is defined by the lead and lag vehicles in that lane (Figure 1). The lead gap is the clear spacing between the rear of the lead vehicle and the front of the subject vehicle. Similarly, the lag gap is the clear spacing between the rear of the subject vehicle and the front of the lag vehicle. Note that both these gaps may be negative if the vehicles overlap.

The driver compares the available space lead and lag gaps to the corresponding critical gaps, which are the minimum acceptable space gaps. An available gap is acceptable if it is greater than the critical gap. Critical gaps are modeled as random variables. Their means are functions of explanatory variables. The individual specific error term captures correlations between the critical gaps of the same driver over time. Critical gaps are assumed to follow lognormal distributions to ensure that they are always non-negative:

$$\ln\left(G_n^{gap\ g\ TL,cr}(t)\right) = X_n^{gap\ g\ TL}(t)\beta^{gap\ g} + \alpha^{gap\ g}\upsilon_n + \varepsilon_n^{gap\ g}(t) \qquad gap\ g = lead, lag \tag{4}$$

$G_n^{gap\ g\ TL,cr}(t)$ is the critical gap *g* in the target lane measured in meters. $X_n^{gap\ g\ TL}(t)$ is a vector of explanatory variables affecting the critical gap *g*. $\beta^{gap\ g}$ is the corresponding vector of parameters. $\varepsilon_n^{gap\ g}(t)$ is a random term: $\varepsilon_n^{gap\ g}(t) \sim N\left(0, \sigma_{gap\ g}^2\right)$. $\alpha^{gap\ g}$ is the parameter of the driver specific random term υ_n.

The gap acceptance model assumes that the driver must accept both the lead gap and the lag gap to change lanes. The probability of executing a lane change, conditional on the individual specific term and the target lane is therefore given by:

$$\begin{aligned} &P_n\left(change\ to\ target\ lane | TL_t, \upsilon_n\right) = P_n\left(l_t^{TL} = 1 | TL_t, \upsilon_n\right) = \\ &P_n\left(accept\ lead\ gap\ | TL_t, \upsilon_n\right) P_n\left(accept\ lag\ gap\ | TL_t, \upsilon_n\right) = \\ &P_n\left(G_n^{lead\ TL}(t) > G_n^{lead\ TL,cr}(t)\ | TL_t, \upsilon_n\right) \cdot P_n\left(G_n^{lag\ TL}(t) > G_n^{lag\ TL,cr}(t)\ | TL_t, \upsilon_n\right) \end{aligned} \quad (5)$$

$TL \in \{RL, LL\}$ is the target lane (that requires a lane-change). $G_n^{lead\ TL}(t)$ and $G_n^{lag\ TL}(t)$ are the available lead and lag gaps in the target lane, respectively. l_t^{TL} is an indicator to the lane-changing action:

$$l_t^{TL} = \begin{cases} 1 & a\ lane\ change\ to\ lane\ TL\ is\ executed\ at\ time\ t \\ 0 & otherwise \end{cases}$$

Assuming that critical gaps follow lognormal distributions, the conditional probability that the lead gap is acceptable is given by:

$$\begin{aligned} &P_n\left(G_n^{lead\ TL}(t) > G_n^{lead\ TL,cr}(t)\ | TL_t, \upsilon_n\right) = \\ &P_n\left(\ln\left(G_n^{lead\ TL}(t)\right) > \ln\left(G_n^{lead\ TL,cr}(t)\right)\ | TL_t, \upsilon_n\right) = \\ &\Phi\left[\frac{\ln\left(G_n^{lead\ TL}(t)\right) - \left(X_n^{lead\ TL}(t)\beta^{lead} + \alpha^{lead}\upsilon_n\right)}{\sigma_{lead}}\right] \end{aligned} \quad (6)$$

$\Phi[\cdot]$ denotes the cumulative standard normal distribution.

Similarly the conditional probability that the lag gap is acceptable is given by:

$$\begin{aligned} &P_n\left(G_n^{lag\ TL}(t) > G_n^{lag\ TL,cr}(t)\ | TL_t, \upsilon_n\right) = \\ &P_n\left(\ln\left(G_n^{lag\ TL}(t)\right) > \ln\left(G_n^{lag\ TL,cr}(t)\right)\ | TL_t, \upsilon_n\right) = \\ &\Phi\left[\frac{\ln\left(G_n^{lag\ TL}(t)\right) - \left(X_n^{lag\ TL}(t)\beta^{lag} + \alpha^{lag}\upsilon_n\right)}{\sigma_{lag}}\right] \end{aligned} \quad (7)$$

The gap acceptance decision is primarily affected by neighborhood variables such as the subject relative speeds with respect to the lead and lag vehicles. Path plan variables, capturing the necessity of the lane-change, may also affect critical gaps.

