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# Modeling Freeway Lane Changing Behavior

by  
Kazi Iftekhar Ahmed

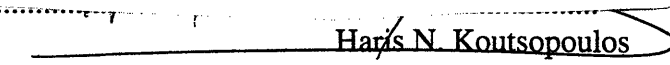
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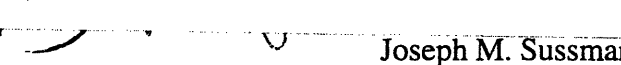
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# MODELING FREEWAY LANE CHANGING BEHAVIOR

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in Transportation

## ABSTRACT

Drivers continuously evaluate the surrounding traffic and the roadway environment, and make decisions about lanes and travel speed. The objective of this thesis is to develop a lane changing model that can be used in microscopic traffic simulation models to capture drivers' lane changing behavior. Lane change is modeled as a sequence of four steps: decision to consider a lane change, choice of left or right lane, search for an acceptable gap to execute the decision, and performing the lane change maneuver. First, a decision is made whether a driver will consider changing lanes. If a decision to consider changing lanes is made, a lane is chosen from the alternatives. Finally, the gap acceptance model determines whether the available gap in the target lane is sufficient for a safe merging and lane change can be completed.

A discrete choice framework is used to model the lane changing behavior. The framework allows for modeling the impact of different elements of the traffic and roadway environment on driver behavior.

The model is applied in the special case of merging from an on-ramp. Results from the estimation of the parameters show that in addition to the gap length, other important factors that affect drivers gap acceptance behavior are relative speed, distance remaining to the point at which lane change must be complete, and delay in completing merging. Finally, the estimated model is tested in a micro-simulation environment.

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# CHAPTER 1

## INTRODUCTION

Congestion in the highways in and around urban areas in the USA and other countries is a major problem that cannot be addressed using the existing transportation and traffic engineering tools. Congestion leads to many problems, such as decline in safety and in mobility of people and freight, as well as increase in travel time, travel cost, and environmental pollution. In most cases, increasing the number of lanes to provide additional capacity is impractical due to financial, environmental, and land use constraints. A potential solution to this problem is to improve traffic flow to achieve better utilization of the roadway capacity. This can be achieved through efficient traffic operations and management. In this context, research in intelligent transportation systems (ITS) aims at providing the necessary tools. Major components of ITS include travel and transportation management, travel demand management, public transportation operations, electronic toll collection, commercial vehicle operations, incident management and emergency response, and advanced vehicle control and safety systems.

To evaluate the impacts of ITS, tools are necessary for planners and traffic engineers to test and evaluate different strategies. Simulation is the most suitable tool for the purpose of evaluation at the operational level. To simulate different ITS elements -- such as dynamic traffic control and surveillance systems, incident detection and response, emergency vehicle operations, and mainline control -- a detailed representation of road network and traffic operations are necessary. This level of detail can only be provided by microscopic simulation. There exists a large number of traffic simulators, for example, INTRAS, FRESIM, and NETSIM. However, these simulators have deficiencies, for example, simplifying assumptions and unsatisfactory performance, that make them unsuitable for evaluating ITS (Yang, 1993). A Microscopic Traffic Simulator (MITSIM) is currently under development at MIT for evaluation of ITS and dynamic traffic

management systems at the operational level (Yang and Koutsopoulos, 1995). MITSIM is capable of simulating each element of the road network including the individual driver, roadway geometry, traffic signs and signals in detail. In addition, the simulator is also capable of supporting ITS technologies, for example, advanced traffic control, electronic toll payment, and surveillance systems.

An important element of the simulator is the behavior of drivers in the presence of external stimuli. This behavior is represented through a route choice model, an acceleration model, and a lane changing model. This thesis presents the development and model parameter estimation of the lane changing model. A data set provided by the Federal Highway Administration (FHWA) is used to estimate the model parameters. A case study is presented that is a special case of the general lane change process -- merging from a freeway on-ramp.

## **1.1 Research Motivation**

Developing appropriate models that capture driver behavior are important because of their role not only in microscopic traffic simulation models but also in developing geometric standards, assessing capacity at weaving sections, and evaluating capacity of and delays at intersections and ramps.

The gap acceptance model parameters are used for empirically estimating capacity and delay at intersections and pedestrian crossings. It is important to understand drivers' gap acceptance behavior before any modeling effort is undertaken. Cassidy et al. (1995) demonstrated the importance of finding the gap acceptance model parameters accurately for assessing capacity and delay at a T-intersection.

The length of an acceleration lane is a very important design element for an on-ramp or a weaving section of a freeway from a safety point of view. To ascertain the appropriate

length of an acceleration lane, in addition to the type of vehicles, volume and speed of traffic both in the mainline and in the on-ramp, drivers' lane change behavior also plays an important role. If the majority of the drivers are conservative, the length requirement increases.

Lane change operations give rise to interactions between drivers that lead to impeding of traffic flow. Generally, near off- and on-ramps drivers change lanes in order to be in a lane connected to their destination and these locations are considered as one of the reasons that create bottlenecks. Potential solutions to this problem include proper lane configurations, improving geometric design, and placing traffic signs at appropriate locations so that the disruption of the traffic flow is minimized. These require understanding drivers' lane changing behavior.

### **1.1.1 Intelligent Transportation Systems (ITS)**

ITS, formerly known as Intelligent Vehicle Highway Systems (IVHS), is the application of advanced and emerging technologies in communications, computers, and sensors to the needs of surface transportation. The broad goals of ITS include increasing capacity of existing and future roadways, reducing environmental pollution, increasing accessibility and reliability of transportation systems, enhancing safety, and increasing productivity. In order to achieve these goals, the ITS program (see Euler et al., 1995) has identified a number of inter-related user services, for example, route guidance, traffic control, emergency vehicle management. These user services are more likely to be deployed in combination with other services. Services that share some common technical functionalities and will be deployed by the same institutional organizations are organized into bundles. The following description are adopted from Euler et al., 1995. Examples of bundles include:

- Travel and Transportation Management,
- Travel Demand Management,

- Public Transportation Operations,
- Electronic Payment,
- Commercial Vehicle Operations,
- Emergency Management, and
- Advanced Vehicle Control and Safety Systems.

The *Travel and Transportation Management* bundle includes user services that collect and process information about the surface transportation system. This bundle disseminates this information to the travelers as well as to the travel demand management and the public transportation operations bundles. Six user services have been identified within this bundle:

- en-route driver information,
- route guidance,
- traveler services information,
- traffic control,
- incident management, and
- emission testing and mitigation.

*Travel Demand Management* includes user services that help in reducing vehicle demand by encouraging use of high occupancy vehicles, and providing information on transit. The user services within this bundle are

- demand management and operations,
- pre-trip travel information, and
- ride matching and reservation.

*Public Transportation Operations* ensures efficient management of public transportation systems and is the responsibility of the transit authority. The user services include:

- public transportation management,
- en-route transit information, and

- personalized public transit.

*Electronic Payment* allows travelers to pay electronically, and thereby reduces queuing at the toll booth.

*Commercial Vehicle Operations* allows for improving the efficiency and safety of commercial fleet operations. The user services are commercial vehicle electronic clearance, automated roadside safety inspection, on-board safety monitoring, commercial vehicle administrative process, hazardous material incident response, and freight mobility.

The *Emergency Management* bundle includes two services: emergency notification and personal security, and emergency vehicle management.

*Advanced Vehicle Control and Safety Systems* include seven user services all of which have a common goal: improving vehicle safety. These services include:

- longitudinal collision avoidance,
- lateral collision avoidance,
- intersection collision avoidance,
- vision enhancement for crash avoidance,
- safety readiness,
- pre-crash deployment service, and
- Automated Highway Systems (AHS).

AHS is a long-term goal of ITS. The vehicles will be guided automatically and the required headway between the vehicles will be greatly reduced. In addition to enhanced safety, AHS benefits include increased roadway capacity, reduced fuel consumption, and emission.

### **1.1.2 Microscopic Traffic Simulation**

To evaluate different traffic management and control strategies under ITS, a Microscopic Traffic Simulator (MITSIM) is currently under development that would allow the simulation of various traffic operations under these strategies (Yang and Koutsopoulos, 1995). The simulator is, however, one of the components of a larger system for evaluation (Ben-Akiva et al., forthcoming, and Ben-Akiva et al., 1995).

The basic components of MITSIM are the road network, the vehicles, the surveillance system, the control signs and signals, and the control logic. Lane configuration and geometric characteristics, functional classification of roads (for example, freeways, ramps, and local roads), lane use regulations (for example, high occupancy vehicle lanes), and toll booth operations are explicitly simulated. The surveillance system includes a wide range of sensors, vehicle to roadside communication devices, over-height detectors, and carbon monoxide sensors. The control signs and signals includes static message signs, signals, variable message signs, lane use signs, highway advisory radio, and blank-out signs. The control logic includes ramp metering, mainline metering.

The main input to the simulator include travel demand, and traffic control and route guidance logic. Travel demand is represented by time dependent origin-destination trip table. The simulator then simulates vehicle movements in the network, and generates different measures of effectiveness (MOE) that are needed for system evaluation.

The output generated by the simulator includes:

- vehicle specific information, such as total travel time, distance traveled, and average speed;
- readings from traffic sensors, such as traffic counts, occupancy, speed, point to point travel time, and incident information;
- segment specific traffic data, such as density, average speed, and travel time; and,

- graphical display of the vehicle movements.

The MOE includes various aggregations over time, space, and vehicles of the above measures.

Vehicle movements are simulated using driver behavior models that model the behavior of an individual driver in the presence of external stimuli. These models are the route choice model, the acceleration model, and the lane changing model. The route choice model models drivers' route choice decision to reach the intended destination; the acceleration model models how drivers decide on what speed to maintain; and the lane changing model models drivers decisions regarding selecting and changing lanes. First, drivers are assumed to decide on which route to take, and then, given this information, acceleration and lane changing decisions are made. In this thesis, only the lane changing model is developed.

