Modeling Gap Acceptance at Freeway Merges

by

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Abstract

This thesis develops a merging model that captures the gap acceptance behavior of drivers that merge from a ramp into a congested freeway. Merging can be classified into three types: normal, forced and cooperative lane changing. The developed merging model uses a single critical gap function, which incorporates explanatory variables that capture all three types of merging behavior. Thus, the model combines all three types in a single model.

The merging gap acceptance model is estimated using the maximum likelihood method with detailed trajectory data that was collected on two freeway sections in California. Estimation results show that the merging gap acceptance model is affected by traffic conditions such as average speed in the mainline, interactions with lead and lag vehicles, and urgency of the merge. Transferability tests for the stability of the model parameters between the two datasets are conducted. The single level gap acceptance model is implemented and compared with an existing gap acceptance model in the microscopic traffic simulation model, MITSIMLab. The results show that the proposed model is better than the existing gap acceptance model.

Thesis Supervisor: **Moshe E. Ben-Akiva**
Title: Edmund K. Turner Professor of Civil and Environmental Engineering

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Chapter 1

Introduction

1.1 Traffic Congestion

Traffic congestion has been one of the major challenges facing contemporary cities around the world. Not only does traffic congestion continue to grow in urban areas, but also in suburb areas. According to the Urban Mobility Report (Schrank and Lomax, 2005), the total cost of congestion incurred in 85 major areas in the U.S. was 62 and 63 billion dollars in 2002 and 2003, respectively. Furthermore, the worst congestion level increased from 12% to 40% during peak hours. The total of drivers experiencing congested situations during peak hours has doubled from 32% to 67% over twenty years from 1982 to 2003, implying two out of three drivers suffer from traffic congestion during rush hours.

One way to suppress the continual increase in the congestion level is to build more infrastructures. Effectiveness of road construction, however, is relatively low due to its high cost as well as the phenomenon of latent traffic (Small and Gomez-Ibanez, 1999). As Figure 1.1 illustrates, the TTI report (2005) shows that not even half of the roadway required to maintain a constant congestion level is built over twenty years, demonstrating that the rate of road construction lags greatly behind the growth of traffic congestion.

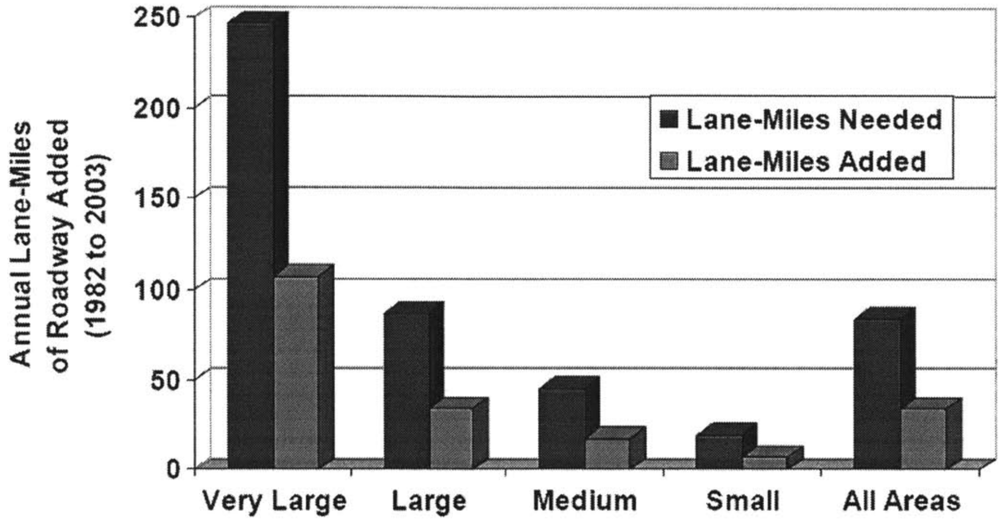

Figure 1.1 Comparison of roadway added to needed

(Source: Urban Mobility Report, TTI 2005)

Due to such inefficiency of road construction, many researchers and engineers have considered traffic management as an alternative solution. The main idea of traffic management is to take advantage of roads and traffic systems that are already built to efficiently minimize the congestion and maximize the safety. In fact, the emergence of Intelligent Transportation Systems (ITS), which integrates technologies such as communications, control, and electronics into transportation system, have enabled great improvements in transportation systems, such as advanced traffic management systems (ATMS) as a main part of ITS.

1.2 Traffic Management at Merging Area

As a significant amount of daily commuting time is spent on freeways, freeway management has emerged as one of major branches of ATMS. Freeway management is also a good example of advanced ITS, which entails surveillance, ramp control, lane management, information dissemination, enforcement, and special event transportation management (U.S. DOT, 2006). An interesting section of the freeway that also plays a significant role in determining the amount of traffic in freeway is the merging area, where traffic from local roads merges into a freeway. This thesis explores such merging areas in freeways.

Various strategies of ramp control exist to improve the traffic congestion and safety at the merging areas with ITS technologies. The three main freeway management technologies used at the merging areas are ramp metering, ramp closures, and priority access. (U.S. DOT, 2006). Ramp metering controls the flow of vehicles entering from on-ramp to main freeway sections by adaptively controlling traffic signals. For example, if traffic volumes in a mainline are heavy, the traffic signal installed at the on-ramp stops vehicles from entering the freeway.

Another management technique to control traffic conditions in freeway is called ramp closures. Using surveillance and control systems, the system allows temporary closures of freeway ramps to avoid the worst traffic conditions during peak hours or to avoid accidents under bad weather conditions.

The last management system often used is priority access, which gives right-of-way to the first priority vehicles, such as emergency or transit vehicles. This access is achieved through communication between a traffic management center and the vehicles such that the first priority vehicles enters freeway regardless of the status of the ramp metering or closure controls.

1.3 Motivation

Many traffic management systems such as ones mentioned in the previous section have been suggested and implemented to improve the traffic congestion in freeway. However, evaluating performance and results of traffic management technologies in the field are difficult due to high installation costs, safety problem, and lack of public acceptance. To overcome the difficulties, microscopic traffic simulation tools that model, analyze, and evaluate possible traffic scenarios are becoming more important in developing ATMS. Microscopic traffic simulation tools have an environment where different scenarios can be provided and evaluated in a controlled setting without installation in real traffic systems. Furthermore, these tools can evaluate complex traffic conditions (i.e., traffic signal, ramp metering, incidents, and traveler information) at the same time. The apparent advantages of the microscopic traffic simulation tools have encouraged researchers to study traveler behaviors for accurate modeling.

Modeling lane changing behavior, in particular, plays an important role in microscopic traffic simulation tools. Lane changing model consists of lane selection model, which concerns driver's decision in changing lanes, and gap acceptance model, which concerns the decision to execute the lane-change. These existing models have been developed under the assumption that a driver makes an independent decision to change lane without any interference from other vehicles in the destination lane (Hidas, 2002). However, Hidas (2002) argued that the assumption no longer holds in congested merging areas. In fact, certain dependent behaviors (e.g., interference and yielding) have been observed in merging areas.

Merging is a special instance of lane changing where vehicles have to move to a target lane because of lane closure or incidents. Merging can be classified into three types: normal, forced and cooperative lane changing, in particular congested conditions. Modeling merging behaviors in congested conditions is difficult because three different types are observed in the merging areas, and the types require complex decision-making processes. Thus, modeling driver's merging behaviors in congested situations is necessary for accuracy.

1.4 Objectives

This thesis develops a gap acceptance model for freeway merging under congested conditions. Such a merging model combines all lane changing types: normal, courtesy, and forced lane changing into a one-stage model, which includes explanatory variables to capture normal, courtesy and forced merging. Once designed, the model is then estimated using maximum likelihood method on two different trajectory data sets, I-80 and U.S. 101, containing information such as vehicles' speed, acceleration, and position. To apply the model in all congested situations, the hypothesis that the goodness of fit in the combined dataset is not significantly different from the individual datasets is tested. Finally, the merging gap acceptance model is implemented into MITSIMLab, which is a microscopic traffic simulator.

1.5 Thesis Outline

This thesis consists of seven chapters. Chapter 2 reviews the literature on merging models and existing lane-changing models, followed by explanation of the model framework and the likelihood function of the proposed model in Chapter 3. Chapter 4, then, describes data analysis of the trajectory data sets, U.S. 101 and I-80., where the estimation results of the proposed models and the results of likelihood ratio test of the estimated models are presented in Chapter 5. In Chapter 6, the proposed model is implemented into MITSIMLab, which a microscopic simulator, and the result of implementation is discussed. Finally, conclusions and direction of further research are summarized in Chapter 7.

Chapter 2

Literature Review

Modeling gap acceptance at freeway merging areas incorporates lane changing models, such as the lane selection and gap acceptance models. Some of these models have been developed and demonstrated in past literature, and a thorough review is necessary to motivate and place this thesis work in its context. This chapter, thus, describes these existing models in the chronological order: merging, lane selection, and gap acceptance models.

2.1 Merging models

Modeling freeway merging behaviors in a congested situation is difficult due to involuntary lane changing behaviors, such as forced merging and courtesy merging. Thus, little literature on the merging models at freeway sections have been published. Nevertheless, the existing merging models, such as those developed by Skabardonis (1985), Kita(1999), Ahmed (1999), and Hidas (2002), provide a good foundation and motivation for this thesis work.

Skabardonis (1985) developed a microscopic simulation model to examine the relations between traffic and geometric variables. In this model, geometric parameters, such as slip road length, gradient, and acceleration lane length, are used as input data. In addition, he developed the merging process of single driver behavior and queuing-multiple entries considering lead and lag times. Skabardonis' model adopts the following mechanisms in a queuing situation:

- When a driver of a queuing vehicle arrives at the merging area, he evaluates the mainstream gaps only if the leading vehicle decides to merge.
- Given a large mainstream gap, many queuing vehicles accept the same lag at the same time.

These mechanisms were implemented in Fortran IV, and were calibrated and validated using a large number of video clips collected during the peak hours in the U.K. With the successful validation, Skabardonis demonstrated the effectiveness of his model in evaluating traffic control strategies at the merging area.

While Skabardonis based his model on geometric parameters, Kita (1999) developed a model based on game theory. In particular, Kita modeled the interaction between through vehicles in mainlines and merging vehicles from on-ramps as a two-person non-zero-sum non-cooperative game. A vehicle entering from an on-ramp has two options: merging into the mainlines or staying in a merging lane (i.e., acceleration lane). A through vehicle in a mainline also has two options: giving a way to the merging vehicle and going through the merging areas without giving courtesy to the merging vehicle. Based on game theory, Kita estimated the merging probability of a merging vehicle and the giveway probability of a through vehicle using a maximum likelihood estimation technique.

In addition, his model incorporated several explanatory variables for the estimation, such as distance between a merging car and the end of the acceleration lane, speed of a merging car, time to collision of a merging car to a through car, and time headway between two consecutive through cars. Kita claims in his paper that the model has capabilities to capture merging and giveway behaviors in the real world.

Ahmed (1999) developed a lane changing model that captures both mandatory lane changing (MLC) and discretionary lane changing (DLC) situations. An MLC situation occurs when a driver must leave current lane, such as due to lane-drop situation or merging situation from on-ramp. A DLC situation occurs when a driver decides that driving conditions in a target lane are better than those in the current lane. Since it is difficult to explain drivers' behavior in MLC situations, Ahmed estimated the parameters of the discretionary and mandatory components of the model separately. The MLC component was estimated for a special case of vehicles merge onto a freeway from the on-ramp. The estimation results from the MLC situation are summarized in Table 2.1.

Table 2.1 Estimation results for MLC model proposed by Ahmed (1999)

Variable	Parameter value
Utility of mandatory lane change	
Constant	-0.654
First gap dummy	-0.874
Delay (sec.)	0.577
Lead critical gap	
Constant	0.384
$\sigma_{\varepsilon}^{lead,MLC}$	0.859
Lag critical gap	
Constant	0.587
Min (0, lag speed - subject speed), m/sec.	0.0483
Max (0, lag speed - subject speed), m/sec.	0.356
$\sigma_{\varepsilon}^{lag,MLC}$	1.073

In addition to this lane changing model, Ahmed (1999) developed and estimated a forced merging model, which captures drivers' lane changing behaviors in heavily congested traffic conditions.

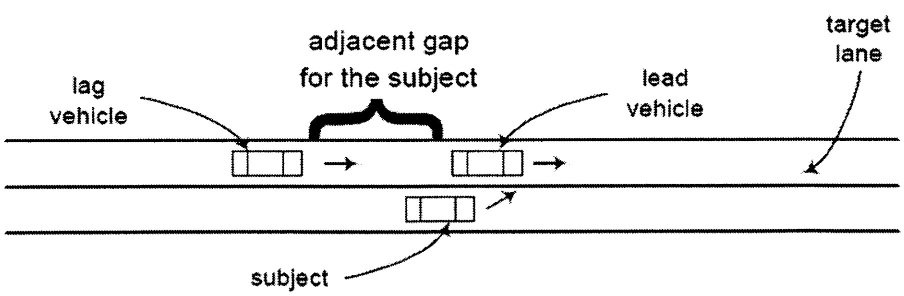

Figure 2.1 Definition of adjacent gap by Ahmed (1999)

The model assumes that after a driver evaluates traffic conditions in his target lane, such as adjacent gaps between lead and lag vehicles. (Figure 2.1), the driver changes lanes either through courtesy yielding of the lag vehicle in the target lane or by forcing the lag vehicle to slow down. Important variables affecting this behavior include lead relative speed, the remaining distance to the point where the lane change must be completed by, and existence of a total clear gap in excess of the subject vehicle length. The estimation results from the forced merging situation are summarized in Table 2.2.

Table 2.2 Estimation results of the forced merging model by Ahmed (1999)

Variable	Parameter value
Constant	-3.16
Min(0, lead veh. speed – subject speed) (m/s)	0.313
Remaining distance impact x 10	2.05
Total clear gap divided by 10 (meters)	0.285

Hidas (2002) developed merging algorithms incorporating both forced merging and courtesy merging under congested traffic conditions in SITRAS. The lane changing procedures in SITRAS are as follows (Figure 2.2):

- Check whether a driver needs necessary lane changing
- Select a target lane into which the driver wants to move
- Evaluate whether lane changing to the target lane is feasible
- Simulate driver courtesy in the target lane if lane changing to the target lane is not feasible
- Execute lane changing to the target lane

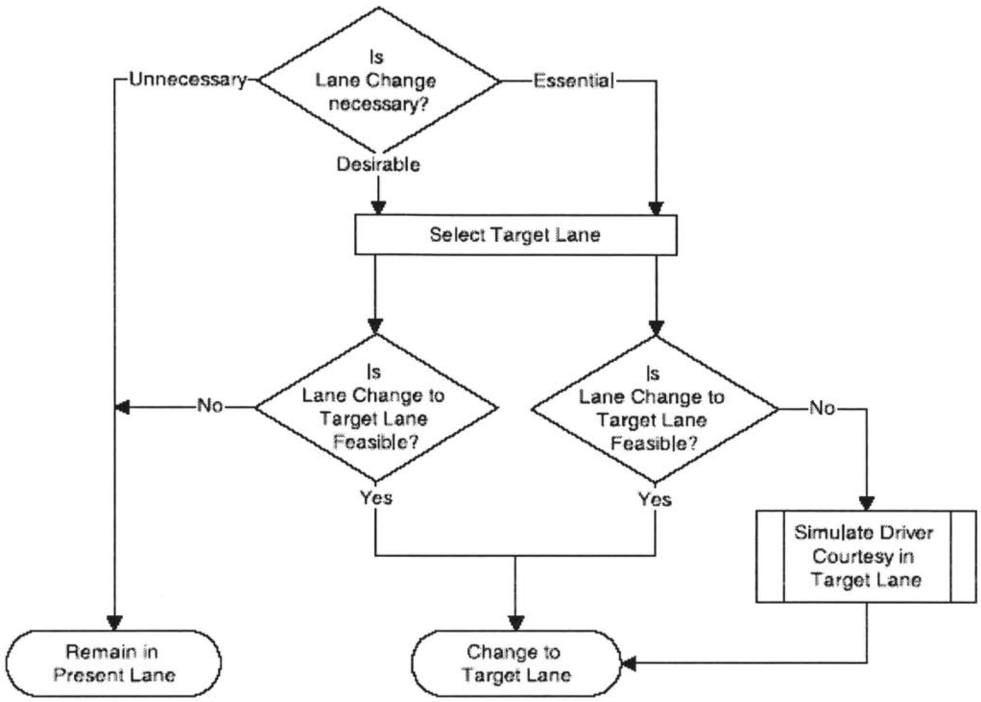

Figure 2.2 Summary flowchart of the lane changing process in SITRAS by Hidas (2002).

Hidas (2005) developed a more advanced lane change model incorporating explicit merging behavior based on his previous research (Hidas, 2002) in ARTEMiS. This model includes three lane change situations in a congested traffic environment—free, cooperative, and forced lane change situation—and selects one of the three lane change behaviors using a set of conditions. To determine if a lane change is feasible, Hidas focused on the minimum space gap, which is a function of the subject vehicle's speed. Thus, each lane changing behavior in the model was formulated by minimum acceptable gaps with respect to the speed, acceleration, and deceleration of the subject vehicle and the follower vehicle (Figure 2.3).

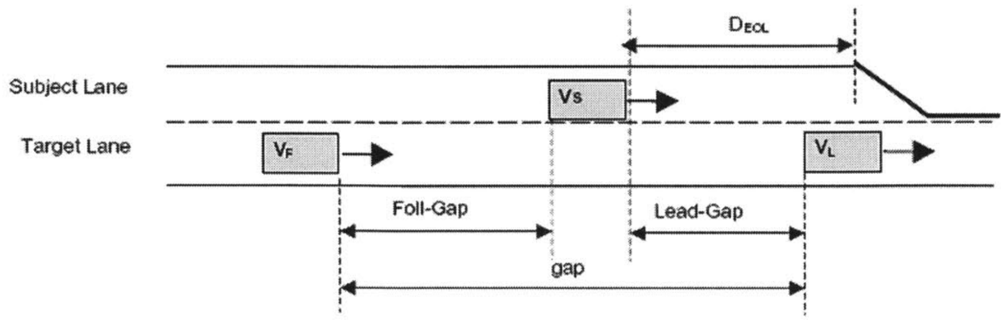

Figure 2.3 Basic notations for a lane change maneuver by Hidas (2005).

2.2 Limitations of existing merging models

Little literature related to merging models at freeway sections have been published because modeling freeway merging behaviors in a congested situation is difficult and complex. The existing merging models are either formulated as a deterministic way or estimated with a number of simplifications. There are no estimation results with the detailed vehicle trajectory except Ahmed's model. However, Ahmed separately estimated the normal gap acceptance model and forced merging model. Furthermore, the vehicle trajectory data for the estimation is free flow, not congested conditions.

2.3 Lane-changing models

This section summarizes the literature on two important lane-changing models: lane-selection and gap acceptance models.

2.3.1 Lane selection models

Gipps (1986) introduced the first lane changing model under various urban driving situations, in which traffic signals, transit lanes, obstructions and the presence of heavy vehicles affect drivers' lane selection. In this work, Gipps categorized lane selection as either physically feasible, necessary, or desirable. Gipps assumed that the driver's behavior is governed by two basic considerations: attaining the desired speed and being in the correct lane to perform turning maneuvers. Based on these, Gipps classified a driver's behaviors into three patterns. The first pattern is when a turn is out-of the way and the driver focuses on maintaining his desired speed. The second pattern is when the driver enters the zone and begins to ignore maintaining his speed and attempts to drive closer to his turning lanes or lanes that are adjacent to them. The third pattern is when the driver focuses only on maintaining the correct lane without considering his desired speed.

CORSIM (Halati et al 1997, FHWA 1998), a microscopic traffic simulation model, which includes a lane changing model, was developed by FHWA. This model classifies lane change as either mandatory (MLC) or discretionary (DLC), and computes a risk factor for each potential lane change and for both the subject vehicle and the intended follower. The risk factor is calculated primarily by the deceleration a driver must apply if its leader is to brake to a stop, and subsequently compared to a threshold value, which is determined by the type of lane change and the urgency. Variability in gap acceptance behavior, however, is ignored in this model.

Yang and Koutsopoulos (1996) implemented a rule-based lane changing model for the first time in MITSIM, in which lane changes are again classified as mandatory (MLC) or discretionary (DLC). MLC is modeled with an assumption that the driver has four goals in performing MLC: to move to the next destination on their travel path, to bypass a lane blockage, to avoid a restricted-use lane and to comply with signs. If there are conflicting goals, probability based on utility theory models is used to resolve, then, DLC, on the other hand, is modeled with the assumption that the primary goal of the driver in changing lanes is to achieve desired speed.