3.3 Likelihood function

The data available for estimation of this type of models consists of observations of the positions of vehicles on a section of road at discrete points in time. Measurement times are equally spaced with short time intervals between them, typically 1 second. Explanatory variables required by the model are inferred from the raw data set (e.g. speeds and relations between the subject vehicle and other vehicles). In this section, the likelihood function of lane-changing actions observed in the data is presented.

Important explanatory variables affecting the target lane choice are those related to the path-plan. However, when studying a section of road, this information may not be observed for some of the vehicles (e.g. vehicles exiting a freeway downstream of the section observed). In order to capture the effect of these variables, a distribution of the distances from the downstream end of the road section being studied to the exit points is used. A discrete distribution, which exploits information regarding the locations of downstream off-ramps is used in this study. The alternatives considered are the first, second and subsequent exits. The probability mass function of the distance beyond the downstream end of the section to the off-ramps used by drivers is given by:

$$p(d_n) = \begin{cases} \pi_1 & \textit{first downstream exit } (d^1) \\ \pi_2 & \textit{second downstream exit } (d^2) \\ 1-\pi_1-\pi_2 & \textit{otherwise } (d^3) \end{cases} \tag{8}$$

π_1 and π_2 are parameters to be estimated. d^1, d^2 and d^3 are the distances beyond the downstream end of the section to the first, second and subsequent exits, respectively.

The first and second exit distances (d^1 and d^2) are measured directly. For the subsequent exits an infinite distance is used ($d^3 = \infty$). This corresponds to an assumption that while on the section being studied, drivers that use these exits ignore path-plan considerations. The parameters of this distribution are estimated jointly with the other parameters of the model.

The joint probability density of a combination of target lane (*TL*) and lane action (*l*) observed for driver *n* at time *t*, conditional on the individual specific variables (d_n, ν_n) is given by:

$$f_n(TL_t, l_t | d_n, \nu_n) = P_n(TL_t \mid d_n, \nu_n) P_n(l_t \mid TL_t, \nu_n) \tag{9}$$

$P_n(TL_t \mid \cdot)$ and $P_n(l_t \mid \cdot)$ are given by Equations (2) and (5), respectively.

Only the lane-changing action is observed. The marginal probability of the lane-action is given by:

$$f_n(l_t | d_n, \nu_n) = \sum_{TL_t} f_n(TL_t, l_t | d_n, \nu_n) \tag{10}$$

The behavior of driver *n* is observed over a sequence of *T* consecutive time intervals. Assuming that, conditional on d_n and ν_n, these observations are independent, the joint probability of the sequence of observations is given by:

$$f_n(\mathbf{l} | d_n, \nu_n) = \prod_{t=1}^{T} f_n(l_t | d_n, \nu_n) \tag{11}$$

l is the vector of lane observations.

The unconditional individual likelihood function is obtained by integrating (summing for the discrete variable d_n) over the distributions of the individual specific variables:

$$L_n = \int_{\nu} \sum_{d} f_n(\mathbf{l} \mid d_n, \nu_n) p(d) \phi(\nu) d\nu \tag{12}$$

$p(d)$ is given by Equation (8). $\phi(\nu)$ is the standard normal probability density function.

Assuming that the observations from different drivers are independent, the log-likelihood function for all *N* individuals observed is given by:

$$L = \sum_{n=1}^{N} \ln(L_n) \tag{13}$$

Maximum likelihood estimators of the model parameters can be found by maximizing this function.

4. DATA FOR ESTIMATION

The model parameters were estimated using data collected in a section of I-395 Southbound in Arlington, VA, shown in Figure 4. The dataset contains observations on the position, lane and dimensions of every vehicle within the section every 1 second. For details of the collection effort see *[11]*. This data set is particularly useful for estimation of the lane-changing model because of the geometric characteristics of the site: the site is 997 meters long with two off-ramps and an on-ramp and therefore included weaving sections that are very important in freeway operations, often being the capacity bottleneck. Thus, it serves to demonstrate our integrated model.

The vehicle trajectory data were used to generate the required explanatory variables including speeds and relations between the subject vehicle and other vehicles. The resulting estimation data set includes 442 vehicle records for a total of 15632 observations. On average, a vehicle was observed for 35.4 seconds (observations). All vehicles were first observed at the upstream end of the freeway section. At the downstream end, 76% stay on the freeway, 8% and 16% use the first and second off-ramps, respectively. Observed speeds range from 0.4 to 25.0 m/sec., with a mean of 15.6 m/sec.. Densities range from 14.2 to 55.0 veh/km/lane, with a mean of 31.4 veh/km/lane. The level of service on the section ranges from D to E.

