A LANE-CHANGING MODEL FOR URBAN ARTERIAL STREETS

By

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To my Mom

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A LANE-CHANGING MODEL FOR URBAN ARTERIAL STREETS

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As one of the most fundamental components in microscopic traffic simulation, lane-changing affects the distribution of vehicles across lanes and contributes to traffic movements. In recent years, the topic of lane-changing has become of increased importance in traffic engineering and safety research. Previous lane-changing models divided the behavior as either mandatory (MLC) or discretionary (DLC) based on the purpose of the maneuver. Generally, MLC occurs when drivers have to change lanes in order to keep the right route. DLC refers to cases in which drivers change lanes to acquire driving benefit, such as overtaking slow vehicles, bypassing a heavy vehicle, avoiding the traffic toward an off-ramp, and so on. It is well accepted that driver characteristics (such as level of aggressiveness, alertness) have large impact on various aspects of both maneuvers (MLC and DLC), such as the level of acceptance on a particular DLC, minimum or maximum acceleration/deceleration adopted, etc. However, the existing models have not incorporated the driver characteristics with much detail.

This thesis contributes to the development of lane-changing models for urban arterials in microscopic traffic simulation. It enhances existing models and develops new ones as appropriate. In this research, the effect of driver characteristics was incorporated in modeling both the acceptance of various DLC reasons and the gap acceptance procedure within lane-

changing maneuvers. To accomplish this, a focus group study was first carried out to capture behavior differences among drivers. Next, an "in-vehicle" field data collection was performed to investigate the effect of driver type on specific MLC and DLC scenarios, and collected microscopic data from the corresponding lane-changing maneuvers. With the field collected values, a comprehensive model was developed to handle the probability of changing lanes under each proposed DLC reason and the gap acceptance procedures. The lane-changing probability for each DLC scenario was modeled as a function of corresponding important factors (obtained from focus group) and driver types. In gap acceptance modeling, the "hand-shaking negotiation" concept (from the TCP/IP protocols in computer network communications) was introduced to describe the vehicle interactions during lane-changing maneuvers under congested traffic flow.

The proposed lane-changing model was developed and implemented in a microscopic traffic simulator, CORSIM. Traffic data were collected along a congested arterial in the City of Gainesville, FL, and used for model calibration and validation purposes. Simulation capabilities of the newly developed model were compared against the original lane-changing model in CORSIM. The results indicate that the new model better replicates the observed traffic under different levels of congestion.

CHAPTER 1
INTRODUCTION

1.1 The Problem Statement

During last several decades, a large amount of work has been done to formulate models of traffic flow and build traffic simulation applications (Chandler et al., 1958; Herman and Rothery, 1969; Gipps, 1981, 1986; Barcelo et al., 1996; Yang and Koutsopoulos, 1996; Zhang et al., 1998; Hidas, 2002, 2005; Liu et al., 2006). Car-following and lane-changing are two most fundamental components in microscopic traffic simulation. Car-following models deal with the time and space relationships of two consecutive vehicles in the same lane, and control the motion of the lag car (Pipes, 1953; Newell, 1961; Gazis et al., 1961). Lane-changing affects the distribution of vehicles across lanes (Rorbech, 1976; Brackstone et al., 1998). Compared to car-following models, in which the behavior of the lead vehicle is relatively unaffected by the lag one, the lane-changing process depends on many parameters, and hence it is more complex.

Generally, a lane-changing process is modeled as a sequence of four decision-making steps, as shown in Figure 1-1. Step 1 considers whether a lane-changing is necessary and whether the potential lane-changing reasons are accepted by the subject driver. Next, the target lane is determined for the lane-changing maneuver in Step 2. Step 3 checks the lead and lag gaps in the target lane, so that an appropriate lane change is chosen or rejected accordingly. In the last step, an acceleration or deceleration is adopted to move the subject vehicle to the target lane. Each of these steps is formulated with the corresponding field-collected or simulated data from interested transportation facilities, respectively.

Many previous studies have focused on lane-changing behavior along freeways (Ahmed 1996; Laval and Daganzo 2006), in which reasons invoking lane-changing are typically to gain speed advantage. Other research investigates the lane-changing behavior on freeway on-ramp

merging area (Kita, 1999; Kita et al., 2002; Choudhury, 2005). For this case, drivers would recognize the necessity of performing a mandatory lane change as they arrive at the merging point.

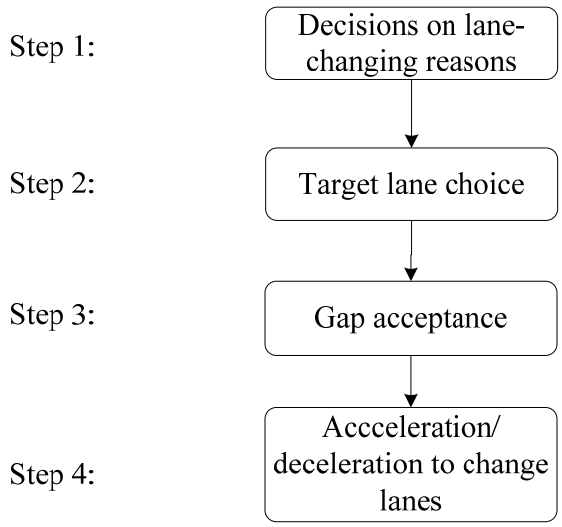


Figure 1-1. Four steps involved in a general lane-changing maneuver

Despite the great significance, lane-changing behaviors, especially those occurring in urban arterials, have not been studied as extensively as car-following behavior. Limited research has been reported regarding lane changes on urban arterials, where the possible lane-changing instances are numerous (Hidas, 2005; Ben-Akiva et al., 2006). Only a few researchers have tried to address important issues of the congested conditions in urban streets' lane-changing maneuvers (Gipps, 1986; Yang and Koutsopoulos, 1996; Wei et al., 2000; Hidas, 2002). Even these models have ignored some complex factors within the lane-changing maneuver, such as the high level of interactions among vehicles and the driver behavior variability involved. Consequently, research documenting drivers' thinking process, as well as support for the assumptions used in existing models, is scarce. One major reason for this is the scarcity of reliable data (Brackstone and McDonald, 1996; Hidas and Wagner, 2004). Data required to develop lane-changing models include the position, speed, acceleration, and length of a subject

vehicle and the vehicles ahead of and behind the subject vehicle in the current lane as well as in the adjacent lanes. In addition, site-specific factors, such as speed limit of the segment and road geometry, also affect lane-changing behaviors. Data collected from cross-sectional detectors are not sufficient to report lane-changing procedures. In the recent ten years, with wide use of video devices in urban traffic areas and the existence of video tracking applications, traffic engineers can collect high quality vehicle trajectory data (Hoogendoorn et al., 2003), which are used to obtain detailed lane-changing maneuvers.

In this thesis, a comprehensive framework for modeling drivers' lane-changing behavior on urban arterials is presented. Emphases are placed on the lane-changing reasons (Step 1 in Figure 1-1) and gap acceptance (Step 3 in Figure 1-1), in which any possible conditions may affect the driver's final decision. One major objective of this thesis is to model the drivers' lane-changing behavior under congested traffic in microscopic perspective. Special attention is placed on the effects of driver characteristics on the lane-changing maneuvers.

1.2 Research Objectives

The objective of this thesis is to develop a comprehensive model for drivers' lane-changing behavior on urban arterials. The model incorporated both non-congested and congested conditions with special attention given to the impact of driver characteristics on lane-changing behavior. More specifically, the three sub-objectives of this research are:

1.2.1 Evaluate the Impact of Driver Characteristics on Urban Lane-Changing Maneuvers

As one category of the ubiquitous and important factors in lane-changing behavior, driver characteristics (level of aggressiveness, alertness, etc) are captured by two well-designed experiments, focus group study and "in-vehicle" data collection, conducted in this thesis research. Factors obtained from the focus groups include both driver behavioral parameters and environmental parameters that affect lane changes. An effective classification is then developed

to categorize participating drivers into different types based on the quantitative results and qualitative verbal expression conclusions from the focus group study. Thus, various drivers can be invited to drive an instrumented vehicle, so that field data are collected for testing and validating the effect of driver type on specific lane-changing actions.

1.2.2 Develop a Probabilistic Model for Each of DLC Reasons

Most existing models assume the decision of change lanes under each DLC scenario is deterministic (Gipps, 1986; Wei et al., 2000; Hidas, 2002, 2005), which means that the DLC reasons are always accepted when the given conditions are satisfied. However, the real situation is probabilistic and stochastic, since the decision depends on many interdependent factors. With the driver behavior information and quantitative data collected under each lane-changing scenario, a probabilistic model can be developed for each of the invoking DLC scenarios, in which the probability of changing lanes can be formulated as a function of surrounding traffic states and driver characteristics. The modeling coefficients can be estimated from the "in-vehicle" field lane-changing data, and then be calibrated with the additional source of field datasets.

1.2.3 Develop a Gap Acceptance Model for Different Lane-Changing Modes

Drivers tend to behave differently and accept different gap criteria under urban traffic conditions. In this thesis, three types of lane-changing modes: free, cooperative/competitive and forced, are defined, so that different gap acceptance procedures can be developed for each. The "hand-shaking negotiation" concept (Stevens, 1990, 1998) are adopted to describe "communication" between vehicles during lane-changing maneuvers under congested traffic flow, through which interactions among the merging vehicle and the lag vehicles on the target lane are captured. In this framework, each vehicle is modeled as an intelligent agent: a reactive, autonomous, internally-motivated entity that inhabits a dynamic, not fully predictable traffic

environment (Weiss, 1999). Each agent can send a lane-changing "request" signal (turning signal) to one or multiple agent(s), and then the receiver(s) evaluate the request and respond accordingly. A detailed procedure of interaction is modeled based on the field observations, and the studies are described in subsequent chapters of this thesis.

The components described above were developed and integrated into a comprehensive lane-changing model. As one of the highlights, driver characteristics affect not only the decision of lane-changing reasons but also the gap acceptance procedure, which correspond closely to the Step 1 and Step 3 in Figure 1-1. The other two steps of the lane-changing maneuver, Step 2 and Step 4, are not within the emphases of this research.

1.3 Thesis Outline

The remainder of this thesis is organized in seven chapters. In Chapter 2, a literature review on existing microscopic lane-changing models is presented. Chapter 3 discusses the methodology for developing the lane-changing model in this thesis. Chapter 4 and Chapter 5 present the detailed procedures of the two experiments, focus group study and "in-vehicle" data collection, for obtaining the lane-changing related behavior data, along with the analysis of results. Development procedures for the scenario-based lane-changing probability model and the gap acceptance model are presented in Chapter 6. In Chapter 7, the two components are implemented and integrated into the lane-changing model within a microscopic traffic simulator, CORSIM. Various comparisons of the newly developed model against CORSIM original model are provided, in terms of goodness-of-fit of model estimation and simulation capabilities. Finally, conclusions and directions for further research are summarized in Chapter 8.

CHAPTER 2
LITERATURE REVIEW

In this chapter, a literature review of lane-changing models is presented. Traditional rule-based lane-changing models, which are widely used in the existing micro-simulators, are discussed in Section 2.1. Section 2.2 reviews discrete choice based lane-changing models. Such a method is used in the Next Generation Simulation (NGSIM) research (Ben-Akiva et al., 2006). Section 2.3 presents other extensively researched microscopic lane-changing models. Findings from the literature review are summarized in Section 2.4, followed by recommendations on a general lane-changing framework for micro-simulation provided at the end of the chapter.

2.1 Rule-Based Microscopic Lane-Changing Models

Since the early 1980s, the subject of lane-changing has received increased attention because of the technological progress on reliable data collection (Brackstone and McDonald, 1999). Several realistic rule-based lane-changing algorithms have been developed. These algorithms have the ability to replicate drivers' actions at the microscopic level, and therefore can be incorporated to model lane-changing behavior in micro-simulators. Additionally, the rule-based models can be calibrated using basic assumptions about driver behavior, and can be verified using field data. Consequently, they have been widely used in commercial and research packages, such as MULTSIM (Gipps and Wilson, 1980; Gipps, 1986), MITSIM (Yang and Koutsopoulos, 1996; Yang et al., 2000), AimSUN2 (Barcelo et al., 1996) and CORSIM (Halati et al., 1997). In this section, three types of rule-based lane-changing algorithms (Gipps' model, Wei's heuristic model and Hidas' multi-agent model) are discussed in detail. Other rule-based lane-changing models are reviewed briefly since no many details are available. Applications of rule-based lane-changing model in several well known commercial micro-simulators are presented at the end of the section.

2.1.1 Gipps' Lane-Changing Model

Gipps' model (Gipps, 1986) is the first rule-based model that is well documented, and widely adopted in commercially available models. By connecting lane-changing decisions to urban driving situations, Gipps' model incorporates the most important factors, such as existence of safety gap, location of permanent obstructions, intent of turning movement, presence of heavy vehicles and speed advantage. Based on the judgment on these criteria, the subject drivers decide whether to move to the target lane or not. The lane-changing reasons provided in Gipps' model are as follows:

- Avoiding permanent obstructions;
- Avoiding the presence of special purpose lanes such as transit lanes;
- Turning at the downstream intersection;
- Avoiding a heavy vehicle's influence; and
- Gaining speed advantage.

Gipps' car-following formula (Gipps, 1981) was adopted to calculate suitable gaps between the subject vehicle and the lead/lag vehicle(s), as well as the deceleration/acceleration required. The formula assumes that the driver of the following vehicle selects his/her speed to ensure he/she can bring the vehicle to a safe stop should the vehicle ahead come to a sudden stop. Thus, vehicle deceleration is used to evaluate the feasibility of changing lanes. The subject vehicle is assigned a special braking rate (b_n), from which a maximum deceleration for a given lane-changing maneuver can be obtained. If the deceleration required for a lane change is not within the acceptance range, the lane change for the subject vehicle is determined as not feasible. Gipps' lane-changing model allows drivers to alter the brake rate parameter b_n depending on the urgency of the lane-changing maneuver. The model equation is as follows:

$$b_n = [2 - (D_n - x_n(t))/10V_n]\, b_n^* \tag{2-1}$$

where,

b_n is the special braking rate that a maximum deceleration for a given lane-changing maneuver can be obtained,

$D_n - x_n(t)$ is the distance between the intended maneuver location and the current vehicle location,

V_n is the desired speed (free flow speed) of the driver, and

b_n^* is the most severe braking the driver would be willing to undertake.

The lane-changing process in Gipps' model can be summarized as a decision tree with a series of fixed conditions, wherein situations that may be encountered on the road (urban arterials) were considered. Invoking of lane changing is a rule-based triggered event, and the final output is a binary choice (change/not change). The overall structure is flexible, and any new or special reasons for lane-changing can be added or replaced. However, this model does not consider the variability in individual driver behavior, especially the different interaction strategies among the subject vehicle and the surrounding vehicles under various traffic conditions. For example, under peak congested traffic, either the lag vehicle in the target lane has to "consent" to the lane change, or the subject vehicle has to force its way into the target lane.

2.1.2 Wei's Heuristic Structured Lane-Changing Model

Based on videotaped observations over eight multi-lane urban streets in Kansas City, Missouri, Wei et al. (2000) derived a heuristic structure for rules of a lane-changing model. In addition to the mandatory lane-changing (MLC) and discretionary lane-changing (DLC), a new type, named preemptive lane-changing (PLC), was defined when a vehicle explores lane-changing to the desirable lane if acceptable gaps are available. The intention is not for an immediate turn, but to proceed through the next intersection and make a turn at the following intersection. It was found that for this long-term lane-changing motivation, drivers accept different gap criteria (Wei et al., 2000). The heuristic structure of the model is presented in Figure 2-1. First, a lane change is categorized as MLC, PLC or DLC according to the maneuver

intention and present location of the subject vehicle. Then three types of headways: T_Ld (to the lead vehicle in the target lane), T_Lg (to the lag vehicle in the target lane) and H_T (to the current head vehicle) are compared to the corresponding thresholds (λ_{1MLC} , λ_{1PLC} , …, λ_{3DLC} , which were estimated from field data). If all three headways are larger than the given thresholds, the lane-changing is acceptable and is completed within a given time interval decided by the lane-changing type and the travel speed. Otherwise, the subject vehicle has to wait until the next time step and re-examine the lane-changing type, and a new lane-changing maneuver is then initiated accordingly.

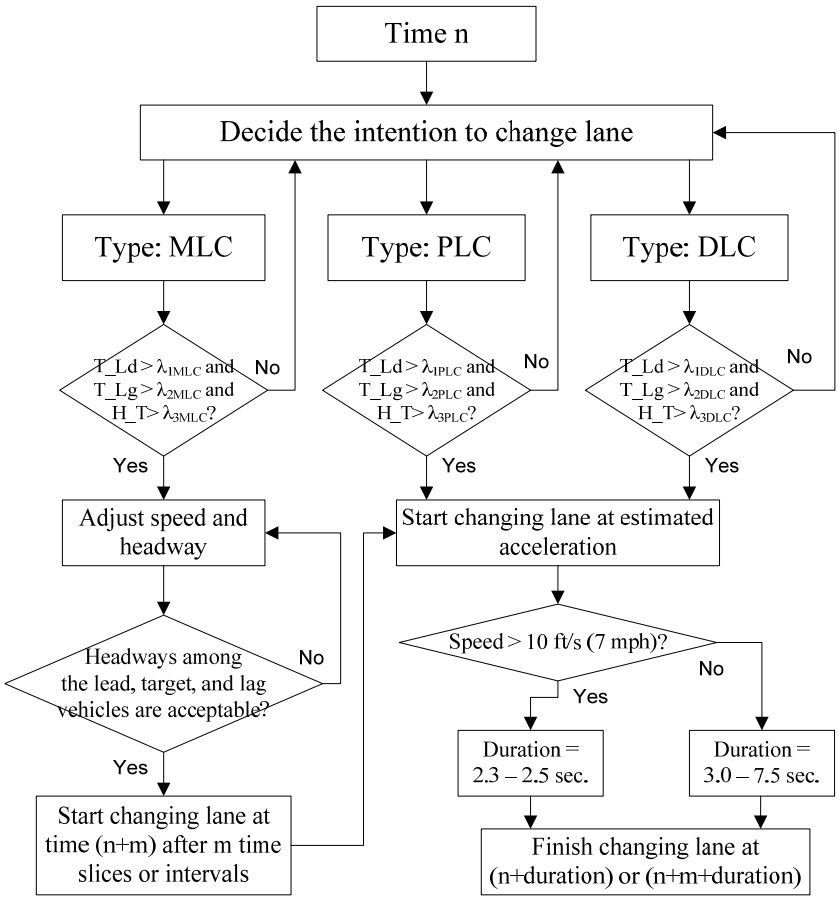


Figure 2-1. Flowchart of the heuristic lane-changing maneuver model (source: Wei et al., 2000)

In this model, for the MLC, additional speed and headway adjustments (m seconds, which may be calibrated from field data) are included after the lane-changing conditions are checked as

acceptable. This is because compared to the DLC and PLC, MLC always takes place within more strict conditions with smaller thresholds, and consequently drivers need to adjust their acceleration or deceleration accordingly. A lane-changing duration is predefined for all maneuvers based on the vehicle speed. If the speed is larger than 7 mph, the time is set as 2.3 – 2.5 seconds. Otherwise, it is between 3.0 and 7.5 seconds, as a function of vehicle position, velocity and acceleration.

This lane-changing model was proposed as an important component in a dynamic lane-assignment on given urban street networks, with which a simulation was developed to represent travel behaviors at lane level. Field-observed trajectory data were used to estimate the thresholds for all types of lane changes. However, this model only addressed the gap acceptance portion of lane-changing modes, and did not consider the reasons for lane-changing. Similar to Gipps' model, Wei's model did not consider interactions and communication among vehicles, and is not able to reflect real lane-changing behavior under congested conditions.

2.1.3 Multi-Agent Lane-Changing Model Used in ARTEMiS

By analyzing the data collected from video-recording, Hidas (2002) found that most urban drivers had to "force" their way into the destination lane during congested conditions, which was not modeled effectively by previous lane-changing algorithms. In ARTEMiS (previously call SITRAS), Hidas (2002) adopted the autonomous agent technique to model drivers' interactions involved in a more complex decision-making process, in which each vehicle was modeled as a driver-vehicle object (DVO). If a DVO perceives that another DVO intends to move into its lane, it may act as giving way, slowing down or not giving way, depending on road congestion conditions and individual driver characteristics. This lane-changing decision process was presented in Figure 2-2. Similar to other rule-based models, the reasons for lane-changing were first evaluated, and the results were classified as "Essential", "Desirable" or "Unnecessary". The

target lane was then selected according to the purpose of lane-changing. Different gap acceptance models were used for different lane-changing modes. The following lane-changing reasons were adopted by Hidas (modified based on Gipps' lane-changing model).

- Turning movement or the end-of-lane,
- Blockage or other obstructions,
- Transit or car pool lane,
- Speed advantage, and
- Queue advantage.

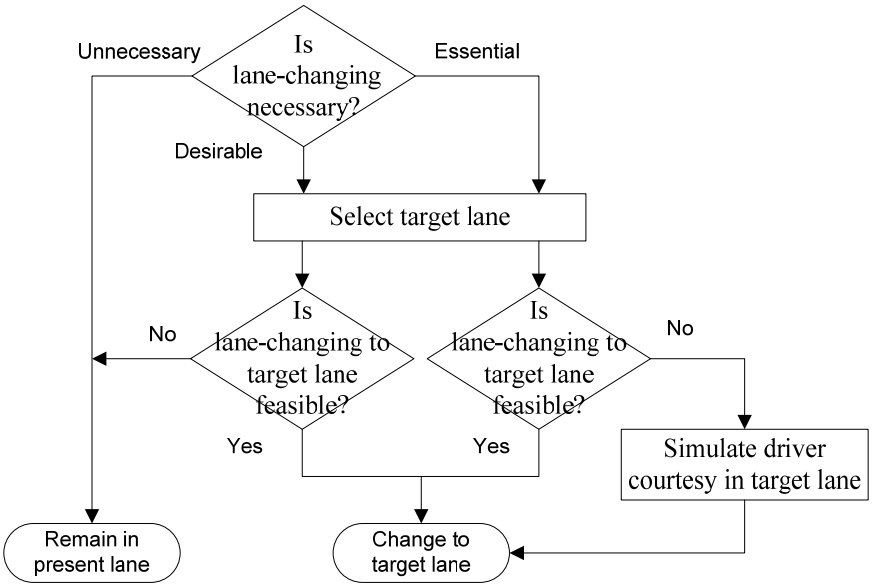


Figure 2-2. Flowchart of the lane-changing process in ARTEMiS (source: Hidas, 2002)

Two lane-changing modes were proposed according to the traffic conditions and the necessity of changing lanes:

Normal lane change: In ARTEMiS, a normal lane change is considered when there is a gap of sufficient size in the target lane so that the subject vehicle can move in without forcing other vehicles in the target lane to slow down significantly. This can be expressed in two conditions as: a) Using the car-following model (Hidas, 1998), the deceleration (or acceleration) required for the subject vehicle to move behind the leader vehicle in target lane is acceptable, and

b) Using the car-following model, the deceleration required for the lag vehicle in target lane to allow the subject vehicle to serve as its leader is acceptable.

The car-following algorithm used in the model is provided as follows:

$$x_{n-1}(t+T) - x_n(t+T) = \varepsilon * D_n(t+T) \tag{2-2}$$

where

$x_i(t)$	is the position of vehicle *i* at time t;
T	is the time interval that the following vehicle (*n*) attempts to reach a desired spacing;
$D_i(t)$	is the desired spacing of vehicle *i* at time t; and
ε	is the driver judgment error parameter.

This equation assumes that when approaching and following a leader vehicle (n-1) at any time t, the driver of the following vehicle (n) attempts to adjust its acceleration so as to reach a desired spacing after a time lag of *T* seconds. The acceleration/deceleration of the following vehicle can be calculated as follows:

$$\begin{aligned} a_n = & \frac{T}{\varepsilon\alpha_n T + 0.5T^2}(v_{n-1} - v_n) \\ & + \frac{1}{\varepsilon\alpha_n T + 0.5T^2}(x_{n-1} - x_n - \varepsilon\alpha_n v_n - \varepsilon\beta_n) + \frac{0.5T^2}{\varepsilon\alpha_n T + 0.5T^2} a_{n-1} \end{aligned} \tag{2-3}$$

where

v_i	is the speed of vehicle *i*; and
α_n and β_n	are the desired spacing constants of the follower vehicle *n*.

Using Eq. (2-2) and Eq. (2-3), the deceleration required for the subject vehicle and the lag vehicle can be calculated. The two decelerations are then compared with the "acceptable deceleration", which is calculated using a modified format originally suggested by Gipps (1986):

$$b_n = [2 - (D - x_n(t))/(10 * V_n)] * b_{LC}\,\theta \tag{2-4}$$

where

b_n	is the acceptable deceleration of vehicle n;
D	is the location of the intended turn or lane blockage;
$x_n(t)$	is the location of vehicle n at time t,
V_n	is the desired (free) speed of vehicle n,
b_{LC}	is the average deceleration a vehicle is willing to accept in lane changing, and

θ is the driver aggressiveness parameter, calculated from the ratio of the subject driver type value to the average driver type value.

Courtesy/forced lane change: The courtesy/forced lane-changing algorithm simulates the subject vehicle sending a "courtesy" signal to the subsequent vehicles in the target lane. Starting from the first lag vehicle, the deceleration required to allow the subject vehicle to merge is calculated by the car-following model as described in Eq. (2-2). An acceptable deceleration b_n is then calculated by Eq. (2-4). Once the new follower is found, the new leader vehicle is the one right in front of the follower. By applying the car-following algorithm to the new leader vehicle, the subject vehicle and new lag vehicle, a gap of sufficient size will be created and the subject vehicle will move into the target lane.

In another more recent paper, Hidas (2005) further classified lane-changing maneuvers into three categories: free, cooperative and forced. The lead and lag gaps are used as the criteria of lane-changing feasibility checking. Based on the status of the three vehicles before changing lanes, the lead and follow gaps at the end of lane-changing were calculated as g_l and g_f. If both gaps are larger than the desired critical gaps ($g_l \geq g_{l,\min}(v_{lead}, v_s)$ and $g_f \geq g_{f,\min}(v_s, v_{lag})$), a free lane-changing is feasible. If this condition is not satisfied and the lane-changing is "essential" for the subject vehicle, cooperative (courtesy) or forced lane-changing needs to be checked. The desired gaps $g_{l,\min}$ and $g_{f,\min}$ are the summation of a constant (minimum safe gap) and a value in direct proportion of speed difference, as follows.

$$g_{l,\min}(v_{lead}, v_s) = g_{\min} + \begin{cases} c_{lead} * (v_s - v_{lead}) & \text{if } v_s > v_{lead} \\ 0 & \text{otherwise} \end{cases} \tag{2-5}$$

and

$$g_{f,\min}(v_s, v_{lag}) = g_{\min} + \begin{cases} c_{lag} * (v_{lag} - v_s) & \text{if } v_{lag} > v_s \\ 0 & \text{otherwise} \end{cases} \tag{2-6}$$

where

$g_{\min}$ is the minimum safe constant,

c_{lead} and c_{lag} are the coefficients for the speed differences, and

v_{lead}, v_{lag} and v_s are the travel speeds for lead, lag and subject vehicles, respectively.

For the cooperative lane-changing, both the willingness of the lag driver and the feasibility of the maneuver need to be checked. A certain maximum speed decrease (D_v) from the lag vehicle is selected to indicate the willingness, which is a function of a vehicle's aggressiveness parameter and the urgency of lane-changing. By setting the deceleration period as $\Delta t = D_v / b_f$, the lag gap at the end of deceleration can be calculated, which is the smallest gap between the subject vehicle and the lag vehicle after changing lanes. If this gap is larger than the minimum acceptable lag gap ($g_f \geq g_{f,\min}$), a cooperative lane-changing is recognized as feasible. The forced lane-changing is similar to the cooperative one, and differs only in that the maximum speed decrease (D_v) and deceleration b_f are assumed by the subject vehicle as average values.

Hidas (2005) validated the model using vehicle trajectories from 73 lane-changing maneuvers in the Sydney CBD, Australia. A total of four hours of video recording was collected from a road section where lane changing or merging maneuvers occurred. The tapes were first viewed and a number of lane-changing maneuvers were identified. Then, each maneuver was analyzed in detail, and the position and speed of each vehicle involved in the maneuver were identified at 0.2 s intervals using frame-by-frame analysis. The criteria parameters for gap acceptance (such as D_v, $g_{\min}$, c_{lead} and c_{lag}) were estimated from the video data and modified in the simulation according to individual driver's aggressiveness. However, it is not clear how the driver aggressiveness was obtained from the data and related to these parameters. A simulation in ARTEMiS was run to test the cooperative and forced lane-changing behavior for a freeway on-ramp situation with gradually increasing input flow rates. The speed and gap curves of both

modes showed similar trends and maneuvers as the field-collected data. A weaving section was also simulated to determine the effect of the lane-changing model on the relationship between average speed and flow rate. Results from multiple runs with and without the cooperative/forced modes showed that the full lane-changing model generated a speed-flow curve consistent with the expected shape, while the model without cooperative/forced modes led to highly congested traffic at much lower flow rates.

In the research, Hidas found that by only using the trajectories from video data, the distinction between forced and cooperative lane changing may be ambiguous. It was concluded by his work that new empirical methods should be designed to collect lane changing related data. Several disadvantages relating to the lane-changing modeling in ARTEMiS were provided as follows:

- The given lane-changing reason set is incomplete. Some reasons, such as giving way to a merging vehicle or to a bus merging from a bus pull-off, or avoiding heavy vehicle influence, were not considered.
- Only the lag vehicle has the ability to initiate a cooperative lane-change. During the simulation, in each time interval, all vehicles regardless of whether they are involved in a lane-changing maneuver are checked with respect to their intention to change lanes. In a situation where a free lane-changing is impossible, if the subject vehicle is checked first, a forced lane change is invoked. Otherwise, if the follower is checked first, it provides courtesy and adopts a cooperative mode. In reality, the interaction between the subject vehicle and the lag vehicle includes two possibilities: cooperation or non-cooperation. The "communication" may last several seconds. Referring to the steps in the TCP communication protocol (3-step handshaking negotiation), interactions between the subject vehicle and the follower can be interpreted as: the subject vehicle first sends a request signal to the lag vehicle. The lag vehicle evaluates the request and decides to decelerate accordingly. Then in the following time interval, the subject vehicle re-evaluates the new gap and speed for the lane change. If the criteria are satisfied, a cooperative lane change is executed. Otherwise, the slowing down of the follower vehicle continues.
- The critical gap values shown in Eq.s (2-5) and (2-6) are the summation of two components: the minimum safe constant gap $g_{\min}$ and a value proportioned to the speed difference. However, in addition to the speed difference, the travel speed also affects the minimum acceptable gaps, and should be considered.

2.1.4 Other Rule-Based Lane-Changing Models

As mentioned at the beginning of this section, the rule-based lane-changing model is widely used in existing micro-simulators. In addition to the three models reviewed in detail, other models have also been proposed and studied. For these models, no detailed implementation information is available, and consequently these algorithms cannot be duplicated. Thus, only briefly discussions are provided in this section.

Zhang et al. (1998) developed a multi-regime traffic simulation model (MRS), in which two types of lane changes, MLC and DLC, are defined similarly to other models. The critical gaps of MLC are randomly distributed with a mean estimated as a function of the remaining distance to the point where the lane change must be completed. Drivers in MLC situations may adjust their acceleration in order to be able to make the exist gaps acceptable. The following cases are considered:

- **No change in acceleration:** The adjacent gap is acceptable.
- **The subject needs to accelerate:** Either the total length of the adjacent gap is sufficient but the lag gap is too small, or the total length of the adjacent gap is unacceptable but the gap ahead of the lead vehicle is acceptable.
- **The subject needs to decelerate:** Either the total length of the adjacent gap is sufficient but the lead gap is too small, or the total length of the adjacent gap is unacceptable but the gap after the lag vehicle is acceptable.

The algorithm was implemented (Visual C++/MFC) using the input and output structure of CORSIM. The .trf files from CORSIM user graphical editor (TRAFED) were used as inputs, and outputs similar to .tsd files were generated for TRAFVU animation. A post-processor was developed to provide additional MOEs. However, compared to CORSIM or other simulators, the simulation functions provided by MRS are very limited. During the model validation, only freeway data were used, with no real-world surface street data. Consequently, the model performance on urban streets, especially for congested traffic is difficult to assess.

The micro-simulator DRACULA (Liu et al., 2006) developed in the University of Leeds, UK, integrated individual drivers' day-to-day route familiarity and route choice models with a traffic micro-simulation model of the car-following and lane-changing behaviors. The lane-changing model within the simulation firstly identifies the lane-changing desire according to a predefined set of rules. Once a lane-changing desire is triggered, a gap-acceptance model is adopted to find the gaps in the target lane. A variational critical gap is modeled to reflect the phenomenon of impatient drivers for whom the critical gap decreases with increasing waiting time. The stimulus required to induce the decrease of critical gap is modeled as the time spent searching for acceptable gaps. A minimum gap is used to set a lower boundary to the gap-reduction formulation. The major functionality of DRACULA is to model individual trip makers' decisions and the vehicle movements across the network. The lane-changing model is relatively simplified because the authors wanted to integrate driver familiarity and route choice into micro-simulation. Two disadvantages are found: first, not all major reasons for lane changing are considered. Second, similar to most of the previous algorithms, the lane-changing model in DRACULA does not incorporate driver characteristics, and no driver interactions are included. Hence, it does not replicate the real-world urban traffic fully and accurately.

Another microscopic traffic simulation and assignment model, INTEGRATION, considers the lane-changing desires as mandatory or discretionary (Rakha and Zhang, 2003). To determine whether a DLC should be made or not, the perceived speeds in the current lane, the left adjacent lane and the right adjacent lane are compared by every second. Passenger cars have priorities to travel toward the middle lanes for roadways with three or more lanes. Trucks are biased toward using the shoulder lane. In situations where a trip destination imposes a constraint on vehicle movement, MLCs are performed to ensure that vehicles maintain appropriate lanes (Prevedouros

and Wang, 1999). Two boundaries were assigned upstream of the diverge point as “softwall” and “hardwall”. The hardwall, located closer to the diver point, indicates the location where subject vehicles are unable to proceed closer to the diverge section on the original lane, and thus must abandon the lane. The softwall defines the location where the driver recognizes the need to change lanes. The mean locations of the softwall/hardwall are at a distance of 100*n/10*n times the distance headway under jam density conditions (n is the minimum number of lane changes required to complete the maneuver). Because the two boundaries (softwall and hardwall) are used, the model is appropriate for modeling lane-changing behavior in weaving sections. Similar boundaries may be brought into the route-deciding MLCs IN urban arterials, such as when changing lanes for a upcoming left/right turn. However, these two boundaries are not appropriate for most DLCs, during which the driver may even choose not to change lanes. The driver characteristics are more important in these situations.

2.1.5 Commercial Simulators with Rule-Based Lane-Changing Models

In CORSIM (FHWA, 1998) lane changes are classified as mandatory (MLC), discretionary (DLC) or random (RLC). The definitions of MLC and DLC are the same as in the previous models. RLC is performed by drivers for no apparent reason, which may or may not result in an advantage for the vehicle over its current position. CORSIM assigns stochastically a certain percentage of drivers who perform such a random lane change (default value is 1 percent).
For a vehicle performing either a RLC or DLC, it needs to stay in the lane for a given time period (the default value is 3 seconds). MLC is not subject to this and may be performed in any time step in response to the downstream geometrics. In fact, the subject vehicle can change more than one lane in one time step in MLC.

For any lane-changing maneuver in CORSIM (MLC, DLC or RLC), acceptable lead and lag gaps must be available in the target lane. Acceptance of the lead gap is modeled through the

amount of the deceleration that is required by the subject vehicle to avoid collision with its leader in the target lane. The target leader is assumed to decelerate with the maximum possible deceleration, and the deceleration required by the subject vehicle in order to avoid collision is computed. This computed deceleration is compared to an acceptable deceleration which is called the acceptable lane changing risk. The lead gap is accepted if the required deceleration is smaller than the acceptable risk. A vehicle with acceptable lead and trailing gaps initiates a lane change into the target lane. Both the FRESIM and NETSIM adopt a similar lane-changing algorithm. The only difference lies in that the gaps in NETSIM are measured in terms of time differences, and the gaps in FRESIM are a function of both time headways and speed differences between the subject vehicle and the lead and lag vehicles in the target lane. One advantage of the lane-changing model in CORSIM is the flexibility of using user provided parameters. However, it does not consider the variability in gap acceptance behavior. The behavior is not modeled in a systematic manner, and all drivers are assumed to have identical gap acceptance behavior.

Researchers in Transport Simulation Systems (TSS) modified the Gipps' lane-changing algorithm and incorporated it into AIMSUN2 (Barcelo et al., 1996; Barcelo et al., 1998; TSS, 2004). Lane-changing in AIMSUN2 is modeled as a decision process evaluating the necessity of changing lanes, the desirability of changing lanes (lane-changing reasons), and the feasibility conditions for the lane change (the availability of gaps) depending on the location of the vehicle on the road network (Barcelo et al., 1996). Two braking values are calculated to decide whether a lane changing is possible. One is the braking imposed by the lead vehicle in the target lane to the subject vehicle, and the other is the braking imposed by the subject vehicle to the lag vehicle in the target lane. If both braking ratios are acceptable, the lane-changing is possible. A special on-ramp lane-changing model is designed to take into account whether a vehicle is stopped or

not, whether it is at the beginning of the on-ramp queue or not providing it is stopped, and how long it has been waiting. Another vehicle parameter, “maximum waiting time”, determines how long a vehicle is willing to wait before getting impatient. After this time, the vehicle becomes more aggressive and will reduce the acceptable gaps. Although it is stated that AIMSUN2 can model incidents, no detailed information is given in any of the references on how the model deals with lane-changing under incident situations.

The lane-changing model in VISSIM is composed of a complex set of rules, which depends much on the type of streets and other parameters (Fellendorf, 1994; PTV, 2004). For example, if a faster driver approaches a slower one on the same lane, it checks if it can improve the position by changing to a neighboring lane. The difference between freeways and urban arterials is considered significant in VISSIM. In urban streets, the next turning direction is one of the most important parameters for deciding the present lane. Some other driver vehicle parameters are considered important in the VISSIM lane-changing model, including: 1) technical description of a vehicle, 2) behavior of a driver, and 3) interaction between several drivers. The parameter “minimum headway (front/rear)” defines the minimum distance that must be available for a lane-changing in standstill conditions.

In PARAMICS, two types of lane-changing are defined as overtaking lane-changing corresponding to the reason of speed advantage, and directional lane-changing corresponding to route choice reasons (Cameron and Duncan, 1996; Quadstone, 2004). The minimal lane-changing gap is a combination of a user-defined value and individual driver type, and is provided in units of time. The lane-changing maneuver is completed successfully if a suitable gap exists continuously within a preset simulation interval required to complete the maneuver. The mean of this interval is four seconds, and the value increases when the vehicle speed becomes lower. Two

important link-related indices determine when a driver recognizes a required lane change. One is the distance that the most aware driver will see the oncoming required lane change, and the other is the distance that the least aware drivers will see the required lane change. For the distances in between, drivers will proportionally see the required lane change. If the distance to the downstream junction is within a given user-defined value, the vehicle will cease to make any overtaking lane-changing decisions, and only consider the directional lane-changing until the turn at the next junction. This distance corresponds to the real distance from the position of a directional signpost at the roadside to the junction. The driver's aggressiveness is taken into account in modeling this signposting lane-changing behavior.

2.2 Discrete Choice-Based (DCB) Microscopic Lane-Changing Models

This section presents the literature review on the discrete-choice-based lane-changing models proposed by researchers in MIT and the Next Generation Simulation (NGSIM) program.

2.2.1 Lane-Changing Model Used in MITSIM

A microscopic traffic simulator, MITSIM (Yang and Koutsopoulos, 1996), was designed to establish a laboratory environment for testing and evaluating new algorithms in ATMS (Advanced Transportation Management System) and ATIS (Advanced Traveler Information System). Similar to previous models, the lane-changing model in MITSIM was implemented to include three steps: (1) checking the necessity of lane-changing, (2) selecting the desired lane, and (3) checking whether gap distances are acceptable or not. Two types of lane changes, mandatory and discretionary, were defined. For the mandatory one, the lane-changing maneuver starts at a distance x_n from the downstream node (or incident, lane drop, red LUS) with probability given by the following equation:

$$p_{\mathrm{n}} = \begin{cases} \exp[(x_n - x_0)^2/\sigma_{\mathrm{n}}^2] & x_n > x_0 \\ 1 & x_n \le x_0 \end{cases} \tag{2-7}$$

where

p_n is the probability that vehicle n starts a mandatory lane-changing maneuver,

x_n is the distance from downstream node or lane blockage,

x_0 is the critical distance, which may be associated to the position of a particular message sign (such as final exit warning), and

σ_n is a variable defined as $\sigma_n = \alpha_0 + \alpha_1 \mathrm{m_n} + \alpha_2 \mathrm{K}$ ($\mathrm{m_n}$ is the number of lanes need to cross; K is the traffic density of the segment; α_0, α_1 and α_2 are parameters).

When a MLC is invoked, the status is kept until the desired lane change has been completed, or the vehicle has moved into the downstream link. Two parameters related to DLC are the impatience factor and the speed indifference factor. These are used to decide whether the speed difference between the current lane and target lane are large enough to invoke a lane change. The target lane choice is based on multiple criteria including lane-changing regulations, driver's lane privilege, lane congestion, current signal state, prevailing traffic conditions, driver's desired speed and lane's maximum speed. Once the target lane is decided, the lead and lag gaps in the target lane are checked. For the DLC, the minimum acceptable gaps are given by the following equation:

$$g_n = g + \varepsilon_n \tag{2-8}$$

where,

g_n is the minimum gap that driver n consider to be acceptable for a discretionary lane change,

g is the average acceptable gap, and

ε_n is an error term.

Both g and ε_n are parameters provided as user input for both lead and lag gaps. For the MLC, the minimum acceptable gaps may decrease as the vehicle approaches the downstream node (same for incidents and lane drops), which is given by the following equation:

$$g_n = \varepsilon_n + \begin{cases} g_{\max} & x_n \geq x_{\max} \\ g_{\min} + (g_{\max} - g_{\min}) * \dfrac{x_n - x_{\min}}{x_{\max} - x_{\min}} & x_{\min} \leq x_n \leq x_{\max} \\ g_{\min} & x_n \leq x_{\min} \end{cases} \tag{2-9}$$

where,

g_n is the minimum gap that driver n considers to be acceptable for a mandatory lane change,

$g_{\min}$ and $g_{\max}$ are the lower and upper bounds for gaps (lead and lag),

x_n is the vehicle's current position,

$x_{\min}$ and $x_{\max}$ are the distances that define the range within which the critical gap varies from $g_{\min}$ and $g_{\max}$, and

ε_n is an error term.

By these two equations, MITSIM models the difference of the gap acceptance between the two types of lane changes. That is, in a MLC drivers tend to accept smaller gaps as they get closer to the last location where the lane change has to take place. However, the reasons of changing lanes are not included in the model, which may have to be defined outside for simulation implementation. In addition, the model handles all issues from the field data, and does not capture driver characteristics.

2.2.2 Other Recent DCB Lane-Changing Models

In Ahmed's dissertation (1999), a general framework that captures lane-changing behavior under both the MLC and DLC ($\overline{\text{MLC}}$) situations was developed. In this model, lane-changing is divided as a sequence of four steps: 1) decision to consider a lane-changing, 2) target lane choice, 3) acceptance of gap conditions in the target lane, and 4) performing the lane-changing maneuver. A discrete choice concept was adopted to model the impact of the surrounding traffic environment and lane configuration as well as driver characteristics. The whole procedure is modeled as a decision tree, shown in Figure 2-3. Four layers, which correspond to the sequence of four steps, are included. The output from one layer is the input for the layer following. In the top level, a driver decides to respond to the MLC or DLC ($\overline{\text{MLC}}$), and the target lane is fixed in a MLC. Gaps in the target lane are checked and a lane change is invoked if the gaps are acceptable. In a DLC ($\overline{\text{MLC}}$), if a driver is not satisfied with the current lane, he/she will

compare the driving conditions on the current lane with those of adjacent lanes and decide on a target lane. Similar to the MLC, the gaps in the target lane are checked and a lane change is invoked if the gaps are acceptable. Otherwise, the driver will stay on the current lane. The probability of observing a change to the left lane is given by the following equation:

$$\begin{aligned}\Pr_t(L \mid v_n) = {} & \Pr_t(\text{change lanes} \mid \text{gap accepable, left lane chosen, MLC}, v_n) * \\ & \Pr_t(\text{gap accepable} \mid \text{left lane chosen, MLC}, v_n) * \\ & \Pr_t(\text{left lane chosen} \mid \text{MLC}, v_n) * \Pr_t(\text{MLC} \mid v_n) \; + \\ & \Pr_t(\textit{change}\ \text{lanes} \mid \text{gap accepable, left lane chosen, DLC}, \overline{\text{MLC}}, v_n) * \\ & \Pr_t(\text{gap accepable} \mid \text{left lane chosen, DLC}, \overline{\text{MLC}}, v_n) * \\ & \Pr_t(\text{left lane chosen} \mid \text{DLC}, \overline{\text{MLC}}, v_n) * \\ & \Pr_t(\text{DLC} \mid \overline{\text{MLC}}, v_n) * \Pr_t(\overline{\text{MLC}} \mid v_n)\end{aligned} \tag{2-10}$$

where,

v_n is the individual specific random term, which indicates the probability of decision to consider a lane change.

Similarly, $\Pr(J_{tn} \mid v_n)$ for J_{tn} = R or C can be formulated (R: right lane, and C: current lane).

Finally, a likelihood function was formulated to estimate the related parameters:

$$L^* = \prod_{n=1}^{N} \int_{-\infty}^{+\infty} \left(\prod_{t=1}^{T_n} \Pr_t(L \mid v_n)^{\delta_{tn}^L} * \Pr_t(R \mid v_n)^{\delta_{tn}^R} * \Pr_t(C \mid v_n)^{\delta_{tn}^C} \right) f(v_n) dv_n \tag{2-11}$$

where

L = change to the left lane
R = change to the right lane
C = continue in the current lane

$$\delta_{tn}^L = \begin{cases} 1 & \text{if driver n changes to the left lane at time t} \\ 0 & \text{otherwise} \end{cases}$$

$$\delta_{tn}^R = \begin{cases} 1 & \text{if driver n changes to the right lane at time t} \\ 0 & \text{otherwise} \end{cases}$$

$$\delta_{tn}^C = \begin{cases} 1 & \text{if driver n does not change lane at time t} \\ 0 & \text{otherwise} \end{cases}$$

$f(v_n)$ is the distribution of v_n and N is the sample size.

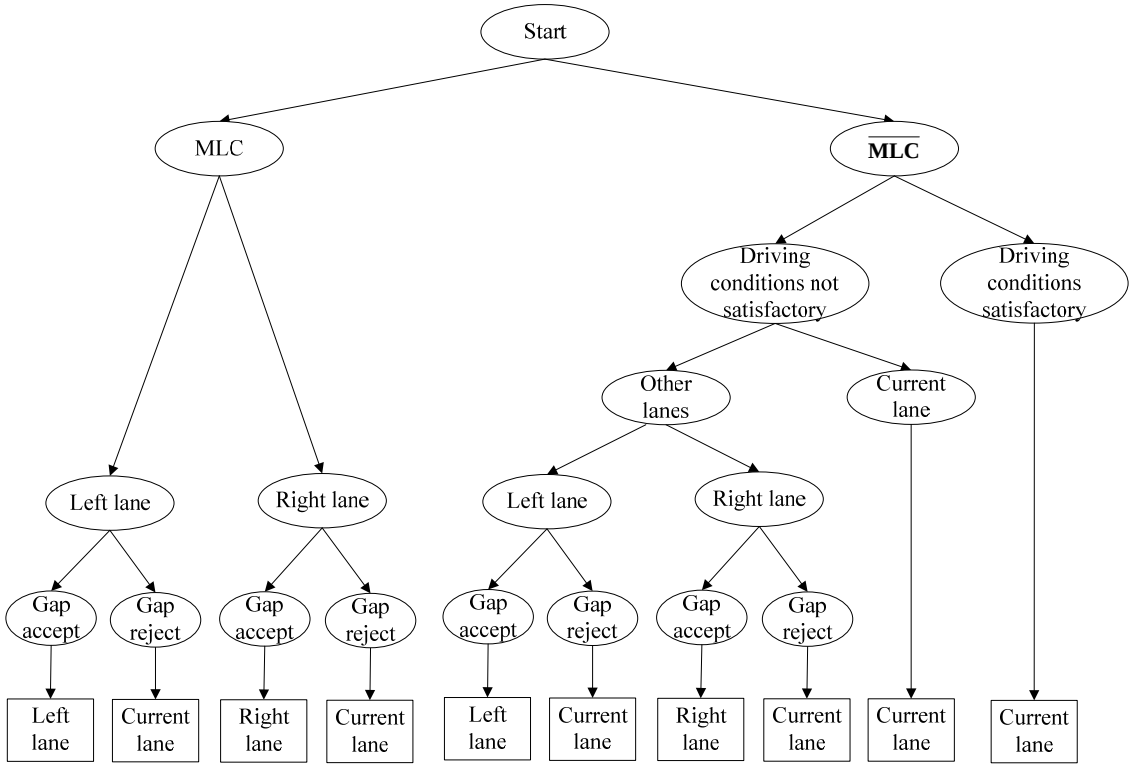


Figure 2-3. The lane-changing model structure from Ahmed's dissertation (source: Ahmed, 1999)

In a numerical example, parameters of the model were estimated for a special simple case: merging from a freeway on-ramp. In this case, all drivers initiate the change to the adjacent mainline as soon as they cross the merge point between the on-ramp and the freeway lane, and continue searching for acceptable gaps in the target lane. Although the given model provides a detailed framework for the lane-changing behavior research, no lane-changing reasons component is included, and the utility value for each candidate has to be calculated to obtain the lane-changing demand. Given the complexity of the lane-changing behavior on urban streets, it is difficult to acquire all necessary important factors to model all lane-changing situations. The author assumes that the existence (or non-existence) of an MLC situation is known. However, except for special cases, such as in the on-ramp merging example used, MLC situations can not be observed. Another weakness is that the model considers the lane-changing maneuver as a

solitary decision, with no "communication" with other vehicles. This may be true for the highway traffic, where the speed is too high to allow "communication" among vehicles. For urban streets, in most situations, drivers inevitably interact with each other for changing lanes, especially during congested traffic.

To capture trade-offs between mandatory and discretionary considerations, Toledo (2003) and Toledo et al. (2003) integrated the two into a single utility mode, so that the awareness to the MLC situation is more realistically represented as a continuously increasing function rather than a binary choice. In this model, the lane-changing process consists of choice of target and gap acceptance decisions. Since traffic is a dynamic and uncertain environment, drivers in the algorithm need to re-evaluate and possibly modify their short-term goals and short-term plans as conditions change. Hence the lane-changing maneuver is modeled in a state-dependent stochastic manner. Under the discrete choice framework, the utilities of target lane and acceptable gaps are decided by vehicle's surroundings, path plan and network knowledge and experiences. The target lane choice was formulated as a multinomial logit model and the probabilities for each lane were given by the following equation:

$$P(TL_{nt}^{i} \mid v_n) = \frac{\exp[(X_{\text{int}}^{TL}\beta_i^{TL} + \alpha_i^{TL} v_n) \mid v_n]}{\sum_{j \in TL} \exp[(X_{jnt}^{TL}\beta_j^{TL} + \alpha_j^{TL} v_n) \mid v_n]} \qquad i \in TL = \{\text{left}, \text{current}, \text{right}\} \qquad (2\text{-}12)$$

where,

X_{int}^{TL} is the vector of explanatory variables that affect the utility of lane i as a target lane to drive n at time t,

β_i^{TL} is the corresponding vector of parameters,

v_n is a driver/vehicle specific latent variable assumed to follow some distribution in the population, and

α_i^{TL} is the parameter of v_n.

In this model, the choice of the target lane dictates the lane-changing direction. A gap acceptance model captures drivers' choice by comparing the available gaps in the target lane

with the critical gaps. The critical gaps are modeled as random variables with means being functions of explanatory variables as in the following equation.

$$\ln(G_{nt}^{gd,cr}) = X_{nt}^{gd}\beta^{g} + \alpha^{g}v_n + \varepsilon_{nt}^{gd} \qquad g \in \{\text{lead, lag}\}, d \in \{\text{right, left}\} \tag{2-13}$$

where

$G_{nt}^{gd,cr}$	is the critical gap g in the direction of changed, measured in meters,
X_{nt}^{gd}	is a vector of explanatory variables,
β^{g}	is the corresponding vector of parameters,
ε_{nt}^{gd}	is a random term: ε_{nt}^{gd} ~N(0, σ_{gap}^{2}), and
α^{g}	is the parameter of the driver specific random term v_n.

The gap acceptance was formulated as a multinomial probit model, which was affected by the spatial relations between the subject vehicle and the lead and lag vehicles in the adjacent lane. The lead/lag gap values were captured by variables such as the subject relative speed and position with respect to the lead and lag vehicles. The probability that gaps at time t are acceptable to driver n is given as:

$$\begin{aligned} P &= P(accept\ lead\ gap \mid d_{nt}, v_n) * P(accept\ lag\ gap \mid d_{nt}, v_n) \\ &= P(G_{nt}^{lead\ d} > G_{nt}^{lead\ d,cr} \mid d_{nt}, v_n) * P(G_{nt}^{lag\ d} > G_{nt}^{lag\ d,cr} \mid d_{nt}, v_n) \\ &= P(\ln(G_{nt}^{lead\ d}) > \ln(G_{nt}^{lead\ d,cr}) \mid d_{nt}, v_n) * P(\ln(G_{nt}^{lag\ d}) > \ln(G_{nt}^{lag\ d,cr}) \mid d_{nt}, v_n) \\ &= \Phi\left[\frac{\ln(G_{nt}^{lead\ d}) - (\beta^{lead})^T X_{nt}^{lead\ d} + \alpha^{lead} v_n}{\sigma_{lead}}\right] * \Phi\left[\frac{\ln(G_{nt}^{lag\ d}) - (\beta^{lag})^T X_{nt}^{lag\ d} + \alpha^{lag} v_n}{\sigma_{lag}}\right] \end{aligned} \tag{2-14}$$

$\Phi(\bullet)$ denotes the cumulative standard normal distribution.