The route choice model is used for en-route decisions whenever the driver receives updated information on traffic conditions from variable message signs, highway advisory radio, the on-board navigation system, or vehicle to roadside communications. The regulations of turning movements at the intersections and the lane use privilege (for example, single occupant vehicles are not allowed to travel in a high occupancy vehicle only lane) are also considered in selecting a particular route.

The acceleration model calculates vehicle's acceleration rate. Several factors are taken into account in determining the acceleration of a vehicle, for example,

- car-following acceleration,
- lane use signs,
- lane blockages,
- traffic signals,
- merging,
- connecting to appropriate downstream link,
- speed limit signs,
- yielding, and

- variable message signs.

The lane changing model describes how drivers make decisions about lanes for travel. If the current lane is chosen no lane change takes place. If any lane other than the current one is chosen, a lane change takes place only if the available gap in the target lane is sufficient for safe merging. The focus of this thesis is the development of the lane changing model.

## **1.2 Scope**

The objective of this research is to develop a lane changing model that captures the impact of different elements of traffic and roadway environment on driver behavior. In addition, the model framework should have the flexibility to model driver behavior in the presence of new and emerging ITS technologies, for example, en-route driver information, variable message signs, lane use signs.

The model should take into account the fact that drivers behave differently from each other and even the same driver may behave differently under identical conditions. From both the modeling and the estimation point of view another source of complexity is that only the action of changing lanes can be observed. The exact time at which a decision to change lanes is made cannot be observed except for a few specialized situations, such as freeway merging from an on-ramp. Finally, state dependence further complicates the estimation process. The term state dependence refers to the influence of past outcomes on the current choice.

The methodology proposed in this research has the following characteristics:

- explicitly takes into consideration the factors that affect the lane changing decision process;
- captures the dynamics of the decision process;



- captures heterogeneity across the driving population; and,
- has the flexibility to incorporate the impact of future technologies on driver behavior.

### **1.3 Thesis Outline**

Chapter 2 provides a literature review of existing lane changing and gap acceptance models. In chapter 3, the conceptual framework and the mathematical derivations of the proposed lane changing model structure are presented. A discussion on data set and a model estimation and validation case study are presented in Chapter 4. The final chapter presents the conclusions of this research and suggestions for future research.

## **CHAPTER 2**

### **LITERATURE REVIEW**

Despite its importance, the lane changing model has not been studied extensively. The principal focus of the research on lane change behavior has been on modeling the execution of the lane change maneuver when a driver is forced to change lanes due to termination of one lane or a driver changes lanes to overtake a slower vehicle. The lane changing decision process has not been addressed thoroughly. However, the gap acceptance model, which models the execution of a decision to change lanes, has received more attention from researchers.

Most of the research on the gap acceptance model focus on modeling driver behavior at intersections rather than during freeway merging. The parameters of a gap acceptance model are used for studying delay and capacity at unsignalized intersections, pedestrian crossings, freeway merging, and lane changing maneuvers. It is assumed that each driver has a critical gap. The term critical gap is defined as the unobservable minimum gap the driver is willing to accept in order to change lanes. The gap acceptance process is probabilistic in nature. Each driver has a different perception of a critical gap and the critical gap varies with different situations even for the same driver. Different gap acceptance models are developed based on different distributional assumptions of the critical gap.

This chapter begins by reviewing previous research on the lane changing model. Then the literature on the gap acceptance model is presented. Finally, the chapter ends by summarizing the findings from the literature.

## **2.1 Literature Review on the Lane Changing Model**

Gipps (1986) presented a structure of the lane change decision processes for urban roadways where the influence of traffic signals, obstructions, and heavy vehicles (for example, bus, truck, semi-trailer) on drivers' selection of lanes are modeled. The framework models the decision process based on safety concern, necessity, and desirability of changing lanes under different driving conditions. Different situations were examined where drivers face conflicting goals, but they were modeled deterministically -- prespecifying priorities of some goals over the others for all the drivers. The proposed model does not capture the inconsistency and non-homogeneity in driver behavior. The term inconsistency refers to the fact that the same driver may behave in a different manner under identical conditions, and the term non-homogeneity refers to the fact that different drivers behave in a different manner. The model parameters were not estimated formally.

In MITSIM (Yang and Koutsopoulos, 1995) a rule-based lane changing model was used that is applicable for freeways only. Lane changes were classified as mandatory and discretionary lane changes. A comprehensive list of conditions were presented under which a mandatory or a discretionary lane change may take place. Priorities, when the drivers face conflicting goals, were modeled in a probabilistic framework that captures the inconsistency and non-homogeneity in driver behavior. The model has the flexibility to incorporate ITS technologies, for example, response to lane use signs or variable message signs. The execution of a decision to change lanes is modeled by using a gap acceptance model that recognizes the fact that the gap length necessary for a mandatory lane change is lower than that necessary for a discretionary lane change. However, no formal estimation of the parameters and validation of the models were conducted.

CORSIM (FHWA,1995), a microscopic traffic simulator, employs the lane changing model used by the traffic simulators FRESIM (for freeways) and NETSIM (for urban streets). Lane change is classified as mandatory and discretionary. Desire for or necessity of changing lanes are determined by computing acceptable risk that is a function of the

driver's position relative to the object that gives rise to the need for a lane change. Again, the parameters associated with this computation are not formally estimated and the simulator users are required to provide the parameter values. The gap acceptance model also involves the use of user defined acceptable gap length and is not modeled systematically.

## **2.2 Literature Review on the Gap Acceptance Model**

The Highway Capacity Manual (HCM, 1985) defined critical gap for a two-way stop controlled intersection as the median value of the all the accepted gap lengths. Kittelson et al. (1991) listed the deficiencies of this definition, for example, the median gap size is an inaccurate estimate of the critical gap length, since, accepting a large gap gives no information regarding the minimum acceptable gap, and the critical gap length does not remain constant over a time period. In the revised HCM (1993) procedure, the critical gap is defined as the largest observed rejected gap length. Cassidy et al. (1995) listed many deficiencies of this approach, for example, only a subset of the data is considered that leads to loss of information, inconsistency in driver behavior (accepting a gap smaller than some of the rejected gap lengths) is addressed either by discarding or by modifying the data. The benefit of using the HCM definition of critical gap are ease in estimation and in subsequent analysis, for example, estimating delay and capacity of an intersection.

Earlier efforts for modeling the gap acceptance behavior using a probabilistic framework were based on the distribution of the critical gap. For example, Herman and Weiss (1961) used exponential distribution, Drew et al. (1967) assumed lognormal distribution, and Miller (1972) used normal distribution.

Daganzo (1981) used a probit model to estimate the parameters of a normally distributed critical gaps at T-intersections. Critical gap or unobserved threshold of acceptance for driver  $n$  facing the  $t$ -th gap was assumed to have the following functional form:

$$G_{tn}' = G_n + \xi_{tn} \quad (2 - 1)$$

where,

$G_{tn}'$  = critical gap length for driver  $n$  at time  $t$ ;

$G_n$  = component of critical gap attributable to driver  $n$ ; and

$\xi_{tn}$  = random term that varies across different gaps for a given individual as well as across individuals.

$G_n$  and  $\xi_{tn}$  are assumed to be mutually independent normally distributed random variable;  $G_n \sim N(G, \sigma^2)$  and  $\xi_{tn} \sim N(0, \sigma_\alpha^2)$ .  $G$ ,  $\sigma^2$ , and  $\sigma_\alpha^2$  are parameters of the model. The individual specific random component ( $G_n$ ) and the generic random term ( $\xi_{tn}$ ) in the critical gap function allowed for capturing heterogeneity in the driver population. This approach accounted for within driver variation, as well as across drivers variation. The data set used was a panel data that included one or more observations from each driver -- therefore, observations from the same driver are likely to be correlated, and the model took that into account. The model had the flexibility to incorporate the impact of other factors, for example, speed, weather, road geometry, impatience phenomenon, and driver population characteristics, by allowing the mean of  $G_n$  to depend on these factors. The term impatience phenomenon refers to the frustration caused to the drivers that make them more aggressive in accepting a gap as their waiting time increases. However, the model had an estimability problem and critical gap lengths are not guaranteed to be non-negative.

Mahmassani and Sheffi (1981) used a probit model to estimate the parameters of the distribution of the critical gap at a T-intersection. The impatience phenomenon on the gap acceptance behavior was captured by using *number of gaps rejected* as an explanatory variable that affects the mean of the critical gap. However, the model structure did not capture the correlation between observations from the same driver.

Kita (1993) modeled drivers' gap acceptance behavior in freeway merging using a logit model. In addition to the gap length, the effect of relative velocity of the merging car to

the corresponding through car, and remaining distance of the acceleration lane on driver behavior were also modeled. The fact that a number of observations from the same driver may be correlated was not modeled.

Cassidy et al. (1995) used a logit model to model the gap acceptance behavior at a T-intersection and addressed the shortcomings of the method proposed by the Highway Capacity Manual. A logit model was used to estimate the mean of a single valued critical gap function (a function that includes only the gap length). In addition, different disaggregate factors that affect gap acceptance behavior at intersections, such as the total delay experienced by the driver up to the occurrence of the gap under consideration and whether the gap is the first gap being considered, were also incorporated. The gap acceptance function with disaggregate factors was demonstrated to have significantly greater predictive power than a function that includes only the gap length.

