Integrated Driving Behavior Modeling

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Abstract

This paper develops, implements and tests a framework for driving behavior modeling that integrates the various decisions, such as acceleration, lane changing and gap acceptance. Furthermore, the proposed framework is based on the concepts of short-term goal and short-term plan. Drivers are assumed to conceive and perform short-term plans in order to accomplish short-term goals. This behavioral framework supports a more realistic representation of the driving task, since it captures drivers' planning capabilities and allows decisions to be based on anticipated future conditions.

An integrated driving behavior model, which utilizes these concepts, is developed. The model captures both lane changing and acceleration behaviors. The driver's short-term goal is defined by the target lane. Drivers who wish to change lanes but cannot change lanes immediately, select a short-term plan to perform the desired lane change. Short-term plans are defined by the various gaps in traffic in the target lane. Drivers adapt their acceleration behavior to facilitate the lane change using the target gap. Hence, inter-dependencies between lane changing and acceleration behaviors are captured.

1 Introduction

Driving behavior models describe vehicles' movements under different traffic conditions. These models include speed/acceleration models and lane changing models. These models are an important component of microscopic traffic simulators. They are also important to several other application areas, such as safety studies and capacity analysis, in which aggregate traffic flow characteristics may be deduced from the behavior of individual drivers. Typically, in the literature, these models have been developed independently and used as such in microscopic simulation models.

Early driving behavior models focused on car following. These models describe the behavior of a vehicle while it is following the vehicle in front of it (the leader). The subject vehicle is assumed to react to the leader's actions (see reviews in Rothery 1997, Brackstone and McDonald 1999). More recently, the advent of microscopic traffic simulation models lead to the development of general acceleration models, which also capture the behavior of drivers that do no closely follow their leaders, and to interest in lane changing behavior. General acceleration models (e.g. Wiedemann 1974, Gipps 1981, Benekohal and Treiterer 1988, Yang and Koutsopoulos 1996, Zhang et al. 1998, Ahmed 1999) define multiple driving regimes, such as free-flow, emergency and various types of car following (e.g. acceleration and deceleration or reactive and non-reactive), and assume different behaviors in each regime. For example, drivers in the free-flow acceleration regime may focus on attaining their desired speed. However, the acceleration decisions are modeled independently. The impact of other driving goals and decisions, such as lane changing, on acceleration behavior has not been modeled in literature.

Lane changing models (e.g. Gipps 1986, Ahmed et al. 1996, Hidas and Behbahanizadeh 1998, Zhang et al. 1998, Ahmed 1999, Salvucci et al. 2001), were also developed independently, and typically include two components: the decision to consider a lane change and the decision to execute the lane change. Lane changes are often classified as either mandatory (MLC) or discretionary (DLC). MLC are performed when the driver must leave the current lane. DLC are performed in order to improve driving conditions. Gap acceptance models are used to model the execution of lane changes. The classification of lane changes as either MLC or DLC does not allow trade-offs between mandatory and discretionary considerations to be modeled. The result is a rigid behavior structure that does not permit, for example, overtaking in MLC situations. Toledo et al. (2003) developed a model that integrates MLC and DLC in a single utility framework. Their model structure is adopted in this paper as a basis for the lane changing component of the integrated model.

Important limitations of current driving behavior models are the assumptions of myopic behavior and independent behaviors: most models assume that drivers make instantaneous decisions in reaction to current or past traffic conditions, and that different driving decisions (e.g. acceleration and lane changing) made and modeled separately. In reality, drivers may adapt one dimension of their behavior in order to facilitate their goals in other dimensions. This requires drivers to use their anticipation of the behavior of other vehicles around them and their own path plan to conceive an action plan and execute it over a period of time. This is particularly important in lane changing behavior, in which drivers may anticipate the behavior of other vehicles and adjust their own acceleration to facilitate completion of a desired lane change.

The situation described in Figure 1 illustrates this behavior. Suppose that driver A tries to change to the right lane (for example, in order to take an off-ramp), and that the total lengths of the gaps between vehicles B and C and between vehicles C and D are both acceptable. In most current models, A only considers the adjacent gap (C-D). This gap is rejected because the lead gap (gap between A and C) is unacceptable, and therefore A does not change lanes. If the acceleration A applies is determined by an independent acceleration model, which ignores the lane changing goal, the process would be repeated in the next time steps until A is able to change lanes. This may result in unrealistic traffic flow characteristics. For example, if the speeds of A and C are similar, the lane change may not be completed until it becomes urgent. At that point, A will force its way to the right lane. This will prompt vehicles behind it to decelerate and may create a shock wave. However, in reality, A may adapt its acceleration over a period of time to facilitate the lane change. For example, by decelerating to be in a position to accept gap C-D or accelerating to be in a position to accept gap B-C. As a result, the simulation may underestimate bottleneck capacities and over-predict congestion (e.g. DYMO 1999, Abdulhai et al. 1999). Hence, driving behavior models need to be able to capture the complexity of human decision-making processes.

<<<< place Figure 1 about here >>>>

The objective of this paper is to present an integrated driving behavior model framework, which integrates lane changing and acceleration models, captures the inter-dependencies between these decisions and recognizes that drivers decisions may be the results of short term plans to accomplish their objectives. The framework is based on the concepts of short-term goal and short-term plan. Drivers are assumed to conceive and perform short-term plans in order to accomplish short-term goals. This behavioral framework captures drivers' planning capabilities and allows decisions to be based on anticipated future conditions. The model incorporates both lane changing and acceleration decisions and so, captures inter-dependencies among these behaviors.

The rest of this paper is organized as follows: we next introduce the concepts that form the basis to the proposed modeling framework and the structure of an integrated driving behavior model based on these concepts. Section 3 details the formulations of the various components within the integrated driving behavior model. Results of two case studies that used a microscopic traffic simulator that implements the integrated model are presented in section 4. Finally, discussion and conclusion are presented in section 5.

2 Structure of the Integrated Model

The proposed model explicitly recognizes that drivers have short-term driving goals and develop short-term plans to achieve these goals. Sukthankar (1997) defines a short-term plan as a sequence of actions a driver performs in order to complete a desired tactical maneuver. This desired maneuver is the short-term goal. More specifically, we define the short-term goal by a target lane, which is the lane the driver perceives as best to be in.

The short-term plan is defined by a target gap, which the driver intends to use to change lane. The acceleration the driver applies is adapted to facilitate the short-term plan. In the example described in Figure 1, the short-term goal of A is to move to the right lane. The short-term plan may be to use gap B-C to accomplish this goal. The sequence of actions required to execute the plan may involve accelerating in order to pass C and then accepting the gap B-C.

A detailed model structure based on these notions is shown in Figure 2. It hypothesizes four levels of decision-making: target lane, gap acceptance, target gap and acceleration. This decision process is latent. The short-term goal (target lane) and short-term plan (target gap) are both unobservable. Only the driver's actions (lane changes and accelerations) are observed. Latent choices are shown as ovals. Observed choices are shown as rectangles. At the top level the driver chooses the target lane. The *Current* branch corresponds to a situation in which the driver decides to stay in the current lane. In this case the acceleration behavior will depend on the relations with the vehicle in front. In the case that either the right lane or the left lane are chosen (the *Right* and *Left* branches, respectively), the driver evaluates the adjacent gap in the target lane and decides whether this gap is acceptable for lane changing or not. If the gap is accepted (*Change right* or *Change left*), the lane change is immediately executed and the short-term goal is accomplished. The acceleration is now affected by the leader in the new lane. If the available gap is rejected (*No change*), the driver evaluates available gaps in the target lane and chooses the one that would be used to perform the desired lane change (*Gap* R_1 to *Gap* R_K or *Gap* L_1 to *GAP* L_M). The acceleration the driver applies is determined to facilitate the short-term plan (i.e. the driver tries to position the vehicle such that the target gap will be acceptable). The acceleration may also be constrained by the leader in the current lane since the lane change is not immediate.