The model parameters were estimated using data collected in a section of I-395 Southbound in Arlington, VA, which show that drivers' lane selection is affected both by path-plan variables and surrounding traffic environment. The critical gaps depend on the relative speeds with respect to the lead and lag vehicles. The implementation and validation results (in MITSIMLab) indicate the integrated model has better simulating ability for congestion build-up and dissipation. However, all estimation results of the model are based on freeway traffic.

Additional factors, such as bus traffic and pedestrian presence may need to be considered if the model is applied to urban streets. The model assumes that lane-changing maneuvers are carried out only when the acceptable gaps exist, which may not be the case in heavily congested traffic. Forced merging and yielding need be considered for such conditions. To this point, this case study for a specific section of freeway is not adequate, and more datasets are required in order to identify geometry and other site-specific effects.

With considering the large differences in the attributes and utilities of the available lanes, Choudhury et al. (2004) and Toledo et al. (2005) developed a lane-changing model with explicit target lane choice, wherein the utility of each candidate lane was calculated from selected lane related variables and vehicle-specific attributes. This model adopts the same gap acceptance algorithm as Eq. (2-13) in the integrated model. The difference is, within this framework the candidate lanes include all eligible lanes on the road. A driver may first change to a low utility lane in order to reach the target lane. The proposed lane-changing model was implemented in MITSIM lab (Choudhury et al., 2004). Validation sensor data and aggregate trajectory data were collected from approximately 1.5 miles of highly congested sections of I-80 in Emeryville and Berkeley, California. One set of aggregate data was used to calibrate the parameters included in the behavioral models in Eq. (2-13) (β^g). Then, a simulation was run with another input dataset from the same source. The performance of the target lane model was compared to the performance of the integrated lane-changing model with myopic change direction (Toledo et al., 2003), i.e. the direction of the immediate lane change is always the adjacent lane. The validation process was based on the comparison of the simulated speeds and lane distributions. The results showed that the proposed lane-changing model provided significantly better prediction on the two indices. However, to apply the proposed model as a general lane-changing module to urban

streets, sampling data are needed to estimate the coefficients in the discrete choice analysis. All existing parameter estimations for the model are based on freeway data, and special attributes (such as bus traffic and pedestrian) need to be incorporated to model the urban streets lane-changing behavior. Next, some attributes, such as trip planning, were chosen as important components of the model. Unfortunately, the effects of how drivers adhere to the trip schedule were difficult to obtain. Finally, similar to the previous DCB models, the target lane model did not consider the forced and cooperative lane-changing behavior under congested traffic. Driver characteristics, which are very important in lane-changing maneuvers, were not considered in this model.

Ben-Akiva et al. (2006) proposed a cooperative and forced merging model for MLC in the NGSIM report. The combined model is the first discrete choice model which considers forced or cooperative merging. It consists of three components: normal lane-changing, cooperative lane-changing and forced lane-changing. A four-level decision-making process for the model is given in Figure 2-4.

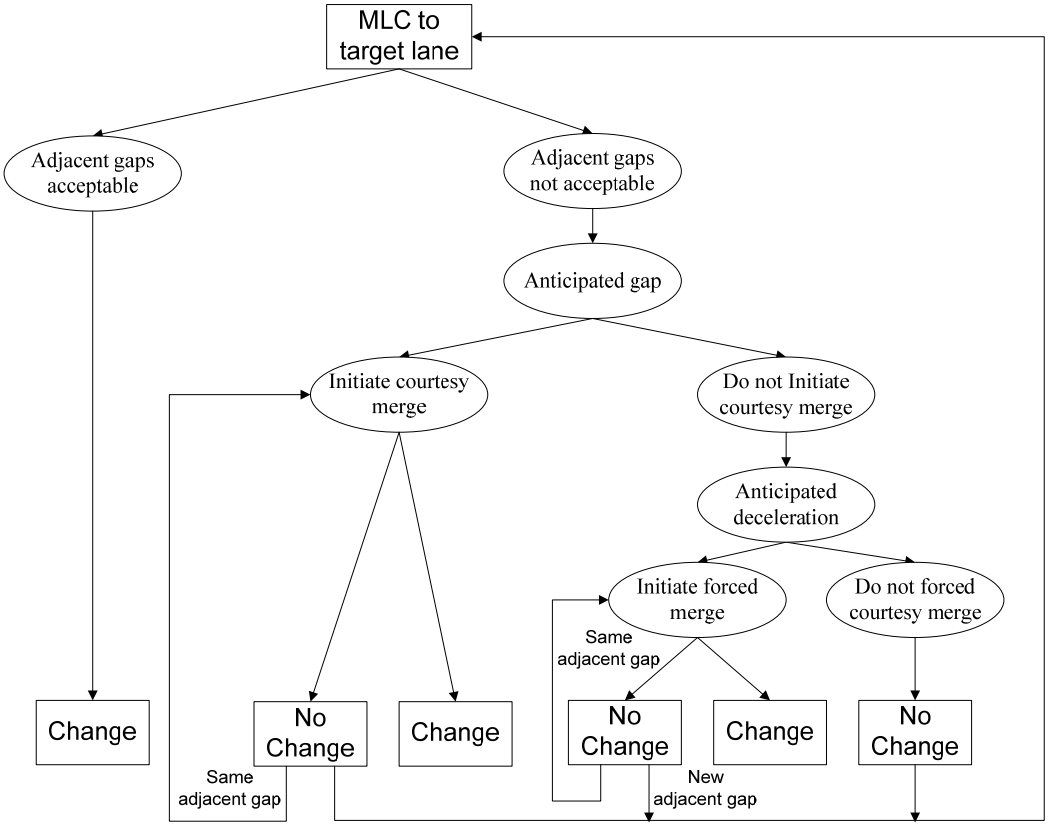


Figure 2-4. Combined lane-changing model in NGSIM (Source: Ben-Akiva et al., 2006)

First, the target lead and lag gaps are compared to the normal lane-changing gap criteria, and a normal lane-changing will be executed, if both gaps are sufficient. Otherwise, the speed, acceleration and relative position of the lead and lag vehicles are checked. The anticipated lead and lag gaps are approximated by incorporating the courtesy from the lag vehicle. If the anticipated gaps are acceptable, a cooperative lane-change under the perception of courtesy yielding from the lag vehicle will be initiated. If the anticipated gaps are still unacceptable, the driver will consider forced merging for MLC. For a forced merging, the driver anticipates the deceleration that the lag driver would apply to accept him/her as a leader to avoid collision. The required deceleration of the lag vehicle is compared to the maximum deceleration a driver is willing to impose. If the anticipated deceleration is acceptable, a forced lane-change will be initiated. Otherwise, the merging vehicle must wait at the original lane with no lane change.

The combined model considers MLC practically and the steps are rather clear. However, only the gap/deceleration acceptance is considered. The authors assume that the factors influencing drivers to change lanes are satisfied and the target lane has already been given. In the data validation, the freeway on-ramp trajectories were adopted so that both lane-changing reasons and target lane are pre-determined. Hence if being applied to the lane-changing maneuver in urban streets, additional modules are necessary. Even though the importance of drivers' willingness and courtesy in the forced and cooperative lane-changing maneuvers was emphasized, the model did not mention how to obtain and use the courtesy parameters, and how to determine to what extent the courtesy is provided from the lag vehicle.

2.3 Other Microscopic Lane-Changing Models

In addition to the rule-based and the discrete-choice-based lane-changing models introduced in the previous sections, other lane-changing models related to game theory, neural networks and kinematic waves have also been proposed.

Kita (1999) and Kita *et al.* (2002) modeled the lane-changing behavior at freeway on-ramp merging section based on game theory. The interaction between two vehicles (the merging vehicle and the lag mainline vehicle) was modeled as a two-person non-zero-sum non-cooperative game with complete information. The merging vehicle has two strategies: merge or pass, and the mainline vehicle can choose to give way or not. The strategy equilibrium (SE) is defined as a particular selection from mixed strategy choices of the players if and only if each player is using the best response to the strategy choices of the other players. No player can gain by unilaterally changing strategy. The data samples for validation were extracted from videotape observation, which recorded the car movements in the section by measuring the speed and headways between various vehicles and the end of merging section. The analysis data includes both actual choice, and theoretical choice probability based on the observed surrounding

conditions. The maximum likelihood method was used to estimate the parameter values for the explanatory variables in the pay-off matrix. Comparison of the estimation results and field data indicate the proposed model has the capability to estimate the probabilities of equilibrium selection of both players. The model can describe the traffic behavior in highway on-ramp merging sections, especially the interactions between the merging vehicle and the lag mainline vehicle during the lane-changing maneuver. However, it would be difficult to apply this model in urban streets. Because of the congested conditions in urban streets, a lag vehicle may choose slowing down instead of giving way to the subject vehicle. The purpose of this study was trying to understand the give way behavior by using activity survey data, and to provide a useful tool for describing interdependent driving behavior with interaction. Hence, this model was focused only on give way, and did not consider other behavior, such as slowing down under certain conditions. A simple assumption for the model is that the driver will select the action with the lower level of risk, where risk is expressed as the time to collision (TTC), and no minimal safe gap is considered. Also, the proposed model does not include the speed adjustment for the merging maneuver, which is an important part for changing lanes on urban arterials, especially in congested traffic.

Hunt and Lyons (1994) explored the application of neural networks (NN) to model lane-changing decisions. A feed-forward network trained using the back propagation learning algorithm was adopted. Input to the neural network at time t consisted of five sets of data, one for each consecutive time interval immediately proceeding t. Each set includes the distance from the subject vehicle to the other 4-surrounding vehicles (in the current lane or the target lane). Two other inputs are the current lane and speed of the subject vehicle. The output of the neural network is the predicted speed and lane of the subject vehicle for the next time interval t+1. This

approach was implemented using video data collected from an urban street section. Comparison of the results from simulation and the real traffic data indicates the NN was able to correctly classify a high proportion of examples during training for both simulated and field data. However, the output predictions of speed and lane from the neural network are continuous variables, and a certain threshold must be imposed to provide a specific lane output. Therefore when the output lane number is close to 1.5 (for a lane change from lane 1 to lane 2), each time interval could result in a different lane, suggesting erratic driving behavior. A previous study of application of neural networks to robot car- following (Pomerleau, 1992) also recognized that limitations in the training set could result in erratic driving. In fact, microscopic lane-changing behavior is not deterministic but stochastic, wherein drivers' characteristics and traffic environment should be considered. The NN in Hunt's model only takes the distances to the surrounding vehicles and the current speed as input, and no probabilistic conditions were included.

Laval and Daganzo (2000) postulated freeway sections away from diverges, wherein the main incentive for drivers to change lanes is the speed advantage. The lane-changing vehicle acts as a moving bottleneck on its destination lane until it accelerates to the prevailing speed, and additional lane changes may be triggered during this time period. Under such a situation, the freeway traffic is modeled as a set of interacting streams linked by lane changes. The kinematic wave (KW) theory is introduced to treat the lane-changing vehicles as a fluid that can accelerate instantaneously. By combining the KW theory with the accuracy of a microscopic model, slow vehicles are treated as moving bottlenecks in a KW stream. Under this framework, Laval and Daganzo (2006) further modeled each lane as a separate KW stream interrupted by lane-changing vehicles which allow no passing on the lane they occupy. Empirical results were

collected from two freeway sections, where obstructions with a range of controlled speeds were introduced to simulate moving bottlenecks. The authors hold that by this model, the reduction in flow observed after the onset of congestion at freeway land-drops and the relationship between the speed of moving bottlenecks and their capacities can be explained. Additional simulations show that lane changes affect bottleneck behavior in ways that can be controlled to improve traffic flow (Tang et al., 2007). The emphasis of the KW model is the macroscopic relationships between flow, density and the net lane-changing rate, wherein a simplified linear flow-density relationship is adopted. For ideal freeway traffic, the simplification may not cause large discrepancy. However, when coming to the capricious urban streets traffic, especially for congested situations, the modeling ability is still in doubt.

2.4 Summary and Conclusions

Lane-changing behavior has attracted more attention with the development of microscopic traffic simulation tools. The maneuver is usually classified as either mandatory (MLC) or discretionary (DLC). Each of these is further modeled in a sequence of three steps: 1) lane-changing necessity checking, 2) target lane choice and 3) gap acceptance decision. Based on a review of the existing lane-changing algorithms, the most popular ones are rule-based models and DCB models. Both of them may be implemented as a lane-changing module for the general micro-simulation.

Rule-based algorithms model lane changes from the perspective of drivers. The reasons for lane changes are first enumerated and checked whether they apply. Then, the target lane is chosen from the adjacent lane(s), the parameters for gap acceptance are retrieved from field/simulation data, and calculated by given formulas. Most of these parameters may be calibrated in the simulation. The DCB algorithms model driver behavior using logit or probit models, by which specific significant attributes are estimated. A driver's decision becomes a

binary or multi-choice selection, and utilities for all alternatives are calculated to get the output at each stage in the lane-changing process. Similar to the rule-based models, parameters for gap acceptance in the DCB models also need to be extracted from sampling data, and calibrated in the simulation.

In addition to the rule-based and DCB models, several other models were reviewed. The model based on game theory is largely limited to the merging-giveway behavior in freeway merging areas, and cannot be easily extended to other lane-changing maneuvers. The neural network model tries to capture the relationship between lane-changing maneuvers and driver/vehicle status (speed and distance to surrounding vehicles). It may be applicable to the type of lane-changing maneuver for speed advantage purposes because of the distance consideration. However, the neural network algorithms do not incorporate the stochastic variability which is important in modeling complex lane-changing behavior in urban streets. The basis for the kinematic-wave (KW) model is the assumption of a linear relationship between the flow, density and lane-changing rate. This is a significant simplification of real traffic flow behavior, and is consequently difficult to be applied to the complex urban traffic.

All these existing lane-changing models can not replicate lane changes on urban arterials accurately. Lane changes on arterial streets, especially under congested conditions, are characterized by several different invoking reasons, driver interactions, and a significant impact of driver characteristics. The rule-based model may be improved by adding a driver interaction component to handle these characteristics. Additional effective field data are necessary, in order to model lane-changing invoking reasons and the impact of driver characteristics correctly.

2.5 Recommendations

Based on the literature review, a general lane-changing framework for urban streets was developed and is summarized in Figure 2-5. The output of the first step is the determination of

the lane-changing type (MLC, DLC or no change). For both the MLC and DLC, the target lane choice model and gap acceptance model need to be formulated. If the gaps in the target lane are acceptable, a lane change is made. Otherwise, for the MLC, the vehicle must adjust its speed and position and attempt another MLC in the following time step. For a DLC, the vehicle may choose to give up the lane-changing attempt or re-evaluate the condition for a new DLC/MLC after the speed and position adjustment.

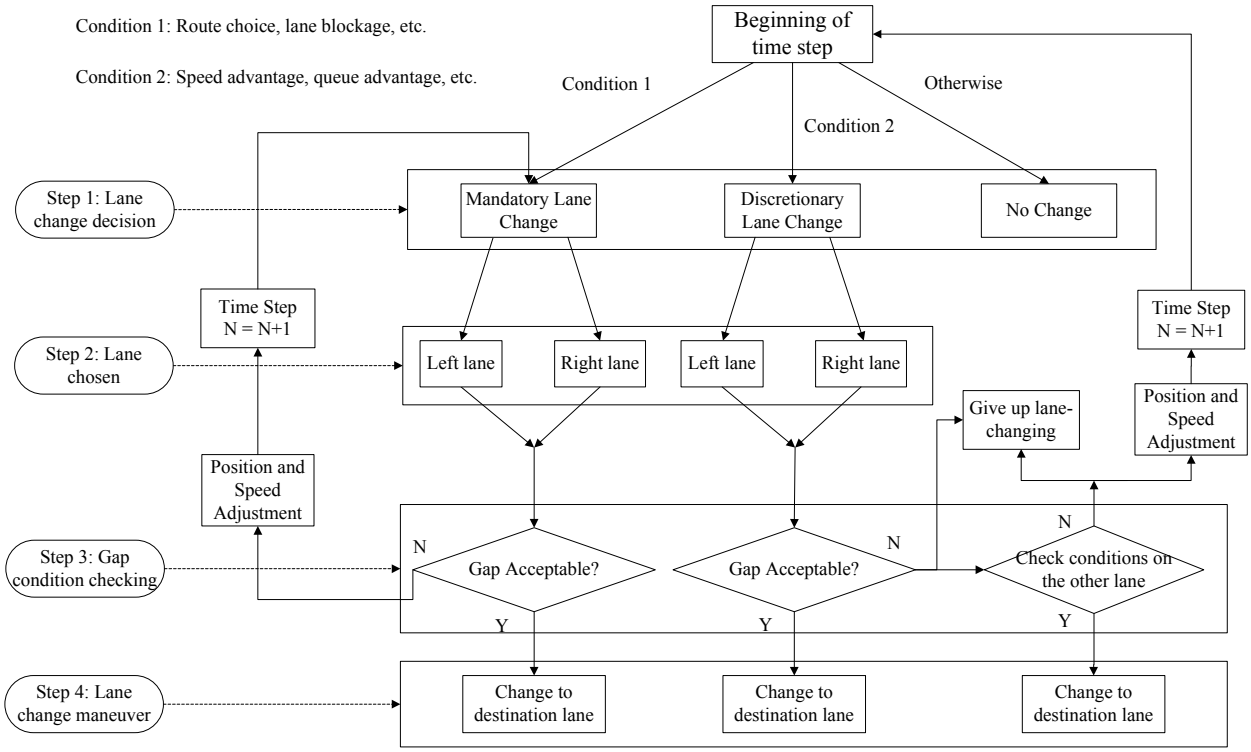


Figure 2-5. Hierarchical framework for a general lane-changing model

Lane changing is a function of driving behavior. The framework given in Figure 2-5 provides a direction for further modeling procedures in this research. The difficulties lie in the uncertainty of environmental factors and variations on driver and vehicle. New experiments should be designed to evaluate the impact of these factors, and consequently to improve the modeling capability of the algorithm.

CHAPTER 3
METHODOLOGY

Although driver behavior and characteristics are important, they have not been incorporated into existing lane-changing models with much detail. The main reason is the diversity and uncertainty involved in human driving behavior. Research in artificial intelligence (AI) indicates that understanding human behavior is a very complex task, which makes modeling and automatic recognition of human activities difficult (Simon, 1996). New methods should be designed to utilize detailed driver behavior information in lane-changing modeling. In addition, more functional data need to be collected to assist in the model development and implementation.

This chapter presents a general methodology in developing a comprehensive lane-changing model for urban arterials, including the tasks at each research stage. Figure 3-1 presents the empirical data based research framework. The first step involves a focus group study, in which discussions among participants help to understand drivers' concerns under various lane-changing reasons and the corresponding behaviors. The results from the study are analyzed, with the expectation that would provide insights for developing a field data collection plan to be implemented in the step followed. In Step 2, participants are recruited to drive an instrumented vehicle, so that field values for specific important factors identified in the focus groups can be collected. The field data are analyzed and categorized by driver characteristics. Results collected from different driver groups were compared to decide the optimal classification scheme. Conclusions from this step are compared with the findings from focus group study to test and validate the effectiveness of the both experiments. In Step 3, the "in-vehicle" field datasets are

used to construct sub-models for modeling drivers' decisions for particular DLC reasons and the gap acceptance procedure. These are eventually used to decide whether a lane change is necessary and the gaps in the target lane are acceptable for changing lanes.

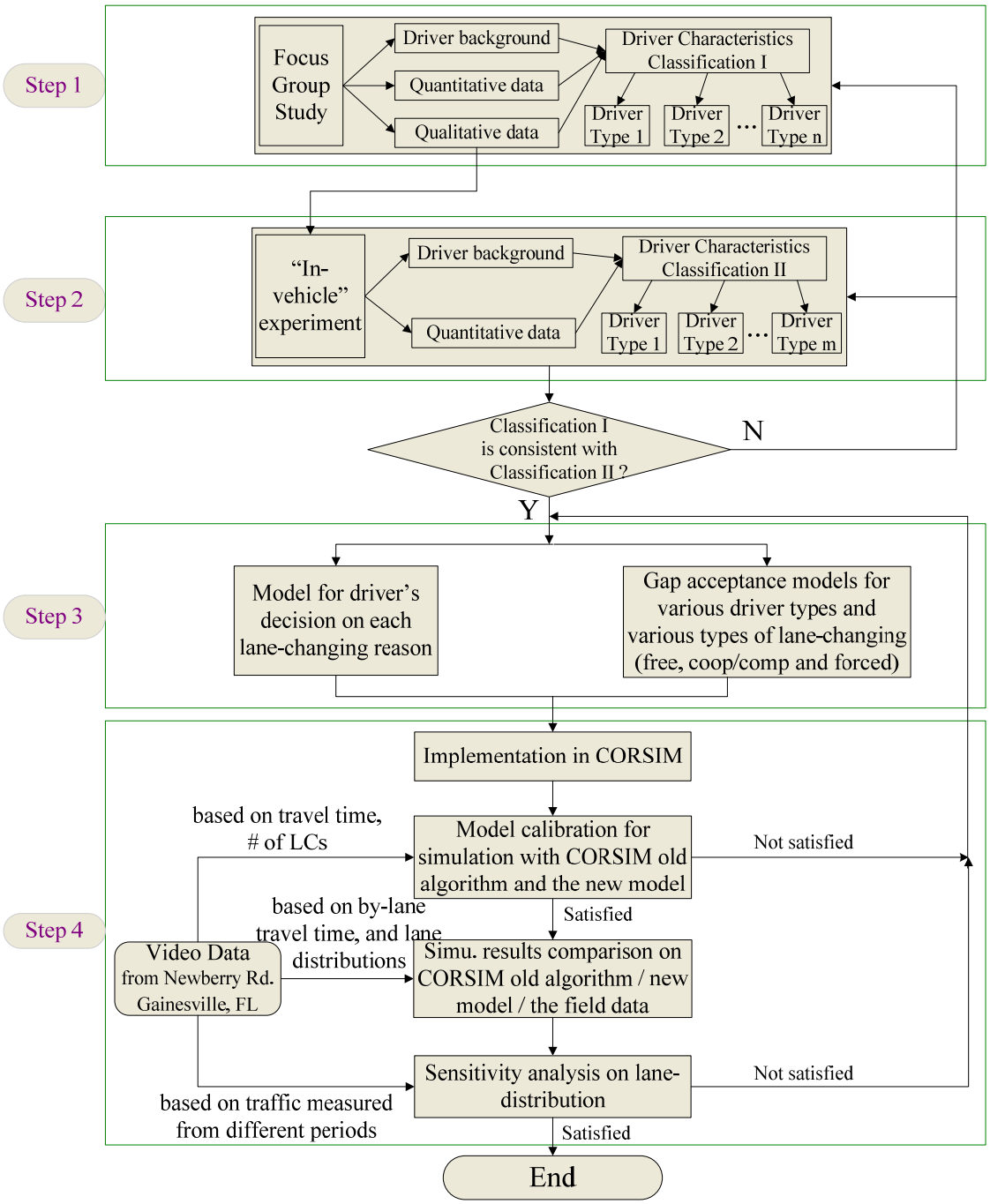


Figure 3-1. Proposed framework

Finally, in Step 4, the newly developed model is implemented and tested in a micro-simulator package, CORSIM. Aggregate statistics from video data collected from Newberry Road in Gainesville, FL (Washburn and Kondyli, 2006), such as lane-based travel time, vehicle lane distributions and number of lane changes by vehicles, are compared with the simulation results from the new model. Results using the existing lane-changing model in CORSIM are provided for comparison purposes. Calibration and validations, as well as a sensitivity analysis, are also conducted.

Each of these four steps is further discussed in the remainder sections of this chapter, focusing on the motivation and the output of each step. Chapter 4 and Chapter 5 provide additional details for the efforts have been conducted in focus group study and "in-vehicle" experiment, while the implementation and simulation endeavors for model development and validation are discussed extensively within the corresponding Chapter 6 and Chapter 7.

3.1 Research Step 1 - Focus Group Study and Information Categorization

For a long time, field-based surveys (revealed preference/stated preference) have been used to indicate drivers' preferences for various transportation scenarios (Crane, 1996; Levinson et al., 2004; Duan, 2006). For these surveys, however, the results may not be accurate either because the participants are not entirely truthful or they are rushed, and have not had the opportunity to fully comprehend each question. During studying on self-disclosure, Jourard (1964) found that individuals decided to reveal based on their perceptions of the other persons, and concluded subjects tended to disclose more about themselves to people who resemble them. This is the theoretical foundation for focus group study, which has emerged as a form of qualitative research

in recent decades. The difference between focus groups and traditional survey is that focus groups involve a number of people at the same time, and discussions are highly encouraged (Stewart et al., 2007). What separates focus groups from other interviewing methods is the fact that they allow group interaction, thereby providing greater insight into why certain beliefs and opinions are held (Loukopoulos et al., 2004). Focus groups encourage more critical thinking on the part of participants as a direct result of interacting with other participants and the moderator. Each of them may question, challenge or agree with the others' beliefs and opinions. However, the purpose of focus groups is to listen and gather information without pressuring participants to vote or reach consensus. Group members can only influence each other by responding to ideas and comments of others.

As the lane-changing behavior is affected by many interdependent factors, and there may be large discrepancies among different types of drivers, focus groups are used in this research to obtain personal perceptions and attitudes regarding lane-changing maneuvers on urban streets. The objective of focus group studies in this research is to obtain the reasons and factors that affect the execution of lane changes. It is expected that this step results in providing lane-changing information from the general driving experience of each participant. The feedback and comments hopefully unveil a useful connection between driver type and lane-changing factors. Each focus group meeting consists of the following three phases:

Phase 1. A pre-selected list of lane-changing reasons is posed and the participants are asked to prioritize them based on their driving experiences. The initial list is as follows (new reasons may be added during the discussion):

R1.1- Passing a stopped-bus at bus stop,
R1.2- Giving way to a merging vehicle,
R1.3- Gaining speed advantage by overtaking a slower moving vehicle,
R1.4- Gaining queue advantage,
R1.5- Avoiding a truck/heavy vehicle influence,
R1.6- Avoiding the pressure imposed by tailgating, and
R1.7- Attracted by a better pavement condition.

Discrepancies may exist on the type and likelihood of DLCs for different of drivers. Five levels of likelihood (probabilities of invoking a lane change for any given reason) were defined as:

Level 1: Generally do not conduct (< 10%, weak),
Level 2: Sometimes conduct but more likely do not (10% - 40%),
Level 3: Sometimes conduct, and sometimes do not (40% - 60%),
Level 4: More likely conduct (60% - 90%), and
Level 5: Generally conduct (> 90%, strong).

In this step, answers from each participant are recorded for future lane-changing model development. The objective of this phase is to connect particular drivers to the acceptance for each of the pre-selected lane-changing reasons. The output is the level (i.e. probability) that a participant would change lanes for each of the identified reasons. Additional DLCs may be added by the participants at this stage.

Phase 2. For each lane-changing reason, the participants are asked to provide factors that they consider when changing lanes. The list of DLCs was given as in Phase 1, and two MLCs are proposed as:

R2.1- Upcoming left/right turn at the immediate/next downstream intersection, and
R2.2- Current lane is not available downstream (e.g. road incident, work zone or change in channelization of the current lane).

Each of the participants discusses and describes his/her behaviors under each lane-changing scenario. The significant factors are obtained, and would be used in developing guidelines for the "in-vehicle" field data collection. The objective of this phase is to connect each particular driver

to the factors within each lane-changing reason. The output is a list of factors affecting the probability of changing lanes for each particular reason:

Reason 1 (Factor11, Factor12, …, Factor1i),
Reason 2 (Factor21, Factor22, …, Factor2j),
…,
Reason n (Factorn1, Factorn2, …, Factornk)

Phase 3. The participants describe the possible interactions involved in lane changes under congested traffic. In this situation, cooperative and competitive strategies within lane-changing maneuvers are obtained. The objective of this step is to get interactions that may be involved in changing lanes, so that they could be modeled accurately.

During the result analysis, drivers are tentatively categorized based on their characteristics. Then the corresponding lane-changing behaviors is used to decide the optimal classification scheme, so that the driver characteristics for each driver type can be identified and incorporated in the further model development. The division on driver type is based on specified level of driver aggressiveness, which was obtained through background survey. Outputs of the focus group study are used to develop guidelines for the "in-vehicle" field data collection. A detailed experimental design and implementation for the focus group study, along with the corresponding results analysis, are provided in Chapter 4.

3.2 Research Step 2 - "In-Vehicle" Field Data Collection and Results Analysis

The focus group study provides the factors that are important to drivers, as well as possible driver interactions during a lane-changing maneuver. The objective of the "in-vehicle" data collection is to obtain field-measured values for the important factors obtained in the focus group

study. The field values collected in this step would be used to develop sub-models that can be incorporated into in a comprehensive lane-changing model. Results from the "in-vehicle" experiment are also used to test and validate conclusions from the focus group study.

In this research, field data are needed to clarify following questions: 1) Whether a driver would accept a lane-changing reason? What is the probability? 2) Of the important factors proposed for a given lane-changing scenario, how do they affect the driver's decision? 3) For the different modes of lane changes, what gap criteria are acceptable? and 4) How does the subject driver interact with the surrounding vehicles when a lane change occurs under congested traffic?

As mentioned, the traditional cross-sectional detector data are not sufficient to describe lane-changing behavior, and no existing video trajectory data cover all lane-changing scenarios proposed in this research. Moreover, it is too costly and time-consuming to set up new video capturing facilities for the lane-changing data collection. Consequently, a Honda Pilot instrumented vehicle was adopted to collect data related to the questions (1-4). In general, an instrumented vehicle is defined as a fully-operating, street legal vehicle that is equipped with flexible data acquisition systems to collect data, such as speed, lane position, GPS, and driver eye movements, etc. (Chrysler et al., 2004). This technology allows the driving behavioral data to be safely collected while the subjects are in a natural state. More and more instrumented vehicles have been used in a variety of traffic domains including driver behavior, road cataloging, and air quality studies, which help to gather more interesting data from drivers in a larger geographic area (Chrysler et al., 2004). The instrumented vehicle technology is a useful tool for

“in-vehicle” trajectory data collection, and has been used to collect data regarding car-following and lane-changing behaviors (Brackstone et al., 2002; Brackstone et al., 2009).

During the driving test, each participant was accompanied by the researcher to drive on the pre-selected routes, where different lane-changing scenarios may be invoked, and collect data related to the lane-changing maneuvers. Answers for questions 1) and 4) can be obtained directly from field observations, while for the rest two questions (2 and 3), special communications with the driver during the test were included to clarify driver’s decision process and actions. Notes are taken by the researcher to help the further data reduction procedure.

In this research, a Honda SUV (Pilot 2006) equipped with a Honeywell Mobile Digital Data Recorder (HTRD400) system are used. Four wider coverage digital cameras (DCs) have been installed to capture video clips from different points of view, from which the necessary driving parameters and interactions with surrounding vehicles can be inferred. As shown in Figure 3-2, DCs were installed to capture traffic in each direction (right, left, front and backward). Vehicle status data, including video and audio data, are recorded directly from the four HTRD cameras via standard CAT5 data/power cabling (Honeywell, 2005). From the GPS system connected, the HTRD400 can retrieve vehicle position, geographic direction, and speed data via a serial interface. Special software – HTRD BusView connects the recorder to a PC/laptop. Video clips are first stored in the local hard disk, and can be transferred to a PC/laptop whenever needed. The player within the BusView can play video online or download clips to the local PC/laptop.

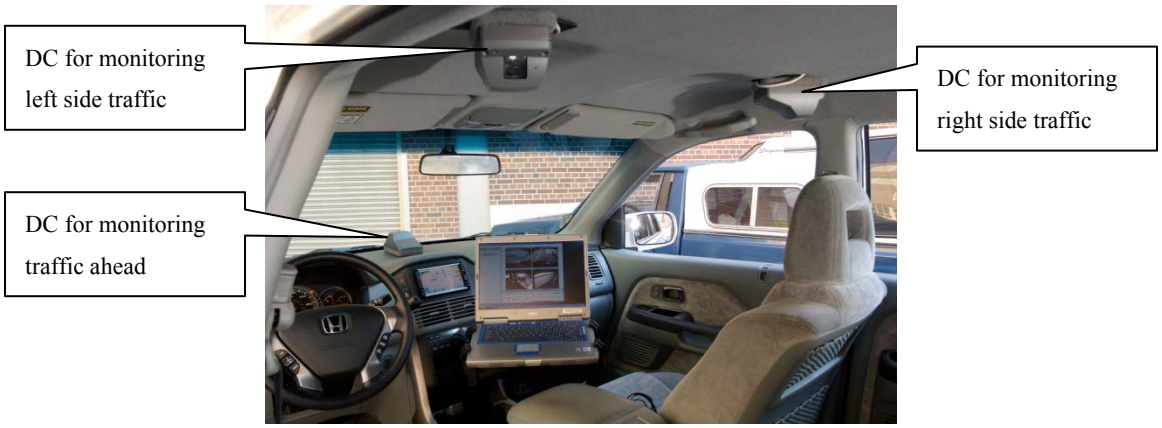
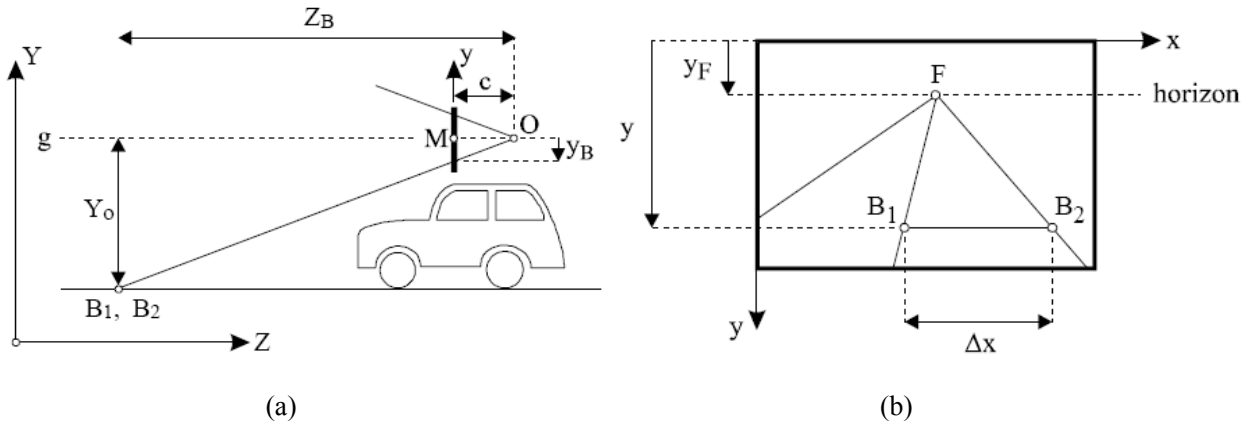


Figure 3-2. The HTRD 400 system and other equipment (i.e. GPS, DCs) in the Honda Pilot

The original video clips from DCs were taken at a 0.1 sec resolution. With the GPS system, the time-based location and speed data of the subject vehicle can be retrieved. A new method has been designed to obtain car-following and lane-changing data as follows. First, the video clips are decomposed into frame-by-frame images (0.5 sec each), so that the time-based relative position between vehicles can be observed. The target images are then selected for estimating the distance and speed of the surrounding vehicles based on the known distance in the camera view (such as lane width) and the dimensions of the instrumented vehicle (Figure 3-3). The computational steps include: 1) conducting some preliminary tests to estimate the camera constant c for each DC; 2) using the formula $\frac{c}{Z_B} = -\frac{y_B}{Y_0} = \frac{\Delta x_B}{\Delta X_B}$ to estimate the real distance $Z_B = c * \frac{\Delta X_B}{\Delta x_B}$ (all related variables are defined as in Figure 3-3). Consequently, the driver performance and the vehicle motions related to surrounding vehicles, such as reaction times, lane-changing gap acceptance, speed-distance relationships, speed perception, vehicle to vehicle communication links, etc. can be measured. With this information, a dynamic time series record

of driver behavior relative to other vehicles can be obtained, which provides first-hand field data for the research on lane-changing behavior.



c is the camera focus length constant,
y_B is the y image coordinate of points B_1, B_2,
Y_O is the camera height above ground level,
Δx_B is the circumference dimension measured from the image (B_1 - B_2),
ΔX_B is the real value for circumference dimension, and
Z_B is the real distance from camera to target vehicle.

Figure 3-3. Image-based vehicle distance estimation (a) Geometry with horizontal camera (b) Measurements on the image

Based on the field data collected from individual drivers, the field values for different lane-changing scenarios and gap acceptance procedures are obtained. A result analysis is adopted to categorize drivers based on their field lane-changing behaviors. The driver classification scheme is compared to the one obtained from the focus group study. If the two results are not consistent with each other, it means either the categorization algorithm is not effective or the participants in any of the experiments do not behave themselves exactly. Iterative steps (experiments and classifications) have to be carried out until the two classification results are consistent.

Outputs of the "in-vehicle" experiment are used to develop lane-changing model components to handle the probability of changing lanes under each scenario and the gap acceptance procedures. A detailed experimental design and implementation for the "in-vehicle" field data collection, as well as the corresponding results analysis, are provided in Chapter 5.

3.3 Research Step 3 - Lane-Changing Probability Model and Gap-Acceptance Model

The objective of this step is to develop the sub-models for reason-based lane-changing probabilities and gap acceptance by using the results obtained from Step 1 and Step 2.

3.3.1 Lane-Changing Probability Model

After successfully categorizing the lane-changing data by reasons, a set of reason-based lane-changing information can be attained. Table 3-1 presents an example of such information for a given reason n, in which the respective factor values from all LC-related maneuvers are recorded (total number of maneuvers is N). Each factor ($Factor_{ij}$) is associated with two indices: the first i is the reason category number (namely n in this case), and the second one j is the index within the reason n. The driver type information is determined by the driver classification in Step 2. The number of factors listed would vary by scenario, and would refer only to the important factors associated with that scenario. For a given reason n, the value of each factor is obtained directly or indirectly from the "in-vehicle" field data collection.

The probability of changing lanes under reason n can be formulated as a function of the respective attributes. The general format is as follows:

$$P\ (\text{lane-changing}) = \text{func}(factor_1, factor_2, \ldots, factor_N, \text{Driver type 1, Driver type 2}, \ldots);$$

For example, when it comes to the reason of "Current lane is not available downstream because of road accident", the function and the factor list may be proposed as:

P (lane-changing) = func($factor_1$, $factor_2$, $factor_3$, Driver type 1, Driver type 2, …);

where,

P: is the probability to change lanes,

$factor_1$: the distance to the lane blockage location because of the road accident,

$factor_2$: level of congestion,

$factor_3$: relative speed,

Driver type 1: the type of subject driver (1: belongs to driver type 1, 0: not), and

Driver type 2: the type of subject driver (1: belongs to driver type 2, 0: not).

Table 3-1. Reason-based lane-changing information table (for Reason n)

Factor	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	…	SN
$Factor_{n1}$													
$Factor_{n2}$													
$Factor_{n3}$													
$Factor_{n4}$													
...													
Driver type 1													
Driver type 2													
...													

Note: For a give lane-changing reason n, each maneuver is used to generate the dataset including the values of each corresponding important factor and the type of the subject driver. Then a total of N datasets (samples) are used to develop the probability function of changing lanes under certain reason n.

In addition to the set of reason-based lane-changing information illustrated in Table 3-1, a driver-reason relationship table is then constructed to store the probability functions and parameters for each reason (driver type i is one of the parameters). An example is provided in Table 3-2, in which for any given reason (j), a probability function of changing lanes (FLC_j) is obtained. The functions and parameters are estimated from the reason-based lane-changing information table (Table 3-1). For example, the function of FLC_n and the corresponding coefficients for each factor (shaded cell in Table 3-2, for reason n) are estimated from

information in Table 3-1 (N lane-changing maneuvers under reason n). Regression analysis is used to develop these functions. Detailed analysis procedure is provided in the corresponding Chapter 6.

Table 3-2. Reason-based probability functions estimated from the "in-vehicle" data

Reasons	Probability functions and parameters
R1	FLC1: [β_{10} , …, DT_1, DT_2, …]
R2	FLC2: [β_{20} , …, DT_1, DT_2, …]
R3	FLC3: [β_{30} , …, DT_1, DT_2, …]
…	…
Rn	FLCn: [β_{n0} , …, DT_1, DT_2, …]

In the model implementation, the function formulations for the lane-changing probability model are stored as in Table 3-2. When the module is invoked within a micro-simulation, non-driver related parameters, such as average speed, average travel time, average headway or queue length, are obtained in each simulation time step. Such information is used to calculate the values for the corresponding important attributes (such as the $factor_2$: level of congestion in the example above) within the reason. Based on these, including the specific driver type j (j $\in$[1, m]), the lane-changing probability for the given reason is calculated, so that the lane-changing decision can be made. During simulation, all applicable reasons are checked for the subject vehicle in a sequence.

3.3.2 Gap Acceptance Model

It is well accepted that different modes, such as free, forced and cooperative ones, exist in lane-changing maneuvers (Hidas, 2005; Wang et al., 2005; Ben-akiva et al., 2006). The gap acceptance criteria may differ across the driver types and the lane-changing modes (Mahmassani and Sheffi, 1981). For example, maneuvers related to the free and forced lane changes are

actions generally conducted in a comparably short time interval as soon as the decision has been made. The cooperative lane change includes interactions with other sounding vehicles in several continuous seconds, and hence is more complex. One of the emphases in this research is to model the negotiation/competition procedures within lane-changing maneuvers. The autonomous agent technique (Das et al., 1999) is adopted to model the gap acceptance decision-making process.

In the proposed algorithm, different lane-changing modes are decided as soon as a lane-changing reason is accepted. Each vehicle involved in cooperative lane-changing is modeled as an "intelligent agent". As presented in Figure 3-4, the merging "agent" (S_1) looks for the "lag agent" (T_2) and negotiates for a feasible lane change. Two functions (MergingAgent and LagAgent) are developed to model the self-government and communications between the two "agents". Only the general framework is provided at this stage. The realistic details are retrieved from the focus group study and refined using the field observations. The negotiation scenarios and lane-changing strategies of individual vehicles are studied. The corresponding figures, flowchart and pseudo codes for the "merging agent" and the "lag agent" are provided in the Chapter 6.

For the free and forced lane changes, successfully categorizing the results from focus groups and field observations help generate mode-based critical gaps. The initial critical gaps for these two modes can be obtained directly from the "in-vehicle" field data collection. The gaps include a deceleration index called the acceptable lane-changing risk, which gets inflated as the need for changing lanes becomes urgent. Gap acceptance in the cooperative lane-changing mode

is modeled as a negotiation procedure, in which parameters, such as the corresponding critical gaps and driver types, are used as inputs. The gap acceptance sub-model is going to be implemented as one of the key components in a comprehensive lane-changing model.

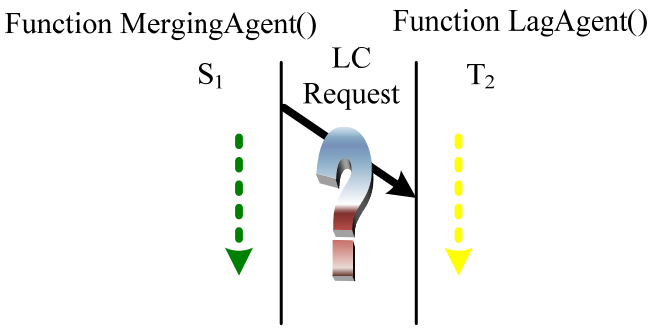


Figure 3-4. Possible interaction scheme within cooperative model

3.4 Research Step 4 - Model Implementation and Validation

The objective of this step is to implement the proposed lane-changing model and validate it in CORSIM micro-simulator. First, each individual component is implemented as a separate function within a lane-changing module, which is invoked as a CORSIM RTE (run time extension) during the simulation. Next, field video data collected from arterials in Gainesville, FL, are used to calibrate CORSIM simulations. Two CORSIM simulation cases, with the newly developed lane-changing model or with the original CORSIM lane-changing model, are calibrated based the field data. Both calibrated models (with the “new” and “original” lane-changing algorithm) are simulated with the additional OD demands other than those calibration dataset, and the results are compared with the field measurements on multiple indices of the measures. Various statistical analyses are conducted to evaluate the agreement between the

results from the simulations and the field observations. The remaining of the section describes each step of the procedures.

3.4.1 Model Implementation Issues

The integrated lane-changing model is implemented as a separate C++ DLL plug-in, which interfaces with CORSIM engine during the simulation. Functions for each component are built and invoked as needed. In CORSIM simulation, the RT_PRE_NETSIM_VEHICLE message is sent just prior to calling the FORTRAN subroutine MOVE, which handles lane-changing, car-following, etc. to move all the vehicles for the current time step. The lane-changing plug-in is set up to respond to this message, and the function within the plug-in is invoked to perform the lane-changing maneuver. By setting CORSIM lane-changing timer to a value that would prevent the embedded lane-changing logic from being applied. The subroutine MOVE would still be called, but vehicles would not be allowed to make a lane change. The set up of the plug-in is the same as the configuration for general COSRIM RTEs. A detailed procedure was provided in CORSIM RTE Developer's Guide (FHWA, 2006).

3.4.2 Model Validation Issues

Field video data from the major arterials, such as Newberry Road and Archer Road, in Gainesville, Florida are collected. The videos are first observed to identify the completed lane-changing maneuvers and the attempted but unsuccessful lane-changes involved. The position and speed of each vehicle involved in the maneuver can be obtained using frame-by-frame image analysis. Consequently, the maximum executing acceleration and deceleration in different types of lane changes can be inferred from the time dependent lead/lag gaps and speeds. Other aggregate parameters, such as flows and travel time can be obtained from the field video for

calibration purposes. Additionally, various measures of performance, such as average lane-based speed, lane-based travel time, vehicle lane distributions and number of lane changes, for each individual arterial segment can be acquired for validation purposes.

As presented in Figure 3-5, the test procedures are designed to validate the capability of the new model as follows.

First, the arterial for data collection are simulated with the field-measured OD demand in CORSIM. The simulation is calibrated by using the measurement from aggregate field data, such as average travel time and average speed. The process of calibration aims to adjust various parameters simultaneously, so that field observed traffic conditions can be accurately replicated. During this calibration, only the driver behavioral related parameters within CORSIM are adjusted. Next, a new simulation scenario is created by loading the new lane-changing model to replace CORSIM original model. The new simulation scenario is calibrated by using the same indices of measurement as in the previous calibration, and only the behavioral parameters within the LC plug-in are adjusted. By the end of this step, two calibrated simulation scenarios are obtained. One is with the original CORSIM lane-changing model, and the other is with the new lane-changing model.

In the second step, multiple simulation runs for both calibrated models are conducted with OD demands measured from different day. Special MOEs (measurement of effectiveness) for lane-changing modeling, such as lane-based average speed, lane-based travel time, vehicle lane distribution and number of lane changes by vehicle, are obtained to compare with the field observations. Results from the newly developed model are expected to have a better match to the

field data. Otherwise, the "new" model should be tuned up until the majority of results are not inferior. Goodness-of-fit statistics may be used to evaluate the effectiveness of the new model quantitatively.

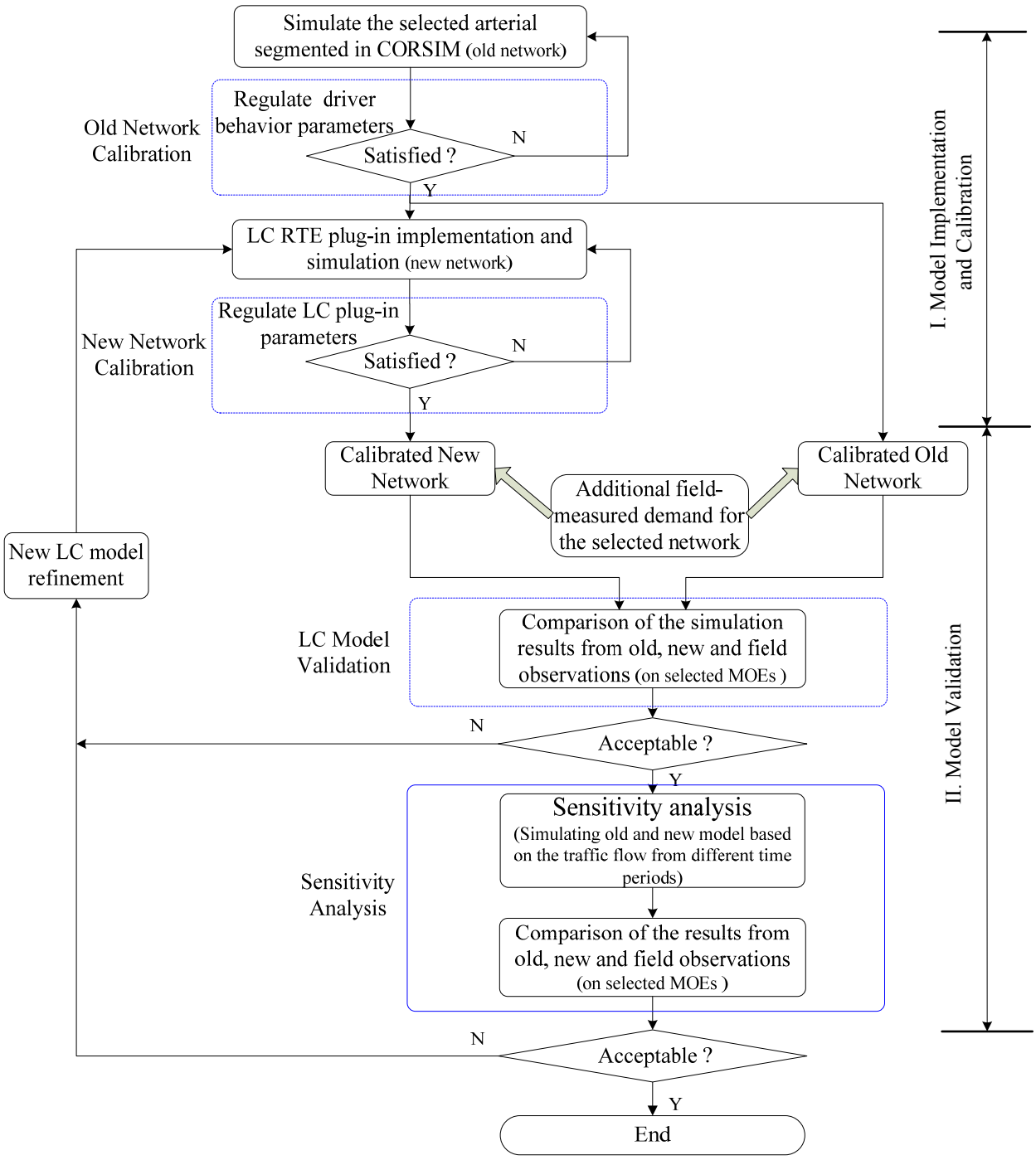


Figure 3-5. Procedures included in the systematic validation

Finally, sensitivity analyses are conducted for the simulations with “new” and “original” lane-changing models. Field traffic flows under different time periods are measured as the inputs. Various MOEs for lane-changing modeling are obtained from the two models, and compared with each other, along with the field observations measured from same traffic conditions. It is anticipated that the results from the existing lane-changing model in CORSIM would serve as a benchmark/test bed for the improvement of simulation capability offered by the “new” lane-changing algorithm.

3.5 Summary and Conclusions

A general methodology and implementation framework for modeling lane-changing behaviors based on driver characteristics and field data have been presented in this chapter. Two experiments, focus group study and “in-vehicle” data collection, are designed to obtain the lane-changing related driver characteristics and field maneuver data. With the inner connection attained from the experiments, a probabilistic lane-changing reason model and a gap acceptance model can be developed based on the empirical data. Strategies of implementing the new lane-changing model in CORSIM are also presented. Various calibration and validation endeavors can be included to test the simulation capabilities of new model.

Structurally, the proposed methodology provides a framework that can be used to modeling other driver behaviors (such as car-following) on urban arterials or the behaviors on other types of facilities besides/in addition to urban arterials. It can be viewed as a hybrid of the human behavior research modeling extended to the transportation settings.

In accordance with the requirements of the University of Florida's Institutional Review Board (IRB), all research involving human subjects needs to be approved by the relevant IRB Office prior to conducting any activities. The materials that are submitted to IRB-02 (UF Campus/Non Medical) for the experiments in this research (focus group study and "in-vehicle" data collection) are provided in APPENDIX A

CHAPTER 4
FOCUS GROUP-BASED STUDIES

In Chapter 3, the research procedure was divided into four steps, and the motivation and anticipated results for each step were discussed. This chapter presents the focus group study conducted in this research to obtain personal perceptions and attitudes regarding lane-changing maneuvers. The main objective is to use focus groups to obtain driver behavior-related data that can be used to model lane changes in an urban street environment. More specifically, the three sub-objectives of this research are:

- To develop an appropriate classification scheme for driver types based on driver background information (such as age, gender, etc.) and responses during the focus group discussion;
- To obtain the likelihood of attempting a given discretionary lane change (DLC) for different types of drivers; and
- To determine factors and parameters affecting the execution of a particular lane changing maneuver (mandatory or discretionary) as a function of driver type.

The remainder of the chapter is structured as follows. Section 4.1 presents the preparation and implementation of the focus group experiment. Typical lane-changing scenarios are examined to obtain the level of likelihood in changing lanes, as well as important factors participants identified to affect their lane-changing behaviors. Next, in Section 4.2, the quantitative and qualitative results for the focus group discussion are analyzed, followed by possible relationships between driver behavior and driver characteristics. Finally, the chapter ends with a summary and conclusions of the study in Section 4.3.

4.1 Focus Group Preparation and Implementation

This section presents the focus group implementation details. First, the questions for the focus group discussion are provided. Next, participants' recruitment and prescreening-related procedures are presented. Finally, moderation issues, including definitions and others are provided.

4.1.1 Preparation of Questions

Developing good questions is very important for the focus groups study, which helps to generate desirable and useful results. Good questions include both a good questioning route and the effectiveness of each question. Krueger and Casey (2000) concluded the qualities of a good questioning route for focus groups studies are: 1) having an easy beginning; 2) being sequenced; 3) moving the topic from general to specific; and 4) using the time available wisely. In the same reference, the qualities of good questions for focus groups studies are described as: 1) including good directions; 2) one-dimensional; 3) open-ended; 4) short but clear; 5) easy to say; 6) adopting words participants would use; and 7) sounding conversational. Each quality is explained in detail in the corresponding chapter of their book. This section introduces how the question route and questions for this research were prepared.