5. ESTIMATION RESULTS

Estimation results of the proposed lane-changing model are presented in Table 1.

5.1 The target lane model

Path-plan variables are critically important in this model. The effect of the path-plan is represented by a group of variables which capture the distance to the point where the driver needs to be in a specific lane (i.e. in order to take an off-ramp) and the number of lane-changes required to be in the correct lane. The functional form adopted for these variables is:

$$path\_plan\_impact\_j_n^{lane\ i}(t) = \left[d_n^{exit}(t)\right]^{\theta^{MLC}} \delta_n^{j,i}(t) \qquad \begin{array}{c} lane\ i = CL, RL, LL \\ j = 1,2,3 \end{array} \qquad (14)$$

$d_n^{exit}(t)$ is the distance from the vehicle's current position to the intended exit point from the freeway in kilometers. θ^{MLC} is a parameter to be estimated. $\delta_n^{j,i}(t)$ are indicators to the number of lane-changes required to follow the path:

$$\delta_n^{j,i}(t) = \begin{cases} 1 & j \text{ lane-changes are required from lane } i \\ 0 & \text{otherwise} \end{cases} \qquad (15)$$

The utility of a lane decreases with the number of lane-changes the driver needs to perform in order to maintain the desired path. This effect is magnified when the distance to the off-ramp decreases (θ^{MLC} = -0.378). The use of a power function to capture the effect of the distance to the off-ramp guarantees that at the limits, the path-plan impact approaches 0 when $d_n^{exit}(t) \to +\infty$ and approaches $-\infty$ when $d_n^{exit}(t) \to +0$. Figure 5 shows the impact of lane-changes required by the path-plan on the probability of targeting the right lane as a function of the distance from the off-ramp.

Drivers' perception and awareness of path-plan considerations are likely to depend on the geometric road layout. In particularly, drivers are more likely to respond to constraints that involve the next road facility they will encounter. Such behavior would present itself for drivers that exit the freeway using the next off-ramp (as opposed to drivers who use subsequent exits). A dummy variable is used to capture the disutility of being in a wrong lane when the driver is taking the next exit:

$$next\_exit\_impact_n^{lane\ i}(t) = \delta_n^{next\ exit}(t)\delta_n^{wrong,i}(t) \qquad lane\ i = CL, RL, LL \qquad (16)$$

The indicator variables $\delta_n^{next\ exit}(t)$ and $\delta_n^{wrong,i}(t)$ are given by:

$$\delta_n^{next\ exit}(t) = \begin{cases} 1 & \text{the next off-ramp is used} \\ 0 & \text{otherwise} \end{cases} \qquad (17)$$

$$\delta_n^{wrong,i}(t) = \begin{cases} 1 & \text{lane-change(s) are required from lane } i \\ 0 & \text{otherwise} \end{cases} \qquad (18)$$

As expected, the estimated coefficient of this variable is negative. The disutility associated with being in a wrong lane is larger when the driver needs to take the next exit. An attempt to interact the next exit dummy variable with the number of lane-changes required did not produce significant improvement to the model. This implies that being in a wrong lane is a more significant factor in drivers' perception relative to the number of lane-changes that are required.

A second group of variables captures driving conditions in the neighborhood of the vehicle. These include the speed of the subject vehicle, the relative speed and spacing with respect to the vehicle in front and the relative speed with respect to lag vehicles in the lanes to the right and to the left of the subject vehicle. The subject speed and the relative speed and spacing of the front vehicle (only appearing in the utility of the current lane) capture the likely satisfaction of the driver with conditions in the current lane. The utility of the current lane increases with the subject speed, the relative front speed and the spacing between the two vehicles. The subject is less likely to perceive the front vehicle as constraining when the front vehicle speed is higher and the spacing is larger, and therefore is less likely to seek a lane-change.

The relative lag speed appears in the utilities of the right and left lanes. The lag vehicle may pose a risk if the driver tries to change lanes. The coefficient of this variable is negative. Hence, suggesting that drivers consider the likelihood of being able to execute the lane-change when selecting a target lane.