This model structure allows state dependency in decisions made over time (e.g. persistence) to be directly captured through appropriate specification of the choice probabilities at the various levels. For example, the probability of targeting a lane change may depend on the lane change goal in previous time steps. An alternative approach, which is adopted in the model presented here, is based on the notion of partial short term plan (Sukthankar 1997). The model assumes that since the situation drivers face constantly changes, they reconsider their decisions at every time step, and so they execute one step of the short-term plan, re-evaluate the situation and decide the next action to take. With this approach, state dependence is only captured through the explanatory variables (e.g. if a driver targeted a lane change and accelerated to facilitate it, it is likely that the probability of targeting the same lane change would increase in the next time step).

<<<< place Figure 2 about here >>>>

The implementation of the above framework in terms of the specific models used at each level should capture the interdependencies and correlations among the various decisions made by the same driver. The econometric framework of random utility choice models, which can capture these interdependencies and correlations, is utilized in constructing a detailed model based on this structure. The model structure is very general and provides several mechanisms to capture interdependencies and correlations. Decisions made at lower levels of the decision process are conditional on those made at higher levels (e.g. the acceleration behavior is conditional on the short-term plan). The expected maximum utilities (*EMU*) of lower level choices may be introduced in the specification of higher-level choices in order to capture the effects of the lower level on higher-level decisions. The *EMU* captures the utility that the driver may extract from the lower level choices that become available when a higher-level alternative is chosen. For example, the gap acceptance *EMU* represents the likelihood that the driver will be able to execute a lane change. If it is introduced in the target lane model, it will capture the effect of gap acceptance decisions on the target lane choice.

The data typically available for estimation of the models include detailed vehicle trajectories of multiple drivers, which include observations of the speed and location of the vehicle at high time resolution. However, it usually does not include information on the characteristics of the drivers, such as aggressiveness and level of driving skill. Nevertheless, individual-specific latent variables may be introduced in the various component models to capture correlations among the decisions made by a given driver that are due to these unobserved characteristics. The model assumes that conditional on the value of these latent variables, the error terms of different observations are independent. Thus, a general expression for the utilities specification is given by:

$$U_n^d\left(t\right)=X_n^d\left(t\right)\beta^d+\gamma^d EMU_n^d\left(t\right)+\alpha^d\nu_n+\varepsilon_n^d\left(t\right) \qquad (1)$$

$U_n^d(t)$ is the utility of decision *d* to individual *n* at time *t*. $X_n^d(t)$ is a vector of explanatory variables. β^d is a vector of parameters. $EMU_n^d(t)$ is the expected maximum utility of lower level choices that are available if decision *d* is made. γ^d is the parameter of the expected maximum utility. υ_n is an individual-specific latent variable. We assume that the distribution of this variable in the population is normalized such that it has a unit variance. α^d is the parameter of υ_n. $\varepsilon_n^d(t)$ is a generic random term with i.i.d. distribution across decisions, time and individuals. $\varepsilon_n^d(t)$ and υ_n are independent of each other. The resulting error structure (see Heckman 1981, Walker 2001 for a detailed discussion) is given by:

$$cov\left(U_n^d(t), U_{n'}^{d'}(t')\right) = \begin{cases} \left(\alpha^d\right)^2 + \sigma_d^2 & if\ n = n',\ d = d'\ and\ t = t' \\ \left(\alpha^d\right)^2 & if\ n = n',\ d = d'\ and\ t \neq t' \\ \alpha^d \alpha^{d'} & if\ n = n',\ d \neq d'\ and\ \forall t \\ 0 & otherwise \end{cases} \tag{2}$$

σ_d^2 is the variance of $\varepsilon_n^d(t)$.

In the acceleration component of the model, reaction times and time headway thresholds (that determine the transition between constrained and unconstrained regimes) also capture correlations among the various acceleration decisions.

3 Model Components

We now present mathematical formulations of the various components of the integrated driving behavior model.

3.1 The target lane model

At this level, the driver chooses a short-term goal. The short-term goal is defined in terms of a target lane (*TL*). The target lane choice set includes up to three alternatives: The driver may decide to stay in the current lane (*CL*) or to target a change to either the right lane (*RL*) or the left lane (*LL*).

This decision is formulated as a discrete choice problem. The model integrates mandatory and discretionary considerations into a single utility function for each lane. This approach, which is based on the model proposed in Toledo et al. (2003), differs from most lane changing models in which MLC and DLC situations are treated separately. The integrated utility captures trade-offs among the various considerations, and avoids the need to define the conditions that trigger an MLC situation. The utilities of the alternative target lanes to driver *n* at time *t* are given by:

$$\begin{aligned} U_n^{lane\,i}(t) &= V_n^{lane\,i}(t) + \varepsilon_n^{lane\,i}(t) \\ &= X_n^{lane\,i}(t)\beta^{lane\,i} + \gamma^{lane\,i} EMU_n^{lane\,i}(t) + \alpha^{lane\,i}\upsilon_n + \varepsilon_n^{lane\,i}(t) \end{aligned} \tag{3}$$

$lane\, i \in \{CL, RL, LL\}$. $V_n^{lane\,i}(t)$ are the systematic utilities of the lane *i*. $\varepsilon_n^{lane\,i}(t)$ are the random terms associated with the lane utilities. $X_n^{lane\,i}(t)$ are vectors of explanatory variables. $\beta^{lane\,i}$ are the corresponding vectors of parameters. $EMU_n^{lane\,i}(t)$ are the expected maximum lower level utilities, which capture the impact of the ease of changing lanes on the decision to pursue a lane change. $\gamma^{lane\,i}$ are the parameters of the *EMU*s. υ_n is an individual specific error term that captures correlations between the observations of a single driver over time. $\alpha^{lane\,i}$ are the parameters of υ_n.

Lane utilities depend on variables that capture path following (e.g. distances to points where drivers must be in certain lanes and the number of lane changes needed in order to be in these lanes) and immediate conditions in the various lanes ach lane (e.g. speeds of the vehicles ahead in each lane and presence of heavy vehicles). Different choice models are obtained depending on the assumption made about the distribution of the random terms $\varepsilon_n^{lane\,i}(t)$. For example, assuming that these random terms are i.i.d. Gumbel distributed, the target lane choice probabilities, conditional on the individual specific error term (υ_n) are given by a logit model:

$$p\left(TL_n(t)=i\middle|\upsilon_n\right)=\frac{\exp\left(V_n^{lane\,i}(t)\middle|\upsilon_n\right)}{\sum\limits_{j\in TL}\exp\left(V_n^{lane\,j}(t)\middle|\upsilon_n\right)} \tag{4}$$

3.2 The gap acceptance model

The gap acceptance model captures the decision whether or not to change lanes using the adjacent gap in the target lane. The model assumes that if the adjacent gap is acceptable the driver executes the lane change and does not consider any other gaps. This assumption is rooted in satisficing behavior theory (Simon 1955), which states that if an available alternative (i.e. changing lanes using the adjacent gap) is satisfactory the driver does not try to find a better one.

The adjacent gap in the target lane is defined by the lead and lag vehicles in that lane as shown in Figure 3. The lead (lag) gap is the clear spacing between the lead (lag) vehicle and the subject vehicle. Note that these gaps may be negative if the vehicles overlap.

<<<< place Figure 3 about here >>>>

The available lead and lag gaps are accepted if they are greater than the corresponding critical gaps, which are the minimum acceptable gaps. Critical gaps may be affected by variables that capture the driving neighborhood, such as traffic density and the speeds of the lead, lag and subject vehicle as well as variables that capture the necessity and urgency of the lane change.

The model assumes that both the lead and the lag gaps must be acceptable in order for the vehicle to change lanes. Conditional on the individual specific term, the probability of accepting the gap and executing a lane change is given by:

$$\begin{aligned}
&p\left(\text{change to target lane}_n(t) \middle| TL_n(t), \upsilon_n\right) = p\left(l_n^{TL}(t) = 1 \middle| TL_n(t), \upsilon_n\right) = \\
&p\left(\text{accept lead gap}_n^{TL}(t) \middle| TL_n(t), \upsilon_n\right) p\left(\text{accept lag gap}_n^{TL}(t) \middle| TL_n(t), \upsilon_n\right) = \qquad (5) \\
&p\left(G_n^{lead\,TL}(t) > G_n^{lead\,TL,cr}(t) \middle| TL_n(t), \upsilon_n\right) p\left(G_n^{lag\,TL}(t) > G_n^{lag\,TL,cr}(t) \middle| TL_n(t), \upsilon_n\right)
\end{aligned}$$

$TL_n(t) \in \{RL, LL\}$ is the target lane. $l_n^{TL}(t)$ is the lane changing indicator for the target lane, which takes a value of 1 if a change to lane *TL* is executed at time *t*, and 0 otherwise. $G_n^{lead\,TL}(t)$ and $G_n^{lag\,TL}(t)$ are the available lead and lag gap in the target lane, respectively. $G_n^{lead\,TL,cr}(t)$ and $G_n^{lag\,TL,cr}(t)$ are the corresponding critical gaps.