## **2.3 Summary**

Although there have been some effort to incorporate the probabilistic nature of the driver behavior in the lane changing decision process, the model parameters were never estimated formally. When drivers face conflicting goals, all drivers may not behave in a prespecified manner and any lane changing decision framework should have the provision to allow for such variations in driver behavior. For the gap acceptance model, important issues include using estimation methods appropriate for a panel data, incorporating the effect of different disaggregate factors and state dependence (for example, delay in finding gap, number of gaps rejected) on driver behavior. Inconsistency and non-homogeneity in driver behavior are important factors that should be accounted for in any driver behavior modeling effort. In addition, when using panel data to estimate model parameters, the correlation between observations from the same individual should be captured.

# **CHAPTER 3**

## **METHODOLOGY**

Drivers continuously evaluate the surrounding traffic and the roadway environment, and make decisions about lanes and travel speed. In this chapter, a model is presented that explicitly captures different elements of a driver's decision process in changing lanes.

This chapter starts with presenting the conceptual framework of the proposed lane changing model and is followed by the formulation of the model. Finally, the likelihood function, necessary for model parameters estimation, is formulated.

### **3.1 The Model**

An observation of a lane change may be viewed as an outcome of the following sequence:

- decision to consider a lane change,
- choice of left or right lane,
- accepting a gap in the desired lane, and
- performing the lane changing maneuver.

These four activities are modeled by two submodels: decision to consider a lane change and choice of left or right lane, and the gap acceptance model. First, a driver decides whether a lane change is necessary or desirable; if a decision is made to change lanes, a lane is chosen from the choices available. The execution of the decision, whether there is sufficient gap in the target lane and merging can be done within the next time period, is modeled by the gap acceptance model.

A driver may continue the gap search process until an acceptable gap is found, or may give up after a while because of unavailability of an acceptable gap and reconsiders the decision to change lanes. The exact time at which the decision to change lanes takes place, or the state of looking for an acceptable gap are not directly observable -- they are latent. Freeway merging at on-ramps and merging or crossing a main street from a minor street (for example, at an unsignalized intersection) are exceptions; in these situations the drivers start seeking an acceptable gap almost immediately upon arrival to the merge point or intersection. The aspects of the more general case make the modeling of the lane changing process very complicated.

The proposed model simplifies the complexities described above by assuming that the drivers make decisions about lanes at every discrete point in time. It implies that the drivers consider the entire lane change decision process at every time period independent of the decisions made at earlier time periods. Therefore, state dependence is not modeled. The term state dependence refers to the effect of past situations and outcomes on present decisions.

### **3.1.1 Conceptual Framework of the Proposed Model**

Lane changing may be mandatory or discretionary. Mandatory lane changing is performed when the current lane ceases to be an option (due to, for example, lane use regulations, incidents, and need to take exit ramps), and thus the driver must move to another lane. Discretionary lane changing is performed when a driver is not satisfied with the driving conditions in the current lane (due to, for example, average speed of the lane as compared to the driver's desired speed, and existence of heavy vehicles). Based on this classification of a lane change the decision tree for a driver is constructed which is presented next.



The tree diagram in Figure 3-1 summarizes the proposed structure of the lane changing model. The ovals correspond to latent decisions while the rectangles correspond to events that are directly observable.

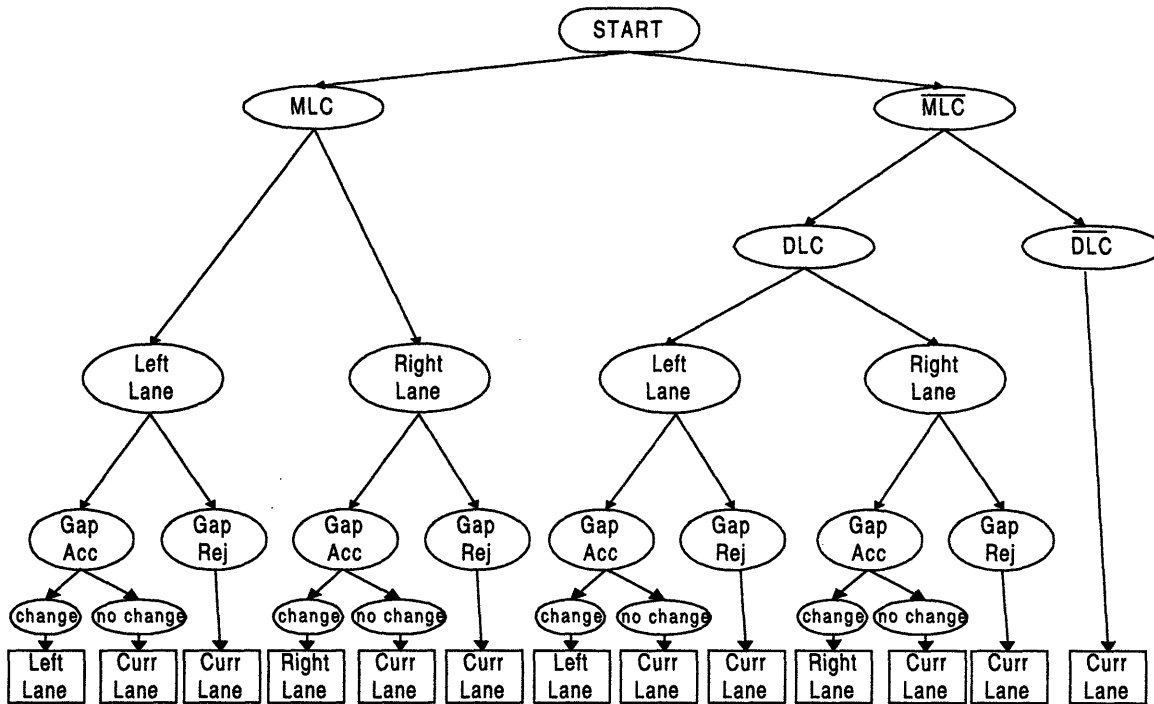


Figure 3-1 The Lane Changing Model Structure

The top two levels capture the decision to consider a lane change. First, a driver who faces a situation that requires a mandatory lane change may respond to it immediately (MLC) or delay the response ( $\overline{\text{MLC}}$ ). This binary decision is only relevant to drivers who face a mandatory lane change situation and is affected by explanatory variables such as the distance to the location at which the lane change must be complete, number of lanes to cross, and density of traffic. Short distances, many lanes to cross, and dense traffic make it more likely that a driver will respond to mandatory lane changing conditions immediately. If the driver decides not to respond temporarily to an existing mandatory lane changing

situation or mandatory lane changing conditions do not apply (both of these situations are characterized by  $\overline{MLC}$ ), the satisfaction with the current lane may be examined. That is, the driver may decide whether to consider a discretionary lane change (DLC) or not ( $\overline{DLC}$ ). Factors that influence this decision may include speed differentials (defined as the difference between the speed of the vehicles ahead in various lanes and the desired speed of the driver considering a discretionary lane change), deceleration indicator (which captures the disutility when the lead vehicle in the lane under consideration decelerates), presence of heavy vehicle indicator (which captures the disutility associated with following a heavy vehicle), and ramp indicator (which captures the disutility for a lane adjacent to a ramp). Under the MLC and the DLC branches, when both the adjacent lanes are candidate lanes, the probability of considering each of the lanes is determined using the desired lane choice model. Important explanatory variables include speed differentials and indicators of deceleration, heavy vehicle, ramp, and need for a mandatory response (which captures the fact that when a mandatory lane change is required but the driver postpones the response, inappropriate lanes for mandatory lane changing conditions are not as desirable).

Finally, after a desired lane is selected, the driver seeks an acceptable gap. Explanatory variables, related to both the roadway environment and gap search characteristics, include relative speed, remaining distance to the point at which lane change must be complete, first gap indicator (which captures the fact that the first gap that a driver encounters is not, for psychological reasons, as desirable as subsequent gaps), the number of gaps rejected, and delay experienced by the driver up to the occurrence of the gap under consideration. Even if an acceptable gap is found, the lane change may not occur immediately due to maneuvering time and reaction time. This is captured by a last stage of the model. If a lane change takes place immediately, the driver will be observed in a new lane; otherwise, the driver will continue in the current lane until a subsequent point in time when the lane change maneuver can be completed. Potential important explanatory variables include delay (time elapsed since the gap searching process began), remaining distance to the point at which lane change must be complete, and speed of the vehicle.

Based on the decision tree described above and assumptions regarding state dependence (dependence of current choice on previous experiences and decisions), the likelihood function corresponding to a set of observations is formulated and presented at the end of this chapter.

### 3.1.2 Formulation of a General Model Appropriate for Panel Data

Generally, different observations from an individual are likely to be correlated. To model this correlation, the random component of a random utility specification is assumed to have two elements: a random term attributable to a specific individual that does not change with time period  $t$  and a random term that varies across different time periods for a given individual, as well as across individuals (see Heckman, 1981). Therefore, the utility of a lane change at time  $t$  to driver  $n$  is written as follows:

$$U_{tn} = X_{tn} \gamma + v_n + \varepsilon_{tn} \quad (3 - 1)$$

where,

$U_{tn}$  = utility for individual  $n$  at time  $t$ ;

$X_{tn}$  = vector of explanatory variables;

$\gamma$  = vector of unknown parameters;

$v_n$  = individual specific random term; and,

$\varepsilon_{tn}$  = random term that varies across different time periods for a given individual, as well as across individuals.

The following assumptions on  $v_n$  and  $\varepsilon_{tn}$  are made:

$$\text{cov}(v_n, v_{n'}) = \begin{cases} \sigma_v^2 & \text{if } n = n' \\ 0 & \text{if } n \neq n' \end{cases}$$

$$\text{cov}(\varepsilon_{tn}, \varepsilon_{t'n'}) = \begin{cases} \sigma_{\varepsilon}^2 & \text{if } n = n', t = t' \\ 0 & \text{otherwise} \end{cases}$$

$$\text{cov}(v_n, \varepsilon_{t'n'}) = 0 \quad \forall t, n, n'$$

where,  $\sigma_v^2$  and  $\sigma_{\varepsilon}^2$  are the variances of  $v_n$  and  $\varepsilon_{tn}$  respectively.