The tailgating dummy variable captures drivers' tendency to move out of their current lanes if they are being tailgated. Tailgating is not directly observable in the data. Instead, tailgating behavior is assumed if the vehicle behind is close to the subject vehicle although traffic conditions allow longer headways. Mathematically, the tailgate dummy variable is defined by:

$$\delta_n^{tailgate}(t) = \begin{cases} 1 & \textit{gap behind} \le \textit{10m and level of service is A, B or C} \\ 0 & \textit{otherwise} \end{cases} \tag{19}$$

The estimated coefficient of the tailgate dummy is negative and its magnitude is large relative to the coefficients of other variables. It implies a strong preference to avoid tailgating situations. This result is consistent with those of Ahmed *[8]*, who also found tailgating to be an important explanatory variable.

The right-most lane variable captures the preference of freeway drivers to avoid the right-most lane because of the merging and weaving activity that takes place there. This variable is defined by:

$$\delta_n^{right\text{-}most,\, i}(t) = \begin{cases} 1 & \textit{lane i is the right-most lane} \\ 0 & \textit{otherwise} \end{cases} \qquad i = CL, RL \tag{20}$$

The heterogeneity coefficients, α^{CL} and α^{RL}, capture the effects of the individual specific error term υ_n on the target lane choice, thus accounting for correlations between observations of the same individual due to unobserved characteristics of the driver/vehicle. Both estimated parameters are positive. Hence, υ_n can be interpreted as positively correlated with timidity: timid drivers are more likely to choose the right lane and the current lane over the left lane compared to more aggressive drivers.

In summary, the target lane utilities are given by:

$$\begin{aligned} V_n^{CL}(t) = {} & 2.490 - 1.230\delta_n^{right\ most,\ CL}(t) + 0.0615V_n(t) + 0.163\Delta V_n^{front}(t) - \\ & -\left[d_n^{exit}(t)\right]^{-0.378}\left(-2.573\delta_n^{1,\ CL}(t) - 5.358\delta_n^{2,\ CL}(t) - 8.372\delta_n^{3,\ CL}(t)\right) + \\ & +0.0192S_n^{front}(t) - 3.162\delta_n^{tailgate} - 1.473\delta_n^{next\ exit,\ CL}(t) + 0.734\upsilon_n \end{aligned} \tag{21}$$

$$\begin{aligned} V_n^{RL}(t) = {} & -0.173 - 1.230\delta_n^{right\ most,\ RL}(t) - 0.0741\Delta V_n^{lag,RL}(t) - \\ & -\left[d_n^{exit}(t)\right]^{-0.378}\left(-2.573\delta_n^{1,\ RL}(t) - 5.358\delta_n^{2,\ RL}(t) - 8.372\delta_n^{3,\ RL}(t)\right) - \\ & -1.473\delta_n^{next\ exit,\ RL}(t) + 1.035\upsilon_n \end{aligned} \tag{22}$$

$$\begin{aligned} V_n^{LL}(t) = {} & -0.0741\Delta V_n^{lag,LL}(t) - 1.473\delta_n^{next\ exit,\ LL}(t) - \\ & -\left[d_n^{exit}(t)\right]^{-0.378}\left(-2.573\delta_n^{1,\ LL}(t) - 5.358\delta_n^{2,\ LL}(t) - 8.372\delta_n^{3,\ LL}(t)\right) \end{aligned} \tag{23}$$

5.2 The gap acceptance model

Lead and lag critical gaps are functions of the relative lead and lag speeds, respectively. The relative speed with respect to a vehicle is defined as the difference between the speed of that vehicle and the speed of the subject vehicle.

The lead critical gap decreases with the relative lead speed, i.e., it is larger when the subject vehicle is faster relative to the lead vehicle. The effect of the relative speed is strongest when the lead vehicle is faster than the subject. In this case, the lead critical gap quickly diminishes as a function of the speed difference. This result suggests that drivers perceive very little risk from the lead vehicle when it is getting away form them.

Inversely, the lag critical gap increases with the relative lag speed: the faster the lag vehicle is relative to the subject, the larger the lag critical gap is. In contrast to the lead critical gap, the lag gap does not diminish when the subject is faster. A possible explanation is that drivers may maintain a minimum critical lag gap as a safety buffer since their perception of the lag gap is not as reliable as it is for the lead gap due to the use of mirrors. Median lead and lag critical gaps, as a function of the relative speeds are presented in Figure 6.

Estimated coefficients of the unobserved driver characteristics variable, υ_n, are positive for both lead and lag critical gaps. Hence, consistent with the interpretation of υ_n as positively correlated with timid drivers, who require larger gaps for lane changing compared to more aggressive drivers.

Contrary to a-priori expectations, the distance to the point the lane-change must be completed did not have a significant effect on critical gap lengths. This may be because traffic conditions (level of service D-E) are such that acceptable gaps are available, and therefore drivers are not forced to take risks (reduce their critical gaps) in order to lane-change.