Hidas and Behbahanizadeh (1999) implemented a similar model with MLC and DLC classification in the micro-simulator SITRAS. The two distinct features that make their model unique are a new definition of goals for DLC and the introduction of cooperative lane changing in MLC. In addition to the speed advantage in DLC, similar to Yang and

Koutsopoulos' model, a queue advantage was added as a motivation for DLC. In other words, if the adjacent lane provides a faster speed or a shorter queue, a driver has a motivation to change lanes.

The second interesting feature of Hidas' model is the cooperative lane changing. In heavily congested traffic conditions, MLC may occur through cooperation with the intended follower. If the intended follower is less aggressive and willing to allow the subject vehicle into his lane (Figure 2.3), he begins to follow the subject vehicle while the subject vehicle starts following the intended leader in the target lane. As a result of this cooperation, the subject vehicle is now able to change lanes into the gap opened up in the target lane.

A general lane changing model that captures both MLC and DLC situations was developed by Ahmed et al (1996) and Ahmed (1999). The lane changing process is modeled in three-steps. First, a decision to consider a lane change is modeled using a discrete choice framework. Then, selection of a target lane is captured by Logit models. Lastly, the acceptance of gaps in the target lane is modeled using different gap acceptance parameters for DLC and MLC situations.

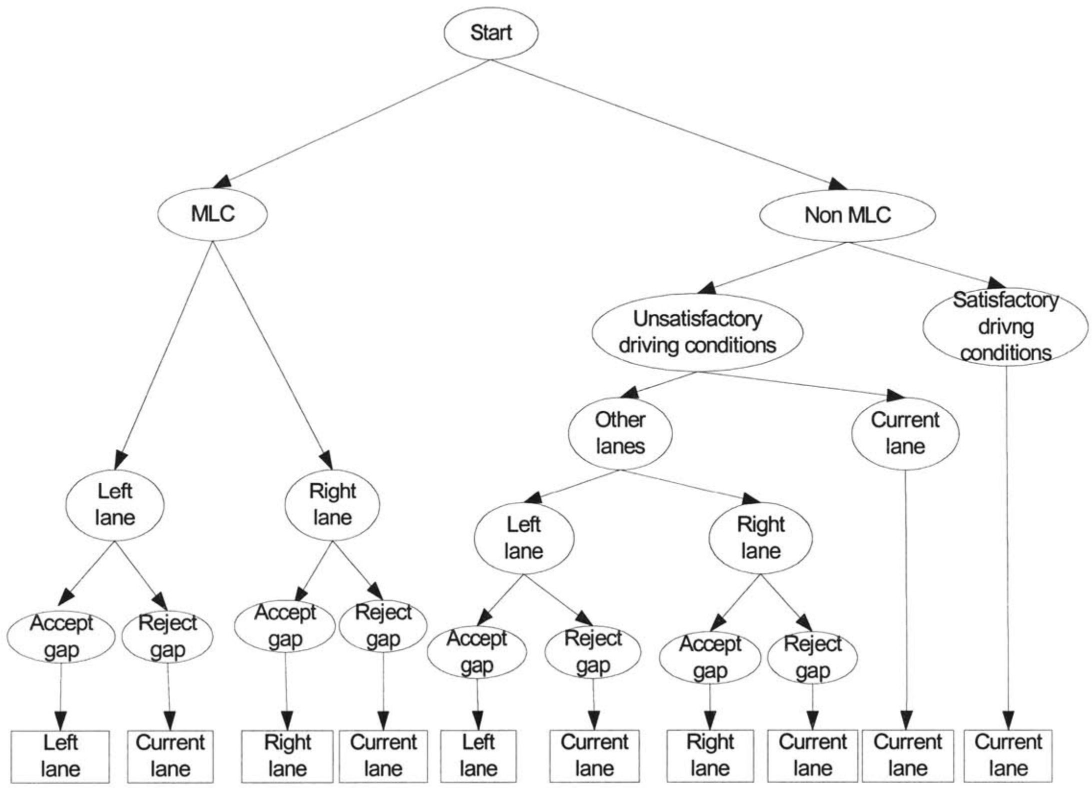

Figure 2.4 - Structure of the lane changing model proposed by Ahmed (1999)

As Figure 2.4 illustrates Ahmed model first considers decisions made in an MLC situation. The utility of responding to an MLC situation is affected by two factors: time delay since the MLC situation arose, and a bias against using the first gap available to the driver. If an MLC situation does not apply or the driver decides not to respond to the MLC situation, then a decision whether to consider a DLC is made using a two-step decision process. First, drivers evaluate their satisfaction with the current driving conditions, which is affected by the difference between the subject speed and its desired speed. Second, if the driver is not satisfied with the current driving conditions, he then compares conditions in neighboring lanes in order to decide the target lane and whether to change lane. The utilities of neighboring lanes are affected by two factors: the speeds of the lead and lag vehicles, and the current and desired speed of the subject vehicle.

This model also incorporates special situations into the structure. For example, different behaviors are implemented for heavy vehicles and are modeled in the presence of tailgating vehicles. This lane changing framework also includes a gap acceptance model, which is discussed in more detail in Section 2.3.2. The estimation results for the MLC and DLC models are summarized in Table 2.3 and Table 2.4, respectively.

Table 2.3 - Estimation results for the DLC model proposed by Ahmed (1999)

Variable	Parameter value
Utility of unsatisfactory driving conditions	
Constant	0.225
(Subject speed - desired speed), m/sec.	-0.0658
Heavy vehicle dummy	-3.15
Tailgate dummy	0.423
Utility of left lane	
Constant	-2.08
(Lead speed - desired speed), m/sec.	0.0337
(Front speed - desired speed), m/sec.	-0.152
(Lag speed - subject speed), m/sec.	-0.0971
Desired speed model	
Average speed, m/sec.	0.768
Lead critical gap	
Constant	0.508
Min (0, lead speed - subject speed), m/sec.	-0.420
$\sigma_{\varepsilon}^{lead,DLC}$	0.488
Lag critical gap	
Constant	0.508
Min (0, lag speed - subject speed), m/sec.	0.153
Max (0, lag speed - subject speed), m/sec.	0.188
$\sigma_{\varepsilon}^{lag,DLC}$	0.526

Table 2.4 - Estimation results for the MLC model proposed by Ahmed (1999)

Variable	Parameter value
Utility of mandatory lane change	
Constant	-0.654
First gap dummy	-0.874
Delay (sec.)	0.577
Lead critical gap	
Constant	0.384
$\sigma_{\varepsilon}^{lead,MLC}$	0.859
Lag critical gap	
Constant	0.587
Min (0, lag speed - subject speed), m/sec.	0.048
Max (0, lag speed - subject speed), m/sec.	0.356
$\sigma_{\varepsilon}^{lag,MLC}$	1.073

Despite the efforts to integrate MLC and DLC situations in one model, Ahmed (1999)'s model had separate estimations for DLC and MLC situations. Toledo (2003) was to the first to overcome the difficulties in joint estimation, and developed an integrated lane-shift model that allows joint evaluation of mandatory and discretionary considerations. In this model, explanatory variables such as the distance to the off-ramp vary the relative importance of MLC and DLC considerations. The awareness to the MLC situation is, then, represented more realistically as a continuously increasing function rather than as a step function.

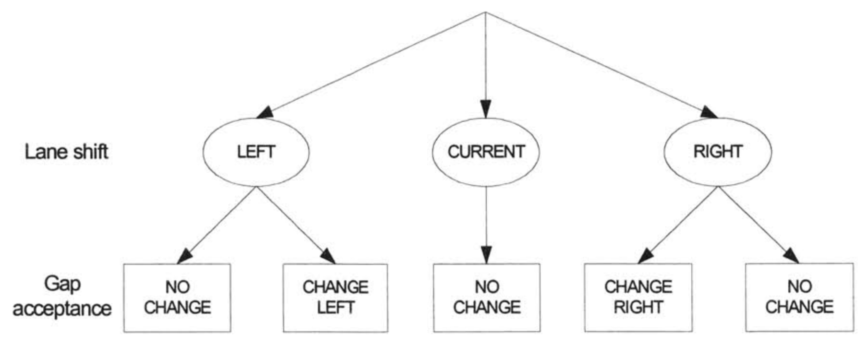

Figure 2.5 - Structure of the lane-changing model proposed by Toledo (2003)

As Figure 2.5 illustrates, the model consists of two levels: choice of a lane shift and gap acceptance decisions, where latent choices are enclosed with ovals and observed ones are enclosed with rectangles. The first step in the decision process, lane shift, is latent since the target lane choice is unobservable and only the driver's lane-changing actions are observed. The first level depicts the driver's two options: to stay in the current lane or to move to an adjacent lane. The CURRENT branch corresponds to a situation where the driver decides to stay in the current lane. In the RIGHT and LEFT branches, the driver decides that changing lanes would improve driving conditions, such as speed and path plan. In these cases, the driver evaluates the adjacent gap in the target lane and decides whether gap acceptance is acceptable to execute lane-change (CHANGE RIGHT or CHANGE LEFT) or not (NO CHANGE). This two-level decision process is repeated every time step.

The explanatory variables used in this model are neighborhood variables, path plan variables, network knowledge and experience, and driving style and capabilities. Since information about the driver's style and characteristics is not available, individual specific error terms are introduced to capture unknown information. The parameters of the model were estimated jointly using second by second trajectory data collected in a section of I-395 Southbound in Arlington, VA. The estimation results of the integrated lane shift model are summarized in Table 2.5.

Table 2.5 - Estimation results for the lane shift model (Toledo, 2003)

Variable	Parameter value	t-statistic
Shift direction model		
CL constant	2.490	3.74
RL constant	-0.173	-0.51
Right-most lane dummy	-1.230	-3.89
Subject speed, m/sec.	0.062	1.59
Relative front vehicle speed, m/sec.	0.163	3.02
Relative Lag speed, m/sec.	-0.074	-1.30
Front vehicle spacing, m.	0.019	3.42
Tailgate dummy	-3.162	-1.68
Path plan impact, 1 lane change required	-2.573	-4.86
Path plan impact, 2 lane changes required	-5.358	-5.94
Path plan impact, 3 lane changes required	-8.372	-5.70
Next exit dummy, lane change(s) required	-1.473	-2.30
θ^{MLC}	-0.378	-2.29
π_1	0.004	0.46
π_2	0.009	0.77
α^{CL}	0.734	4.66
α^{RL}	2.010	2.73
Lead Critical Gap		
Constant	1.353	2.48
$Max\left(\Delta V_n^{lead}(t),0\right)$, m/sec.	-2.700	-2.25
$Min\left(\Delta V_n^{lead}(t),0\right)$, m/sec.	-0.231	-2.42
α^{lead}	1.270	2.86
σ^{lead}	1.112	2.23
Lag Critical Gap		

Constant	1.429	6.72
$Max\left(\Delta V_n^{lag}(t),0\right)$, m/sec.	0.471	3.89
α^{lag}	0.131	0.64
σ^{lag}	0.742	3.68

Choudhury (2005) developed a lane-changing model with explicit choice of target lane, and estimated jointly using a maximum likelihood estimator and detailed vehicle trajectory data. The model consists of two levels of decision-making: the target lane choice and the gap acceptance. The structure of the model is shown in Figure 2.6.

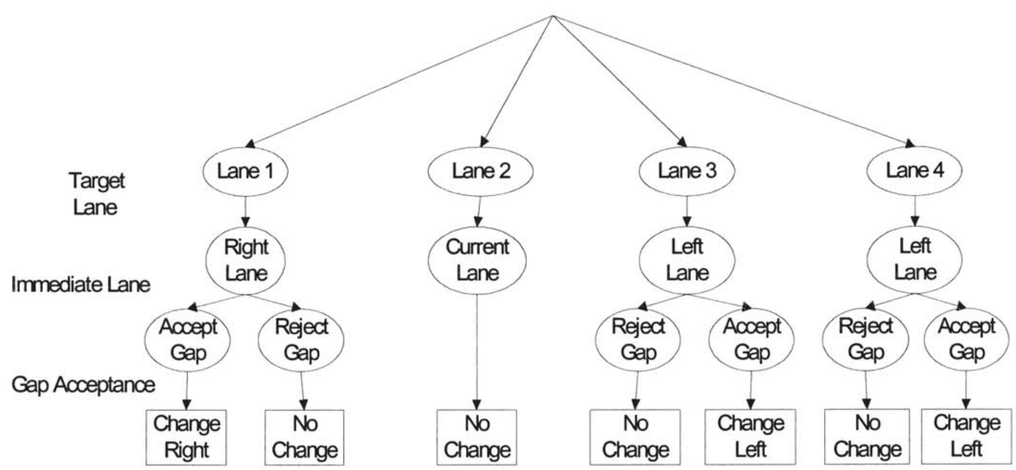

Figure 2.6 - Example of the structure of the Choudury(2005) lane-changing model

The lane-changing decision process is latent, and only the driver's actions are observed. Latent choices are shown as ovals and observed choices are represented as rectangles. The decision structure shown on the top is for a vehicle that is currently in the second lane to the right (Lane 2) in a four-lane road. Therefore, Lane 3 and Lane 4 are on its left, and Lane 1 is on its right. At the highest level, the driver chooses the target lane. In contrast with existing models the choice set constitutes of all available lanes in the road (Lane 1, Lane 2, Lane 3, Lane 4 in this example). The driver chooses the lane with the highest utility as the target lane. If the target lane is the same as the current lane (Lane 2 in this case), no lane change is required (No Change). Otherwise, the direction of change is to the right (Right Lane) if the target lane is Lane 1, and to the left (Left Lane) if the target lane is either Lane 3 or Lane 4. If the target lane choice dictates a lane change, the driver evaluates the gaps in the adjacent lane corresponding to the direction of change and either accepts the available gap and moves to the adjacent lane (Change Right or Change Left) or rejects the available gap and stays in the current lane (No Change).

Explanatory variables affecting the target lane utilities of a driver are lane attributes, surrounding vehicle attributes, and path plan. Information about the driver's style and characteristics is however not available and is captured by introducing individual specific error terms.

The parameters of the model were estimated jointly using second by second trajectory data collected in a section of I-395 Southbound in Arlington, VA. The estimation results of the target lane model are summarized in Table 2.6.

Table 2.6 - Estimation results of the target lane model

Variable	Parameter value	t-statistic
Target Lane Model		
Lane 1 constant	-1.696	-3.03
Lane 2 constant	-0.571	-1.68
Lane 3 constant	0.059	1.16
Lane density, vehicle/km	-0.013	-1.21
Average speed in lane, m/sec	0.176	1.59
Front vehicle spacing, m.	0.024	3.86
Relative front vehicle speed, m/sec.	0.115	1.46
Tailgate dummy	-4.935	-1.96
CL dummy	2.686	1.55
1 lane-change from the CL	-0.845	-1.15

Each additional lane-change from the CL	-3.338	-1.91
Path plan impact, 1 lane change required	-2.549	-4.57
Path plan impact, 2 lane changes required	-4.953	-2.19
Path plan impact, 3 lane changes required	-6.955	-1.65
Next exit dummy, lane change(s) required	-0.872	-1.35
θ^{MLC}	-0.417	-2.48
π_1	0.001	0.68
π_2	0.086	1.38
α^{lane1}	-1.412	-2.29
α^{lane2}	-1.072	-0.50
α^{lane3}	-0.071	-3.61
α^{lane4}	-0.089	-1.56
Lead Critical Gap		
Variable	Parameter value	t-statistic
Constant	1.541	5.59
$Max\left(\Delta S_{nt}^{lead},0\right)$, m/sec.	-6.210	-3.60
$Min\left(\Delta S_{nt}^{lead},0\right)$, m/sec.	-0.130	-2.09
α^{lead}	-0.008	-3.17
σ^{lead}	0.854	1.29
Lag Critical Gap		
Constant	1.426	5.35
$Max\left(\Delta S_{nt}^{lead},0\right)$, m/sec.	0.640	3.36
α^{lag}	-0.205	-0.48
σ^{lag}	0.954	4.80

Number of drivers = 442	$L(0) = -1434.76$
Number of observations = 15632	$L(\hat{\beta}) = -875.81$
Number of parameters = 31	$\bar{\rho}^2 = 0.368$

2.3.2 Gap acceptance models

One of the interesting and important behaviors modeled in lane-changing is gap acceptance. Once a target lane is selected, the driver evaluates the positions and speeds of the lead and lag vehicles (see Figure 2.7), and decides whether the gap between them is adequate to execute a lane-change.

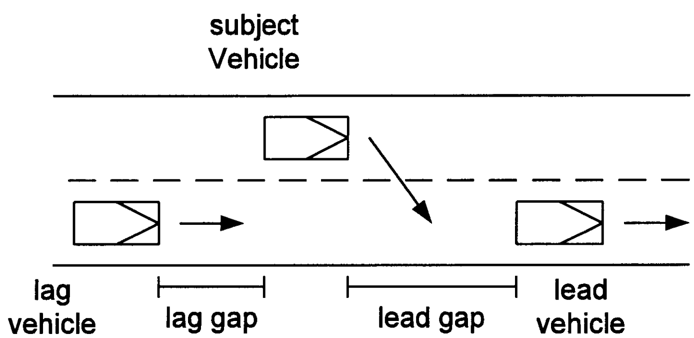

Figure 2.7 - Gap acceptance elements

Gap acceptance is formulated as a binary choice problem as shown below:

$$Y_n(t) = \begin{cases} 1 & \text{if } G_n(t) \geq G_n^{cr}(t) \\ 0 & \text{if } G_n(t) < G_n^{cr}(t) \end{cases} \tag{2.1}$$

,where $Y_n(t)$ is the choice indicator variable, $G_n(t)$ is the available gap and $G_n^{cr}(t)$ is the critical gap. The driver accepts ($Y_n(t)$=1) or rejects ($Y_n(t)$=0) the observed gap by comparing the gap to an unobserved critical gap:

The key parameter of this formulation is critical gap, $G_n^{cr}(t)$. Due to the probabilistic nature of gap acceptance decisions, critical gaps are modeled as random variables. Various distributions have been suggested in the past, such as exponential by Herman and Weiss (1961), lognormal by Drew et al (1967), normal by Miller (1972) and multivariate normal by Daganzo (1981). In particular, Daganzo (1981)'s multivariate normal distribution captures critical gap variation in the population as well as in the behavior of a driver over time. To estimate parameters of the multivariate normal distribution of critical gaps, he used a multinomial probit model formulation appropriate for panel data. The critical gap for driver n at time t is given by:

$$G_n^{cr}(t) = G_n + \varepsilon_n^{cr}(t) \tag{2.2}$$

where G_n is a driver specific random component of the critical gap, which captures the within driver variability over time. $\varepsilon_n^{cr}(t)$ is the random term associated with variability across drivers. G_n and $\varepsilon_n^{cr}(t)$ are assumed to be mutually independent normally distributed random variables.

In the same year, Mahmassani and Sheffi (1981) introduced impatience functions to gap acceptance models, which capture the impatience and frustration of drivers standing at the stop lines. The model was estimated for a stop-controlled intersection under the assumption that critical gaps are normally distributed and that the mean of distribution is a function of explanatory variables. They were the first to show that the number of rejected gaps (or waiting time at the stop line) was found to have a significant impact on gap acceptance behavior.

Further works on the impatience function were followed by Madanat (1993) and Velan (1996). While Madanat et al (1993) used total queuing time to model impatience, Velan and Van Aerde (1996) employed a decaying critical gap function. Velan (1996) showed that critical gaps decay linearly with waiting time through implementation in INTEGRATION, a mesoscopic traffic simulator.

Cassidy et al (1995) captured gap acceptance behavior at stop controlled T-intersections using a logit model. They achieved a great improvement in the fit of the gap acceptance model by differentiating lags (the first gap) from subsequent gaps and gaps in the near lane from gaps in the far lane.

Gap acceptance models are often embedded in the overall lane changing model. For example, Kita (1993) estimated a logit gap acceptance model for the case of vehicles merging to a freeway from a ramp in his lane-changing model. He found that important factors are the length of the available gap, the relative speed of the subject with respect to mainline vehicles and the remaining distance to the end of the acceleration lane.

Ahmed (1999) also postulated a gap acceptance model within the framework of the lane changing model described in Section 2.1 and 2.3.1. Ahmed postulated that drivers consider the lead gap and the lag gap separately and only execute lane change if both gaps are acceptable. This behavior is mathematically formulated as below:

$$G_n^{cr,g}(t) = exp\left(X_n^g(t)\beta^g + \alpha^g \upsilon_n + \varepsilon_n^g(t)\right) \qquad g=lead,\ lag \tag{2.3}$$

where $X_n^g(t)$ and β^g are vectors of explanatory variable and the corresponding parameters, υ_n is an individual specific random term with normal distribution, and α^g is the parameter of υ_n. $\varepsilon_n^g(t)$ is also a normally distributed generic random term.

The critical gap functional form is shown above guarantees that it is always non-negative. These gap acceptance parameters were estimated jointly with other components of the model. A similar critical gap approach was used by Toledo (2003) in the lane-shift model and by Choudhury (2005) in the target lane model.