These assumptions imply:

$$\text{cov}(U_{tn}, U_{t'n'}) = \begin{cases} \sigma_v^2 + \sigma_{\varepsilon}^2 & \text{if } t = t', n = n' \\ \sigma_v^2 & \text{if } t \neq t', n = n' \\ 0 & \text{if } n \neq n', \forall t \end{cases}$$

Conditional on  $v_n$  and depending on the assumption on  $\varepsilon_{tn}$ , different discrete choice models can be obtained, such as logit or probit.

Furthermore, the random terms associated with the same driver but at different nodes in the drivers' decision hierarchy are likely to be correlated. To capture this correlation without increasing the computational burden significantly, the driver specific random term is expressed as  $\alpha_h v_n$ . The random variable  $v_n$  is a generic random term, and the parameter  $\alpha_h$  (to be estimated) is associated with node  $h$  (or level  $h$ ) of the decision tree hierarchy.

### 3.1.3 Decision to Consider a Lane Change and Choice of left or right lane

With the above formulation of the random term, appropriate for panel data, the binary decision, whether to respond to a mandatory lane change requirement or not (the top level in Figure 3-1), can be modeled using an appropriate discrete choice model. For example, using a binary logit model, the probability that driver  $n$  at time  $t$  will respond to a mandatory lane change requirement is

$$\Pr_i(MLC | v_n) = \frac{1}{1 + \exp(-X_{in}\theta - \alpha_{MLC} v_n)} \quad (3 - 2)$$

where,

$X_{in}$  = vector of explanatory variables;

$\theta$  = vector of parameters; and,

$\alpha_{MLC}$  = parameter (specific to the *MLC* option) that captures the correlation among different decisions for a given driver.

Drivers consider a discretionary lane change when they are unhappy with the driving conditions of the current lane and compare the current lane with the best alternative option, i.e., the best among the left or right lane. Since there is an effort/hassle associated with changing lanes that are not captured, the utilities of the left and right lanes may be correlated. A natural choice of model structure that captures this phenomenon is a nested logit model (see, for example, Ben-Akiva and Lerman, 1985). A proposed nested structure is shown in Figure 3-2. The lower level compares the utility of the left and right lanes, and the upper level compares the utility of performing a discretionary lane change or not.

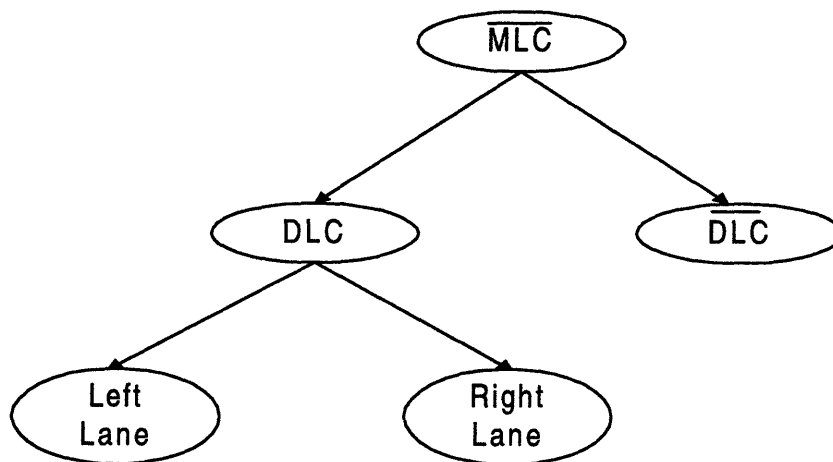


Figure 3-2 The nested logit model structure

### 3.1.4 The Gap Acceptance Model

The gap acceptance model models whether the adjacent gap in the target lane is safe for merging (level four in Figure 3-1) and whether lane change will take place immediately given the gap is acceptable (level five in Figure 3-1).

The proposed gap acceptance model addresses limitations of existing models by capturing heterogeneity, and utilizing estimation methods appropriate for panel data. Although state dependence is not modeled in the lane changing model, it can be easily incorporated into the proposed gap acceptance model when the instant at which drivers' start looking for gaps are known.

In freeway operations, a gap is acceptable when both the lead and lag gaps are acceptable. Figure 3-3 illustrates the definition of lead and lag gaps. The critical lead (lag) gap for a driver is defined as the unobservable minimum lead (lag) gap the driver is willing to accept in order to change lanes. It is assumed that the critical lead (lag) gap depends on traffic conditions and previous decisions made by the driver, and, therefore, is modeled as a random variable.

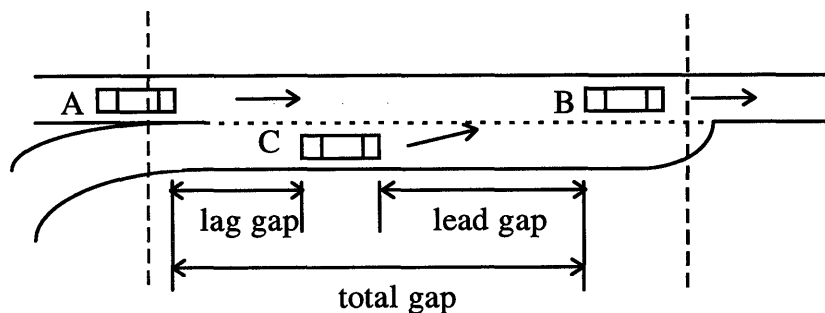


Figure 3-3 The lead and the lag gap

In the literature, the unit of a gap length is seconds. For a vehicle stopped at an unsignalized T-intersection, the gap length between two vehicles is defined as the time elapsed between the two vehicles crossing the location of the stationary waiting vehicle. However, for a freeway gap acceptance process, in Figure 3-3 the subject vehicle (C) may run parallel to the vehicles ahead (A) and behind (B) in the target lane and the headway between the two vehicles in the target lane cannot be measured with respect to a unique reference cross-section. If all three vehicles are running at the same speed, then vehicle C would not require a big gap and gap length measured by dividing the distance by velocity would give a too conservative measurement of the gap available. For freeway merging, Yang and Koutsopoulos (1995) defined lag headway as the lag gap length divided by the speed of the lag vehicle and lead headway as the lead gap divided by the speed of the subject vehicle. If vehicle C runs at a speed higher than the vehicle A, depending on their relative speed, a nominal gap length might be sufficient, however, by using the definition of Yang et al. this phenomenon cannot be captured. Using distance headway resolves this ambiguity between the definition of time gap headway and the actual time the driver of the merging vehicle perceives as available to her/him.

To capture the heterogeneity in the driver population, the critical gap  $G_{cr,m}^g$  for driver  $n$  at time  $t$  is assumed to have the following form:

$$G_{cr,m}^g = \exp(X_{in}^g \beta^g + v_n^g + \epsilon_{in}^g) \quad (3 - 3)$$

where,

$g$  = index indicating whether the gap is a lead or a lag critical gap;

$G_{cr,m}^g$  = value of the critical gap for driver  $n$  at time  $t$ ;

$X_{in}^g$  = vector of explanatory variables;

$\beta^g$  = vector of unknown parameters;

$v_n^g$  = driver specific random term; and,

$\varepsilon_{in}^g$  = random term that varies across different gaps for a given individual, as well as across individuals.

The assumptions on  $v_n$  and  $\varepsilon_{in}$  made in formulating equation 3-1 apply here as well. In addition, for modeling the correlation between lead and lag critical gaps the following assumptions are made. The random terms  $v_n^{lead}$  and  $v_n^{lag}$  are expected to be correlated when they are associated with the same driver. This correlation is captured by setting  $v_n^{lead} = \alpha_{lead} v_n$  and  $v_n^{lag} = \alpha_{lag} v_n$ , where,  $v_n \sim N(0,1)$ . These assumptions imply:

$$\text{var}(v_n^{lead}) = \alpha_{lead}^2;$$

$$\text{var}(v_n^{lag}) = \alpha_{lag}^2; \text{ and,}$$

$$\text{cov}(v_n^{lead}, v_{n'}^{lag}) = \begin{cases} \alpha_{lead} \alpha_{lag} & \text{if } n = n' \\ 0 & \text{if } n \neq n' \end{cases}$$

That is,  $v_n^{lead}$  and  $v_n^{lag}$  have different variances and are perfectly correlated. As for  $\varepsilon_{in}^g$ ,  $\text{cov}(\varepsilon_{in}^{lead}, \varepsilon_{t'n'}^{lag}) = 0 \forall t, t', n, n'$ . Finally,  $\text{cov}(v_n^g, \varepsilon_{t'n'}^{g'}) = 0 \forall t, n, n', g, g'$ . Hence, the lead and the lag components of the critical gap of an individual driver are correlated and critical gaps for the same driver over time are also correlated. The exponential form of the critical gap guarantees that the critical gap is non-negative.