Typically, a focus group discussion includes about 10-12 questions within two hours, and each question may function differently in the questioning route to facilitate the moderating process. Krueger and Casey (2000) divided the categories of questions according to the purpose, in which an effective question route may include open questions, introductory questions, transitory questions, key questions and ending questions.

Opening questions are ice-breaker questions, which get every participant to talk early and help them to feel comfortable. The regular time is less than 30 seconds per person, and it's important that the question does not highlight power and status differences among participants. In this study, the opening question (Table 4-1 Q1) is planned to let the participants introduce themselves, as follows: "Tell us who you are, and do you enjoy driving? Why?" The overall time for this question is scheduled as about 3 minutes.

The introductory question introduces the topic of discussion and helps people start thinking about their connection to the topic of lane changing. Generally, they are open-ended questions which encourage conversation on the understanding of participants. In our research, one introductory question (Table 4-1 Q2) is: "What comes to your mind when you hear about the term – 'change lanes'?" The overall time is scheduled as 5-6 minutes.

The transitory question (Table 4-1 Q3) moves the conversation from general lane changing to the key content of the study, the potential reasons that may invoke a lane change, and made the participants aware of how others view the topic. During this question, participants are becoming aware of how others view the topic, and refresh their thoughts from another perspective. Although the introductory question surfaces the topic of discussion, it is the transition question which makes "real" connection between the participants and the topic. In this research, such a question is proposed as: "Think about the reasons invoking a lane change. Do you consider there are many differences between you and other drivers?"

Table 4-1. Focus group categories and questions

Q1	Opening Question
Tell us a few things about yourself. Do you enjoy driving? Do you spend a lot of time on driving? How long have you been driving?	
Q2	Introductory Question
What comes to your mind when you hear "lane change"?	
Q3	Transition Question
Are there any differences between the way you change lanes and that of other drivers (on urban streets)?	
Q4	Key Questions (Category 1: Likelihood of a Lane Change Discussion)
Suppose you are driving on an urban street with three lanes. Please evaluate how likely you are to conduct a lane change for each given DLCs (the proposed list is given out in Table 2). Please list any additional reasons you may have thought of.	
Q5	Key Questions (Category 2: Significant Factors in Lane Changing)
In this category, a set of lane-changing scenario is given. Please identify factors affecting the manner and timing of your decision.	
Sce.1	Upcoming left/right turn: a. Left turn situation, b. Right turn situation, c. Any differences between two turnings?
Sce.2	Current lane is not available downstream: a. Road incident, b. Work zone, c. Change in channelization of the current lane
Sce.3	Stopped bus at bus-stop: When driving on your lane, a bus (city bus, not school bus) in front is loading/unloading passengers
Sce.4	Another vehicle merges into your lane: When driving in your lane, another vehicle is attempting to enter into your lane.
Sce.5	Slow moving vehicle: When driving in your lane, the vehicle in front of you is driving slower than you would like.
Sce.6	Queue length advantage: When approaching an intersection, the queue in your lane is longer than that of other lanes.
Sce.7	Truck/heavy vehicle influence: There is a truck/HV in front of you blocking your view, and is traveling at desired speed.
Sce.8	Tailgating by another vehicle: When driving in the center lane, you find that the vehicle behind you is tailgating you.
Sce.9	Pavement condition: When driving in your lane, you find the other lanes of the road have better pavement conditions.
Q6	Key Questions (Category 3: Vehicle Interaction Discussion)
In the next few slides, I will ask you about your actions during a lane-changing maneuver assuming the traffic is congested. Please describe your thoughts in planning and completing the maneuver.	
Sce.1	You need to change lanes: a. You are planning to merge to the curb-side lane; b. You are planning to merge to the middle lane.
Sce.2	The other vehicle is changing lanes: a. The other vehicle is attempting to merge to the curb-side lane in front of you; b. The other vehicle is planning to merge to the median-side lane in front of you; c. Any differences between the two scenarios?
Q7	Ending Question:
Today, we began with the major possible reasons that would invoke a lane change and the level of likelihood in executing it. Next, for each reason, the major effective factors which affect drivers' decisions regarding lane changing were enumerated and examined. Finally, the possible driver interactions involved in a lane change behavior were discussed. Is there anything you want to say but didn't get a chance?	

This question first moves the conversation from the general lane-changing to the topic of lane-changing reasons, and then it makes the participants become aware of how others view the topic. The scheduled time is 5-8 minutes.

Key questions are the ones that require the greatest attention. Three key questions (Table 4-1Q4 to Q6) were used in this study. The first one (Table 4-1 Q4) starts with introducing the definitions of MLC and DLC, and a list of DLC reasons is provided to participants. Next, they were asked to choose the level of likelihood that they may change lanes for each reason listed based on their driving experiences. Participants were encouraged to add new lane-changing situations to the pre-selected list, and answers from each participant were recorded. The form used to assess DLC reasons is shown in Table 4-2. Five levels of likelihood for attempting a lane change for a given reason were defined. During this part of the discussion, only the discretionary lane changes (DLCs) were considered since the likelihood of attempting to change lanes for mandatory lane changes (MLCs) would be close to 100%. The output of this discussion is a comprehensive list of reasons, along with the level of likelihood that a participant would change lanes for each of the identified reasons.

The second key question (Table 4-1 Q5) demonstrates example scenarios for each particular lane change. Participants are asked to discuss and describe their behaviors under each lane-changing scenario (for both DLC and MLC), so that the major factors that affect their decision on attempting a lane change can be obtained.

Table 4-2. Form for documenting the level of likelihood for DLC reasons

List of Discretionary Lane-Changing (DLC) Scenarios	[a]Levels of Likelihood				
	Lev. 1	Lev. 2	Lev. 3	Lev. 4	Lev. 5
R1. Change lanes to pass a stopped-bus at a bus stop	☐	☐	☐	☐	☐
R2. Change lanes to allow a vehicle to merge into your lane	☐	☐	☐	☐	☐
R3. Change lanes to pass a slower moving vehicle	☐	☐	☐	☐	☐
R4. Change lanes when the line of queuing vehicles is shorter in other lanes	☐	☐	☐	☐	☐
R5. Change lanes because there is a heavy vehicle/truck in front of you	☐	☐	☐	☐	☐
R6. Change lanes to avoid a vehicle tailgating you	☐	☐	☐	☐	☐
R7. Change lanes due to pavement conditions;	☐	☐	☐	☐	☐
R8. Other reason(s) please specify					

Notes:[a] Definitions of the levels of likelihood

Lev. 1: Generally do not conduct (< 10%, weak)
Lev. 2: Sometimes conduct but more likely do not (10% - 40%)
Lev. 3: Sometimes conduct, and sometimes do not (40% - 60%)
Lev. 4: More likely conduct (60% - 90%)
Lev. 5: Generally conduct (> 90%, strong)

Figure 4-1 presents the sketches used to describe each scenario to the participants.

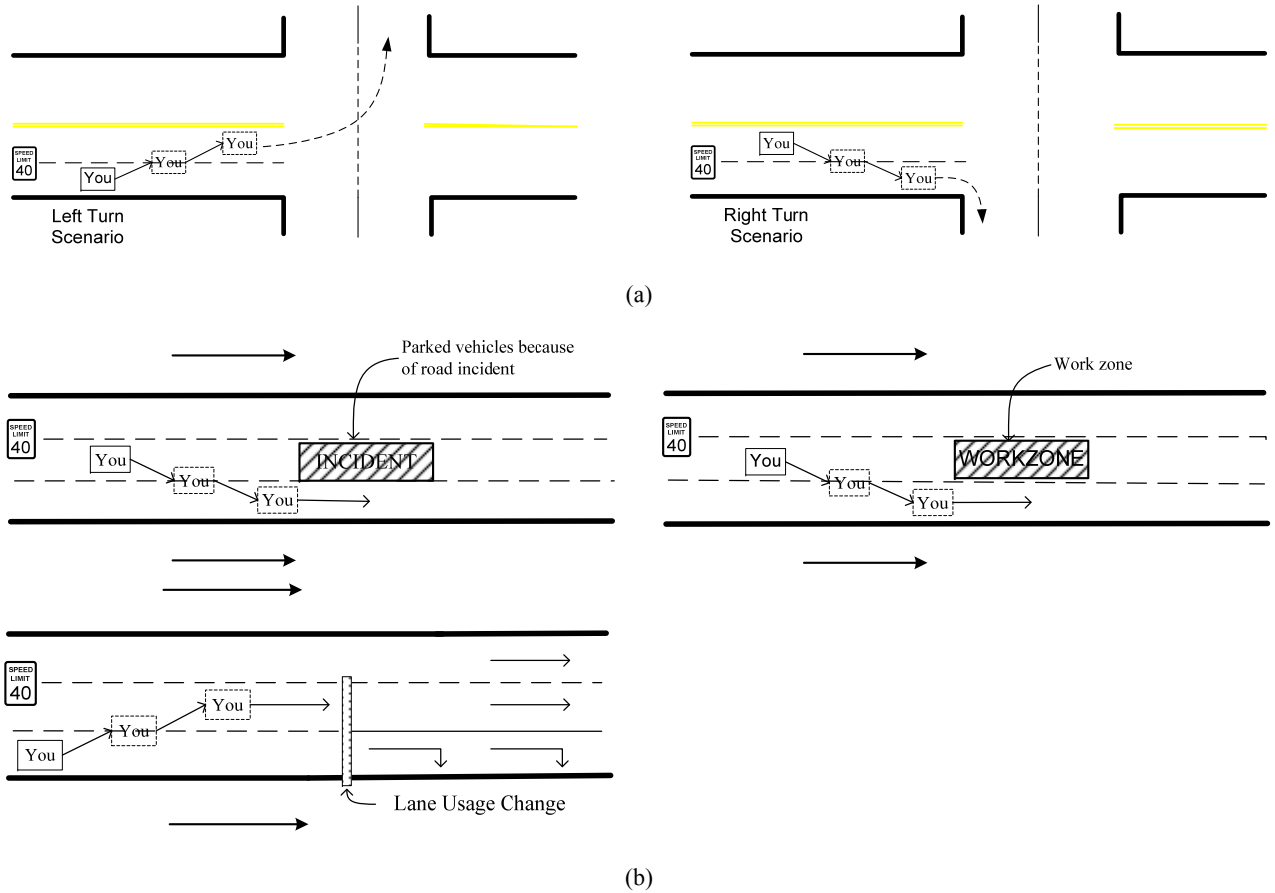


Figure 4-1. Typical lane-changing scenarios occurred on urban streets (a) Lane change for the upcoming right/left turn (b) Upcoming lane is not available (c)Stopped bus at bus-stop (d) Another vehicle merges into your lane (e) Slow moving vehicle (f) Queue length advantage (g) Truck/heavy vehicle influence (h) Tailgating by another vehicle (i) Pavement conditions

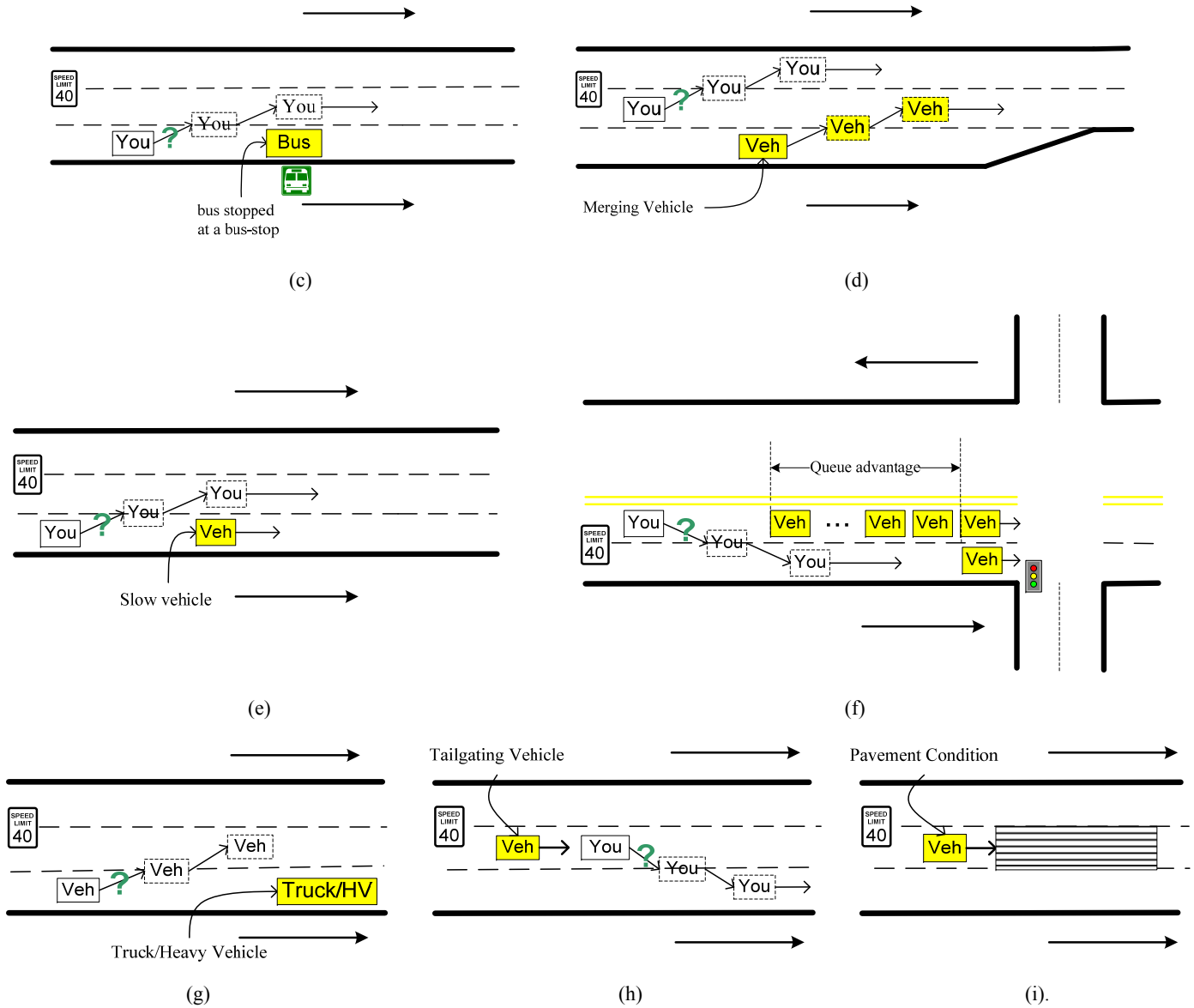


Figure 4-1. Continued

The output from this question is a list of factors affecting the likelihood of changing lanes for a particular reason. An example is presented in Table 4-3 for the work zone lane closure, with factors and their respective importance from a particular driver. The factors were identified by this participant as: lane-changing by the front vehicles, congestion on the current/target lane and the presence of worker and machinery. The corresponding levels of importance are: very important, important and not so important. The objective of this discussion is to identify the factors affecting lane-changing behavior under different scenarios, and link the driver type to the factors considered in each lane-changing situation. The third key question (Table 4-1 Q6) aims to capture the interactions (cooperation and competition) among drivers during lane-changing maneuvers. In this question, two directions of maneuvers (merging toward the curb-side lane or the median-side lane) were investigated. The participants were asked to describe their actions under each type of maneuver assuming that the traffic is congested. The objective of this part of discussion is to unveil possible driver interactions affecting lane changing, so that new algorithms can be developed to model these interesting behaviors. Ending questions intent to close the discussion and enable participants to reflect on previous comments. The ending question (Table 4-1 Q7) of this research was designed as: "Today, we began with the major possible reasons that would invoke a lane change and the level of frequency for executing it. Then for each reason, the major effective factors which affect drivers' decision on lane change were enumerated and examined. Finally, the possible interactions involved in a lane change behavior were discussed. Did I correctly describe what was said here? Is there anything you want to say but didn't get a chance?"

The detailed lists of questions and figures used in the focus groups study are provided in Table 4-1 and Figure 4-1, with the moderating scripts are presented in APPENDIX H.

Table 4-3. Factors and the respective importance for a given lane-changing situation

Q5.2.b) Work zone lane closure;	Very important	Important	Not so important
Factor 1: lane-changing by the front vehicles	⊙	○	○
Factor 2: congestion on current/target lane	⊙	○	○
Factor 3: presence of worker and machinery	○	○	⊙
Factor 4:	○	○	○

4.1.2 Participant Recruitment and Prescreening

In accordance with Institutional Review Board (IRB) requirements, all research involving human subjects needs to be approved by the relevant IRB Office prior to conducting any activities. An application was submitted to IRB-02 (UF Campus/Non Medical) for this study in Dec. 2007, and a formal approval was obtained in Jan. 2008.

The advertisement for recruitment was posted at public locations including the University of Florida campus, Gainesville downtown transit transfer station, Alachua county library and several supermarkets (APPENDIX E). In addition, the advertisement was placed on the classifieds in the local newspaper (Alligator), and sent to the UF ASCE student chapter and UF graduate students and staff. A web page was created and posted on the project website (http://grove.ufl.edu/~jiansun). A prescreening procedure was designed to obtain age, gender, race, residence, drive experience, and vehicle ownership information. Respondents could choose to complete the prescreening questionnaire and submit answers online, or download the questionnaire from the server and respond offline through email or mail.

For lane-changing behavior, there is no special “information-rich” participant, and no such focus group study has really been conducted previously. Consequently, no specific criteria were used in the prescreening procedure. Any person with a valid driver license can be considered as a qualified candidate. Two other general criteria for participants’ recruitment were set as: 1. must have driving experience no less than three years; 2. should have lived in Gainesville, FL, for at least one year.

The discussion time and the compensation were set as two hours, $50 per participant. By the end of the recruitment, responses from 84 participants were received. Previous focus groups studies in the transportation area (Loukopoulos et al., 2004; Loukopoulos, 2005) indicated that a candidate prescreening procedure is important for the quality of final results. The prescreening questionnaire (APPENDIX F) helped to identify qualified participants and collect useful background information. Participant selection was based on age, gender, driving experience, and vehicle ownership to ensure a diverse group of participants. A total of 21 participants were invited to join the three focus groups. Four of these participants unexpectedly didn’t attend. Two of the sessions had six participants, and the third had five. The detailed background information of the participants in these three groups is presented in Table 4-4.

Table 4-4. Personal background information of the focus group participants

ID	Gender	Age Group	Experience	Occupation	Driving Frequency	Hours Per Week	Peak/ Nonpeak	Vehicle Ownership
02-01	Female	20-29	3-9 years	UF undergraduate	Everyday	< 4 hours	Peak	Sedan/coupe
02-03	Female	30-39	> 10 years	Promotion representative	Everyday	8-14 hours	Peak	Sedan/coupe
02-04	Male	50-59	> 10 years	Film maker	Sometimes	4-8 hours	Non-peak	Sedan/coupe
02-05	Male	20-29	3-9 years	Undergraduate	Everyday	8-14 hours	peak	Sedan/coupe
02-06	Male	30-39	> 10 years	UF graduate	Usually	4-8 hours	Peak	Sedan/coupe
03-01	Male	30-39	> 10 years	UF undergraduate	Sometimes	4–8 hours	Peak	Pickup/SUV
03-02	Male	20-29	3-9 years	Just graduated	Everyday	8-14 hours	Peak	Sedan
03-03	Female	30-39	3-9 years	UF graduate	Everyday	4-8 hours	Peak	Sedan/coupe
03-05	Male	50-59	> 10 years	Vocation instructor	Everyday	4-8 hours	Peak	Sedan/coupe
03-06	Female	20-29	> 10 years	Truck driver	Everyday	> 14 hours	Any Time	Truck
03-07	Male	40-49	> 10 years	Shop owner	Usually	> 14 hours	Peak	Pickup/SUV
04-01	Female	30-39	> 10 years	Secretary	Everyday	8-14 hours	Peak	Sedan/coupe
04-02	Male	20-29	3-9 years	UF undergraduate	Sometimes	4-8 hours	Peak	Sedan/coupe
04-04	Male	20-29	> 10 years	UF graduate	Everyday	4-8 hours	Peak	Sedan/coupe
04-05	Female	20-29	3-9 years	UF graduate	Everyday	8-14 hours	Any Time	Pickup/SUV
04-06	Male	30-39	> 10 years	Pizza delivery	Everyday	> 14 hours	Any time	Sedan/coupe
04-07	Male	40-49	> 10 years	Fitness trainer	Sometimes	8-14 hours	Peak	Pickup/SUV

4.1.3 Other Issues

Upon arrival and before the discussion, a check-in procedure was followed and each participant was asked to 1) show their drivers' license for identification, 2) sign the informed consent form (APPENDIX C) and 3) complete a background survey by answering six multiple-choice driver habits-related questions (APPENDIX G). On the informed consent form, participants were fully briefed about the objectives of the experiment. The discussion of each focus group was audio-taped with the permission of the participants (Washburn and Ko, 2007).

Since it is difficult to anticipate the implementation of results of focus groups during the planning, a small pilot focus group study was planned and carried out in advance. The proposed pilot participants consist of faculty, staff and students from the University of Florida. Starting from the background survey and participants check-in, the whole procedure and moderating questions were the same as those enumerated for the real focus groups study. With the pilot study, defects within the current questions and moderating scripts were exposed, so that significant flaws could be avoided during the real discussion. However, results from this pilot study were not included in the further analysis.

Three focus group discussions were conducted from April to July, 2008. By studying and comparing answers from each participant, it was found that the range of ideas weren't getting new information, which is referred as the reach of saturation point (Morgan, 1997). As a result, no additional focus groups were needed. The reason for planning multiple groups is because focus groups are analyzed across groups, so that the patterns and themes can be obtained across groups.

4.2 Analysis of the Results

The information obtained directly from the focus groups are: 1) participants' personal background information; 2) likelihood level of changing lanes for each driver and for each DLC reason; 3) factors that affect the lane-changing maneuver for the situations examined; and 4) driver interactions that may occur when changing lanes. Various analyses were conducted to obtain information related to the research objectives. First, the drivers were classified into groups used cluster analysis (Tibshirani et al., 2001). Second, for each of the groups identified using cluster analysis, the probability of various actions was obtained. Lastly, the critical factors affecting lane changing for each lane-changing scenario were identified. The detailed description of each procedure is provided below.

4.2.1 Driver Type Classification Scheme

To classify drivers into groups, first the driver background information (driver aggressiveness) was used to divide the participants into groups/clusters. Then the overall intra-cluster variance on the likelihood of changing lanes for each scenario is calculated and aggregated to select the most appropriate number of groups that should be used in this study. The number of groups was further confirmed qualitatively based on verbal expressions obtained from the focus group discussions.

Table 4-5 presents the driver aggressiveness reported by each participant along with their corresponding likelihood of executing a lane change, as specified by each participant during the focus group discussions (Table 4-1 Q4).

Table 4-5. Driver-based likelihood of executing a discretionary lane change

ID	Aggressiveness (1-10)			Discussion Results (Level of Likelihood, 1 – 5)										
	Self-	Friends	Overall	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	Avg.
02-01	7	8	7.5	4	3	5	5	5	2	5	3	-	3	3.8
02-03	6	7	6.5	1	3	5	5	5	1	5	5	-	3	3.6
02-04	2	4	3	2	3	4	3	5	3	2	4	-	4	3.5
02-05	6	5	5.5	4	3	5	4	5	1	4	4	-	4	3.9
02-06	5	6	5.5	1	3	5	4	5	2	3	3	-	5	3.5
03-01	5	7	6	2	3	4	2	4	2	3	-	5	4	3.4
03-02	6	8	7	5	1	5	4	5	3	4	-	4	4	4.0
03-03	7	6	6.5	5	3	5	4	5	3	4	-	5	5	4.3
03-05	5	5	5	4	4	3	1	3	3	1	-	5	3	3.0
03-06	5	6	5.5	5	4	4	4	4	2	3	-	4	4	3.8
03-07	6	6	6	4	3	5	4	4	2	5	-	5	3	3.9
04-01	5	6	5.5	5	4	3	4	4	3	5	5	-	-	4.2
04-02	5	5	5	5	4	4	3	5	3	4	5	-	-	4.0
04-04	3	3-4	3.25	4	3	3	4	4	2	5	4	-	-	3.7
04-05	6	6	6	4	5	5	4	3	1	4	5	-	-	3.9
04-06	6	7	6.5	1	5	5	4	1	1	2	5	-	-	3.2
04-07	5	6	5.5	2	5	4	5	4	2	4	3	-	-	3.8
Avg.	5.3	6.0	5.65	3.4	3.5	4.4	3.8	4.2	2.1	3.7	4.2	4.7	3.9	3.8

The left part of the table provides the self-evaluation and the perceived friends' evaluation obtained from the background survey. An overall aggressiveness for each participant is calculated by averaging the self-evaluation and the friends' evaluation values. The results show that the self-evaluation value is generally slightly less than the friends' evaluation (Selfavg.= 5.3, Friendsavg.= 6). The right part of the table provides the likelihood of changing lanes under various scenarios, as reported by each participant. In addition to the pre-selected list of discretionary lane-changing (DLC) reasons shown in Table 2, four other DLC reasons were proposed by the participants:

R8: In a corridor with many traffic lights, changing lanes to avoid backed-up turning movements;
R9: Changing lanes to avoid scooters/pedestrians;
R10: Changing lanes to avoid an erratic driver

The level of likelihood to change lanes was averaged across all situations (from R1 to R10) for each participant. However, the relationship between the average level of likelihood to change lanes and driver's aggressiveness is not straightforward. For some situations, such as changing lanes to give way to merging vehicles (R2), a defensive driver may have a high probability of changing lanes, and a more aggressive driver may speed up rather than change lanes.

To classify drivers into groups, the K-means algorithm (Kanungo et al., 2002) was used to cluster n (n = 17) participants based on overall aggressiveness into k (k = 1, 2, 3, 4, or 5) partitions, k < n. The algorithm (provided in APPENDIX I) attempts to find the centers of natural clusters in a given data set, and assumes that the drivers' aggressiveness form a vector space. Eq. (4-1) gives the objective of the algorithm to minimize total intra-cluster variance over all partitions:

$$\min V = \sum_{i=1}^{k} \sum_{x_j \in S_i} (x_j - \mu_i)^2 \tag{4-1}$$

where:

x_j is the overall aggressiveness level for each participant j, obtained from Table 4-5,

k is the number of clusters within each lane-changing situation,

S_i represents each cluster (i = 1, 2, …, k), and

μ_i is the centroid point of cluster i.

In Eq. (4-1), each element x_j is grouped to the cluster i, which has a minimal distance from x_j to its centroid μ_i compared to the other cluster centroids. By setting the cluster number as 1, 2, 3, 4, and 5 respectively, centroids for the clusters were obtained as follows:

1) for cluster number = 1, centroid for each cluster is 5.73;
2) for cluster number = 2, centroids for each cluster are 4.68 and 6.57;
3) for cluster number = 3, centroids for each cluster are 3.1, 5.62, and 7.02;
4) for cluster number = 4, centroids for each cluster are 3.1, 5.2, 6.12 and 7.02;
5) for cluster number = 5, centroids for each cluster are 3.1, 5.2, 6.12, 6.78 and 8.

Next, the reason-based likelihood information is used to decide the most appropriate cluster number. The overall intra-cluster variance on the level of likelihood for each lane-changing situation (as reported in Table 4-5) was calculated, and accumulated across all reasons using Eq. (4-2):

$$W(k) = \sum_{R1}^{R10} \sum_{i=1}^{k} \sum_{l_j \in S_i} (l_j - \mu_i)^2 \tag{4-2}$$

where:

l_i is the level of likelihood to change lanes for situation i for participant j,

k is the number of clusters within each lane-changing situation,

S_i represents each cluster (i = 1, 2, …, k), and

μ_i is the centroid point of cluster i.

The W value for each classification was calculated as: $W(1) = 161.92$, $W(2) = 154.59$, $W(3) = 145.14$, $W(4) = 137.04$ and $W(5) = 135.68$. Since the clustering method aims to put participants into clusters according to "closest" similarity rules, and no a priori hypotheses were made, statistical significance testing is not appropriate. Consequently, intra-cluster dissimilarity

(low values when the partition is good) is used to determine the appropriate number of clusters. The Hartigan index (Tibshirani et al., 2001), which indicates the dissimilarity that will be removed by splitting the k clusters into k+1 clusters, was used:

$$H(k) = (n-k-1) * \frac{W(k) - W(k+1)}{W(k+1)} \tag{4-3}$$

where:

n is number of objects to be clustered, n = 17,

k is the number of clusters used, and

W(k) is the value calculated from Eq. (4-2).

Using Eq. (4-3), the indices for the number of clusters equaling 2, 3, 4 and 5 were calculated as H(1) = 0.71, H(2) = 0.91, H(3) = 0.77 and H(4) = 0.12. A large descent is found to occur from H(3) to H(4), which means by splitting the 3 clusters into 4, the dissimilarity is removed largely, while by splitting into 5, the dissimilarity is not removed as much. Figure 4-2 provides the results of analysis for number of clusters ranging from 1 to 5. When the cluster number is larger than 4, the intra-cluster dissimilarity does not decrease much. Therefore, it is recommended that the appropriate number of clusters used is 4.

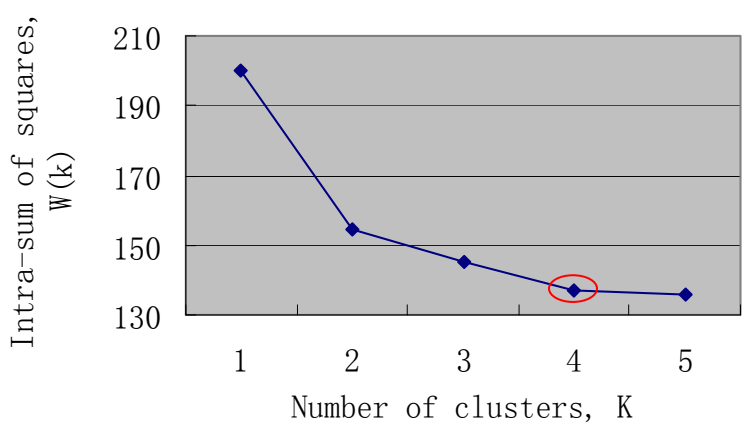


Figure 4-2. Results for the clustering with different number of cluster

Using the overall aggressiveness obtained together with the above K-mean cluster analysis, the participants can be categorized into four groups defined as L1 (<= 4.1), L2 (4.2 – 5.6), L3

(5.7 – 6.5) and L4 (>= 6.6). In the remainder of this section, this grouping is further linked to verbal expressions the participants used during the focus groups.

During the focus group discussion, for the set of discretionary lane changes on urban streets, participants were asked to explain their thought process and how they would behave in each situation. The responses, along with the extent of the risk they would take and how much they focus on themselves vs. on surrounding vehicles, were evaluated. It was found that four elements were frequently considered by the participants: desirability of speed advantage, tendency for risk taking, consideration of consequences and degree of selfishness. Based on verbal expressions on these four elements, the following types of drivers were identified:

- **Type A:** Drivers would not change lanes for most situations. They always want to keep the current lane because they are risk averse. Meanwhile, this type of drivers always considers other vehicles and would likely give way to vehicles merging into the current lane, or try not to block others. They can be described as the least aggressive drivers.

- **Type B:** Drivers would like to get a better position or speed advantage for some situations (the number is close to 4) under very low risk, but wouldn't on others. They mentioned more details such as landscape or pictures and bumper stickers on the front vehicles in deciding whether to change lanes. This type of driver says lane changing depends on their mood: they would likely slow down if they are not in a hurry. Compared to the previous group, drivers in this group have more willingness to change lanes to obtain speed advantage, and consequently are somewhat more aggressive. However they generally don't like to take risks.

- **Type C:** Drivers aim to get a better position or speed advantage if they have a chance. However, they would also consider other factors, such as traffic congestion or destination, which they consider more important than speed advantage and better positioning. Compared to the previous driver group, this group of drivers is more ambitious in getting speed advantage, and would take increasing risks in changing lanes.

- **Type D:** Drivers in this group would always try to get a better position or speed advantage whenever they have a chance. They barely think about other drivers. Position and speed are their first consideration. They would change lanes without any hesitation, and would risk without caring much about the environment or other drivers.

The categorization, with the corresponding observation of characteristics of the participants, is summarized in Table 4-6. It was found that some of the four driver characteristics factors

correlate highly to each other. For example, the high risk-taking drivers generally desire speed advantage highly.

Table 4-6. Driver type categorization by the characteristics demonstrated in verbal expression

Driver Type	Desiring Speed Adv.	Risk Taking	Consideration of Consequence	Selfishness
Type A	No	No	No	No
Type B	Sometime	No	Yes, always	No
Type C	Yes, always	Sometime	Sometime	Yes, always
Type D	Yes, always	Yes, always	No	Yes, always

By tagging each participant with a corresponding driver type (A, B, C or D), it was found that for most of them, the driver type information obtained from the focus group discussion is consistent to the groups defined in the K-mean cluster analysis (L1 to Type A, L2 to Type B, L3 to Type C, and L4 to Type D), as shown in Table 4-7.

Table 4-7. Consistency between the clustering result and driver type demonstrated

ID	Overall Aggressiveness	K-Mean Cluster	Type	Agree or not
02-01	7.5	L4	D	Y
02-03	6.5	L3	C	Y
02-04	3	L1	A	Y
02-05	5.5	L2	B	Y
02-06	5.5	L2	C	N
03-01	6	L3	C	Y
03-02	7	L4	D	Y
03-03	6.5	L3	C	Y
03-05	5	L2	B	Y
03-06	5.5	L2	B	Y
03-07	6	L3	C	Y
04-01	5.5	L2	C	N
04-02	5	L2	B	Y
04-04	3.25	L1	A	Y
04-05	6	L3	C	Y
04-06	6.5	L3	C	Y
04-07	5.5	L2	B	Y

The only exceptions are participants 02-06 and 04-01. Both of these participants were in the aggressiveness group L2, with an overall aggressiveness value as 5.5. However, they were assigned to type C instead of type B since they demonstrated ambition in getting speed advantage during the discussion, and generally won't give way to more than one vehicle. This is probably due to the fact that groups L2 and L3 are rather close to each other. However, since only 2 of 17 samples do not agree, it was deemed reasonable to divide the drivers into four groups as recommended above.

4.2.2 Probability of Various Actions for Different Driver Types

The classification of drivers developed in the previous section was next applied to each of the lane-changing situations. The number of drivers in each group (L1, L2, L3 and L4) is 2, 6, 7 and 2 respectively. Table 4-8 presents the frequency of likelihood level for each lane-changing maneuver by driver type along with the mean and the standard deviation. For example, for R1 (change lanes to pass a stopped-bus at a bus stop), the average acceptance levels for the four groups (L1, L2, L3 and L4) are 3, 3.6, 3 and 4.5 respectively. This means that the drivers in group L4, which are more aggressive, are more likely to change lanes to pass a stopped-bus. This is consistent with the expectation for such a maneuver. Similar trends can be observed for reasons R3, R4, R5, R7 and R8, where the more aggressive drivers are more likely to make lane changes. For reason R2 (change lanes to allow a vehicle to merge into your lane), the likelihood level for the four groups L1, L2, L3 and L4 are 3, 4, 3.5 and 2 respectively. In this case, the most aggressive drivers are typically not willing to allow the merge. Instead of giving way by changing lanes, they accelerate or at least maintain their speed to prevent the merging vehicle from changing lanes. Meanwhile, defensive drivers (L1) typically choose to decelerate instead of changing lanes. The other drivers (L2 and L3) are found with the largest likelihood to change lanes in this situation. Reasons R6 and R10 have similar trends as R2. The other reason, R9

Table 4-8. Lane-changing likelihood level for each driver group (L1-L4)

Reasons	Freq.	Total #	Frequency by likelihood level					Likelihood ($\hat{\mu}$ / $\hat{\sigma}$)
			1	2	3	4	5	
R1 (Stopped bus)	L1	2	0	1	0	1	0	3.0 /1.4
	L2	6	1	1	0	1	3	3.7 /1.8
	L3	7	2	1	0	3	1	3.0 /1.6
	L4	2	0	0	0	1	1	4.5 /0.7
R2 (Vehicle merge)	L1	2	0	0	2	0	0	3.0 /0.0
	L2	6	0	0	1	4	1	4.0 /0.6
	L3	7	0	0	5	0	2	3.6 /1.0
	L4	2	1	0	1	0	0	2.0 /1.4
R3 (Slow vehicle)	L1	2	0	0	1	1	0	3.5 /0.7
	L2	6	0	0	2	3	1	3.8 /0.8
	L3	7	0	0	0	1	6	4.9 /0.4
	L4	2	0	0	0	0	2	5.0 /0.0
R4 (Queue advantage)	L1	2	0	0	1	1	0	3.5 /0.7
	L2	6	1	0	1	3	1	3.5 /1.4
	L3	7	0	1	0	5	1	3.9 /0.9
	L4	2	0	0	0	1	1	4.5 /0.7
R5 (Heavy vehicle)	L1	2	0	0	1	1	0	3.5 /0.7
	L2	6	0	0	1	3	2	4.2 /0.8
	L3	7	1	0	1	2	3	3.9 /1.5
	L4	2	0	0	0	0	2	5.0 /0.0
R6 (Tailgating)	L1	2	0	1	1	0	0	2.5 /0.7
	L2	6	0	3	3	0	0	2.5 /0.6
	L3	7	4	2	1	0	0	1.6 /0.8
	L4	2	0	1	1	0	0	2.5 /0.7
R7 (Pavement)	L1	2	0	1	0	0	1	3.5 /2.1
	L2	6	1	0	2	2	1	3.3 /1.4
	L3	7	0	1	1	3	2	3.9 /1.1
	L4	2	0	0	0	1	1	4.5 /0.7
R8 (Backup turning)	L1	2	0	0	0	2	0	4.0 /0.0
	L2	4	0	0	2	0	2	4.0 /1.2
	L3	4	0	0	0	1	3	4.8 /0.5
	L4	1	0	0	1	0	0	3.0 /0.0
R9 (Pedestrian/scooter)	L1	0	0	0	0	0	0	-
	L2	2	0	0	0	1	1	4.5 /0.7
	L3	3	0	0	0	0	3	5.0 /0.0
	L4	1	0	0	0	1	0	4.0 /0.0
R10 (Erratic driver)	L1	1	0	0	0	1	0	4.0 /0.0
	L2	3	0	0	1	1	1	4.0 /1.0
	L3	5	0	0	2	1	2	4.0 /1.0
	L4	2	0	0	1	1	0	3.5 /0.7

(changing lanes to avoid scooters/pedestrians), does not have large differences across the four groups. Most drivers tend to change lanes for this particular reason, no matter the driver type,

which means the classification may not have significant impact on this situation. The comparative small sample size (6, instead of 17) for R9 is another possible cause for this similarity.

In summary, likelihoods for lane changes are different depending on the scenarios. For some lane-changing reasons, aggressive drivers always have a higher likelihood to change lanes, while for other reasons they don't. Consequently, in modeling lane changes, both the driver type and the individual lane-changing scenario should be considered.

4.2.3 Critical Factors for Each Lane-Changing Scenario

Another important objective of the focus group study is to obtain the significant factors considered by drivers for various lane-changing scenarios. These include all the DLC scenarios originally listed and the two MLCs (Table 4-1 Q5, Sce.1 - 9). The factors identified, as well as the driver-assigned importance levels ("very important", "important", and "not so important") were collected from each participant during the focus group discussions and aggregated by lane-changing scenario. A quantitative evaluation was next designed by assigning each of three levels of importance (for "very important", "important" and "not so important" as in Table 4-3) 9, 6 and 3 credits respectively. Only factors listed by the participants received credits. These credits were used only to provide a quantitative analysis base; any set of weights or credits could be assigned without alter the results f this analysis.

Let X_{ij} represent the credit(s) that participant j assigned to factor i, then $S_i = \sum_j X_{ij}$ is the total credits earned by factor i from all participants. Thus X_{ij} is as follows:

$$X_{ij} = \begin{cases} 9 & \textit{factor } i \text{ is chosen by } \textit{participant } j, \text{and weighed as "very important";} \\ 6 & \textit{factor } i \text{ is chosen by } \textit{participant } j, \text{and weighed as "important";} \\ 3 & \textit{factor } i \text{ is chosen by } \textit{participant } j, \text{and weighed as "not so important";} \\ 0 & \textit{factor } i \text{ is not chosen by } \textit{participant } j. \end{cases} \tag{4-4}$$

By comparing the total credit earned by each factor i ($\forall i, S_i = \sum_j X_{ij}$), the ones with higher credits were chosen by more participants, thus are more important. Table 4-9 presents the factors found to affect drivers' lane-changing maneuvers for the lane-changing scenarios examined (see Table 4-1 Q5). Table 9 presents the factors in decreasing order of significance, as indicated by the participants. A discussion for each lane-changing scenario and the respective factors found to be important is provided below:

Scenario 1 - Upcoming left/right turn (1a and 1b): The left turn and right turn scenarios were believed to be similar, and the factors found to be important for both are traffic congestion on the current lane and the target lane, the posted speed limit and travel speed, and the distance to the downstream intersection. The difference is that for the left turn scenario, drivers pay more attention to the traffic signal, while in the right turn scenario, the familiarity with road/alternative and the presence of pedestrian/bike lanes tend to affect drivers more.

Scenario 2 - Current lane is not available downstream (2a, 2b and 2c): The factors found to be important for these three scenarios are traffic congestion on the current lane and the target lane, the posted speed limit and travel speed, and the distance to the lane termination location. The difference is that for road incidents, drivers have to pay attention to oncoming emergency vehicles. In work zones, drivers pay attention to the signs and the presence of workers or machinery.

Scenario 3 - Stopped bus at bus-stop: Four factors found to be important are the distance to the bus, the traffic congestion/queue ahead, the number of passengers at the bus stop and the location of the next bus stop. Other factors, such as passenger loading stage and subject vehicle type were also mentioned. However, these factors were either not chosen by many participants or not assigned as high a level of importance.

Table 4-9. Important factors for individual lane-changing scenario

Sce.		Factors	Frequency			Si: Total Credits
			3:weak	6:middle	9:strong	
Sce. 1. Upcoming left/right turn	1a. Left-turn	Congestion on the left lane/easy to get a gap	2	5	7	99
		Traffic signal/left turn signal	3	5	5	84
		Speed limit/travel speeds	3	4	4	69
		Distance to the intersection	4	5	2	60
		Number of lanes	3	1	2	33
		Vehicle type	1	1	1	18
		Driver mood/in a rush	1	0	1	12
		Pedestrian/scooter	0	0	1	9
		Weather condition	0	1	0	6
	1b. Right-turn	Distance to the intersection	2	3	5	69
		Speed limit/ travel speeds	4	3	4	66
		Familiarity with road/alternative	3	5	2	57
		Congestion on current and adjacent lane	1	2	4	51
		Pedestrian/bike lane	5	3	1	42
		Traffic signal/RTOR	3	1	2	33
		Lane changes by other vehicles	2	1	1	21
		Vehicle type	1	1	0	9
		Weather condition	0	1	0	6
Sce. 2. Current lane is not available downstream	2a. Road incident	Congestion on current and merging lane	3	3	5	72
		Lane changes by front vehicles	1	5	4	69
		Distance to incident	3	2	4	63
		Oncoming emergency vehicle	2	4	3	57
		Relative speed	2	4	3	57
		People in the roadway	1	2	1	24
		Visibility	1	2	0	15
		Debris in the roadway	1	1	0	9
		Weather condition	1	1	0	9
		Vehicle type	0	1	0	6
	2b. Workzone	Lane changes by front vehicles	3	5	4	75
		Presence of worker or machinery	4	5	2	60
		Congestion on current and merging	2	4	3	57
		Number of lanes	3	2	4	57
		Location of the first warning sign	3	2	3	48
		Speed limit/travel speeds	2	0	1	15
		Vehicle type	1	1	0	9
		Weather condition	0	1	0	6
		Visibility	1	0	0	3
	2c. Lane channel. change	Level of congestion	2	5	7	99
		Distance to the lane drop	3	6	5	90
		Speed limit/travel speeds	4	7	2	72
		Lane changes by front vehicles	1	2	1	24
		Pedestrians/bikers	2	2	0	18
		Vehicle type	1	2	0	15
		Weather condition	0	1	0	6
		Signal ahead	1	0	0	3

Table 4-9. Continued

Sce.	Factors	Frequency			Si: Total Credits
		3:weak	6:middle	9:strong	
3. Stopped-bus	Traffic congestion and queue ahead	2	3	6	78
	Location of the next stop	1	5	3	60
	Distance to the bus	1	3	4	57
	Number of persons at the bus-stop	2	4	1	39
	Stage of loading/unloading	3	2	0	21
	Distance to my next turn	3	2	0	21
	Speed limit/travel speeds	1	2	0	15
	Mood/urgency	1	0	1	12
	Vehicle type	1	1	0	9
	Weekday or weekend	0	1	0	6
	Weather condition	0	1	0	6
4. Vehicle merge	Congestion on the target lane	2	7	4	84
	Speed limit/travel speeds	2	5	4	72
	Aggressiveness of the merge	3	6	2	63
	Distance to my next turn	4	5	2	60
	Merge and my vehicle type	1	4	3	54
	With a turning signal or not	0	1	1	15
	Direction of the merge	1	1	0	9
	Presence of signal control	2	0	0	6
	Weather and my mood	1	0	0	3
5. Slow vehicle	Distance to my next turn	2	8	3	81
	Speed limit/travel speeds	1	7	4	81
	Congestion on target lane	1	5	4	69
	My mood, hurry or not	5	4	2	57
	Merge vehicle type	3	1	0	15
	Presence of signal control/status	0	2	0	12
	Weather or visibility	0	2	0	12
6. Queue advantage	Queue length difference	2	4	7	93
	Distance to my next turn	4	6	3	75
	Congestion on the target lane	1	4	3	54
	Current signal status/green time	3	5	1	48
	Vehicle type of the queuing vehicles	1	0	2	21
	Number of lanes	2	1	1	21
	Weather condition/visibility	0	2	0	12
	My vehicle type	1	0	0	3
7. Heavy vehicle	Travel speed/desired speed	1	5	6	87
	Congestion on all lanes	1	5	4	69
	Personally uncomfortable with HV	3	4	2	51
	My vehicle type	3	3	2	45
	Weather and visibility	2	3	1	33
	Distance b/t mine and the HV	2	1	0	12
	Time driving on current lane	1	1	0	9
8. Tailgating	Speed limit/travel speeds	2	5	6	90
	Congestion on all lanes	3	4	5	78
	The lane I am driving on	2	7	2	66
	Vehicle type (mine and other's)	5	2	2	45
	Mood	3	1	1	24
	Time driving on current lane	1	2	0	15
	Distance to my next turn	1	1	0	9
9. Pavement	Distance to my next turn	3	3	5	72
	How large the difference of the pavement	4	5	2	60
	How long of the pavement diff. segment	6	3	2	54
	Speed difference	4	1	3	45
	Congestion on the other lanes	0	2	3	39
	Weather and visibility	0	1	0	6
	My vehicle type	1	0	0	3

Scenario 4 - Another vehicle merges into your lane: Five factors were found to be important. In addition to the posted speed limit, travel speed and traffic congestion on the target lane, the distance to the next turn, aggressiveness of the merge and vehicle types of the merger and the subject were also considered as important.

Scenario 5 - Slow moving vehicle: Most of the factors found to be important, such as traffic congestion on the target lane, the posted speed limit and travel speed, and the distance to the next turn, are similar to previous lane-changing scenarios. Only one factor, the mood and urgency of the subject driver, is somewhat unique to this scenario.

Scenario 6 - Queue length advantage: Four factors were found to be important. In addition to the previously mentioned distance to the next turn and the traffic congestion on the target lane, two other factors offered are the queue length difference and the current signal status, both of which are more related to queuing. It was generally found that in most lane-changing scenarios, if there is a traffic signal in the vicinity, the signal status is always an important factor.

Scenario 7 - Truck/heavy vehicle influence: Four factors were found to be important: traffic congestion on all available lanes, the posted speed limit and travel speed, personally uncomfortable with HV, and the subject vehicle type. The latter two factors are related closely to the driver's line of sight. The participants express more willingness to change lanes, when the line of sight is blocked.

Scenario 8 - Tailgating by another vehicle: Four factors were found to be important. First, the posted speed limit and travel speed, and traffic congestion on all available lanes were considered important. Next, the participants also considered subject and follower vehicle types, and the subject lane (median or curb-side) as important. If the tailgating occurs on the median lane, they are even more willing to change lanes.

Scenario 9 - Pavement condition: Five factors were found to be important. As for the previous scenarios, the distance to the next turn, speed difference and congestion on the other lanes were considered important. Other factors considered as important are the difference of the pavement quality and the length of the different pavement segment.

As shown, some factors, such as congestion levels and speed differences are common to all scenarios. Other factors applicable to particular lane change(s), were also found in each individual scenario. In addition to the factors identified by focus group participants as important, there are other types of data, such as vehicle acceleration/deceleration and road geometry data, which are essential in lane-changing modeling. These need to be considered in conjunction with the driver-related factors identified in this analysis.

Question Q6 (Table 4-1) focused on driver interactions that may occur during lane changing. The related conclusions are provided below:

- In general, the variability of driver behavior when they are in the lag vehicle (with respect to the lane changing vehicle) is much larger than the variability of behavior in drivers making the lane change. Drivers in the lag vehicle generally consider the traffic conditions when deciding how to react to a merging vehicle..
- The type of driver in the lag vehicle is important. Under heavy traffic, lag drivers have to "interact" with merging drivers.. However, driver types A and B typically choose to give way and cooperate, while driver types C and D would accelerate or at least maintain their speed.
- The presence of intersections or drive ways is important to the lag vehicle drivers. They are more willing to cooperate if there are intersections or driveways in the vicinity of the lane changing maneuver, since they consider that the lane changing vehicle might need to turn soon.

4.3 Summary and Conclusions

The lane-changing decision-making process on urban arterials depends largely on driver characteristics, which cannot be obtained from traditionally collected field data. In this research,

a focus group study was conducted to document the drivers' thinking process and perceptions related to lane-changing maneuvers. The following conclusions were drawn from this study:

- Considering both personal background data and stated behavior data related to urban arterial lane-changing situations, the participating drivers were classified into four groups using cluster analysis. Quantitative results from the questionnaire were found to be consistent to the qualitative verbal expression-based conclusions.
- The probabilities of changing lanes were obtained for each of the four driver type groups and for each lane-changing scenario. .
- Factors affecting each lane-changing scenario were obtained from the focus group discussion. Some of the factors, such as congestion level and speed difference were found be apply to all scenarios, while several factors were found to be unique to each lane-changing scenario.

The results of this study can be implemented into micro-simulators to better replicate driver behavior in urban street networks: the classification into four driver types as well as their corresponding behavior can be used to model lane changes more accurately. For example, CORSIM currently allows the use of ten different driver types, however it is possible that only four driver types are needed to describe the traffic stream accurately. These four driver types could be modeled to attempt and execute lane changes as described above, by considering the factors identified to be important to that group for each maneuver type.

CHAPTER 5
"IN-VEHICLE" EXPERIMENT AND ANALYSIS

In Chapter 4, the procedure and result analysis of the focus group study on lane-changing behaviors were presented. One of the issues with using the focus group study is that the research was based on focus group discussions and background surveys, wherein the participants may "over-think" their actions, while many actual driving decisions were made instantaneously or in a very short time. Consequently, a field experiment was designed to observe and validate the stated driver preferences. This chapter describes the "in-vehicle" data collection experiment and the corresponding analysis procedure. The objective of this experiment is to observe the drivers' action under various lane-changing scenarios, and to obtain the quantitative values for the important factors identified during the focus group study. The experimental results are used to develop new lane-changing models on urban arterials in further Chapter 6.

This chapter is organized as follows: Section 5.1 discusses the preparation and implementation of the "in-vehicle" experiment. The composition of the participating drivers, the testing routes and the techniques used during driving for this experiment are presented. Results from the "in-vehicle" data collection experiment are analyzed in Section 5.2. The quantitative values for the important factors in each lane-changing related maneuver were obtained from the "in-vehicle" video clips, so that further analysis regarding driver type classification can be conducted. The chapter ends with a summary of the findings from the "in-vehicle" experiment.

5.1 "In-Vehicle" Experiment Preparation and Implementation

During the "in-vehicle" experiment, an instrumented vehicle was used to verify the lane-changing process and the gap acceptance characteristics of a diverse group of drivers. Implementation details for the experiment are provided in this section. First, the participant

characteristics are presented. Next, the route used in testing is provided. Finally, the driving test procedure, as well as recording techniques used during the "in-vehicle" experiment, is discussed.

5.1.1 Participant Characteristics

The same recruiting website and prescreening procedure as the focus group study (http://grove.ufl.edu/~jiansun) were used for participant recruitment in the "in-vehicle" experiment. From more than 150 responses, 40 drivers were invited with an intention to select a diverse group based on age, gender, driving experience, occupation and vehicle ownership. In addition, diverse drivers were purposely invited based on the indicated aggressiveness. With an eye on verifying the results from the focus group study, ten of the subjects had participated in the focus group discussion. The compensation was set at $50 per participant. Table 5-1 presents a summary of the statistics related to age and gender for the participants. The detailed background information about the participants is provided in Table 5-2.