In summary, the estimated lead and lag critical gaps are given by:

$$G_n^{lead\ TL,cr}(t) = \exp\begin{pmatrix} 1.353 - 2.700 Max\left(0, \Delta V_n^{lead,TL}(t)\right) - \\ -0.231 Min\left(0, \Delta V_n^{lead,TL}(t)\right) + 1.270\upsilon_n + \varepsilon_n^{lead}(t) \end{pmatrix} \quad (24)$$

$$G_n^{lag\ TL,cr}(t) = \exp\left(1.429 + 0.471 Max\left(0, \Delta V_n^{lag,TL}(t)\right) + 0.131\upsilon_n + \varepsilon_n^{lag}(t)\right) \quad (25)$$

$\varepsilon_n^{lead}(t) \sim N\left(0, 1.112^2\right)$ and $\varepsilon_n^{lag}(t) \sim N\left(0, 0.742^2\right)$.

6. CONCLUSION

Existing lane-changing models classify lane-changes as either MLC or DLC. As a result, trade-offs between these considerations are ignored. In addition, these models require determination of the conditions that trigger MLC. In most cases simple rules are used to define these conditions. In this paper, an integrated lane-changing model that overcomes both these limitations is proposed. The model combines mandatory and discretionary considerations into a single utility model. The lane-changing process consists of two steps: choice of target lanes and gap acceptance decisions. A logit model is used to model the choice of target lanes. Gap acceptance behavior is modeled by comparing the available space gaps to the critical gaps. The model requires that both the lead and lag gaps are acceptable. The effect of unobserved driver/vehicle characteristics on the lane-changing process is captured by a driver specific random term included in all model components. Missing data due to limitations of the data collection are also account for.

Parameters of all components of the model were estimated jointly using detailed vehicle trajectory data. Estimation results show that drivers' lane selection is affected both by path-plan variables and traffic conditions in their neighborhood. Hence, suggesting that trade-offs between mandatory and discretionary considerations are important. Critical gaps depend on the relative speeds with respect to the lead and lag vehicles. Further research with more datasets is required in order to identify geometry and other site-specific effects and develop robust and more general models that can be used in any urban freeway section.

REFERENCES

1. Gipps P.G. (1986) A Model for the Structure of Lane Changing Decisions, Transportation Research, 20B, pp. 403-414.
2. Halati A., Lieu H. and Walker S. (1997) CORSIM – Corridor Traffic Simulation Model, in Proceedings of the Traffic Congestion and Traffic Safety in the 21st Century Conference, pp. 570-576.
3. FHWA (1998) CORSIM User Manual (1.04 ed.), Federal Highway Administration, US Department of Transportation, McLean, Virginia.
4. Yang Q. and Koutsopoulos H.N. (1996) A Microscopic Traffic Simulator for Evaluation of Dynamic Traffic Management Systems, Transportation Research, 4C, pp. 113-129.
5. Hidas P. and Behbahanizadeh K. (1999) Microscopic Simulation of Lane Changing under Incident Conditions, in Proceedings of the 14th International Symposium on the Theory of Traffic Flow and Transportation, pp. 53-69.
6. Zhang Y., Owen L.E. and Clark J.E. (1998) A Multi-regime Approach for Microscopic Traffic Simulation, in Preprints of the 77th Transportation Research Board Annual Meeting, Washington DC, January 1998 (CD-ROM).
7. Ahmed K.I., Ben-Akiva M., Koutsopoulos H.N. and Mishalani R.G. (1996) Models of Freeway Lane Changing and Gap Acceptance Behavior, in Proceedings of the 13th International Symposium on the Theory of Traffic Flow and Transportation, pp. 501-515.
8. Ahmed K.I. (1999) Modeling Drivers' Acceleration and Lane Changing Behavior, PhD Dissertation, Department of Civil and Environmental Engineering, MIT.
9. Wei H., Lee J., Li Q. and Li C.J. (2000) Observation-based Lane-vehicle-assignment Hierarchy for Microscopic Simulation on an Urban Street Network, in Preprints of the 79th Transportation Research Board Annual Meeting, Washington DC, January 2000 (CD-ROM).
10. Kita H. (1993) Effect of Merging Lane Length on the Merging Behavior at Expressway On-ramps, in Proceedings of the 12th International Symposium on the Theory of Traffic Flow and Transportation, pp. 37-51.
11. FHWA (1985) Freeway Data Collection for Studying Vehicle Interactions, Technical Report FHWA/RD-85/108, Federal Highway Administration, US Department of Transportation, McLean, Virginia.