Assuming  $\varepsilon_{in}^g \sim N(0, \sigma_{\varepsilon, g}^2)$  (that is, the critical gap follows a lognormal distribution), the probability that the  $g$ -component of gap  $t$  observed by driver  $n$ ,  $G_{in}^g$ , is acceptable is given by:



$$\begin{aligned}
\Pr(G_m^g \text{ acceptable} \mid v_n) &= \Pr(G_m^g > G_{cr,m}^g \mid v_n) \\
&= \Pr(G_m^g > \exp(X_m^g \beta^g + \alpha_g v_n + \varepsilon_m^g) \mid v_n) \\
&= \Pr(\ln(G_m^g) > X_m^g \beta^g + \alpha_g v_n + \varepsilon_m^g \mid v_n) \\
&= \Pr(\varepsilon_m^g < \ln(G_m^g) - X_m^g \beta^g - \alpha_g v_n \mid v_n) \\
&= \Phi \left( \frac{\ln(G_m^g) - X_m^g \beta^g - \alpha_g v_n}{\sigma_{\varepsilon,g}} \right) \tag{3 - 4}
\end{aligned}$$

where,  $\Phi(\bullet)$  denotes the cumulative distribution function of a standard normal random variable. Therefore, the probability that the gap at time  $t$  is acceptable to driver  $n$  is

$$\begin{aligned}
&\Pr(\text{gap at time } t \text{ acceptable to driver } n \mid v_n) \\
&= \Pr(G_m^{lead} \text{ acceptable and } G_m^{lag} \text{ acceptable} \mid v_n) \\
&= \Pr(G_m^{lead} > G_{cr,m}^{lead} \text{ and } G_m^{lag} > G_{cr,m}^{lag} \mid v_n) \\
&= \Phi \left( \frac{\ln(G_m^{lead}) - X_m^{lead} \beta^{lead} - \alpha_{lead} v_n}{\sigma_{\varepsilon,lead}} \right) * \Phi \left( \frac{\ln(G_m^{lag}) - X_m^{lag} \beta^{lag} - \alpha_{lag} v_n}{\sigma_{\varepsilon,lag}} \right) \tag{3 - 5}
\end{aligned}$$

Parameters to be estimated include  $\alpha_{lead}$ ,  $\alpha_{lag}$ ,  $\beta^{lead}$ ,  $\beta^{lag}$ ,  $\sigma_{\varepsilon,lead}^2$ , and  $\sigma_{\varepsilon,lag}^2$ .

The *change lanes* model, the last level in the decision tree in Figure 3-1, is assumed to be binary logit. The two alternatives are '*change lanes*' and '*no change lane*'. The probability that lane change takes place at time  $t$ , given the gap is acceptable, is as follows:

$$\Pr_i(\text{change lanes} \mid \text{gap acceptable}, v_n) = \frac{1}{1 + e^{-Z_m \psi}} \tag{3 - 6}$$

where,

$Z_{tn}$  = vector of explanatory variables for driver  $n$  at time  $t$ ;

$\psi$  = vector of unknown parameters.

### 3.2 The Likelihood Function

Assuming that observations of a driver's location and traffic conditions are available at discrete points in time (for example, every second), denote the sequence of observations for a given driver as follows:

$$(J_{1n}, J_{2n}, J_{3n}, \dots, J_{T_n n}) \quad (3 - 7)$$

where,

$J_{tn}$  = index of the lane (Current, Left, or Right) driver  $n$  is observed at time  $t$ ; and,

$T_n$  = number of time periods driver  $n$  is observed.

As mentioned above, it was assumed that the drivers consider the entire lane change decision process at every discrete point in time and the execution of the decision is completed within the next time period. The sequence of observations (for example, every second) for a given individual is likely to be correlated; using the formulation of error term discussed in the previous section, the probability of observing a pattern for a given driver can be expressed, conditional on  $v_n$ , as follows:

$$\begin{aligned}
\Pr(\{J_{1n}, J_{2n}, J_{3n}, \dots, J_{T_n n}\} | v_n) &= \prod_{t=1}^{T_n} \Pr(J_{tn} | v_n) \\
&= \prod_{t=1}^{T_n} \Pr_t(L|v_n)^{\delta_{tn}^L} \Pr_t(R|v_n)^{\delta_{tn}^R} \Pr_t(C|v_n)^{\delta_{tn}^C} \quad (3 - 8)
\end{aligned}$$

where,

$$J_{tn} \in \{L, R, C\}$$

$L$  = change to the left lane;

$R$  = change to the right lane;

$C$  = continue in the current lane;

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

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

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

Finally, the likelihood function is given by

$$L^* = \prod_{n=1}^N \left\{ \int_{-\infty}^{\infty} \left( \prod_{t=1}^{T_n} \Pr_t(L|v_n)^{\delta_{tn}^L} \Pr_t(R|v_n)^{\delta_{tn}^R} \Pr_t(C|v_n)^{\delta_{tn}^C} \right) f(v_n) dv_n \right\} \quad (3 - 9)$$

where,  $f(v_n)$  is the distribution of  $v_n$  and  $N$  is the number of drivers observed.

The probability  $\Pr(J_{tn} | v_n)$  can be formulated from the decision tree of Figure 3-1. To formulate  $\Pr(J_{tn} | v_n)$  for  $J_{tn} = L$ , for example, observe that there are two possible ways that a *change to the left lane* can be observed:

- A mandatory lane change is necessary and the driver is responding to it ( $MLC$ ), the left lane is considered among the choices available, the gap in the left lane is acceptable, and the lane change takes place; or,
- A mandatory lane change is necessary but the driver is not responding to it ( $\overline{MLC}$ ) or mandatory lane change is not required, the driver is not satisfied with the current lane, the left lane is considered among the choices available, the gap in the left lane is acceptable, and the lane change takes place.

Therefore, the probability of observing a *change to the left lane* is

$$\begin{aligned}
Pr_t(L | v_n) = & [ Pr_t(\text{change lanes} | \text{gap acceptable, left lane chosen, } MLC, v_n) \cdot \\
& Pr_t(\text{gap acceptable} | \text{left lane chosen, } MLC, v_n) \cdot \\
& Pr_t(\text{left lane chosen} | MLC, v_n) \cdot Pr_t(MLC | v_n) ] + \\
& [ Pr_t(\text{change lanes} | \text{gap acceptable, left lane chosen, } DLC, \overline{MLC}, v_n) \cdot \\
& Pr_t(\text{gap acceptable} | \text{left lane chosen, } DLC, \overline{MLC}, v_n) \cdot \\
& Pr_t(\text{left lane chosen} | DLC, \overline{MLC}, v_n) \cdot \\
& Pr_t(DLC | \overline{MLC}, v_n) \cdot Pr_t(\overline{MLC} | v_n) ] \tag{3 - 10}
\end{aligned}$$

Similarly,  $Pr_t(J | v_n)$  for  $J = R$  or  $C$  can be formulated.

### 3.3 Conclusions

Modeling drivers lane change decision process precisely is computationally burdensome due to its latent nature. The proposed model assumes that drivers make decisions at discrete time periods and execute the decision within the next time period; therefore, state dependence is not modeled. Finally, the likelihood function necessary for estimating the model parameters is formulated.

## CHAPTER 4

### CASE STUDY

In this chapter a case study is presented that includes estimation of the lane changing model parameters and assessment of the performance of the model. The model was validated using micro simulation of a network for which real data was available.

The lane changing model parameters were estimated using the data set obtained from FHWA (Smith, 1985). The data set consists of vehicle trajectories, recorded at discrete times. Data necessary for estimating the model parameters were then extracted from the FHWA data.

Three types of assessment are presented:

- statistical properties of the estimated parameters,
- behavioral aspects of the model that includes calculation of probability of acceptance of gaps that were actually accepted and calculation of the median gap length and comparison with values found in the literature, and
- validation of the gap acceptance model using micro simulation by comparing the observed field data with the data obtained using the existing simulator and with the data obtained from the simulator in which the proposed model parameters are implemented.

This chapter starts with presenting estimation background for the case study and is followed by discussion of the data used for estimating the model parameters. Estimation results are presented next. Finally, validation results are presented.

## 4.1 Estimation Background and Data

The application of the model presented in Chapter 3 is demonstrated for the case of merging from a freeway on-ramp as shown in Figure 4-1. The case study considers only the vehicles traveling from the on-ramp at the upstream end of the weaving section and merging with the mainline. In this case, all drivers initiate the change to the adjacent mainline lane as soon as they cross the merge point between the on-ramp and the freeway lane (that is, everybody responds to the mandatory lane change requirement and the adjacent freeway lane is the only choice), and continue searching for acceptable gaps in the

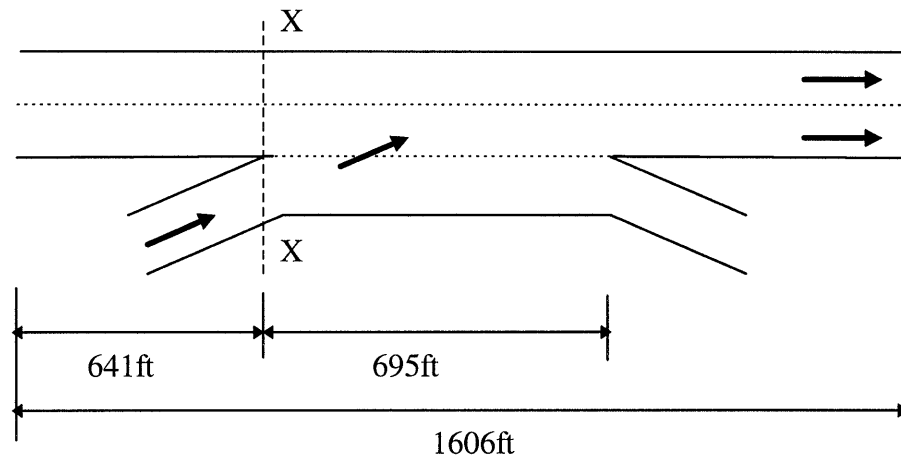


Figure 4-1 Data collection site for the case study at I-95 NB near the Baltimore-Washington Parkway

target lane. The above situation is a case of mandatory lane changing for which the lane changing model structure presented in Figure 3-1 reduces to the structure shown in Figure 4-2.

