

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 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 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 with 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 with 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 an 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 (nontarget) lane—a lane (not) connecting to the turn the driver wishes to perform at the next intersection.
- Preemptive (nonpreemptive) 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 from which the driver is turning into the arterial.

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 in their lanes.

Gap acceptance is an important element in most lane-changing models. 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 with 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 the 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 with 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 previously, assumed that the driver considers the lead gap and the lag gap separately. Both gaps must be acceptable to execute the lane change. Critical gaps are assumed to follow a lognormal distribution to guarantee that they are nonnegative. 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

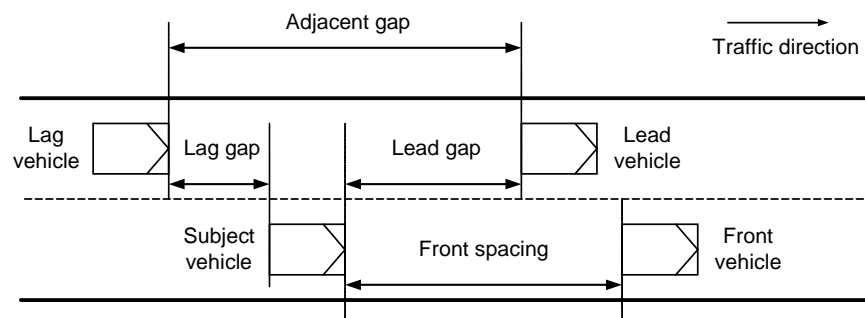


FIGURE 1 Definitions of front, lead, and lag vehicles and their relations with the subject vehicle.

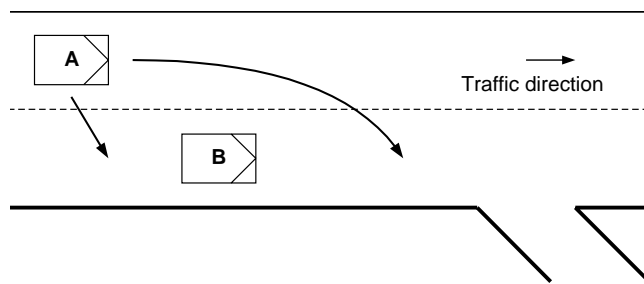


FIGURE 2 Lane-changing situation illustrating integrated lane-changing model.

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 nonexistence) 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, microsimulators use simple rules to determine whether MLC conditions apply. The parameters of these rules usually are 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 of the MLC situation is more realistically represented as a continuously increasing function instead of a step function. To illustrate the advantage of the integrated utility approach, consider the situation presented in Figure 2. Suppose Vehicle A is planning to use the off-ramp, and 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 or she passes Vehicle B.

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 because the target lane choice is unobservable; only the driver's lane-changing actions are observed. The structure of the model is presented in Figure 3. Latent choice variables are indicated as ovals, observed ones are 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 or her 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 is the lane change 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 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 the vehicles surrounding it. Other elements in the vehicle's surroundings that may affect 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 because drivers change lanes 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 a 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, free-

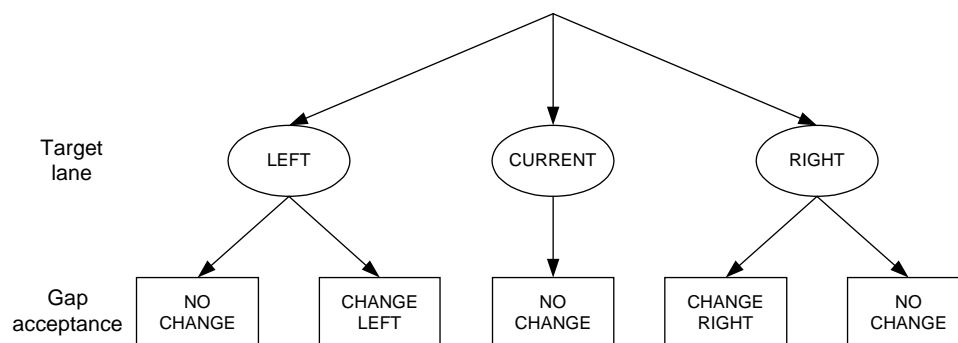


FIGURE 3 Structure of lane-changing model.

way lane choices may be affected by a preference to avoid using the rightmost 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 and vehicle characteristics, such as the aggressiveness of the driver and performance capabilities of the vehicle.