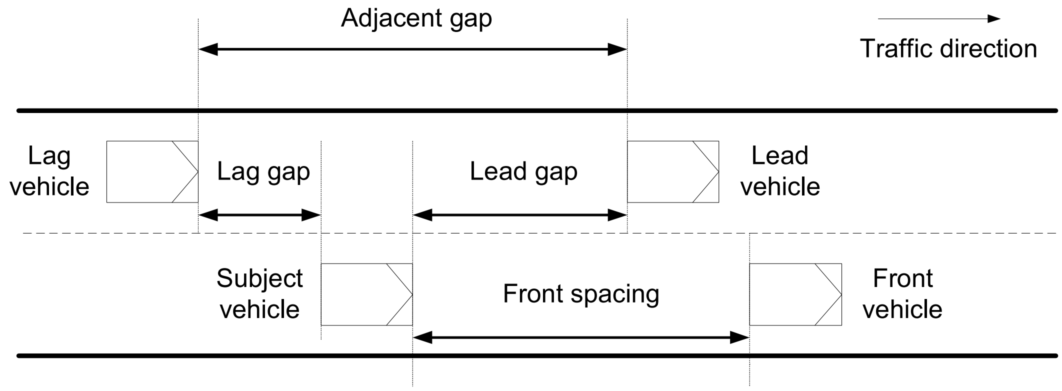

FIGURE 1 Definitions of the front, lead and lag vehicles and their relations with the subject vehicle.

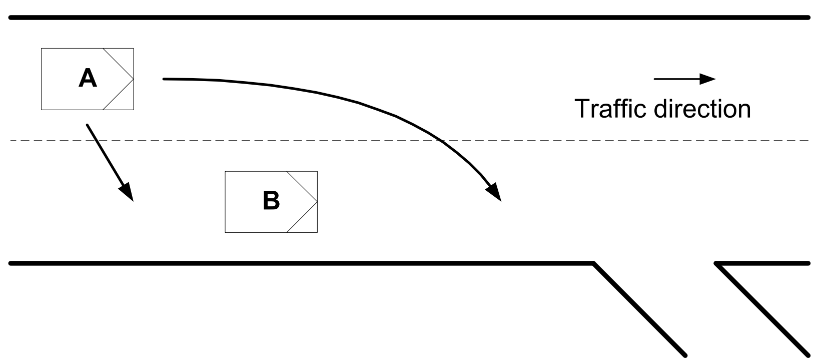

FIGURE 2 A lane-changing situation illustrating the integrated lane-changing model.

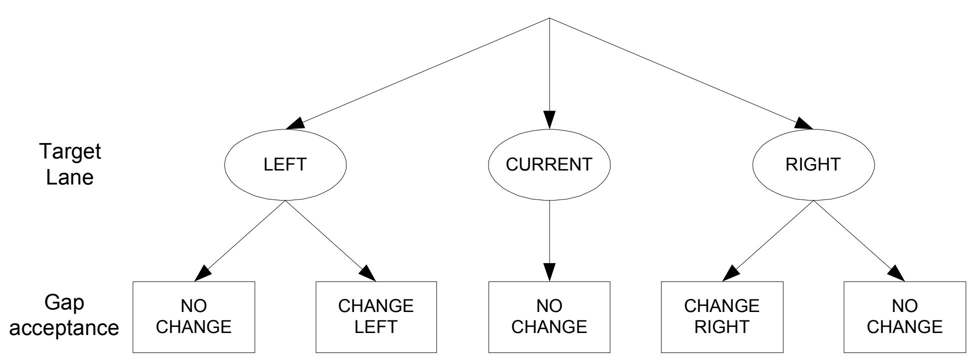

FIGURE 3 Structure of the lane-changing model.