2.4 Summary

In this chapter, the existing merging models are reviewed and general lane changing model, lane selection and gap acceptance models, are studied. There exist only a few studies related to the merging gap acceptance model in congested situations. Furthermore, there are no rigorous estimated results of the merging models using detailed vehicle trajectory data except Ahmed's model. Ahmed developed the model without data including the congested traffic conditions, and separately estimated normal and forced merging models. Therefore, it is important to develop a merging gap acceptance model combining all three types, normal, cooperative, and forced merging, in a single model using the detailed vehicle trajectory data.

Chapter 3

Modeling Framework

In this chapter, the concept of the merging gap acceptance model is presented. Next, the model framework and structure are presented.

3.1 The model concept

Lane changes are classified into two types: mandatory lane changing (MLC) and discretionary lane changing (DLC). Discretionary lane changing is defined as the case when a driver makes a lane change to improve perceived driving conditions. On the other hand, mandatory lane changing is defined when a lane change is required due to a lane drop or lane closure. Merging is a case of mandatory lane changing situations because a driver has to change lanes into a target lane through the available gaps. Merging can be classified into three types: normal, forced, and cooperative lane changing. Normal lane changing occurs when vehicles normally make a lane change through available gaps without interfering with other vehicles. Forced lane changing occurs when merging by a subject vehicle forces the lag vehicle to slow down. Cooperative lane changing occurs when the lag vehicle yields to allow the change to take place. These three types are more often observed in congested situations. The merging gap acceptance model has been developed for congestion situations. The model combines all three lane type, normal, cooperative, and forced lane changes, in a single level model. The model is formulated as a binary choice problem: change and no change. The driver will either accept or reject an available gap based on a comparison of the gap with an unobserved critical gap under mandatory lane changing situation. The three lane changing types of the merging model are described by explanatory variables that capture interactions between the subject vehicle and other vehicles.

3.2 Modeling Framework

The framework of the one stage model is summarized in Figure 3.1. The model hypothesizes one level of decision-making: gap acceptance (lane change if adjacent gaps are acceptable, no lane change if not). The decision process about gap acceptance is latent, and only the end action of the driver is observed. Latent choices are shown as ovals, and observed choices are represented as rectangles.

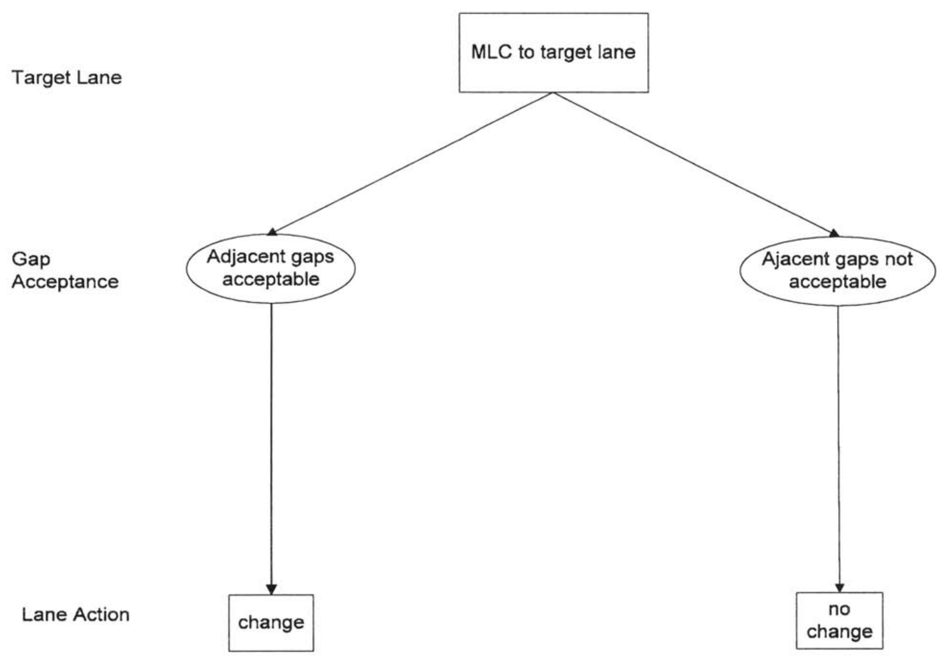

Figure 3.1- Modeling framework of merging gap acceptance model

In the figure, the driver evaluates the available gaps in the direction of the target lane for gap acceptance. In the case of merging from the on ramp, the target lane is the right most lane of the mainline. If the available lead and lag gaps are acceptable, the driver makes a lane change under gap acceptance in the immediate time step. The model combines all three lane changing types, normal, cooperative, and forced, in a one stage model including variables that capture courtesy and forced merging. Variables such as acceleration of lag vehicle and remaining distance to MLC point can capture courtesy and forced merging behaviors.

3.3 Model Structure

The gap acceptance model indicates whether a lane change is possible or not using the adjacent gaps. The merging driver first compares the available lead and lag gaps to the corresponding critical gaps for gap acceptance. An available gap is acceptable if it is greater than the critical gap. Critical gaps can be modeled as random variables. Their means are functions of explanatory variables. The estimation data is likely to include repeated observations of drivers' merging behaviors over time period. Thus, it is important to capture the correlations among the choices made by a given driver over time and choices dimensions. However, the characteristics of the drivers and their vehicles: aggressiveness, vehicle's speed, and acceleration capabilities are not likely to be included in the data. Therefore, it is necessary to introduce individual-specific latent variables. The individual specific random term captures correlations between the critical gaps of the same driver over time. The individual specific random term can be assumed that conditional on the value of the latent variable, the error terms of different utilities are independent. Critical gaps are assumed to follow lognormal distributions to ensure that they are always non-negative:

$$\ln\left(G_{nt}^{g,cr}\right) = \beta^{g^T} X_{nt} + \alpha^g \upsilon_n + \varepsilon_{nt}^g \quad g \in \{lead, lag\} \tag{3.1}$$

where $G_{nt}^{g,cr}$ denotes critical gap g of individual n at time t for gap acceptance, $g \in \{lead, lag\}$. X_{nt} is a vector of explanatory variables corresponding to the adjacent gap for individual n at time t. β^g is corresponding vector of parameters for gap acceptance. ε_{nt}^g

is random term for gap acceptance of individual n at time t: $\varepsilon_{nt}^{g} \sim N\left(0, \sigma_{g}^{2}\right)$. υ_{n} denotes driver specific random term. α^{g} is coefficient of the driver specific random term for gap acceptance.

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

$$
\begin{aligned}
&P\left(l_{nt} \mid \upsilon_{n}\right)= \\
&P\left(accept\ lead\ gap \mid \upsilon_{n}\right).P\left(accept\ lag\ gap \mid \upsilon_{n}\right) \\
&=P\left(G_{nt}^{lead} > G_{nt}^{lead,cr} \mid \upsilon_{n}\right).P\left(G_{nt}^{lag} > G_{nt}^{lag,cr} \mid \upsilon_{n}\right)
\end{aligned}
\tag{3.2}
$$

Where, l_{nt} is lane-changing indicator of individual n at time t , 1 if a lane-change is performed by individual n at time t , 0 otherwise. G_{nt}^{lead} is available lead gap of individual n at time t, and G_{nt}^{lag} is available lag gap of individual n at time t.

Assuming that critical gaps follow lognormal distributions, the conditional probabilities that gap $g \in \{lead, lag\}$ is acceptable is given by:

$$
\begin{aligned}
&P\left(G_{nt}^{g} > G_{nt}^{g,cr} \mid \upsilon_{n}\right)=P\left(\ln\left(G_{nt}^{g}\right) > \ln\left(G_{nt}^{g,cr}\right) \mid \upsilon_{n}\right)= \\
&\Phi\left[\frac{\ln\left(G_{nt}^{g}\right)-\left(\beta^{g^{T}} X_{nt}+\alpha^{g} \upsilon_{n}\right)}{\sigma_{g}}\right]
\end{aligned}
\tag{3.3}
$$

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

Gap acceptance is affected by the state of the merging driver and the interaction between the subject vehicle and the lead and lag vehicles in the adjacent lane. Candidate variables affecting gap acceptance include:

- average speed in the mainline
- relative speed of the subject vehicle with respect to the lead vehicle

- relative speed of the subject vehicle with respect to the lag vehicle
- status of the merging driver
- remaining distance to the MLC point
- acceleration of lag vehicle

3.4 Summary

In this chapter, the model framework for this gap acceptance model was developed, and mathematical formulations of the model have been presented. The model is based on the assumption that, in heavily congested situations, a vehicle entering from the on-ramp makes available gaps through explanatory variables to capture normal, courtesy yielding, or forced lane changing behaviors.

Chapter 4

Data

In this chapter, the data requirements for estimating the model parameters have been summarized. The process involves two trajectory data sets obtained from real traffic: I-80 and U.S. 101, CA. The characteristics of the two datasets are also described in the chapter.

4.1 Data Requirement

In the Section 3.3, the important explanatory variables affecting merging behaviors were introduced. For the merging gap acceptance model estimation, detailed disaggregate data to capture normal, courtesy and forced merging behaviors are required. These include neighborhood variables, traffic conditions, urgency of the merge, and driver specific attributes:

- Neighborhood variables: The neighborhood variables describe the subject vehicle and its relations with lead and lag vehicles. The variables also include the vehicles' speed and acceleration, position of lane, relative speed and spacing between subject vehicle and lead and lag vehicles in adjacent lanes. In the model estimation, the variables: relative speed of the subject vehicle with respect to the lead and lag vehicle, acceleration of lag vehicle are considered as the neighborhood variables.

- Traffic conditions: Merging vehicles can be affected by the current traffic condition such as density, average speed in the mainline. For the model estimation, the average speed in the mainline is considered.

- Driver specific attributes and urgency of merge: The driver specific attributes capture the individual characteristics of drivers: aggressive and timid drivers. The remaining distance to MLC point captures the urgency of the merge.

Trajectory data, which consists of observations of the positions of vehicles at discrete points in time, provides useful information about some of these variables. Trajectory data points are equally spaced in time with short time intervals between them, typically 1 second or less. Speeds, accelerations and lane changes are extracted from the time series of positions. Additional explanatory variables required by the model, such as relations between the subject and other vehicles: relative speed, time, and spacing, may also be inferred from the raw dataset.

4.2 The collection site

4.2.1 I-80 Trajectory Dataset

I-80 trajectory dataset used in this study was collected in April, 2005 by FHWA in a segment of Interstate freeway I-80 in Emeryville, California. Data represent travel on northbound direction of Interstate 80. Seven video cameras are installed on a 30 story-building, Pacific Park Plaza, which is located in 6363 Christie Avenue. The seven cameras recorded seven sub-sections of the study area, respectively. I-80 trajectory dataset has three data sets each 15 minutes (4:00 p.m. ~ 4:15 p.m., 5:00 p.m. ~ 5:15 p.m., and 5:15 p.m. ~ 5:30 p.m.), 45 minutes in total. Figure 4.1 provides the location covered by I-80 vehicle trajectory dataset. The study site is approximately 1650 feet in length, with six mainline including high occupancy vehicle (HOV) lane and with an on-ramp at Powell Street. Thus, this dataset is particularly useful for estimation of the proposed merging model in congested situations because the geometric characteristics of the site including merging area and data are collected during peak hours.

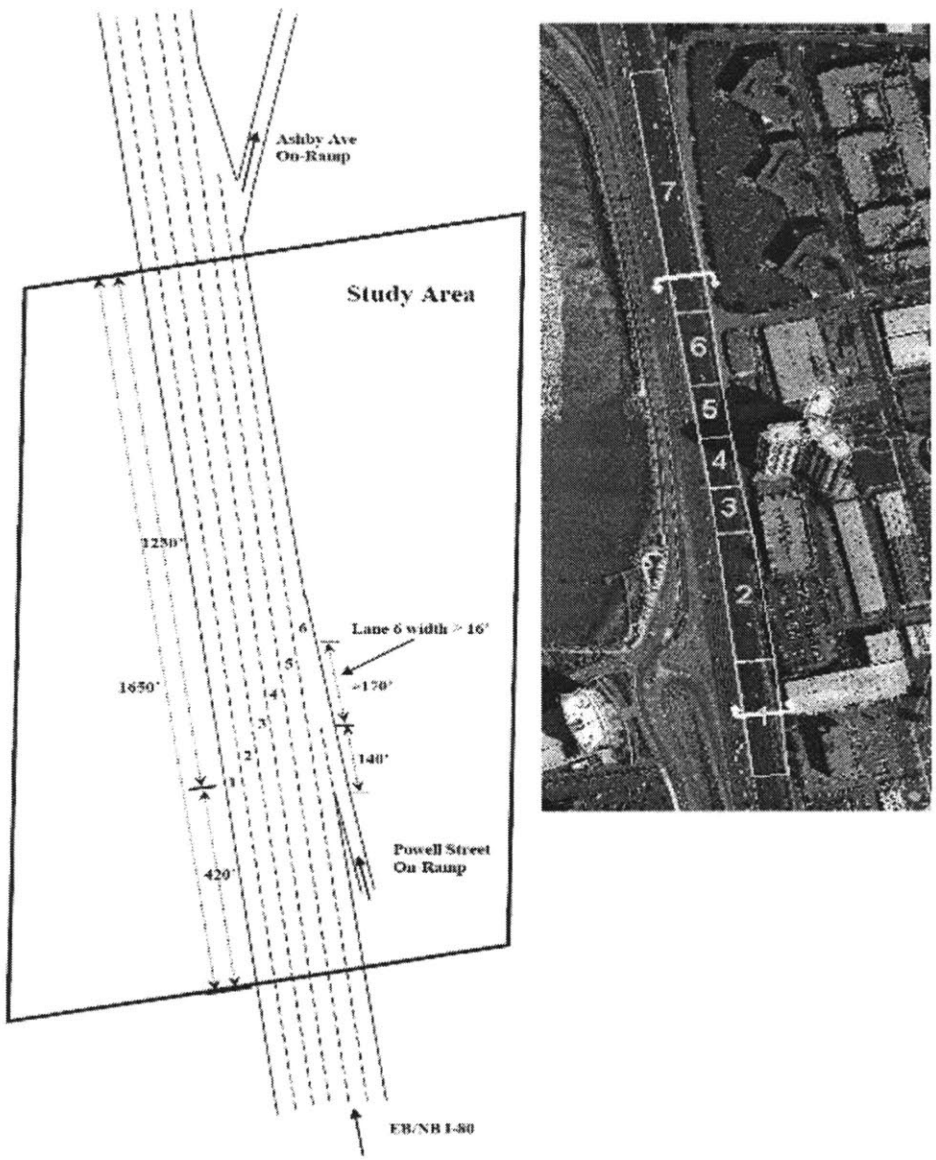

Figure 4.1- Study area covered by I-80 vehicle trajectory dataset

(source: NGSIM 2006)

4.2.2 U.S.101 Trajectory Dataset

Another dataset is U.S. 101 trajectory dataset. U.S. 101 dataset was collected in June, 2005 by FHWA in a segment of U.S. Highway 101, called Hollywood Freeway, in Los Angeles, California. Data represent travel on southbound direction of U.S. Highway 101. Eight video cameras are installed on a 36 story-building, 10 Universal City Plaza adjacent to U.S. 101. Similarly with I-80, the eight cameras recorded eight sub-sections of the study area, respectively. U.S.101 trajectory dataset has also three data sets each 15 minutes (7:50 a.m. ~ 8:05 a.m., 8:05 a.m. ~ 8:20 a.m., and 8:20 a.m. ~ 8:35 a.m.), 45 minutes in total (Figure 4.2). The study site is approximately 2100 feet in length, with five mainline and one auxiliary lane connecting to Ventura on-ramp and Cahuenga off-ramp. This U.S. 101 vehicle dataset is also useful for estimation of the proposed merging model in congested situations because the geometric characteristics of the site including merging on-ramp and off-ramp and data are collected during morning peak hours.

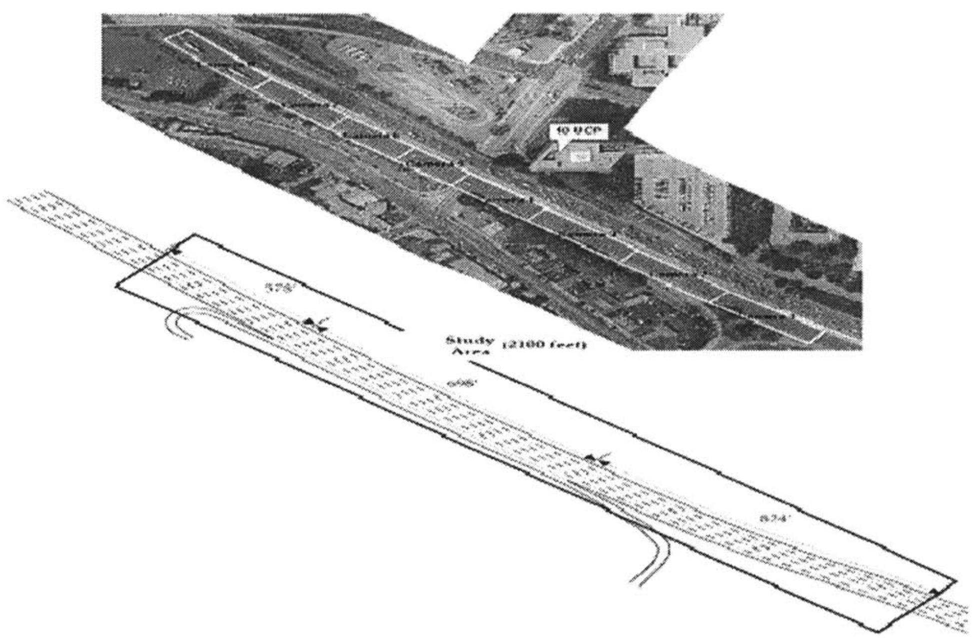

Figure 4.2- Study area covered by US 101 vehicle trajectory dataset (source: NGSIM 2006)

4.3 Characteristics of vehicle trajectory dataset

To generate require variables for the estimation, speeds, accelerations, current lane identification, positions, and time frame of the various vehicles in the dataset are used. Due to estimate single level gap acceptance in merging areas, only merging vehicle's trajectory data and vehicle data in rightmost lane are used.

4.3.1 I-80 vehicle trajectory dataset

Of observed vehicles in I-80 trajectory dataset, 540 vehicles entering from Powell on-ramp during 45 minutes are sampled from I-80 vehicle trajectory dataset. The sample dataset for the estimation has a total of 17352 observations at a 1 second time resolution. All 540 vehicles entering from Powell on-ramp made a lane change to mainline within observed data. To execute merging, the vehicles entering from on-ramp, which are subject vehicles, interact with neighboring vehicles such as lead and lag vehicles in rightmost lane (Figure 4.3).

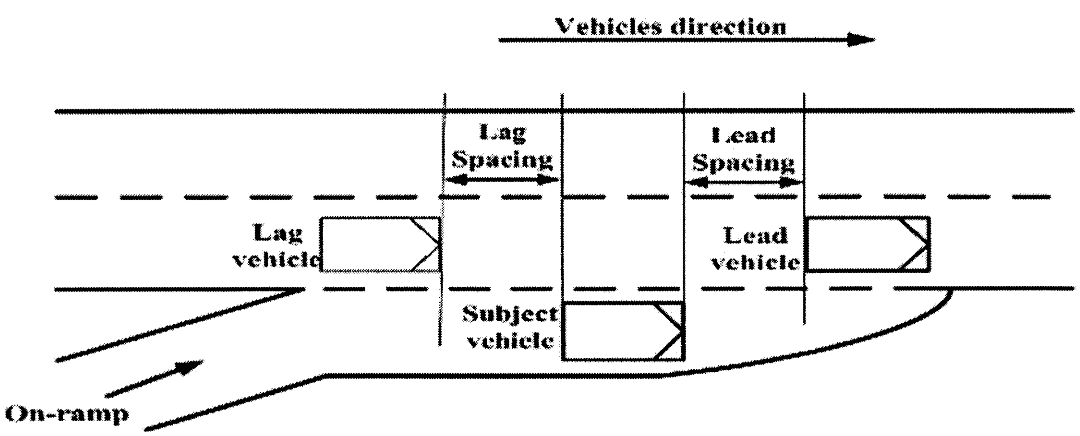

Figure 4.3- The subject, lead, and lag vehicles and related variables

Table 4.1- Statistics describing the lead and lag vehicles of I-80 dataset

Variable	Mean	Std	Median	Minimum	Maximum
Relations with Lead vehicle					
Relative speed (m/sec)	0.3 (-0.3)	1.2 (2.2)	0.3 (0)	-6.2 (-16.8)	5.6 (8.1)
Average speed – subject speed (m/sec)	0.03 (0.4)	1.8 (2.3)	0.04 (0.7)	-8.4 (-13.5)	5.7 (7.3)
Lead spacing (m)	9.9 (4.8)	8.8 (8.8)	7.8 (3.0)	0.13 (-19.4)	102.9 (160.6)
Relations with Lag vehicle					
Relative speed (m/sec)	-0.5 (-0.4)	1.6 (2.2)	-0.5 (-0.1)	-10.9 (-14.3)	5.4 (18.1)
Acceleration of Lag vehicle ($m/\sec^2$)	0.11 (0.02)	1.36 (1.45)	0 (0)	-3.41 (-3.41)	3.41 (3.41)
Lag spacing (m)	11.3 (5.3)	11.4 (8.9)	8.3 (3.4)	0.5 (-19.9)	172.9 (178.2)
Relation with Lead and Lag vehicle					
Remaining distance to MLC point (10 m)	6.9 (13.3)	3.6 (4.3)	6.6 (13.6)	0 (0)	19.6 (26.2)
Statistics are for the accepted gaps only, in parentheses for the entire dataset					

Relative speeds with respect to various vehicles are defined as the speed of these vehicles less the speed of the subject. For example, in lag case, relative speed is that the speed of lag vehicle in rightmost lane less the speed of subject speed entering from on ramp. In average speed case in lead gap, the definition is the speed of lead vehicles in rightmost lane less the speed of the subject entering from on-ramp. Remaining distance to MLC is defined as the distance from mandatory lane changing point less current position of the subject vehicle.