Table 5-1. Overview of the participants' characteristics for the "in-vehicle" experiment

Age and Gender		20 - 29	30 - 39	40 - 49	50 - 59	Total
# of participant (percentage, %)	Male	6 (15)	5 (12.5)	6 (15)	6 (15)	23 (57.5)
	Female	4 (10)	6 (15)	3 (7.5)	4 (10)	17 (42.5)
	Total	10 (25)	11 (27.5)	9 (22.5)	10 (25)	40 (100)

Table 5-2. Personal background information of the "In-Vehicle" experiment participants

ID	Gender	Age Group	Experience	Occupation	Driving Frequency	Hours per Week	Peak/ Non-peak	Vehicle Ownership
05-01	Male	20-29	3 – 9 years	UF undergraduate	Usually	8 – 14 hr	Peak	Pickup/SUV
05-02	Male	40-49	> 10 years	Shopper owner	Usually	> 14 hr	Peak	Pickup/SUV
05-03	Female	20-29	3 – 9 years	Insurance company	Everyday	< 4 hr	Peak	Sedan/coupe
05-04	Male	50-59	> 10 years	Film maker	Sometimes	4 – 8 hr	Non-peak	Sedan/coupe
05-05	Female	30-39	> 10 years	UF graduate	Sometimes	4 – 8 hr	Non-peak	Sedan/coupe
05-06	Male	20-29	3 – 9 years	Medical student	Usually	4 – 8 hr	Peak	Sedan/coupe
05-07	Female	30-39	> 10 years	UF graduate	Sometimes	4 – 8 hr	Non-peak	Sedan/coupe
05-08	Female	30-39	> 10 years	Advertisement promoter	Everyday	8 – 14 hr	Peak	Sedan/coupe
05-09	Male	20-29	3 – 9 years	UF undergraduate	Sometimes	4 – 8 hr	Peak	Sedan/coupe
05-10	Male	30-39	> 10 years	UF graduate	Usually	4 – 8 hr	Peak	Sedan/coupe
05-11	Female	50-59	> 10 years	Clerk at supermarket	Sometimes	> 14 hr	Peak	Sedan/coupe
05-12	Male	40-49	> 10 years	Environment consultant	Sometimes	4 – 8 hr	Non-peak	Sedan/coupe
05-13	Male	20-29	3 – 9 years	Lawyer	Everyday	4 – 8 hr	Peak	Sedan/coupe
05-14	Female	20-29	3 – 9 years	UF undergraduate	Sometimes	4 – 8 hr	Peak	Sedan/coupe
05-15	Female	50-59	> 10 years	Unemployed	Sometimes	< 4 hr	Non-peak	Pickup/SUV
05-16	Male	20-29	3 – 9 years	UF staff	Everyday	8 – 14 hr	Peak	Pickup/SUV
05-17	Female	20-29	3 – 9 years	UF undergraduate	Everyday	4 – 8 hr	Peak	Sedan/coupe
05-18	Male	30-39	> 10 years	Body trainer	Sometimes	< 4 hr	Non-peak	Sedan/coupe
05-19	Male	50-59	> 10 years	Fire truck driver	Usually	4 – 8 hr	Non-peak	Mini-Van
05-20	Male	40-49	> 10 years	Post-doctor researcher	Usually	< 4 hr	Non-peak	Truck

Table 5-2. Continued

ID	Gender	Age Group	Experience	Occupation	Driving Frequency	Hours per Week	Peak/ Non-peak	Vehicle Ownership
05-21	Male	30-39	> 10 years	Translator	Sometimes	< 4 hr	Non-peak	Sedan/coupe
05-22	Female	50-59	> 10 years	Unemployed	Everyday	8 – 14 hr	Non-peak	Jeep
05-23	Male	20-29	3 – 9 years	UF graduate	Everyday	8 – 14 hr	Peak	Sedan/coupe
05-24	Male	30-39	> 10 years	Biology consultant	Everyday	4 – 8 hr	Peak	Sedan/coupe
05-25	Female	30-39	> 10 years	Secretary	Everyday	8 – 14 hr	Peak	Sedan/coupe
05-26	Male	50-59	> 10 years	Vocation consultant	Everyday	4 – 8 hr	peak	Sedan/coupe
05-27	Male	40-49	> 10 years	Veteran, resell desktops	Usually	4 – 8 hr	Non-peak	Pickup/SUV
05-28	Male	40-49	> 10 years	Small business owner	Sometimes	4 – 8 hr	Non-peak	Pickup/SUV
05-29	Male	30-39	> 10 years	Chef and painter	Usually	< 4 hr	Non-peak	Jeep
05-30	Female	30-39	> 10 years	Criminal lawyer	Everyday	4 – 8 hr	Peak	Sedan/coupe
05-31	Male	50-59	> 10 years	Construction worker	Everyday	8 – 14 hr	Non-peak	Jeep
05-32	Male	50-59	> 10 years	Retired, consultant	Sometimes	< 4 hr	Non-peak	Pickup/SUV
05-33	Female	50-59	> 10 years	School instructor	Sometimes	4 – 8 hr	Peak	Sedan/coupe
05-34	Female	30-39	> 10 years	Urban planner	Everyday	4 – 8 hr	Peak	Sedan/coupe
05-35	Female	40-49	> 10 years	UF staff	Sometimes	< 4 hr	Non-peak	Sedan/coupe
05-36	Male	40-49	> 10 years	Real estate seller	Everyday	4 – 8 hr	Non-peak	Truck, sedan
05-37	Male	50-59	> 10 years	College instructor	Sometime	< 4 hr	Non-peak	Sedan, scooter
05-38	Female	40-49	> 10 years	Part-time job	Everyday	4 - 8 hr	Peak	Mini-Van
05-39	Female	20-29	3 – 9 years	UF undergraduate	Everyday	4- 8 hr	Non-peak	Sedan/coupe
05-40	Female	40-49	> 10 years	Part-time job	Everyday	8 – 14 hr	Non-peak	Truck

5.1.2 Testing Route

In addition to the participants' recruitment, another important issue during the preparation is the selection of the driving route. The road segments selected were located in the city of Gainesville, FL, and each may invoke one or more lane-changing scenario(s), such as left turn, right turn, work zone, stopped-bus, right-lane merging, and so on. By connecting these segments, two routes, shown in Figures 5-1 and 5-2, were established for different time-of-day traffic data collection (with different levels of congestion).

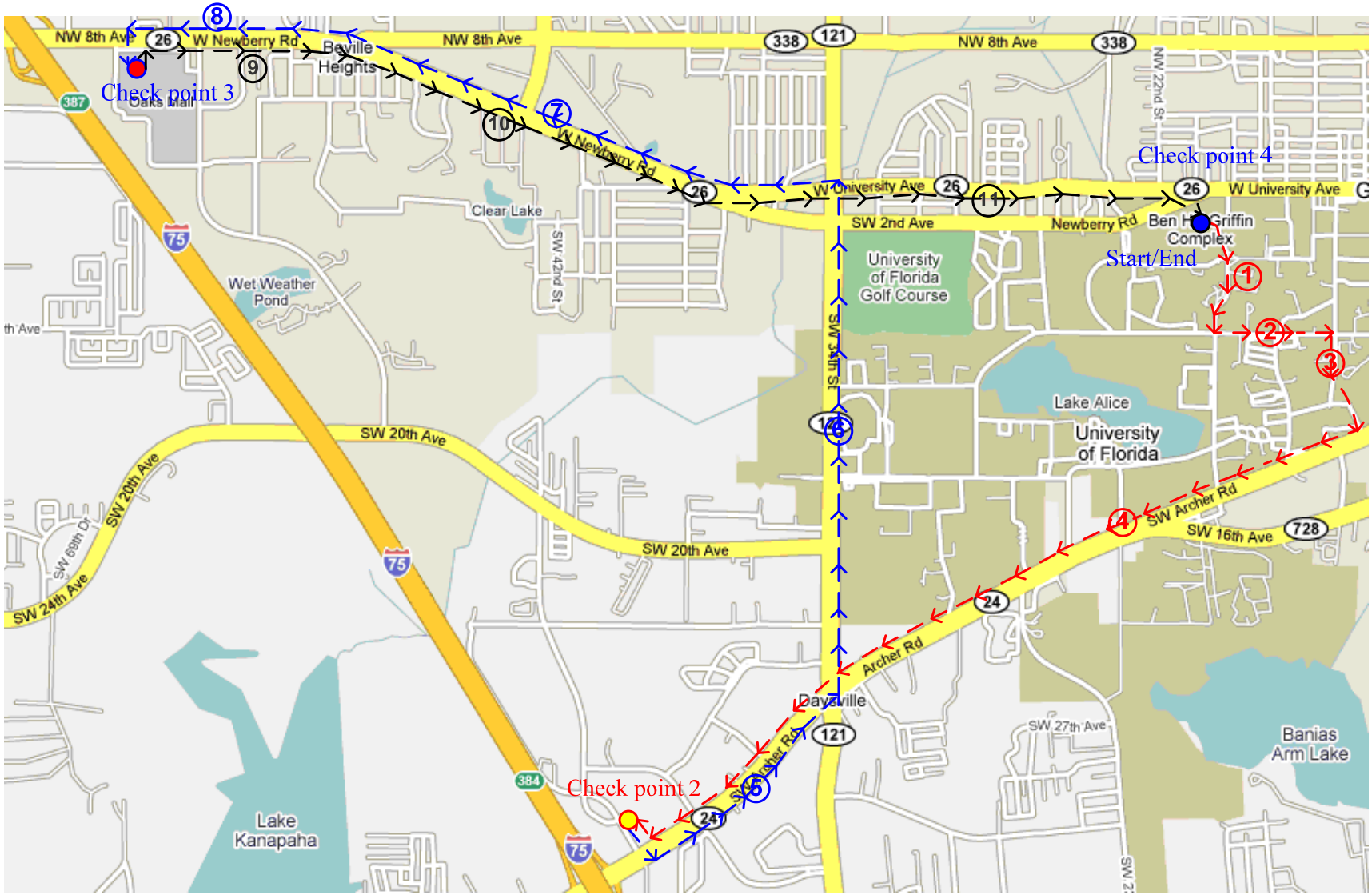


Figure 5-1. Proposed route for the field data collection (Newberry Road route)

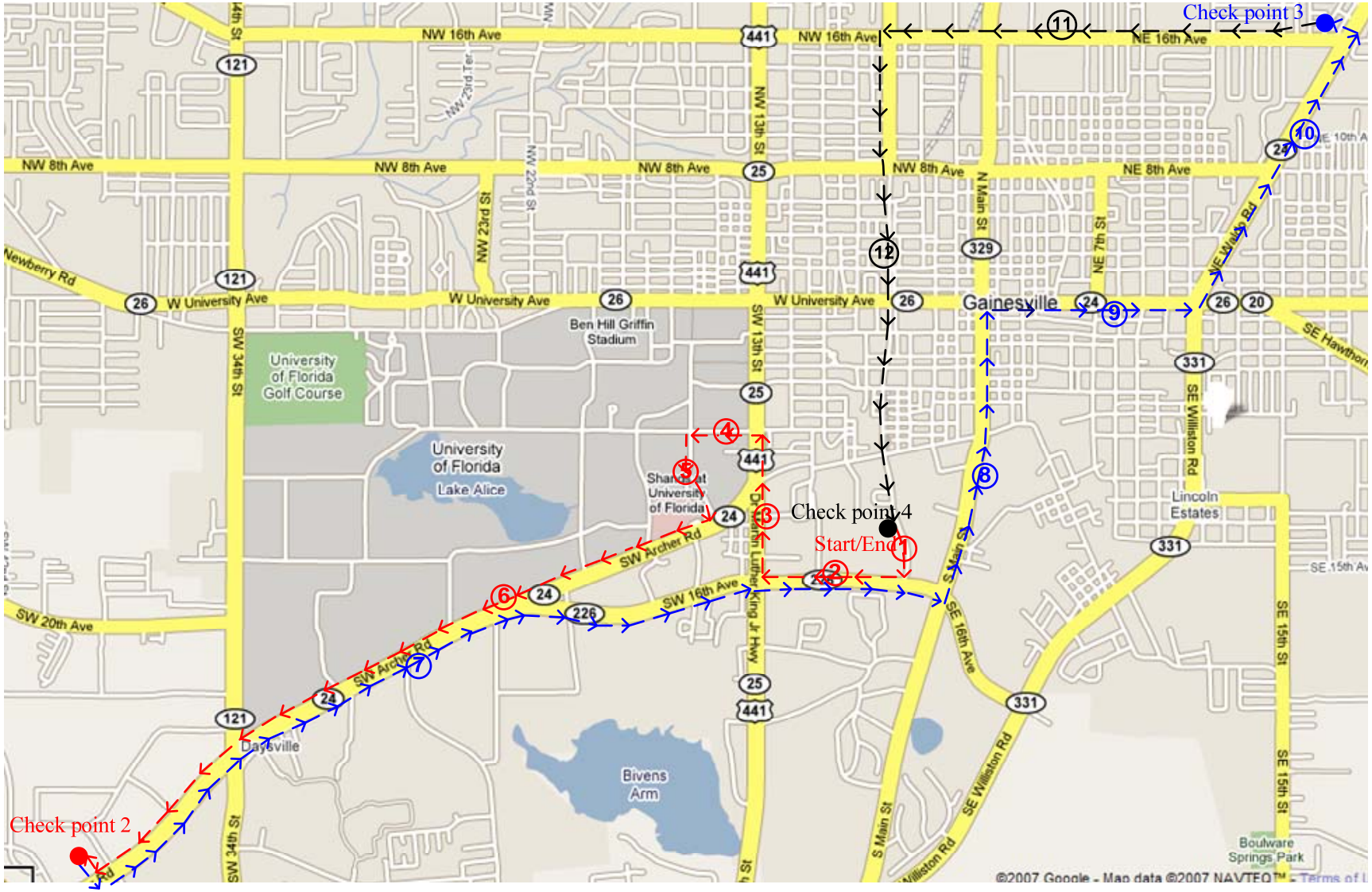


Figure 5-2. Proposed route for the field data collection (Waldo Road route)

Figure 5-1 presents the Newberry Rd route, which was followed in the early afternoon (3:15 pm to 4:20 pm). The total distance is about 16 miles, and the estimated non-congested travel time is about 40 - 50 minutes. Participants were asked to stop at check points during the test to discuss the lane-changing related maneuvers that occurred on the road, so that driver behavior related information can be better understood. Three check points were selected: the O'Connell center parking garage, Butler plaza and Oaks mall. By including the discussion time in each check point, which was set as 3-5 minutes each, the total experiment time was close to or slightly more than one hour. The various anticipated and potential lane-changing situations, with detailed information for check points and segments of the route, are listed in Table 5-3. The index number of each route segment is posted on Figure 5-1.

Figure 5-2 presents the Waldo Rd route, which was used during the PM peak hour (4:30 pm to 5:30 pm). The total distance is about 14.5 miles, and the estimated travel time for PM congested traffic is about 50 minutes. Three check points were selected: the Coastal Eng. lab, Butler plaza and NE 16 Ave. gas station. By including the discussion time in each check point, which is set as 3-5 minutes each, the total experiment time is slightly more than one hour. The various anticipated and potential lane-changing situations, with detailed information for check points and segments of the route, are listed in Table 5-4. The index number of each route segment is posted on Figure 5-2.

Table 5-3. Detailed route information for the "In-Vehicle" data collection experiment (Newberry Road route)

Segment Index No.	From	To	Turning at end of the segment	Distance (mile)	# of lanes	Anticipated scenarios*	Potential scenarios*
Check point 1	Start Point: O'Connell Center Parking Garage (University Ave. & Lemerand Dr)						
Segment 1	O'Connell	Museum Rd. (SW 8th Street)	Left turn	0.3	1	N/A	N/A
Segment 2	Museum Rd. (SW 8th Street)	Newell Dr.	Right turn	0.4	1	N/A	N/A
Segment 3	Newell Dr.	SW Archer Rd.	Right turn	0.4	2	R1, R2, R3, R4	R8
Segment 4	SW Archer Rd.	Butler Plaza (SW 37th Blvd)	Right turn	3.2	2	R1, R2, R3, R4, R6	R8
Check point 2	Butler Plaza (SW Archer Rd. & SW 37th Blvd)						
Segment 5	Butler Plaza (SW 37th Blvd)	SW. 34th Street	Left turn	0.8	3	R1, R2, R3, R4, R6, R9	R8
Segment 6	SW. 34th Street	Newberry Rd. (W. Univ. Ave.)	Left turn	1.8	3	R2, R3, R4, R6, R7	R8
Segment 6	Newberry Rd. (W. Univ. Ave.)	NW 8th Ave	Right merge	1.9	2	R4, R6,	R8
Segment 8	NW 8th Ave	Oaks Mall	Left turn	1.1	2	R1, R2, R3, R4, R7, R9	R8
Check point 3	Oaks Mall (6419 W Newberry Rd.)						
Segment 9	Oaks Mall	NW 8th Ave	Left turn	1.1	2	R2, R3, R4, R6, R7,	R8
Segment 10	NW 8th Ave	W. Univ. Ave.	-	1.9	2	R2, R6,	R8
Segment 11	W. Univ. Ave.	O'Connell	Right turn	1.6	2 -> 1	R2, R3, R4, R6, R10	R8
Check point 4	End Point: O'Connell Center Parking Garage (University Ave. & Lemerand Dr)						
*Note: Abbreviations for *Anticipated* & *Potential* Scenarios	R1- Upcoming left/right turn at the immediate/next downstream intersection; R2- Current lane is not available downstream (e.g. road incident, work zone or change in channelization of the current lane); and R3- Passing a stopped-bus at bus stop; R4- Giving way to a merging vehicle; R5- Gaining speed advantage by overtaking a slower moving vehicle; R6- Gaining queue advantage; R7- Avoiding a truck/heavy vehicle influence; R8- Avoiding the pressure imposed by tailgating; R9- Attracted by a better pavement condition;						

Table 5-4. Detailed route information for the "In-Vehicle" data collection experiment (Waldo Road route)

Segment Index No.	From	To	Turning at end of the section	Distance (mile)	# of lanes	Anticipated scenarios*	Potential scenarios*
Check point 1	Start Point: Coastal Eng. Lab (1300 SW 6th Street)						
Segment 1	SW 6th Street	SW16th Ave.	Right turn	0.2	2	N/A	N/A
Segment 2	SW 16th Ave.	SW 13th Street	Right turn	0.6	2	R1, R2, R3	R8
Segment 3	SW 13th Street	SW 8th Ave. (Museum Rd.)	Left turn	0.5	2	R1, R2, R3, R4	R8
Segment 4	SW 8th Ave. (Museum Rd.)	Newell Dr.	Left turn	0.2	2	N/A	R8
Segment 5	Newell Dr.	SW Archer Rd.	Right turn	0.4	2	N/A	N/A
Segment 6	SW Archer Rd.	Butler Plaza (SW 37th Blvd)	Right turn	3.2	3	R1, R2, R3, R4, R6	R8
Check point 2	Butler Plaza (SW Archer Rd. & SW 37th Blvd)						
Segment 7	Butler Plaza (SW 37th Blvd)	S. Main Street	Left turn	3.8	3 -> 2	R1, R2, R3, R4, R6, R9	R8
Segment 8	S. Main Street	E. Univ. Ave	Right turn	1.2	2	R2, R3, R4, R6, R7	R8
Segment 9	E. Univ. Ave.	NE Waldo Rd.	Left turn	0.8	2	R1, R2, R3, R4, R7, R9	R8
Segment 10	NE Waldo Rd.	NE 16th Ave.	Left turn	1.2	2	R2, R3, R4, R5, R6, R7, R9, R10	R8
Check point 3	Gas station (NE Waldo Rd. & NE 16th Ave.)						
Segment 11	NE 16th Ave.	SW 6th Street	Left turn	1.8	2 -> 1	R2, R3, R4, R6, R7,	R8
Segment 12	SW 6th Street	Coastal lab	Right turn	2.1	2 -> 1	R2, R3, R4, R6, R10	R8
Check point 4	End Point: Coastal Eng. Lab (1300 SW 6th Street)						
*Note: Abbreviations for *Anticipated* & *Potential* Scenarios	R1- Upcoming left/right turn at the immediate/next downstream intersection; R2- Current lane is not available downstream (e.g. road incident, work zone or change in channelization of the current lane); and R3- Passing a stopped-bus at bus stop; R4- Giving way to a merging vehicle; R5- Gaining speed advantage by overtaking a slower moving vehicle; R6- Gaining queue advantage; R7- Avoiding a truck/heavy vehicle influence; R8- Avoiding the pressure imposed by tailgating; R9- Attracted by a better pavement condition;						

5.1.3 Driving Test Procedure

Upon arrival, a check-in procedure was followed to ask each participant to 1) sign the "in-vehicle" experiment informed consent form (APPENDIX D), 2) complete the background survey form (APPENDIX G), and 3) show their driver's license to confirm their identity and qualifications for driving. With the informed consent form, the participants were fully briefed about the aims of the experiment.

During the "in-vehicle" data collection, each participant was accompanied by the researcher to drive on one of the pre-selected routes and collect data related to the lane-changing maneuvers. Participants were informed about the driving route and the types of questions they might be asked during driving. Moreover, each driver was briefed about the three pre-selected check points during the experiment, where they would stop and discuss their actions. As drivers were proceeding through the developed route, the followings were recorded:

- **Potential lane change:** the situation in which a lane change could have been attempted, but was not.
- **Attempted (but not successful) lane change:** the driver attempted a lane change, but the maneuver was not completed.
- **Completed lane change:** the driver completed the maneuver successfully.

The space gaps from the completed and attempted lane changes reflect the gap acceptance characteristics for that maneuver. For each of the maneuvers (potential, attempted and completed) occurring during the test, the time and location information, as well as the corresponding lane-changing scenario, were recorded for further analysis. The scenarios were verified by communicating with the subject. Occasionally, the driver was asked if he/she was considering lane-changing, in order to identify the potential and attempted but not completed maneuvers for such scenario. Table 5-4 presents an example of the raw data collected for the participant with ID 05-11, including the maneuver types identified.

Table 5-5. "In-Vehicle" experiment notes for subject ID: 05-11

Location (including posted spd. limit)	Time	Scenario	Maneuver type
Archer Rd, 40mph	4:00	Queue advantage	1
Archer Rd, 40mph	4:03	Queue advantage	3
Archer Rd, 45mph	4:09	Stopped bus	2
Archer Rd, 45 mph	4:15	Overtaking Slow vehicle	1
Archer Rd, 45mph	4:16	Overtaking slow vehicle	3
SW 34th St, 45mph	4:24	Heavy vehicle	2
Newberry Rd, 40mph	4:27	Stopped bus	1
Newberry Rd, 40mph	4:33	Overtaking slow vehicle	2
Newberry Rd, 40mph	4:34	Heavy vehicle	1
SW 34th St, 45mph	4:37	Incoming left turn	3
Newberry Rd, 40mph	4:45	Backup Turning	2
Newberry Rd, 35mph	4:55	Incoming left turn	3
…	…	…	…

Driver ID: 05-11
Maneuver type = 1 (potential maneuver), 2 (attempted maneuver), 3 (completed maneuver).

Two types of video clips were collected during the driving test. The first is from the four DCs installed in the instrumented vehicle, which capture the traffic on the road, and can be used to generate quantitative field values for each maneuver. The other is recorded by a fixed digital camcorder to capture the drivers' head/eye movement and the discussions between the investigator and the drivers, so that the drivers' behavior and verbal communication can be retrieved during the data reduction. In the check points, the lane-changing related maneuvers that

occurred during the previous stage were discussed. Each driver was asked to clarify their interactions with other vehicles during the driving test.

The "in-vehicle" data collection experiment was conducted from Sept. 2008 to Jan. 2009. All participants drove on a weekday afternoon to avoid large traffic pattern differences between weekdays and the weekend, or between the AM and the PM. A total of 40 driving tests were conducted; 24 were conducted during the early afternoon traffic on the Newberry route (Figure 5-1), and the remaining 16 were conducted during the PM peak traffic on the Waldo route (Figure 5-2).

5.2 Data Reduction and Analysis

Information obtained directly from the "in-vehicle" experiment include: 1) participants' personal background information; 2) "in-vehicle" video clips for each driving test; 3) the researcher's notes for the lane-changing related maneuvers (potential, attempted and completed maneuvers) during the driving test. Various analyses were conducted to summarize the information related to the research objectives. First, each of the three types of maneuvers was identified from the video clips using the researcher's notes. Quantitative values for the important factors identified from the focus groups as affecting each lane-changing related scenario were then obtained. Next, the statistical summaries of the lane-changing behavioral variables related to the subject and surrounding vehicles, such as gaps, speeds and accelerations, were presented with the corresponding distributions. Lastly, various cluster analyses were performed (similar to that conducted for the focus group data) to categorize the participating drivers according to their behavior. The detailed description of each analysis procedure, along with a summary of the results, is provided below.

5.2.1 Video Data Reduction

During the 40 "in-vehicle" driving tests, a total of 601 completed lane changes and 199 attempted but unsuccessful lane changes were collected. In addition, the researcher found another 205 potential lane-changing maneuvers. Table 5-6 presents the number of maneuvers for each driver in the experiment.

Table 5-6. Driver-based number of maneuvers collected in the "In-Vehicle" experiment

ID	Number of maneuvers		
	Potential	Attempted	Completed
05-01	3	9	15
05-02	5	3	11
05-03	3	4	17
05-04	6	3	9
05-05	4	5	14
05-06	7	4	17
05-07	3	3	14
05-08	5	3	16
05-09	8	4	21
05-10	3	3	10
05-11	4	5	12
05-12	7	2	23
05-13	4	6	10
05-14	3	6	9
05-15	5	4	18
05-16	5	3	15
05-17	4	7	11
05-18	6	4	10
05-19	5	5	14
05-20	7	6	17
05-21	5	7	19
05-22	9	7	25
05-23	4	4	16
05-24	3	8	14
05-25	2	6	9
05-26	6	5	15
05-27	7	8	21
05-28	3	4	13
05-29	8	7	17
05-30	7	6	19
05-31	5	5	16
05-32	6	4	13
05-33	6	4	16
05-34	3	3	8
05-35	8	8	22
05-36	4	3	9
05-37	3	5	16
05-38	6	6	20
05-39	7	4	16
05-40	6	6	14
Total	205	199	601

Using the maneuver time recorded during the driving tests, each lane-changing related maneuver (potential, attempted and completed) was located in the video clip. The following information was obtained from this "in-vehicle" experiment (related to the important factors identified from the focus groups):

1. Information obtained directly from video clips. This information was observed directly from the video clips for each lane-changing related within the driving test, which includes:

   - **Traffic Signal Status:** the traffic signal status for the downstream signal intersection; the two alternative states are red and green (including yellow).
   - **Number of Lanes:** the number of lanes of the current road segment.
   - **Vehicle Type:** the type of the vehicles involved in the lane-changing situation.
   - **Subject Vehicle Speed and Location:** the speed and the geographical coordinates of the subject vehicle can be observed directly from the video, and captured by the GPS installed in the vehicle.
   - **Presence of Pedestrians and Cyclists:** whether there are pedestrians and cyclists present in the scenario.
   - **Level of Congestion:** the number of vehicles in a 600-ft vicinity, 300 ft behind and 300 ft in front of the subject vehicle at the time, were obtained and used as a surrogate for congestion level.

2. Information interpolated from frame-by-frame images. First, the lane-changing video clips were separated into frame-by-frame images (0.5 sec). Next, the estimation method proposed in Section 3.2 (using lane width and focal distance of the digital cameras) was used to approximate the vehicle gaps before and after initiating the lane change. Space gaps, rather than time gaps, were measured to minimize errors, since under congested conditions the speeds of the vehicles do not vary significantly, and a minimal safe spacing is always maintained by drivers. The change of the spacing was estimated using frame-by-frame analysis to obtain other vehicles' speeds (the speed of the subject vehicle was acquired directly from the GPS instrument). Thus, the speed change (acceleration/deceleration) was

estimated by considering the time interval between successive frames and the speeds measured from these frames. The information obtained from this procedure includes:

- **Vehicle Gaps:** the space gaps between any two vehicles of interest in the image.
- **Surrounding Vehicle's Speeds:** the speed of any surrounding vehicles.
- **Acceleration/Deceleration:** the speed change of any surrounding vehicles appeared.
- **Lane-Changing Duration:** it is measured manually starting as the subject vehicle moves laterally and the edge of its first headlight crosses the lane delimiter, and ending as the last taillight crosses that line (Salvucci and Liu, 2002).

3. Information obtained from Google Earth/Maps by using the necessary information from the video/images. For some of the distances, the starting point is the location of the subject vehicle, which can be acquired from the GPS instrument (geographic coordinates). For some cases, the ending point is out of the image's scale, and consequently the position can only be obtained by referring to landmarks or position/location references along the test routes. By mapping the ending position as a geographic reference in Google Earth (using the "ruler function"), the corresponding distance can be obtained. The distances obtained from this procedure include:

- **Distance to the Downstream Intersection:** distance from the current position of the subject vehicle to the downstream intersection.
- **Distance to the Next Bus Stop:** distance from the current position of the subject vehicle to the next bus stop.
- **Distance to the Upcoming Right/Left Turn:** distance from the current position of the subject vehicle to the upcoming right/left turn.

By the end of the data reduction, each lane-changing scenario was associated with a list of important factors, with multiple sets of corresponding field values collected from the "in-vehicle" experiment. Three types of datasets: completed lane-changing data, attempted but unsuccessful lane-changing data, and potential lane-changing data were obtained. An example of

the lane-changing data for the participant with ID 05-11 is provided in Tables 5-7 (completed maneuvers), 5-8 (attempted but unsuccessful maneuvers), and 5-9 (potential maneuvers).

Table 5-7. Data collected from completed lane changes (ID = 0511)

LC #	Invoking scenarios	Important factors & values	Lag gap (ft)	Lead gap (ft)
1	Upcoming left turn	Cgst. = 4 , Signal = red Spdl/ts = 20/23, Dist. = 96 ft	N/A	34
2	Queue advantage	Que diff = 3 vehs, Dist. = 4 blk Cgst = 13, Sig. = red	248	15
3	Overtaking slow vehicle	Dist. = 2363 ft, Spdl/ts = 45/35 Cgst. = 15, Mood = relax	53	22
4	Stopped bus	Cgst. = 9, Next stop = 1971 ft Dist bus = 60 ft, # waiting = 2	35	19
5	Incoming right turn	Dist. = 150 ft, Spdl/ts = 45/30 familiar, Cgst. = 14, Ped = no	41	23
6	Incoming left turn	Cgst. = 11 , Signal = red Spdl/ts = 35/30, Dist. = 113 ft	30	18
7	Overtaking slow vehicle	Dist. = 2594 ft, Spdl/ts = 45/40 Cgst. = 3, Mood = med.	212	233
8	Vehicle merge	Cgst. = 8, Spdl/ts = 40/44 Agg. = low, Dist. = 3 blocks VType = sedan/suv	276	219
9	Overtaking slow vehicle	Dist. = 2910 ft, Spdl/ts = 45/40 Cgst. = 10, Mood = med.	48	31
10	Incoming left turn	Cgst. = med , Signal = red Spdl/ts = 40/30, Dist. = 150 ft	110	85
11	Lane channel. change	Cgst. = 18, Dist. = 55 ft. Spdl/ts = 40/42	13	17.5
12	Incoming right turn	Dist. = 85 ft, Spdl/ts = 45/40 Fam. = Y, Cgst. = 12, Ped = N	27	16

Driver ID: 05-11

Note:

Spdl/ts: speed limit and the real travel speed, mph.
Cgst: level of traffic congestion on the target lane.
Dist: distance to the incoming turn position, the next bus stop, etc.

Table 5-8. Data collected from attempted but unsuccessful lane changes (ID = 0511)

LC #	Invoking scenarios	Important factors & values	Lag gap (ft)	Lead gap (ft)
1	Incoming left turn	Cgst. = 3, Signal = red Spdl/ts = 20/18, Dist. = 66 ft	N/A	24
2	Overtaking slow vehicle	Dist. = 3 blk, Spdl/ts = 45/30 Cgst. = 15, mood = relax	13	7.4
3	Vehicle merge	Cgst. = 7, Spdl/ts = 40/28 Agg. = low, dist. = 3 blocks veh type = sedan/suv, left mer.	11.5	14.5
4	Overtaking slow vehicle	Dist. = 1 blk, Spdl/ts = 45/30 Cgst. = 13, mood = med.	35	23
5	Incoming left turn	Cgst. = 17, Signal = red Spdl/ts = 45/35, Dist. = 526 ft	8.5	9
Driver ID: 05-11				

Table 5-9. Data collected from potential lane changes (ID = 0511)

LC #	Invoking scenarios	Important factors & values	Lag gap (ft)	Lead gap (ft)
1	Heavy vehicle	Spdl/ts = 45/35, Uncft = N Cgst. = 19, VType = SUV	14.5	7
2	Backup turning	-	9	21.5
3	Queue advantage	Que diff = 2 vehs, Dist. = 2 blk Cgst = 9, Sig. = red	47	6.5
4	Stopped bus	Cgst. = 13, Next stop = 1.5 blk Dist bus = 46 ft, # waiting = 4	31.5	13
Driver ID: 05-11				

5.2.2 Distributions of Selected Lane-Changing Variables

The lane-changing related quantitative values obtained from the "in-vehicle" data collection include speeds, accelerations, traffic density, different types of spacing gaps, etc. A sketch of the vehicles involved in lane changing and the corresponding variables is presented in Figure 5-3.

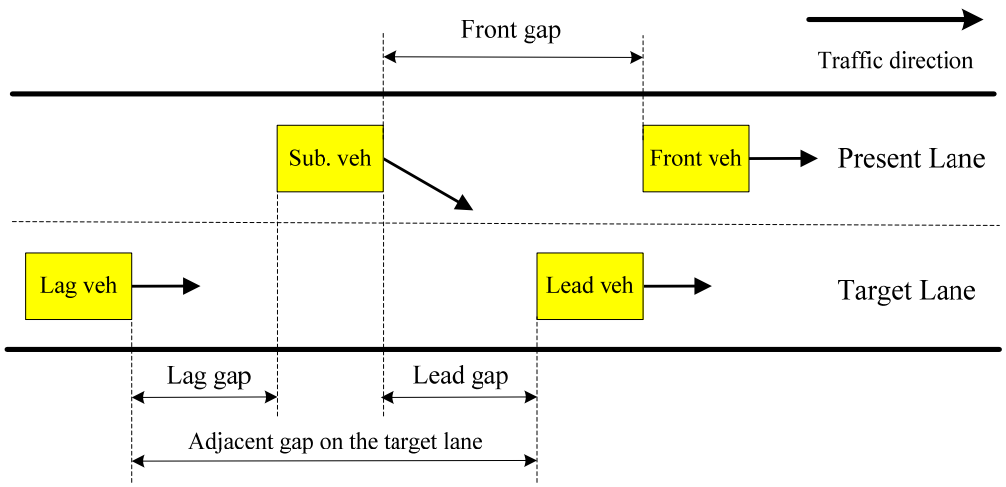


Figure 5-3. Vehicles involved in a lane-changing maneuver and related variables

Table 5-10 summarizes statistics of the variables obtained from the completed lane changes related to the subject, front, and lead/lag vehicles.

Table 5-10. Statistics of variables related to completed lane changes

Variables	Mean	Std dev.	Median	Min.	Max.
Subject vehicle					
Sub. spd (mph)	21.4	7.23	23.7	2.6	44.6
Sub. acc (mph/s)	-0.14	1.21	0.07	-4.96	3.27
Sub. lane den.①	10.4	4.63	10	0	23
Relation with lead & lag vehicles					
Lead gap (ft)②	63.1	55.1	55.3	2.3	295.6②
Lag gap (ft)②	73.4	46.9	64.2	4.1	221.7②
Rela. lead spd. (subject – lead)	-0.84	4.92	-0.5	-13.8	9.5
Rela. lag spd. (subject – lag)	0.55	5.45	0.3	-11.6	10.2
Tar. lane den.①	8.93	5.37	10	1	22
Relation with front vehicle					
Front gap (ft)	69.3	47.2	66.1	6.6	232.1②
Rela. front spd. (subject –front)	-0.23	3.12	-0.9	-9.4	8.4

Note: ① The traffic densities on the subject and target lanes were interpolated with the number of vehicles in a 600 ft vicinity, 300 ft behind and 300 ft in front of the subject vehicle, since generally the lane-changing drivers only consider the congestion in the vicinity.
② As some lane changes didn't have lead/lag vehicle, the lead/lag gaps for these cases were not included in the statistics.

As shown in Table 5-9, the accepted lead gaps for successful lane changes vary from 2.3 to 295.6

feet, with a mean of 63.1 feet. The accepted lag gaps vary from 4.1 to 221.7 feet, with a mean of 73.4 feet. The front gaps vary from 6.6 feet to 232.1 feet, with a mean of 69.3 feet. The relative speeds for lead/lag/front vehicles are defined as the speed of the subject vehicle less the speed of the lead/lag/front vehicle. As expected, the mean of the relative lead speeds is positive, and the mean of the relative lag speeds is negative. This indicates that in a lane-changing maneuver, for accepted situations on average, the subject vehicle is slower relative to the lead vehicle and faster relative to the lag vehicle. Similarly, the mean density of the target lane is slightly lower than that of the subject lane, which means that the drivers are more capable and/or willing to merge to the less congested lane. The distributions of these variables within all completed lane changes are presented in Figure 5-4.

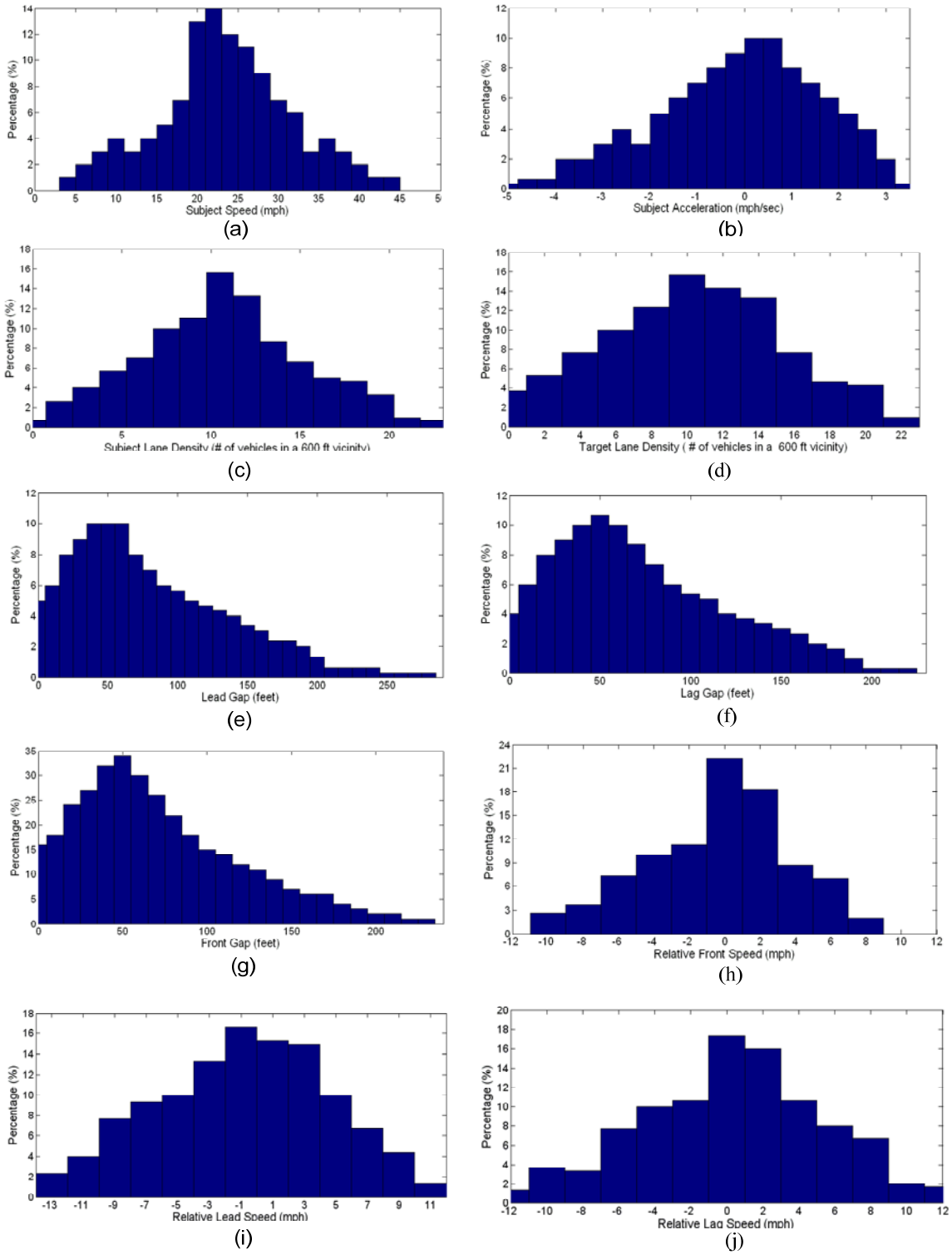


Figure 5-4. Distributions of lane-changing variables for the completed maneuvers (a) Subject speed (b) Subject acceleration (c) Subject lane density (d) Target lane density (e)Lead gap (f) Lag gap (g) Front gap (h) Relative front speed (i) Relative lead speed (j) Relative lag speed

In addition to the completed lane changes, the statistical summaries of the variables obtained from the attempted and potential maneuvers are presented in Table 5-11 and Table 5-12 respectively. As shown in Table 5-11, compared to the completed lane changes, the lead and lag gaps in the attempted lane changes have much smaller means and variances. The target lane density is higher. There may be because that the main reason for the attempted lane-changes to not be completed is that the gaps in the target lane are too small, which is generally caused by the high density in the target lane. Consequently, such maneuvers always have smaller lead and lag gaps, and larger target lane density. The mean subject speed in the attempted maneuvers is also smaller since drivers in these situations may adjust speeds to place the subject vehicle in an appropriate position for merge, and the most frequently used adjustment is to slow down slightly. This additionally causes the relative smaller value of the average front gap.

Table 5-11. Statistics of variables related to attempted lane changes

Variables	Mean	Std dev.	Median	Min.	Max.
For subject vehicle					
Sub. spd (mph)	17.7	3.58	19.6	5.9	32.6
Sub. acc (mph/s)	-0.22	1.03	-0.16	-4.58	3.31
Sub. lane den.①	11.2	3.83	11	2	19
Relation with lead/lag vehicle					
Lead gap (ft)	7.62	5.43	7.3	-3.6	25.6
Lag gap (ft)	6.47	3.97	6.2	-4.3	19.7
Rela. lead spd. (subject – lead)	-5.49	3.05	-5.2	-10.1	6.9
Rela. lag spd. (subject – lag)	-4.42	3.76	-4.7	-9.7	5.3
Tar. lane den.①	15.2	3.03	15	10	26
Relation with front vehicle					
Front gap (ft)	53.7	40.8	51.6	4.8	249.3②
Rela. front spd. (subject – front)	1.54	3.83	1.9	-9.4	10.7

Note: ① The traffic densities on the subject and target lanes were interpolated with the number of vehicles in a 600 ft vicinity, 300 ft behind and 300 ft in front of the subject vehicle, since generally the lane-changing drivers only consider the congestion in their vicinity.
② As some lane changes didn't have lead/lag vehicle, the front gaps for these cases were not included in the statistics.

Table 5-12. Statistics of variables related to potential lane changes

Variables	Mean	Std dev.	Median	Min.	Max.
For subject vehicle					
Sub. spd (mph)	25.3	10.27	25.7	3.9	42.1
Sub. acc (mph/s)	-0.21	1.44	-0.09	-4.47	3.74
Sub. lane den.①	7.43	3.19	8	0	21
Relation with lead/lag vehicle					
Lead gap (ft)	54.3	29.7	49.7	3.5	273.8②
Lag gap (ft)	47.6	36.3	44.3	4.5	232.5②
Rela. lead spd. (subject – lead)	-0.75	3.83	-0.6	-9.6	7.6
Rela. lag spd. (subject – lag)	0.69	4.92	0.5	-10.3	8.4
Tar. lane den.①	11.2	5.96	11	2	18
Relation with front vehicle					
Front gap (ft)	55.2	59.8	51.1	8.6	281.9②
Rela. front spd. (subject – front)	-0.41	3.92	-0.5	-11.9	10.2

Note: ① The traffic densities on the subject and target lanes were interpolated with the number of vehicles in a 600 ft vicinity, 300 ft behind and 300 ft in front of the subject vehicle, since generally the lane-changing drivers only consider the congestion in their vicinity.
② As some lane changes didn't have lead/lag vehicle, the lead/lag gaps for these cases were not included in the statistics.

The distributions of these variables within all attempted lane changes are presented in Figure 5-5.

For the potential maneuvers (Table 5-12), both the average lead and lag gaps (49.3 ft and 47.3 ft) are smaller than those of the completed lane changes (63.1 ft and 73.4 ft), which therefore caused the higher target lane density values. The average front gap is smaller, which may be because of the higher traffic density. The rest of factors, such as the subject speed, acceleration, relative lead/lag speed, do not change much. The distributions of the variables within all potential lane changes are presented in Figure 5-6.

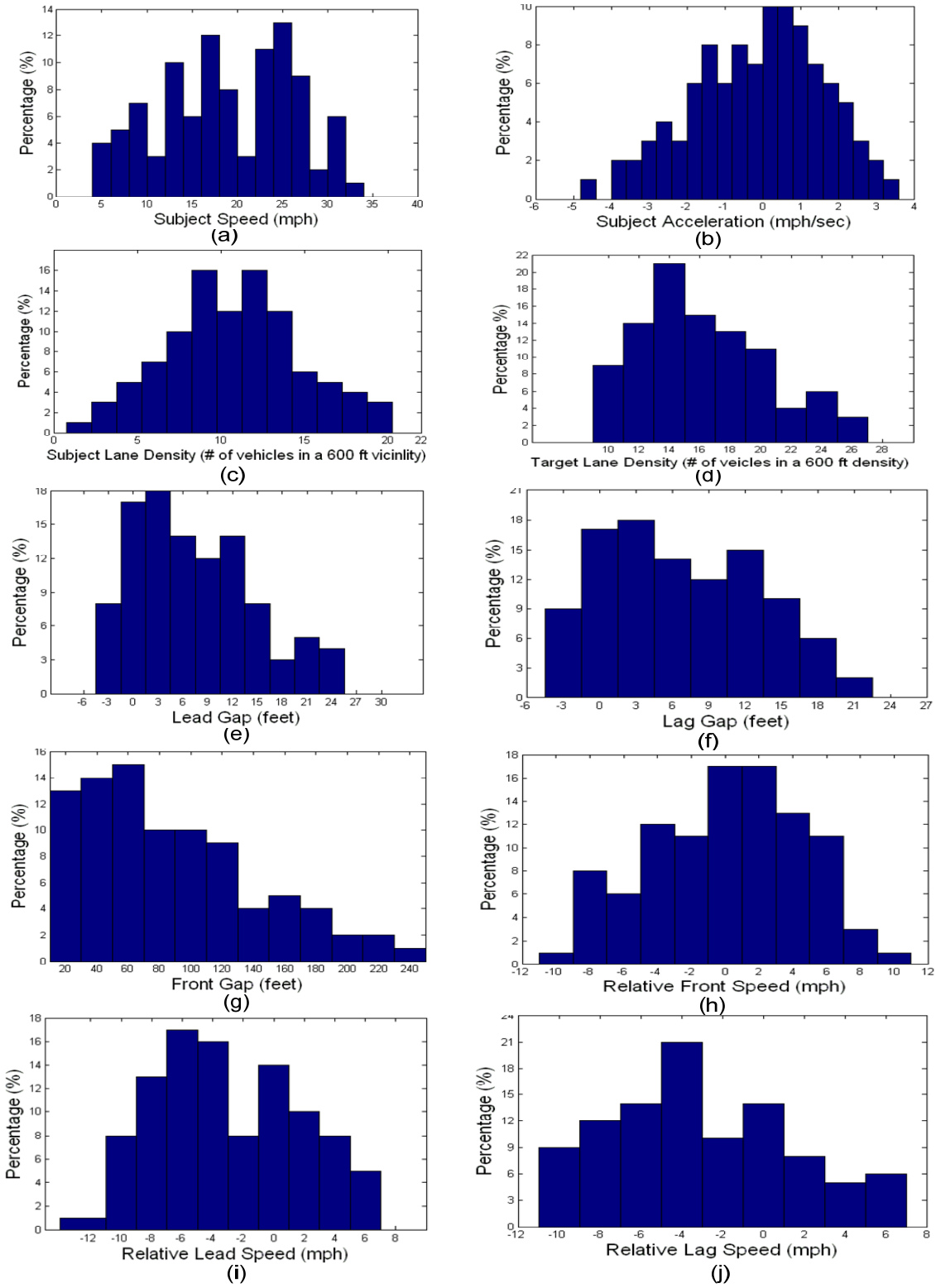


Figure 5-5. Distributions of lane-changing variables for the attempted maneuvers (a) Subject speed (b) Subject acceleration (c) Subject lane density (d) Target lane density (e)Lead gap (f) Lag gap (g) Front gap (h) Relative front speed (i) Relative lead speed (j) Relative lag speed

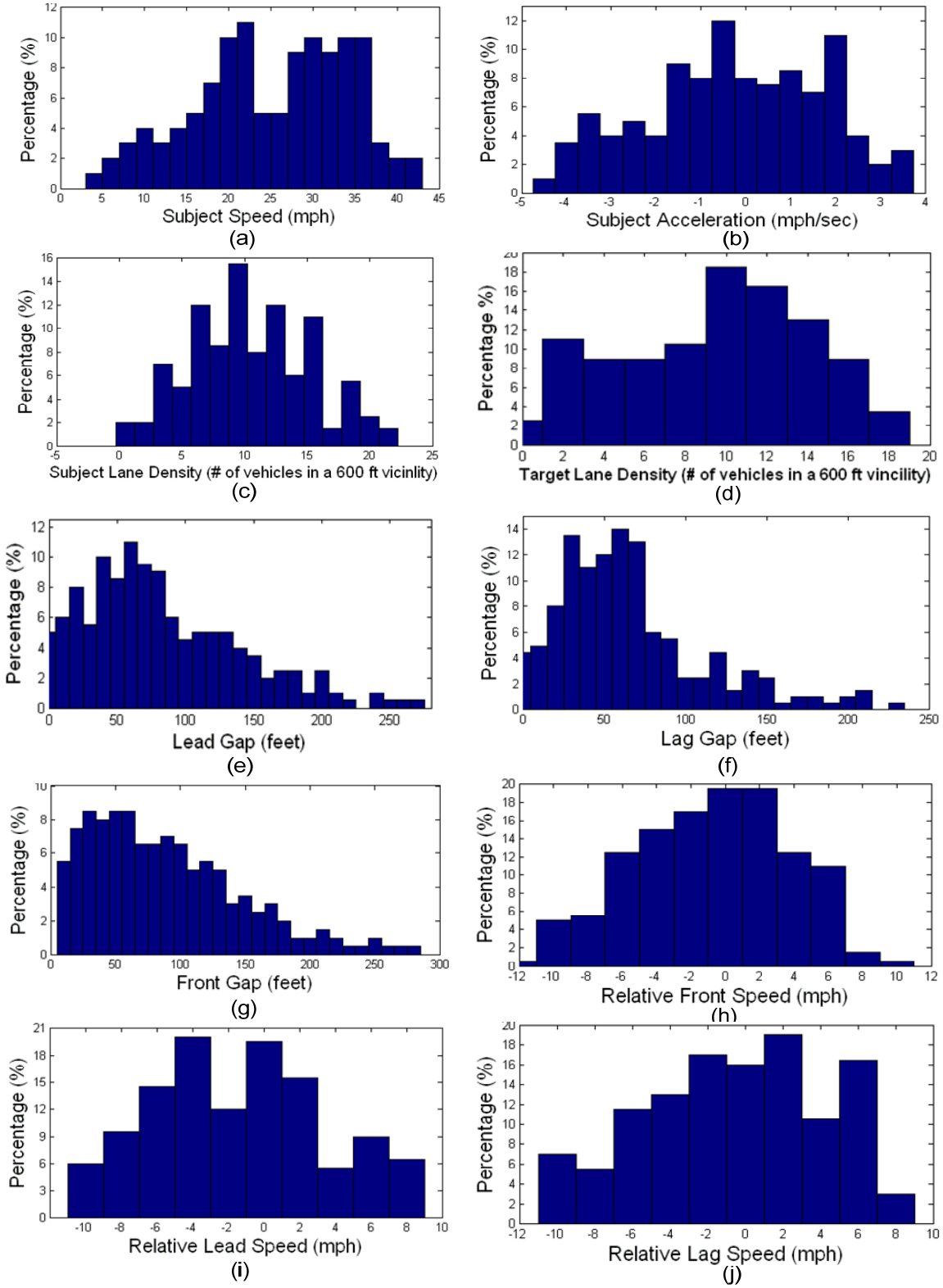


Figure 5-6. Distributions of lane-changing variables for the potential maneuvers (a) Subject speed (b) Subject acceleration (c) Subject lane density (d) Target lane density (e)Lead gap (f) Lag gap (g) Front gap (h) Relative front speed (i) Relative lead speed (j) Relative lag speed

5.2.3 Cluster Analysis for Driver Type Classification

With the three types of "in-vehicle" lane-changing datasets obtained for each driver (completed, attempted and potential), clustering analysis similar to what was conducted for the focus group study was performed to classify the "in-vehicle" drivers. The objective of this step is to obtain a scheme that can effectively classify drivers into different groups. Two classification schemes were designed and conducted. One was based on the driver's background information acquired from the participants "check-in" procedure. The other used the driver's lane-changing aggressiveness indices measured from the behaviors that occurred during the "in-vehicle" driving test. These classification results were compared, along with the one obtained from the focus group study.

5.2.3.1 Classification scheme I – driver background-based scheme

In this scheme, the same driver background information (driver aggressiveness) as the one used in the focus group study was used. As presented in Table 5-13, the "Aggressiveness" columns on the left side provide the self-evaluation and the perceived friends' evaluation obtained from the background survey during the participant prescreening. An overall aggressiveness for each participant was calculated by averaging the self-evaluation and the friends' evaluation values. The results show that the self-evaluation value is generally slightly less than the friends' evaluation (Selfavg.= 5.14, Friendsavg.= 5.53), which was also found to be true in the focus group data.