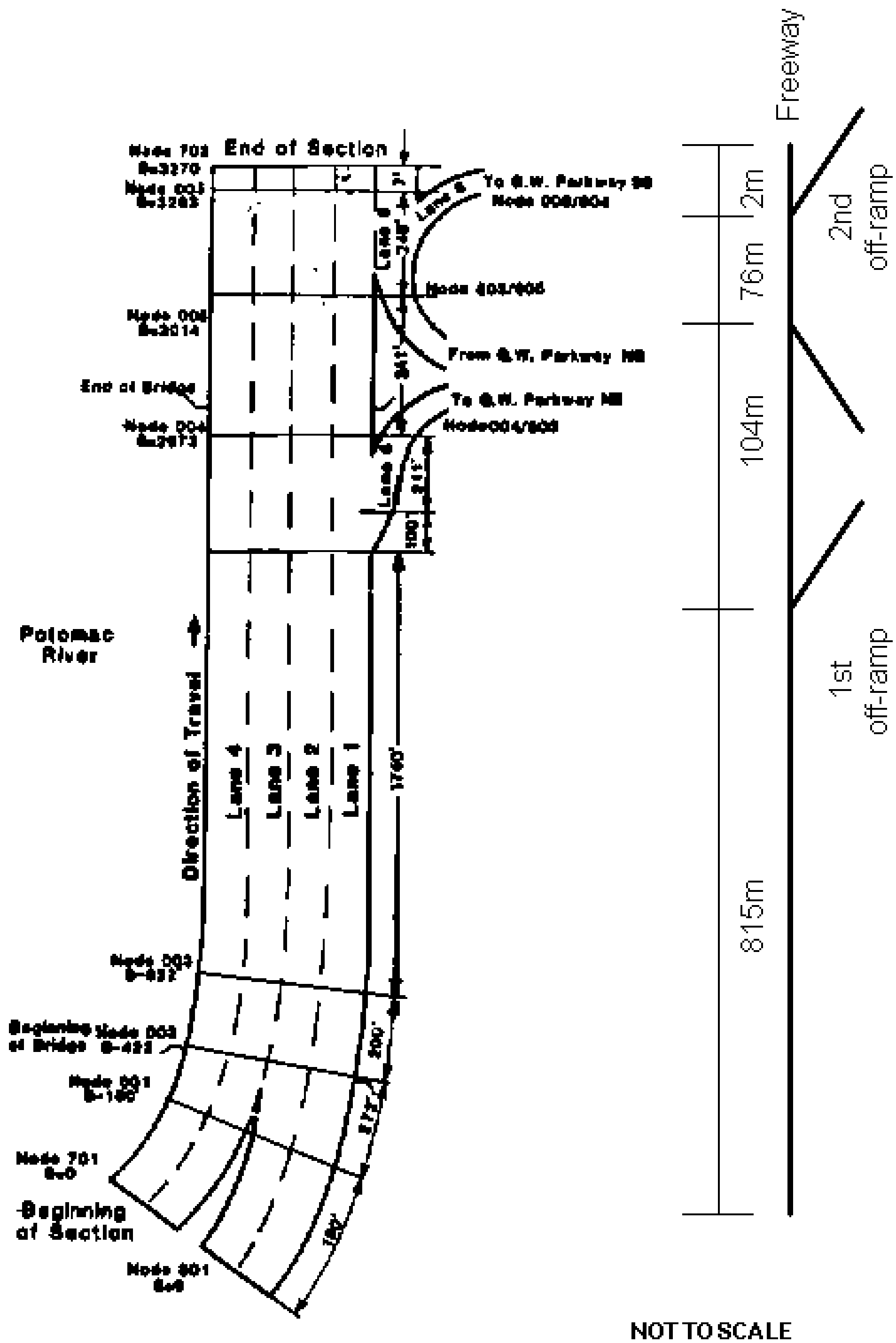

FIGURE 4 Data collection site (Source: FHWA, 1985).

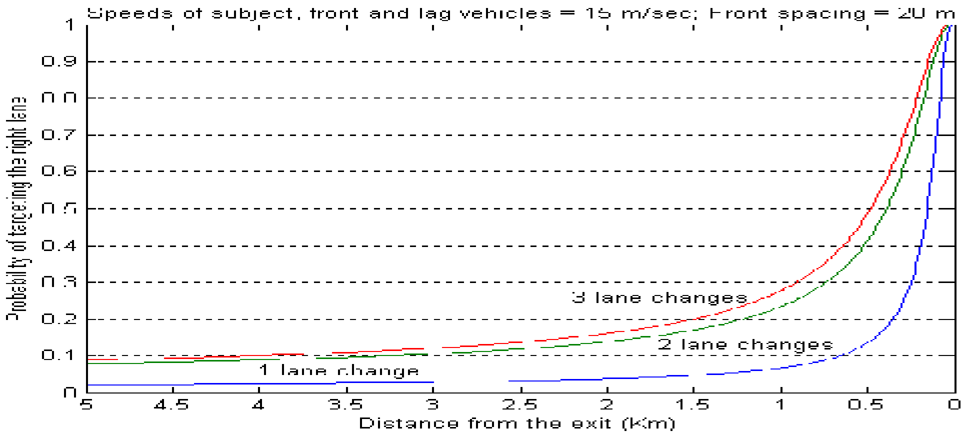

FIGURE 5 Impact of the path-plan on the probability of targeting the right lane.