Table 4.4 summarizes statistics of the accepted lead and lag gaps (i.e., the gaps vehicle changed lanes into). Accepted lead gaps vary from 0.13 to 102.9 meters. On average, vehicles in the merging areas made a lane changing with the lead gaps, 9.9meters. In lag case, although accepted lag gaps vary from 0.5 to 172.9, the mean of lag gaps is 11.3 and most observations are between 0 and 20 meters in the distribution of lag gaps. A mean of average speed less subject speed, 0.03, indicates that the average speed in rightmost lane is faster than the speed of the subject vehicle entering from on-ramp. With these statistics, negative spacing values indicate that the subject and the lead vehicles or lag vehicles partly overlap. It is possible because current conditions are congested, and subject vehicles and lead vehicles (or lag vehicles) are in different lanes. As expected, the mean accepted gaps are larger than the mean gaps in the traffic stream. In remaining distance variable, the average remaining distance is 69 meters. It means that vehicles entering from on-ramp make a lane changing with the remaining distance on average. A mean of acceleration of lag vehicle is almost 0.11. In the distribution of the acceleration of lag vehicle, deceleration of lag vehicles between 0 and -1 m/sec^2 is indicated in the merging areas. The distributions of relative speeds, average speed, remaining distance, and spacing are shown in Figure 4.4, Figure 4.5, and Figure 4.6, respectively.

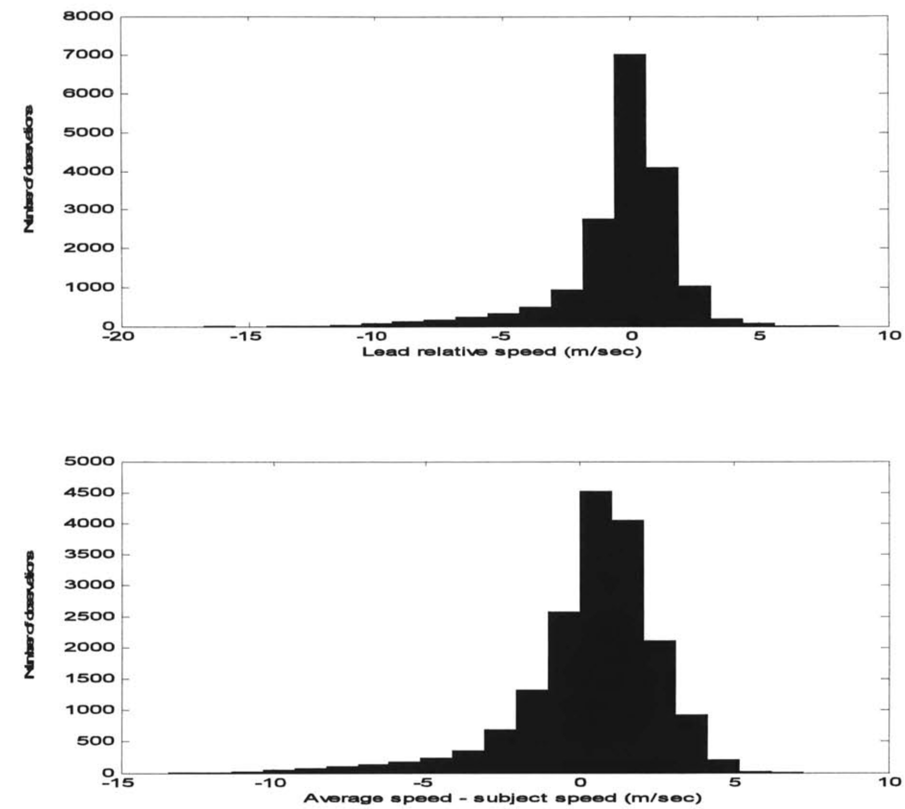

Figure 4.4 Distributions of relative speed and average speed with lead vehicles

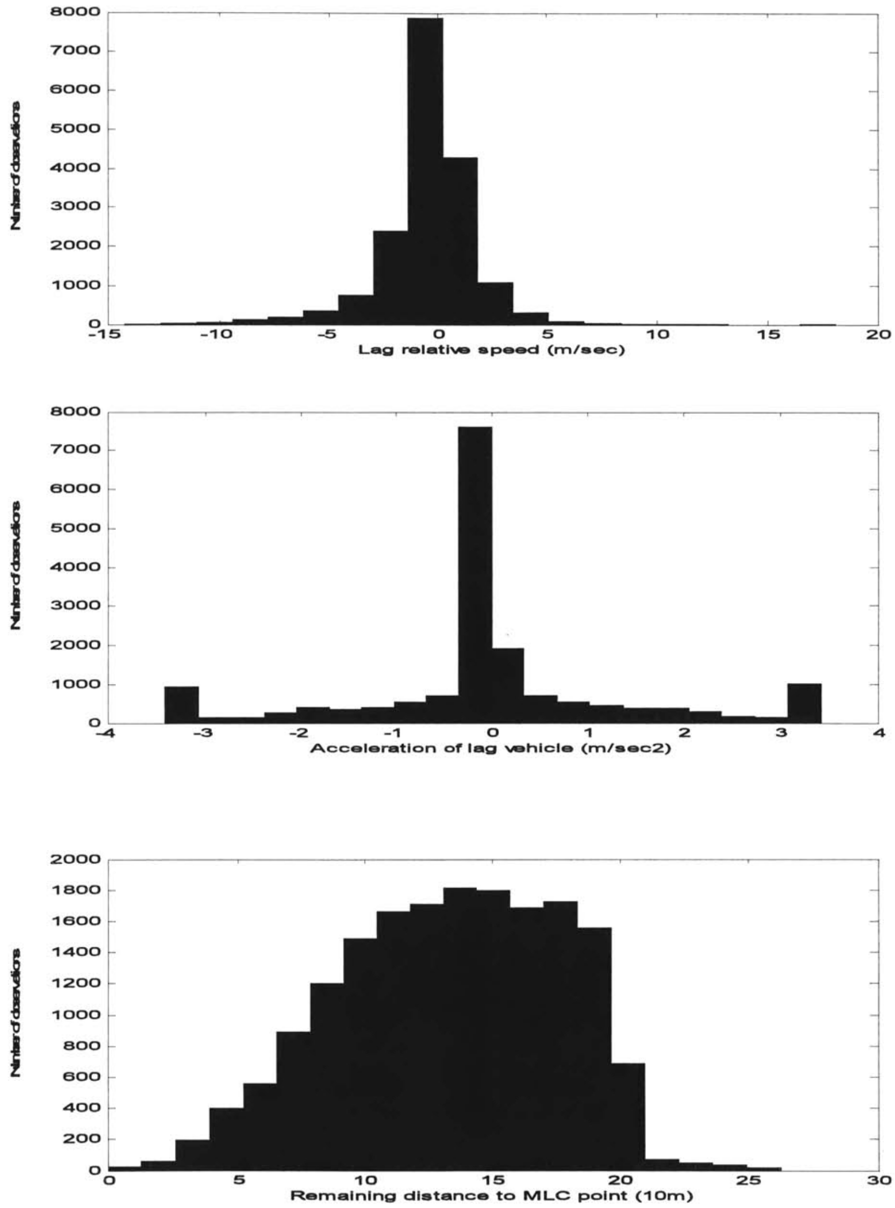

Figure 4.5- Distributions of relative speed, acceleration with lag and remaining distance

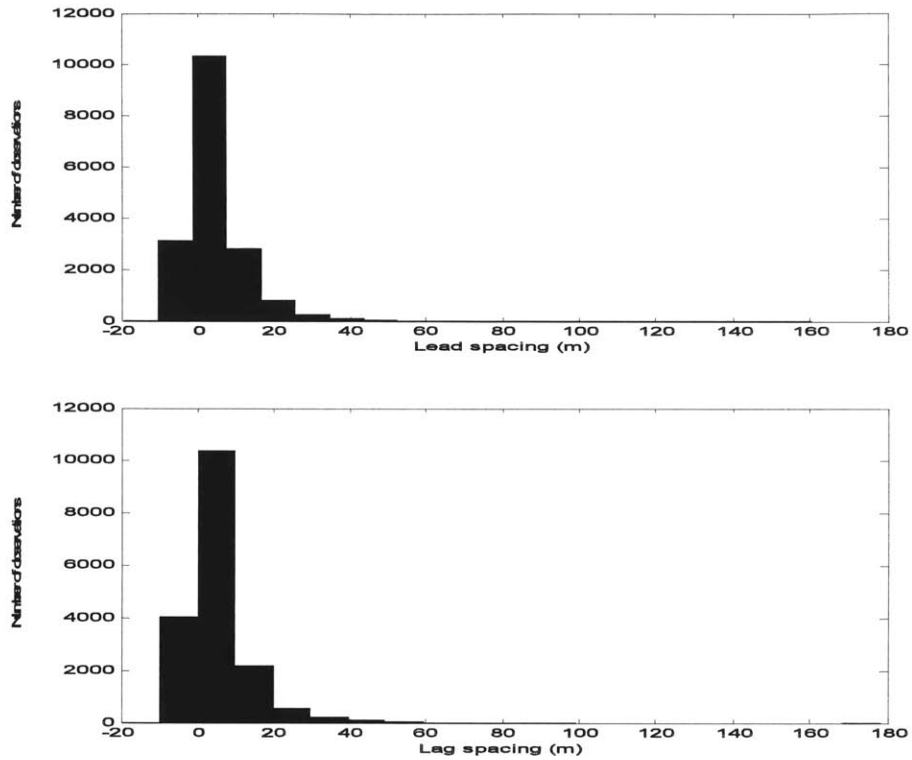

Figure 4.6- Distributions of spacing with respect to the lead and lag vehicles

4.3.2 U.S. 101 vehicle trajectory dataset

In U.S. 101 trajectory dataset, 374 vehicles entering from Ventura on-ramp of observed vehicles in the trajectory dataset are sampled during 45 minutes. The sample dataset for the estimation has a total of 3623 observations at a 1 second time resolution. All 374 vehicles entering from Ventura on-ramp made a lane change to mainline in the trajectory dataset. The relations between the subject vehicle, merging vehicle from Ventura on-ramp, and the lead and lag vehicles in the rightmost lane affect the gap acceptance in merging areas. In the case of U.S. 101, the same variables are considered as in the I-80 case. Table 4.2

summarizes statistics of the accepted lead and lag gaps sampled from U.S. 101 trajectory dataset.

Table 4.2- Statistics describing the lead and lag vehicles of U.S. 101 dataset

Variable	Mean	Std	Median	Minimum	Maximum
Relations with Lead vehicle					
Relative speed (m/sec)	-0.9 (-2.9)	2.4 (3.5)	-0.6 (-2.5)	-15.2 (-19.8)	4.8 (12.2)
Average speed – subject speed (m/sec)	-1.6 (-3.4)	2.4 (3.2)	-1.3 (-2.9)	-14.2 (-16.7)	4.7 (13.6)
Lead spacing (m)	14.2 (10.5)	16.1 (15.2)	9.5 (7.0)	0 (-21.5)	161.3 (168.4)
Relations with Lag vehicle					
Relative speed (m/sec)	-1.5 (-3.4)	2.3 (3.3)	-1.3 (-2.9)	-15.2 (-19.2)	4.9 (11.5)
Acceleration of Lag vehicle ($m/\sec^2$)	0.03 (0.1)	1.3 (1.4)	0 (0)	-3.4 (-3.4)	3.4 (3.4)
Lag spacing (m)	15.0 (9.9)	14.3 (13.6)	10.6 (6.8)	0.07 (-7.1)	131.7 (131.7)
Relation with Lead and Lag vehicle					
Remaining distance to MLC point (10 m)	11.6 (15.5)	6.6 (6.1)	13.9 (17.1)	0 (0)	22.4 (24.3)
Statistics are for the accepted gaps only, in parentheses for the entire dataset					

Accepted lead gaps vary from 0 to 161.3 meters. On average, vehicles in the merging areas made a lane changing with lead gaps around 14.2 meters. In lag case, the mean of lag gaps is 15.0 meters and most observations are between 0 and 20 meters in the distribution of lag gaps. A mean of average speed less subject speed, -1.6, indicates that the average speed in rightmost lane is slower than the speed of the subject vehicle. In the case of remaining distance variable, the average remaining distance is 116 meters. On average, merging vehicles make a lane change at the remaining distance. A mean of acceleration of lag vehicle is 0.03 m/sec^2. In the distribution of the acceleration of lag vehicle, deceleration of lag vehicles between 0 and -1 m/sec^2 is indicated in the merging areas. The distributions of relative speeds, average speed, remaining distance, and spacing are shown in Figure 4.7, Figure 4.8, and Figure 4.9, respectively.

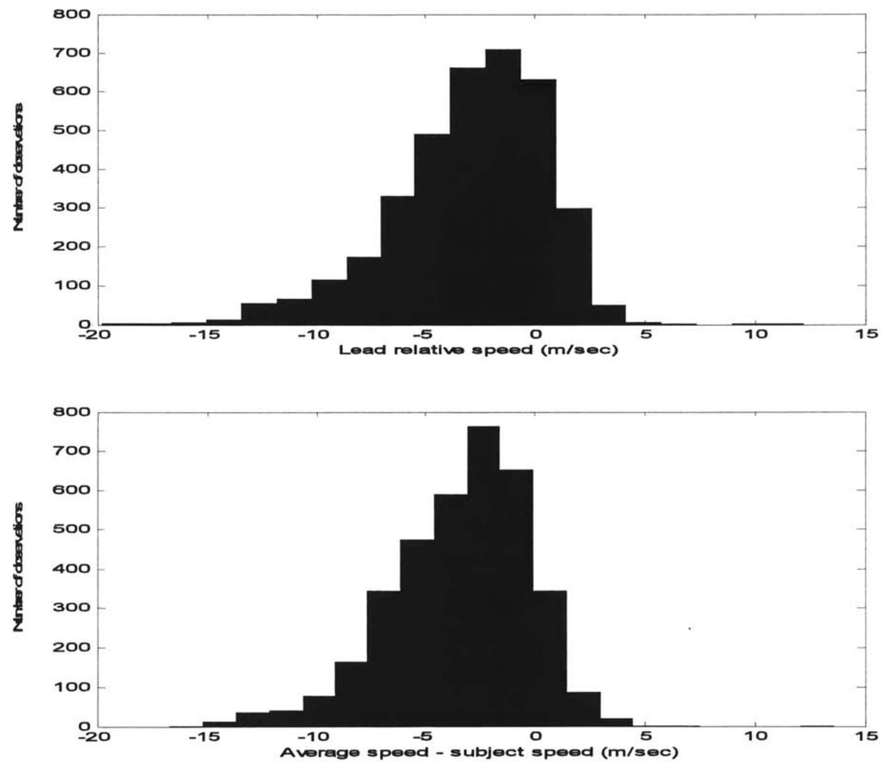

Figure 4.7- Distributions of relative speed and average speed with lead vehicles

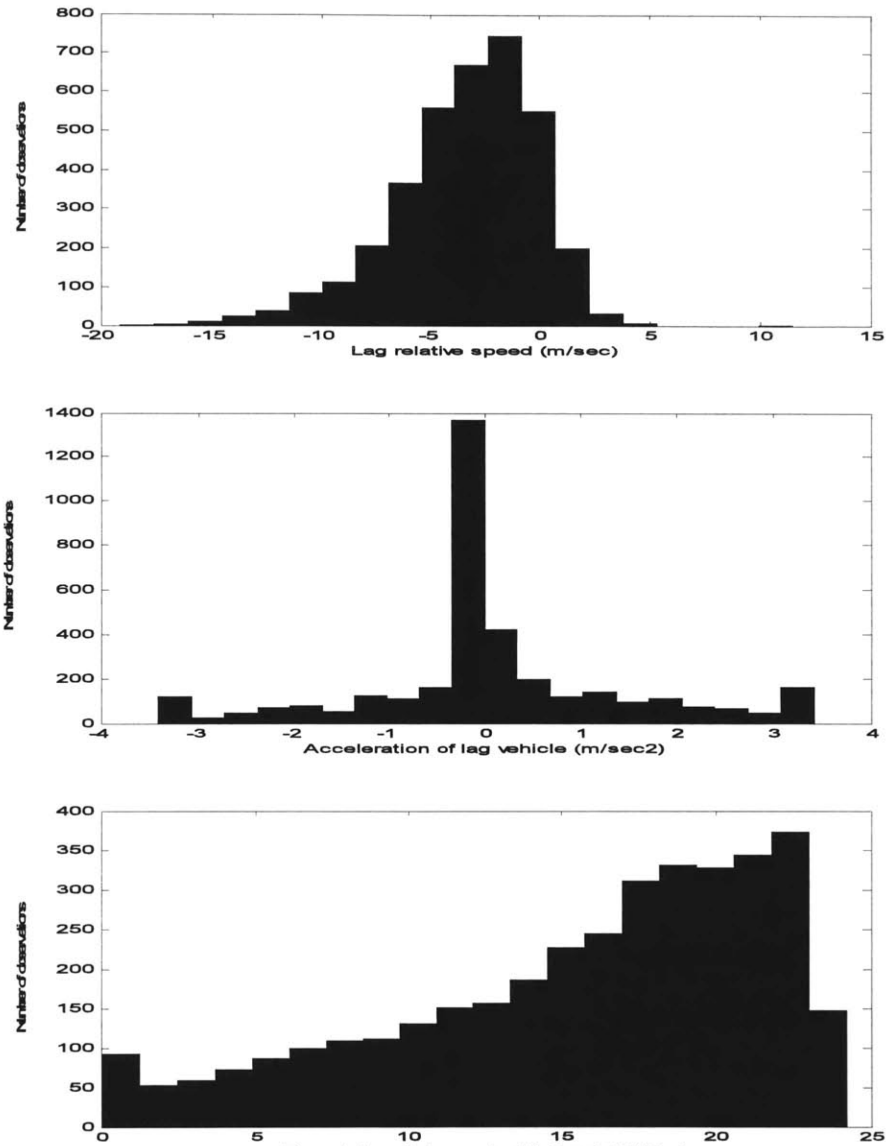

Figure 4.8- Distributions of relative speed, acceleration with lag and remaining distance

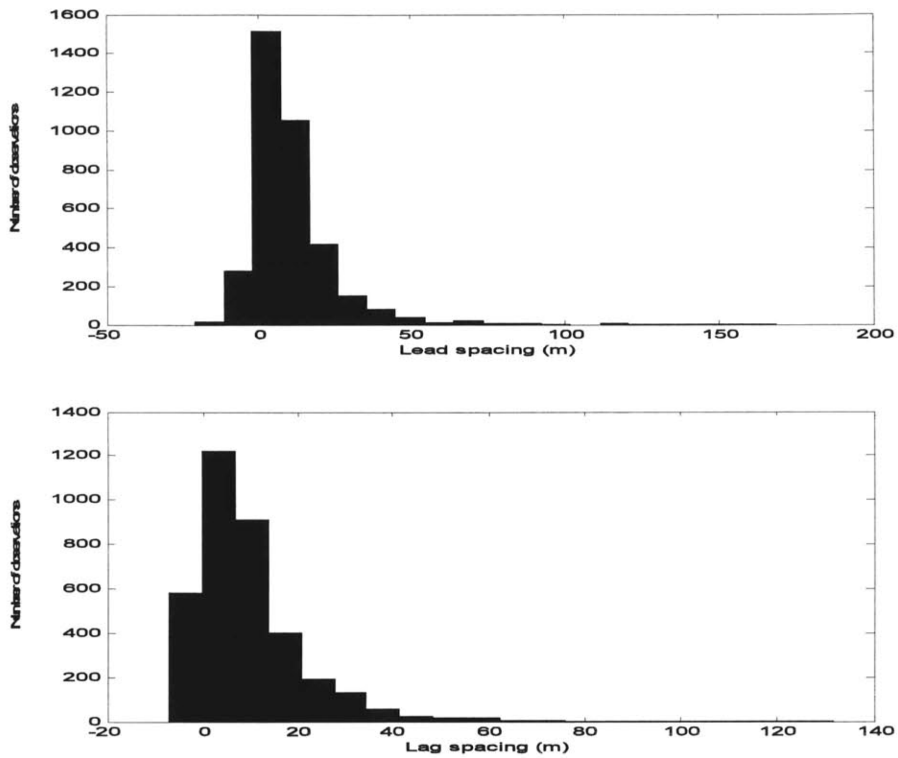

Figure 4.9- Distributions of spacing with respect to the lead and lag vehicles

4.4 Discussion of Datasets

In the previous sub sections, statistical analyses of two trajectory dataset are described for the model estimation. Two data sets: both I-80 and U.S. 101 include merging areas such as merging on-ramp in I-80 and merging on-ramp and off-ramp in U.S. 101. The two datasets are in the congested traffic conditions. Thus, two datasets are useful for estimating the proposed gap acceptance model in congested merging areas.