Critical gaps vary for different individuals and with the situation. They are modeled as random variables whose means are functions of explanatory variables that include the speeds of the subject vehicle and the lead and lag vehicles in the target lane. The *EMU* of the lower levels (Target Gap) can be used to capture the impact of opportunities to pursue other gaps on the decision to accept the adjacent gap. The individual specific error term captures correlations among the critical gaps of the same individual over time. In order to ensure that critical gaps are always positive, they are assumed to follow a lognormal distribution (see Mahmassani and Sheffi (1980) and Ahmed (1999) for reviews of earlier applications of this distribution in modeling critical gaps):

$$\ln\left(G_n^{lead\,TL,cr}(t)\right) = X_n^{lead\,TL}(t)\beta^{lead} + \gamma^{lead} EMU_n^{lead\,TL}(t) + \alpha^{lead}\upsilon_n + \varepsilon_n^{lead}(t) \tag{6}$$

$$\ln\left(G_n^{lag\,TL,cr}(t)\right) = X_n^{lag\,TL}(t)\beta^{lag} + \gamma^{lag} EMU_n^{lag\,TL}(t) + \alpha^{lag}\upsilon_n + \varepsilon_n^{lag}(t) \tag{7}$$

$X_n^{lead\,TL}(t)$ and $X_n^{lag\,TL}(t)$ are vectors of explanatory variables affecting the lead and lag critical gaps, respectively. β^{lead} and β^{lag} are the corresponding vectors of parameters. $EMU_n^{lead\,TL}(t)$ and $EMU_n^{lag\,TL}(t)$ are the expected maximum lower level utilities. γ^{lead}

and γ^{lag} are the parameters of the expected maximum utilities. $\varepsilon_n^{lead}(t)$ and $\varepsilon_n^{lag}(t)$ are normally distributed random terms associated with the critical gaps: $\varepsilon_n^{lead}(t) \sim N\left(0, \sigma_{lead}^2\right)$ and $\varepsilon_n^{lag}(t) \sim N\left(0, \sigma_{lag}^2\right)$. α^{lead} and α^{lag} are the parameters of the individual specific random term υ_n for the lead and lag critical gaps, respectively.

3.3 The target gap model

If the adjacent gap is rejected, the driver cannot change lanes immediately. The target gap model captures the drivers' plan how to accomplish the desired lane change by adjusting speed and position over a short period of time. This short-term plan is defined by a target gap in the target lane traffic.

The alternatives in the target gap choice set include available gaps in the vicinity of the subject vehicle (e.g. the adjacent gap, forward gap and backward gap shown in Figure 4). Note that the adjacent gap, although not acceptable at the time of the decision, may still be chosen in anticipation that it will become acceptable. Although the definition of short-term plans in terms of explicit target gaps is simple and intuitive, it is not a requirement of the model structure. For example, the target gap choice set may also incorporate alternatives such as to look for gaps between vehicles that are currently either downstream or upstream of the subject vehicle, without committing to a specific gap.

<<<< place Figure 4 about here >>>>

The utilities of the different target gaps to driver *n* at time *t* are given by:

$$U_n^{gap\,i}(t) = V_n^{gap\,i}(t) + \varepsilon_n^{gap\,i}(t) = X_n^{gap\,i}(t)\beta^{gap\,i} + \alpha^{gap\,i}\upsilon_n + \varepsilon_n^{gap\,i}(t) \tag{8}$$

$V_n^{gap\,i}(t)$ is the systematic utility of gap *i*. $X_n^{gap\,i}(t)$ is a vector of explanatory variables affecting the utility of gap *i*. $\beta^{gap\,i}$ is the corresponding vector of parameters. $\varepsilon_n^{gap\,i}(t)$ are the random terms associated with the gap utilities. $\alpha^{gap\,i}$ are the parameters of the individual specific error term υ_n.

The utilities of the different gaps are affected by variables such as the size of the gap, the speeds of the intended lead and lag and the subject vehicle. Assuming a logit error structure, the conditional gap choice probabilities for the various alternatives are given by:

$$p\left(TG_n(t) = i \middle| TL_n(t), l_n^{TL}(t) = 0, \upsilon_n\right) = \frac{exp\left(V_n^{gap\,i}(t)\middle|\upsilon_n\right)}{\sum_{j \in TG_n(t)} exp\left(V_n^{gap\,j}(t)\middle|\upsilon_n\right)} \tag{9}$$

$TG_n(t)$ is the choice set of target gaps for driver *n* at time *t*.

3.4 Acceleration models

The integration of acceleration and lane changing models requires extension of current acceleration models to cover a wider range of situations, since the acceleration behavior is expected to differ depending on the driver’s short-term goal and short-term plan. In our formulation, different acceleration models are used for the various combinations of target lane, gap acceptance decision and target gap. More specifically, three different cases are considered:

1. Stay-in-the-lane acceleration, which applies when the driver wishes to stay in the current lane.
2. Acceleration during a lane change, which applies when the driver accepts the available adjacent gap and executes a lane change.
3. Target gap acceleration, which applies when the driver wishes to change lanes but rejects the adjacent gap, and so does not change lanes immediately. In this case different models are used depending on the target gap choice.

The overall acceleration model is expressed by:

$$a_n(t) = \begin{cases} a_n^s(t) & \text{if } TL_n(t) = CL \\ a_n^{lc}(t) & \text{if } TL_n(t) = RL \text{ or } LL \text{ and } l_n^{TL}(t) = 1 \\ a_n^{tg}(t) & \text{otherwise} \end{cases} \tag{10}$$

$a_n(t)$ is the acceleration vehicle *n* applies at time *t*. $a_n^s(t)$ is the stay-in-the-lane acceleration. $a_n^{lc}(t)$ is the lane changing acceleration. $a_n^{tg}(t)$ is the target gap acceleration.

In order to capture the effect of the subject's leader on the acceleration behavior, two driving regimes, car-following and unconstrained, are defined within each one of these acceleration behaviors. In the car following regime the subject vehicle is close to its leader and therefore reacts to the behavior of the leader. In the unconstrained regime the subject is not close to its leader and so can determine the acceleration to facilitate the short-term plan. The time headway between the subject and the leader determines the driving regime. If the time headway is less than a threshold, the driver is in the constrained regime; otherwise the driver is in the unconstrained regime. Mathematically, this is expressed by:

$$a_n^k(t) = \begin{cases} a_n^{cf}(t) & \text{if } h_n(t-\tau_n) \leq h_n^* \\ a_n^{k,uc}(t) & \text{otherwise} \end{cases} \qquad (11)$$

$a_n^{cf}(t)$ and $a_n^{k,uc}(t)$ are the car-following and unconstrained acceleration that applies in case $k \in \{s, lc, tg\}$, respectively. τ_n is the reaction time of driver *n*. $h_n(t-\tau_n)$ and h_n^* are the time headway at time $t-\tau_n$ and the headway threshold for driver *n*, respectively.

Different models describe the acceleration behavior under the various situations. In order to create a consistent set of acceleration behaviors, the stimulus-sensitivity framework, which the GM model (Gazis et al. 1961) is based on, is adapted for all these acceleration models. Thus, the acceleration driver *n* applies in each situation *r* is assumed to be a response to stimuli from the environment:

$$response_n^r(t) = sensitivity_n^r(t) \times stimulus_n^r(t-\tau_n) + \varepsilon_n^r(t) \qquad (12)$$

$\varepsilon_n^r(t)$ are random error terms.