Table 5-13. Driver-Based likelihood of executing a DLC ("In-Vehicle" experiment)

ID	Aggressiveness (1 - 10)			"In-Vehicle" Results (calculated by Eq. 5-1)									
	Self-	Friends	Overall	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10
05-01	7-8	7	7.25	4.2	2.8	4.8	4.5	4.2	4.9	3.5	2.8	3.9	4.0
05-02	5	6	5.5	3.9	3.2	4.5	4.2	4.0	1.1	2.6	4.2	4.4	3.8
05-03	6	8	7.0	4.4	2.8	4.8	4.0	4.2	1.1	3.6	2.7	3.9	4.7
05-04	6	5	5.5	4.3	4.2	3.7	4.4	3.8	1.7	1.9	4.5	4.1	4.6
05-05	4	4-5	4.25	4.2	4.3	3.8	4.5	3.8	1.7	2.0	4.4	4.2	4.5
05-06	3	3-4	3.25	3.2	3.8	3.9	3.7	2.9	1.5	3.2	3.9	3.3	3.9
05-07	7	8	7.5	4.3	2.7	4.8	3.6	4.2	1.3	3.6	2.8	3.9	4.0
05-08	5-6	7	6.25	4.4	2.8	4.7	4.0	4.1	4.9	3.7	2.7	3.9	3.6
05-09	3	4	3.5	3.2	3.8	3.9	3.7	2.9	1.5	3.2	3.9	3.1	3.9
05-10	6-7	7	6.75	4.3	2.8	4.8	4.1	4.2	5.0	3.6	2.7	3.9	3.0
05-11	5-6	6	5.75	3.8	3.2	4.5	4.0	4.0	1.2	2.6	4.2	4.4	3.8
05-12	3	4	3.5	4.3	4.4	3.8	4.4	3.8	1.7	2.0	4.5	4.2	4.5
05-13	6	5	5.5	4.2	4.3	3.9	4.5	3.8	1.8	1.9	4.4	4.3	3.5
05-14	3	3	3.0	4.4	3.8	3.9	3.7	2.9	1.5	3.2	4.0	3.1	3.9
05-15	4	3-4	3.75	4.3	4.3	3.8	4.4	3.8	1.7	1.9	4.4	4.2	4.5
05-16	7	8	7.5	4.4	2.9	4.7	4.5	4.2	5.0	3.6	2.7	3.9	4.0
05-17	6	6-7	6.25	4.3	4.2	3.8	4.4	3.8	1.7	1.9	4.4	4.3	4.5
05-18	8	8-9	8.25	4.2	2.8	4.8	3.1	4.2	3.3	3.7	2.8	3.9	3.7
05-19	6	7	6.5	4.3	2.7	4.9	4.0	4.2	5.0	3.6	2.7	3.9	4.0
05-20	4	5	4.5	3.5	3.8	3.9	3.7	2.9	3.9	3.2	3.9	3.1	3.9
05-21	4-5	6	5.25	4.2	4.3	3.8	4.5	3.8	1.7	1.9	4.5	4.2	4.4
05-22	5	5	5.0	4.3	4.4	3.7	4.4	3.8	1.9	1.9	4.4	4.3	4.5
05-23	7	8	7.5	3.8	3.2	4.5	4.7	4.0	1.1	2.6	4.3	4.4	3.8
05-24	7	6	6.5	3.8	3.2	4.5	4.2	4.0	1.2	2.7	4.2	4.4	3.9
05-25	2	3	2.5	3.3	3.8	3.9	3.7	2.9	1.5	3.2	3.9	3.1	3.9
05-26	5	5-6	5.25	3.8	3.2	4.5	4.1	4.0	1.1	2.6	4.2	4.4	3.3
05-27	7	6-7	6.75	4.4	2.7	4.8	4.0	4.2	1.5	3.6	2.7	3.9	4.5
05-28	5	6	5.5	3.7	3.2	4.5	4.6	4.0	1.1	2.7	4.3	4.4	3.8
05-29	7	7	7.0	3.8	3.2	4.6	3.4	4.0	1.2	2.6	4.2	4.4	3.7
05-30	6	6-7	6.25	2.9	3.8	3.9	3.7	2.9	1.5	3.2	3.9	3.1	3.9
05-31	4	3-4	3.75	4.3	4.2	3.8	4.4	3.8	1.7	1.9	4.4	4.2	4.5
05-32	4-5	4-5	4.5	4.2	4.3	3.7	3.5	3.8	1.8	1.9	4.5	4.3	4.6
05-33	3	3-4	3.25	3.3	3.8	3.9	3.6	2.9	1.5	3.2	3.9	3.1	2.9
05-34	2	3	2.5	3.2	3.7	3.9	3.6	2.9	1.5	3.3	3.9	3.2	3.9
05-35	4	4	4.0	3.1	4.3	3.8	4.4	3.8	1.7	1.9	4.4	4.2	4.5
05-36	5	4-5	4.75	3.7	3.2	4.5	4.7	4.0	5	2.6	4.2	4.4	3.8
05-37	6	6-7	6.25	3.8	3.2	4.4	4.2	4.0	1.2	2.6	4.3	4.5	3.7
05-38	6	5	5.5	3.9	3.2	4.5	3.7	4.0	5.0	2.6	4.2	4.4	3.8
05-39	4	5	4.5	4.3	4.4	3.8	4.4	3.8	1.7	1.9	4.4	4.2	4.5
05-40	5-6	6	5.25	3.1	3.8	3.9	3.7	2.9	5	3.3	3.9	3.1	3.9
Average	5.14	5.54	5.33	3.9	3.6	4.2	4.1	3.7	2.3	2.8	3.9	4.0	4.0

The right side of the table ("'In-Vehicle' Results") presents the likelihood of changing lanes on each DLC scenario (R1 through R10) for each participant, which was calculated from the lane-changing maneuvers occurring during the "in-vehicle" test by Eq. (5-1):

$$P = \frac{5 \ * \ (\#\text{ of completed lane changes} + \#\text{ of attempted lane changes})}{\#\text{ of completed lane changes} + \#\text{ of attempted lane changes} + \#\text{ of potential maneuvers}} \tag{5-1}$$

To obtain the numbers used in this calculation, the "in-vehicle" field data were first grouped by

driver and lane-changing scenarios. For each driver under a DLC scenario, the number of completed lane changes plus the number of attempted lane changes indicates the number of situations accepted by the particular driver. This number reflects the corresponding level of acceptance for this DLC scenario by the particular driver. The likelihood value *P* in Eq. (5-1) was then calculated and scaled to five to obtain the same quantitative range (0-5) as used in the focus group study.

By following the same classification procedure as in the focus group analysis, the K-means algorithm (provided in APPENDIX I) was first used to cluster the n (n = 40) participants based on overall aggressiveness into k (k = 1, 2, 3, 4, or 5) partitions, k < n. By setting the cluster number as 1, 2, 3, 4, and 5 respectively, centroids for the clusters were obtained as follows:

1) for cluster number = 1, centroid for each cluster is 5.33;
2) for cluster number = 2, centroids for each cluster are 3.78 and 6.35;
3) for cluster number = 3, centroids for each cluster are 3.39, 5.16 and 6.90;
4) for cluster number = 4, centroids for each cluster are 3.30, 4.81, 5.83 and 7.14;
5) for cluster number = 5, centroids for each cluster are 3.22, 4.42, 5.4, 6.55 and 7.60.

Next, the scenario-based level of likelihood values, as presented in the right side of Table 5-12, were used to decide the most appropriate cluster number. The overall intra-cluster variance on the level of likelihood for each lane-changing situation was calculated, and accumulated across all scenarios (R1 through R10) by using Eq. (4-2). The overall intra-cluster variance (*W*) value for each classification was calculated as $W(1) = 177.79$, $W(2) = 158.40$, $W(3) = 140.92$, $W(4) = 133.31$ and $W(5) = 129.59$. The Hartigan index, which indicates the intra-cluster dissimilarity that will be removed by splitting the k clusters into k+1 clusters, was then calculated to determine the appropriate number of clusters. By using Eq. (4-3), the indices for k equaling 1, 2, 3 and 4 were calculated as H(1) = 4.65, H(2) = 5.59, H(3) = 2.05 and H(4) = 1.00. A rather small Hartigan index was found to occur in both H(3) (=2.05) and H(4) (=1.00), which

means by splitting the 3/4 clusters into 4/5, the dissimilarity is not removed as much. Given that the selection of the number of clusters is not quantitatively strict, either of these may be chosen as the appropriate number of clusters. Figure 5-7 provides the results of analysis for the number of clusters ranging from 1 to 5. When the cluster number is larger than 4, the intra-cluster dissimilarity does not decrease much. However, it is difficult to infer/deduce the exact optimal number from the figure. Further behavior-based clustering analysis is conducted to help the classification.

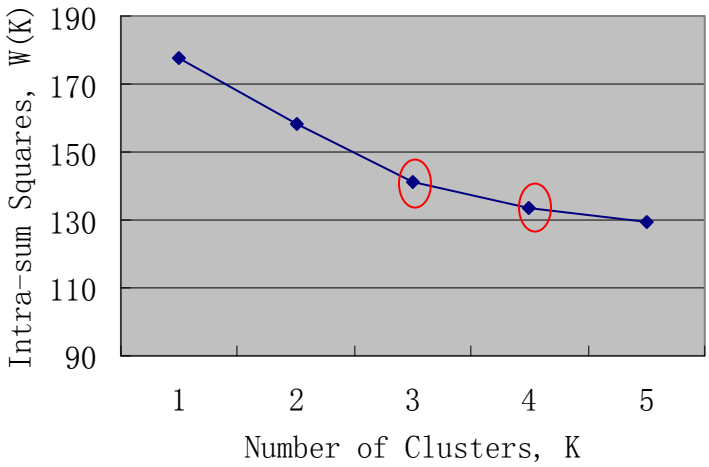


Figure 5-7. Clustering analysis results based on driver background

5.2.3.2 Classification scheme II – driver behavior based scheme

In this scheme, a second classification scheme was proposed based on the driver behavior that occurred during the "in-vehicle" driving test. Three quantitative measures of driver behavior were selected to evaluate the field driving aggressiveness of each participant as follows (AAA Foundation, 2009):

- Number of attempted and completed discretionary lane changes,
- Number of completed lane changes without turn signal, and
- Number of improper driving behaviors, including
  1) failure to yield right of way,
  2) failure to obey traffic signs, and
  3) driving too fast for conditions or in excess of posted speed limit.

Table 5-14 presents the number of various maneuvers that occurred during the "in-vehicle" driving test, as well as the corresponding aggressiveness index (AI) values calculated from the measures. An overall field aggressiveness index (FAI) was measured for each of the participants. For the "number of attempted and completed DLCs (Attempted and completed DLCs)", the AI (AI_1) value is calculated by Eq. (5-2):

$$AI_1 = \frac{N_i - \min(N)}{\max(N) - \min(N)} * 10 \tag{5-2}$$

where,

AI_1: is the aggressiveness index for the measurement of "number of attempted and completed DLCs,"

N_i: is the number of attempted and completed DLCs by participant i,

min(N): is the minimal number of attempted and completed DLCs for all participants, and

max(N): is the maximal number of attempted and completed DLCs for all participants.

For the "number of completed lane changes without signal ahead (Completed LCs w/o signal ahead)", the AI (AI_2) value is calculated by Eq. (5-3):

$$AI_2 = \frac{N_{w/o,i} / N_{total,i} - \min(N_{w/o} / N_{total})}{\max(N_{w/o} / N_{total}) - \min(N_{w/o} / N_{total})} * 10 \tag{5-3}$$

where,

AI_2: is the aggressiveness index for the measurement of "number of completed lane changes without signal ahead,"

$N_{w/o}$: is the number of completed lane changes without signal ahead by participant i, and

N_{total}: is the total number of completed lane changes by participant i.

For the "number of improper driving behaviors (Improper driving behaviors)," the *AI* (AI_3) value is calculated by Eq. (5-4):

$$AI_3 = \frac{N_{total,i} - \min(N_{total})}{\max(N_{total}) - \min(N_{total})} * 10 \tag{5-4}$$

where,

AI_3: is the aggressiveness index for the measurement of "number of improper driving behaviors,"

$N_{total,\,i}$: is the total number of improper driving behaviors by participant i, which is calculated by adding the number of failures to yield right of way ($N_{yield,i}$), the number of failures to obey the traffic signs ($N_{obey,i}$), and the number of driving too fast for

conditions or in excess of posted speed limit ($N_{speedy,i}$),

min(N_{total}): is the minimal number of improper driving behaviors, and

max(N_{total}): is the maximal number of improper driving behaviors.

Table 5-14. Driver's FAI interpolated from selected field behaviors

ID	Attempted and completed DLCs		Completed LCs w/o signal		Improper driving behaviors (#)				FAI
	N	AI_1	$N_{w/o}$ / N_{total}	AI_2	N_{yield}	N_{Obey}	N_{Speedy}	AI_3	
05-01	19	6.19	8 / 20	7.11	13	5	8	10	7.77
05-02	9	1.43	9 / 16	10	9	4	7	7.39	6.27
05-03	16	4.76	10 / 22	8.08	13	7	5	9.57	7.47
05-04	12	2.86	5 / 14	6.35	6	2	5	4.35	4.52
05-05	14	3.81	5 / 19	4.68	9	6	6	7.83	5.44
05-06	16	4.76	3 / 22	2.42	5	4	5	4.78	3.99
05-07	20	6.67	7 / 19	6.55	8	5	8	7.83	7.02
05-08	22	7.62	9 / 21	7.62	7	6	7	7.39	7.54
05-09	14	3.81	5 / 20	3.42	3	1	3	1.74	2.99
05-10	18	5.71	7 / 15	8.30	10	2	5	6.09	6.70
05-11	12	5.24	6 / 17	6.27	8	5	5	6.52	6.01
05-12	20	6.67	4 / 28	2.54	7	4	7	6.52	5.24
05-13	11	2.38	8 / 15	9.48	5	3	4	3.91	5.26
05-14	10	1.90	5 / 14	6.35	2	1	3	1.30	3.18
05-15	17	5.24	5 / 23	3.86	8	4	5	6.09	5.06
05-16	17	5.24	8 / 20	7.11	13	5	5	8.70	7.02
05-17	16	4.76	6 / 16	6.67	6	5	4	5.22	5.55
05-18	27	10	6 / 15	7.11	9	4	6	6.96	8.02
05-19	17	5.24	9 / 19	8.42	12	3	7	8.26	7.31
05-20	18	5.71	5 / 22	4.04	4	2	2	2.17	3.97
05-21	21	7.14	4 / 24	2.96	8	3	7	6.52	5.54
05-22	13	3.33	9 / 30	5.33	8	7	6	7.83	5.50
05-23	15	4.29	8 / 31	6.77	12	4	6	8.26	6.44
05-24	17	5.24	6 / 19	5.61	11	3	5	6.96	5.94
05-25	12	2.86	3 / 14	3.81	2	0	1	0	2.22
05-26	15	4.29	7 / 20	6.22	8	6	8	8.26	6.26
05-27	24	8.57	7 / 26	4.79	10	5	7	8.26	7.21
05-28	15	4.29	7 / 18	6.91	10	3	6	6.96	6.05
05-29	19	6.19	5 / 22	4.04	13	4	7	9.13	6.45
05-30	20	6.67	1 / 24	0.74	8	2	4	4.78	4.06
05-31	16	4.76	4 / 21	3.39	9	6	7	8.26	5.47
05-32	12	2.86	5 / 18	4.94	7	4	7	6.52	4.77
05-33	15	4.29	2 / 21	1.69	5	2	3	3.04	3.01
05-34	6	0	3 / 13	4.10	7	2	4	4.35	2.82
05-35	25	9.05	0 / 27	0	8	5	7	7.39	5.48
05-36	7	0.48	6 / 14	7.62	10	5	9	9.13	5.74
05-37	16	4.76	6 / 21	5.08	9	4	7	7.39	5.74
05-38	21	7.14	4 / 25	2.84	14	4	7	9.57	6.52
05-39	15	4.29	3 / 21	2.54	10	3	9	8.26	5.03
05-40	15	4.29	1 / 19	0.94	4	3	5	3.91	3.05
Average	16.10	4.87	5.5 / 19.9	5.17	8.25	3.83	5.70	6.44	5.49

With these calculations, the overall field aggressiveness index (FAI) was then calculated as the average of the three indices AI_1, AI_2, and AI_3, which was used for the driver clustering analysis that followed.

By following the same classification procedure as in scheme 1, the K-means algorithm (as provided in APPENDIX I) was first used to cluster the n (n = 40) participants based on FAI into k (k = 1, 2, 3, 4, or 5) partitions, k < n. By setting the cluster number as 1, 2, 3, 4, and 5 respectively, centroids for the clusters were obtained as follows:

1) for cluster number = 1, centroid for each cluster is 5.49;
2) for cluster number = 2, centroids for each cluster are 3.51 and 6.24;
3) for cluster number = 3, centroids for each cluster are 3.25, 5.43, and 7.0;
4) for cluster number = 4, centroids for each cluster are 3.25, 5.24, 6.19 and 7.42;
5) for cluster number = 5, centroids for each cluster are 3.25, 4.98, 5.60, 6.34 and 7.42.

Next, the reason-based level of likelihood values, as presented in the right columns of Table 5-12, were used to decide the most appropriate cluster number. The overall intra-cluster variance on the level of likelihood for each lane-changing situation was calculated, and accumulated across all reasons using Eq. (4-2). The overall intra-cluster variance (W) value for each classification was calculated as: $W(1) = 177.79$, $W(2) = 155.63$ $W(3) = 106.36$, $W(4) = 83.91$ and $W(5) = 79.85$. The Hartigan index, which indicates the intra-cluster dissimilarity that will be removed by splitting the k clusters into k+1 clusters, was calculated to determine the appropriate number of clusters. By using Eq. (4-3), the indices for k equaling 1, 2, 3 and 4 were calculated as H(1) = 5.41, H(2) = 17.14, H(3) = 9.63 and H(4) = 1.78. A rather small Hartigan index was found to occur in H(4), which means by splitting the 4 clusters into the 5, the dissimilarity is not removed as much. Figure 5-8 provides the results of analysis for the number of clusters ranging from 1 to 5. When the cluster number is larger than 4, the intra-cluster dissimilarity does not decrease much. Therefore, it is recommended that the appropriate number of clusters for this scheme is 4. As we can see, this number is also the result obtained from the focus group study, and is rather close to the number of clusters acquired from background-based classification. Additional comparison between the two classifications

(background-based and behavior-based) is provided in the following section.

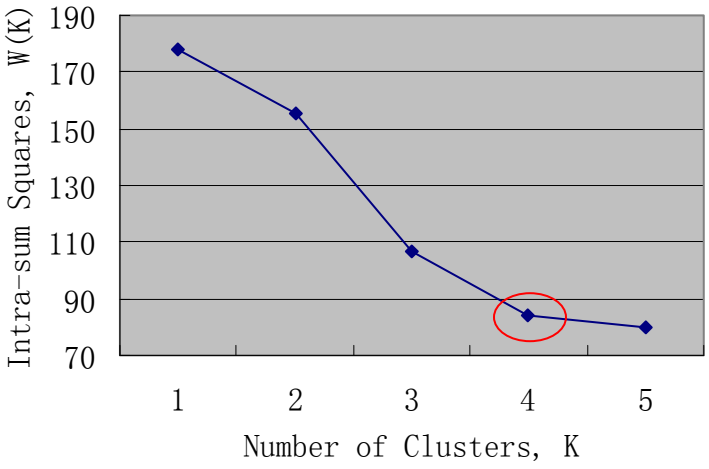


Figure 5-8. Clustering analysis results based on driver behavior

5.2.3.3 Results comparison

In this section, results from the two classifications (background-based and behavior-based) are compared and analyzed. Given that the number of clusters obtained from the background-based analysis is 3 or 4, and the cluster number from the behavior-based analysis is 4, the ranges for four groups under the two classification schemes are obtained. For the background-based classification, the overall aggressiveness is used to categorize the participants into four groups defined as L1 (<= 4.0), L2 (4.1 – 5.3), L3 (5.4 – 6.4) and L4 (>= 6.5). For the behavior-based one, the FAI is used to categorize the participants into four groups defined as L1 (<= 4.2), L2 (4.3 – 5.7), L3 (5.8 – 6.8) and L4 (>= 6.9). Since the overall aggressiveness is also used to categorize the focus group drivers, it was found that the range values for each background-based group were slightly lower than those obtained from the focus groups (<= 4.1, 4.2 – 5.6, 5.7 – 6.5 and >= 6.6). This may be because of the inner discrepancy between the participants in the two experiments. By going through the participants' overall aggressiveness values, it was found the average overall aggressiveness value is 5.65 for the focus group participants and 5.33 for the "in-vehicle" participants, which means the focus group drivers are slightly more aggressive.

By applying the clustering ranges from both classifications (background-based and behavior-based) on the 40 participants, each of the drivers is tagged with a corresponding driver type (A for group L1, B for group L2, C for group L3 or D for group L4) as presented in Table 5-15. It was found that for more than half of the drivers (23/40 = 57.5%), the driver type information obtained from the background-based classification is consistent with that from the behavior-based classification.

Table 5-15. Consistency between the background-based and behavior-based classifications

ID	Background-based		Behavior-based		Consistent or not
	Overall Agg.	Driver Group	FAI	Driver Group	
05-01	7.25	D	7.77	D	Y
05-02	5.5	C	6.27	C	Y
05-03	7.0	D	7.47	D	Y
05-04	5.5	C	4.52	B	N
05-05	4.25	B	5.44	B	Y
05-06	3.25	A	3.99	A	Y
05-07	7.5	D	7.02	D	Y
05-08	6.25	C	7.54	D	N
05-09	3.5	A	2.99	A	Y
05-10	6.75	D	6.70	C	N
05-11	5.75	C	6.01	C	Y
05-12	3.5	A	5.24	B	N
05-13	5.5	C	5.26	B	N
05-14	3.0	A	3.18	A	Y
05-15	3.75	A	5.06	B	N
05-16	7.5	D	7.02	D	Y
05-17	6.25	C	5.55	B	N
05-18	8.25	D	8.02	D	Y
05-19	6.5	D	7.31	D	Y
05-20	4.5	B	3.97	A	N
05-21	5.25	B	5.54	B	Y
05-22	5.0	B	5.50	B	Y
05-23	7.5	D	6.44	C	N
05-24	6.5	D	5.94	C	N
05-25	2.5	A	2.22	A	Y
05-26	5.25	B	6.26	C	N
05-27	6.75	D	7.21	D	Y
05-28	5.5	C	6.05	C	Y
05-29	7.0	D	6.45	C	N
05-30	6.25	C	4.06	A	N
05-31	3.75	A	5.47	B	N
05-32	4.5	B	4.77	B	Y
05-33	3.25	A	3.01	A	Y
05-34	2.5	A	2.82	A	Y
05-35	4.0	A	5.48	B	N
05-36	4.75	B	5.74	C	N
05-37	6.25	C	5.74	C	Y
05-38	5.5	C	6.52	C	Y
05-39	4.5	B	5.03	B	Y
05-40	5.25	B	3.05	A	N
		% of Consistency			57.5%

Further investigation was conducted to obtain the statistical distribution of each driver to the corresponding driver types by the two classifications, as shown in Table 5-16. From the table, in addition to the drivers whose types are consistent within two classifications (# = 23), another 16 drivers were found to be tagged with the adjacent groups, which account for 40% of the total number of drivers. This may be explained as that many of these drivers have the overall aggressiveness or FAI values rather close to the boundary of group ranges, which may result in being categorized into the adjacent group(s) instead of remaining in the same group. Only one driver (05-30) is tagged as type C in background-based classification, while as type A in the behavior-based classification. The quantitative overall aggressiveness and the FAI values (6.25 and 4.06) from Table 5-15 indicate that the real/actual difference is not so large. By referring to the "in-vehicle" video clips, it was found that the driving occurred on a Friday PM peak, and the field-collected driving behavior is much less aggressive because of the heavy traffic. Consequently, the conclusion was drawn that for urban lane-changing behaviors, the field driving maneuvers can be somewhat reflected by the background survey results, although discrepancies do exist.

Table 5-16. Statistical distribution of drivers by the two classifications

Behavior / Background	Type A	Type B	Type C	Type D
Type A	6 (15%)	4 (10%)	N/A	N/A
Type B	2 (5%)	5 (12.5%)	2 (5%)	N/A
Type C	1 (2.5%)	3 (7.5%)	5 (12.5%)	1 (2.5%)
Type D	N/A	N/A	4 (10%)	7 (17.5%)

The comparison and analysis further confirmed that the "in-vehicle" drivers can be generalized into four groups, as recommended in the focus group study. Compared to the driver classification scheme used in the focus group study, which is fully dependent on the drivers'

perceived experience data, the background-based classification is based on both background and field data, while the behavior-based classification depends entirely on the field data. As presented, the results from these three different classification schemes show similarities by connecting the driver characteristics (overall aggressiveness) to the lane-changing maneuvers (FAI). The behavior-based classification and the corresponding ranges were selected to be applied to further lane-changing model development. As a result, the "in-vehicle" maneuver data can be classified and used to model the lane-changing behaviors with different driver characteristics.

5.3 Summary and Conclusions

In this chapter, the design and implementation processes of the "in-vehicle" experiment were presented. The results were analyzed to verify the lane-changing process as documented during the focus group study. Two classification schemes were proposed to cluster the "in-vehicle" drivers into different groups based on the driver's background and the driving behavior measured during the data collection. Results from this chapter, including the "in-vehicle" field data and the selected classification scheme, are to be used for further model development. More specifically, the findings from this experiment are:

- The quantitative values for the important factors were obtained from the various (completed, attempted and potential) maneuvers that occurred during the driving tests, which are used to develop the scenario-based lane-changing probability model and the gap acceptance model in Chapter 6.
- With the lane-changing likelihoods for the DLCs calculated from the "in-vehicle" field data, both the drivers' background information and the measurements of driving behavior were used to group the drivers into different types. Two classification schemes, background-based and behavior-based, were conducted. The number of clusters obtained from the background-based analysis is 3 or 4, while the cluster number from the behavior-based analysis is 4, which is also the number obtained from the focus group study.
- Comparison between the two classifications indicates that the major results of driver classification are consistent except the differences induced by some particular immediate field situations. The result of grouping the participating drivers into four types is to be

further used in the scenario-based probability model and gap acceptance model development. By this method, the "in-vehicle" lane-changing data can be categorized by driver groups, so that the lane-changing behaviors for different type of drivers can be modeled.

- The "in-vehicle" experiment is rather helpful in validating and confirming the conclusions from the focus group study, and in collecting the parameters for lane-changing model development and implementation. However, as discussed, one of the issues is that this type of data collection might have some bias in that drivers are likely to modify their behavior when they know they are being observed. Consequently, simulation and calibration endeavors are included to address this driver/human-related problem in the following chapters.

CHAPTER 6
MODEL DEVELOPMENT

As discussed in Chapter 1, the lane-changing process is generally modeled as a sequence of four decision-making steps: lane-changing decision for particular scenario, target lane selection, gap acceptance and vehicle movement to target lane. This chapter is focused on the modeling components for the probabilistic decision under various DLC scenarios and the gap acceptance procedure. Driver characteristics and field data obtained from the "in-vehicle" lane-changing maneuvers (potential, attempted and completed) were used to develop the two components. A hierarchical modeling framework for the strategies in choice of plan (decision to change lanes) and choice of action (gap acceptance), with the incorporation of driver characteristics, is presented in Figure 6-1.

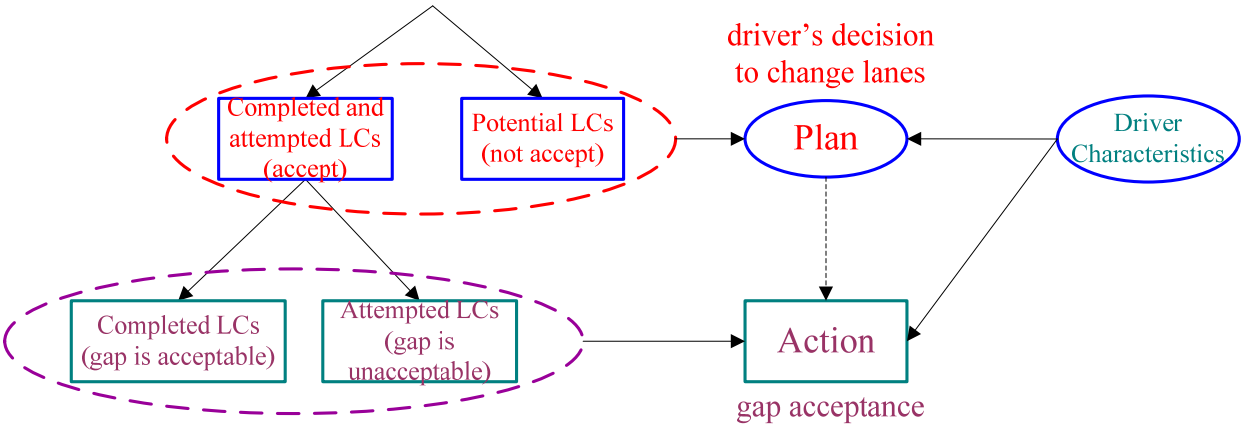


Figure 6-1. Modeling framework for choices of plan and action in lane-changing behavior

First, in order to model the lane-changing probability under each particular scenario, the combination of completed lane changes and attempted maneuvers are deemed as "accept" response, while potential maneuvers are recognized as "not accept" response. Next, during the gap acceptance modeling, only the attempted and completed maneuvers are considered. The completed lane changes are labeled as "acceptable" response, while the attempted maneuvers are

recognized as “unacceptable” response. By this method, the two processes form a special nested logit model (Peot and Smith, 1992; Bhat, 1997; Carrasco and Ortuzar, 2002), even though the target lane selection should be considered in between.

The chapter is organized as follows: the development of the lane-changing probability component for the DLC scenarios is presented in Section 6.1. In Section 6.2, with analysis of the gap acceptance characteristics, along with vehicle interactions that occurred in the “in-vehicle” experiment, the lane changes on urban arterials were classified into three modes: (i) free, (ii) forced, and (iii) competitive/cooperative. A new gap acceptance algorithm is proposed to distinguish and model each of these three modes, respectively. The chapter concludes with a summary of the newly developed lane-changing probability and gap acceptance models.

6.1 Scenario-Based Lane-Changing Probability Model

In this section, the development of the probability function for modeling the lane-changing decision under each DLC scenario is presented. First, the field lane-changing maneuvers were grouped by lane-changing scenario. Next, different maneuvers (the combination of completed and attempted maneuvers versus potential maneuvers) were identified. With the provided outcome (“accept” for completed and attempted maneuvers, “not accept” for potential ones) for each lane-changing behavior, the probability of changing lanes under each DLC scenario was estimated as a function of the associated important factors and driver types. The following subsections discuss the details of the modeling procedure.

6.1.1 Dataset Overview

As presented in Table 6-1, the driver behavior-based FAI was used to categorize the participants into four groups. The number of drivers for types A, B, C and D are 9, 12, 11 and 8, respectively.

Table 6-1. Classification of driver groups for the "in-vehicle" experiment (based on FAI)

Driver Group	ID	FAI (0-10)
Type A-L1 (number of drivers = 9)	05-25	2.22
	05-34	2.82
	05-09	2.99
	05-33	3.01
	05-40	3.05
	05-14	3.18
	05-20	3.97
	05-06	3.99
	05-30	4.06
Type B-L2 (number of drivers = 12)	05-04	4.52
	05-32	4.77
	05-39	5.03
	05-15	5.06
	05-12	5.24
	05-13	5.26
	05-05	5.44
	05-31	5.47
	05-35	5.48
	05-22	5.5
	05-21	5.54
	05-17	5.55
Type C-L3 (number of drivers =11)	05-36	5.74
	05-37	5.74
	05-24	5.94
	05-11	6.01
	05-28	6.05
	05-26	6.26
	05-02	6.27
	05-23	6.44
	05-29	6.45
	05-38	6.52
	05-10	6.7
Type D-L4 (number of drivers = 8)	05-07	7.02
	05-16	7.02
	05-27	7.21
	05-19	7.31
	05-03	7.47
	05-08	7.54
	05-01	7.77
	05-18	8.02

Note: The field aggressiveness index (FAI) scales for various driver types were obtained as Type A (<= 4.2), Type B (4.3-5.7), Type C (5.8-6.8) and Type D (>= 6.9).

There are a total of 601 completed lane changes, 199 attempted lane changes and 205 potential maneuvers occurring during the "in-vehicle" data collection. These maneuvers are grouped by scenario with the number of maneuvers for each DLC scenario as shown in Table 6-2. For each maneuver, in addition to the subject driver type, which can be obtained from Table 6-2, the associated important factors were identified from the focus group study as shown in Table 4-9.

Table 6-2. Number of lane changes collected for each scenario

LC Reasons	Actions	Number of Maneuvers
R1 (Stopped bus)	Potential	15
	Attempted	13
	Completed	45
R2 (Vehicle merge)	Potential	23
	Attempted	14
	Completed	47
R3 (Slow vehicle)	Potential	36
	Attempted	41
	Completed	167
R4 (Queue advantage)	Potential	15
	Attempted	20
	Completed	49
R5 (Heavy vehicle)	Potential	12
	Attempted	9
	Completed	27
R6 (Tailgating)	Potential	20
	Attempted	0
	Completed	10
R7 (Pavement)	Potential	28
	Attempted	11
	Completed	29
R8 (Backup turning)	Potential	17
	Attempted	16
	Completed	43
R9 (Pedestrian/scooter)	Potential	13
	Attempted	11
	Completed	30
R10 (Erratic driver)	Potential	15
	Attempted	20
	Completed	47

6.1.2 Lane-Changing Probability Function Estimation

In studying the maneuvers under each of the lane-changing scenarios, the dependent variable is the outcome of a binary choice ('1: accept' for completed and attempted cases; '0: not accpet' for potential ones). A logistic regression with a binary dependent variable was chosen to estimate the probability of changing lanes under each DLC scenario as a function of the associated important factors and driver types (Ben-Akiva, 1973; Ben-Akiva and Lerman, 1985; Ben-Akiva and Bierlaire, 2003). The logistic regression is essentially a generalized linear model with special advantages for binomial regression (Hosmer and Lemeshow, 2000). The advantages of using the logistic regression instead of the ordinary linear regression in this research are listed below (Albert and Anderson, 1984):

- If a linear regression is used, the predicted values may become greater than 1 or less than 0 if any of the independent variables were moved far enough on the X-axis. Such values are theoretically inadmissible.
- One of the assumptions of regression is that the variance of Y is constant across values of X (homoscedasticity). This cannot be the case with a binary variable, because the variance is P*Q (P, the proportion of 1s; Q, the proportion of 0s). As P approaches 1 or 0, the variance approaches 0.
- The significance testing of the coefficients rests upon the assumption that errors of prediction (Y-Y') are normally distributed. Because Y only takes the values 0 and 1, this assumption is hard to justify, even approximately. Therefore, the tests of the regression coefficients are suspect if the linear regression were used with a binary dependent variable.

By using the logistic regression approach (Nakanishi and Cooper, 1974), the probability function of changing lanes under each scenario is calculated as:

$$P(LC) = \frac{e^{V(LC)}}{1 + e^{V(LC)}}, \tag{6-1}$$

where,

$P(LC)$: is the probability of changing lanes under given scenario, and

$V(LC)$: is the utility of changing lanes under a given scenario, which is generally formulated as $\beta_0 + \beta^T * X$, X is the independent variable vector, β_0 is the constant and β^T are the corresponding coefficients.

To assess the impact of important factors on each of the corresponding DLCs, and formulate the lane-changing utility function, the maneuvers related to each of the pre-selected DLC scenarios were analyzed as described below.

Table 6-3 presents the number of maneuvers for different driver types that occurred during the "stopped-bus" scenario. The important factors identified for this scenario from focus group study (see Table 4-9) are:

factor 1: Traffic congestion in the target lane (Cgst);
factor 2: Queue ahead (Que);
factor 3: Location of the next downstream stop (LocStop, mile);
factor 4: Distance to the bus (Dist, feet); and
factor 5: Number of persons at the bus-stop (NPson).

Table 6-3. Number of LCs for different driver types during "Stopped-Bus" scenario

Maneuvers	Type A(L1)	Type B(L2)	Type C(L3)	Type D(L4)
Potential	5	5	3	2
Attempted	2	6	2	3
Completed	7	21	9	8
Total	14	32	14	13

Consequently, a utility function of changing lanes for this scenario is developed as follows:

$$V(LC) = \beta_0 + \beta_1 * Cgst + \beta_2 * Que + \beta_3 * LocStop + \beta_4 * Dist + \beta_5 * NPson + \alpha_1 * DrvTypeA + \alpha_2 * DrvTypeB + \alpha_3 * DrvTypeC \quad (6\text{-}2)$$

In this instance, three dummy variables were created as $DrvTypeA$, $DrvTypeB$, and $DrvTypeC$, which are used in regression analysis to represent different driver groups (Types A, B and C) included in this study. If a subject driver belongs to type A, then "$DrvTypeA$" would be equal to 1, and "$DrvTypeB$" and "$DrvTypeC$"would be equal to 0. If a subject driver is in type D, all three dummy variables would be equal to 0. In fact, each dummy variable acts as a switch that turns the corresponding driver type parameter on and off in the equation, so that a single regression function can be used to represent multiple driver groups (Kinnear et al., 1974; Khattak

et al., 1996). By this, it is not necessary to develop separate models for each driver group (Golob and McNally, 1997; Brownstone et al., 2000).

With the field values obtained from 73 maneuvers (as shown in Table 6-3), the binomial logistic regression tools in SPSS were used to capture the relationship between these factors and the lane-changing probability (Norusis, 2005; Allison, 1999). The estimated results are presented in Table 6-4 as follows.

Table 6-4. Estimated coefficients for the factors in "Stopped Bus" scenario

Factors	Coefficients	T Value
Constant	6.480	3.902
Traffic congestion in the target lane (Cgst)	-0.236	-4.517
Queue ahead (Que)	1.218	0.652
Location of the next stop (LocStop)	-19.116	-2.778
Distance to the bus (Dist)	-0.381	-2.703
Number of persons at the bus-stop (NPson)	0.227	0.217
Driver Type A (DrvTypeA)	-2.533	-1.935
Driver Type B (DrvTypeB)	-1.303	-1.736
Driver Type C (DrvTypeC)	-1.139	-1.807

Among these parameters, the factor of "Traffic congestion in the target lane (Cgst)" made the most significant contribution to the probability of changing lanes, both in terms of relative magnitude and statistical significance. The factor captures the impact of traffic conditions on the target lane. The negative sign means when the target lane is congested, a vehicle has a lower probability to change lanes to avoid the stopped bus. In addition, the estimated results indicate that "Location of the next bus stop (LocStop)" and "Distance to the bus (Dist)" are significant, and both factors have a negative coefficient. These make sense, since the field data were collected from urban arterials without pullouts. As the subject vehicle approaches the bus, or the bus approaches the next bus stop, it would become more willing to change lanes. As presented in Table 6-4, the driver types affect the lane-changing probability differently, and the defensive drivers (type A) tend to have a low probability to change lanes. Two other factors: "Queue ahead

(Que)" and "Number of persons at the bus stop (NPson)" are not significant at a 90% confidence, although the estimated coefficients (1.218 and 0.227) seem feasible (with the increasing number of queue length and persons at the bus stop, the probability of changing lanes increases). By excluding the factors which are not significant at the 90% confidence, the explanatory variables for this scenario were selected as: "Traffic congestion in the target lane (Cgst)," "Location of the next stop (LocStop)," "Distance to the bus (Dist)," and the four driver types. Consequently, the utility function of changing lanes for this scenario is estimated as:

$$V(LC) = 6.48 - 0.236 * Cgst - 19.116 * LocStop - 0.381 * Dist - \\ 2.533 * DrvTypeA - 1.303 * DrvTypeB - 1.139 * DrvTypeC \quad (6\text{-}2)$$

Table 6-5 presents the number of maneuvers for different driver types that occurred during the "vehicle merge" scenario. The important factors identified for this scenario (see Table 4-9) are:

factor 1: Traffic congestion on the target lane (Cgst);
factor 2: Travel speed, and the difference b/t travel speed and speed limit (Spd1, Spd1-Spd2);
factor 3: Aggressiveness of the merge (Agg);
factor 4: Distance to the next turn (Dist); and
factor 5: Merger and the subject vehicle type (VehT1, VehT2).

Table 6-5. Number of LCs for different driver types during "Vehicle Merge" scenario

Maneuvers	Type A(L1)	Type B(L2)	Type C(L3)	Type D(L4)
Potential	5	4	6	8
Attempted	3	5	3	3
Completed	13	19	8	7
Total	21	28	17	18

Since the subject vehicle is always the instrumented vehicle (Honda Pilot), the effect of "Subject vehicle type (VehT2)" was not captured in this experiment. Consequently, the utility function of changing lanes for this scenario is developed as follows:

$$V(LC) = \beta_0 + \beta_1 * Cgst + \beta_2 * Spd1 + \beta_3 * (Spd1 - Spd2) + \beta_4 * Agg + \beta_5 * Dist + \beta_6 * VehT1 \\ \alpha_1 * DrvTypeA + \alpha_2 * DrvTypeB + \alpha_3 * DrvTypeC \quad (6\text{-}3)$$

With the field values obtained from 84 maneuvers (as shown in Table 6-5), the regression tool in SPSS was used to capture the relationship between these factors and the lane-changing probability. The results are presented in Table 6-6 as follows.

Table 6-6. Estimated coefficients for the factors in "Vehicle Merge" scenario

Factors	Coefficients	T Value
Constant	4.398	4.49
Traffic congestion in the target lane (Cgst)	-0.397	-1.89
Subject travel speed (Spd1)	0.422	0.56
Diff. b/t travel speed and speed limit (Spd1-Spd2)	-0.285	-1.99
Aggressiveness of the merge (Agg)	-0.693	-0.28
Distance to the next turn (Dist)	-0.011	-2.17
Merger vehicle type (VehT1) 0:car, 1: others	1.090	2.02
Driver Type A (DrvTypeA)	-1.091	-2.16
Driver Type B (DrvTypeB)	1.711	2.33
Driver Type C (DrvTypeC)	3.166	2.49

Among these parameters, the factor of "Diff. b/t travel speed and speed limit (Spd1-Spd2)" made the most significant contribution to the probability of changing lanes. The negative sign means when a vehicle is at a higher speed than the posted speed, it may have a lower probability to change lanes to give way to the merge vehicle. In addition, the estimated results indicate that "Traffic congestion in the target lane (Cgst)," "Distance to the next turn (Dist)" and "Merger vehicle type (VehT)" are significant, which reflect the impact of drive environment on the driver. As presented in Table 5-13, the driver type parameters affect the lane-changing probability differently. The median aggressive drivers (types B and C) tend to have a larger probability to change lanes, which is consistent with the findings from the focus group study. The least and most aggressive drivers (types A and D) may choose to slow down to give way or accelerate to prohibit the merge. Two other factors, "Subject travel speed (Spd1)" and "Aggressiveness of the merge (Agg)" are not significant at 90% confidence. By excluding these two parameters, the explanatory variables for this scenario were selected as: "Traffic congestion in the target lane

(Cgst)," "Diff. b/t travel speed and speed limit (Spd1-Spd2)," "Distance to the next turn (Dist)" and "Merger vehicle type (VehT)." Consequently, the utility function of changing lanes for this scenario is estimated as:

$$V(LC) = 4.398 - 0.397 * Cgst - 0.285 * (Spd1 - Spd2) - 0.018 * Dist + 1.09 * VehT1 - 1.091 * DrvTypeA + 1.711 * DrvTypeB + 3.166 * DrvTypeC \quad (6\text{-}4)$$

Table 6-7 presents the number of maneuvers for different driver types that occurred during the "slow vehicle" scenario. The important factors identified for this scenario (see Table 4-9) are:

factor 1: Distance to the next turn (Dist);
factor 2: Travel speed, and the difference between travel speed and speed limit (Spd1, Spd1-Spd2);
factor 3: Congestion on the target lane (Cgst); and
factor 4: Driver's mood, hurry or not (Mood) .
Note: The factor 4 (Mood) is excluded from the estimation, since the value of the factor is difficult to be collected from the "in-vehicle" test, and is almost impossible to be modeled.

Table 6-7. Number of LCs for different driver types during "Slow Vehicle" scenario

Maneuvers	Type A(L1)	Type B(L2)	Type C(L3)	Type D(L4)
Potential	14	15	5	2
Attempted	8	13	11	9
Completed	39	53	41	34
Total	61	81	57	45

Consequently, a utility function of changing lanes for this scenario is developed as follows:

$$V(LC) = \beta_0 + \beta_1 * Dist + \beta_2 * Spd1 + \beta_3 * (Spd1 - Spd2) + \beta_4 * Cgst \quad \alpha_1 * DrvTypeA + \alpha_2 * DrvTypeB + \alpha_3 * DrvTypeC \quad (6\text{-}5)$$

With the field values obtained from 244 maneuvers (as shown in Table 6-7), the regression tool in SPSS was run to capture the relationship between these factors and the lane-changing probability. The results are presented in Table 6-8.

Among these parameters, the factors "Distance to the next turn (Dist)," "Traffic congestion in the target lane (Cgst)," "Subject speed (Spd1)" and "Diff. between travel speed and speed limit (Spd1-Spd2)" are significant, which reflect the traffic dynamics surrounding the subject

driver. As presented in Table 6-8, the driver types affect the lane-changing probability differently. The most aggressive drivers (type D) tend to have a larger probability to change lanes, which is consistent with the findings from the focus groups. The only conflict is that that driver type B tends to have higher intention to change lanes than driver type C, while according to the classification, drivers in type B are characterized as less aggressive than those in type C. Considering the coefficients for the two factors (*DrvTypeB* and *DrvTypeC*) are rather close to each other (-0.376 and -0.389), the two variables may be grouped together as one united variable with an averaged coefficient value. Consequently, the explanatory variables for this scenario were selected as: "Distance to the next turn (Dist)," "Traffic congestion in the target lane (Cgst)," "Subject travel speed (Spd1)" and "Diff. between travel speed and speed limit (Spd1-Spd2)." The utility function of changing lanes for this scenario is estimated as:

$$V(LC) = 3.743 - 0.031 * Dist - 0.281 * Cgst + 0.037 * Spd1 - 0.155 * (Spd1 - Spd2) - 0.703 * DrvTypeA - 0.382 * (DrvTypeB + DrvTypeC) \quad (6\text{-}6)$$

Table 6-8. Estimated coefficients for the factors in "Slow Vehicle" scenario

Factors	Coefficients	T Value
Constant	3.743	3.26
Distance to the next turn (Dist)	-0.031	-2.57
Traffic congestion in the target lane (Cgst)	-0.281	-3.46
Subject travel speed (Spd1)	0.037	1.66
Diff. b/t travel speed and speed limit (Spd1-Spd2)	-0.155	-2.89
Driver Type A (DrvTypeA)	-0.703	-3.24
Driver Type B (DrvTypeB)	-0.376	-6.23
Driver Type C (DrvTypeC)	-0.389	-2.91

Table 6-9 presents the number of maneuvers for different driver types that occurred during the "queue advantage" scenario. The important factors identified for this scenario (see Table 4-9) are:

factor 1: Queue length difference (QueDiff);
factor 2: Distance to the next turn (Dist);
factor 3: Congestion on the target lane (Cgst); and

factor 4: Current signal status/green time (CurSig).

Consequently, a utility function of changing lanes for this scenario is developed as follows:

$$V(LC) = \beta_0 + \beta_1 * QueDiff + \beta_2 * Dist + \beta_3 * Cgst + \beta_4 * CurSig$$
$$\alpha_1 * DrvTypeA + \alpha_2 * DrvTypeB + \alpha_3 * DrvTypeC \quad (6\text{-}7)$$

Table 6-9. Number of LCs for different driver types during "Queue Advantage" scenario

Maneuvers	Type A(L1)	Type B(L2)	Type C(L3)	Type D(L4)
Potential	5	5	3	2
Attempted	3	7	4	6
Completed	11	22	9	7
Total	19	34	16	15

With the field values obtained from 84 maneuvers (as shown in Table 6-9), the regression tool in SPSS was used to capture the relationship between these factors and the lane-changing probability. The results are presented in Table 6-10.

Table 6-10. Estimated coefficients for the factors in "Queue Advantage" scenario

Factors	Coefficients	T Value
Constant	2.503	7.41
Queue length difference (QueDiff)	0.254	9.39
Distance to the next turn (Dist)	-0.013	3.74
Congestion on the target lane (Cgst)	-0.085	-0.29
Current signal status/red time (CurSig) red:1, not:0	0.492	2.13
Driver Type A (DrvTypeA)	-1.694	-4.28
Driver Type B (DrvTypeB)	-0.703	-3.93
Driver Type C (DrvTypeC)	-0.277	-2.79

Among these parameters, the factor of "Queue length difference (QueDiff)" made the most significant contribution to the probability of changing lanes. The positive sign means if the "queue length difference" is larger, the probability of changing lanes increases. Estimation results indicate that "Distance to the next turn (Dist)" and "Current signal status/red time (CurSig)" are also significant, which reflect the concerns of the trade-off between the destination and time spent at the signal. The factor of "CurSig" has a positive coefficient, which means

drivers are more likely to change lane under red signal. This seems contradict to our general driving experience. However, considering that most of the driving tests occurred in PM congested traffic, all vehicles would slow down when approaching a red signal. This may facilitate lane changes since the drivers have more time to observe traffic in the target lane and make appropriate lane changes. As presented in Table 6-10, all driver types affect the lane-changing probability significantly. Aggressive drivers (Type D) tend to have a larger probability to change lanes, which is consistent with the findings from the focus groups. Compared to the other types of driver, driver type A has a much lower probability to change lanes. Another factor, "Congestion on the target lane (Cgst)," is not significant at 90% confidence. This may be due to the fact that this factor is highly correlated with the "Queue length difference (QueDiff)" factor, and the effect was somewhat captured by the QueDiff. Drivers tend to consider the queue length in front instead of traffic congestion around under PM congested traffic. By excluding the "congestion on the target lane (Cgst)," the explanatory variables for this scenario were selected as: "Queue length difference (QueDiff)," "Distance to the next turn (Dist)," and "Current signal status/red time (CurSig)." Consequently, the utility function of changing lanes for this scenario is estimated as:

$$V(LC) = 2.503 + 0.254 * QueDiff - 0.013 * Dist + 0.492 * CurSig - 1.694 * DrvTypeA - 0.703 * DrvTypeB - 0.277 * DrvTypeC \quad (6\text{-}8)$$

Table 6-11 presents the number of maneuvers for different driver types that occurred during the "heavy vehicle" scenario. The important factors identified for this scenario (see Table 4-9) are:

factor 1: Travel speed, and the difference b/t travel speed and speed limit (Spd1, Spd1-Spd2);
factor 2: Congestion on all lanes (Cgst);
factor 3: Personal uncomfortable with HV (PerUcft); and
factor 4: Subject vehicle type (VehT).

Note: The factor 3 (PerUcft) is excluded from the estimation, since the value of factor is difficult to be collected from the "in-vehicle" test, and is almost impossible to be modeled.

Since the subject vehicle is always the instrumented vehicle (Honda Pilot), the effect of "Subject vehicle type (VehT)" was not captured in this experiment. Consequently, a utility function of changing lanes for this scenario is developed as follows:

$$V(LC) = \beta_0 + \beta_1 * Spd1 + \beta_2 * (Spd1 - Spd2) + \beta_3 * Cgst + \alpha_1 * DrvTypeA + \alpha_2 * DrvTypeB + \alpha_3 * DrvTypeC \quad (6\text{-}9)$$

Table 6-11. Number of LCs for different driver types during "Heavy Vehicle" scenario

Maneuvers	Type A(L1)	Type B(L2)	Type C(L3)	Type D(L4)
Potential	5	4	2	1
Attempted	2	4	1	2
Completed	5	11	6	5
Total	12	19	9	8

With the field values obtained from 48 maneuvers (as shown in Table 6-11), the regression tool in SPSS was used to capture the relationship between these factors and the probability value. The results are presented in Table 6-12.

Table 6-12. Estimated coefficients for the factors in "Heavy Vehicle" scenario

Factors	Coefficients	T Value
Constant	3.314	13.41
Subject travel speed (Spd1)	-0.003	-0.36
Diff. b/t travel speed and speed limit (Spd1-Spd2)	-0.065	-1.19
Congestion on the target lane (Cgst)	-0.214	-7.39
Driver Type A (DrvTypeA)	-1.946	-3.17
Driver Type B (DrvTypeB)	-0.781	-2.39
Driver Type C (DrvTypeC)	0.008	-0.83

Among these parameters, only the factors of "Congestion on the target lane (Cgst)" contributed to the probability of changing lanes. The negative sign means drivers are less likely to change lanes to avoid following an HV if the target lane is congested. Results from this estimation indicate that the speed-related factors, such as "Subject travel speed (Spd1)" and "Diff.

b/t travel speed and speed limit (Spd1-Spd2)" are not significant. This may be due to the factor that compared to "Cgst," drivers under this situation may not care too much about speed and speed difference. In addition, the speed and speed difference may be highly correlated with the "Cgst" factor, and the effects were captured by "Cgst." As presented in Table 6-12, the driver types affect the lane-changing probability differently. The driver types C tends to have similar effect as the driver type D, which may be grouped together as one united variable, while the driver types A and B are not willing to change lanes compared to the driver types C and D. By excluding those factors which are not significant at 90% confidence, the explanatory variables for this scenario were selected as: "congestion on the target lane (Cgst)." Consequently, the utility function of changing lanes for this scenario is estimated as:

$$V(LC) = 3.314 - 0.214 * Cgst - 1.946 * DrvTypeA - 0.781 * DrvTypeB \tag{6-10}$$

Table 6-13 presents the number of maneuvers for different driver types that occurred during the "tailgating" scenario. The important factors identified for this scenario (see Table 4-9) are:

factor 1: Travel speed, and the difference b/t travel speed and speed limit (Spd1, Spd1-Spd2);
factor 2: Congestion on all lanes (Cgst1 and Cgst2);
factor 3: The subject lane position (LanePos); and
factor 4: Type of the lag vehicle (VehT).

Table 6-13. Number of LCs for different driver types during "Tailgating" scenario

Maneuvers	Type A(L1)	Type B(L2)	Type C(L3)	Type D(L4)
Potential	9	6	5	1
Attempted	0	0	0	0
Completed	4	4	1	0
Total	13	10	6	1

In this case, only one tailgating maneuver was found for driver type D, which means this type of drivers doesn't get tailgating regularly because of their higher aggressiveness. Or even if they get, they don't change lanes. Consequently, the lane-changing probability for drivers with type D is

set as constant 0. Only two dummy variables ($DrvTypeA$ and $DrvTypeB$) were used in this model, and a utility function of changing lanes (driver types A, B and C) for this scenario is developed as follows:

$$V(LC) = \beta_0 + \beta_1 * Spd1 + \beta_2 * (Spd1 - Spd2) + \beta_3 * Cgst1 + \beta_4 * Cgst2 + \beta_5 * VehT + \alpha_1 * DrvTypeA + \alpha_2 * DrvTypeB \quad (6\text{-}11)$$

With the field values obtained from 30 maneuvers (as shown in Table 6-13), the regression tool in SPSS was used to capture the relationship between these factors and the probability value. The estimated results are presented in Table 6-14.