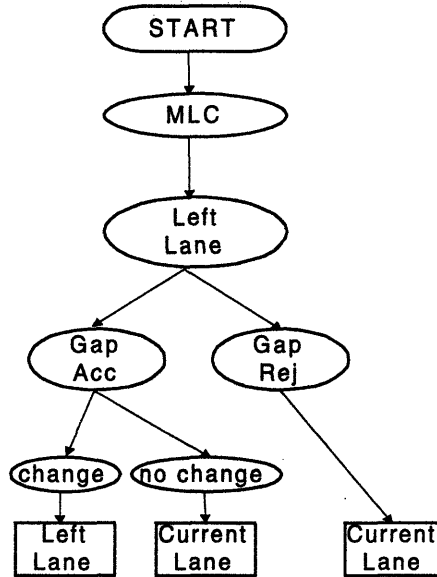


Figure 4-2 Lane changing model structure for the special case

As shown in Figure 4-2, the main elements of the decision process for the special case involve acceptance of a gap and actual lane change maneuver. There are two observable states: *change to the left lane* and *continue in the current lane*. A *change to the left lane* can be observed only when the gap is acceptable and lane change maneuver is completed. Otherwise, the driver will *continue in the current lane*.

Following Figure 4-2, the likelihood function for this special case reduces from the expression in equation 3-9 to

$$L^* = \prod_{n=1}^N \left\{ \int_{-\infty}^{\infty} \left( \prod_{t=1}^{T_n} \Pr_t(L|v_n)^{\delta_m^L} \Pr_t(C|v_n)^{\delta_m^C} \right) f(v_n) dv_n \right\} \quad (4 - 1)$$

The probability that driver  $n$  will change to the left lane is given by

$$\Pr_t(L|v_n) = \Pr_t(\text{change lanes} | \text{gap acceptable}, v_n) \cdot \Pr_t(\text{gap acceptable} | v_n) \quad (4 - 2)$$

and the probability that driver  $n$  will continue in the current lane is given by

$$\Pr_t(C | v_n) = 1 - \Pr_t(L | v_n) \quad (4 - 3)$$

In formulating  $\Pr_t(L | v_n)$ , therefore, the main elements are the gap acceptance and the lane change maneuver models.

Since, drivers start searching for gaps as soon as they cross the merge point between the on-ramp and the freeway lane (section X-X in Figure 4-1), the gap searching process as well as the initial conditions are well defined.

Data necessary for estimating the model parameters was extracted from the data set provided by the FHWA (Smith, 1985) which is discussed next.

#### **4.1.1 The Federal Highway Administration (FHWA) Data**

The data set provided by the FHWA (Smith, 1985) consists of vehicle trajectories, recorded at discrete times, on freeway sections of varying geometric configurations. The objective of the data collection effort by FHWA was to develop data sets which could be used in empirical research on freeway traffic flow and the validation of freeway simulation models. Since the driver behavior models presented in this research are primarily intended for use in a microscopic traffic simulator, the FHWA data sets are suitable for estimating the corresponding parameters.

The data collection sites were selected from the freeways in Los Angeles and Washington D. C. Metropolitan areas. Fourteen sites were filmed at a rate of one frame per second,



and a full-frame 33 mm motion picture camera mounted in a fixed-wing, short-takeoff-and-landing (STOL) was used.

The following six types of freeway segments were considered in selecting sites that are potential causes of bottlenecks or congested points:

- ramp merges,
- weaving sections,
- upgrade sections,
- reduced width sections,
- lane drops, and,
- horizontal curves.

One hour of data was gathered for each site. The site lengths vary between 1,200 and 3,200 ft. A microcomputer based digitizing system was used for extracting data from the films.

Table 4-1 shows the format of the data file for each site. The first column is the frame number that starts from an arbitrary number. Data with the same frame number correspond to a snapshot on the freeway section. The second column is the vehicle identification number which is unique for each vehicle. The third column records vehicle type, where, 1 = passenger car, 2 = pickup truck, 3 = no. 1 or 2 with trailer, 4 = single unit truck, 5 = tractor-trailer truck, and 6 = bus. Vehicle length and speed are stored in the next two columns. The sixth column records the distance from the beginning of the section to the front bumper of the vehicle at that instant. The seventh column is lateral distance from the right edge of the mainline to the middle front of the vehicle. The eighth column is vehicle color code and the last column is lane number.

Table 4-1 Sample record format of the FHWA data file

| column number | description  |
|---------------|--|
| 1             | frame number   |
| 2             | vehicle identification number  |
| 3             | vehicle type   |
| 4             | vehicle length (ft)  |
| 5             | speed (mph)  |
| 6             | distance from the beginning of the section to the front of the vehicle (ft)          |
| 7             | distance from the right edge of the mainline to the middle front of the vehicle (ft) |
| 8             | vehicle color code   |
| 9             | lane number  |

Data necessary for estimating the lane changing model parameters includes the speed, type, length, acceleration, and gaps between different vehicles in the left, right, and current lanes including the subject vehicle. Speed, type, and length of different vehicles are already included in the original data files while acceleration can be computed by taking the difference of the speeds of a vehicle in successive frames. Since the position of each vehicle is available from the beginning of the section, the gap between any two vehicles can be easily calculated.

The FHWA data with the variety of sites, geometric configurations, and traffic conditions is a very useful source of data for estimating the parameters of different driver behavior models.

#### **4.1.2 Description of the Data Extracted for Estimating the Parameters of the Gap Acceptance Model**

As mentioned above, the case study involves parameter estimation for the special case of merging from a freeway on-ramp, where the lane changing model reduces to a gap

acceptance model. This section includes a description of the site from where the data was collected and a description of the data extracted from the original FHWA data.

The selected freeway section, as shown in Figure 4-1, has two mainline lanes and a weaving section on the right. Only vehicles traveling from the upstream end of the weaving section and merging with the mainline are considered. The data set includes observations on 286 drivers. Each observation corresponds to the trajectory of a vehicle. The sequence observed for each driver is a series of gaps in which the last observed gap in the acceleration lane is an acceptable gap and the driver completed merging. The total number of gaps observed was 1447.

For each gap for each driver, information is extracted relevant to the gap acceptance process. For example, vehicle speed, lane, and position are directly available in the FHWA data set every second. The lead gap is obtained by subtracting the length of the lead vehicle in the target lane from the difference in positions of the lead and the subject vehicle (see Figure 3-3).

For each vehicle, observation number, vehicle identification number, type, and vehicle length are recorded. Then, for each gap considered by the driver, the following data is generated:

- time period (time elapsed since the driver crossed the merge point between the on-ramp and the mainline lane, section X-X in Figure 4-1, seconds),
- lateral position of the vehicle from the right edge of the mainline (feet),
- lead and lag gap (feet),
- speed and acceleration of the lead, lag and the subject vehicle (mph and mph/sec respectively),
- remaining length to the point at which lane change must be complete (feet),
- total gap ahead of the lead vehicle and behind the lag vehicle, and

- density of vehicles in the adjacent mainline lane and the average mainline density (vehicle/lane-mile).

The density of vehicles in a lane at any time point is calculated by observing the total number of vehicles in that lane that are behind the subject vehicle but not more than 500ft behind. It is assumed that the visibility distance for any driver is 500ft on the freeway section. Therefore, the density measurement corresponds to the density perceived by an individual driver at a particular time period.

In the FHWA data set, when a vehicle is spotted for the first time period, its speed is reported as zero; speeds at subsequent time period are computed by taking the distance traveled between the earlier time period and the current time period divided by the time. The speed for the first time period was computed by doing backward extrapolation assuming that the driver's acceleration rates in periods 1-2 and 2-3 is the same. Therefore, the speed at time period 1-2 is

$$V_1 = V_2 - a_2 \quad (4 - 4)$$

where,

$V_i$  = speed at time period  $i$ ,  $i \in \{1,2\}$ ; and,

$a_2$  = acceleration in time period 2-3.

There were cases where vehicles traveling from the upstream end of the weaving section were reported for the first time after they have crossed the merge point (section X-X in Figure 4-1). These vehicles were not considered for the gap acceptance model data set, because they might have showed up on the acceleration lane at an earlier time period. In addition, it was assumed that drivers do not consider a gap if the lead or the lag gap is negative -- since it is physically impossible to accept a negative lead or lag gap.

When there was no lead vehicle in the target lane at any time period within the length of the site filmed, earlier frames were searched to find the first vehicle that left the site from the downstream end of the target lane. Assuming that the vehicle continued with the speed at which it left the site and in the same lane, the position of the vehicle for the time period in question was extrapolated. Similarly, when there was no lag vehicle at any time period, later frames were searched to find the first vehicle that appears on the upstream end of the target lane. Assuming that the vehicle was traveling with the same speed at those earlier time periods, the position of the vehicle for the current time period was calculated by backward extrapolation.

Table 4-2 shows some of the statistics of the data corresponding to the gaps that the drivers found acceptable and they merged into. The maximum and the minimum delay in merging into the left lane was 18sec. and 0sec. (that is, the first observed gap was acceptable and the driver merged into it) respectively with a mean of 5 sec. and a standard deviation of 3.02sec. The median delay and remaining length were 5sec. and 473ft respectively implying that the majority of the drivers merged into the target lane when they were closer to the upstream end of the acceleration lane. The adjacent mainline lane density and the average mainline density varied from close to zero (that is no vehicle

Table 4-2 Statistics of the gap acceptance model data corresponding to the gaps that the drivers found acceptable and they merged into

|                    | speed, mph | delay, sec. | remaining length, ft | adjacent mainline lane density, veh/lane-mile | mainline density, veh/lane-mile | lead veh. speed, mph | lag veh. speed, mph | lead gap, ft | lag gap, ft | Total gap, ft |
|--------------------|------------|-------------|----------------------|---|---------------------------------|----------------------|---------------------|--------------|-------------|---------------|
| maximum            | 48         | 18          | 686                  | 106   | 90                              | 57                   | 63                  | 859          | 855         | 1209          |
| minimum            | 14         | 0           | 26                   | 0   | 5                               | 19                   | 14                  | 1            | 2           | 35            |
| mean               | 32         | 5           | 441                  | 49  | 43                              | 38                   | 34                  | 127          | 110         | 254           |
| median             | 33         | 5           | 473                  | 48  | 42                              | 38                   | 33                  | 70           | 81          | 204           |
| standard deviation | 6.18       | 3.02        | 131                  | 22.5  | 17.8                            | 7.31                 | 8.74                | 147          | 106         | 187           |

within the visibility distance or 500ft) to around 100 veh/lane-mile -- which implies that a wide range of traffic conditions were represented in the data set.