The driver reacts to different stimuli in the various situations, depending on constraints imposed by the driving neighborhood and on the driver's short-term goal and short-term plan.

<u>Car following acceleration models</u>

The car-following acceleration model assumes that the stimulus is the subject relative speed with respect to the leader (defined here as the speed of the leader less the speed of the subject vehicle). In lane changing acceleration, however, the subject is already committed to the lane changing maneuver and so the model assumes that the driver follows the leader in the lane the subject is changing to. The sensitivity is a function of explanatory variables.

The expected value of the response to the stimuli is positive (acceleration) for positive leader relative speeds (i.e., when the leader is faster than the subject vehicle) and negative (deceleration) for negative leader relative speeds. However, the response to positive and negative stimuli may differ because the nature of these situations are different: the main factor in the reaction to negative leader relative speeds is collision avoidance, whereas the acceleration applied in response to positive leader relative speed stimuli may be aimed to obtain speed advantage. To capture these differences the model allows the coefficients of explanatory variables to be different for positive and negative stimuli. The car following acceleration is therefore given by:

$$a_n^{cf}(t) = \begin{cases} a_n^{cfacc}(t) & \text{if } \Delta V_n(t-\tau_n) \geq 0 \\ a_n^{cfdec}(t) & \text{otherwise} \end{cases} \tag{13}$$

$a_n^{cfacc}(t)$ and $a_n^{cfdec}(t)$ are the car following acceleration and car following deceleration, respectively. $\Delta V_n(t-\tau_n)$ is the leader relative speed.

The car following acceleration and car following deceleration models are given, respectively, by:

$$a_n^g(t) = s^g\left[X_n^g(t)\right] f^g\left[\Delta V_n(t-\tau_n)\right] + \varepsilon_n^g(t) \tag{14}$$

$g \in \{cfacc, cfdec\}$. $s^g\left[X_n^g(t)\right]$ are the sensitivity functions for car following. $X_n^g(t)$ are vectors of explanatory variables. $f^g\left[\Delta V_n(t-\tau_n)\right]$ are the stimulus functions. $\varepsilon_n^g(t)$ are random terms.

Unconstrained acceleration models

The stimuli in the unconstrained acceleration regime depend on the short-term plan and short-term goal. The model assumes that unconstrained stay-in-the-lane and lane-changing drivers are trying to attain their desired speeds. The stimulus for these vehicles depends on the difference between their desired speed and current speed. The free-flow acceleration is given by:

$$a_n^{ff}(t) = s^{ff}\left[X_n^{ff}(t)\right] f^{ff}\left[V_n^{DS}(t-\tau_n) - V_n(t-\tau_n)\right] + \varepsilon_n^{ff}(t) \tag{15}$$

$a_n^{ff}(t)$ is the free-flow acceleration. $s^{ff}\left[X_n^{ff}(t)\right]$ is the free-flow acceleration sensitivity function. $X_n^{ff}(t)$ is a vector of explanatory variables. $f^{ff}\left[V_n^{DS}(t-\tau_n) - V_n(t-\tau_n)\right]$ is the stimulus function. $\varepsilon_n^{ff}(t)$ is a random term. $V_n^{DS}(t-\tau_n)$ is the unobservable desired speed, which is modeled as a function of explanatory variables:

$$V_n^{DS}(t-\tau_n) = X_n^{DS}(t-\tau_n)\beta^{DS} + \alpha^{DS}\upsilon_n \tag{16}$$

$X_n^{DS}(t-\tau_n)$ is a vector of explanatory variables. β^{DS} is the corresponding set of parameters. α^{DS} is the parameter of the individual specific random term υ_n.

Drivers that target changing lanes but reject the available adjacent gap and therefore cannot immediately change lanes apply accelerations to facilitate the short-term plan. We assume that these drivers try to reach a desired position with respect to the target gap, which they perceive would allow the lane change to be executed. The stimulus the driver reacts to is the difference between the desired position and the vehicle's current position. Figure 5 illustrates this behavior. Suppose that the short-term plan for vehicle A is to change to the left lane using the gap between vehicles B and C (the forward gap). Assuming it is unconstrained by the vehicle in front of it (vehicle D), vehicle A would facilitate the lane change by accelerating to the desired position relative to the target gap.

<<<< place Figure 5 about here >>>>

The desired position with respect to the target gap is expressed as a fraction of the total length of the target gap. The sensitivity term is affected by variables that capture the relations between the subject vehicle and the vehicles that define the target gap, such as spacing and relative speeds, and so the target gap acceleration is expressed by:

$$a_n^{uctg,TL}\left(t\right) = s^{tg}\left[X_n^{tg,TL}\left(t\right)\right] f^{tg}\left[D_n^{tg,TL}\left(t-\tau_n\right)\right] + \varepsilon_n^{tg}\left(t\right) \tag{17}$$

$a_n^{uctg,TL}\left(t\right)$ is the unconstrained target gap acceleration. $TL \in \left\{RL,\ LL\right\}$. $s^{tg}\left[X_n^{tg,TL}\left(t\right)\right]$ and $f^{tg}\left[D_n^{tg,TL}\left(t-\tau_n\right)\right]$ are the target gap acceleration sensitivity and stimulus functions, respectively. $\varepsilon_n^{tg}\left(t\right)$ is the random term associated with the unconstrained target gap acceleration.

In each one of the acceleration models presented above, the random error terms $\varepsilon_n^{r}\left(t\right)$ capture unobserved effects on the acceleration. It is assumed that these terms follow a normal distribution and that they are independent of each other, for different drivers and over time. Correlations among the accelerations of the same driver over time are captured by the reaction time and the time headway thresholds, which are individual specific. Under these assumptions the probability density functions of the various accelerations are given by:

$$f\left(a_n^{r}\left(t\right) \mid \tau_n\right) = \frac{1}{\sigma_r}\phi\left(\frac{a_n^{r}\left(t\right) - s^{r}\left[\cdot\right] f^{r}\left[\cdot\right]}{\sigma_r}\right) \tag{18}$$

σ_r is the standard deviation of the acceleration error terms.

The distribution of the combined car following acceleration is given by:

$$f\left(a_n^{cf}\left(t\right) \mid \tau_n\right) = f\left(a_n^{cfacc}\left(t\right) \mid \tau_n\right)^{\delta\left[\Delta V_n\left(t-\tau_n\right)\right]} f\left(a_n^{cfdec}\left(t\right) \mid \tau_n\right)^{\left(1-\delta\left[\Delta V_n\left(t-\tau_n\right)\right]\right)} \tag{19}$$

$\delta\left[\Delta V_n\left(t-\tau_n\right)\right]$ is an indicator, which takes a value of 1 when the relative speed is non-negative, and 0 otherwise.

The probability density function of the combined car following and unconstrained acceleration for each case $k \in \left\{s, lc, tg\right\}$ is given by:

$$f\left(a_n^{k}\left(t\right) \mid h_n^*, \tau_n, \upsilon_n\right) = f\left(a_n^{cf}\left(t\right) \mid \tau_n\right)^{\delta\left[h_n\left(t-\tau_n\right)\right]} f\left(a_n^{k,uc}\left(t\right) \mid \tau_n\right)^{\left(1-\delta\left[h_n\left(t-\tau_n\right)\right]\right)} \tag{20}$$

$\delta\left[h_n\left(t-\tau_n\right)\right]$ is the time headway indicator:

$$\delta\left[h_n\left(t-\tau_n\right)\right] = \begin{cases} 1 & if\ h_n\left(t-\tau_n\right) \le h_n^* \\ 0 & otherwise \end{cases} \tag{21}$$

<u>Time headway threshold distribution</u>

The time headway threshold determines the driving regime. If the leader time headway is less than the threshold, the driver is in the car following regime, otherwise the appropriate unconstrained regime applies. Following Ahmed (1999) we assume that the distribution of time headway thresholds in the driver population follows a double-truncated normal distribution. The truncation is needed since the time headway threshold must be positive and is finite. The probability density function of the time headway threshold is given by:

$$f\left(h^*\right)=\begin{cases}\dfrac{\frac{1}{\sigma_h}\phi\left(\frac{h^*-\mu_h}{\sigma_h}\right)}{\Phi\left(\frac{h^*_{max}-\mu_h}{\sigma_h}\right)-\Phi\left(\frac{h^*_{min}-\mu_h}{\sigma_h}\right)} & if\ h^*_{min}\le h^*\le h^*_{max} \\ 0 & otherwise\end{cases} \tag{22}$$

h^* is the time headway threshold. h^*_{min} and h^*_{max} are the minimum and maximum values of the threshold, respectively. μ_h and σ_h are the mean and standard deviation of the un-truncated distribution, respectively. $\phi(\cdot)$ and $\Phi(\cdot)$ are the probability density function and the cumulative density function of a standard normal random variable, respectively.