However, there exist some limitations to the two dataset. In the case of I-80 trajectory data, the width of lane 6, which is rightmost lane, becomes wider from 12 ft to 24 ft near the merging area without an auxiliary lane connecting between on-ramp and rightmost lane (Figure 4.10).

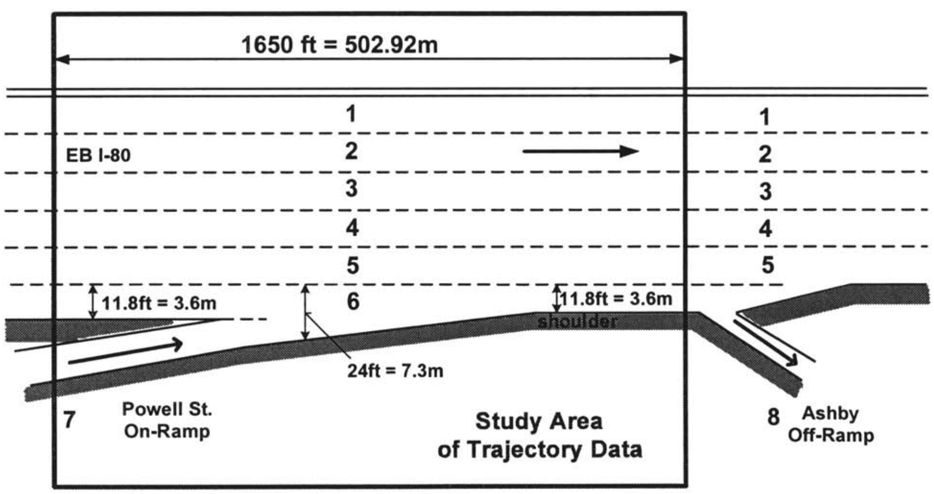

Figure 4.10- Wider width of rightmost lane in the study area of I-80

In the wider merging area, it is obvious that entering vehicles make lane changes into the mainline, but it is ambiguous when the vehicles entering from on-ramp make lane merges into the mainline and how the vehicles define the merging point. In not so congested situations, the definition of the merging point does not result much difference since the execution of the lane change generally takes less than one time step. However, in the situations with high congestion level and low speeds, whether or not the merge is completed strongly depends on the choice of this point. Therefore, assume that the lane demarcation, imaginary line, is denoted by the line that connects the end point of the physical lane marks of the on-ramp to the MLC point where the normal width of lane becomes 12 ft (3.6 meters) (Figure 4.11). Assume that defining the merge is complete when the center point of the vehicle has crossed the imaginary lane separating lane 6 and the on-ramp/wider extension of lane 6.

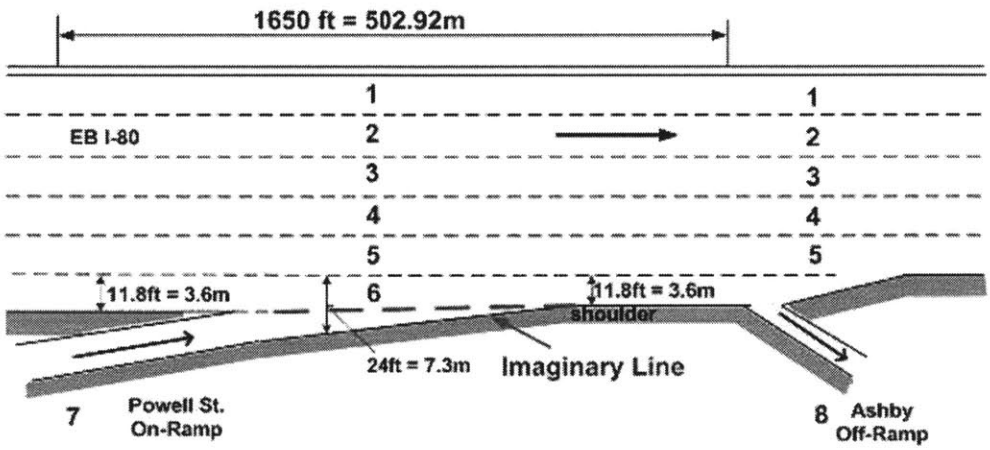

Figure 4.11- Imaginary line of rightmost lane in the study area of I-80

In the case of U.S. 101 vehicle trajectory dataset, there exists clear lane identification because an explicit acceleration lane exists between on-ramp and rightmost lane in mainline. However, average density in merging area of U.S. 101 is relatively lower than that of I-80. In the case of I-80, average density of down stream and of up stream in rightmost lane are 62.2 veh/km/lane and 60.6 veh/km/lane respectively. On the other hand, that of down stream and of up stream in U.S. 101 are 45.6 veh/km/lane and 46.8 veh/km/lane. In the variable of average speed in rightmost lane, the difference of average speed between U.S.

101 and I-80 dataset is doubled. The average speed of U.S. 101 dataset is much faster than that of I-80 dataset. (Table 4.3) Thus, the U.S. 101 dataset may not be representative of highly congested situations.

Table 4.3- Statistics comparison between I-80 and U.S. 101 dataset

Variable	Mean	Std	Median	Minimum	Maximum
I-80 dataset					
Average density down stream (veh/km/lane)	62.2	15.3	60	0	126.7
Average density up stream (veh/km/lane)	60.6	22.8	60	0	126.6
Average speed (m/sec)	4.6	1.9	4.3	1.1	15.4
U.S. 101 dataset					
Average density down stream (veh/km/lane)	45.6	15.2	46.7	0	93.3
Average density up stream (veh/km/lane)	46.8	15.7	46.7	0	100
Average speed (m/sec)	9.8	3.0	10.3	2.8	17.4

4.5 Combined dataset

Combined dataset is needed to test transferability for the stability of the model parameter between two datasets: U.S.101 and I-80. This dataset combines two vehicle trajectory data sets: I-80 and U.S. 101. Total merging vehicles are 914 which are 374 vehicles from U.S 101 dataset and 540 vehicles from I-80 dataset. The number of observations is 20975: 3623 from U.S. 101 and 17352 from I-80 dataset. Table 4.4 summarizes statistics of combined dataset, and the distributions of relative speeds, average speed, remaining distance, and spacing are shown in Figure 4.12, Figure 4.13, and Figure 4.14, respectively.

Table 4.4- Statistics describing the lead and lag vehicles of combined dataset

Variable	Mean	Std	Median	Minimum	Maximum
Relations with Lead vehicle					
Relative speed (m/sec)	-0.2 (-0.7)	1.9 (2.6)	0.01 (-0.05)	-15.2 (-19.8)	5.6 (12.2)
Average speed – subject speed (m/sec)	-0.7 (-0.2)	2.2 (2.8)	-0.5 (0.4)	-14.3 (-16.7)	5.7 (13.6)
Lead spacing (m)	11.7 (5.8)	12.6 (10.4)	8.5 (3.5)	0.0 (-21.5)	161.3 (168.4)
Relations with Lag vehicle					
Relative speed (m/sec)	-0.9 (-0.9)	1.9 (2.7)	-0.7 (-0.4)	-15.2 (-19.1)	5.4 (18.1)
Acceleration of Lag vehicle ($m/\sec^2$)	0.1 (0.03)	1.3 (1.4)	0 (0)	-3.4 (-3.4)	-3.4 (3.4)
Lag spacing (m)	12.9 (6.1)	12.9 (10.1)	9.3 (3.8)	0.0 (-19.9)	172.9 (178.3)
Relation with Lead and Lag vehicle					
Remaining distance to MLC point (10 m)	8.9 (13.7)	5.6 (4.8)	7.7 (13.9)	0.0 (0.0)	22.4 (26.2)
Statistics are for the accepted gaps only, in parentheses for the entire dataset					

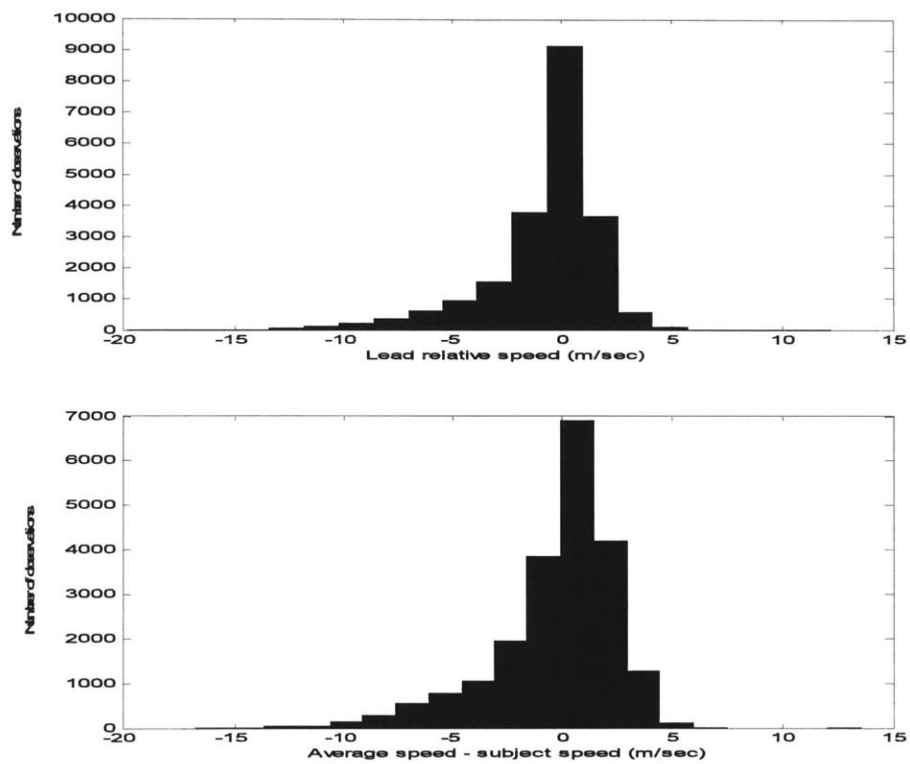

Figure 4.12- Distributions of relative speed and average speed with lead vehicles

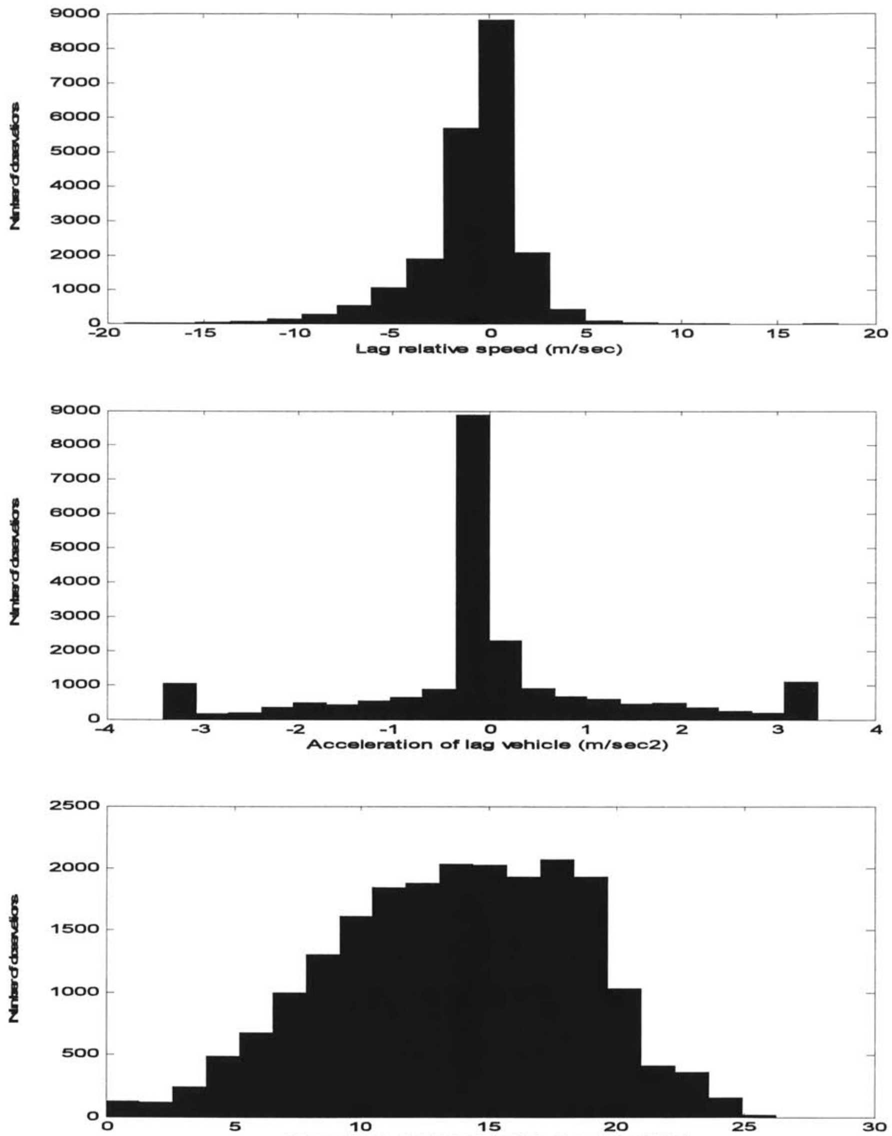

Figure 4.13- Distributions of relative speed, acceleration with lag and remaining distance

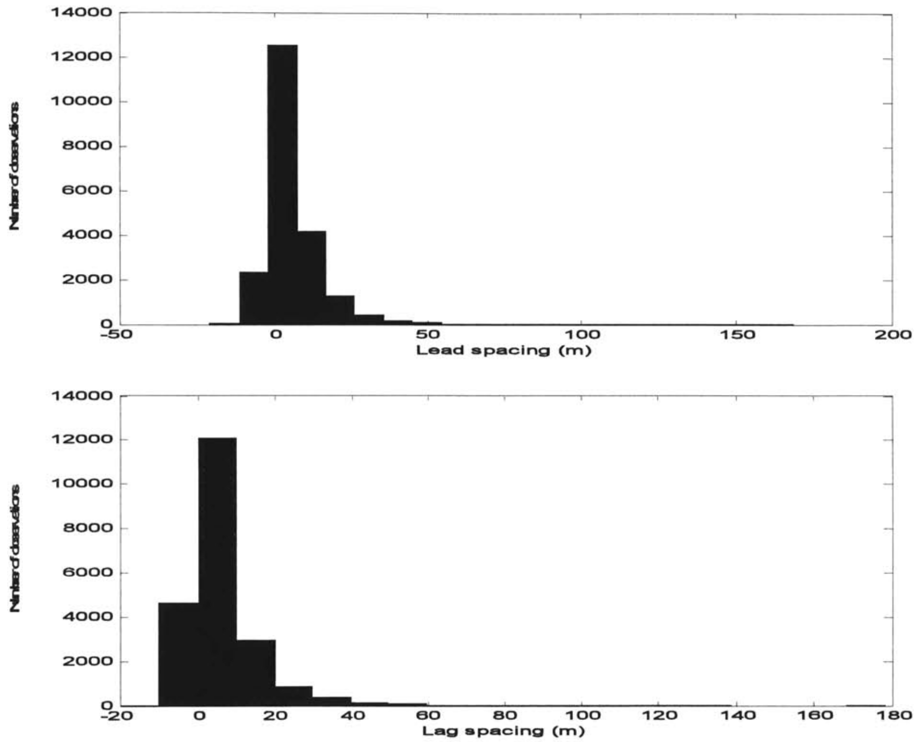

Figure 4.14- Distributions of spacing with respect to the lead and lag vehicles

4.6 Summary

In this chapter, the data requirements: neighborhood variables, traffic conditions, urgency of merge, and driver specific attribute for the model estimation have been discussed. The detailed two disaggregated datasets: I-80 and U.S. 101 are analyzed, and discussed some limitations of the data sets: ambiguous merging definitions in I-80 dataset and less congested traffic conditions in US 101 dataset. However, the two datasets are both in the congested traffic conditions and include merging areas. Thus, it is appropriate for the merging gap acceptance model in the congested traffic situations. To test transferability of the stability of the model parameter between two datasets, combined dataset including two trajectory dataset is also analyzed. The three datasets will be used to estimate the model parameters.

Chapter 5

Estimation

The estimation results of the proposed gap acceptance model in the congested merging area using the I-80, U.S. 101, and combined dataset are presented in this chapter. The proposed model has been estimated using a maximum likelihood estimation procedure. Six models are estimated: two models with I-80 and U.S. 101, respectively, four models with combined dataset. The estimation results are presented first. Next, the estimated models are compared with likelihood ratio test.

5.1 Likelihood Function

In this section, the likelihood function of lane-changing actions observed in the data is presented. The single level gap acceptance model assumes that a driver evaluates the available gaps in a target lane which the driver wants to move into. The driver decides whether to change lanes immediately or not. For example, a driver entering from on-ramp evaluates the available gaps such as lead gap and lag gap in the rightmost lane of mainline. If the both gaps are available, the driver changes lanes immediately.

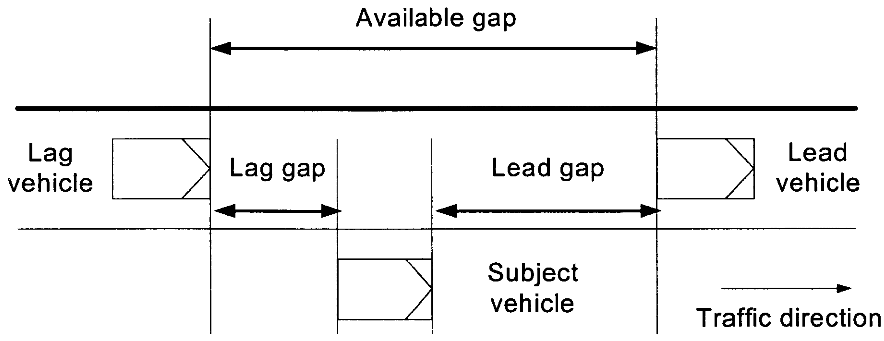

Figure 5.1 - The available gap, subject, lead and lag vehicles and the lead and lag gaps

The single level gap acceptance behavior is conditioned on the individual-specific characteristics υ_n. At time *t*, the probability of individual *n* being performing lane action (l_{nt}) is given by:

$$
\begin{aligned}
&P\left(l_{nt} \mid \upsilon_n\right) = P\left(accept\ lead\ gap \middle| \upsilon_n\right).P\left(accept\ lag\ gap \middle| \upsilon_n\right) \\
&= P\left(G_{nt}^{lead} > G_{nt}^{lead,cr} \middle| \upsilon_n\right).P\left(G_{nt}^{lag} > G_{nt}^{lag,cr} \middle| \upsilon_n\right)
\end{aligned}
\qquad (5.1)
$$

where, G_{nt}^{lead} and G_{nt}^{lag} denote the lead and lag gaps of individual *n* at time *t*, respectively. l_{nt} denotes lane changing action of individual *n* at time *t*.

If a driver is observed over his trajectory, a sequence of consecutive time interval, the combined probability of observing a lane change can be expressed as:

$$P(l_n \mid \upsilon_n) = \prod_t P\left(l_{nt} \mid \upsilon_n\right) \qquad (5.2)$$

The unconditional individual likelihood is obtained by integrating over the distributions of the individual specific variables:

$$L_n = \int_{\upsilon} P(l_n \mid \upsilon_n)\, f(\upsilon)\, d\upsilon \qquad (5.3)$$

where, $f(\upsilon)$ is the standard normal probability density function.