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:

$$U_n^{\text{lane } i}(t) = X_n^{\text{lane } i}(t)\beta^{\text{lane } i} + \alpha^{\text{lane } i}v_n + \epsilon_n^{\text{lane } i}(t) \quad \text{lane } i = CL, RL, LL \quad (1)$$

where

- $U_n^{\text{lane } i}(t)$ = utility of lane i to driver n at time t ;
- $X_n^{\text{lane } i}(t)$ = vector of explanatory variables;
- $\beta^{\text{lane } i}$ = corresponding vector of parameters;
- $\epsilon_n^{\text{lane } i}(t)$ = random term associated with lane utility;
- v_n = driver-specific random term that represents unobservable characteristics of the driver and vehicle, thus capturing correlations between observations of the same driver over time (v_n is assumed to be normally distributed in the drivers' population); and
- $\alpha^{\text{lane } i}$ = parameters of v_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 $\epsilon_n^{CL}(t)$, $\epsilon_n^{RL}(t)$, and $\epsilon_n^{LL}(t)$ are independently and identically Gumbel distributed, the choice probabilities of target lanes, conditional on the individual specific error term (v_n), are given by:

$$P_n(\text{lane } i | v_n) = \frac{\exp[V_n^{\text{lane } i}(t) | v_n]}{\sum_{j \in I} \exp[V_n^{\text{lane } j}(t) | v_n]} \quad \text{lane } i \in I = \{CL, RL, LL\} \quad (2)$$

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

$$V_n^{\text{lane } i}(t) | v_n = X_n^{\text{lane } i}(t)\beta^{\text{lane } i} + \alpha^{\text{lane } i}v_n \quad \text{lane } i = CL, RL, LL \quad (3)$$

Lane utility functions may depend on explanatory variables from the four categories discussed previously. 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 a specific lane and the number of lane changes needed to be in that lane), 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 v_n .

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 of these gaps may be negative if the vehicles overlap.

The driver compares the available space lead and lag gaps with 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 nonnegative.

$$\ln[G_n^{\text{gap } g TL, cr}(t)] = X_n^{\text{gap } g TL}(t)\beta^{\text{gap } g} + \alpha^{\text{gap } g}v_n + \epsilon_v^{\text{gap } g}(t) \quad \text{gap } g = \text{lead, lag} \quad (4)$$

where

- $G_n^{\text{gap } g TL, cr}(t)$ = critical gap g in target lane (m),
- $X_n^{\text{gap } g TL}(t)$ = vector of explanatory variables affecting the critical gap g ,
- $\beta^{\text{gap } g}$ = corresponding vector of parameters,
- $\epsilon_v^{\text{gap } g}(t)$ = random term: $\epsilon_v^{\text{gap } g}(t) \sim N(0, \sigma_{\text{gap } g}^2)$, and
- $\alpha^{\text{gap } g}$ = parameter of driver-specific random term v_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:

$$\begin{aligned} P_n(\text{change to target lane} | TL_t, v_n) &= P_n(I_t^{TL} = 1 | TL_t, v_n) \\ &= P_n(\text{accept lead gap} | TL_t, v_n)P_n(\text{accept lag gap} | TL_t, v_n) \\ &= P_n[G_n^{\text{lead } TL}(t) > G_n^{\text{lead } cr}(t) | TL_t, v_n] \\ &\quad \cdot P_n[G_n^{\text{lag } TL}(t) > G_n^{\text{lag } cr}(t) | TL_t, v_n] \end{aligned} \quad (5)$$

where

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

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

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

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

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

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

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

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.