The probability that driver *n* is car following the leader at time *t* is given by:

$$p\left(cf_n\left(t\right)\right)=p\left(h_n\left(t\right)\le h^*_n\right)=\begin{cases}1 & if\ h_n\left(t\right)\le h^*_{min} \\ 1-\dfrac{\Phi\left(\frac{h_n(t)-\mu_h}{\sigma_h}\right)-\Phi\left(\frac{h^*_{min}-\mu_h}{\sigma_h}\right)}{\Phi\left(\frac{h^*_{max}-\mu_h}{\sigma_h}\right)-\Phi\left(\frac{h^*_{min}-\mu_h}{\sigma_h}\right)} & if\ h^*_{min}\le h_n\left(t\right)\le h^*_{max} \\ 0 & otherwise\end{cases} \tag{23}$$

<u>Reaction time distribution</u>

The reaction time captures the time delay from the appearance of the stimulus to the application of the response due to perception time, foot movement time and vehicle response time. The truncated lognormal probability function, which is widely accepted to describe the distribution of reaction times in the population (Koppa 1997), is adopted here:

$$f\left(\tau_n\right)=\begin{cases}\dfrac{\frac{1}{\sigma_\tau \tau_n}\phi\left(\frac{ln\left(\tau_n\right)-\mu_\tau}{\sigma_\tau}\right)}{\Phi\left(\frac{ln\left(\tau_{max}\right)-\mu_\tau}{\sigma_\tau}\right)} & if\ 0<\tau\leq\tau_{max} \\ 0 & otherwise\end{cases} \tag{24}$$

τ_n is the reaction time. μ_τ and σ_τ are the mean and standard deviation of the distribution of $ln\left(\tau\right)$, respectively. τ_{max} is the maximum value of the reaction time.

4 Case Studies

The parameters of the integrated driving behavior model were estimated using a set of detailed trajectory data that were collected in Arlington VA. The estimation results are reported in detail in Toledo (2003). For completeness, Table 1 presents final likelihood values and the number of parameters for the integrated model and for a combination of independent lane changing and acceleration models. The independent models differ from the integrated model in the following:

- Acceleration and lane changing behaviors are modeled independently. Thus, the effect of lane changing on acceleration behaviors is not modeled. The target gap choice and acceleration behaviors to facilitate lane changing are excluded from the independent models. Correlations between the various decisions drivers make are captured within each one of the independent models by the unobserved driver/vehicle characteristics, reaction times and headway thresholds, but correlations between lane changing and acceleration decisions are not captured.

- The independent lane changing model considers MLC and DLC separately and therefore does not capture trade-offs between mandatory and discretionary considerations.
- The conditions that trigger an MLC were not estimated previously. The model used in this research assumes that the probability of being in an MLC state depends only on the distance from the relevant off-ramp.

The models cannot be considered nested and so likelihood ratio tests for model selection are not applicable. Instead, Akiake (1974) proposed the use of the Akaike information criterion (AIC), which penalizes the maximum likelihood value of each model to account for model complexity:

$$AIC = -2L\left(\beta^*\right) + 2K \tag{25}$$

$L(\beta^*)$ is the maximum log-likelihood value. K is the number of estimated parameters.

In model selection, the model with the smallest AIC is selected. In this case, there is a difference of 60.8 points between the models that recommends the integrated model over the independent ones.

<<<< place Table 1 about here >>>>

The estimated model was implemented within the framework of the microscopic traffic simulator MITSIMLab (Yang and Koutsopoulos 1996, Yang et al. 2000). The ability of the simulator with the integrated model to replicate observed traffic patterns was tested and compared against another version of the simulator that incorporates the combination of independent lane changing and acceleration models. In both cases the parameter values that were estimated with the same trajectory data were used. Two case studies were studied: a road section in Arlington VA (that was also used for estimation of the models) and a freeway corridor in Southampton, UK.

The goodness-of-fit measures that were used are the root mean square error (RMSE), root mean square percent error (RMSPE), and Theil's inequality coefficient (U) which quantify the overall error of the simulator; the mean error (ME) and mean percent error (MPE), which indicate the existence of systematic under- or over-prediction in the simulated measurements (Pindyck and Rubinfeld 1997):

$$RMSPE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left[\frac{Y_n^s - Y_n^o}{Y_n^o}\right]^2} \tag{26}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(Y_n^s - Y_n^o\right)^2} \tag{27}$$

$$MPE = \frac{1}{N}\sum_{n=1}^{N}\left[\frac{Y_n^s - Y_n^o}{Y_n^o}\right] \tag{28}$$

$$ME = \frac{1}{N}\sum_{n=1}^{N}\left(Y_n^s - Y_n^o\right) \tag{29}$$

$$U = \frac{\sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(Y_n^s - Y_n^o\right)^2}}{\sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(Y_n^s\right)^2} + \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(Y_n^o\right)^2}} \tag{30}$$

Y_n^o and Y_n^s are the n^{th} observed and simulated measurements, respectively. The simulation results are averages of the simulation replications. In both case studies 10 replication were made, which were sufficient to estimate the mean simulation outcome with an error that is less than 1%.

4.1 Arlington, VA case study

The two MITSIMLab versions were applied to the freeway corridor shown in Figure 6. This four-lane highway section is 1 kilometer long with two off-ramps and a single on-ramp. Detailed trajectory data were collected in this section over a period of 1 hour in which the average traffic density was 31.4 veh/km/lane and the average speed 15.6 m/sec (FHWA 1985). These statistics correspond to level of service D-E. The availability of vehicle trajectories enabled us to setup the simulation such that simulated vehicles would enter the simulation network at the exact times they appeared in the real system and in the correct lanes. The two models are compared based on two statistics: the travel times of 7608 vehicles traveling through the section and the distribution of these vehicles among the four lanes at the four locations shown in Figure 6.

<<<< place Figure 6 about here >>>>

Table 2 summarizes the goodness of fit statistics for travel times. The table also shows the percent improvement in fit with the integrated model compared to the independent models. The integrated model shows a better fit to observed data compared to the independent models. The travel times comparison indicates that the MITSIMLab version with independent models shows more congestion relative to the integrated driving behavior model and to the observed data. This explains the larger bias in travel times, which is captured by the ME and MPE statistics: 4.8 sec. and 9.5% against 0.9 sec. and 3.2%.

<<<< place Table 2 about here >>>>

Table 3 summarizes the comparison between the two models relative the distributions of flows among the four lanes. The integrated model outperforms the independent models in all the goodness of fit measures calculated for the lane distributions. Since the total fraction of vehicles in all four lanes is equal to 1 at each location, the ME statistic is by definition equal to zero and therefore omitted. Figure 7 illustrates the actual lane distributions.

<<<< place Table 3 about here >>>>

<<<< place Figure 7 about here >>>>

Both models, but especially the independent models, overestimate the usage of the right-most lane and underestimate the usage of the two left-most lanes. This may suggest that the tendency of vehicles that are not using any of the off-ramps to move to the left is stronger than captured in the models. This behavior is most evident at location 4. Some of the error at this location may be explained by the lack of information about downstream effects on the behavior of vehicles that enter the network from the on-ramp: in the simulation, these vehicles ignore any considerations downstream of the network boundary (e.g. downstream speeds and densities) and therefore have no incentive to change lanes.