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

$$L = \sum_{n=1}^{N} \ln(L_n) \qquad (5.4)$$

The maximum likelihood estimates of the model parameters are found by maximizing this function. For the model estimation, the statistical estimation software GAUSS (Aptech Systems 1994) has been used. To find maximizing the likelihood function, the Broyden-

Flectcher-Goldfarb-Shanno (BFGS) optimization algorithm is used. BFGS is a quasi-Newton method, which maintains and updates an approximation of the Hessian matrix based on first-order derivative information (see, for example, Bertsekas 1999). The integrals in the likelihood function were calculated numerically using the Gauss-Legendre quadrature method (Aptech Systems 1994) because numerical integration only the explanatory variables values for the points used for the integration need to be calculated. The likelihood function is not globally concave. To avoid obtaining a local solution, different starting points have been used in the optimization procedure.

5.2 Estimation Results

The merging gap acceptance model is estimated using a maximum likelihood estimation procedure as described in the previous section. In this section, the six estimation results of the merging model: two models with I-80 and U.S. 101, respectively, are presented and discussed. The estimation results of four models with the dataset combining I-80 and U.S. 101 are also described.

5.2.1 Estimation results with I-80 dataset

Model 1: Merging gap acceptance model with the I-80 dataset

The estimation results of the proposed model with I-80 dataset are presented in Table 5.1.

Table 5.1 – Estimation results for the Model 1

Final log likelihood			-1639.69
Number of vehicles			540
Number of observations			17352
Number of parameters			17
	Variable	Parameter value	t-statistic
Lead gap	Constant	0.182	0.20
	$Max\left(0,\Delta V_{nt}^{avg}\right)$, m/sec	1.45	4.60
	$Min\left(0,\Delta V_{nt}^{lead}\right)$, m/sec	-0.571	-3.54
	d_{nt}^{lead}, 10 meters	1.03	4.29
	$v^{RemDist,lead}$	0.798	2.66
	Constant, d_{nt}^{lead}	-0.492	-0.81
	v^{lead}	-0.00016	-0.0033

	σ^{lead}	4.28	5.86
Lag gap	Constant	0.379	0.89
	$Max\left(0,\Delta V_{nt}^{lag}\right)$, m/sec	0.179	1.36
	$Min\left(0,\Delta V_{nt}^{lag}\right)$, m/sec	0.0909	0.71
	d_{nt}^{lag}, 10 meters	0.179	1.74
	$v^{RemDist,lag}$	2.88	0.73
	Constant, d_{nt}^{lag}	-2.22	-0.55
	$Max(0,a_{nt}^{lag}),\ m/\sec^2$	0.0766	0.81
	v^{lag}	-0.00011	-0.0025
	σ^{lag}	0.91	5.63

The lead critical gap is a function of the average speed in the mainline relative to the subject vehicle's speed, the relative speed of the lead with respect to the subject and the remaining distance to the mandatory lane changing point. The lag critical gap is a function of the subject relative speed with respect to the lag vehicle, the remaining distance to the mandatory lane changing point and the acceleration of the lag vehicle.

The variable relative average speed is assumed to follow the functional form:

$$\frac{\beta}{1+\exp(-Max\left(0,\Delta V_{nt}^{avg}\right))}$$

where, ΔV_{nt}^{avg} is relative speed of the average mainline speed with respect to the subject. Estimated β is 1.45. General functional form of the relative average speed is tested for the model estimation, but the estimated values of the parameters are not significant. The general functional form is the following:

$$\frac{\beta}{1+\exp(-\gamma Max\left(0,\Delta V_{nt}^{avg}\right)+\alpha)}$$

where, estimated values and t-statistics of α, β, and γ are 1.98 (3.21), 3.55 (0.89), and -0.463 (-0.83).

The functional form of the relative average speed applied in this model implies that if average speed in the mainline is faster than a driver's speed in the merging areas, the driver needs larger gaps to adjust his speed to the speed of the mainline and the effect of relative average speed is less when it is larger than a certain threshold. The lead critical gap is also larger when the subject vehicle is faster than lead vehicle to minimize the risk of collision. The lag critical gap increases with the relative lag speed: the faster the lag vehicle is relative to the subject, the larger the critical gap is. The sensitivity of the median critical gaps as a function of relative average speed, relative speed in the lead, and relative speed is shown in Figure 5.2, Figure 5.3, and Figure 5.4, respectively.

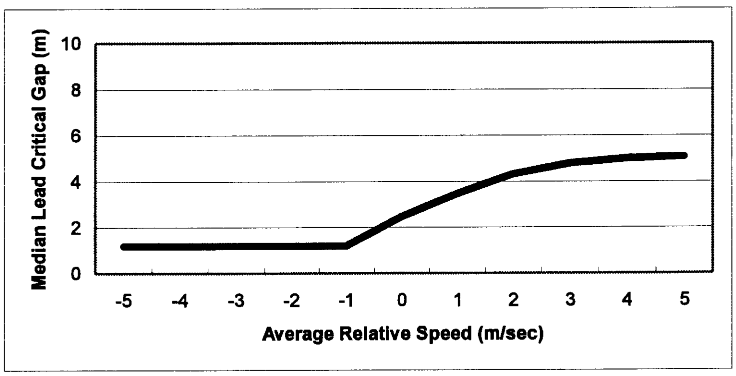

Figure 5.2 - Median critical lead gap as a function of average relative speed

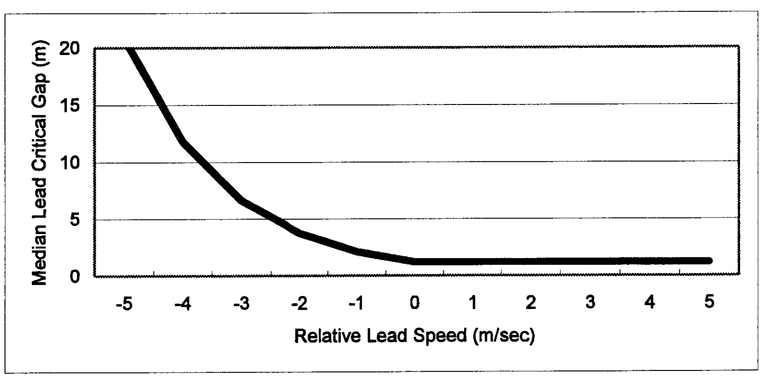

Figure 5.3 - Median critical lead gap as a function of relative speed

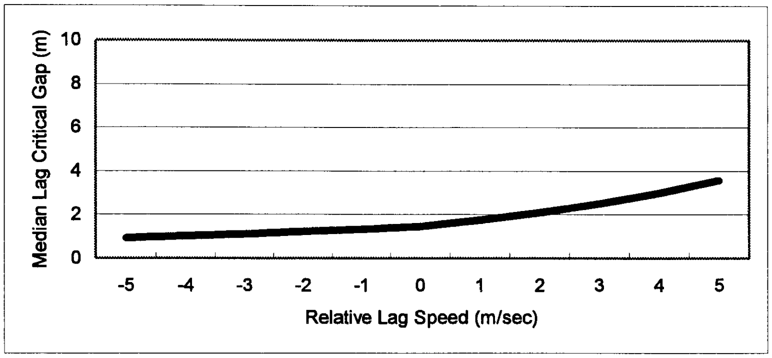

Figure 5.4 - Median critical lag gap as a function of relative speed

The variable, acceleration of lag vehicle indirectly captures the courtesy merging behavior. If the lag vehicle is decelerating, the merging driver perceives that he is getting courtesy from the lag. In such cases, he needs a smaller buffer space with the lag and can make a lane change with a smaller gap. Similarly, the merging driver requires a larger critical lag gap to avoid collision if the lag vehicle is accelerating. The lag critical gap therefore increases as the acceleration of the lag vehicle increases. The median critical gap as a function of the acceleration of lag vehicle is presented in Figure 5.5.

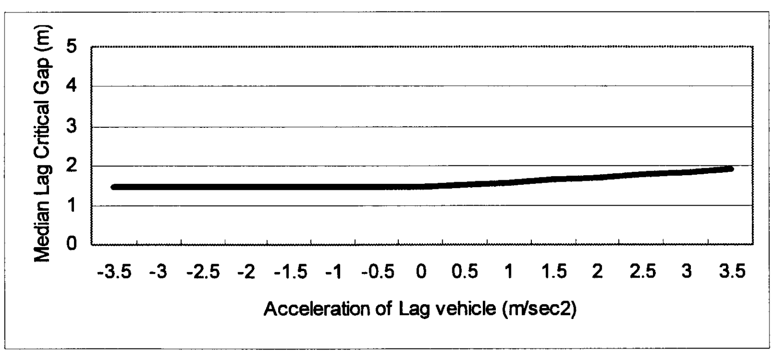

Figure 5.5 - Median critical lag gap as a function of the acceleration of lag vehicle

This variable, remaining distance to MLC point, indirectly captures the forced merging phenomena: the driver is willing to accept smaller critical gaps to make a lane change as he approaches the endpoint of the on-ramp. The remaining distance to MLC point is a function of the remaining distance of the subject vehicle and the characteristics of the drivers. To capture drivers' heterogeneity, individual specific random term has been introduced in the coefficient of the remaining distance. Aggressive and timid drivers can have different critical gaps, the remaining distance being equal. For example, all other variables having no effect, the lead and lag critical gaps as a function of remaining distance for the aggressive drivers are much smaller than the gaps of timid and normal drivers. Thus, aggressive drivers can find lead and lag gaps to be acceptable even when they are far from the MLC point. The timid drivers have large critical gaps till they reach the end of the ramp, implying that they do not consider lane changes in the beginning of the on-ramp. The sensitivity of the mean lead and lag critical gaps as a function of the remaining distance according to the individual characteristics of the driver is shown in Figure 5.6 and Figure 5.7, respectively.

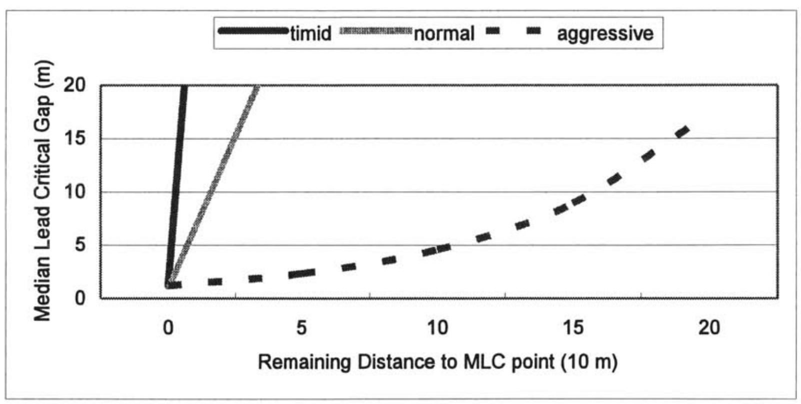

Figure 5.6 - Median critical lead gap as a function of remaining distance

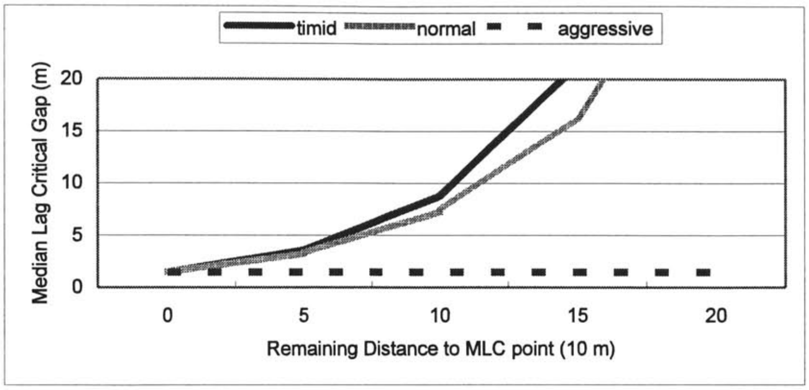

Figure 5.7 - Median critical lag gap as a function of remaining distance

Estimated coefficients of the unobserved driver characteristics are negative for both the lead and lag critical gaps. This implies that aggressive drivers require smaller gap for lane changing compared to timid drivers.

In summary, the estimated lead and lag critical gaps for the merging gap acceptance model with I-80 dataset are given by:

$$G_{nt}^{lead,cr} = \exp\left(\begin{array}{l} 0.182 + \dfrac{1.45}{1+\exp(-Max\left(0,\Delta V_{nt}^{avg}\right))} - 0.571 Min\left(0,\Delta V_{nt}^{lead}\right) + \\ + \dfrac{1.03 d_{nt}}{1+\exp(-0.492+0.798\upsilon_n)} - 0.00016\upsilon_n + \varepsilon_{nt}^{lead} \end{array} \right) \tag{5.5}$$

$$G_{nt}^{lag,cr} = \exp\left(\begin{array}{l} 0.379 + 0.179 Max\left(0,\Delta V_{nt}^{lag}\right) + 0.0909 Min\left(0,\Delta V_{nt}^{lag}\right) + \\ + \dfrac{0.179 d_{nt}}{1+\exp(-2.22+2.88\upsilon_n)} + 0.0766 Max(0, a_{nt}^{lag}) - 0.00011\upsilon_n + \varepsilon_{nt}^{lag} \end{array} \right) \tag{5.6}$$

$\varepsilon_{nt}^{lead} \sim N\left(0, 4.28^2\right)$ and $\varepsilon_{nt}^{lag} \sim N\left(0, 0.91^2\right)$

where, $G_{nt}^{lead,cr}$ and $G_{nt}^{lag,cr}$ denote lead and lag critical gap, respectively. ΔV_{nt}^{avg} is relative speed of the average mainline speed with respect to the subject. ΔV_{nt}^{lead} denotes relative speed of the lead vehicle with respect to the subject. d_{nt} is the remaining distance to the mandatory lane changing point. ΔV_{nt}^{lag} is relative speed of the lag vehicle with respect to the subject. a_{nt}^{lag} is the acceleration of the lag vehicle. υ_n is unobserved driver characteristics. ε_{nt}^{lead} *and* ε_{nt}^{lag} denote random error terms.

5.2.2 Estimation results with U.S. 101 dataset

Model 2: Merging gap acceptance model with the U.S.101 dataset

The estimation results of the proposed model with U.S.101 dataset are presented in Table 5.2.

Table 5.2 - Estimation results for the Model 2

Final log likelihood			-1278.97
Number of vehicles			374
Number of observations			3623
Number of parameters			17
	Variable	Parameter value	t-statistic
Lead gap	Constant	-1.26	-0.49
	$Max\left(0, \Delta V_{nt}^{avg}\right)$, m/sec	1.28	1.16
	$Min\left(0, \Delta V_{nt}^{lead}\right)$, m/sec	-0.338	-2.41
	d_{nt}^{lead}, 10 meters	0.481	1.46
	$v^{RemDist,lead}$	0.449	1.10
	Constant, d_{nt}^{lead}	-0.963	-0.34
	v^{lead}	-0.0358	-0.25
	σ^{lead}	0.432	0.21
Lag gap	Constant	1.54	5.91
	$Max\left(0, \Delta V_{nt}^{lag}\right)$, m/sec	0.151	0.71
	$Min\left(0, \Delta V_{nt}^{lag}\right)$, m/sec	0.425	0.56
	d_{nt}^{lag}, 10 meters	0.181	1.87
	$v^{RemDist,lag}$	2.83	0.38
	Constant, d_{nt}^{lag}	-2.29	-0.37
	$Max(0, a_{nt}^{lag})$, $m/\sec^2$	0.173	1.24

	ν^{lag}	-0.0317	-0.12
	σ^{lag}	3.19	7.63

Table 5.2 shows estimation results of the merging gap acceptance model using the U.S. 101 dataset. The explanatory variables of the model estimation are the same as those of the model estimation with I-80. The signs of the estimated coefficients in the model are correct to what was expected. In this estimation results, the estimated constant in the lag is larger than that in the lead. It means that drivers consider larger lag critical gaps for their safe merging. The estimated lead constant, 0.283 meter, is very small. The sigma in lead is smaller than in lag. The estimated values of sigma in lead and lag are opposite to those in the I-80. These may be explained by different driving behaviors of the drivers in the U.S 101. The lead and lag gaps of the aggressive drivers do not have significant differences according to the remaining distance. On the other hand, the lead and lag gaps of the timid drivers are affected by the remaining distance. The sensitivity of median lead and lag critical gaps of U.S. 101 as a function of remaining distance to MLC point with the drivers' individual characteristics is shown in Figure 5.8 and Figure 5.9.

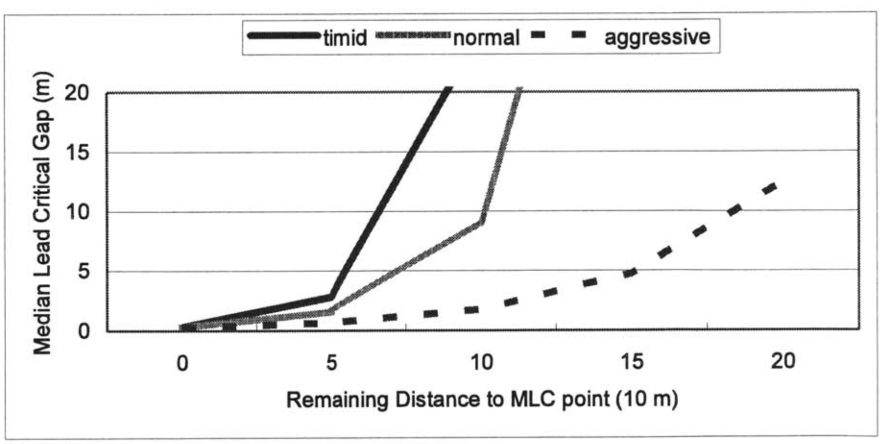

Figure 5.8 - Median critical lead gap as a function of remaining distance

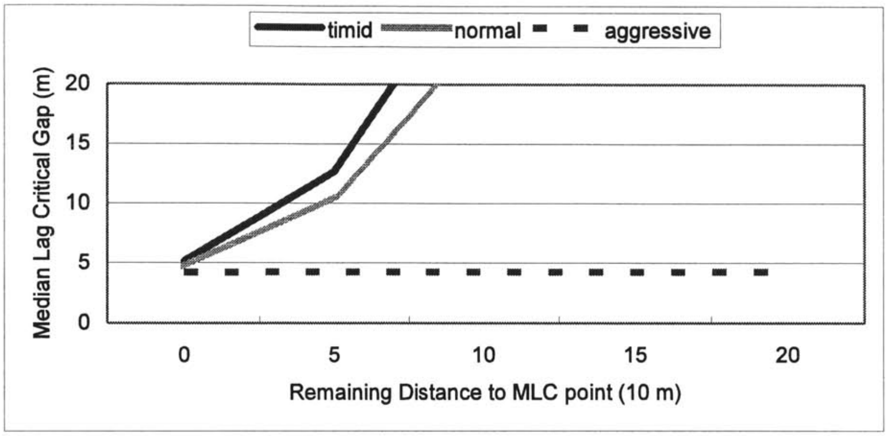

Figure 5.9 - Median critical lag gap as a function of remaining distance

The estimated lead and lag critical gaps for the merging gap acceptance model with U.S. 101 dataset are given by:

$$G_{nt}^{lead,cr} = \exp\begin{pmatrix} -1.26 + \dfrac{1.28}{1+\exp(-Max\left(0,\Delta V_{nt}^{avg}\right))} - 0.338Min\left(0,\Delta V_{nt}^{lead}\right) + \\ + \dfrac{0.481 d_{nt}}{1+\exp(-0.963+0.449\upsilon_n)} - 0.0358\upsilon_n + \varepsilon_{nt}^{lead} \end{pmatrix} \tag{5.7}$$

$$G_{nt}^{lag,cr} = \exp\begin{pmatrix} 1.54 + 0.151Max\left(0,\Delta V_{nt}^{lag}\right) + 0.425Min\left(0,\Delta V_{nt}^{lag}\right) + \\ + \dfrac{0.181 d_{nt}}{1+\exp(-2.29+2.83\upsilon_n)} + 0.173Max(0,a_{nt}^{lag}) - 0.0317\upsilon_n + \varepsilon_{nt}^{lag} \end{pmatrix} \tag{5.8}$$

$\varepsilon_{nt}^{lead} \sim N\left(0, 0.432^2\right)$ and $\varepsilon_{nt}^{lag} \sim N\left(0, 3.19^2\right)$

5.2.3 Estimation results with combined dataset

In this section, the merging gap acceptance models have been estimated with the dataset combining I-80 and U.S. 101. Four estimation results with the combined dataset are described. The first result is estimated with the same explanatory variables as in I-80 and U.S. 101. The second estimated with two more location specific constants to be allowed. The third model is estimated with allowing location specific constants and sigmas. Lastly, the fourth model is estimated with allowing location specific constants, sigmas, and individual specific random errors in the remaining distance term.