Likelihood Function

The data available for estimation of this type of model consist 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 s. 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). 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 about 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:

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

where

π_1 and π_2 = parameters to be estimated, and
 d^1 , d^2 , and d^3 = 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 who 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, v_n), is given by:

$$f_n(TL_t, l_t | d_n, v_n) = P_n(TL_t | d_n, v_n)P_n(l_t | TL_t, v_n) \quad (9)$$

$P_n(TL_t | \cdot)$ and $P_n(l_t | \cdot)$ 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:

$$f_n(l_t | d_n, v_n) = \sum_{TL_t} f_n(TL_t, l_t | d_n, v_n) \quad (10)$$

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

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

where \mathbf{l} is the vector of lane observations.

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

$$L_n = \int_v \sum_d f_n(\mathbf{l} | d_n, v_n) p(d) \phi(v) dv \quad (12)$$

$p(d)$ is given by Equation 8, and $\phi(v)$ 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:

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

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

DATA FOR ESTIMATION

The model parameters were estimated with data collected in a section of I-395 southbound in Arlington, Virginia, presented schematically in Figure 4. The data set contains observations on the position, lane, and dimensions of every vehicle in the section every 1 s. Details of the collection effort are presented elsewhere (11). This data set is particularly useful for estimating the lane-changing model because of the geometric characteristics of the site: the site is 997 m 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 the integrated model.

The vehicle trajectory data were used to generate the required explanatory variables including speeds and relations between the

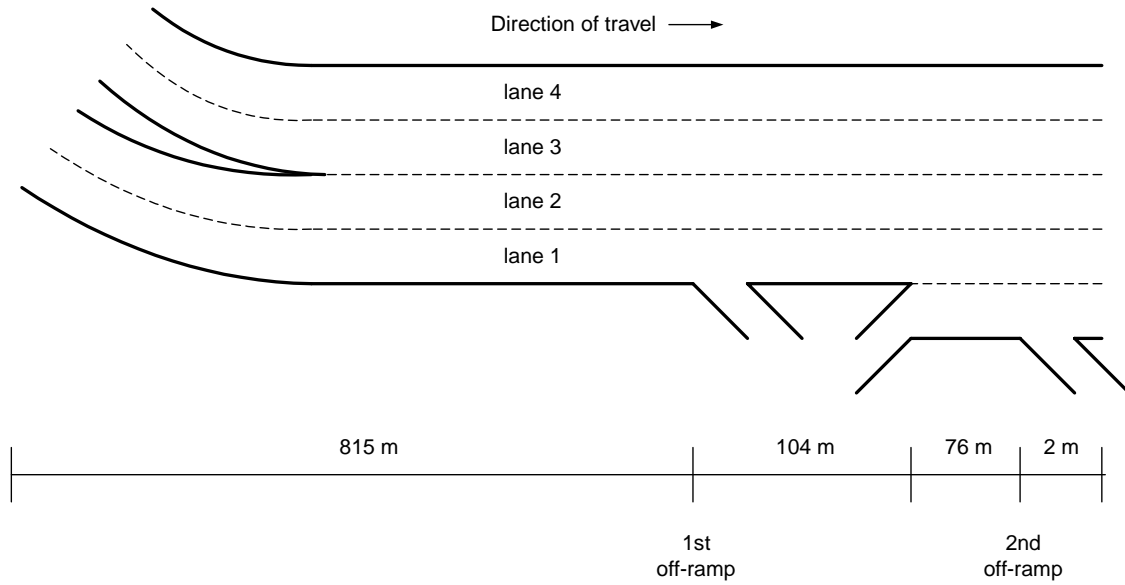


FIGURE 4 Data collection site (not to scale).

subject vehicle and other vehicles. The resulting estimation data set includes 442 vehicle records for a total of 15,632 observations. On average, a vehicle was observed for 35.4 s (observations). All vehicles were first observed at the upstream end of the freeway section. At the downstream end, 76% stay on the freeway, and 8% and 16% use the first and second off-ramps, respectively. Observed speeds range from 0.4 to 25.0 m/s, with a mean of 15.6 m/s. Densities range from 14.2 to 55.0 vehicles/km/lane, with a mean of 31.4 vehicles/km/lane. The level of service on the section ranges from D to E.