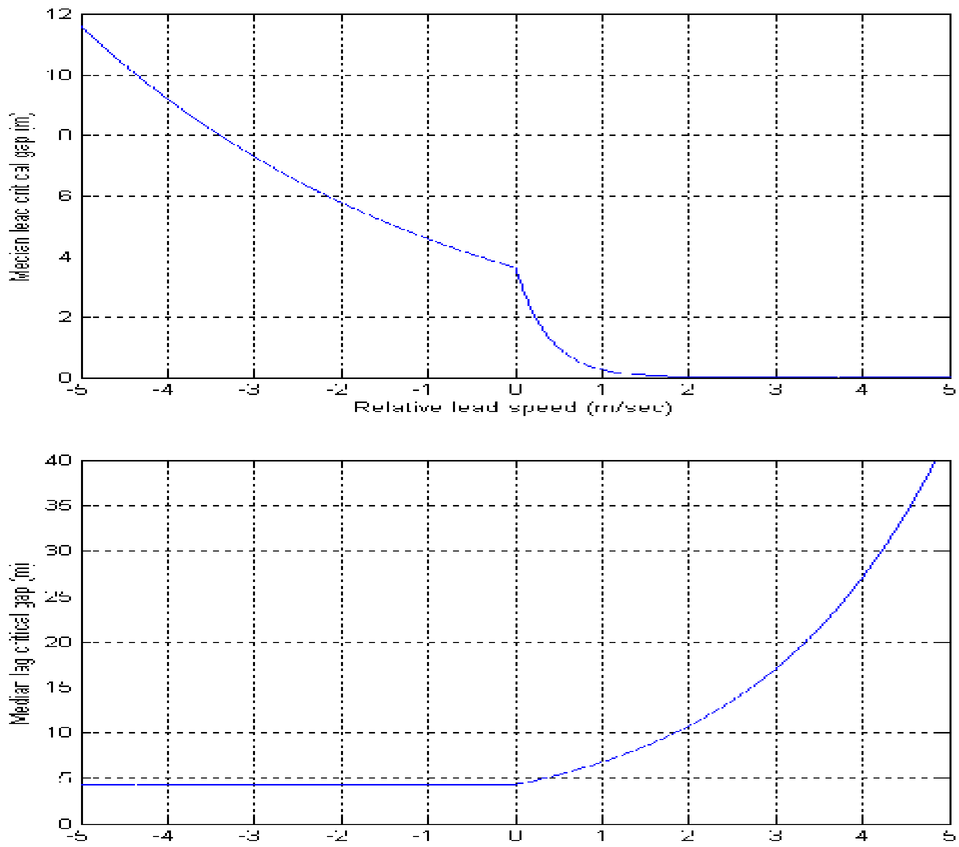

FIGURE 6 Median lead and lag critical gaps as a function of the relative speeds.

TABLE 1 Estimation results of the integrated lane-changing model

Variable	Parameter value	t-statistic
Target lane model		
CL constant	2.490	3.74
RL constant	-0.173	-0.51
Right-most lane dummy	-1.230	-3.89
Subject speed, m/sec.	0.0615	1.59
Relative front vehicle speed, m/sec.	0.163	3.02
Relative Lag speed, m/sec.	-0.0741	-1.30
Front vehicle spacing, m.	0.0192	3.42
Tailgate dummy	-3.162	-1.68
Path plan impact, 1 lane change required	-2.573	-4.86
Path plan impact, 2 lane changes required	-5.358	-5.94
Path plan impact, 3 lane changes required	-8.372	-5.70
Next exit dummy, lane change(s) required	-1.473	-2.30
θ^{MLC}	-0.378	-2.29
π_1	0.0035	0.46
π_2	0.0095	0.77
α^{CL}	0.734	4.66
α^{RL}	2.010	2.73
Lead Critical Gap		
Constant	1.353	2.48
$Max\left(\Delta V_n^{lead}(t),0\right)$, m/sec.	-2.700	-2.25
$Min\left(\Delta V_n^{lead}(t),0\right)$, m/sec.	-0.231	-2.42
α^{lead}	1.270	2.86
σ^{lead}	1.112	2.23
Lag Critical Gap		
Constant	1.429	6.72
$Max\left(\Delta V_n^{lag}(t),0\right)$, m/sec.	0.471	3.89
α^{lag}	0.131	0.64
σ^{lag}	0.742	3.68
Number of drivers = 442 Number of observations = 15632 $L(0)=-1434.76$ $L(c)=-1037.05$ $L(\hat{\beta})=-888.78$ $\bar{\rho}^2=0.362$		