Model 3: Merging gap acceptance model with the combined dataset without allowing any variables to be different

The merging gap acceptance model is estimated with the dataset combining I-80 and U.S. 101. The estimated results with the same explanatory variables as in I-80 and U.S. 101 are presented in Table 5.3.

Table 5.3 Estimation results for the Model 3

Final log likelihood			-3121.31
Number of vehicles			914
Number of observations			20975
Number of parameters			17
	Variable	Parameter value	t-statistic
Lead gap	Constant	0.627	1.09
	$Max\left(0, \Delta V_{nt}^{avg}\right)$, m/sec	1.90	2.71
	$Min\left(0, \Delta V_{nt}^{lead}\right)$, m/sec	-0.314	-5.13
	d_{nt}^{lead}, 10 meters	1.76	0.47

	$V^{RemDist,lead}$	0.282	1.03
	Constant, d_{nt}^{lead}	2.21	1.20
	v^{lag}	-0.00104	-0.0600
	σ^{lead}	2.72	8.48
Lag gap	Constant	0.509	1.77
	$Max\left(0,\Delta V_{nt}^{lag}\right)$, m/sec	0.116	1.52
	$Min\left(0,\Delta V_{nt}^{lag}\right)$, m/sec	0.034	0.78
	d_{nt}^{lag}, 10 meters	0.560	3.18
	$V^{RemDist,lag}$	2.21	1.20
	Constant, d_{nt}^{lag}	1.35	4.12
	$Max(0,a_{nt}^{lag}),\ m/\sec^2$	0.105	2.02
	v^{lag}	-0.0004	-0.0190
	σ^{lag}	0.94	6.49

In the estimation result with combined dataset, the signs of all the explanatory variables are intuitively correct. If all the variables are being equal, the lead gap is larger than the lag gap. The magnitude of the estimated values of constant and sigma term is similar to the estimated values of the model with the I-80 data. This may cause that two third of all the observations in the combined data comes from I-80 dataset. The sensitivity of the median lead and lag critical gaps as a function of the various variables affecting them is presented from Figure 5.10 to Figure 5.15.

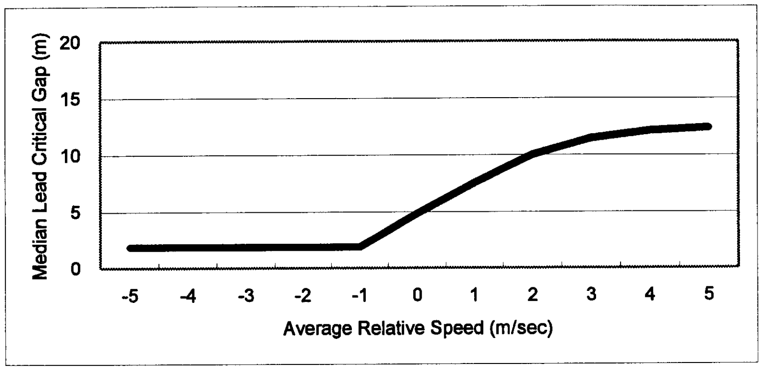

Figure 5.10 - Median critical lead gap as a function of average relative speed

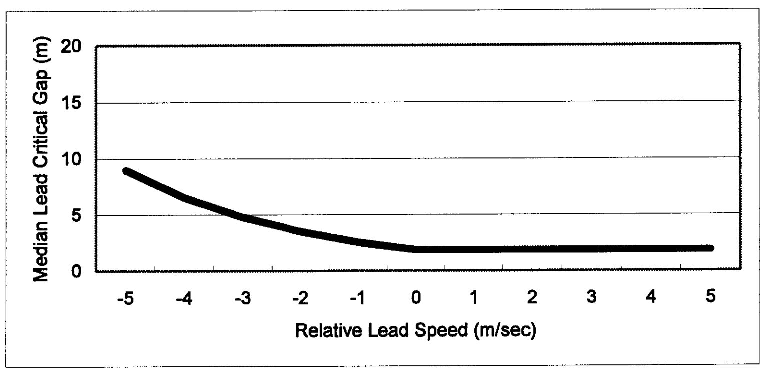

Figure 5.11 - Median critical lead gap as a function of relative speed

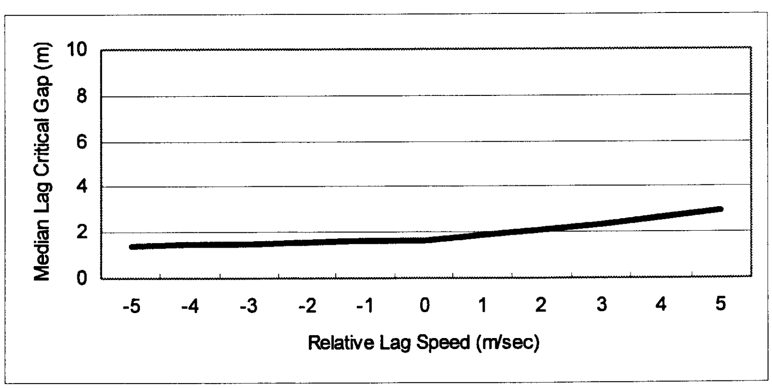

Figure 5.12 - Median critical lag gap as a function of relative speed

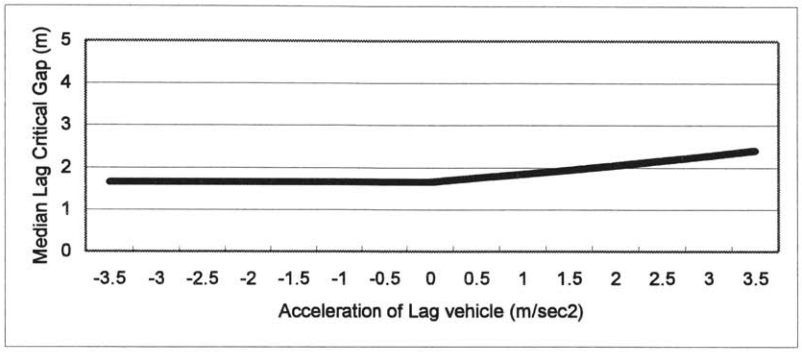

Figure 5.13 - Median critical lag gap as a function of the acceleration of lag vehicle

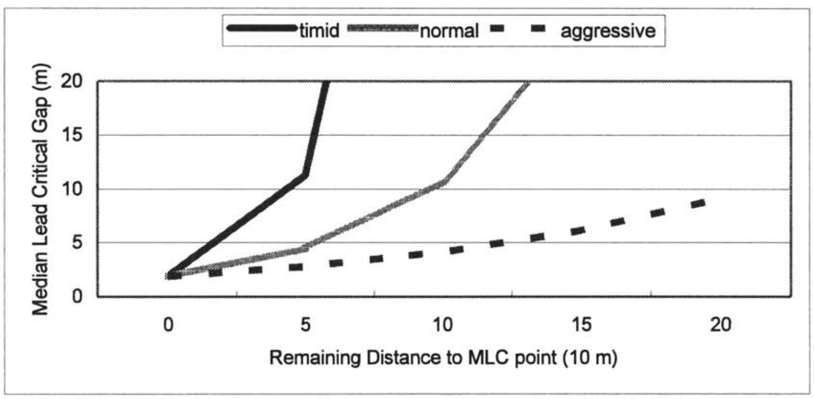

Figure 5.14 - Median critical lead gap as a function of remaining distance

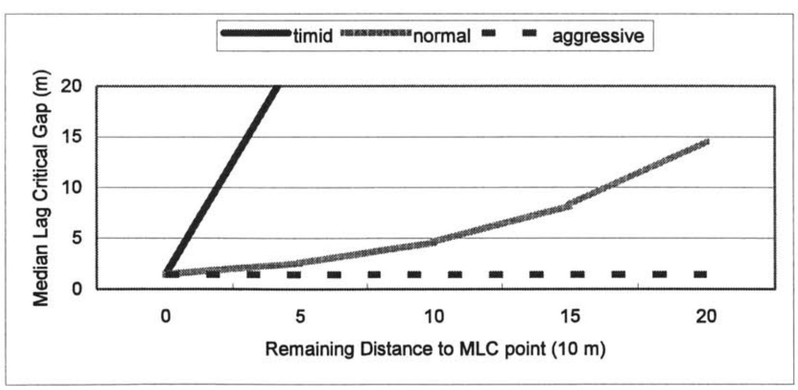

Figure 5.15 - Median critical lag gap as a function of remaining distance

In summary, the estimated lead and lag critical gaps for the merging gap acceptance model with the combined dataset without allowing any variables to be different are given by:

$$G_{nt}^{lead,cr} = \exp\left(\begin{array}{l} 0.627 + \dfrac{1.90}{1+\exp(-Max\left(0,\Delta V_{nt}^{avg}\right))} - 0.314 Min\left(0,\Delta V_{nt}^{lead}\right) + \\ + \dfrac{1.76 d_{nt}}{1+\exp(2.21+0.282\upsilon_n)} - 0.00104\upsilon_n + \varepsilon_{nt}^{lead} \end{array} \right) \tag{5.9}$$

$$G_{nt}^{lag,cr} = \exp\left(\begin{array}{l} 0.509 + 0.116 Max\left(0,\Delta V_{nt}^{lag}\right) + 0.034 Min\left(0,\Delta V_{nt}^{lag}\right) + \\ + \dfrac{0.56 d_{nt}}{1+\exp(1.35+2.21\upsilon_n)} + 0.105 Max(0,a_{nt}^{lag}) - 0.0004\upsilon_n + \varepsilon_{nt}^{lag} \end{array} \right) \tag{5.10}$$

$\varepsilon_{nt}^{lead} \sim N\left(0,2.72^2\right)$ and $\varepsilon_{nt}^{lag} \sim N\left(0,0.94^2\right)$

Model 4: Merging gap acceptance model with the combined dataset allowing location specific constants to be different

The estimation results with allowing location specific constants to be different are summarized in Table 5.4.

Table 5.4- Estimation results for the Model 4

Final log likelihood			-2972.05
Number of vehicles			914
Number of observations			20975
Number of parameters			19
	Variable	Parameter value	t-statistic
	Constant, US101	-1.629	-2.68
	Constant, I-80	-0.042	-0.33

Lead gap	$Max\left(0,\Delta V_{nt}^{avg}\right)$, m/sec	1.82	1.94
	$Min\left(0,\Delta V_{nt}^{lead}\right)$, m/sec	-0.571	-5.76
	d_{nt}^{lead}, 10 meters	3.30	4.64
	$\nu^{RemDist,lead}$	0.43	1.49
	Constant, d_{nt}^{lead}	2.78	2.83
	ν^{lead}	-0.00043	-0.02
	σ^{lead}	3.61	4.98
Lag gap	Constant, US 101	1.24	3.54
	Constant, I-80	0.898	1.04
	$Max\left(0,\Delta V_{nt}^{lag}\right)$, m/sec	0.111	0.65
	$Min\left(0,\Delta V_{nt}^{lag}\right)$, m/sec	0.023	0.48
	d_{nt}^{lag}, 10 meters	0.141	3.30
	$\nu^{RemDist,lag}$	0.85	6.44
	Constant, d_{nt}^{lag}	-0.0134	-0.38
	$Max(0,a_{nt}^{lag})$, $m/\sec^2$	0.034	1.03
	ν^{lag}	-0.0047	-0.25
	σ^{lag}	1.84	6.46

In the estimation results, two constants in lead and lag gap are allowed to be different. One of the two constant is only for I-80, and another is only for U.S.101. In other words, if the observations of the combined dataset come from I-80, the parameter value of I-80 constant is only affected. The magnitude each location specific constant is similar to that of the estimated results each dataset. From the estimated values of the location specific constants, drivers in U.S.101 do not consider lead gaps while making a lane change but consider lag gaps for their safety. On the other hand, drivers in I-80 consider both lead and lag gap. In terms of the goodness of fit, this model is improved than the combined model without allowing location specific constants.

In summary, the estimated lead and lag critical gaps for the merging gap acceptance model with combined dataset allowing location specific constants to be different are given by:

$$G_{nt}^{lead,cr} = \exp\begin{pmatrix} -1.629\delta_{nt}^{US101} - 0.042\delta_{nt}^{I-80} + \dfrac{1.82}{1+\exp(-Max\left(0,\Delta V_{nt}^{avg}\right))} - \\ -0.571Min\left(0,\Delta V_{nt}^{lead}\right) + \dfrac{3.3d_{nt}}{1+\exp(2.78+0.43\upsilon_n)} - 0.00043\upsilon_n + \varepsilon_{nt}^{lead} \end{pmatrix} \quad (5.11)$$

$$G_{nt}^{lag,cr} = \exp\begin{pmatrix} 1.24\delta_{nt}^{US101} + 0.898\delta_{nt}^{I-80} + 0.111Max\left(0,\Delta V_{nt}^{lag}\right) + 0.023Min\left(0,\Delta V_{nt}^{lag}\right) + \\ + \dfrac{0.141d_{nt}}{1+\exp(-0.0134+0.85\upsilon_n)} + 0.034Max(0,a_{nt}^{lag}) - 0.00047\upsilon_n + \varepsilon_{nt}^{lag} \end{pmatrix}$$

$$\varepsilon_{nt}^{lead} \sim N\left(0,3.61^2\right) \text{ and } \varepsilon_{nt}^{lag} \sim N\left(0,1.84^2\right) \quad (5.12)$$

where, δ_{nt}^{US101} denotes location specific dummy variable. δ_{nt}^{US101} is 1 if the observation n at time t belongs to U.S.101 dataset. Otherwise, δ_{nt}^{US101} is 0. δ_{nt}^{I-80} denotes location specific dummy variable. δ_{nt}^{I-80} is 1 if the observation n at time t belongs to I-80 dataset. Otherwise, δ_{nt}^{I-80} is 0.

Model 5: Merging gap acceptance model with the combined dataset allowing location specific constants and sigma's to be different

The estimation results with allowing location specific constants to be different are summarized in Table 5.5.

Table 5.5- Estimation results for the Model 5

Final log likelihood			-2947.38
Number of vehicles			914
Number of observations			20975
Number of parameters			21
	Variable	Parameter value	t-statistic
Lead gap	Constant, US101	-3.25	-2.40
	Constant, I-80	2.17	3.28
	$Max\left(0, \Delta V_{nt}^{avg}\right)$, m/sec	1.64	1.85
	$Min\left(0, \Delta V_{nt}^{lead}\right)$, m/sec	-0.468	-5.88
	d_{nt}^{lead}, 10 meters	2.12	4.41
	$\nu^{RemDist,lead}$	0.19	1.82
	Constant, d_{nt}^{lead}	1.34	2.63
	ν^{lead}	-0.0467	-0.18
	σ_{US101}^{lead}	0.205	0.75
	σ_{I80}^{lead}	4.98	7.63
Lag gap	Constant, US 101	2.05	6.78
	Constant, I-80	0.221	0.46
	$Max\left(0, \Delta V_{nt}^{lag}\right)$, m/sec	0.120	0.96
	$Min\left(0, \Delta V_{nt}^{lag}\right)$, m/sec	0.247	5.31
	d_{nt}^{lag}, 10 meters	0.180	2.16
	$\nu^{RemDist,lag}$	5.08	0.89
	Constant, d_{nt}^{lag}	-1.13	-0.20
	$Max(0, a_{nt}^{lag})$, $m/\sec^2$	0.0084	0.06
	ν^{lag}	-0.0471	-0.04
	σ_{US101}^{lag}	2.78	6.91
	σ_{I80}^{lag}	0.97	1.52

The estimated results of the model have two different constants and sigma in the lead and the lag, respectively. In estimated sigma, sigma I-80 in the lead gap is larger than that in the lag gap. On the other hand, sigma U.S.101 in the lead gap is smaller than that in the lag gap. The magnitude of the estimated sigma values is similar to that of the estimated results in each dataset. All signs of estimated parameters are intuitively correct. The variable to capture the forced merging behavior, remaining distance to the MLC point, is statistically significant. In the goodness of fit, this model is improved than the combined models with and without allowing location specific constants.

In summary, the estimated lead and lag critical gaps for the merging gap acceptance model with combined dataset allowing location specific constants and sigma's to be different are given by:

$$G_{nt}^{lead,cr} = \exp\left(\begin{array}{l} -3.25\delta_{nt}^{US101} + 2.17\delta_{nt}^{I-80} + \dfrac{1.64}{1+\exp(-Max(0,\Delta V_{nt}^{avg}))} - \\ -0.468Min(0,\Delta V_{nt}^{lead}) + \dfrac{2.12d_{nt}}{1+\exp(1.34+0.19\upsilon_n)} - 0.0467\upsilon_n + \varepsilon_{nt}^{lead} \end{array}\right) \quad (5.13)$$

$$G_{nt}^{lag,cr} = \exp\left(\begin{array}{l} 2.05\delta_{nt}^{US101} + 0.221\delta_{nt}^{I-80} + 0.12Max(0,\Delta V_{nt}^{lag}) + 0.247Min(0,\Delta V_{nt}^{lag}) + \\ + \dfrac{0.18d_{nt}}{1+\exp(-1.13+5.08\upsilon_n)} + 0.0084Max(0,a_{nt}^{lag}) - 0.0471\upsilon_n + \varepsilon_{nt}^{lag} \end{array}\right)$$

$$\varepsilon_{nt}^{lead,US101} \sim N(0,2.05^2) \text{ and } \varepsilon_{nt}^{lead,I-80} \sim N(0,4.98^2) \quad (5.14)$$

$$\varepsilon_{nt}^{lag,US101} \sim N(0,2.78^2) \text{ and } \varepsilon_{nt}^{lag,I-80} \sim N(0,0.97^2)$$

where, δ_{nt}^{US101} denotes location specific dummy variable. δ_{nt}^{US101} is 1 if the observation n at time t belongs to U.S.101 dataset. Otherwise, δ_{nt}^{US101} is 0. δ_{nt}^{I-80} denotes location specific dummy variable. δ_{nt}^{I-80} is 1 if the observation n at time t belongs to I-80 dataset. Otherwise, δ_{nt}^{I-80} is 0.

Model 6: Merging gap acceptance model with the combined dataset allowing location specific constants, sigma's, and individual specific random errors in the remaining distance to be different

The estimation results with allowing location specific constants, sigmas, and individual specific random errors in the remaining distance terms to be different are summarized in Table 5.6.

Table 5.6- Estimation results for the Model 6

Final log likelihood			-2925.71
Number of vehicles			914
Number of observations			20975
Number of parameters			23
	Variable	Parameter value	t-statistic
Lead gap	Constant, US101	-3.41	-2.69
	Constant, I-80	0.851	1.20
	$Max\left(0, \Delta V_{nt}^{avg}\right)$, m/sec	0.81	1.24
	$Min\left(0, \Delta V_{nt}^{lead}\right)$, m/sec	-0.56	-7.92
	d_{nt}^{lead}, 10 meters	1.83	3.84
	$v^{RemDist,lead}$, US101	0.06	1.16
	$v^{RemDist,lead}$, I-80	1.20	6.82
	Constant, d_{nt}^{lead}	1.03	3.12
	v^{lead}	-0.569	-2.54
	σ_{US101}^{lead}	0.18	0.92
	σ_{I80}^{lead}	3.79	7.49
Lag gap	Constant, US 101	1.96	6.82
	Constant, I-80	0.197	0.74
	$Max\left(0, \Delta V_{nt}^{lag}\right)$, m/sec	0.263	2.52

	$Min\left(0,\Delta V_{nt}^{lag}\right)$, m/sec	0.236	5.20
	d_{nt}^{lag}, 10 meters	0.187	5.85
	$\nu^{RemDist,lag}$, US101	5.00	3.03
	$\nu^{RemDist,lag}$, I-80	1.90	1.37
	Constant, d_{nt}^{lag}	-1.08	-1.04
	$Max(0,a_{nt}^{lag}),\ m/\sec^2$	0.0325	0.49
	ν^{lag}	-0.271	-1.20
	σ_{US101}^{lag}	2.68	8.77
	σ_{I80}^{lag}	1.12	4.20

The estimated results of the model have two different constants, sigma's, individual specific random errors in the remaining distance term in the lead and the lag, respectively. All signs of estimated parameters are intuitively correct. To capture drivers' heterogeneity, individual specific random errors in the remaining distance term are significant in the lead and lag. In terms of the goodness of fit, this model is improved than the combined models: Model 3, Model 4, and Model 5.