ESTIMATION RESULTS

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

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 that capture the distance to the point where the driver needs to be in a specific lane (i.e., 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 as follows:

$$\text{path_plan_impact}_{j_n^{\text{lane } i}}(t) = [d_n^{\text{exit}}(t)]^{\theta^{\text{MLC}}} \delta_n^{j,i}(t) \quad \text{lane } i = CL, RL, LL; j = 1, 2, 3 \quad (14)$$

where

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

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

The utility of a lane decreases with the number of lane changes the driver needs to perform to maintain the desired path. This effect is magnified when the distance to the off-ramp decreases ($\theta^{\text{MLC}} = -0.378$). 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 $d_n^{\text{exit}}(t) \rightarrow +\infty$ and approaches $-\infty$ when $d_n^{\text{exit}}(t) \rightarrow +0$. Figure 5 indicates 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 particular, drivers are more likely to respond to constraints that involve the next road facility they will encounter. Such behavior would present itself for drivers who 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:

$$\text{next_exit_impact}_n^{\text{lane } i}(t) = \delta_n^{\text{next exit}}(t) \delta_n^{\text{wrong}, i}(t) \quad \text{lane } i = CL, RL, LL \quad (16)$$

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

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

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

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

TABLE 1 Estimation Results of 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
$\max(\Delta V_n^{lead}(t), 0)$, m/sec	-2.700	-2.25
$\min(\Delta V_n^{lead}(t), 0)$, 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
$\max(\Delta V_n^{lag}(t), 0)$, 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 $L(0) = 1434.76$ $L(c) = 1037.05$ $L(\hat{\beta}) = 888.78$ $\bar{\rho}^2 = 0.362$		

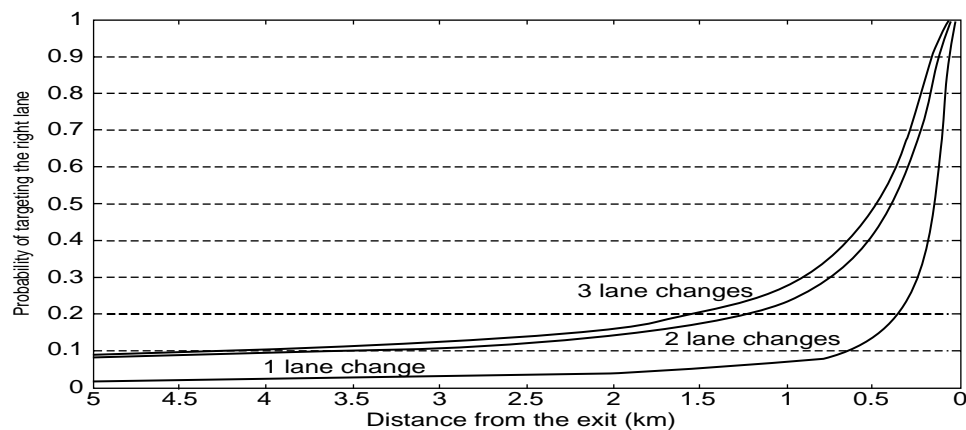


FIGURE 5 Impact of path plan on probability of targeting the right lane (speeds of subject, front, and lag vehicles = 15 m/s; front spacing = 20 m).

dummy variable with the number of lane changes required did not significantly improve 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 (appearing only 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

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

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:

$$\delta_n^{\text{rightmost},i}(t) = \begin{cases} 1 & \text{lane } i \text{ is the} \\ & \text{rightmost lane} \quad i = CL, RL \\ 0 & \text{otherwise} \end{cases} \quad (20)$$

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

In summary, the target lane utilities are given by:

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

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

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

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—that is, 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 from 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 because their perception of the lag gap is not as reliable as it is for the lead gap because of 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, v_n , are positive for both lead and lag critical gaps and hence are consistent with the interpretation of v_n as positively correlated with timid drivers, who require larger gaps for lane changing than 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 or E) are such that acceptable gaps are available, and therefore drivers are not forced to take risks (reduce their critical gaps) to lane change.