## 4.2 Estimation Results

The Maximum Likelihood estimates of the unknown parameters of the model are given in Table 4-3. The explanatory variables include the *lag relative speed*, *remaining distance* to the point at which lane change must be complete, *first gap dummy*, and *delay* in merging. *Lag relative speed* is the speed of the lag vehicle in the target lane less the speed of the subject vehicle. In this particular model, a piecewise linear approximation of the variable *lag relative speed* is used to capture the fact that the variable has a different impact on the critical gap length at different values (non linear relationship). *First gap dummy* equals one for the first second and zero otherwise. A variable *remaining\_distance\_impact*, a function of the remaining distance, was used to capture the fact that *remaining distance* does not have impact on drivers gap acceptance behavior when it is greater than a certain threshold, while at small values, drivers become concerned and hence more aggressive. The variable *remaining\_distance\_impact* was assumed to have the following form:

$$\text{remaining\_distance\_impact} = 1/(1+\exp(\lambda D_t)) \quad (4 - 5)$$

where,  $D_t$  is the remaining distance at time  $t$  and  $\lambda$  is a parameter. *Delay* in merging is the number of seconds elapsed since the gap searching process started.

Parameters of the gap acceptance model were estimated by fixing  $\lambda$  to different values and Figure 4-3 shows the plot of the likelihood function at convergence for different values of  $\lambda$ . At  $\lambda$  equal to -0.020, the likelihood function attained its maximum value (-587.137) and the corresponding model parameters were adopted.

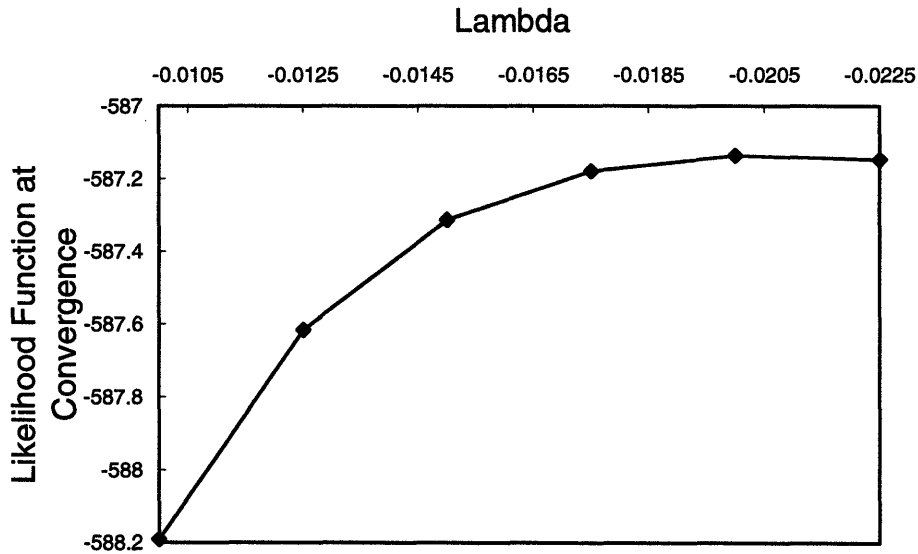


Figure 4-3 The likelihood function at convergence for different values of  $\lambda$

The estimated lead and lag critical gaps (in feet) are:

$$G_{cr,tn}^{lead} = \exp(2.66 - 0.095 v_n + \epsilon_{tn}^{lead}) \quad (4 - 6)$$

$$G_{cr,tn}^{lag} = \exp(-19.25 + 1.24 \{ \min(V_{t,rel\_lag}, 10)/10 \} + 1.28 \{ \max(0, V_{t,rel\_lag} - 10)/10 \} + 1.58 \text{ first\_gap\_dummy} + \overset{21.35}{1.58} \{ 1/(1+\exp(-0.02 D_t)) \} + \overset{1.57}{1.90} v_n + \epsilon_{tn}^{lag}) \quad (4 - 7)$$

where,

$V_{t,rel\_lag}$  = relative speed in mph with respect to the lag vehicle at time period  $t$

=  $V_{t,lag\_vehicle} - V_{t,subject}$ ; and,

$\text{first\_gap\_dummy} = 1$  for the first gap, and 0 otherwise.

The estimated model of changing lanes (using logit model), given that both the lead and lag gaps are acceptable, is:

$$\Pr_t(\text{change lanes} \mid \text{gap acceptable}, v_n) = \frac{1}{1 + \exp\{2.12 - 0.51(t - 1)\}} \quad (4 - 8)$$

where,  $t$  is the time elapsed since the gap searching process began.

Table 4-3 Estimated parameters of the gap acceptance model

| Variable                            | Parameter Estimate | t-statistic                                  |
|-------------------------------------|--------------------|--|
| Lead Critical Gap                   |                    |  |
| $\alpha_{lead}$                     | -0.099             | -0.26  |
| $\sigma_{\epsilon, lead}$           | 1.57               | 4.74   |
| constant                            | 2.66               | 10.23  |
| Lag Critical Gap                    |                    |  |
| $\alpha_{lag}$                      | 1.57               | 4.93   |
| $\sigma_{\epsilon, lag}$            | 1.07               | 1.97   |
| constant                            | -19.25             | -2.02  |
| relative speed (10mph and less)/10  | 1.24               | 3.13   |
| relative speed (above 10mph)/10     | 1.28               | 2.31   |
| first gap dummy                     | 1.58               | 1.47   |
| 1/(1+exp(-0.02 remaining distance)) | 21.35              | 2.25   |
| change lanes vs. no change lane     |                    |  |
| constant                            | -2.12              | -8.19  |
| delay (seconds)                     | 0.51               | 5.74   |
| Number of drivers = 286             |                    | Number of gaps observed = 1447               |
| $L(0) = -706.7$                     | $L(c) = -682.2$    | $L(\hat{\beta}) = -587.1$ $\bar{p}^2 = 0.15$ |

The lead critical gap was found to be insensitive to traffic conditions, whereas the lag critical gap was found to be a function of the relative speed (with respect to the lag vehicle in the target lane), remaining distance to the point at which lane change must be complete, and whether the gap is the first gap being considered or not. Variance of the lead critical gap was found to be significantly lower than that of the lag critical gap. The correlation between two different lead critical gaps, two different lag critical gaps, and between the lead and the lag critical gaps for a given individual were small.



A positive sign on the parameter of an explanatory variable implies that the critical gap increases as the value of the variable increases. The lag critical gap length increases as the lag relative speed increases. Higher sensitivity of critical gap at a higher lag relative speed is demonstrated by relatively higher estimated value of the parameter for the variable 'relative speed above 10mph' (compare to the variable 'relative speed equal to or below 10mph'). The initial hesitation of the drivers to merge into the mainline as soon as they appear at the upstream end of an acceleration lane is captured by the first gap dummy, which has the expected positive sign, implying a lower probability of acceptance of a gap observed at the first time period. As the remaining distance to the merge point decreases, drivers become more aggressive and therefore are willing to accept smaller gaps -- the corresponding parameter has the desired positive sign. State dependence is captured by the variable delay. As drivers wait longer and longer in searching for gaps and trying to merge into the target lane they become impatient, and therefore, more aggressive -- this is reflected by the positive sign of the corresponding parameter of the variable delay in '*change lanes vs. no change lane*'.

All the parameters, except the parameters of  $\sigma_v$  for the lead critical gap and first gap dummy, have significant  $t$ -statistic at the 10% level of significance. The likelihood ratio test was used to test the null hypothesis that all the coefficients except the constants and the variance are zero. This statistic,  $-2(L(c) - L(\hat{\beta}))$ , is  $\chi^2$  distributed with 5 degrees of freedom and is equal to 190. Hence, the null hypothesis can be rejected.

To assess how the proposed models replicate the actual gap acceptance process, the probability of acceptance of the gaps that were actually accepted and that the driver merged into was estimated for each driver. The probability that the  $t$ -th gap is acceptable to driver  $n$  is (using the notation described in section 3.1.4):

Pr(gap at time  $t$  acceptable to driver  $n$ )

$$\begin{aligned}
 &= \int_{-\infty}^{\infty} \Pr(\text{gap at time } t \text{ acceptable to driver } n \mid v_n) f(v_n) dv_n \\
 &= \int_{-\infty}^{\infty} \Phi \left( \frac{\ln(G_{tn}^{lead}) - X_{tn}^{lead} \beta^{lead} - \alpha_{lead} v_n}{\sigma_{\epsilon, lead}} \right) * \\
 &\quad \Phi \left( \frac{\ln(G_{tn}^{lag}) - X_{tn}^{lag} \beta^{lag} - \alpha_{lag} v_n}{\sigma_{\epsilon, lag}} \right) \phi(v_n) dv_n \quad (4 - 9)
 \end{aligned}$$

where,  $\phi(v_n)$  is the probability density function of a standard normal random variable.