The estimated lead and lag critical gaps for the merging gap acceptance model with combined dataset allowing location specific constants, sigma's, and individual specific random errors in the remaining distance term to be different are given by:

$$G_{nt}^{lead,cr} = \exp\left(\begin{array}{l} -3.41\delta_{nt}^{US101} + 0.851\delta_{nt}^{I-80} + \dfrac{1.83}{1+\exp(-Max\left(0,\Delta V_{nt}^{avg}\right))} - \\ -0.56Min\left(0,\Delta V_{nt}^{lead}\right) + \dfrac{1.83d_{nt}}{1+\exp(1.03+0.06\upsilon_n \times \delta_{nt}^{US101} + 1.20\upsilon_n \times \delta_{nt}^{I-80})} - \\ -0.569\upsilon_n + \varepsilon_{nt}^{lead} \end{array}\right) \tag{5.15}$$

$$G_{nt}^{lag,cr} = \exp\begin{pmatrix} 1.96\delta_{nt}^{US101} + 0.197\delta_{nt}^{I-80} + 0.263Max\left(0, \Delta V_{nt}^{lag}\right) + 0.236Min\left(0, \Delta V_{nt}^{lag}\right) + \\ + \dfrac{1.90d_{nt}}{1+\exp(-1.08+5.00\upsilon_n \times \delta_{nt}^{US101} + 1.90\upsilon_n \times \delta_{nt}^{I-80})} + 0.0325Max(0, a_{nt}^{lag}) - \\ -0.271\upsilon_n + \varepsilon_{nt}^{lag} \end{pmatrix}$$

$$\varepsilon_{nt}^{lead,US101} \sim N\left(0, 0.18^2\right) \text{ and } \varepsilon_{nt}^{lead,I-80} \sim N\left(0, 3.79^2\right) \tag{5.16}$$

$$\varepsilon_{nt}^{lag,US101} \sim N\left(0, 2.68^2\right) \text{ and } \varepsilon_{nt}^{lag,I-80} \sim N\left(0, 1.12^2\right)$$

where, δ_{nt}^{US101} denotes location specific dummy variable. δ_{nt}^{US101} is 1 if the observation n at time t belongs to U.S.101 dataset. Otherwise, δ_{nt}^{US101} is 0. δ_{nt}^{I-80} denotes location specific dummy variable. δ_{nt}^{I-80} is 1 if the observation n at time t belongs to I-80 dataset. Otherwise, δ_{nt}^{I-80} is 0.

In summary, six models are estimated with two different datasets: I-80 and U.S.101 and one combined dataset. The models are affected by the subject relative speed with respect to the lead and lag vehicle in the mainline, traffic condition such as average speed in the mainline, remaining distance to the MLC point, and individual specific random term. The variable, acceleration of the lag vehicle, indirectly captures the courtesy merging behavior. The remaining distance terms are statistically very significant in the estimation results and indirectly capture the forced merging behavior. Furthermore, individual specific random term has been introduced in the coefficient of the remaining distance to capture drivers' heterogeneity. The estimation results show that aggressive and timid drivers can have different critical gaps the remaining distance being equal.

The estimation results for the merging gap acceptance models also indicate that the drivers' merging behaviors of the two datasets are a little bit different; drivers in both U.S. 101 and I-80 consider relatively larger critical lag gaps for their safe merges. On the other hand, the driving behaviors in the lead critical gaps are different. The drivers in U.S. 101 consider very small lead critical gaps; the drivers in I-80 consider larger critical lead gaps. These different behaviors may be caused by the different level of the congested traffic situations and the different highway structure of the merging ramps. In the case of I-80, traffic condition in the merging areas is extremely congested, so highly frequent stop-and-go situation and queuing vehicles in the merging on-ramp are observed. On the other hand, traffic condition in the U.S. 101 is less congested and vehicles merge without queuing in the on-ramp.

5.3 Model Comparisons

The merging gap acceptance model is estimated using the maximum likelihood method with vehicle trajectory dataset. The explanatory variables affect the drivers' merging behaviors in the congested situations of each dataset. To apply the model in all congested situations, the estimated models are compared to between combined dataset and individual datasets: U.S.101 and I-80 data. The hypothesis that the goodness of fit in the combined dataset is not significantly different from the individual datasets is tested. The likelihood ratio test, which is used to compare log likelihood functions for unrestricted and restricted models of interest, can be used to compare the estimated models. To do the likelihood ration test, the estimated merging models with the combined dataset are considered as restricted models and the estimated models with two dataset: I-80 and U.S.101 are regarded as unrestricted models, respectively.

The test statistic for the null hypothesis that the goodness of fit in the combined dataset is same as the individual dataset: U.S.101 and I-80:

$$-2\left(L^R - L^U\right) \tag{5.17}$$

which is asymptotically distributed as χ^2 with r degrees of freedom.

where, L^R is log-likelihood function value of the restricted model. L^U is log-likelihood function value of the unrestricted model. r is number of independent restrictions imposed.

Before the likelihood ratio test, recall that the following models were estimated in Section 5.2:

- Model 1: Merging gap acceptance model with the I-80 dataset.
- Model 2: Merging gap acceptance model with the U.S.101 dataset.
- Model 3: Merging gap acceptance model with the combined dataset without allowing any variables to be different.
- Model 4: Merging gap acceptance model with the combined dataset allowing

location specific constants to be different.

- Model 5: Merging gap acceptance model with the combined dataset allowing location specific constants and sigma's to be different.
- Model 6: Merging gap acceptance model with the combined dataset allowing location specific constants, sigma's, and individual specific random term in the remaining distance to be different.

The likelihood values of the estimated models are presented in Table 5.7.

Table 5.7- Summary of likelihood values

Model		Likelihood Function	Number of Parameters
Unrestricted Model	Model 1	-1641.60	17
	Model 2	-1278.97	17
Restricted Model	Model 3	-3121.31	17
	Model 4	-2972.05	19
	Model 5	-2947.38	21
	Model 6	-2925.71	23

Likelihood ratio test for the Model 3 vs. Model 1 and Model 2:

The likelihood ratio is given by:

-2(-3121.31 - (-1641.60-1278.97)) = 401.48

The number of degrees of freedom is 17 and $\chi^2_{17,0.95} = 27.6$.

Thus, we can reject the null hypothesis at a 0.95 level of significance. The model with combined data is significantly different from the model with individual datasets.

Likelihood ratio test for the Model 4 vs. Model 1 and Model 2:

The likelihood ratio is given by:

-2(-2972.05 - (-1641.60-1278.97)) = 102.96

The number of degrees of freedom is 15 and $\chi^2_{15,0.95} = 25.0$

Based on the LR test, we can reject the null hypothesis at a 0.95 level of significance. The model with the combined dataset allowing location specific constants to be different is not significantly the same as the estimated models with individual datasets.

Likelihood ratio test for the Model 5 vs. Model 1 and Model 2:

The likelihood ratio is given by:

-2(-2947.38 - (-1641.60-1278.97)) = 53.26

The number of degrees of freedom is 13 and $\chi^2_{13,0.995} = 22.4$.

In the comparison between Model 5 and Model 1, 2, we can not reject the null hypothesis at a 0.95 level of significance. The estimated model with the combined dataset allowing location specific constants and sigmas to be different is significantly different from the estimated models with individual datasets.

Likelihood ratio test for the Model 6 vs. Model 1 and Model 2:

The likelihood ratio is given by:

-2(-2925.71 - (-1641.60-1278.97)) = 10.28

The number of degrees of freedom is 11 and $\chi^2_{11,0.995} = 19.7$.

Thus, we can not reject the null hypothesis at a 0.95 level of significance. The model with the combined dataset allowing location specific constants, sigma's, and individual specific random terms in the remaining distance be different is not significantly different from the estimated model with individual datasets.

The summary of the comparisons is presented in Table 5.8.

Table 5.8– Summary of comparisons

Restricted Model	Unrestricted Model	Degrees of freedom	Likelihood ratio Test	Chi-Squared Distribution (0.95 Level of Significance)
Model 3	Model 1 and Model 2	17	401.48	27.6
Model 4		15	102.96	25.0
Model 5		13	53.26	22.4
Model 6		9	10.28	19.7

In summary, the results of the likelihood ratio test indicate that the estimated merging gap acceptance model can not be directly applied to all congested situation. To apply the estimated model, at least six parameters: constants, sigmas, and individual specific random errors in the remaining distance term should be changed. For example, the estimated model with I-80 dataset can be applied to merging situation of the U.S.101 after calibrating at least six parameters: constants, sigmas, and individual specific random errors in the remaining distance terms.

5.4 Summary

In this chapter, the likelihood function for the merging gap acceptance model observed in the trajectory data has been derived and estimation results of the model using Gauss estimation software has been presented.

The six merging gap acceptance models are estimated in this chapter. Two models are estimated with two different datasets: U.S.101 and I-80. The merging gap acceptance decisions are affected by the subject relative speed with respect to the lead and lag vehicle in the mainline, traffic condition such as average speed in the mainline, urgency of the merges such as remaining distance to the MLC point, and driving style: individual specific random term. The variable, acceleration of the lag vehicle, indirectly captures the courtesy merging behavior. The remaining distance terms are statistically very significant in the estimation results and indirectly capture the forced merging behavior.

The likelihood ratio test was performed between the model with the combined dataset as restricted models and the models with two different datasets as unrestricted models for the model transferability test. Through the model comparisons, the estimated merging gap acceptance model can be applied to the congested situation after calibrating at least six parameters: constants, sigmas, and individual specific random errors in the remaining distance term.

Chapter 6

Implementation

In this chapter, the merging gap acceptance model is implemented and evaluated within the framework of a microscopic traffic simulation tool MITSIMLab. The simulated results of the merging gap acceptance model are compared with the observed data from the I-80 vehicle trajectory and the simulated output of normal gap acceptance model. The first section gives an overview of MITSIMLab. Next, the comparison results with the merging gap acceptance model are presented.

6.1 Overview of MITSIMLab

MITSIMLab (Yang and Koutsopoulos, 1996) is a simulation-based laboratory that was developed for evaluating advanced traffic management system designs (ATMS) and advanced traveler information system (ATIS) at the operational level. MITSIM represents the real-world with detailed traffic and network elements and individual drivers' behavior. MITSIMLab consists of three main components:

- Microscopic Traffic Simulator (MITSIM)
- Traffic Management Simulator (TMS)
- Graphical User Interface (GUI)

Traffic Flow Simulator (MITSIM)

MITSIM represents the real world. The traffic and network elements are represented in detail to capture the sensitivity of traffic flows to the control and routing strategies. The main elements of MITSIM are:

- Network Components: The road network along with the traffic controls and surveillance devices are represented at the microscopic level. The road network consists of nodes, links, segments, and lanes.

- Travel Demand and Route Choice: The traffic simulator accepts as input time-dependent origin to destination trip tables. These OD tables represent either expected conditions or are defined as part of a scenario for evaluation. A probabilistic route choice model is used to capture drivers' route choice decisions.

- Driving Behavior: The OD flows are translated into individual vehicles wishing to enter the network at a certain time. Behavior parameters (such as desired speed, aggressiveness, etc.) and vehicle characteristics are assigned to each vehicle/driver combination. MITSIM moves vehicles based on car-following and lane-changing models. The car-following model captures the response of a driver to conditions ahead as a function of relative speed, headway and other traffic measures. The lane changing model classifies mandatory and discretionary lane changes. Merging, drivers' responses to traffic signals, speed limits, incidents, and toll booths are also captured. Rigorous econometric methods have been developed for the calibration of the various parameters and driving behavior models.

Traffic Management Simulator (TMS)

The traffic management simulator mimics the traffic control system under evaluation. A wide range of traffic control and route guidance systems can be evaluated, such as:

- Ramp control
- Freeway mainline control
    - lane control signs (LCS)
    - variable speed limit signs (VSLS)
    - portal signals at tunnel entrances (PS)
- Intersection control
- Variable Message Signs (VMS)

- In-vehicle route guidance

TMS has a generic structure that can represent different designs of such systems with logic at varying levels of sophistication (from pre-timed to responsive).

Graphical User Interface (GUI)

The simulation laboratory has an extensive graphical user interface that is used for both, debugging purposes and demonstration of traffic impacts through vehicle animation.

The proposed gap acceptance model has been implemented in MITSIM. The lane selection model by Choudhury (2005) and acceleration model proposed by Ahmed (1999) have been used.

6.2 Implementation Results

For running MITSIMLab, detailed OD data is required, so OD data is calculated from I-80 vehicle trajectory dataset. I-80 trajectory dataset is collected from three time sets each 15 minutes (4:00 p.m. ~ 4:15 p.m., 5:00 p.m. ~ 5:15 p.m., and 5:15 p.m. ~ 5:30 p.m.), 45 minutes in total. However, one of the three time sets is not consecutive. Thus, the OD data of 4:00 p.m. ~ 4:15 p.m. is assumed as the OD data of 4:45~5:00. For comparing with simulated output of the merging model, the observed data between 5:00~5:30 is only used. Table 6.1 shows number of input vehicles by lane and time period.

Table 6.1- Number of entering vehicles by lane and time period

	4:00-4:05	4:05-4:10	4:10-4:15	5:00-5:05	5:05-5:10	5:10-5:15	5:15-5:20	5:20-5:25	5:25-5:30	Sum
Lane 1	110	113	125	121	139	122	127	128	126	**1111**
Lane 2	116	114	102	112	104	69	84	91	57	**849**
Lane 3	100	93	82	96	81	48	78	89	38	**705**
Lane 4	122	95	93	99	93	51	94	89	52	**788**
Lane 5	96	109	86	104	88	51	96	83	60	**773**
Lane 6	89	98	65	85	72	49	76	78	48	**660**
On-ramp	62	64	64	81	71	53	81	71	48	**595**
Sum	**695**	**686**	**617**	**698**	**648**	**443**	**636**	**629**	**429**	**5481**

The simulated outputs of the merging gap acceptance model is compared with the simulated output of Choudhury (2005)'s normal gap acceptance model. The Choudhury's normal gap acceptance model is re-estimated with I-80 vehicle trajectory dataset to obtain parameter values under the same situations. The parameters of the normal gap acceptance model are subject relative speed with respect to the lead and lag vehicles. The simulated output of the merging model is also compared with the observed data collected from I-80 data. Travel time from the time entering on-ramp to the time ending merging, and the remaining distance to the merging point are used as measures of performance.

Figure 6.1 and Figure 6.2 show the comparison results between the merging gap acceptance model, normal gap acceptance model, and real data by the travel time and remaining distance to MLC point until vehicles merge with the mainline.

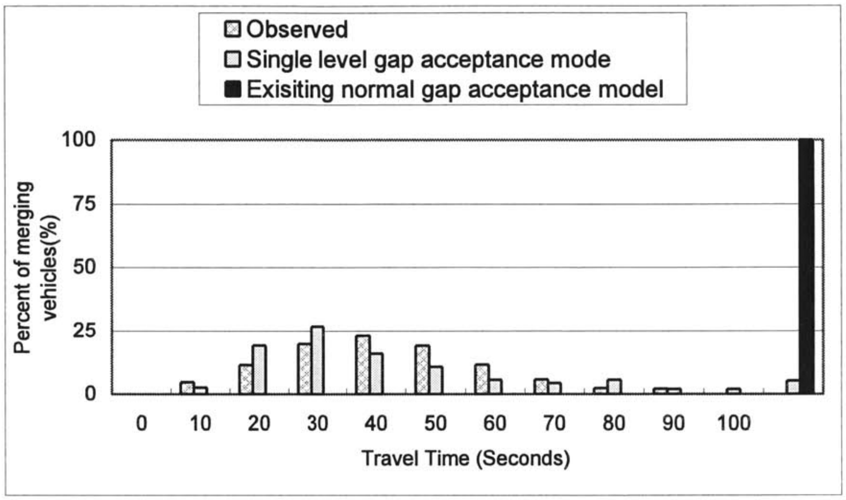

Figure 6.1 – Observed and simulated travel time in the I-80 dataset

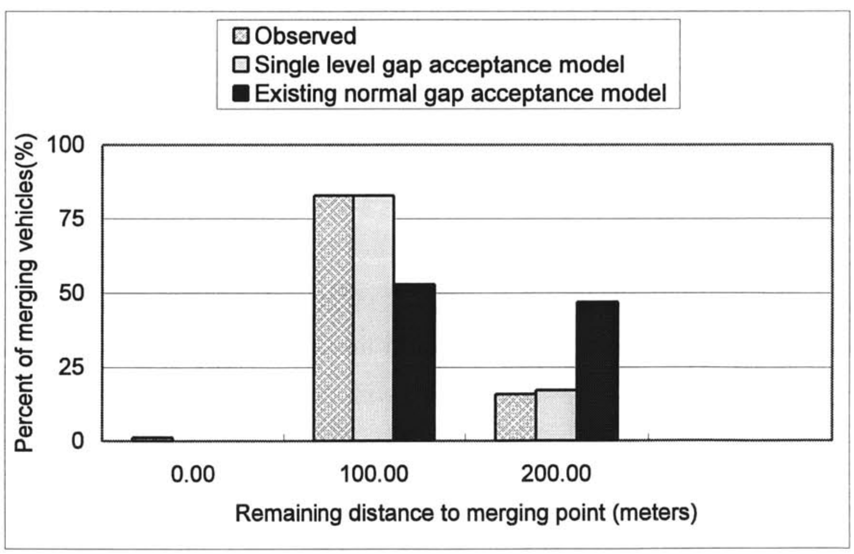

Figure 6.2 – Distribution of observed and simulated remaining distance to MLC point

Travel time of the merging gap acceptance model, or single level model, is similar to the travel time of real data collected from I-80. However, the travel time of the normal gap acceptance model is over 100 seconds in all the cases, and does not match with real data of I-80. It means that normal gap acceptance can not explain the congested merging situations. In the case of the remaining distance to MLC, 80% vehicles in real data make lane changes remaining 100 meters or less to the MLC point. The remaining distance to MLC point in the merging gap acceptance model case is also similar to that of real data. On the other hand, almost half of all the vehicles in the normal gap acceptance model make lane changes within 100 meters.

6.3 Summary

The merging gap acceptance model is implemented in a microscopic traffic simulator MITSIMLab and simulated with data from a section of I-80, CA network. The performance of the merging gap acceptance model has been compared with that of normal gap acceptance model and the observed data from I-80. The merging gap acceptance model outputs have better than the simulated outputs of the normal gap acceptance model. In addition, the simulated outputs of the merging model are a closer match with the observed data from I-80 in term of travel time and remaining distance to MLC point. Thus, it can be concluded that the impact of the merging gap acceptance model has been better captured in the normal gap acceptance model under the congested merging situation.

Chapter 7

Conclusions

In this chapter, the contributions of this thesis have been summarized. Suggestions for future research are suggested.

7.1 Summary

A merging gap acceptance model is presented to capture drivers' behavior in the congested merging areas. The model structure is formulated as a binary choice problem: make a lane change and do not make a lane change. The merging gap acceptance model incorporates explanatory variables that capture all three types of merging behavior: normal, forced, and courtesy merging. The model is included in a driver-specific random error to capture unobserved individual-specific random errors such as aggressiveness.

Parameters of the model have been estimated using a maximum likelihood estimator with detailed vehicle trajectory datasets: U.S.101 and I-80. In the estimation results, the explanatory variables affect the drivers' merging behaviors in congested conditions: the variable, which is remaining distance to the MLC point, captures forced merging behavior and the variable, the acceleration of lag vehicle, captures courtesy merging behavior. Six models are estimated with individual trajectory dataset and combined dataset for the transferability tests for the stability of the model parameters between the two datasets. Statistical test using the estimation results shows that the model is applied when constants, sigmas, and individual specific random errors in the remaining distance term are to be different.

The estimated model is implemented and tested in a microscopic traffic simulator, MITSIMLab using the observed data from a section of I-80, CA. The simulated outputs of the merging gap acceptance model are compared against the observed data of I-80 and the simulated outputs of the normal gap acceptance model. From the comparisons, the merging gap acceptance model has been better prediction under the congested merging situation in term of measures of performance: travel time and remaining distance to MLC point.

In summary, the contributions of this thesis are as follows: (i) a merging gap acceptance model is developed using a single critical gap function. (ii) The parameters of the merging gap acceptance model are estimated using vehicle trajectory data. Estimation results show that the estimated model is affected by traffic conditions such as average speed in the mainline, interactions with lead and lag vehicles, and urgency of the merge. (iii) The transferability tests for the stability of the model parameters between the two datasets are conducted. (iv) The estimated is implemented and tested in a microscopic simulator MITSIMLab. Through the comparison results, the merging gap acceptance model has better prediction than the normal gap acceptance model under the congested merging situations.

7.2 Future Research

The following are some of the further research issues:

- The framework of the merging gap acceptance model is formulated as a binary choice problem. Furthermore, forced and courtesy merging behaviors are only captured by the explanatory variables of the model. Further research for the model explicitly considering cooperation and competition between merging vehicles and vehicles on the mainline is required.

- Sensor data, aggregate data, collected from the merging areas were not available. During this research, the observed data from the trajectory data were used as the inputs of the implementation. Thus, future research is required to use the sensor data to implement, calibrate, and validate the merging model.

- The interaction between the lane-selection and acceleration behavior of the driver is ignored in this research. However, drivers in the merging areas are likely to consider not only merging gap acceptance behavior, but also acceleration and lane-selection behavior. Thus, it needs to develop more detailed merging driver behavior model with acceleration and lane-selection behavior.

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