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

$$G_n^{\text{lead},TL,cr}(t) = \exp \left\{ \begin{aligned} & 1.353 - 2.700 \max [0, \Delta V_n^{\text{lead},TL}(t)] - \\ & -0.231 \min [0, \Delta V_n^{\text{lead},TL}(t)] \\ & + 1.270v_n + \epsilon_n^{\text{lead}}(t) \end{aligned} \right\} \quad (24)$$

$$\begin{aligned} G_n^{\text{lag},TL,cr}(t) = & \exp \{ 1.429 + 0.471 \max [0, \Delta V_n^{\text{lag},TL}(t)] \\ & + 0.131v_n + \epsilon_n^{\text{lag}}(t) \} \end{aligned} \quad (25)$$

$$\epsilon_n^{\text{lead}}(t): N(0, 1.112^2) \text{ and } \epsilon_n^{\text{lag}}(t): N(0, 0.742^2).$$

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

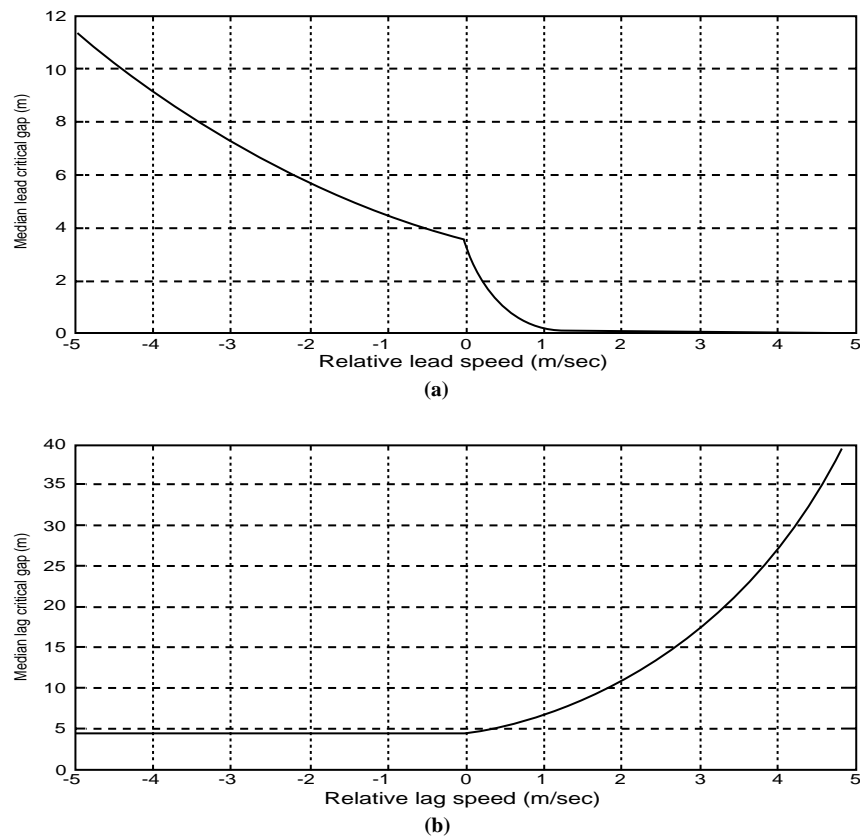


FIGURE 6 Median (a) lead and (b) lag critical gaps as a function of relative speeds.

overcomes both of 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 with the critical gaps. The model requires that both the lead and lag gaps are acceptable. The effect of unobserved driver and 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 data collection are also accounted for.

Parameters of all components of the model were estimated jointly with detailed vehicle trajectory data. Estimation results indicate that drivers' lane selection is affected by both 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 data sets is required to identify geometry and other site-specific effects and develop robust and more general models that can be used in any urban freeway section.

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