4.2 Southampton, UK case study

This freeway corridor is shown in Figure 8. The section is a 4.3 kilometer long, three-lane freeway that includes two on-ramps and an off-ramp. Both on-ramps are two-lane, but with different geometric layout. In the upstream ramp, the two ramp lanes merge into a single lane, which then merges into the mainline. In the other ramp the left ramp lane merges into the freeway while the right one remains as an additional lane, physically separated from the mainline, for another 500 meters and only then merges into the freeway. The two on-ramps are controlled by ramp metering with the control logic implemented in the simulation model.

<<<< place Figure 8 about here >>>>

Traffic data for that network was available for the four sensor locations indicated by the numbers 1-4 in Figure 8 and for the two on-ramps. The sensors recorded traffic counts and speeds on multiple days. The validation focused on the 7:00-9:00 AM peak period.

Light traffic was observed at the beginning and end of the simulation period with congested traffic within the AM peak. While traffic counts were used in estimating OD flows at 15-minute intervals for the network, sensor speeds were not used in calibrating the two models and so facilitate an independent validation.

Goodness-of-fit statistics for the traffic speeds are presented in Table 4. These statistics are based on 15-mniutes average speeds at the 4 sensor locations. The integrated model performed consistently better than the independent models. Goodness of fit measures expressing the total error (RMSE and RMSPE) of the integrated model are around 14% lower than the corresponding statistics for the independent models. The measures related to bias in the models (ME and MPE) are more than 40% lower for the integrated model compared with the independent models.

<<<< place Table 4 about here >>>>

Observed and simulated time-dependent travel speeds at the four sensor locations are shown in Figure 9. At all sensor locations, congestion build-up in the first four time intervals occurs faster with the independent models relative to the integrated model. As a result, simulated speeds are significantly lower with the independent models. In general, both models underestimate observed speeds at this stage. In the observed data, high speeds are maintained longer but the reduction in speed is steeper once capacity is reached.

<<<< place Figure 9 about here >>>>

A similar effect is observed in the dissipation stage: simulated traffic takes longer to recover speed. This effect is again more pronounced with the independent models relative to the integrated model. Hence, the independent models exhibit more gradual changes in traffic speeds compared to the integrated model and the observed data. A possible explanation is that drivers are able to adjust their behavior to avoid speed loss when congestion build up and dissipates. The integrated model captures some of these effects through short-term planning and acceleration to facilitate lane changing. However, these behaviors are not captured with the independent behavior models. It should be noted that in the furthest downstream location (location 4), both models fail to capture the dynamics of the observed speed profile. This may be a result of downstream phenomena beyond the limit of the network. However, this sensor is 1.9 kilometers downstream of the nearest upstream sensor (location 3) and therefore it is reasonable to assume that the other measurements are not affected by the downstream boundary conditions.

5 Conclusion

This paper presents a framework for integrated driving behavior modeling, which is based on the concepts of short-term goal and short-term plan. Drivers are assumed to conceive short-term plans to accomplish short-term goals. The short-term goal is defined by a target lane, which is the lane the driver perceives as best to be in. A target gap, which the driver intends to use to change lanes, defines the short-term plan. The acceleration the driver applies is adapted to facilitate the short-term plan. This modeling framework supports specification and estimation of models that capture inter-dependencies between lane changing and acceleration and represent drivers' planning capabilities.

We discuss several mechanisms that may be used to capture inter-dependencies among the various decisions. Decisions made at lower levels of the decision process are conditional on those made at higher levels (e.g. the acceleration behavior is conditional on the short-term plan). The expected maximum utilities (*EMU*) of lower level choices may be introduced in the specification of higher-level choices in order to capture the effects of the lower level on higher level decisions. Individual-specific latent variables are introduced in the various component models to capture correlations among the decisions made by a given driver that are due to unobserved characteristics of the driver and the vehicle.

The lane-changing component of this model integrates MLC and DLC into a single model, thus capturing trade-offs between mandatory and discretionary considerations. Drivers that target lane changing evaluate the available adjacent gap in the target lane to decide whether they can immediately change lanes or not. The gap acceptance model requires that both the lead gap and the lag gap are acceptable. If the adjacent gap is rejected the driver chooses a short-term plan to accomplish the desired lane change by selecting a target gap from the available gaps in the target lane traffic.

Different acceleration behaviors apply depending on the driver's short-term goal and short-term plan: stay-in-the-lane acceleration, lane changing acceleration and target gap accelerations. In each of these situations, drivers are assumed to be either in a car-following regime, which applies when the driver is close to the vehicle in front or in an unconstrained regime. The stimulus-sensitivity framework is adapted for all these acceleration models, but the driver reacts to different stimuli in each case. Reaction time and time headway thresholds are explicitly modeled in the acceleration model. New models that capture Drivers' acceleration behaviors to facilitate lane changing using the target gap are presented. These accelerations assume that drivers try to position their vehicles relative to the target gap such that they can accept this gap.

The results of the case studies support the need for integration and situation-specific acceleration models. The integrated driving behavior model was validated and compared against a combination of independent lane changing and acceleration models using a microscopic traffic simulator. Overall, the integrated model performed better than the independent models in both case studies. Congestion build-up was generally faster with the independent models relative to the integrated model and the real-world observations. Similarly, dissipation of congestion was slowest with the independent models and fastest in the observed data. However, there were some time-space points in which the integrated model did not replicate reality better. This suggests that further work may be needed to improve the detailed specification of the various component models.

These improvements come at the cost of increased complexity of the model, which also increases the computational effort required to calibrate the model. However, it should be pointed out that the calibration of the integrated model requires similar type of data as the individual calibration of the independent models. In practice, a two-stage calibration approach proposed in Toledo et al. (2004) may be used: First, the parameters of the behavioral models, such as those presented here, are estimated using detailed disaggregate data. Ideally, this is done by the simulation developers. Then, for a given application, readily available aggregate data, such as sensor measurements, are used to calibrate only a small subset of key model parameters to capture specific characteristics of the network being studied. This approach significantly reduces the effort to calibrate the model by practitioners. However, it assumes that the estimated model parameters remain stable when transferred across time and space. The question of transferability is left for future research where trajectory data sets from additional locations could be used to re-estimate the model parameters. This may also help identify simplifications and adjustments to the model that would maintain its behavioral realism and improve its computational performance.

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Key Words: Driving behavior, lane changing, acceleration, traffic simulation

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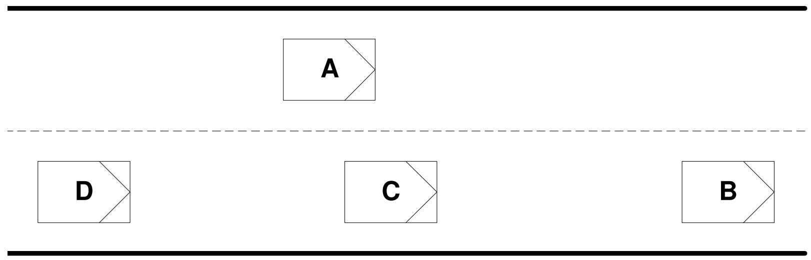

Figure 1 A lane changing situation illustrating the limitations of existing models