Table 6-14. Estimated coefficients for the factors in "Tailgating" scenario

Factors	Coefficients	T Value
Constant	-0.627	8.32
Subject travel speed (Spd1)	-0.047	-0.66
Diff. b/t travel speed and speed limit (Spd1-Spd2)	-0.026	-2.32
Traffic congestion in the target lane (Cgst1)	-0.018	-3.46
Traffic congestion in the subject lane (Cgst2)	0.029	-0.06
Subject lane position (LanePos) 0:left, 1: others	-0.197	-12.39
Type of the lag vehicle (VehT) 0:car, 1: others	0.126	5.03
Driver Type A (DrvTypeA)	0.261	3.24
Driver Type B (DrvTypeB)	0.172	1.53

Among these parameters, the factor "Subject lane position (LanePos)" made the most significant contribution to the probability of changing lanes. The negative sign means drivers in left lane are more likely to change lanes to avoid tailgating (compared to the drivers in the median and right lanes), which is consistent with findings in the focus groups. Other significant factors include "Diff. b/t travel speed and speed limit (Spd1-Spd2)," "Traffic congestion in the target lane (Cgst1)" and "Type of the lag vehicle (VehT)," which reflect the traffic dynamics on the road. As presented in Table 6-14, driver type B is not significant (at 90% confidence), and even though the driver type A is significant, the coefficient is only 0.261. By excluding the insignificant parameters, the explanatory variables for this scenario were selected as: "Diff. b/t travel speed and speed limit (Spd1-Spd2)," "Traffic congestion in the target lane (Cgst),"

"Subject lane position (LanePos)" and "Type of the lag vehicle (VehT)." Consequently, the utility function of changing lanes for this scenario (driver types A, B and C) is estimated as:

$$V(LC) = -0.627 - 0.026*(Spd1 - Spd2) - 0.018*Cgst1 - 0.197*LanePos + 0.126*VehT + 0.261*DrvTypeA + 0.172*DrvTypeB \quad (6\text{-}12)$$

Table 6-15 presents the number of maneuvers for different driver types that occurred during the "pavement" scenario. The important factors identified for this scenario are:

factor 1: Distance to the next turn (Dist);
factor 2: Difference of the pavement (PavDiff);
factor 3: Length of the pavement segment (LenPav);
factor 4: Travel speed, and the difference b/t travel speed and speed limit (Spd1, Spd1-Spd2); and
factor 5: Traffic congestion in the target lane (Cgst).
Note: The factor 2 (PavDiff) is excluded from the estimation, since the value of factor is difficult to be collected from the "in-vehicle" test, and is almost impossible to be modeled.

Table 6-15. Number of LCs for different driver types during "Pavement" scenario

Maneuvers	Type A(L1)	Type B(L2)	Type C(L3)	Type D(L4)
Potential	4	12	7	5
Attempted	1	3	4	3
Completed	6	10	4	5
Total	11	25	15	13

Consequently, a utility function of changing lanes for this scenario is developed as follows:

$$V(LC) = \beta_0 + \beta_1 * Dist + \beta_2 * LenPave + \beta_3 * Spd1 + \beta_4 * (Spd1 - Spd2) + \beta_5 * Cgst + \alpha_1 * DrvTypeA + \alpha_2 * DrvTypeB + \alpha_3 * DrvTypeC \quad (6\text{-}13)$$

With the field values obtained from 64 maneuvers (as shown in Table 6-15), the regression tool in SPSS was used to capture the relationship between these parameters and the probability value. The results are presented in Table 6-16.

Among these parameters, the significant factors for this scenario include "Distance to the next turn (Dist)," "Length of the pavement segment (LenPav)" and "Traffic congestion in the target lane (Cgst)," which reflect the traffic dynamics on the road. The driver type seems to not

affect the lane-changing decisions significantly in this scenario. As presented in Table 6-16, driver types A and B are not significant (at 90% confidence). Even though the driver type C is significant, the coefficient is not large (0.016). By excluding the insignificant parameters, the explanatory variables for this scenario were selected as: "Distance to the next turn (Dist)," "Length of the pavement segment (LenPav)" and "Traffic congestion in the target lane (Cgst)." Consequently, the utility function of changing lanes for this scenario is estimated as:

$$V(LC) = 1.273 - 0.005 * Dist + 0.0015 * LenPav - 0.153 * Cgst - 0.016 * DrvTypeC \quad (6\text{-}14)$$

Table 6-16. Estimated coefficients for the factors in "Pavement" scenario

Factors	Coefficients	T Value
Constant	1.273	4.71
Distance to the next turn (Dist)	-0.005	-1.74
Length of the pavement segment (LenPav)	0.0015	13.77
Subject travel speed (Spd1)	-0.019	-0.32
Diff. b/t travel speed and speed limit (Spd1-Spd2)	0.112	0.63
Traffic congestion in the target lane (Cgst)	-0.153	-4.92
Driver Type A (DrvTypeA)	-0.548	-0.97
Driver Type B (DrvTypeB)	-0.329	-1.32
Driver Type C (DrvTypeC)	0.016	2.14

By the end of the lane-changing probability model development, each preselected DLC scenario is related to a utility function of the respective factors and driver types, as shown in Table 6-16. By reviewing the formula and coefficients used in these probability functions, with additional attention on the likelihood results obtained from the focus groups (see Table 4-8), it is believed that the trend of these functions are reasonable. By assuming the random components are independently and identically extreme value distributed, the kernel of this binary choice model is logit, and the probability function of changing lanes for each DLC scenario can be calculated by Eq. (6-1). For the new added DLC scenarios (backup turning, pedestrian/scooter and erratic drivers), the number of maneuvers for different driver types that occurred were presented in Tables 6-17 through 6-19. However, no utility function was obtained at this stage,

Table 6-16. Scenario-based utility functions $V(LC)$ estimated from the "in-vehicle" data

Scenario	Utility functions and parameter
R1:Stopped bus	$6.48-0.236*Cgst-19.116*LocStop-0.381*Dist-2.533*DrvTypeA-1.303*DrvTypeB-1.139*DrvTypeC$
R2:Vehicle merge	$4.398-0.397*Cgst-0.285*(Spd1-Spd2)-0.018*Dist+1.09*VehT1-1.091*DrvTypeA+1.711*DrvTypeB+3.166*DrvTypeC$
R3:Slow vehicle	$3.743-0.031*Dist-0.281*Cgst+0.037*Spd1-0.155*(Spd1-Spd2)-0.703*DrvTypeA-0.382*(DrvTypeB+DrvTypeC)$
R4:Queue advantage	$2.503+0.254*QueDiff-0.013*Dist+0.492*CurSig-1.694*DrvTypeA-0.703*DrvTypeB-0.277*DrvTypeC$
R5:Heavy vehicle	$3.314-0.214*Cgst-1.946*DrvTypeA-0.781*DrvTypeB$
R6:Tailgating	$-0.627-0.026*(Spd1-Spd2)-0.018*Cgst1-0.197*LanePos+0.126*VehT+0.261*DrvTypeA+0.172*DrvTypeB$
R7:Pavement	$1.273-0.005*Dist+0.0015*LenPav-0.153*Cgst-0.016*DrvTypeC$

Table 6-18. Number of LCs for different driver types during "Back Turning" scenario

Maneuvers	Type A(L1)	Type B(L2)	Type C(L3)	Type D(L4)
Potential	5	7	3	2
Attempted	4	5	4	3
Completed	12	15	9	7
Total	21	27	16	12

Table 6-19. Number of LCs for different driver types during "Pedestrian/Scooter" scenario

Maneuvers	Type A(L1)	Type B(L2)	Type C(L3)	Type D(L4)
Potential	4	5	2	2
Attempted	3	1	4	3
Completed	7	10	8	5
Total	14	16	14	10

Table 6-20. Number of LCs for different driver types during "Erratic Drivers" scenario

Maneuvers	Type A(L1)	Type B(L2)	Type C(L3)	Type D(L4)
Potential	3	5	3	4
Attempted	4	6	7	3
Completed	10	13	15	9
Total	17	24	25	16

since the significant factors for these DLC scenarios were not generated in the focus group meetings. Consequently, the fixed probabilities ($\hat{\mu}$) obtained from the focus group study (see Table 4-8) were used for these scenarios. Further focus group studies may include these scenarios into the preselected DLC list, so that the important factors can be obtained.

6.2 Gap Acceptance Model for Urban Arterials

In addition to the scenario-based probability model, the gap acceptance procedure is studied in this section. A new algorithm was proposed to model the lane-changing gap acceptance into three modes (free, forced, and cooperative/competitive). The free and forced lane changes are modeled as instantaneous events conducted during the time interval immediately following the driver's decision, while the competitive/cooperative lane changes include more complex vehicle interactions. The emphasis is to model lane changes with interactions as a sequence of "hand-shaking negotiations" between vehicles. Various interaction scenarios are modeled based on drivers' actions and responses by referring to the negotiation procedure used in computer network communications (Stevens, 1990, 1998).

During the model formulation, first, different lane-changing modes (free, forced, and cooperative/competitive) were identified from the field maneuvers, and the gap acceptance characteristics for different modes and driver types were assessed using field data. Next, notations used in the modeling framework are provided, followed by a set of quantitative criteria for distinguishing different types of lane changes. Finally, scenarios related to the cooperative/competitive lane changes are analyzed in detail, and then are modeled with the corresponding values obtained from the "in-vehicle" data.

6.2.1 Gap Acceptance Characteristics

This subsection presents the gap acceptance characteristics of the lane-changing related maneuvers obtained in the field. For the gap acceptance model development, only the completed and attempted lane changes are used (the potential lane changes are not considered). By studying a total of 601 completed lane changes and 199 attempted but unsuccessful lane changes, the maneuvers were classified into (i) free, (ii) forced, and (iii) competitive/cooperative based on previous studies (Hidas, 2005; Ben-Akiva et al., 2006; Choudhury, 2007; Sun et al., 2008) considering vehicle interactions as follows:

- **Free lane change:** there is no noticeable interaction between the subject and lag vehicle(s). The relative gap between the lead and lag vehicle(s) is large enough, so that the subject vehicle can move to the target lane with or without a change in its acceleration.
- **Forced lane change:** this type of lane change is followed by deceleration of the lag vehicle. Generally, the subject driver does not use turn signals or uses them very briefly before changing lanes. The lag vehicle does not slow down until part of the subject vehicle has entered the target lane.
- **Competitive/Cooperative (C/C) lane change:** this type of lane change involves a sequence of interactions. First, the merging vehicle sends a lane-changing request to the lag vehicle by turning on the turn signal. The lag vehicle evaluates the request and may either cooperate by slowing down or not cooperate. The subject vehicle re-evaluates the response based on the new gap and the speed of the lag vehicle. If the lane-changing criteria are satisfied, a cooperative lane change is executed. Otherwise, if the lane-changing request is rejected by the first lag vehicle, the subject vehicle would have to adjust its speed and re-send the request to the next follower. This process may last for several seconds, and the merging vehicle may give up the lane-changing attempt during the process.

To distinguish between the forced and C/C lane changes, in addition to the turn signals, the spacing gaps between the subject vehicle and the lag vehicle were recorded during a 6-second period, 3-second before and 3-second after the merge. If the gap is increasing before the entry point, it is a C/C merge. If the gap is either constant or narrowing before the entry point, and starts to widen after merging, it is assumed that the subject vehicle has forced the lag vehicle to

slow down. The maneuvers that occurred during the "in-vehicle" experiment were grouped based on lane-changing modes for each given driver type and are summarized in Table 6-21.

In a total of 601 completed lane-changing maneuvers, 329 free, 124 forced and 148 competitive/cooperative lane changes (54.7%, 20.6% and 24.6% respectively of the total lane changes) were observed. By relating the lane-changing modes to the driver types, it was found that only two successful forced maneuvers were conducted by type A drivers, which is reasonable since these drivers would be too timid to change lanes forcefully. All 199 attempted but unsuccessful lane changes belong to the competitive/cooperative mode, since no rejection behaviors occurred during the free and forced maneuvers. As a results, the drivers of these maneuvers either changed lanes successfully (129 maneuvers for 64.8%), or gave up the attempt (70 maneuvers for 35.2%).

Table 6-21. Number of completed/attempted LCs based on modes and driver types

LC Modes		Type A	Type B	Type C	Type D	Total
Free	Completed	86	112	69	62	329 (54.7%)
Forced	Completed	2	22	58	42	124 (20.6%)
C/C	Completed	31	50	36	31	148 (24.6%)
	Attempted ①	23	41	39	26	129 (64.8%)
	Attempted ②	9	24	16	21	70 (35.2%)
Total	Completed	119	184	163	135	601
	Attempted	32	65	55	47	199

Note: ①: The numbers indicate the unsuccessful lane-changing attempts included in situations which are finally successful.
②: The numbers indicate the unsuccessful lane-changing attempts included in situations which are finally aborted.

Table 6-22 presents a summary of the acceptable spacing gaps measured from the completed lane changes, along with the rejected spacing gaps measured from the attempted but unsuccessful maneuvers. For the completed lane changes, the median gap length decreases from free to C/C, and then to forced lane changes for each of driver types, which means all drivers tend to accept smaller gaps from free to C/C, and to forced lane changes. However, by

examining the spacing gaps across different driver types, no distinct trend was found. In addition to the spacing gap characteristics, vehicle accelerations/decelerations were obtained from the completed lane changes as shown in Table 6-23. By examining the deceleration/acceleration values across different driver types, no significant differences were found. This means the acceleration/deceleration depends largely on the driver's instantaneous perception on spacing/speed differences, which is not a good indicator for reflecting the variation among driver types. With the numerical results for spacing gaps and accelerations presented, it is believed that although the type of subject driver somewhat affects the gap acceptance results, it doesn't affect the gap acceptance procedure as largely as in the lane-changing probability modeling. Consequently, the factor of driver type is only used in some special components, and doesn't affect the major decisions throughout the gap acceptance procedure.

Table 6-22. Observed spacing gap characteristics for the completed/attempted lane changes

LC Modes		Gaps Type A (ft)			Gaps Type B (ft)			Gaps Type C (ft)			Gaps Type D (ft)		
		max	min	med	max	min	med	max	min	med	max	min	med
Free	Completed	504①	79	115	469①	83	105	492①	87	109	477①	85.5	111
Forced	Completed	73.5	38.5	61	71	42.5	53	79.5	33.5	56.5	67.5	28.5	43
C./ C.	Completed	95	46	63	99.5	47	61.5	96	42	57.5	84.5	38	51
	Attempted	35.5	19	26	45	16	31.5	39.5	21	29	36	17.5	26.5

Note: ①: In the "in-vehicle" video, as some free lane changes don't have lead/lag vehicle, such cases were not included in computing the statistics of the spacing gaps.

Table 6-23. Observed accelerations/decelerations within vehicle interactions

Driver Type	# of Obs.	Accel./ Decel.	Subject vehicle, mph/s			Lag vehicle, mph/s		
			Max	Min	Median	Max	Min	Median
Type A	119	Accel.	3.27	0.23	2.03	3.11	0.14	1.96
		Decel.	4.71	0.17	2.61	4.93	0.16	2.71
Type B	184	Accel.	3.74	0.31	2.43	3.54	0.07	2.12
		Decel.	5.23	0.06	2.72	5.19	0.04	3.06
Type C	163	Accel.	3.18	0.15	1.87	2.97	0.12	1.75
		Decel.	5.12	0.28	2.44	5.41	0.13	2.93
Type D	135	Accel.	3.36	0.14	1.53	3.61	0.06	1.64
		Decel.	4.73	0.17	2.07	5.31	0.12	2.87

6.2.2 Notations and Modeling Framework

Basic notations for describing vehicle interactions in the lane-changing process are illustrated in Figure 6-2. Vehicle S_1 is the subject vehicle, which has an intention to merge into the target lane from the present lane. S_0 is the vehicle in front of S_1 in the present lane. T_1, T_2 and T_3 are vehicles in the target lane, which may affect or be affected by the lane-changing attempt of S_1. T_1 and T_2 are the potential lead and lag vehicles, respectively. T_3 is the lag vehicle following T_2. If S_1 is not able to merge in front of T_2, then T_1 or T_3 becomes the potential lag vehicle. Gap_1 is the initial existing spacing gap between T_1 and T_2, and H_{lag} is the spacing headway between S_1 and T_2.

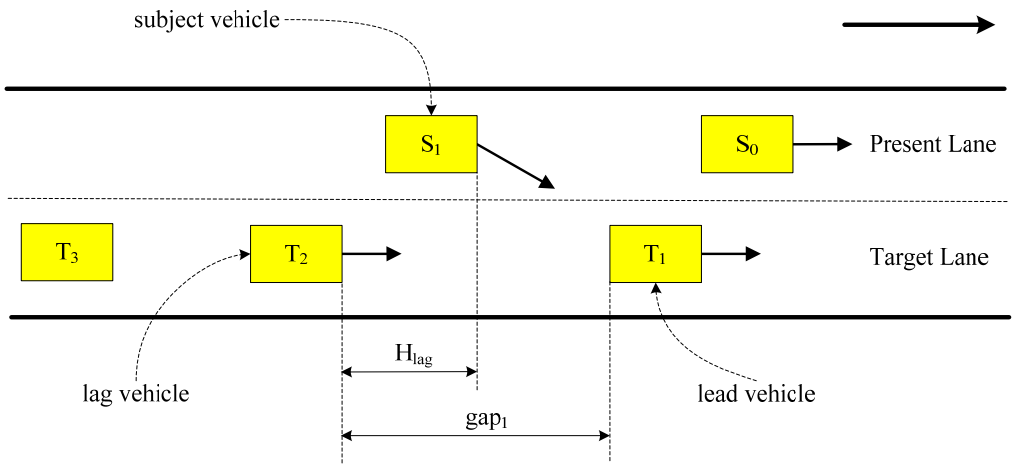


Figure 6-2. Initial scenario and notations adopted for the gap acceptance model

Figure 6-3 presents the flowchart for the gap acceptance model. After accepting a lane-changing reason and deciding the target lane, the subject vehicle S_1 checks the existing adjacent gap (gap_1) to decide the lane-changing mode as: forced, free, C/C or even no lane-changing. Next, the lane-changing "request" is sent to the lag vehicle T_2, only if the C/C mode is selected. Otherwise, a forced or free lane change is invoked, and the subject vehicle S_1 will be moved to the target lane in the subsequent time interval. After T_2 receives the lane-changing request S_1, it

has to decide whether to give way according to the spacing headway H_{lag}, along with the corresponding driver characteristics. If "courtesy" is provided, a cooperative lane-changing is invoked, and S_1 will re-check the adjacent gap (gap_1) until a successful lane change becomes possible. Otherwise, competitive lane-changing is invoked. S_1 will consider a forced lane change or adjust speed to consider a new merge (in front of T_1 or T_3). Under this framework, "multi-agent" techniques were used to model the subject vehicle (S_1) and the lag vehicles (T_1, T_2, T_3, etc) on the target lane, and each vehicle is considered as an autonomous intelligent agent. The detailed communication scheme and reactive strategies from each of the vehicles are presented in sections 6.2.3 and 6.2.4.

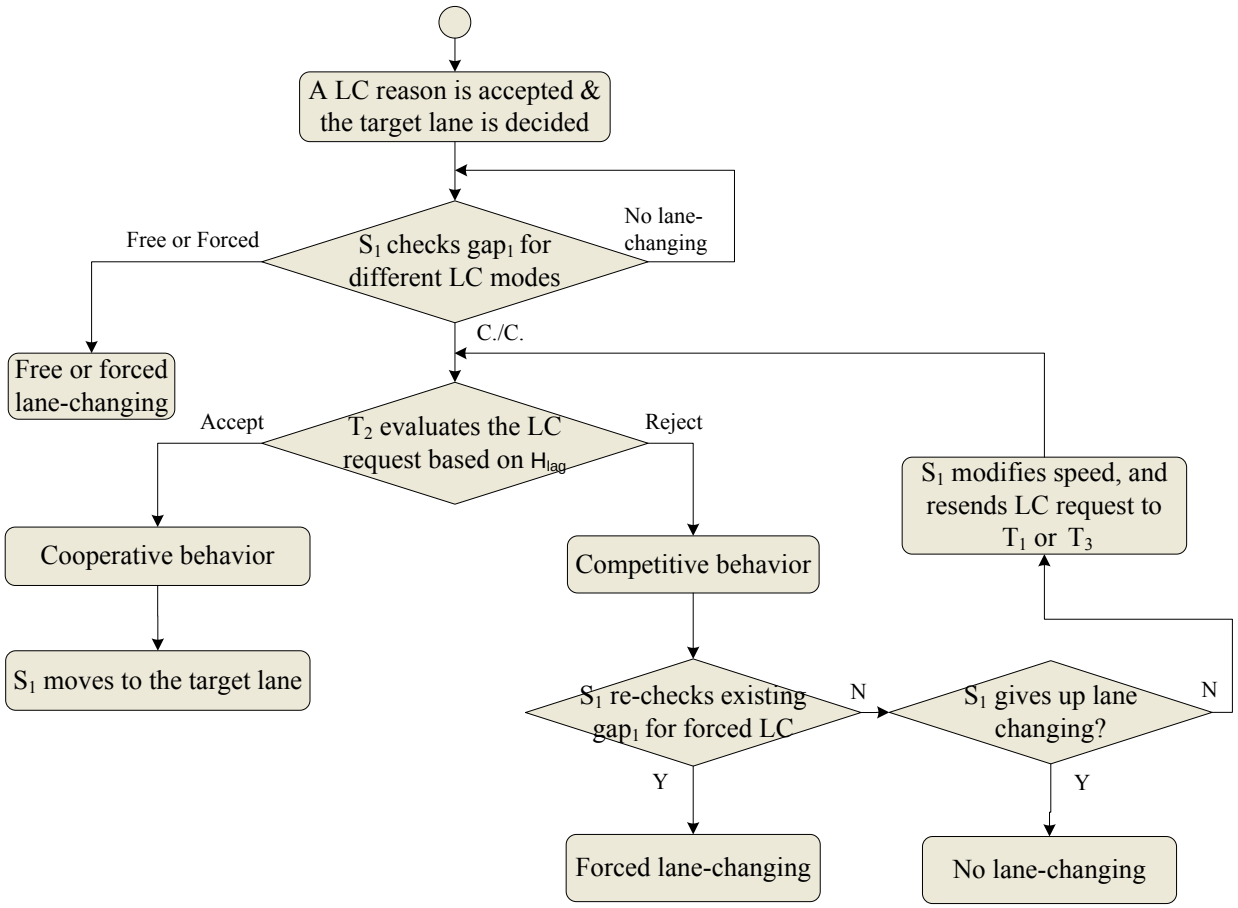


Figure 6-3. Framework of the lane-changing algorithm

6.2.3 Decision Framework of the Subject Vehicle S_1

As the first step of gap acceptance, rules are proposed in this section to distinguish between C/C lane changes and the other two types of lane changes, so that the free and forced lane changes can be modeled as an instantaneous event, while the C/C lane changes are modeled as a negotiation process.

The rules for distinguishing between C/C lane changes and the other two types of lane changes are based on the initial gap on the target lane (gap_1), critical gaps for different lane-changing modes, the subject vehicle length (L_{S1}) and the subject driver type. The output of this step is the probability of occurrence for each lane-changing mode. Figure 6-4 presents the situations in which different lane-changing modes may occur. There are six possible spacing intervals for gap_1: I, II, III, IV, V and VI. For example, if gap_1 falls into any intervals of I, II, IV, and VI, a deterministic maneuver occurs as no lane-changing, forced lane-changing, C/C lane-changing and free lane-changing, respectively. Otherwise, if the gap_1 falls into the intervals III or V, two probabilistic alternatives may happen. Mathematical formulas and rules for each situation, along with the output lane-changing mode(s), are expressed as follows.

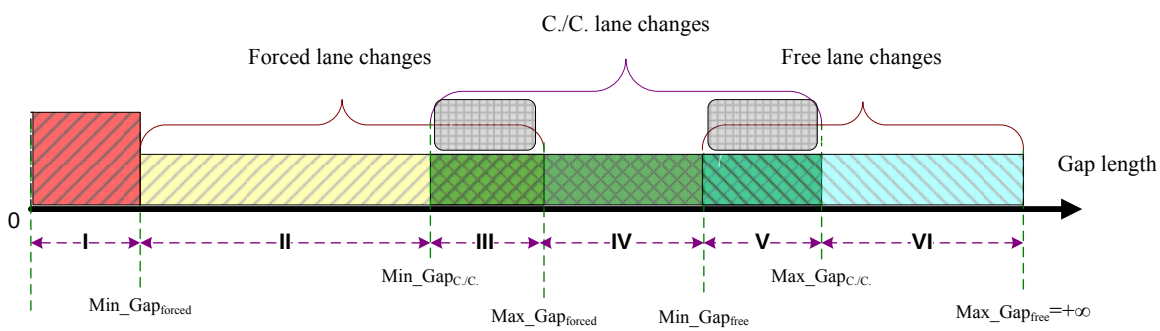


Figure 6-4. Gap length on the target lane for different lane-changing modes

Situation I: No lane-changing:

Rule(s): $gap_1 < Min\_gap_{Forced}$, (6-15)

Output: P(forced) = 0; P(C/C) = 0; P(free) = 0;

Situation II: Forced lane-changing:

Rule(s): $gap_1 \geq Min\_gap_{Forced}$, (6-16)

$gap_1 < \min(Min\_gap_{C/C}, Max\_gap_{Forced})$, (6-17)

Driver type $\neq$ A (6-18)

Note: From the field driving test, it was found that type A drivers seldom conducted forced lane changes. Consequently, for this situation, if the driver type is A, the output will be the same as Situation I (no lane-changing)

Output: P(forced) = 1; P(C/C) = 0; P(free) = 0;

<u>Situation III: Forced or C/C lane-changing:</u>

Rule(s): $gap_1 \geq Min\_gap_{C/C}$, (6-19)

$gap_1 < Max\_gap_{Forced}$, (6-20)

Output: $$P(forced) = \frac{gap_1 - Min\_gap_{C/C}}{Max\_gap_{Forced} - Min\_gap_{C/C}};$$ (6-21)

$$P(C/C) = 1 - \frac{gap_1 - Min\_gap_{C/C}}{Max\_gap_{Forced} - Min\_gap_{C/C}};$$ (6-22)

P(free) = 0;

<u>Situation IV: C/C lane-changing:</u>

Rule(s): $gap_1 \geq \max(Min\_gap_{C/C}, Max\_gap_{Forced})$, (6-23)

$gap_1 < \min(Min\_gap_{Free}, Max\_gap_{C/C})$, (6-24)

Output: P(forced) = 0; P(C/C) = 1; P(free) = 0;

<u>Situation V: C/C or Free lane-changing:</u>

Rule(s): $gap_1 \geq Min\_gap_{Free}$, (6-25)

$gap_1 < Max\_gap_{C/C}$, (6-26)

Output: P(forced) = 0;

$$P(C/C) = \frac{gap_1 - Min\_gap_{free}}{Max\_gap_{C/C} - Min\_gap_{free}};$$ (6-27)

$$P(free) = 1 - \frac{gap_1 - Min\_gap_{free}}{Max\_gap_{C/C} - Min\_gap_{free}};$$ (6-28)

<u>Situation VI: Free lane-changing:</u>

Rule(s): $gap_1 \geq \max(Min\_gap_{Free}, Max\_gap_{C/C})$, (6-29)

Output: P(forced) = 0; P(C/C) = 0; P(free) = 1;

where,

gap_1 is the initial gap on the target lane (as shown in Figure 6-1),
Min_gap_{Forced} is the minimum distance for the forced lane changes,
$Min\_gap_{C/C}$ is the minimum distance for the cooperative and competitive lane changes,
Max_gap_{Forced} is the maximum distance for the forced lane changes,
Min_gap_{Free} is the minimum distance for the free lane changes,
$Max\_gap_{C/C}$ is the maximum distance for the cooperative and competitive lane changes,
Max_gap_{Free} is the maximum distance for the free lane changes, assumed as $+\infty$ in this experiment, and
L_{S1} is the vehicle length for the subject vehicle S_1.

After deciding the lane-changing mode, each type of maneuvers is modeled separately. If gap_1 is too small to allow a lane change ($<Min\_gap_{Forced}$), the following adjacent gap will be evaluated for the next attempt. The free and forced lane changes are modeled as an instantaneous event by simply moving the subject vehicle to the target lane during the following time interval (t+1), while the C/C lane changes may last for several seconds. The subsequent section 6.2.4 presented the negotiation process between the vehicles when a C/C lane change is chosen.

6.2.4 Decision Framework of the Lag Vehicle T_2

As the C/C mode has been adopted, S_1 sends a request to the lag vehicle T_2 (by turn on the signal), and waits for the response from T_2. Two alternative strategies from T_2 may be invoked: if the request is accepted by T_2, it's a cooperative lane change; otherwise, competition is introduced. The spacing headway between S_1 and T_2 (H_{lag}), as shown in Figure 6-5, is used to decide whether T_2 chooses to reject the lane-changing request or not. The various components that affect the acceptance of H_{lag} are illustrated in the figure. A C/C lane-changing request is accepted when the following condition is satisfied, otherwise it is rejected:

$$H_{lag} > d_{T2} - d_{S1} + L_{S1} + g_{min}, \quad (6\text{-}30)$$

where,

H_{lag} is the existing spacing headway between S_1 and T_2,

d_{T2} is the distance traveled at the deceleration (D_{T2}, driver type related parameter) that T_2 would like to provide in this maneuver, calculated from the formula: $u_{T2} * t_{LC}$ - $0.5 * D_{T2} * t_{LC}^2$ (u_{T2} is the speed for vehicle T_2, t_{LC} is the time for moving a vehicle from one lane to the adjacent lane),

d_{S1} is the distance traveled by S_1 during the lane change, calculated according to the formula: $u_{S1} * t_{LC}$ (u_{S1} is the speed for vehicle S_1), and

g_{min} is the minimum safe constant gap between the subject vehicle and the lag vehicle, which is independent of the speed difference.

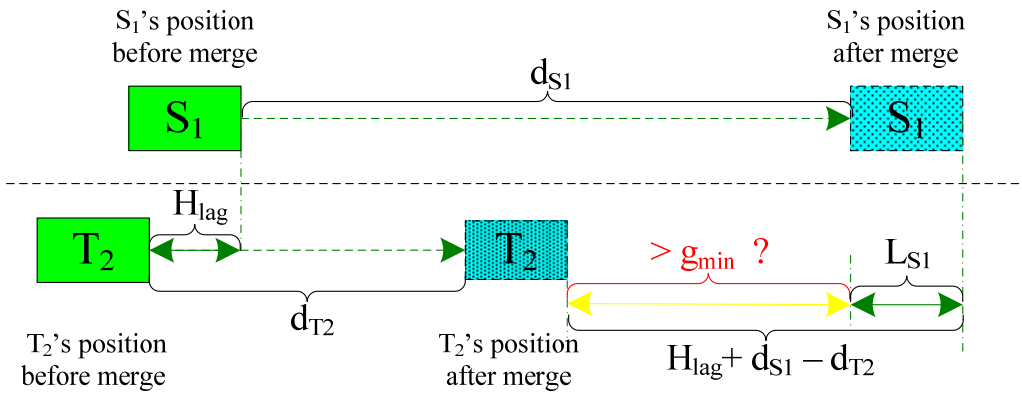


Figure 6-5. Effective components included in the lag spacing headway

Formula 6-30 indicates that the existing H_{lag} (before merge) ensures the spacing headway between S_1 and T_2 larger than $L_{S1} + g_{min}$ at the end of the merging maneuver. Here it assumes the speed of S_1 is constant, and T_2 uses D_{T2} deceleration. Thus, the decision tree for the process of competitive/cooperative behavior is illustrated in Figure 6-6, followed by descriptions of the two strategies.

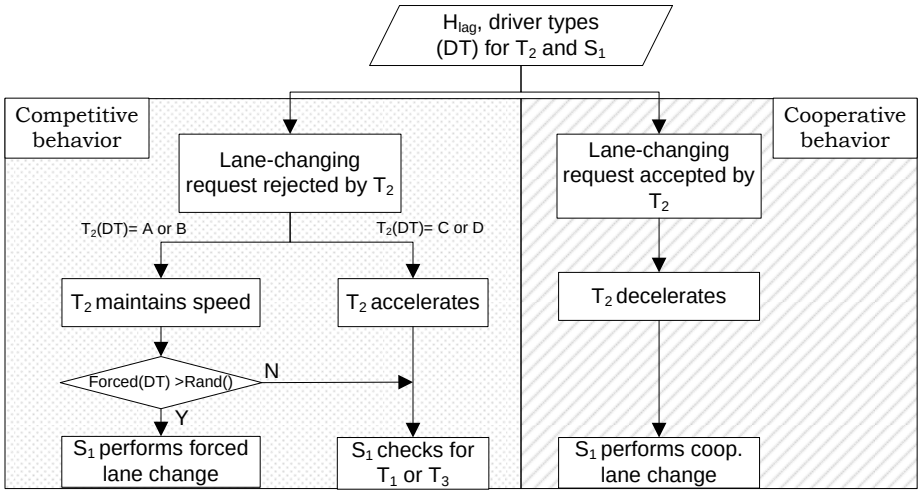


Figure 6-6. Decision tree for modeling competitive/cooperative behavior

6.2.4.1 Competitive behavior

As shown in the left part of Figure 6-6, T_2 chooses to reject the lane-changing request as H_{lag} is unacceptable. In this case, the response of T_2, as presented in Figure 6-7, needs to be re-evaluated. Two possible scenarios may occur: 1) T_2 maintains its speed or 2) T_2 decides to accelerate. Detailed analyses on the two potential sequences of T_2 are given as follows.

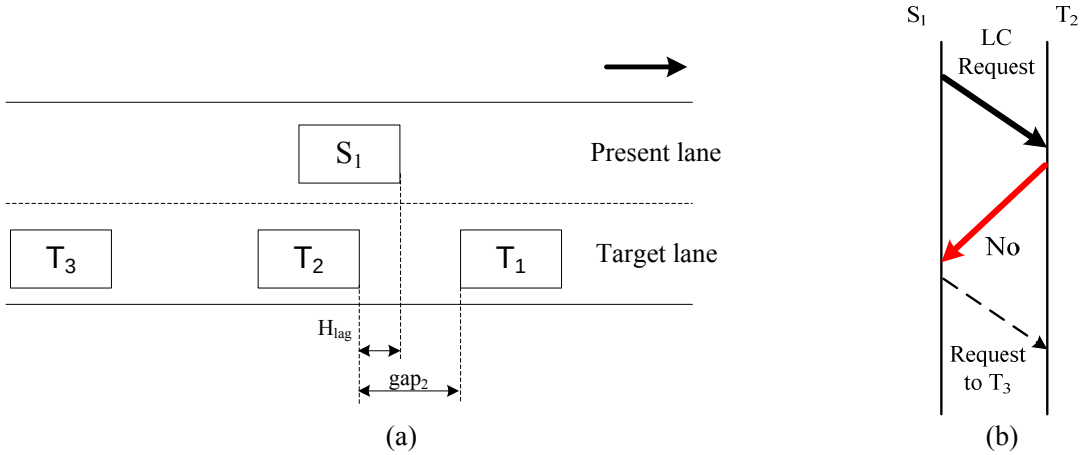


Figure 6-7. Competition scenario in the competitive/cooperative lane changes (a) Negotiation with the immediate lag vehicle (b) Lane-changing communication scheme

T_2 maintains speed: A normal/defensive driver of T_2 (driver types A or B) would reject the lane-changing request, and maintain the current car-following state. In this case, S_1 either

attempts a forced lane change, or considers T_1/T_3 as the new candidate lag vehicle and adjusts speed accordingly. The driver type of S_1 was used to decide the probability for attempting a forced lane change. The conducting probabilities of the four driver types were calculated from the field data (in Table 6-21) as follows:

- Forced(A) = 2/33 = 6.1%
- Forced(B) = 22/72 = 30.1%
- Forced(C) = 58/94 = 61.7%
- Forced(D) = 43/72 = 59.7%

In this calculation, only the number of forced lane changes and C/C were considered, since the traffic situation is far from the definition of free lane changes. Then, if a forced lane change is initiated, the new speed for S_1 is calculated using the car-following formula by adopting the T_1 as the lead vehicle. Otherwise, S_1 considers T_1 or T_3 as the new candidate lag vehicle and adjusts speed accordingly.

If S_1 considers T_3 as the candidate lag vehicle, the new speed for S_1 is calculated as:

$$u_{S1}^{new} = \begin{cases} \max(u_{S1}^{old} - D_{max},\ u_{T2}^{old} - b_{S1} * D_{max}) & u_{S1} > u_{T2} \\ \min(u_{S1}^{old} + A_{max},\ u_{T2}^{old} - b_{S1} * D_{max}) & u_{S1} \le u_{T2} \end{cases}, \qquad (6\text{-}31)$$

where

u_{S1}^{new} is the new speed for the vehicle S_1,
u_{S1}^{old} is the initial speed for the vehicle S_1,
u_{T2}^{old} is the initial speed for the vehicle T_2,
D_{max} is the maximum deceleration for the given traffic flow,
A_{max} is the maximum acceleration for the given traffic flow, and
b_{S1} is the driver aggressiveness related deceleration parameter for S_1, and will be calibrated in the model implementation.

Eq (6-31) indicates S_1 tries to decelerate to a speed value at $b_{S1} * D_{max}$ lower than T_2, so that it can attempt a lane changing in front of T_3. If S_1 considers T_1 as the candidate lag vehicle, the new speed for S_1 is calculated as:

$$u_{S1}^{new} = \begin{cases} \max(u_{S1}^{old} - D_{max},\ u_{T1}^{old} + b_{S1} * D_{max}) & u_{S1} > u_{T2} \\ \min(u_{S1}^{old} + A_{max},\ u_{T1}^{old} + b_{S1} * D_{max}) & u_{S1} \le u_{T2} \end{cases}, \tag{6-32}$$

where

u_{T1}^{old} is the initial speed for the vehicle T_1, all other notations are as Eq. (6-31).

Eq (6-32) indicates S_1 tries to accelerate to a speed value at $b_{S1} * D_{max}$ higher than T_1, so that it can attempt a lane changing in front of T_1.

T_2 accelerates: An aggressive driver of T_2 (driver types C or D) would reject the lane-changing request and accelerate so that the subject vehicle S_1 cannot force its way into the target lane. In this situation, T_1 and T_3 would keep the previous car-following state, while T_2 accelerates so that the new gap (gap_2 in Figure 6-7a) reaches the value $b_1*(g_{min}+L_{S1})$ (b is the driver aggressiveness related gap acceptance parameter) to impede the merging maneuver. The new speed for T_2, u_{T2}^{new}, is then calculated as:

$$u_{T2}^{new} = u_{T2}^{old} + \min\left(A_{max}, \frac{gap_2 - b_1 * (g_{min} + L_{S1})}{t_{LC}}\right), \tag{6-33}$$

where

u_{T2}^{new} is the new speed for the vehicle T_2,

b_1 is the driver aggressiveness related gap acceptance parameter, and will be calibrated in the model implementation.

In this case, S_1 has to consider T_3 or T_1 as the new candidate lag vehicle and adjust speed by using Eq.s (6-31) and (6-32) accordingly.

6.2.4.2 Cooperative behavior

Instead of competing with the merging vehicle, as shown in the right part of Figure 6-6, T_2 may accept the lane-changing request, if H_{lag} is acceptable. In this case, T_2 responds to the request by decelerating, as presented in Figure 6-8, and S_1 tries to accelerate to the center position of gap_2. The new speed for T_2 and S_1 can be calculated as:

$$u_{T2}^{new} = \begin{cases} \max(u_{T2}^{old} - D_{max}, u_{S1}^{old} - b_{T2} * D_{max}) & u_{T2} > u_{S1} \\ u_{T2}^{old} - b_{T2} * D_{max} & u_{T2} \le u_{S1} \end{cases}, \tag{6-34}$$

and

$$u_{S1}^{new} = \begin{cases} \min(u_{S1}^{old} + A_{max}, u_{S1}^{old} + d) & d > 0 \\ \max(u_{S1}^{old} - D_{max}, u_{S1}^{old} + d) & d \le 0 \end{cases}, \tag{6-35}$$

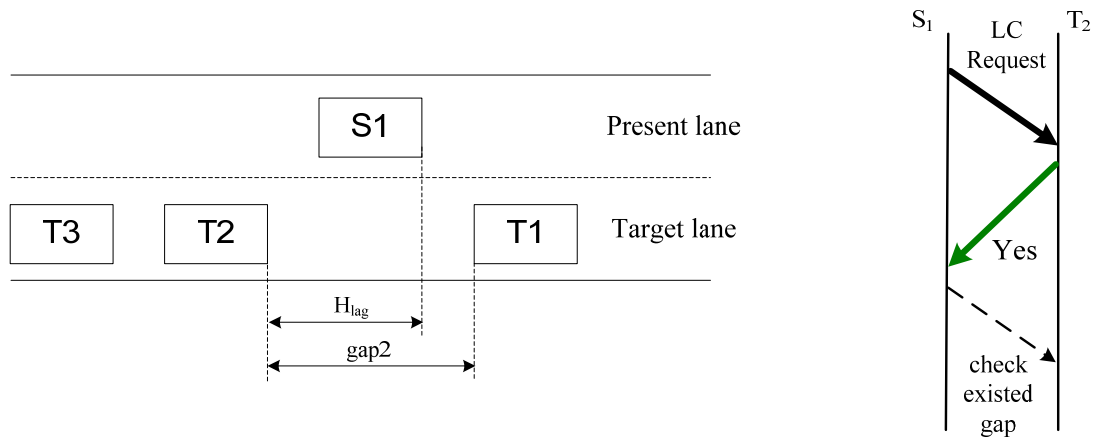
where,

u_{T2}^{new} is the new speed for the vehicle T_2,

u_{T2}^{old} is the initial speed for the vehicle T_2,

b_{T2} is the driver aggressiveness related deceleration parameter for T_2, and will be calibrated in the model implementation, and

d is the distance from the position of S_1 to the center position of gap_2, all other notations are as Eq.s (6-31) and (6-32) .



(a) (b)

Figure 6-8. Cooperation scenario in the competitive/cooperative lane changes (a) Negotiation with the immediate lag vehicle (b) Lane-changing communication scheme

6.3 Summary and Conclusions

In this chapter, two key components of the lane-changing model, the scenario-based probability model and the gap acceptance model, are presented.

In the scenario-based probability model, drivers' actions under different DLC scenario are examined and modeled. The acceptance of each particular lane-changing scenario (scenario-based probability) is modeled as a function of the corresponding important factors and driver types. The modeling parameters were estimated using a regression method (logistic regression) with detailed lane-changing data obtained in the field. The driver type classification scheme

found in the focus groups and confirmed in the "in-vehicle" experiment was incorporated, so that the lane-changing behaviors for different type of drivers can be modeled. The proposed algorithm enumerates all DLC scenarios occurring in urban arterials, and it models each one probabilistically.

In the gap acceptance model, the three lane-changing modes (free, forced and competitive/cooperative) are modeled with an emphasis on capturing vehicle interactions during lane changing. For the free and forced lane changes, the subject vehicle is moved to the target lane, and the car-following strategy is applied subsequently to the corresponding vehicles. The procedure of the competitive/cooperative lane changes is modeled as a sequence of "hand-shaking negotiations" with more complex interactions. This approach differs from existing models that assume that lane changes are always conducted instantaneously or within fixed time intervals and the different lane-changing modes are not interchangeable. In the proposed model, the "games" between the subject vehicle and the lag vehicle may be a competition or cooperation depending on the characteristics of the surrounding traffic and drivers. Under this modeling framework, the strategies of "not change," "free change," "C/C change" and "forced change" are interchangeable, which better reflects the reality of urban arterial lane changes.

To implement the proposed lane-changing model and validate the capabilities of the new algorithm, the selected parameters for the gap acceptance model were estimated from the "in-vehicle" field data. The gaps and acceleration values, as presented in Table 6-17 and Table 6-18, along with the other information obtained during the driving tests, were used to initialize the parameter settings for the lane-changing gap acceptance model as follows:

- Minimum distance for the forced lane changes, Min_gap_{Forced}: 36 ft,
- Maximum distance for the forced lane changes, Max_gap_{Forced}: 73 ft,
- Minimum distance for the C/C lane changes, $Min\_gap_{C/C}$: 44 ft,

- Maximum distance for the C/C lane changes, $Max\_gap_{C/C}$: 94 ft,
- Minimum distance for the free lane changes, Min_gap_{Free}: 83 ft,
- Maximum distance for the free lane changes, Max_gap_{Free}: assumed as $+\infty$,
- Vehicle length for the subject vehicle S1 (Honda Pilot), L_{S1}: 16 ft,
- Time for moving vehicle from the present lane to the adjacent lane, t_{LC} : 1.0 sec,
- Minimum safe constant gap, g_{min}: 18 ft,
- Maximum deceleration, D_{max}: 5 mph/s,
- Maximum acceleration, A_{max}: 3 mph/s,
- Driver aggressiveness related deceleration parameters, b_{S1} or b_{T2} : 2.8/5 = 0.56, and will be calibrated in the model implementation
- Driver aggressiveness related gap acceptance parameter, b_1: 1.0, and will be calibrated in the model implementation.

The unobserved parameters, such as driver aggressiveness related parameters (b_{S1}, b_{T2} and b_1), were initialized based on the relationship inferred from field data.

CHAPTER 7
MODEL IMPLEMENTATION AND VALIDATION

This chapter presents the implementation and validation details of the developed lane-changing model, as presented in Chapter 3 (Figure 3-5). Section 7.1 presents the validation field dataset collection and analysis effort. Next, in Section 7.2, the proposed model is implemented as an RTE (run time extension) plug-in in CORSIM, followed by an aggregate calibration to tune up the selected behavioral parameters within the simulation model. Section 7.3 presents the systematic validation to evaluate the agreement between the simulation results (for both "new" and CORSIM "original" lane-changing models) and the field observations based on the selected indices of measures. The chapter concludes with the results from various analyses designed to test the effectiveness of the newly developed lane-changing model and a summary of the findings.

7.1 Datasets

As the first step of model validation, a heavily congested arterial segment in Gainesville, FL was selected. The segment is on Newberry Road, stretching from I-75 on the west to the main Oaks Mall entrance toward the east, with a distance of about 1,650 ft (Figure 7-1). The posted speed limit for the three-lane segment is 35 mph. Characteristics of the arterial are the high daily traffic attracted by the adjacent shopping center (Oaks Mall) and closely spaced intersections in the vicinity, which result in a high number of lane changes. Drivers are free to select the lane with the highest utility as the target lane and make subsequent lane changes depending on availability of gaps along the stretch of the arterial.

Figure 7-1. The Newberry Road segment for data collection (source: Microsoft Bing Maps)

A sketch of the data collection site with the lane channelization is shown in Figure 7-2. Video data were collected from the arterial segment by using traffic surveillance cameras mounted on street lamp poles along the roadway.

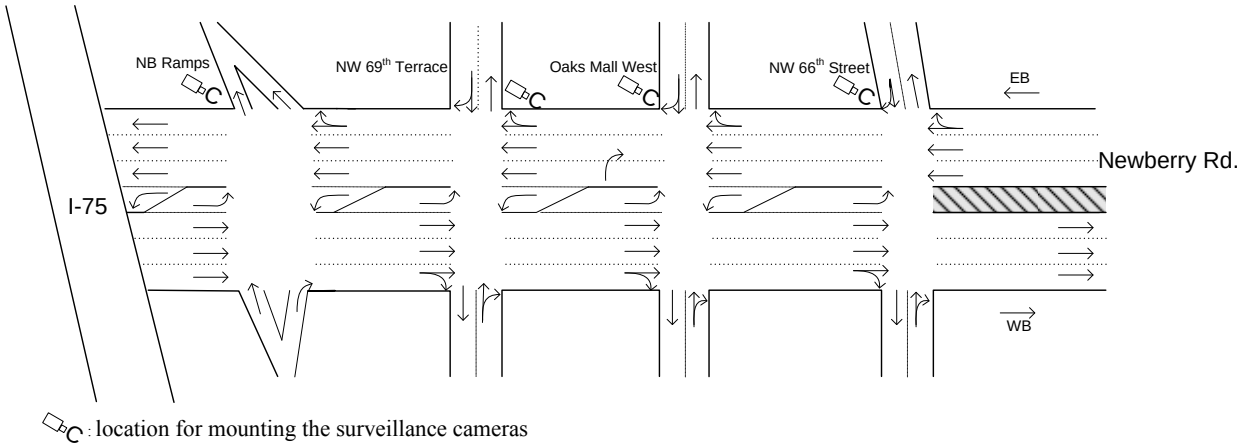


Figure 7-2. Sketch of the segment selected for validation data collection (not to scale)

The Newberry Road video data were collected along the arterial on May 3rd, 2005, from 10 am to 6 pm (Washburn and Kondyli, 2006). From approximately 32 hours of video recording, eight hours of data during heavy traffic conditions are selected to study lane-changing behaviors.

A total of 138 successful lane-changing maneuvers are identified in the video, including 79 free, 34 forced and 25 C/C lane changes (57.2%, 24.6% and 18.1% to the total lane changes respectively). Table 7-1 presents the summary of the acceptable spacing gaps and vehicle acceleration/deceleration that occurred within the three types of lane changes. Similar to the "in-vehicle" gaps, the median gap length decreases from free to C/C, and then to forced lane changes, while no significant difference was found in acceleration/deceleration. This further confirms that the acceleration/deceleration depends largely on the driver's instantaneous perception on spacing/speed differences. However, the field collected acceleration/deceleration values provide a quantitative range for simulation parameter estimation. Only the traffic flow related datasets were obtained, since characteristics of the drivers, such as aggressiveness, were not available.

Table 7-1. Summary of the Newberry Road video data (a) Observed spacing gaps on the adjacent lane (b) Observed acceleration/deceleration for the subject and lag vehicles

(a)

LC Type	# of Obs.	Adjacent Spacing (ft)		
		Max	Min	Median
Free①	79	324	89.5	133
Forced	34	91.5	37	54.5
C/C	25	102	42.5	72

(b)

LC Type	# of Obs.	Acc. (subject veh, mph/s)			Acc. (lag veh, mph/s)		
		Max	Min	Median	Max	Min	Median
Free	79	2.5	-1.3	0.2	1.9	-0.8	0.1
Forced	34	4.5	-3.0	-0.3	-2.2	-6.9	-4.6
C/C	25	3	-5	-0.6	2.8	-5	-0.4

Note: ①: In the video, as some lane changes don't have lead/lag vehicle, such cases were not included in computing the statistics of the spacing gaps.

7.2 Model Implementation and Calibration

This section presents the lane-changing model implementation and validation efforts, referred as stage I (Model Implementation and Calibration) in Figure 3-5. First, the Newberry Road network was simulated based on the field data. Calibrations were conducted to make sure

the simulated network replicated the actual traffic conditions. Next, the new lane-changing model was implemented as an RTE plug-in, which is invoked dynamically during the simulation to replace CORSIM's default lane-changing strategies. Finally, an aggregate calibration is conducted to tune up the selected behavioral parameters within the newly developed model.

7.2.1 Model Implementation

The traffic volume data obtained from the video were used for simulating the network in CORSIM, and these pertain to mainline and cross-street volumes as well as percentages of heavy vehicles. Figure 7-3 contains hourly volume data along the study segment, which were obtained through the data reduction. As described by Washburn and Kondyli (2006), four categories of vehicles were recorded: passenger car, medium truck, large truck and bus. The truck and bus categories were combined to obtain a heavy vehicle percentage for each approach along the arterial. Signal timing data for each intersection were obtained from the City of Gainesville, which were further confirmed from the video observation. Travel times for both directions between I-75 NB ramps and NW 66th St. were obtained through vehicle matching (manual observation of vehicles in video), and were used for model calibration.

Figure 7-3. Volume data from video reduction taken on May 3rd 2005 PM peak period (Washburn and Kondyli, 2006)

As the first step of model calibration, the Newberry Road network was simulated and calibrated using CORSIM's default lane-changing algorithm (for 15 runs). The calibration at this stage was performed by adjusting simulation parameters settings such that:

1) The CORSIM simulated travel times were within +/- 10% of the field-measured travel time for both approaches (WB and EB), and

2) The total numbers of lane-changing maneuvers were within +/- 20% of the field-measured values for both approaches (WB and EB).

Table 7-2 presents CORSIM's lane-changing parameters and LC-related driver behavior parameters chosen for this calibration, along with their initial and calibrated values. The values of the parameters were adjusted mainly based on the field collected lane-changing maneuvers. Table 7-3 presents the average travel time and number of lane changes for both approaches (WB and EB) by 15 simulation runs, as well as the corresponding field data values. As seen, the simulated travel times in both approaches were successfully adjusted into +/-10% of the field measured values, and the numbers of lane-changing were within +/-20%, which mean all calibration criteria were met.

Table 7-2. Initial and calibrated values of the parameters in CORSIM lane-changing model

Calibrated Parameter		Parameter Value	
		Initial	Calibrated
Duration of LC maneuver		3 sec	2 sec
Min deceleration for a LC		5 ft/sec*sec	7.5 ft/sec*sec
Diff. in min/max acceptable dece.	MLC	10 ft/sec*sec	9 ft/sec*sec
	DLC	5 ft/sec*sec	6 ft/sec*sec
Headway all drivers will attempt a LC		2.0 sec	1.5 sec
Headway no drivers will attempt a LC		5.0 sec	3.0 sec

Table 7-3. Travel time and number of lane-changing measurements

Measurements		Simulated	Field-measured	Error
Travel Time	WB	53.7 sec	59 sec	-8.98%
	EB	73.4 sec	67 sec	9.55%
Number of LCs	WB	26	32	18.7%
	EB	37	44	15.9%

In the next step, the new lane-changing model was implemented as a C++ plug-in (.dll), which interfaces with CORSIM engine during the simulation. Commands in TShell environment were used for the RTE deployment (FHWA, 2006). In CORSIM v6.1, as shown in Figure 7-4, for each simulation time step, CORSIM Server calls a series of functions within CORSIM to drive the simulation event loop (FHWA, 2006). The RT_PRE_NETSIM_VEHICLE message is sent just prior to calling the FORTRAN subroutine MOVE, which handles lane-changing, car-following, etc., to move all the vehicles for the current time step. The lane-changing plug-in is set up to respond to that message, and the function within the plug-in would perform the lane-changing maneuver. With the completion of lane-changing function, the CORISM lane-changing timer is set to a value that would prevent the embedded lane-changing logic from being applied. The subroutine MOVE would still be called, but vehicles would not be allowed to make a lane change. A configuration file (.cfg) is used to store the values of the calibrated driver behavioral parameters for the model implementation.

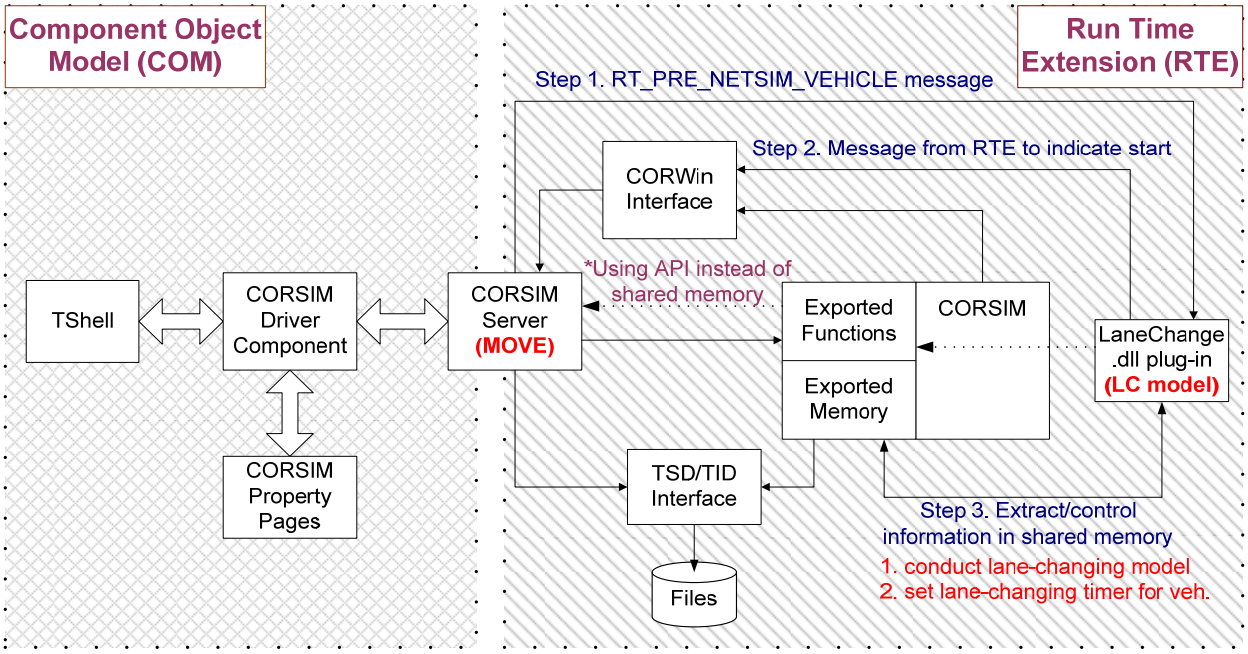


Figure 7-4. CORSIM entire architecture and the communication with lane-changing plug-in (source: FHWA, 2006; modified by the author)

Figure 7-5 presents the flow of the lane-changing decision implementation procedure. The main function within the plug-in first tries to determine whether any DLCs or MLCs may be invoked. The lane-changing probability for a MLC is always 1. For a DLC, the corresponding probability function is used to calculate the probability of changing lanes.

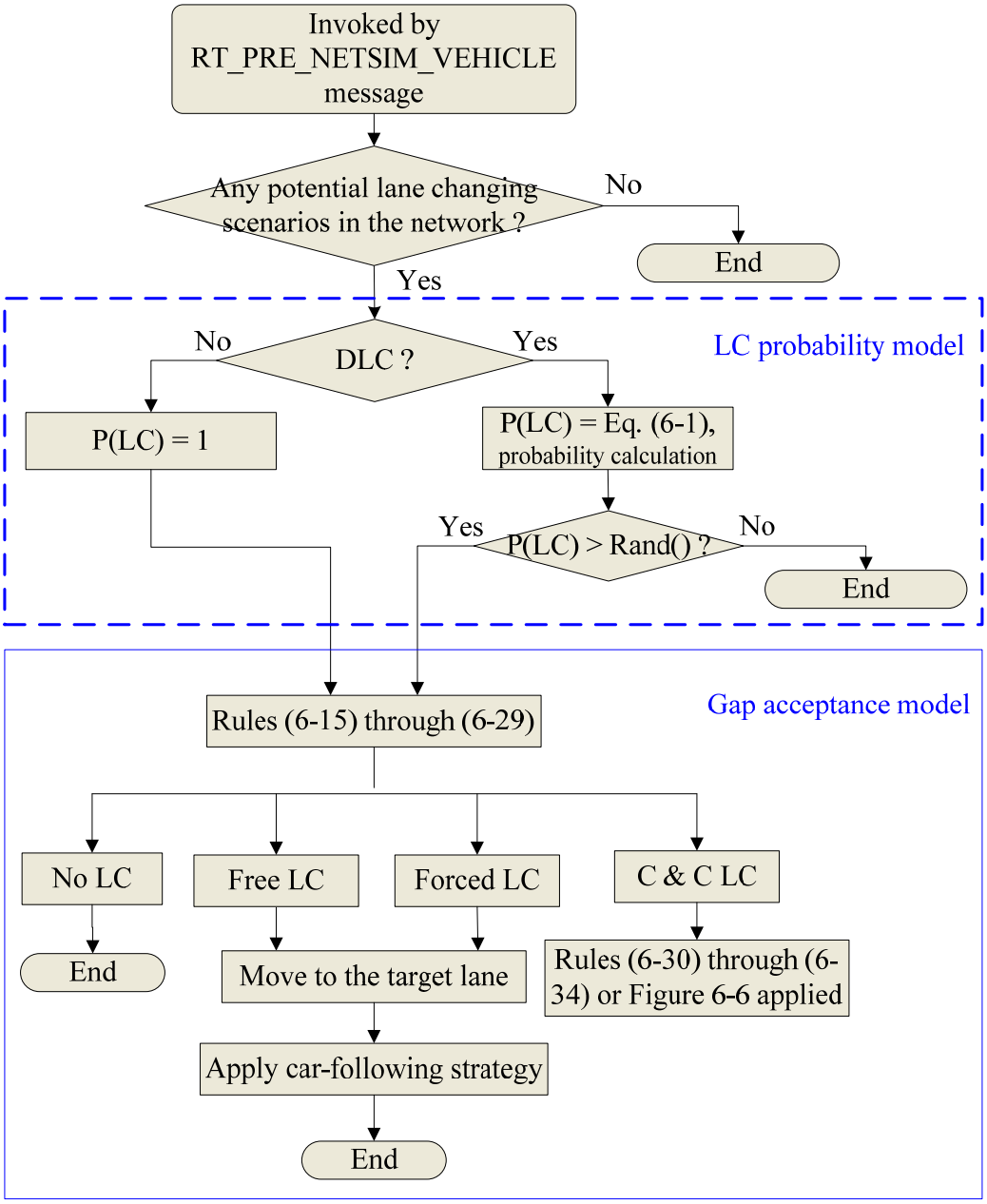


Figure 7-5. Implementation of the lane-changing decision procedure in CORSIM

When a lane change is decided, the rules (6-15) – (6-29) are used to distinguish the maneuver as free, forced or C/C or no lane change. The free and forced lane changes are modeled as an instantaneous event by simply moving the subject vehicle to the target lane during the following time interval (t+1), so that CORSIM's default car-following algorithm can be applied to the subject vehicle on the target lane. For the C/C lane changes, the strategies as proposed in Eq.s (6-30) through (6-34) are used to model the maneuver as a sequence of "hand-shaking negotiations." Afterwards, by setting CORSIM's lane-changing timer to a value that would prevent the embedded lane-changing logic from being applied, the subroutine MOVE would still be called, but no vehicle is allowed to change lanes. During this implementation, only the pre-selected lane changes were captured and modeled by the RTE plug-in. Other types of lane changes are ignored, and CORSIM embedded lane-changing logic is invoked to handle those issues.

Practically, CORSIM sets the maximum number of lanes for any link as 7, and a global index for any given lane K on road link IL is calculated as: ILL = (IL-1)*7+K. All vehicles in this lane (K) are stored in a double-linked list data structure, which can be exported and accessed by the RTE plug-in. As illustrated in Figure 7-6, in modeling a lane change, the subject vehicle has to be removed from the original lane linked list and inserted into the corresponding position on the target lane link list. Both operations are completed in the same simulation time step (t+1). First, the subject vehicle S_1 is deleted from the original list by connecting S_2 directly to S_0. Next, the connection between T_1 and T_2 is broken, and both vehicles are connected to S_1. Once the new connections between vehicles are set, the accelerations of all vehicles are calculated by the car-following model in CORSIM, with respect to the lead vehicle in the same lane.

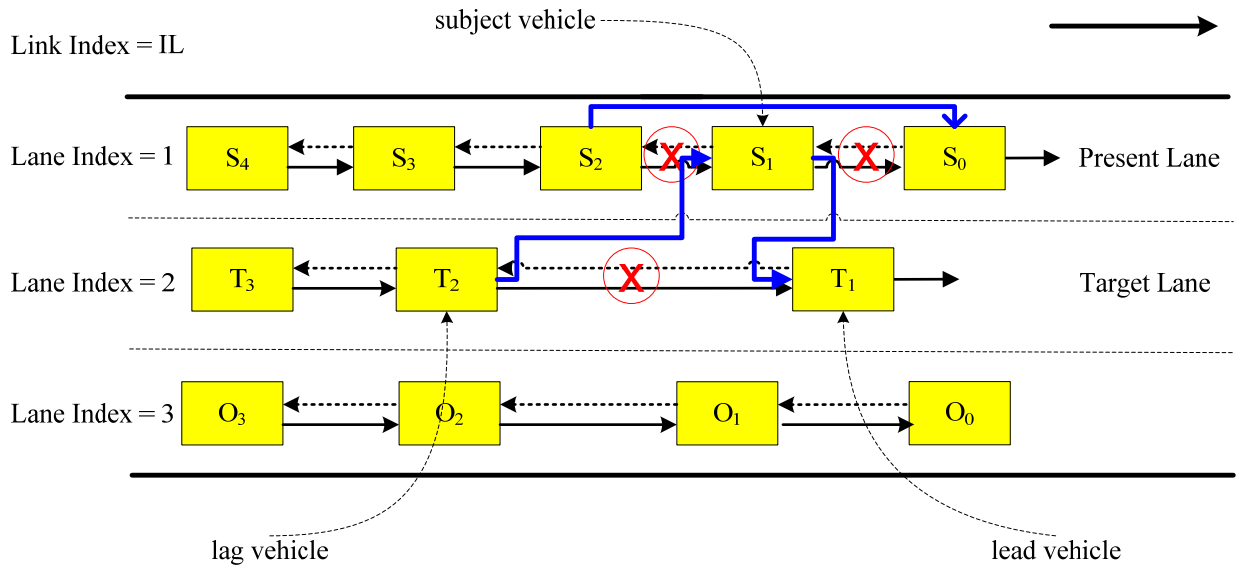


Figure 7-6. Schematic representation of a lane change in CORSIM

Another important issue during this implementation is how to assign CORSIM's 10 driver types to the proposed four groups. As discussed in Chapter 5, the behavior-based index, FAI, is used to categorize the 40 driving participants into four groups as A (<= 4.2), B (4.3 – 5.7), C (5.8 – 6.8) and D (>= 6.9). In CORSIM simulation, 10 different driver types, ranging from most passive (i.e., driver type 1) to the most aggressive (i.e., driver type 10), are generated to represent driving behavioral characteristics. Driver type for each CORSIM vehicle is randomly selected from the embedded discrete uniform distribution (Chien, et al., 2001), which means each type accounts 10% of the total number of driver. Initially, the above FAI values were used directly to classify all CORSIM simulation drivers into four groups, as shown in Figure 7-7.

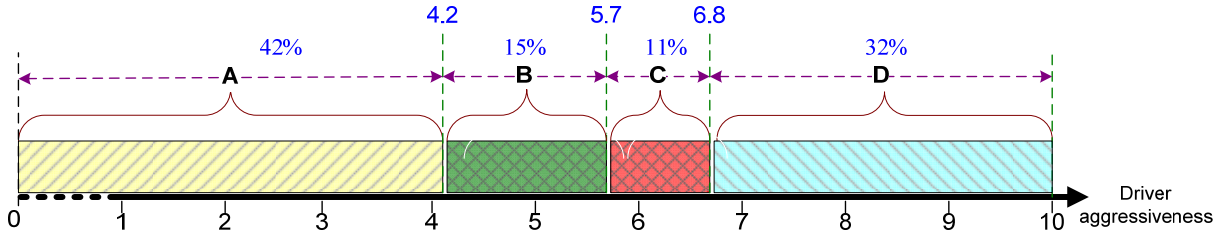


Figure 7-7. CORSIM driver classification based directly on the FAI values

According to the three boundary points (4.2, 5.7 and 6.8), CORSIM simulation drivers can be easily classified into four groups. The percentage of drivers for each corresponding type (A, B, C and D) in the simulation was calculated as 42%, 15%, 11% and 32%, respectively. This contradicts the actual percentages of driver types, wherein the percentages of drivers for A, B, C, and D are 9/40 = 22.5%, 12/40 = 30%, 11/40 = 27.5%, and 8/40 = 20%.

Consequently, the percentages from the sampling participants for each driver type were used to assign CORSIM's 10 driver types to the driver types A, B, C, and D used in this study. As shown in Figure 7-8, the type A has 22.5% of all drivers, and the types B, C, and D have 30%, 27.5%, and 20%, respectively. Three boundary points are set as 2.25, 5.25 and 8, respectively.

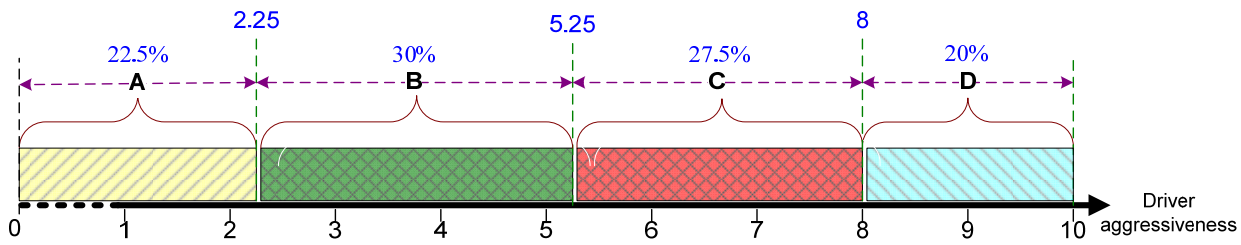


Figure 7-8. CORSIM driver classification based directly on the sampling percentages

Table 7-4 presents the final assignment of driver types. All CORSIM types 1 and 2 drivers were assigned to type A. CORSIM type 3 drivers were split into two parts, 25% was assigned to type A, and the rest 75% goes to type B. The types 4 and 5 drivers were assigned to type B. 25% of the type 6 drivers were assigned to type B, and the rest 75% were assigned to type C. All types 7 and 8 drivers were assigned to type C and types 9 and 10 drivers were assigned type D.

Table 7-4. Strategy for distributing CORSIM drivers into the lane-changing groups

CSM drv Clusters	1	2	3	4	5	6	7	8	9	10
Type A (%)	100	100	25	0	0	0	0	0	0	0
Type B (%)	0	0	75	100	100	25	0	0	0	0
Type C (%)	0	0	0	0	0	75	100	100	0	0

Type D (%)	0	0	0	0	0	0	0	0	100	100

7.2.2 Aggregate Calibration

To be distinguished from CORSIM "original model," the newly developed lane-changing model is referred to as the "new model." In this stage, the estimated coefficients and parameters for the "new model" were included as the initial settings of the CORSIM plug-in. Given that CORSIM's lane-changing and behavior-related parameters have already been calibrated, the following behavior-related parameters in the "new model" were selected for calibration:

- Minimum safe constant gap, g_{min},
- Maximum deceleration for the given traffic, D_{max},
- Maximum acceleration for the given traffic, A_{max},
- Driver aggressiveness related deceleration parameter for the subject vehicle in the lane change, b_{S1},
- Driver aggressiveness related deceleration parameter for the lag vehicle in the lane change, b_{T2}, and
- Driver aggressiveness related gap acceptance parameter, b_1.

During this calibration effort, each gap or acceleration/deceleration parameter was set to change from -50% to +50% while keeping the rest of the parameters fixed (Ben-Akiva et al., 2004). Each driver aggressiveness related parameter (b_{S1}, b_{T2} and b_1) was changed from 0.2 to 1.2. The group of parameters that generates travel times and number of lane changes closest to the field-measured values was identified for the simulation and validation followed. By the end of the adjustment, the average simulated travel times for the new model were obtained as 56.1 sec and 69.8 sec for westbound (WB) and eastbound (EB) traffic, respectively, which are within the +/- 5% range of the field-measured travel time. The numbers of lane-changing are also within +/- 20% for both approaches (37 for WB, and 50 for EB). As shown in Table 7-4, most of the parameters do not change significantly during calibration except the minimum safety gap for lane changes (g_{min}), and the driver aggressiveness related gap acceptance parameter (b_1). This is

expected since the calibration datasets (collected from Newberry Road segment) and the "in-vehicle" datasets (collected from the Newberry route and the Waldo route) are similar to each other both in the time-of-day and road geometry, as well as driver characteristics. The only two big differences are: 1) the posted speed limit for Newberry Road is 35 mph, but the speed limits for the "in-vehicle" route change from 30 mph to 45 mph in its different segments; and 2) for the Newberry Road WB traffic, the number of left turns is much higher than right turns during the peak hours because of the large attraction of the Oaks Mall Shopping Center. The calibration parameters and their before-and-after values are listed in Table 7-5.

Table 7-5. Initial and calibrated values of the parameters in the new lane-changing model

Calibrated Parameter	Index	Parameter Value	
		Initial	Calibrated
Minimum safe gap	g_{min}	18 ft	14 ft
Maximum deceleration	D_{max}	5 mph/s	5.5 mph/s
Maximum acceleration	A_{max}	3 mph/s	3 mph/s
Decel. parameter for S1	b_{S1}	0.56	0.60
Decel. parameter for T2	b_{T2}	0.56	0.50
Aggr. related parameter	b_1	1.0	0.9

7.3 Model Validation

The purpose of system validation is to test and determine the extent to which the simulation model replicates the real system under different traffic conditions (Toledo and Koutsopoulos, 2004; Ramanujam, 2007; Ramanujam et al., 2008). The following section presents the comparison between the simulated results of the two models (CORSIM and new) and the field data, referred as stage II (Model Validation) in Figure 3-5. Both calibrated models were simulated with OD demands measured from different day (April 30th, 2005) video data under congested traffic conditions, as presented in Figure 7-9. Three measures of performance, average lane-based travel time, vehicles lane distribution, and cumulative lane changes by vehicles, were selected to evaluate the model performance because of their close relevance to the lane-changing

behavior. Finally, a sensitivity analysis (Badra, 2007) was conducted to demonstrate how the variation in the output of the simulated model can be apportioned quantitatively. Various goodness-of-fit measures were used to evaluate the overall performance of both simulation models.

Figure 7-9. Volume data from video reduction taken on April 30th, 2005 PM peak period (Washburn and Kondyli, 2006)

7.3.1 Comparison of the Lane-Based Travel Time

As introduced previously, the Newberry Road segment is divided into three sections by the four signalized intersections. The lane-based average travel time was obtained from the video data by matching vehicles at the entrance and exit of each arterial section manually. Traffic flows on approaches for both directions were used to obtain the average travel time.

Figure 7-10 shows the comparison of average lane-based travel time between the "new model," the validation field data, and the "original model" for each section. From the results shown, we found that the "original model" tends to underestimate the travel time. By incorporating the "new model," travel time, especially for the right and the left lanes, becomes closer to the field data. Additionally, the differences in the by-lane travel time are more significant after applying the new strategy, and closer to the field data than the "original" CORSIM simulation. Although the average travel times are similar, the "new model" gives a better representation of the lane-by-lane differences.

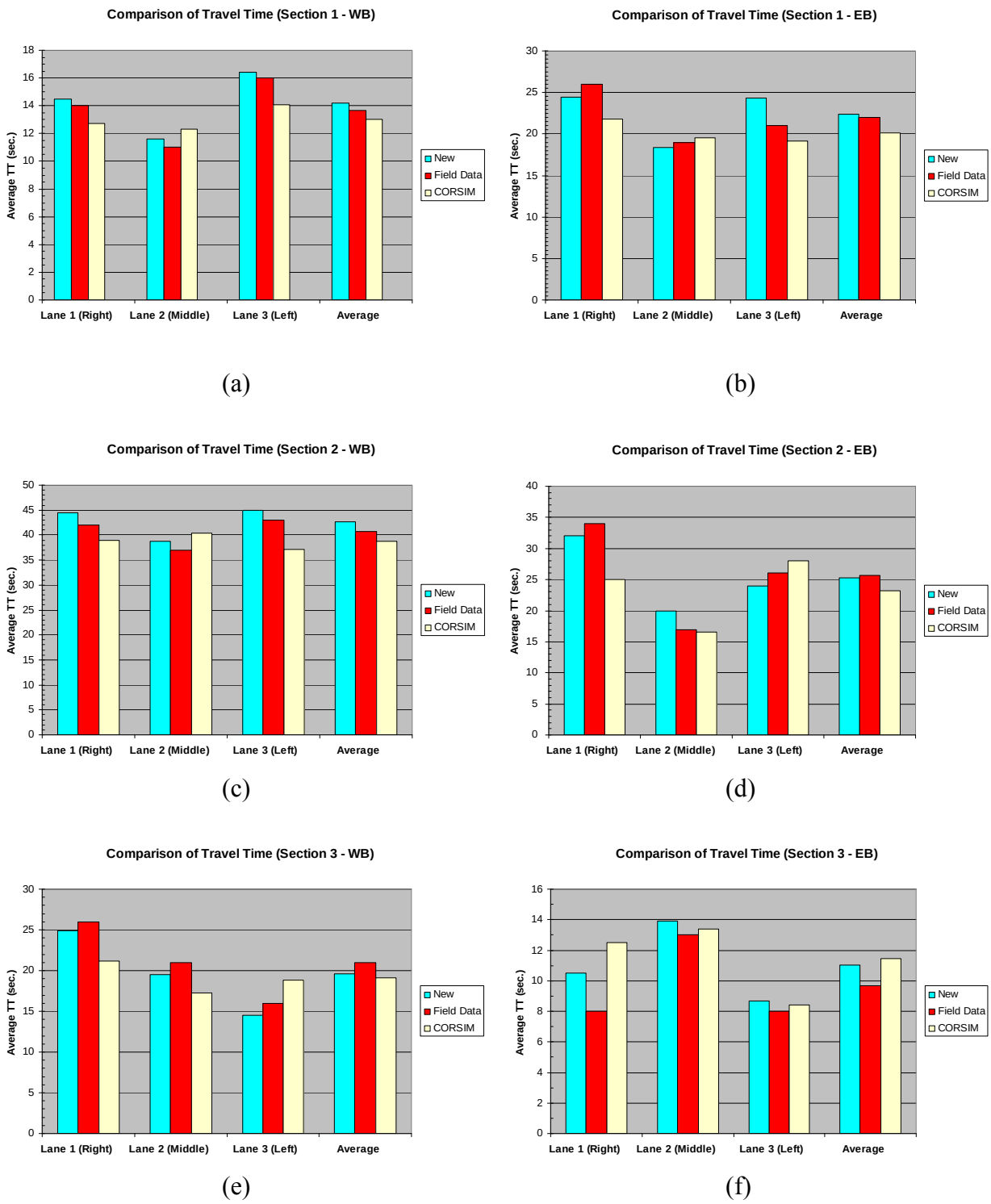


Figure 7-10. Comparison of the lane-based average travel time (a) Section 1 – westbound (b) Section 1 – eastbound (c) Section 2 – westbound (d) Section 2 – eastbound (e) Section 3 – westbound (f) Section 3 – eastbound

The two algorithms (new and original) were compared in relation to the validation field data. Chi-Square tests were performed between the expected travel time (from field data) and the two observed travel times (from simulation) for both WB and EB traffic, as shown in Table 7-6. For the WB traffic, the simulated travel times for both cases (new and original) were not statistically different from the field travel times, with the χ^2 value as 2.107 and 4.370 respectively. However, there is greater level of confidence associated in this statement when using the new algorithm (97% for χ^2=2.107) than using the existing CORSIM algorithm (82% for χ^2=4.370). Similar Chi-Square results were obtained from the EB traffic as that the simulated travel times for both new and original cases were not statistically different from the field travel times, with the χ^2 value as 2.695 and 5.955 respectively. Result from the new algorithm is with higher level of confidence 95% for χ^2=2.695 instead of 65% for χ^2=5.955.

Table 7-6. Comparison of simulation travel time between "new" and CORSIM models (χ^2 Test)

Location	T.T. (sec.) - WB			T.T. (sec.) - EB			$(O_i - E_i)/E_i$ - WB		$(O_i - E_i)/E_i$ - EB	
	New	CORSIM	Field	New	CORSIM	Field	New	CORSIM	New	CORSIM
Section 1										
Lane1	15.3	12.7	14	24.4	21.8	26	0.121	0.121	0.098	0.678
Lane2	11.7	12.3	11	18.4	19.5	19	0.045	0.154	0.019	0.013
Lane3	17.5	14.1	16	24.3	19.2	21	0.141	0.226	0.519	0.154
Section 2										
Lane1	44.8	39	42	30	25	34	0.187	0.214	0.471	2.382
Lane2	39.7	39.4	37	20	16.6	17	0.197	0.156	0.529	0.009
Lane3	45.9	37.1	44	24	28	26	0.082	1.082	0.154	0.154
Section 3										
Lane1	23.4	21.6	26	10.5	12.5	8	0.260	0.745	0.781	2.531
Lane2	19.9	17.3	18	13.9	13.4	13	0.201	0.027	0.062	0.012
Lane3	17.5	18.8	14	8.7	8.4	8	0.875	1.646	0.061	0.020
Overall Value (χ^2)							2.107 (97%)	4.370 (82%)	2.695 (95%)	5.955 (65%)

Two-sided T tests were performed to investigate whether (i) lane-based travel time of "new model" is equal to that of the field data, and (ii) lane-based travel time of "original model" is equal to that of the field data. Results of the first test showed no evidence that the travel time is

different for all travel time at a 95% confidence level except the EB right lane travel time in section 3. The second test showed that the EB right lane travel time (for Section 3) and the WB left lane travel time (for all three sections) are significantly different from the field-measured values at a 95% confidence level.

In addition, a comparison between the two algorithms was performed as shown in Table 7-7. An *F* test was first conducted to compare variances, and it was found that in all but one case (4.372 > F(95%) = 2.480, Section 3 - WB, Lane 1 at Table 7-6) the variances are the same. Since the sample size was relatively small (15 simulation runs), *T* test with equal and unequal (and unknown) variances was selected to compare the means at a 95% confidence level.

Table 7-7. Comparison of simulation travel time between "new" and CORSIM models (T Test)

Location	Mean T.T. (sec.)		St. Dev. (sec.)			F Test	T Test	Is T.T. statistically different?
	New	CORSIM	New	CORSIM	Pooled			
Section 1 – WB								
Lane1	15.3	12.7	2.66	2.93	2.798	1.213	2.545	YES
Lane2	11.7	12.3	2.71	2.63	2.670	1.062	0.615	NO
Lane3	17.5	14.1	3.12	2.05	2.640	2.316	3.527	YES
Section 1 – EB								
Lane1	24.4	21.8	3.13	3.72	3.438	1.413	2.071	YES
Lane2	18.4	19.5	2.67	3.26	2.980	1.491	1.011	NO
Lane3	24.3	19.2	3.32	2.49	2.934	1.778	4.760	YES
Section 2 – WB								
Lane1	44.8	39	5.07	5.96	5.533	1.382	2.871	YES
Lane2	39.7	39.4	5.34	5.62	5.482	1.108	0.150	NO
Lane3	45.9	37.1	7.23	6.94	7.086	1.085	3.401	YES
Section 2 – EB								
Lane1	30	25	4.77	4.06	4.429	1.380	3.092	YES
Lane2	20	16.6	4.23	5.01	4.636	1.403	2.008	YES
Lane3	24	28	3.61	4.49	4.074	1.547	2.689	YES
Section 3 – WB								
Lane1	23.4	21.6	4.83	2.31	3.786	4.372	1.302	NO
Lane2	19.9	17.3	4.32	5.34	4.857	1.528	1.466	NO
Lane3	17.5	18.8	2.06	1.49	1.798	1.911	1.980	YES
Section 3 – EB								
Lane1	10.5	12.5	1.83	2.31	2.084	1.593	2.628	YES
Lane2	13.9	13.4	2.32	2.34	2.330	1.017	0.588	NO
Lane3	8.7	8.4	1.56	1.79	1.679	1.317	0.489	NO

The comparison results show that by introducing the "new model," the changes of the travel time on the left lane and right lane are different for all three sections (except Lane 1 in the Section 3 –

WB, and Lane 3 in Section 3 - EB). However, the travel time for the middle lane (except Lane 2 in the Section 2 - EB) does not differ much between the two algorithms. One potential explanation is that most defensive or "unwilling" to change lane drivers would keep driving in the middle lane, which induces that the new lane-changing model doesn't affect vehicles on the middle lane as much as those on the left/right lanes.

7.3.2 Comparison of the Lane Distribution

The vehicle lane distributions were obtained from the video data and compared with the simulated counterparts. In both simulations implemented in CORSIM, surveillance detectors were placed on each lane for every 50 feet to record the number of vehicles using the lane. The field lane utilizations were observed from all four locations, and aggregated to obtain the percentages of the traffic distributions on each lane. Figure 7-11 shows a comparison of lane distribution from the "new model," the validation field data and the "original model."

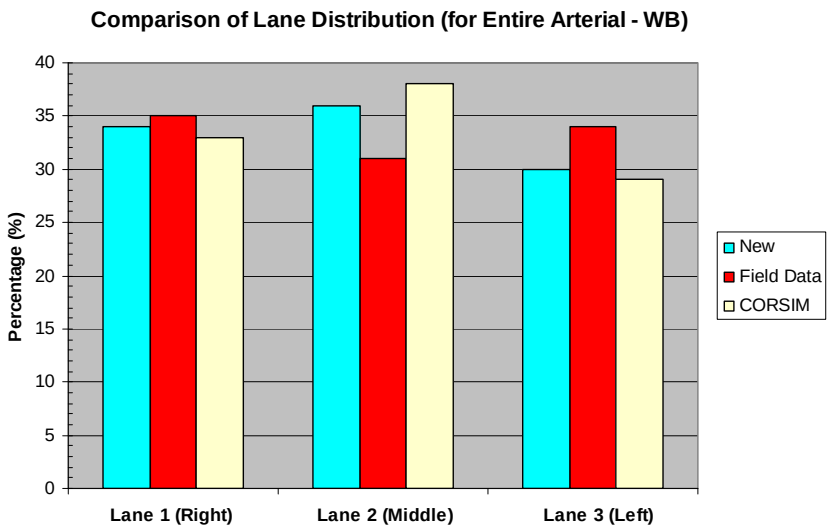
Figure 7-11a presents the simulation results of the "new model" and the "original model" for the WB traffic, which are similar to each other. Both simulations tend to overestimate the utilization of the middle lane (lane 2), and underestimate the utilization of the left lane (lane 3). However, the results from the "new model" are closer to field observations for both lanes (lanes 2 and 3). The root mean square error (RMSE), as defined in Eq. 7-1, is calculated for the vehicle lane distributions in CORSIM "original" model and the "new" lane model as 0.051 and 0.0374 respectively, which indicate an improvement of 26.62 %.

$$RMSE = \sqrt{\frac{1}{3}\sum_{i=1}^{3}(Y_i^{sim} - Y_i^{obs})^2} \tag{7-1}$$

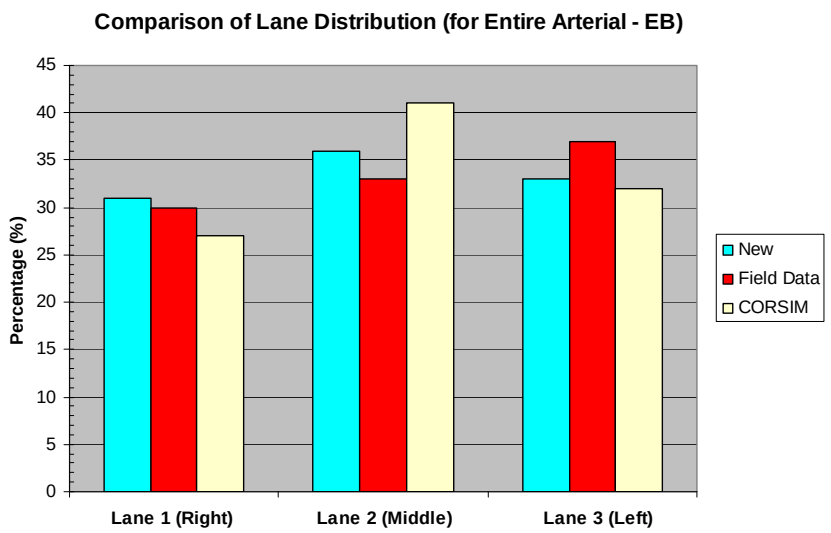
where:

i is the lane index, (1: right lane, 2: middle lane, and 3: left lane),

Y_i^{sim} and Y_i^{obs} are the observed and simulated percentage of vehicle lane distributions on lane i.



(a)



(b)

Figure 7-11. Comparison of the lane distribution (a) Lane distributions for the WB traffic (b) Lane distributions for the EB traffic

Figure 7-11b presented the results of the "new model" and the "original model" for the EB traffic. Similar to what observed from the WB traffic, both simulations tend to overestimate the utilization of the middle lane (lane 2), and underestimate the utilization of the left lane (lane 3). The only difference is that the "new model" tends to overestimate the utilization of the right lane

(lane 1), while the "original model" tends to underestimate this value. The overall results from the "new model" are closer to field observations for all three lanes. The RMSE is calculated for the vehicle lane distributions in CORSIM "original" model and the "new" lane model as 0.0571 and 0.0294 respectively, which indicate an improvement of 48.49 %.

7.3.3 Comparison of the Vehicle-Based Cumulative Number of Lane Changes

The cumulative number of lane changes by vehicles as observed from the video was obtained and compared against the simulation results of the "new" model and the "original" model. As presented in Figure 7-12, CORSIM "original" model under predicted the number of more-than-one lane changes, which is probably because CORSIM model only considers the destination, incident (including work zone) and lane use restrictions as the invoking reasons for lane changes. The other potential scenarios prevailing on the road are not being taken into account. By incorporating the new scenario-based lane-changing probability model, the "new" model performs much better than the "original" model, particularly in terms of predicting the higher number of lane changes. The RMSE, as defined in Eq. 7-2, is calculated for the percentage of vehicles in CORSIM "original" model and the "new" lane-changing model as 0.0397 and 0.0275 respectively, which indicate an improvement of 30.71%.

$$RMSE = \sqrt{\frac{1}{4}\sum_{i=1}^{4}(Y_i^{sim} - Y_i^{obs})^2} \tag{7-2}$$

where:

i is the number of lane changes by vehicles, (i = 1, 2, 3 and 4),

Y_i^{sim} and Y_i^{obs} are the observed and simulated percentage of vehicles with number of lane changes equaling to i.

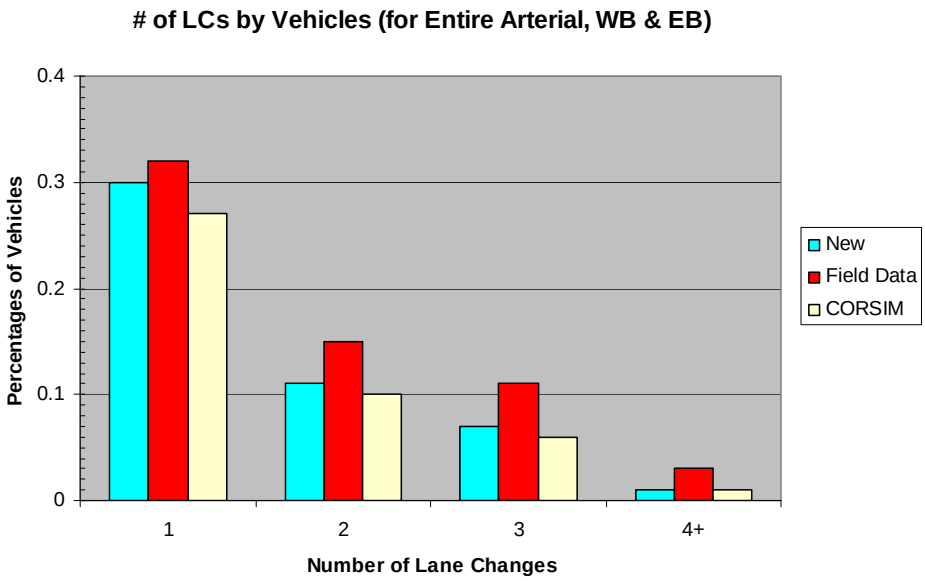


Figure 7-12. Comparison of the cumulative number of lane changes by vehicles

7.3.4 Sensitivity Analysis

To capture the uncertainty of how the lane-changing model affects the simulation output quantitatively, both calibrated networks (CORSIM and new) were simulated by the O-D flows measured from different day's Newberry Road video data under various traffic conditions (Pet-Armacost et al., 1999):

- Off-peak period (1 hour, from 12:00 pm – 1:00 pm on May 3rd, 2005);
- Transitional traffic period (0.5 hour, from 3:50 pm – 4:20 pm, May 3rd, 2005);
- PM peak period (1 hour, from 5:00 pm – 6:00 pm, April 29th, 2005).

The simulation outputs include measurements from multiple runs for each traffic condition. The goodness-of-fit measures to evaluate the overall performance of both simulation models, in terms of average lane travel speed, average lane vehicle counts and vehicle-based number of lane changes, can be assessed numerically by standard linear statistics, such as mean error (ME), mean percent error (MPE), RMSE and root mean square percent error (RMSPE). These statistics help to quantify the overall error of the simulation results (Toledo and Koutsopoulos, 2004).

(1) Lane-based travel speeds from the three sections (for every 5 minutes): The lane-based average travel speeds for each section (both in WB and EB) were obtained from field data on every 5-minute interval under different traffic conditions. The simulated measurements were then obtained from multiple surveillance detectors. The comparisons of the goodness-of-fit measures are presented in Table 7-8 (the upper part). As shown, for both transitional period and peak traffic conditions, the "new model" outperforms CORSIM "original model" in terms of all four statistical indices. The largest improvement occurred in the simulation within the period of transitional traffic flows, during which the highest percentage of vehicle cooperation and competition may be involved. In general, drivers during off-peak period are likely to take free lane changes, while they may either have to force merge or choose to keep on the same lane under peak congested traffic. One interesting point is that under off-peak traffic condition, simulation results from the "new model" are not as good as that of the CORSIM "original model" in several indices (ME, MPE and RMSPE). This reduction of performance was believed due to the fact that many drivers during off-peak are not likely to negotiate even though the criteria are satisfied. During particular lane-changing scenarios, vehicles may choose to accelerate or decelerate to change lane instead of negotiate with vehicles on the target lane. Consequently, the cooperative and competitive behaviors were not universally adopted in off-peak traffic. In addition, the stochastic dynamics in micro-simulation were also considered as possible sources.

Table 7-8. Goodness-of-fit statistics for lane-based travel speeds, vehicle counts and number of lane changes

Statistics Measure	Off-Peak (60 min)			Transitional (30 min)			PM-Peak (60 min)		
	Original	New	Impro.	Original	New	Impro.	Original	New	Impro.
Average Lane-based Travel Speeds (WB & EB)									
ME (mph)	-1.98	-2.09	-5.6%	-1.79	1.02	43%	-1.67	1.35	19.2%
MPE (%)	-4.96	-5.41	-9.1%	-7.63	4.74	37.9%	-8.92	6.74	24.4%
RMSE (mph)	5.73	5.51	3.8%	3.14	2.53	19.4%	3.45	2.83	18%
RMSPE (%)	16.42	18.12	-10.4%	12.81	9.21	28.1%	12.19	9.62	21.1%
Average Lane-based Vehicle Counts (WB & EB)									
ME (veh/5min)	1.15	1.24	-7.8%	1.52	1.09	28.3%	2.06	1.94	5.8%
MPE (%)	6.03	5.72	5.1%	5.36	3.57	33.4%	11.24	10.26	8.7%
RMSE (veh/5min)	5.26	4.83	8.2%	4.28	3.11	27.3%	4.12	3.85	6.6%
RMSPE (%)	21.08	18.14	13.9%	16.43	10.02	39%	17.43	14.87	14.7%
Vehicle-based number of lane changes (WB & EB)									
ME (veh)	-0.028	0.020	27.3%	-0.048	-0.014	70.5%	-0.043	-0.030	29.4%
MPE (%)	-0.369	0.381	-3.1%	-0.637	-0.308	51.7%	-0.403	-0.340	15.6%
RMSE (veh)	0.043	0.029	31.75%	0.063	0.040	36.7%	0.044	0.032	28.8%
RMSPE (%)	0.068	0.102	-50%	0.358	0.287	19.7%	0.197	0.163	17.1%

(2) Lane-base vehicle counts from the four locations (for every 5 minutes): The field lane-based vehicle counts (both in WB and EB) were observed from the four locations as mentioned in Figure 7-2, and aggregated on every 5-minute interval to obtain the traffic counts on each lane. The simulated lane specific vehicle counts from the two models were obtained and compared against the actual observations under different traffic conditions. As presented in Table 7-8 (the middle part), the "new model" has a significantly better match with the actual observations during the transitional traffic period. For PM peak condition, the performance of the "new model" is also better than CORSIM "original model." For the off-peak traffic, most of the statistics from the "new model" indicate the improvement of performance except ME, which deceases as compared to the results from CORSIM "original model." Since the "new model" outperformed the "original model" particularly in terms of transitional traffic and PM peak traffic, the reduction in ME is probably caused by the "white noise" points in the micro-simulation instead of systematic outcomes. Consequently, it was concluded that the overall performance of the "new model" is better in matching with the field observations.

(3) Cumulative vehicle-based number of lane changes (for entire simulation period): The cumulative number of lane changes for vehicles were observed from the different field videos, and aggregated to the percentages of lane-changing number equaling to 1, 2, 3 and 4+. The simulated vehicle-based number of lane changes from the two models were obtained and compared against the actual observations under different traffic conditions. Here, an additional plug-in has been developed to record the number of lane changes for CORSIM model. As presented in Table 7-8 (the lower part), both models have a pretty good match with the actual observations for the off-peak traffic. For the transition traffic, the performance of the "new" model is much better than CORSIM "original model." All four statistics from the "new model"

were improved by at least 19%, which means that the "new" model replicates field observations much better. For PM peak traffic, both models tend to underestimate the number of lane changes. This may be because under congested traffic, many other potential reasons may invoke a lane change, which depend largely on the driver's human behavior and mental status. Both the original and new models may not fully capture these invoking reasons. However, the performance of the "new model" is also better than CORSIM "original model," which may be interpreted that the new model captured more invoking reasons than the original model. Since the "new model" outperformed the "original model" in terms of all three levels of traffic, it was concluded that the overall performance of the "new model" is better in matching with the field observed vehicle-based number of lane changes.

7.4 Summary and Conclusions

The lane-changing model was implemented and validated using CORSIM simulator in this chapter. With the Newberry Road (Gainesville, FL) arterial segment and the field-measured traffic and control data, the "new" model was evaluated and compared to the original CORSIM lane-changing model.

First, the Newberry Road (Gainesville, FL) arterial segment was simulated and calibrated with the original lane-changing algorithm in CORSIM. The calibration at this stage is to tune up CORSIM embedded sensitive behavioral parameters related to lane-changing. Next, the new lane-changing algorithm was implemented as an RTE plug-in and invoked in the simulation to replace the "original" lane-changing strategy. The "new" model was applied to simulate the Newberry Road (Gainesville, FL) arterial segment. The calibration endeavor of the "new" simulation is to tune up behavior-related parameters within the newly developed lane-changing model. Lastly, the "new" lane-changing model was simulated with the additional OD demands measured from congested traffic and validated against the CORISM "original" lane-changing

model. The measures of validation include comparison of average lane-based travel time, lane distribution of vehicles, and cumulative lane changes by vehicles. The validation results support significant improvement over CORSIM "original" lane-changing model, which ignores some possible lane-changing scenarios and vehicle interactions involved.

The improvement in the model performance was demonstrated through a sensitivity analysis with traffic from different times of the day. Standard statistics for comparing the goodness of fit measures ("new" and CORISM) indicate that the "new" lane-changing model performs best during the early afternoon (3:50 pm to 4:20 pm) traffic, which represents a moderately congested arterial situation. Large percentages of improvement on each measure of performance were found. In addition, the "new" model also outperforms CORSIM "original" model during the later afternoon peak hour (4:30 pm to 5:30 pm) traffic, even though the improvement values are not as large as those from the early afternoon traffic. For the non-peak hour (non-congested) traffic, the performances of the "new" and "original" models are very close to each other. However, the validation results support that the "new" model has better capabilities to replicate lane-changing maneuvers under moderately congested and congested traffic in terms of various measures of performance. This, consequently, demonstrates improvement in the simulation capabilities of the "new" models.

Validation is an essential step of model development. In this research, CORSIM (NETSIM) microscopic simulator was selected to implement and simulate the proposed lane-changing model. By implementing the proposed model as an RTE plug-in within CORSIM, various analyses and comparisons were conducted to prove the effectiveness of the model. The validation field data were collected from a highly congested arterial segment, Newberry Road. Unfortunately, one particular lane-changing scenario, a work zone, was not involved, and the

lane-changing probability function for the corresponding scenario was not tested and validated. Moreover, one of the DLC scenarios, “changing lanes due to attracted by a better pavement condition,” can not be simulated in CORSIM. Consequently, additional arterial segments and modeling techniques may be introduced for validation purposes. Additionally, CORSIM microscopic simulator is selected as the test platform in this validation. Other widely used commercial simulators, such as AIMSUN, PARAMICS and VISSIM, may also be considered as test beds for the model validation, which would form a very important extension to the current research.

CHAPTER 8
CONCLUSIONS

This chapter summarizes the research results presented in the thesis and highlights the major contributions. Future research directions are provided at the end of the chapter.

8.1 Research Summary

As one of the fundamental driver behaviors, the decision to change lanes depends on many factors. In this thesis, a comprehensive framework was presented to model drivers' lane-changing behavior on arterials as a four-step decision-making procedure: decision under particular lane-changing reasons, target lane selection, gap acceptance and vehicle movement to the target lane. Emphases are placed on the first and third steps, in which any possible conditions may affect the driver's final decision. One major objective of this thesis is to model the drivers' lane-changing behavior under congested traffic in a microscopic perspective, with special attention to the effects of driver characteristics upon the maneuvers.

The lane-changing model presented in this thesis integrates a lane-changing probability component and a gap acceptance component, which capture drivers' lane-changing decision under each of the DLC reasons and different gap acceptance situations. The emphasis is to model the lane-changing maneuvers by using the driver behavior-related data along with driver background and characteristics. Traditional external observations based vehicle data, such as vehicle trajectories, only provide rudimentary traffic information and are not sufficient to expose the drivers' thinking process during the maneuver. As a result, the driver characteristics were not able to incorporate into the driver behavior research. In this study, focus group study was conducted to obtain driver behavior related data, such as personal perceptions and attitudes regarding lane-changing maneuvers, which can be used to model lane changes within an urban street environment. Taking into consideration both the personal background data and the stated

behavior data obtained from the discussions, the focus group participating drivers were classified into four groups using clustering analysis. The important factors for each of the lane-changing scenarios were obtained from the study, so that a further "in-vehicle" field experiment could be designed to collect the corresponding field lane-changing data.

As the verbal responses of the focus group participants may not reflect their actual driving behavior, an "in-vehicle" field experiment was conducted as follow-up research to test and validate the lane-changing process and the stated preferences from a diverse group of drivers. The quantitative values for the important factors proposed by the focus group participants were collected from the "in-vehicle" field driving tests. Cluster analysis, similar to the one conducted for the focus group data, was then performed to categorize the participating drivers based on the selected measures of driver behavior. The clustering result (into four groups) was found to be consistent with the result obtained from the focus group analysis, which confirms the effectiveness of driver classification scheme in the urban arterial lane-changing modeling.

Three types of lane-changing related maneuvers (potential, attempted but unsuccessful, and completed) were collected during the "in-vehicle" driving test. The combination of attempted and completed lane changes indicates the driver accepted the particular DLC scenario, while the potential maneuvers indicate a rejection in the lane-changing reason level. With the important factors obtained from the focus group study and the quantitative values collected from the "in-vehicle" experiment, the lane-changing probability under each of the DLC scenarios is modeled as a function of corresponding important factors and driver types. The modeling coefficients were estimated using the binary logistics (accept or not) regression method. This component tries to enumerate all DLC scenarios occurring in urban arterials and models each one individually.

With the gap acceptance strategies observed and the behavioral-related values collected from the "in-vehicle" experiment, a new lane-changing gap acceptance algorithm was developed to model lane changes on urban arterials into three modes: (i) free, (ii) forced, and (iii) competitive/cooperative. The free and forced lane changes were modeled as instantaneous events conducted during the time interval immediately following the driver's decision. The subject vehicle is moved to the target lane, and the car-following strategy is applied subsequently to the corresponding vehicles. The procedure of competitive/cooperative lane changes is modeled as a sequence of "hand-shaking negotiations" between vehicles with more complex interactions. Various strategies were developed to model the interactions that may occur during the maneuver. The "multi-agent" techniques were adopted to model each vehicle as an intelligent and autonomous entity, which observes and acts upon the driving environment.

The new lane-changing model was implemented as an individual module within the microscopic traffic simulator, CORSIM and validated using aggregate real-world data: the field data collected from Newberry Road (Gainesville, FL). Part of the available aggregate data was first used to calibrate the overall simulation system. The remaining aggregate data (not used for calibration) were then compared with the corresponding outputs of the calibrated CORSIM "new" model and those generated from the "original" CORISIM lane-changing model. Various goodness-of-fit measures were calculated to validate the improvement of the "new" model. The aggregate validation results demonstrated that the newly developed model performed consistently better than the original CORSIM model for both moderately congested and heavy congested traffic conditions, which exhibited the improved performance in simulation capabilities to replicate the lane-changing behaviors.

8.2 Contributions

This thesis advances the state of the art in modeling drivers' lane-changing behavior on urban arterials. The major contributions are the methods used to introduce driver characteristics into the lane-changing study. Focus group surveys and "in-vehicle" observations were conducted to collect microscopic data for the modeling purpose. The "in-vehicle" field data were used to estimate the lane-changing probability models by statistically rigorous methods (regression analysis). The developed lane-changing model has bridged some of the significant gaps in the existing simulation tools. The specific contributions of each empirical study are listed below:

(1) Contribution to the modeling framework on driver characteristics: In this research, two important components within the lane-changing behavior, reason-based lane-changing probability and gap acceptance, are studied. The existing lane-changing models either borrow the reasons and the acceptable gaps from other models, or extract them from the given video data (Hidas, 2002, 2005; Liu et al., 2006), or estimate them from field data (Ahmed, 1999; Choudhury et al., 2004; Ben-Akiva et al., 2006). No one considers driver characteristics in much detail, since the information is hardly be deduced from the existing videos or other sources of field data. This research was started with the focus group study, and thus the factor of driver characteristics was incorporated into the lane-changing behavior data collection from the beginning. By using both personal background and the stated behavior data related to urban arterial lane changes, the focus group participants were categorized into four groups. Then with the "in-vehicle" data collected from field lane-changing maneuvers, a further cluster analysis was conduct to classify the "in-vehicle" drivers. The result was found to be consistent with the one obtained from the focus group study, which in turn validates and confirms the output from the focus group study. With the field-collected lane-changing values and the corresponding driver types, a comprehensive model was developed to handle the probability of changing lanes

under each particular scenario and the strategies adopted in the subsequent gap acceptance procedure.

(2) Contribution to the empirical work of data collection: Driver behavior is largely dependent on personal characteristics and driving experience. To obtain representative lane-changing data, three types of data collections were included in this research. Driving experience based focus group discussions were first conducted. A diverse pool of participants was recruited based on age, gender, driving experience, occupation and vehicle ownership. Driver background and the qualitative lane-changing data were collected from the focus group study. Next, according to the results of the focus group study, an "in-vehicle" experiment was designed to collect field quantitative values. The testing drivers were accompanied by the researcher on the pre-selected route to collect the behavior data related to completed, attempted but unsuccessful, and potential lane changes. Additional clustering analysis was conducted to validate the consistency of the "in-vehicle" data with the focus group results. Finally, in addition to the focus group study and the "in-vehicle" data collection, external observation based field video data were also collected and used for model calibration and validation purposes.

(3) Contribution to model vehicle interactions during lane changing: Three lane-changing modes were identified based on vehicle interactions as: free, forced and cooperative/competitive lane changes. The procedure of the competitive/cooperative lane changes is modeled based on drivers' actions and responses as a sequence of "hand-shaking negotiations", by referring to the protocols in computer network communications. Strategies were developed according to the immediate surrounding environment and the corresponding driver characteristics, so that vehicle actions can be modeled correctly. This approach differs from existing models which assume that lane changes are all conducted instantaneously or within fixed time intervals, and different lane-

changing modes are not interchangeable. In the new gap acceptance model, the "games" between the subject vehicle and the lag vehicle may be either competition or cooperation, depending on the surrounding traffic and the characteristics of drivers. The strategies of "not change," "free change," "cooperative/competitive change" and "forced change" are interchangeable, which better reflects the lane-changing reality on urban arterials.