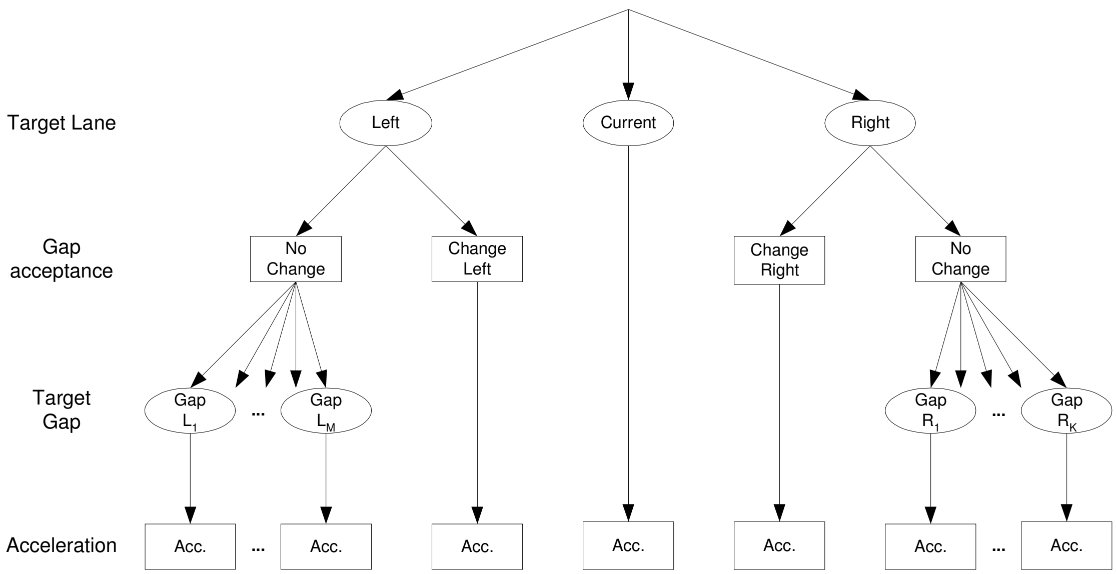

Figure 2 Structure of the integrated driving behavior model

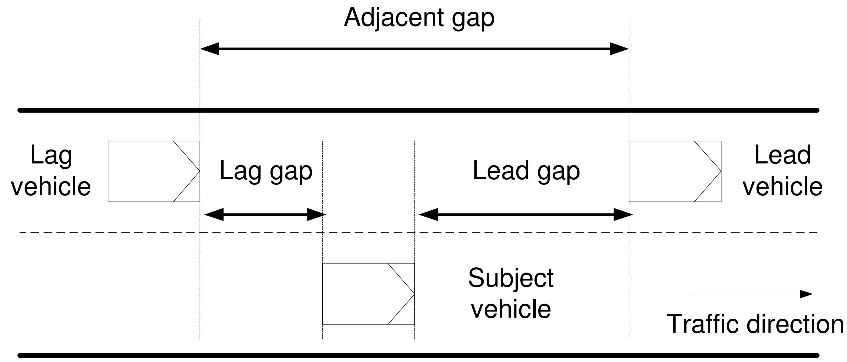

Figure 3 The adjacent gap, subject, lead and lag vehicles and the lead and lag gaps