(4) Contribution to model implementation and validation: The proposed lane-changing model was implemented as a dll in VS .net C ++ 2008, and validated in CORSIM microscopic simulator. First, the individual component, including the probability functions for the lane-changing reasons and the gap acceptance procedure, is implemented as a separate function (or called subroutine) within the lane-changing module, which is invoked as a CORSIM RTE (run time extension) during the simulation. Next, two CORSIM simulation cases, the one with the newly developed lane-changing model and the one with CORSIM's original lane-changing model, were calibrated using aggregate data (field video data) collected from arterials in Gainesville, FL. Once the calibrations were completed, values of the full set of behavioral parameters were fixed. Both calibrated models are simulated with the additional set of OD demands for validation purpose. The results are compared with the field measurements on multiple indices of the measures. Various goodness-of-fit statistics were generated to determine the agreement between the results from the simulation system and the field observations. The simulation results from the existing lane-changing model in CORSIM served as a test bed for the model ability improvement offered by the "new" algorithm. The analyses of results indicated, by incorporating the new lane-changing model into micro-simulation tools, more realistic traffic flow and congestion can be represented and assessed, which hence results in better planning and policy analysis tools.

8.3 Directions for Future Research

In this thesis, a general framework for modeling lane-changing behavior on urban arterials was presented. The focus group study and "in-vehicle" experiment were conducted to obtain information on driver characteristics, which were then incorporated into the lane-changing behavior modeling. The research concept and the proposed framework have enormous potential both in modeling driving decisions and modeling decisions in other scenarios. Some of the directions in which further research is needed are presented below:

(1) Target lane selection component: The lane-changing process is generally modeled as a sequence of four decision-making steps: acceptance of lane-changing reasons, target lane selection, existing gap acceptance and vehicle movement to target lane. The two highlighted components developed in this thesis are the lane-changing probability model and the gap acceptance model. The target lane was assumed to be always the adjacent lane, which is generally referred to as a myopic target lane model. This assumption does make sense for modeling the regular urban arterial traffic. However, it can not be applied to the special situations on urban arterials, such as the existence of BRT (Bus Rapid Transit) or HOV (High Occupancy Vehicle) lanes, which require additional considerations. To this end, a target lane choice model can be adopted to evaluate the utilities of all candidate lanes, so that the lane with highest utility is chosen as the target lane. Variables likely to influence the target lane choice of the driver include path-plan, lane attributes, driving style and capabilities, and so on.

(2) Additional DLC scenarios and the corresponding important factors: One highlight of the research results is the scenario-based lane-changing probability model, which models the probability of changing lanes under each pre-selected DLCs as a function of indicated important factors and the subject driver type. The important factors for each DLC were obtained from the

focus group study and are not inclusively applicable to all other pervasive DLCs on urban arterials. Consequently, the current model can only handle the scenarios discussed in the focus group meetings. More focus group discussions are required for incorporating new DLCs into the probability model.

(3) Vehicle type effect: During the focus group meetings, all lane-changing related questions and scenarios assumed that the subject vehicle was a passenger vehicle. Furthermore, the subject vehicle was fixed as the Honda Pilot throughout the "in-vehicle" experiment. Consequently, the proposed model only captures the lane-changing behavior of passenger vehicles. As revealed during the focus group discussions, the lane-changing behavior of heavy vehicles differs largely from that of passenger cars, which is an interesting direction to extend this research in the future.

(4) Other promising data collection technologies: One significant component in driver behavior modeling is the data collection, which is especially important in the lane-changing behavior research. In this thesis, two methods, video and film methods and instrumented vehicles (with GPS systems), were used to collect field data on typical urban arterial segments. Further studies may consider technologies for collecting data from more versatile geometric characteristics. To this end, virtual reality driving simulators may be used to collect data in situations that are otherwise difficult to observe, such as emergency situations, and to control some of the latency in the behavior (e.g. by asking drivers to perform a specific maneuver, thus eliminating the uncertainty in modeling the drivers' short-term goals).

APPENDIX A
MEMORANDUM OF THE SUBMIT MATERIALS CHECKLIST

TRANSPORTATION RESEARCH CENTER (TRC)
UNIVERSITY OF FLORIDA

518A Weil Hall, P.O. Box 116580

MEMORANDUM (UFIRB #2008-U-0019)

DATE: January 8th, 2008

TO: UF IRB-02 (UF Campus/Non Medical)

FROM: 1. Daniel (Jian) Sun,
Graduate student,
Department of Civil and Coastal Engineering
jiansun@ufl.edu

2. Lily Elefteriadou,
Ph.D., Associate professor
Department of Civil and Coastal Engineering
elefter@ufl.edu

SUBJ.: UFIRB Submission Checklist - Survey of the Lane-Changing Behavior in Urban Arterials

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In accordance with the requirements of the University of Florida's Institutional Review Board (IRB), all research involving human subjects needs to be approved by the relevant IRB Office prior to conducting any activities. This document lists the materials hereby submitted to IRB-02 (UF Campus/Non Medical) for the project titled "survey of lane-changing behavior in urban arterials". The project constitutes Mr. Daniel (Jian) Sun's dissertation supervised by Dr. Lily Elefteriadou in the department of Civil and Coastal Engineering, wherein two types of

experiments – focus group discussion and "in-vehicle" field data collection are proposed. The items attached are:

- ✔ One copy of the UFIRB protocol form (with original signatures, APPENDIX B),
- ✔ Three copies of the two informed consent forms (one form for each experiment, APPENDIX C and APPENDIX D),
- ✔ Advertisement for participants' recruitment (APPENDIX E),
- ✔ One copy of the complete methods section from the proposal of dissertation research (Chapter 3), and
- ✔ Other research instruments, including

    1. One copy of the prescreening questionnaire for participant selection (APPENDIX F),
    2. One copy of the driving background survey questionnaire to be used during the participants check-in procedure of the both experiments (APPENDIX G),
    3. One copy of the script to be used during the focus group discussion (APPENDIX H),
    4. Description of the instrumented vehicle which will be used by participants in the field data collection (Chapter 3), and
    5. Proposed routes that the study participants will drive during the field data collection (Chapter 5).

APPENDIX B
UFIRB PROTOCOL FORM

UFIRB 02 – Social & Behavioral Research Protocol Submission	
Title of Protocol: Survey of Lane-Changing Driving Behavior in Urban Arterials	
Principal Investigator: Daniel(Jian) Sun	**UFID #: 8068-6760**
Degree / Title: Graduate Student **Department: Civil and Coastal Engineering**	**Mailing Address: 518A Weil Hall, PO Box 116580** **Email Address & Telephone Number: jiansun@ufl.edu / (352)682-8390**
Co-Investigator(s):	**UFID#:**
Supervisor: Lily Elefteriadou	**UFID#: 1319-1914**
Degree / Title: PH.D, Associate Professor **Department: Civil and Coastal Engineering**	**Mailing Address: 512 Weil Hall, PO Box 116580** **Email Address & Telephone Number: elefter@ce.ufl.edu / 392-9537 ext 1452**
Date of Proposed Research: *Jan. 2008 to Jan. 2009*	
Source of Funding *N/A*	
Scientific Purpose of the Study: *To capture the significant factors which affect lane-changing maneuvers for different types of drivers, so that lane-changing driving behavior can be modeled in a more realistic way considering individual driver behavior.*	
Describe the Research Methodology in Non-Technical Language: ***(****Explain what will be done with or to the research participant.****)*** *In this research, participants will be recruited for two experiments to collect lane-changing behavior data. In the first experiment, participants will join a focus group to discuss lane-changing related questions from their personal driving experiences. Next, participants, not necessary the same as the ones involved in the focus groups, will drive an instrumented vehicle along pre-specified routes to collect personal lane-changing behavior data. A background survey, which contains questions regarding age, gender, driving experience, nationality, occupation and vehicle ownership, will be conducted for each driver, so that the observed lane-changing behavior could be connected with particular driver's characteristics in the further research stages.*	
Describe Potential Benefits and Anticipated Risks: (*If risk of physical, psychological or economic harm may be involved, describe the steps taken to protect participant.)* *The survey will help model lane-changing behavior in a more realistic and accurate way. Based on this fundamental component, the performance of various traffic operation models will be improved. The survey method adopted in this research provided a new*	

methodology for the driver-oriented research in traffic engineering. No risk is anticipated during the focus group discussion experiment. For the field data collection, since all drivers will be accompanied by the researcher, and be instructed to drive as they usually do, the risks will be those a driver usually assumes during driving. The consent form includes language regarding potential injury during the experiment.

Describe How Participant(s) Will Be Recruited, the Number and AGE of the Participants, and Proposed Compensation:

A diverse pool of participants will be selected based on age, gender, driving experience, nationality, occupation and vehicle ownership. A prescreening questionnaire has been developed to help identify qualified participants. The questions will be posted on the project website (http://grove.ufl.edu/~jiansun). Respondents can choose to submit responses online or download the prescreening questionnaire from the server, and submit responses offline through email or mail. Advertisements for recruitment will be announced through various publications and several list servers. The proposed public locations for posting the announcement include the University of Florida campus, downtown transit transfer station, Alachua county library and supermarkets. In addition, the advertisement will be placed on the Classifieds in Alligator, and sent to several large organizations and communities, such as ASCE, FACSS and ISA, through their list servers. The advertisement will also be posted on the researcher's personal website.

Criteria for the participant recruitment are as follows: 1. must be a regular driver with a driving experience no less than three years; 2. must be a Gainesville resident for more than 1 year; and 3. must indicate a willingness to join either the focus group or agree to test drive the instrumented vehicle, or both. In the focus group studies, three groups will be recruited with 5-7 participants each. The discussion time is set as two hours, and the compensation is $50 per participant. For the "in-vehicle" field data collection, the number of participants is set as 30-40, and the compensation is $50 each.

Describe the Informed Consent Process. Include a Copy of the Informed Consent Document: *The recruiting advertisement explains the purpose of the project and the objectives of the research. It is clearly stated that participation is optional and that the outcome will be summarized in a manner that does not identify any participant. A separate copy of the informed consent document attached will be used to advise potential participants and obtain voluntary agreement at the beginning of the experiments.*

Principal Investigator(s) Signature:	**Supervisor Signature:**
Department Chair/Center Director Signature:	**Date:**

APPENDIX C
INFORMED CONSENT FORM – FOCUS GROUP STUDY

Protocol Title: Focus Group Survey of Lane-Changing Driving Behavior in Urban Arterials

Please read this consent document carefully before you decide to participate in this study.

Purpose of the research study:

The purpose of this study is to capture the significant factors which affect lane-changing maneuvers for different types of drivers, so that lane-changing driving behavior can be modeled in a more realistic way.

What you will be asked to do in the study:

You will join another 4-6 volunteers to form a focus group. Then a moderator will ask you questions related to lane-changing behavior, and you will be required to think and answer these questions from your personal driving experience. During the session, the moderator will first present a list of possible lane-changing scenarios, and ask you to evaluate the likelihood you would change lanes for those reasons. Then the moderator will ask you to describe how you execute such maneuvers. During the experiment, you will be encouraged to interact with the other participants in your group, thereby providing greater insight into why certain beliefs and opinions are held. You will not be required to vote or reach consensus. With your permission, I would like to tape record the discussion so that I can more accurately record your responses after we finish today. Only researchers involved in this project will have access to the tape. Your identity will not be revealed in the final manuscript. The time required for this activity is about two hours.

Risks and Benefits:

No risk is anticipated during the focus group discussion experiment, and we do not anticipate that you will benefit directly by participating in this experiment.

Compensation:

You will be paid $50 compensation for participating in the focus groups experiment of two hours.

Confidentiality:

Information collected from this experiment will be used for traffic engineering research only. Your identity will be kept confidential to the extent provided by law. In accordance with the Confidential Information Protection and Statistical Efficiency Act of 2002 (Title 5 of Public Law 107-347) and other applicable Federal laws, your responses will not be disclosed in identifiable form without your consent.

Voluntary participation:

Your participation in this study is completely voluntary. There is no penalty for not participating.

Right to withdraw from the study:

You have the right to withdraw from the focus group discussion at anytime without consequence. The compensation will be recalculated based on your participating time. If you withdraw after one hour of discussion, you will be paid $20. No compensation will be paid if the participating time is less than one hour.

Whom to contact if you have questions about the study:

Daniel(Jian) Sun, Graduate Student, Department of Civil and Coast Engineering, Room 518, Weil hall, (352)682-8390.
Lily Elefteriadou, Ph.D., Department of Civil and Coast Engineering, Room 512, Weil hall, (352)392-9537 x1452.

Whom to contact about your rights as a research participant in the study:

UFIRB Office, Box 112250, University of Florida, Gainesville, FL 32611-2250; ph 392-0433.

Agreement:

I have read the procedure described above. I voluntarily agree to participate in the procedure and I have received a copy of this description.

Participant: _____ Date: _____
Principal Investigator: _____ Date: _____

APPENDIX D
INFORMED CONSENT FORM – "IN-VEHICLE" EXPERIMENT

Protocol Title: "In-vehicle" Data Collection Survey for Lane-Changing Driving Behavior in Urban Arterials

Please read this consent document carefully before you decide to participate in this study.

Purpose of the research study:

The purpose of this study is to collect the significant factors which affect lane-changing maneuvers for different types of drivers, so that lane-changing driving behavior could be modeled in a more realistic way.

What you will be asked to do in the study:

In this experiment, you will be accompanied by our researcher to drive in an instrumented vehicle (Honda Pilot) for 40-60 minutes. Before starting the vehicle, the check-in procedure will be as follows: 1) Sign the informed consent form (this form); 2) Finish the background survey form; this form contains questions regarding your age, gender, driving experience, nationality, occupation and vehicle ownership; 3) Provide your drivers license for authentication; and 4) Turn off your cell phone, if you have one. You will be shown the map of a pre-selected route. Please review the route carefully, and try to clarify any questions you may have. If during driving you make the wrong turn for more than 3 times, the "in-vehicle" data collection will have to be terminated. A camera will be monitoring your face movement throughout the test. During the experiment, please follow the researcher's instructions as closely as possible. To avoid driver distraction, the researcher will not be communicating with you while you are driving. However, you will be instructed to stop at specific check points, and spend approximately 3-5 minutes to communicate with the researcher, so that information from each driving stage can be obtained. For a successful lane change, you may be asked to give out the reasons for the maneuver, and the major factors during the lane change. For an unsuccessful one, you may need to explain the reasons you felt it was unsuccessful. The field data collected in the experiment, including both the vehicle trajectory and the information obtained during your interactions with the researcher, will be used for traffic engineering research only. With the information from the background form, your driving behavior will be connected with some of your characteristics. Your identity will not be revealed in the final manuscript. The time planned for this activity is 40 minutes driving and an additional 10-20 minutes communicating with the researcher.

Risks and Benefits:

The risks for this experiment are those a driver usually assumes during driving. Please be fully attentive to your driving, and have safety as your first priority. There is an increased risk of accidents when the driver is distracted by other activities, such as talking on the phone. You will be accompanied by the principal investigator, and you will be instructed to drive as you usually do during the data collection. We do not anticipate that you will benefit directly by participating in this experiment.

Compensation:

You will be paid $50 compensation for participating in this field data collection experiment. No compensation will be paid for withdrawing early, making the wrong turn for more than 3 times or being involved in a road accident.

Research-related injury:

In the event that this research activity results in an injury, treatment will be available, including first aid, emergency treatment and follow-up care as needed. Care for such injuries will be billed in the ordinary manner to you or your insurance company. If you think that you have suffered a research related injury, let the study researcher know right away.

Confidentiality:

Information collected from this experiment will be used for traffic engineering research only. Your identity will be kept confidential to the extent provided by law. In accordance with the Confidential Information Protection and Statistical Efficiency Act of 2002 (Title 5 of Public Law 107-347) and other applicable Federal laws, your responses will not be disclosed in identifiable form without your consent.

Voluntary participation:

Your participation in this study is completely voluntary. There is no penalty for not participating.

Right to withdraw from the study:

You have the right to withdraw from the study at anytime without consequence.

Whom to contact if you have questions about the study:

Daniel(Jian) Sun, Graduate Student, Department of Civil and Coast Engineering, Room 518, Weil hall, (352)682-8390.
Lily Elefteriadou, Ph.D., Department of Civil and Coast Engineering, Room 512, Weil hall, (352)392-9537 x1452.

Whom to contact about your rights as a research participant in the study:

UFIRB Office, Box 112250, University of Florida, Gainesville, FL 32611-2250; ph 392-0433.

Agreement:

I have read the procedure described above. I voluntarily agree to participate in the procedure and

I have received a copy of this description.

Participant: _____ Date: _____

Principal Investigator: _____ Date: _____

APPENDIX E
ADVERTISEMENT FLYER FOR THE PARTICIPANTS RECRUITMENT

UNIVERSITY OF FLORIDA

Transportation Research Center

Participants Recruitment for Lane-Changing Driving Behavior Research

Background and Objectives : Current models for evaluating traffic conditions do not consider lane-changing in much detail. This research will develop improved methods for considering lane-changing behavior in traffic modeling tools.

Experiments: Two experiments are designed to obtain driver behavior information related to lane-changing.

Experiment 1 (A total of 15 – 21 participants are needed to form three focus groups, with 5-7 each). Focus group discussions will be held to get information from drivers on lane-changing maneuvers. During the discussion, participants will be asked to respond to questions related to lane-changing behavior from their personal driving experiences. Each focus group discussion will last no more than 2 hours.

Experiment 2 (A total of 30 – 40 participants are needed): Individual participants will be asked to drive an instrumented vehicle on pre-selected routes in the city of Gainesville for about 40-60 minutes accompanied by the investigator. This experiment will collect driver behavior data, which will be used to develop a lane-changing model for microscopic traffic simulation.

Requirements: Participants must have a valid driver license, and driving experience no less than three years. It is preferable that participants have been Gainesville residents for more than one year, so that they are familiar with the test routes. The age limitation is 20 – 60 years. You will be paid $50 compensation for participating in any ONE activity in this research.

To Participate: Please go to the recruiting webpage http://grove.ufl.edu/~jiansun, or call Daniel Sun at (352)682-8390 for detailed information. A prescreening procedure is required, and you may choose to answer the prescreening questions online, or get the questionnaire by fax or mail/email. Responses should be submitted to: Daniel Sun, 392-3394 (fax), jiansun@ufl.edu (email), 518A Weil Hall, PO Box 116580, Gainesville, FL 32611 (mail).

APPENDIX F
PRESCREENING QUESTIONAIRE FOR PARTICIPANTS SELECTION

UNIVERSITY OF FLORIDA

Transportation Research Center

Prescreening Questionnaire for Lane-Changing Behavior Research

To Participants: This questionnaire is used to select a diverse pool of drivers to participate in two experiments – focus groups or 'in-vehicle' data collection. Information collected in this form will be used for traffic engineering research only. All responses will be held in complete confidential and exempted from public disclosure by law. In accordance with the Confidential Information Protection and Statistical Efficiency Act of 2002 (Title 5 of Public Law 107-347) and other applicable Federal laws, your responses will not be disclosed in identifiable form without your consent. Since drivers' diversities are highly encouraged, only the most suitable responders will be chosen. Other criteria will be used for prescreening including age, gender, driving experience, nationality, occupation and vehicle ownership. Please answer as many as possible.

Return Address:

By Email: **jiansun@ufl.edu**
By Mail: **Daniel (jian) sun, 518A Weil Hall, PO Box 116580, Gainesville, FL 32611**

1) Which experiment would you like to participate in?
   - O Focus group discussion
   - O Test driving on an instrumented vehicle
   - O Both
2) What is your gender?
   - O Male O Female
3) What is your age?
   - O 20 to 29 years O 30 to 39 years O 40 to 49 years
   - O >= 50 years
4) Which of the following groups do you most identify yourself as?
   - O Caucasian O Native American
   - O African American O Hispanic
   - O Asian O Pancific Islander O Other_____(please specify)
5) Where did you begin your driving practice and obtained your driver's license?
   - O North America O Latin America O Asia O Europe
   - O Australia O Other_____ (please specify)
6) How long have you been driving in the U.S.?
   - O < 1 year O 1 to 3 years O 3 to 9 years O >= 10 years

7) How long have you been living in Gainesville, FL?

○ < 1 year ○ 1 to 3 years ○ 3 to 9 years ○ >= 10 years

8) What is your occupation?

○ Full time student ○ University faculty/staff ○ Professional driver

○ Other _____ (please specify)

9) Do you drive to work/school?

○ Everyday ○ Usually ○ Sometimes

○ Almost Never

10) How much time do you spend approximately in driving per week?

○ < 4hr ○ 4 to 8 hr ○ 8 to 14 hr ○ > 14hr

11) What time of the day do you usually drive?

○ Am/pm peak hour (6 am - 10 am; 4 pm - 7 pm) during work days

○ Non-peak hours (including holiday and weekend)

12) What type of vehicle do you usually drive?

○ Sedan/Coupe ○ Pickup/SUV ○ Jeep ○ Truck

13) What time are you typically available for participating in these experiments? Please check as many as possible.

- ☐ Monday morning (9:00 am to 12:00 pm)
- ☐ Monday afternoon (1:00 am to 5:00 pm)
- ☐ Monday evening (6:00 am to 10:00 pm)
- ☐ Wednesday morning (9:00 am to 12:00
- ☐ Wednesday afternoon (1:00 am to 5:00
- ☐ Wednesday evening (6:00 am to 10:00
- ☐ Friday morning (9:00 am to 12:00 pm)
- ☐ Friday afternoon (1:00 am to 5:00 pm)
- ☐ Friday evening (6:00 am to 10:00 pm)
- ☐ Sunday morning (9:00 am to 12:00 pm)
- ☐ Sunday afternoon (1:00 am to 5:00 pm)
- ☐ Sunday evening (6:00 am to 10:00 pm)
- ☐ Tuesday morning (9:00 am to 12:00 pm)
- ☐ Tuesday afternoon (1:00 am to 5:00 pm)
- ☐ Tuesday evening (6:00 am to 10:00 pm)
- ☐ Thursday morning (9:00 am to 12:00 pm)
- ☐ Thursday afternoon (1:00 am to 5:00 pm)
- ☐ Thursday evening (6:00 am to 10:00 pm)
- ☐ Saturday morning (9:00 am to 12:00 pm)
- ☐ Saturday afternoon (1:00 am to 5:00 pm)
- ☐ Saturday evening (6:00 am to 10:00 pm)
- ☐ Any time by appointment

14) Participant contact information (at least 1 from phone/email/mail)

Name : _____ (Required) Phone : _____

Email : _____ Date : _____

Mail Address : _____

APPENDIX G
PARTICIPANTS DRIVING BACKGROUND SURVEY QUESTIONAIRE

UNIVERSITY OF FLORIDA

Transportation Research Center

Participants' Background Survey Form

Participant's ID: _____

Note: Information collected in this form will be used for traffic engineering research only. All responses will be held confidential and exempt from public disclosure by law. The linking information between the ID and your identity will be kept in a secure place until the study is complete, then destroyed. In accordance with the Confidential Information Protection and Statistical Efficiency Act of 2002 (Title 5 of Public Law 107-347) and other applicable Federal laws, your responses will not be disclosed in identifiable form without your consent. By law, every interviewer, as well as every agent, is subject to a jail term, a fine, or both if he or she makes public ANY identifiable information you reported.

1) If the speed limit for an urban street is 45 mph, what speed are you likely to drive (assuming good visibility and good weather conditions)?
   ☐ < 40 mph ☐ 40 to 45 mph ☐ 45 to 50 mph ☐ 50 to 55 mph ☐ > 55 mph

2) When driving on campus where the posted speed limit is 20mph, what speed are you likely to drive at (assuming good visibility and good weather conditions)?
   ☐ < 15mph ☐ 15 to 20mph ☐ 20 to 25mph ☐ 25 to 30 mph ☐ > 30 mph

3) How likely are you to change lanes if the vehicle in front of you is about 5 mph slower?
   ☐ Often ☐ Sometimes ☐ Seldom

4) When planning your driving trip, do you allow additional time for possible delays due to congestion, construction, or bad weather? ☐ Yes, always ☐ Sometimes ☐ Never

5) You are approaching a work zone with the road sign indicating that the current lane is closed ahead, and a moving queue is already forming in the open lane. When do you typically change lanes?
   ☐ At the first sight at the sign
   ☐ As soon as you see an appropriate gap in the open lane
   ☐ When all other vehicles ahead of you have merged
   ☐ When you arrival lane was ended

6) You are approaching a work zone with the road sign indicating that the adjacent lane is closed ahead, and someone driving down the lane that is about to end, is trying to merge in front of you. You have already been waiting in line for at least 10 minutes. How you would respond?
   ☐ Step on the gas and close the gap between you and the next car until it is impossible for the merging vehicle to get in
   ☐ Do nothing, and maintain your current speed
   ☐ Slow down so that the merging vehicle could merge easily and in safety

APPENDIX H
FOCUS GROUP MODERATIING SCRIPTS

Thank you for taking time out of your busy schedule to be here today. Daniel Sun (under advising of Dr. Lily Elefteriado) is interested in understanding how drivers perceive the lane-changing behavior for his ph.d studies, which includes why drivers change lanes and how they behave during the maneuver. As you may know, multiple surveys have been conducted as useful data collection methods by professors in UF TRC in the past several years. However, focus groups such as this one have the unique advantage of gathering information without constraining participants to a predetermined set of responses.

I will be asking you as a group a number of questions over the next two hours. I would like you to be completely honest with me, and answer questions from your own drive experience. I assure you that all of your responses will be held in complete confidence. I would like to ask your permission to tape record the whole discussion so that I can more accurately study your responses after we finish today. I will not link you with any of your comments after the discussion, and no identifying information will leave this room. Are all of you comfortable with this?

Opening question **(**Ice-breaker question, which will get everyone to talk and help participants to feel comfortable.)

1. Let the participants introduce themselves to one another. Open the discussion with the following question "Tell us who you are. Do you enjoy driving? Why?" (3-4 minutes)

Introductory question (Introduce the topic of discussion and get people to start thinking about their connection with the topic.)

2. What comes to your mind when you hear the term - "change lanes"? (5-7 minutes)

Transition question **(**Move the conversation into the key questions.)

3. Think about the reasons invoking a lane change. Do you consider there are many differences between you and other drivers? (5-8 minutes)

Key questions (Key questions drive the study)

4. In general, lane-changing behavior could be divided into mandatory lane changes (MLC) and discretionary lane changes (DLC). MLCs are those initiated to follow a special route. The purpose of DLC is for drivers to improve their position in the traffic stream to expedite their trip. Not all drivers make DLC in given a certain situation. In this question, you will be given a list of DLC types. Please evaluate each one and select the frequency that you would conduct such a lane change from your own driving experience. (20 minutes)

The given list of DLCs (Discretionary lane-changing) is:
R1) Passing a stopped-bus at bus stop;
R2) Giving way to a merging vehicle or to a bus merging from a bus pull-off;
R3) Gaining speed advantage by overtaking a slower moving vehicle;

R4) Gaining queue advantage;
R5) Avoiding a heavy vehicle's influence;
R6) Avoiding the closed-following pressure imposed by the vehicle behind you (only applied to the lane-changing maneuver to curb-side);

R7) Attracted by a better pavement condition, such as away off snowy/icy pavement lane

Five levels of frequency are as:
Level 1: generally do not conduct (< 10%)
Level 2: sometimes conduct but more likely do not (10% - 40%)
Level 3: sometimes conduct, sometimes not. It hard to conclude which one is preferred (40% - 60%)
Level 4: sometimes do not conduct but more likely conduct (60% - 90%)
Level 5: generally conduct (> 90%)

Table 1 as follow will be used to collect the frequency for each reason from the participants.

Table 1: Survey form used to collect the acceptable extent for each reason

Reason / Fre.	R1	R2	R3	R4	R5	R6	R7	R8
Level 1	Y		Y		Y			
Level 2		Y				Y		
Level 3				Y			Y	
Level 4								
Level 5								

5. In addition to the list of DLCs given in question 4, the list of MLCs (Mandatory Lane-Changing) is given as:
1) Making turning (left/right) movement at the immediate/next downstream intersection;
2) Avoiding an incident/permanent obstruction (e.g. parked vehicles because of accidents or other emergencies, or work zone lane closure,);
3) Avoiding the end of current lane

Do you think besides above MLC and DLC reasons, are there any other reasons could also be account for your behavior of changing lanes (please enumerate them, and give out the level of frequency accordingly)? (5 minutes)

6. I'll give out a scenario for each particular lane change, could you enumerate the major factors that affect your decision to attempt a lane change for each of those scenarios? Try to explain how much importance you would assign to applicable factors for each scenario? (45 minutes)

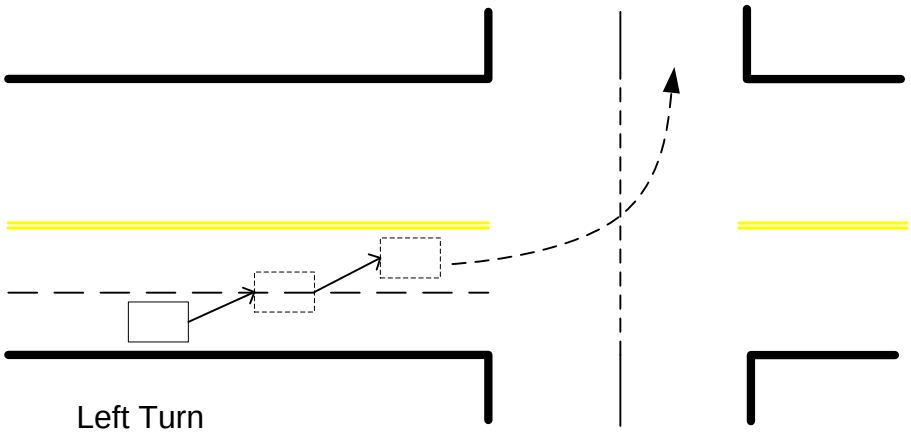
Five levels of importance are as:
Level 1: very important, no other factors are more important than this
Level 2: important, but very important
Level 3: not so important, at middle level

Level 4: this factor will be considered, but it is not an important one

You may be asked to explain briefly how some acceptable DLCs are executed, and how the given MLCs are executed.

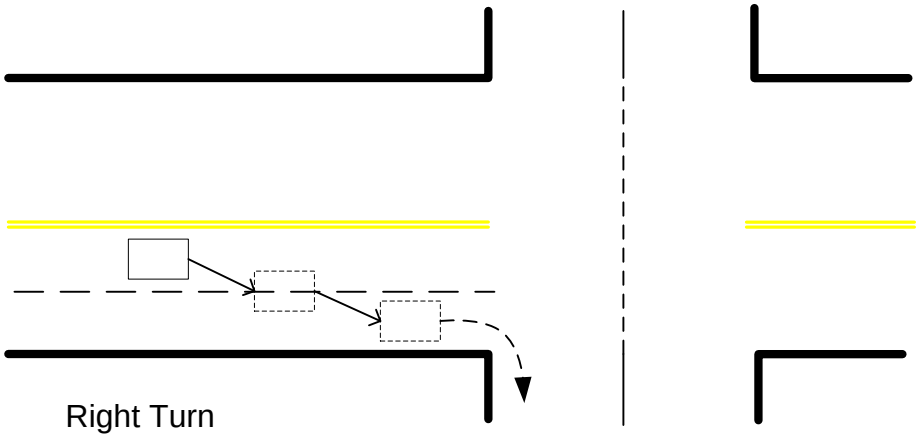
Scenario 1):

6.1.a) You are approaching an intersection where a left turn will be made. Suppose you are not in the correct lane to execute the turn and need at least one lane change to the correct lane. When (how far do you from the intersection) and how will you consider a lane change? (Please describe your concerns and possible maneuvers during the process, 5-6 minutes)



Left Turn Scenario

6.1.b) You are approaching an intersection where a right turn will be made. Suppose you are not driving on a lane for the turn and need at least one lane change to the correct lane. When and how will you consider a lane change? Is there any difference between this and the above situation? (Please describe your concerns and possible maneuvers during the process, 5-6min)

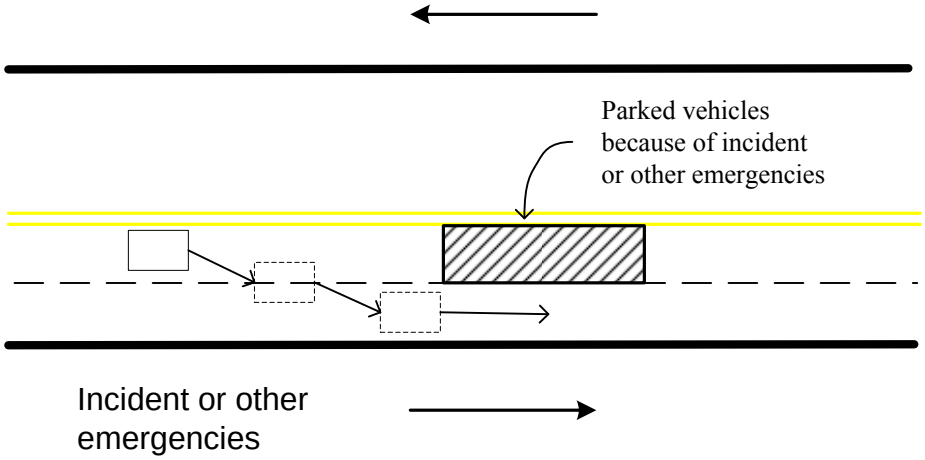


Right Turn Scenario

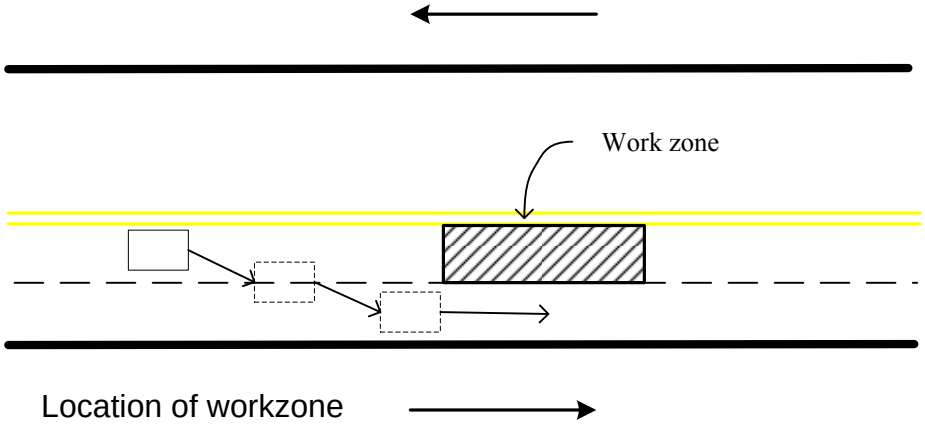
Scenario 2):

6.2.a) You are approaching a location of parked vehicles blocking your lane ahead because of an incident or other specific emergencies. When and how will you consider a lane change to the

open lane to avoid the lane obstruction? (Please describe your concerns and possible maneuvers during the process)

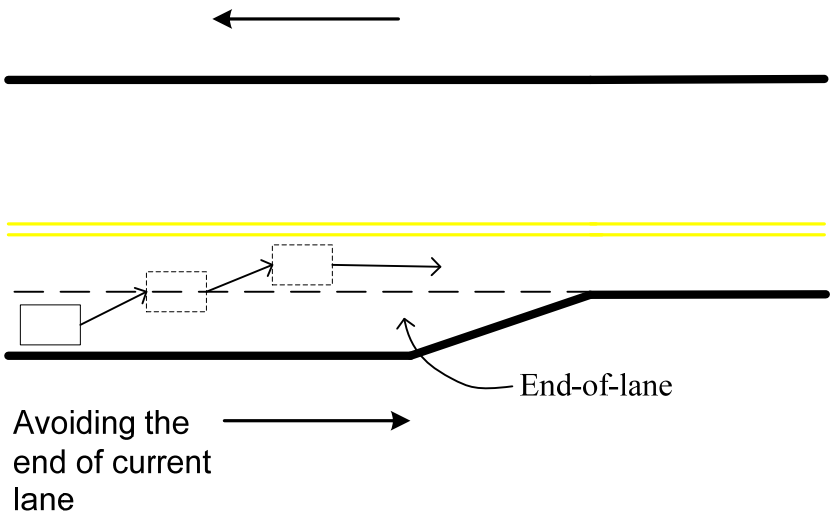


6.2.b) You are approaching a location of a work zone, and the current lane is closed. When and how will you consider a lane change to the open lane to avoid the lane obstruction? (Please describe your concerns and possible maneuvers during the process)



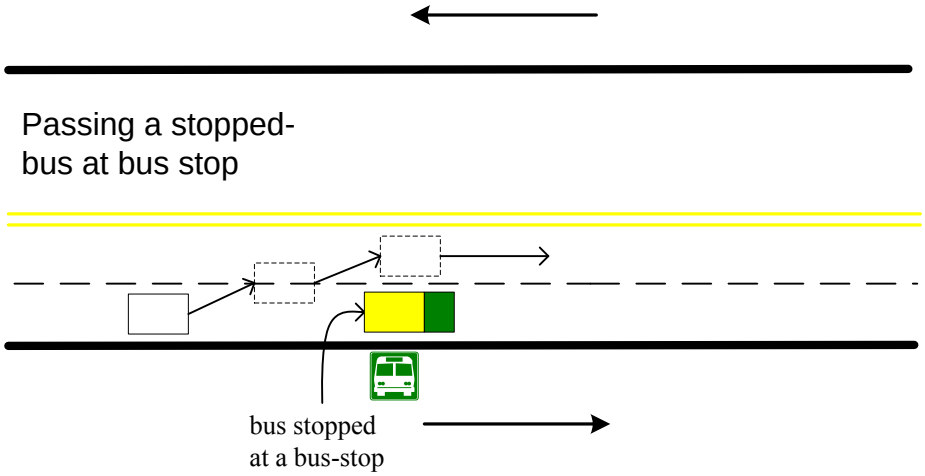
Scenario 3):

6.3) If you see a sign that the lane you are in will end in 1,000 ft, when and how will you consider a lane change to merge into the adjacent lane? (Please describe your concerns and possible maneuvers during the process, 5-6min)



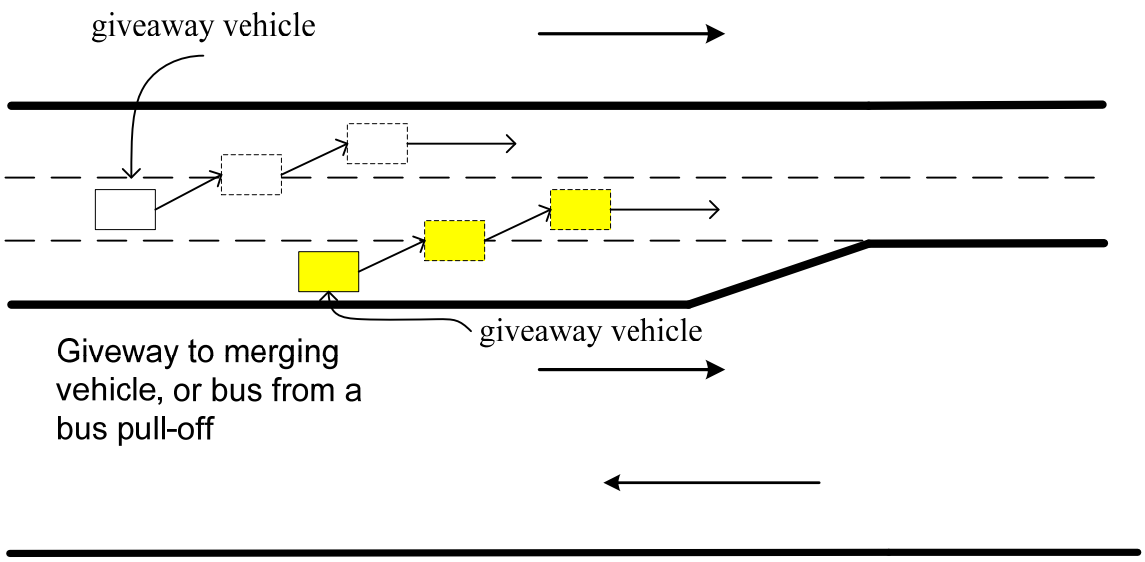
Scenario 4):

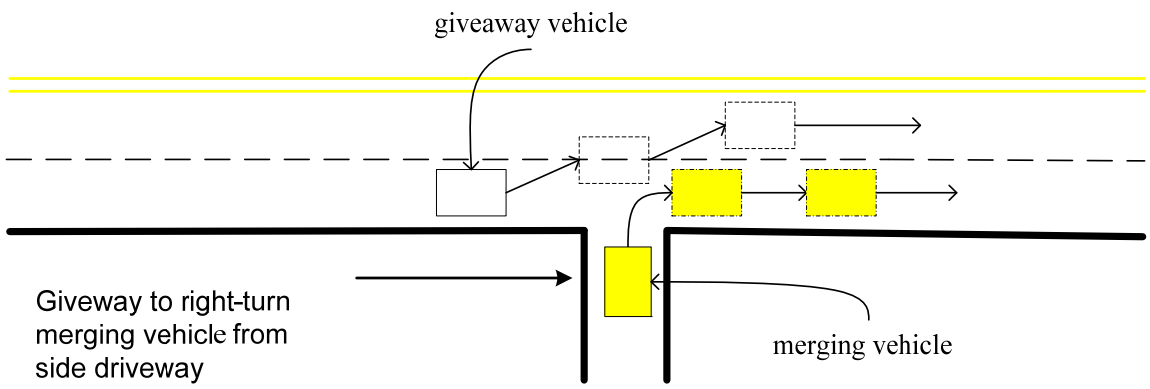
6.4) When driving on your current lane, you find a bus in front is loading or unloading passengers. Will you consider a lane change? If yes, when and how will you consider a lane change to pass the bus? (Please describe your concerns and possible maneuvers during the process, 5-6min)



Scenario 5):

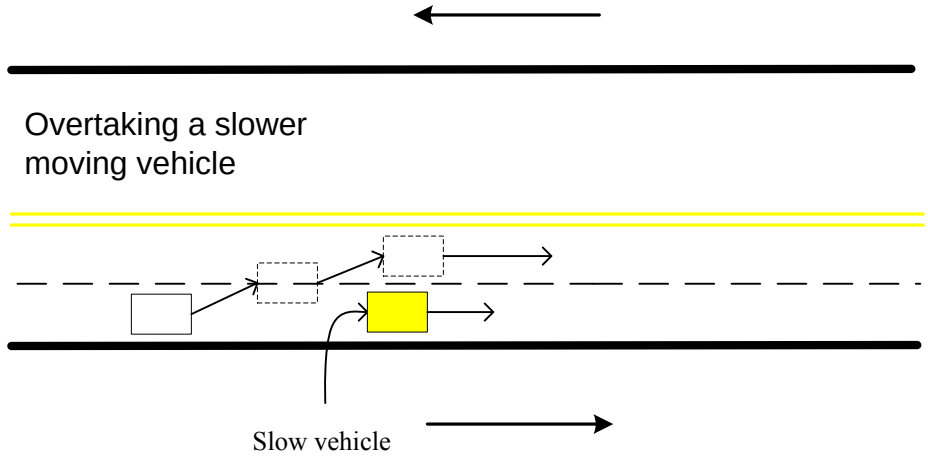
6.5) You find a merging vehicle or a bus from a bus pull-off is entering into your lane. Will you consider a lane change? If yes, when and how will you consider a lane change to pass the vehicle/bus? (Please describe your concerns and possible maneuvers during the process, 5-6min)





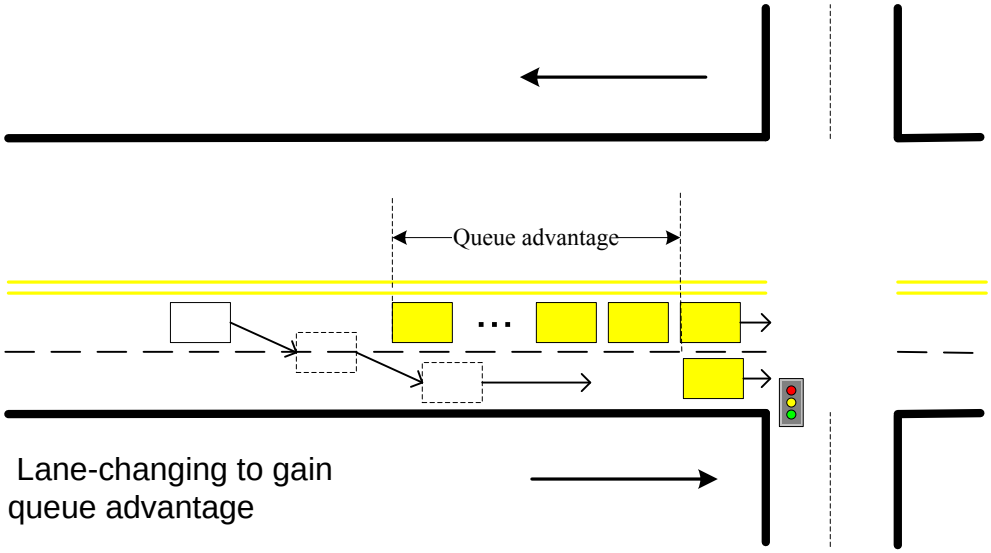
Scenario 6):

6.6) You find the vehicle in front of you is driving slower than you would like speed. Will you consider a lane change? If yes, when and how will you consider a lane change to pass the slow vehicle? (Please describe your concerns and possible maneuvers during the process, 5-6min)



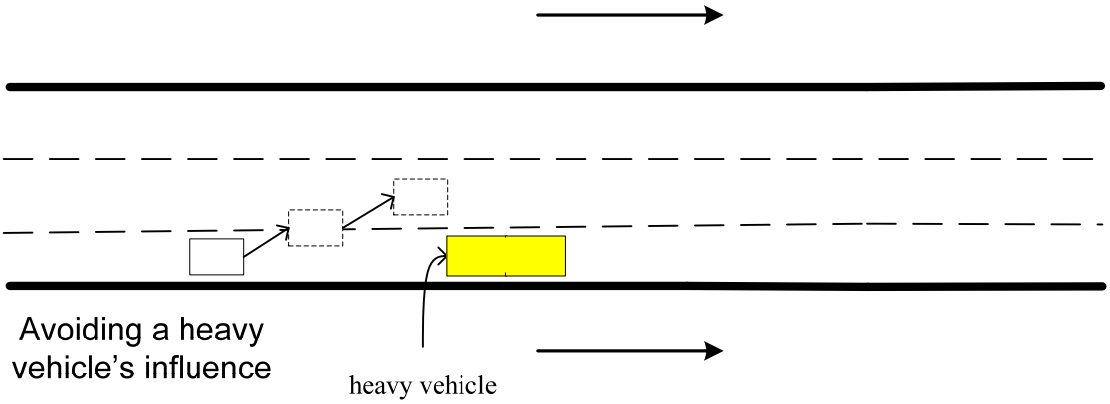
Scenario 7):

6.7) When approaching an intersection, you find the queuing vehicles in your current lane are much longer than that of other lanes. Will you consider a lane change? If yes, when and how will you consider a lane change to gain the queue advantage without other negative influences? (Please describe your concerns and possible maneuvers during the process, 5-6min)



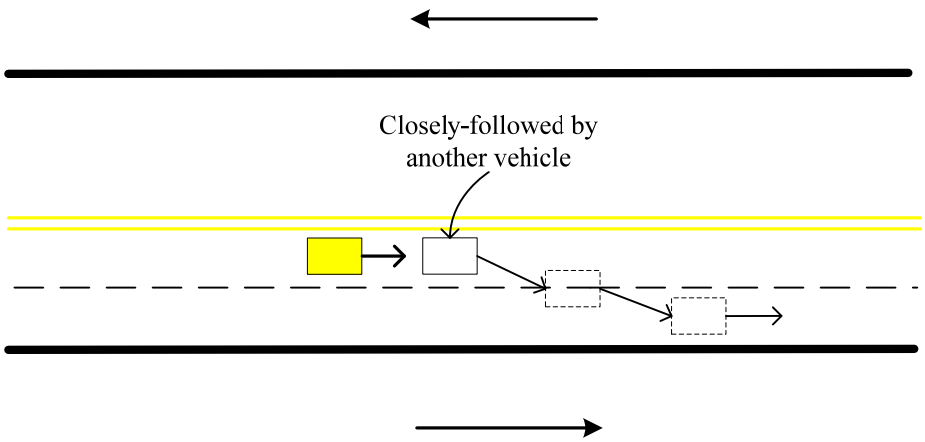
Scenario 8):

6.8) When driving on the current lane, you find a heavy vehicle in front influences your driving state. Will you consider a lane change? If yes, when and how will you consider a lane change to avoid the heavy vehicle's influence? (Please describe your concerns and possible maneuvers during the process 5-6min)



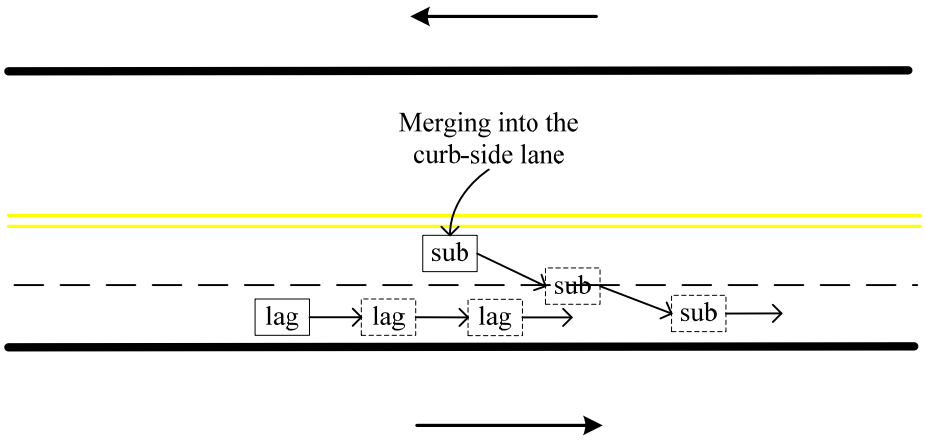
Scenario 9):

6.9) When driving on the center lane, you find you are tailgating by the vehicle behind you. Will you consider a lane change? If yes, when and how will you consider a lane change to avoid the pressure from behind? (Please describe your concerns and possible maneuvers during the process, 5-6 min)

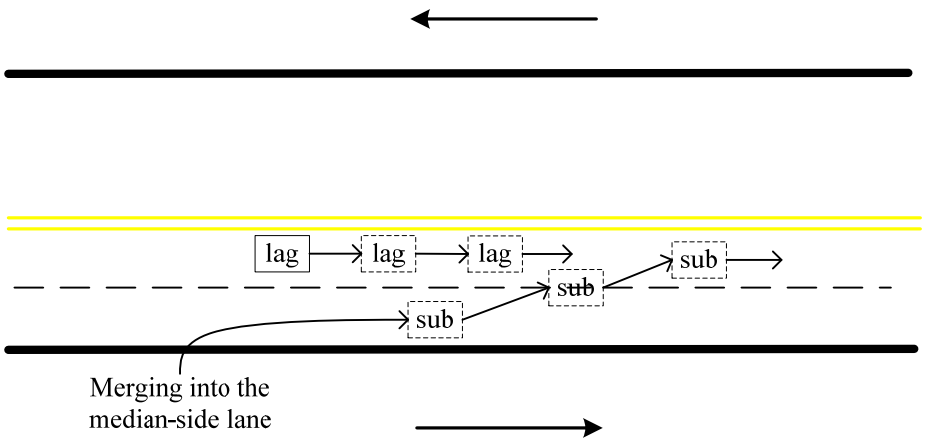


7. Now we want to capture interactions among drivers during a lane change maneuver. Please describe your actions during a lane change maneuver assuming the traffic is congested. Two lane-changing scenarios including both merging to the curb-side lane and the median-side lane will be investigated. Answers from this question would help to indicate the cooperation and competition among drivers for lane changing during congested traffic, so that new model may be developed for the interesting behaviors. (Note: 1. Considering the actions you will adopt if you are a merging driver or lag driver in the target lane respectively? 2. How is the gap acceptance difference between the congested traffic and normal traffic for each scenario?) (25 minutes)

Scenario 1:



Scenario 2:



Ending questions (Intent to close the discussion, enable participants to reflect on previous comments.)

8. Today, we began with the major possible reasons that would invoke a lane change and the procedure for executing it. Then for each reason, the major effective factors which affect drivers' decision on lane change were enumerated and examined. Finally, the possible interactions involved in a lane change behavior were discussed. Did I correctly describe what was said here? Is there anything you want to say but didn't get a chance? (4-5 minutes)

APPENDIX I

K-MEAN ALGORITHM USED TO OBTAIN THE CENTROIDS

Data: *x(j)*, $\forall j \in N$: driver aggressiveness for each participant *j*;

K: number of cluster;

u_i , $\forall i \in [1, K]$: centroid value for cluster *i*;

$\{\mathrm{M}(i)\}$, $\forall i \in [1, K]$: cluster set for each cluster *i*;

initialization: $\{u_1^0, u_2^0, \ldots, u_i^0, \ldots\} \leftarrow \{x\left(1+(i-1)*\left\lfloor \frac{N}{K} \right\rfloor\right)\}$, $\forall i \in K$;

while $(\{u_i^m\} \neq \{u_i^{m+1}\})$ **do** ; centroid for each cluster moves (converge)

for each participant *x(j)* **do**

x(j) $\in$ M(*i*) $\leftarrow$ arg min$(u_i^m)(x(j)-u_i^m)^2$; find the nearest cluster center and assign it to the cluster;

end

x(j) $\in \{u_i^m\} \leftarrow \min(x(j)-u_i^m)^2$;

for each cluster M(*i*) **do**

u_i^{m+1} = avg (M(*i*)); recompute the centroid μ_i for each cluster;

end

m = m + 1

end

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BIOGRAPHICAL SKETCH

Daniel(Jian) Sun received his Ph.D. from Transportation Engineering at the University of Florida in 2009. Before he started his Ph.D. study, Daniel(Jian) Sun received his bachelor's and master's degrees in China in the 2000 and 2003, respectively. He has published more than 10 journal and conference papers related to information integration for the Chinese railway in his master's degree study. His current major research interest is in modeling the driver characteristics in microscopic simulation. He has already published one paper in a related area in "the10th International Conference on Application of Advanced Technologies in Transportation", and has several papers submitted to the peer reviewed journals. Additionally, his research interest also includes urban transportation planning, traffic signal and traffic control. He received the Bill & Bryon Bushnell Graduate Fellowship in 2008. In his spare time, he is a fan of many sports activities. He likes to play badminton, tennis, and volleyball, and watches a lot of soccer games, as well as football and basketball games whenever GATORS are involved.