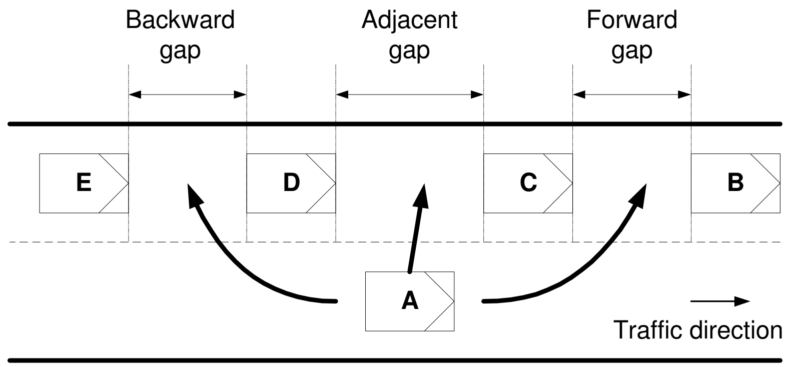

Figure 4 The target gap choice set: adjacent, forward and backward gaps

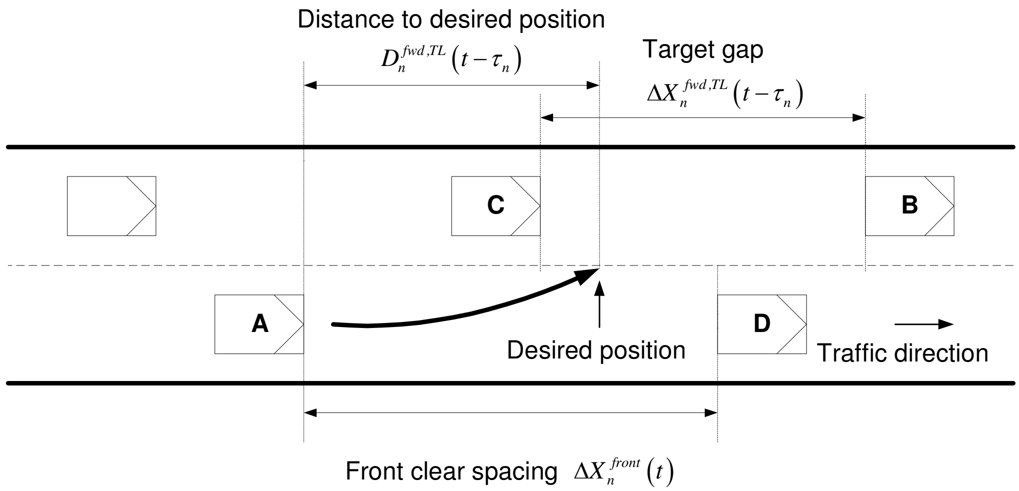

Figure 5 Target gap acceleration situation and variables

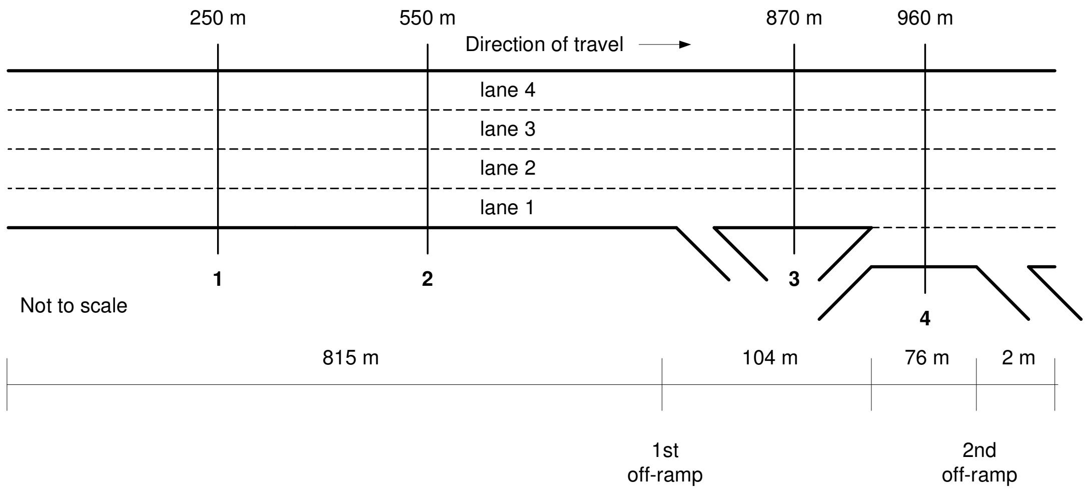

Figure 6 The Arlington, VA case study network

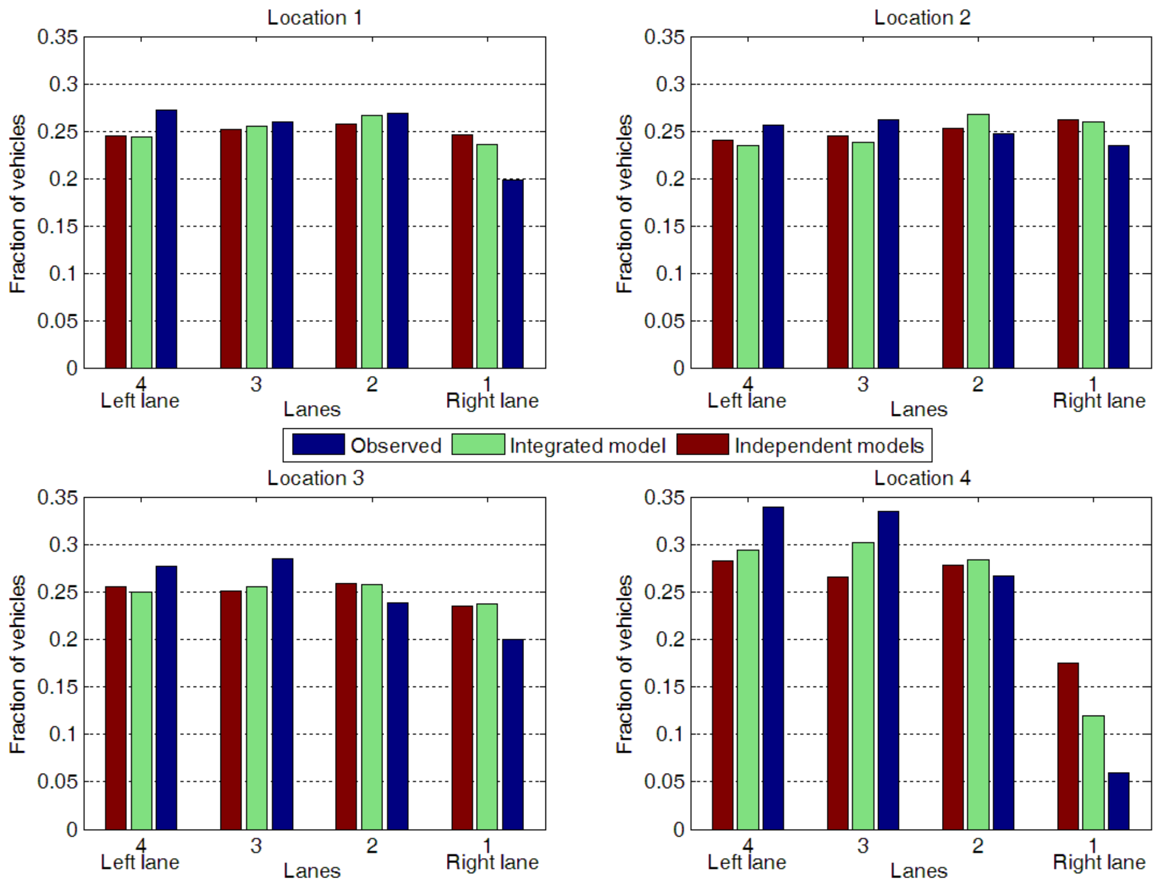

Figure 7 Lane distributions in the Arlington, VA case study network

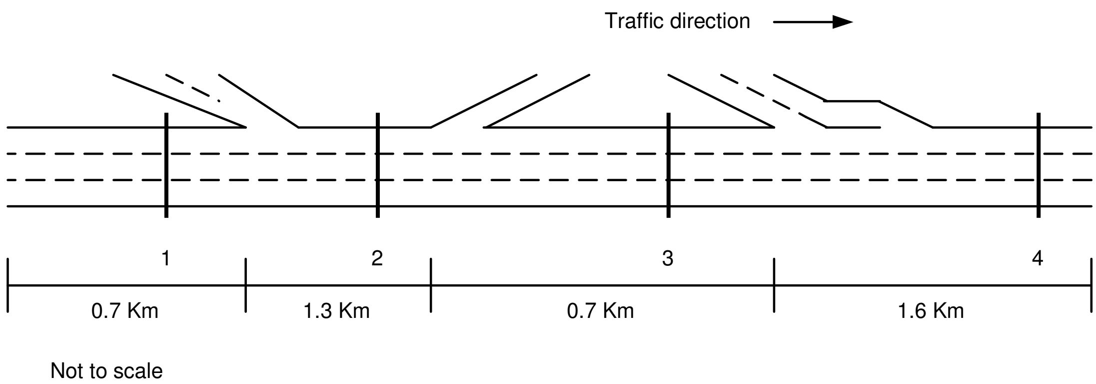

Figure 8 The Southampton, UK case study network

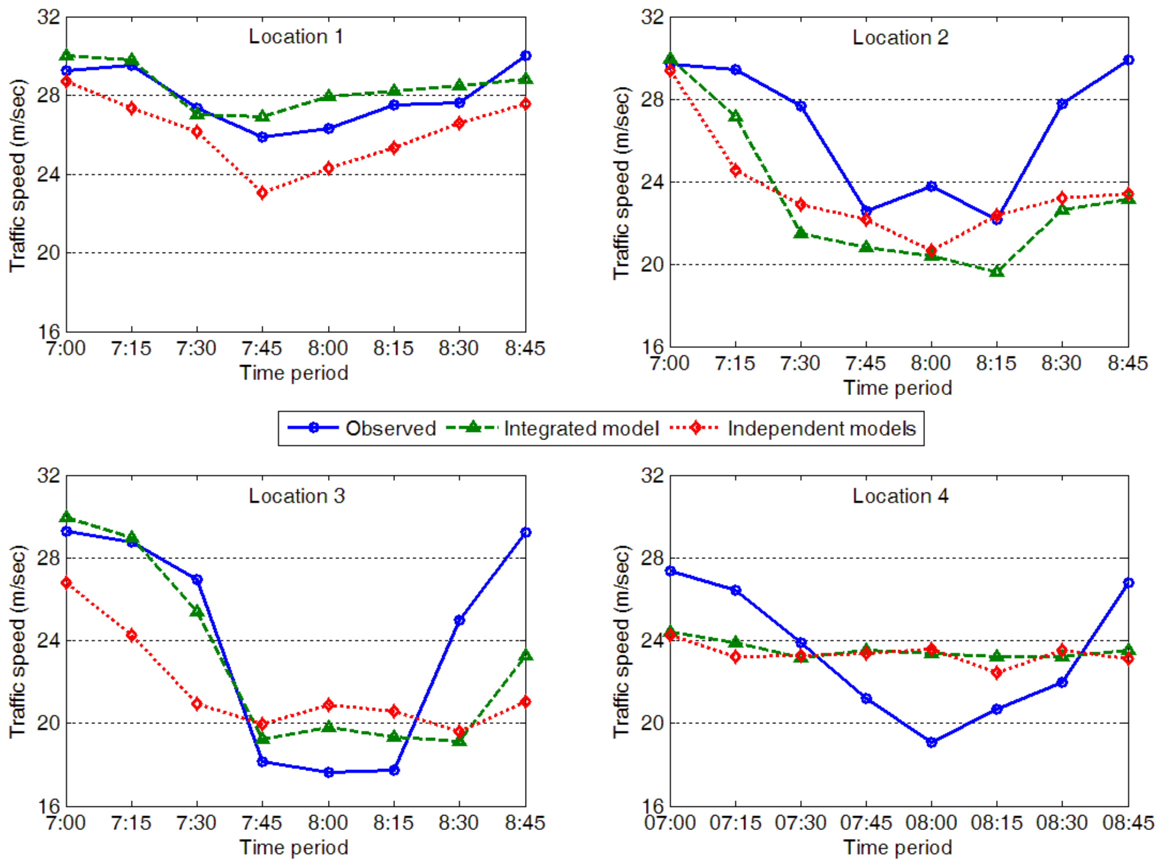

Figure 9 Time dependent traffic speeds in the Southampton, UK network

Table 1 Likelihood values of the estimated models

Model	**Likelihood value**	**Parameters**	**AIC**
Integrated driving behavior	-25469.7	71	51081.4
Independent lane changing and acceleration	-25524.1	47	51142.2

Table 2 Statistics for the travel time comparison in the Arlington, VA network

Statistic	**Integrated model**	**Independent models**	**Improvement (%)**
RMSPE (%)	15.3	20.2	24.2
RMSE (sec.)	9.4	11.7	19.7
MPE (%)	3.2	9.5	66.3
ME (sec.)	0.9	4.8	81.3
U (fraction)	0.075	0.091	17.6

Table 3 Statistics for the lane distribution comparison in the Arlington, VA network

Statistic	**Integrated model**	**Independent models**	**Improvement (%)**
RMSPE (%)	10.8	11.2	3.6
RMSE (%)	3.0	28.6	19.7
MPE (%)	9.0	9.3	3.2
U (fraction)	0.059	0.091	35.2

Table 4 Statistics for the traffic speed comparison in the Southampton, UK network

Statistic	**Integrated model**	**Independent models**	**Improvement (%)**
RMSPE (%)	11.7	13.6	14.0
RMSE (m/sec.)	3.0	3.5	14.3
MPE (%)	-2.9	-5.6	48.2
ME (m/sec.)	-1.0	-1.8	44.4
U (fraction)	0.059	0.071	16.9