Ideally the estimated probability of a gap that was actually accepted should be greater than 0.5 for the majority of the drivers. Figure 4-4 shows the frequency distribution of the estimated probability. The mean of the estimated probability was 0.644. The majority of

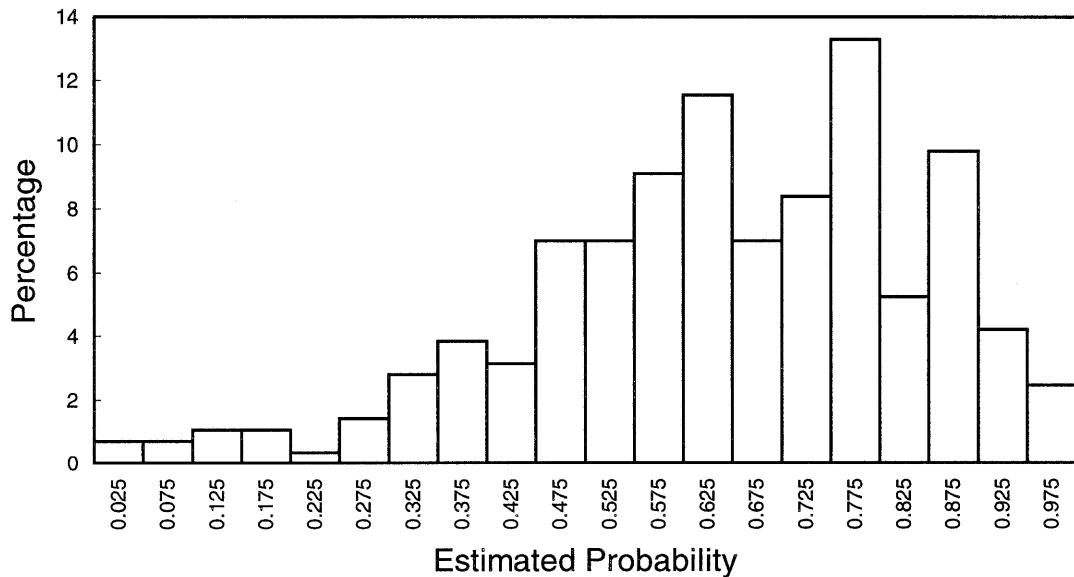


Figure 4-4 Frequency distribution of the estimated probability of acceptance

the estimated probabilities were clustered around 0.6 to 0.8. A small number of accepted gaps had very small estimated probability -- probably they represent aggressive drivers. Figure 4-5 shows a plot of the cumulative estimated probability. The median or the fifty

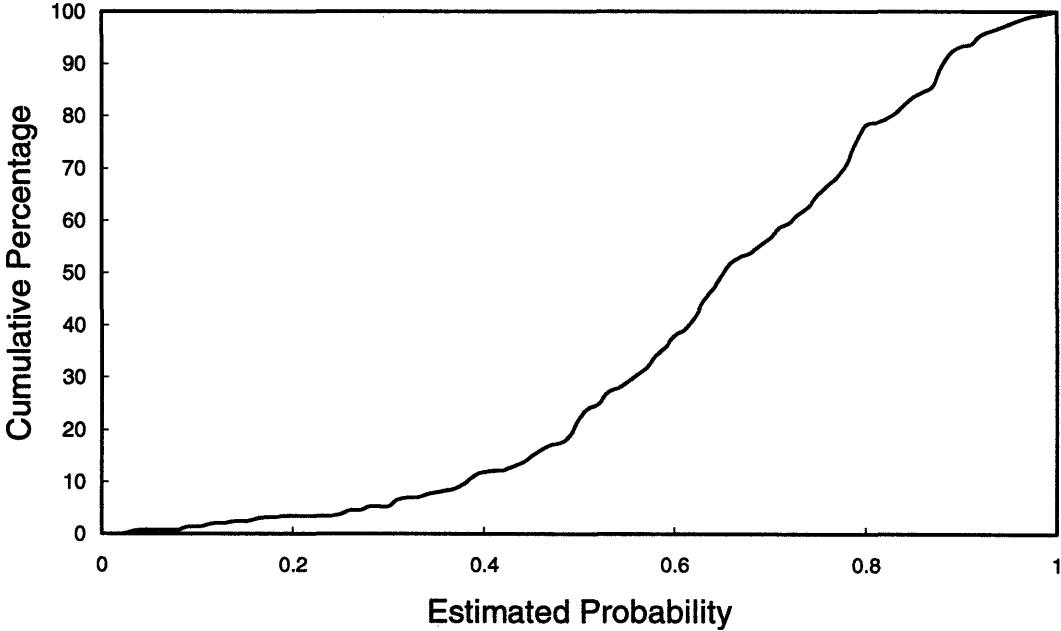


Figure 4-5 Cumulative estimated probability of acceptance of gaps that were actually accepted

percentile probability was 0.78. Only on 22 percent of the occasions the estimated probability was below 0.5. The estimates are consistent with expectation.

In addition, the median value of the lead and the lag critical gaps were calculated to see how they match the values found in the literature. Median of a lognormally distributed random variable is given by:

$$\text{Median}(G) = \exp(X\beta) \tag{4 - 10}$$

where,

$$G \sim \text{lognormal}; \text{ and, } \ln(G) \sim N(X\beta, \sigma^2).$$

The median value of the lead critical gap is unaffected by traffic conditions and is 14ft. The median value of the lag critical gap is sensitive to traffic conditions. Figure 4-6 shows the variation of the median value of the lag critical gap for different values of the remaining distance and lag relative speed. When the remaining distance is greater than 500 ft, remaining distance has no impact on drivers gap acceptance behavior and the median lag critical gap length remains unchanged. However, as the remaining distance decreases, the median lag critical gap length starts decreasing at a faster rate. Similarly, for a given remaining distance, the median value of the lag critical gap progressively decreases as the lag relative speed decreases. When the lag relative speeds are negative (that is, the subject

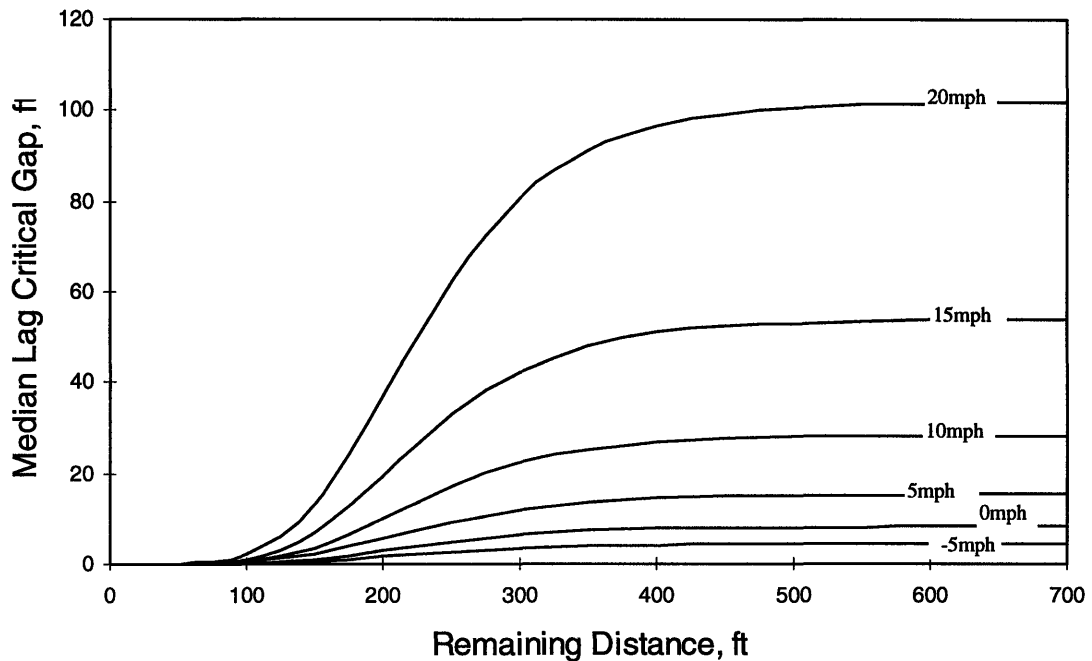


Figure 4-6 Median value of the lag critical gap vs. remaining distance for different values of the lag relative speed

vehicle is traveling faster than the lag vehicle in the target lane) the median value of the lag critical gap, as expected, becomes very small. For the purposes of this discussion, let us assume that the lag vehicle speed is 50mph. For a 20mph lag relative speed, the median lag critical gap is 102ft (equivalent to 1.4sec. time headway) for a 500 to 700ft remaining distance. When the remaining distance is 300ft, the lag critical gap becomes 80ft (1.1sec. time headway).

### **4.3 Validation using Simulation**

In this section application of the gap acceptance model is demonstrated using MITSIM (see Yang and Koutsopoulos, 1995). As mentioned in the introduction, MITSIM is a microscopic traffic simulator that is capable of simulating each element of the road network including the individual driver, roadway geometry, traffic signs and signals in detail. Performance of the original MITSIM and revised MITSIM (in which the proposed gap acceptance model is applied for merging from freeway on-ramp only) are examined and compared to the actual field data. Actual speed and flow measures, aggregated over ten minute time intervals for two hours and twenty minutes, are available across different sensor stations and each of them can be compared to their simulated counterparts.

First a critique of the gap acceptance model used in the original MITSIM is presented. This is followed by a discussion on two issues relevant to the validation exercise: number of replications necessary to get an estimate of the outputs generated by the simulator (which is stochastic in nature) and statistical measures for comparing the outputs. Finally, the validation results are presented.

### 4.3.1 Limitations of the Gap Acceptance Model Used in MITSIM

The gap acceptance model in MITSIM uses time-headway as opposed to the distance headway proposed in this thesis. The lag headway (see Figure 3-3 for a definition of lead/lag gap length) is calculated by dividing the lag gap by the speed of the lag vehicle in the target lane; the lead headway is calculated by dividing the lead gap length by the velocity of the subject vehicle. Both lead and lag gaps are modeled as a random variable.

When drivers intend to perform a discretionary lane change, the minimum acceptable gap (in time headway) for driver  $n$  is given by:

$$G_n^g = G_n + \varepsilon_n \quad g \in \{\text{lead, lag}\} \quad (4 - 11)$$

where,

$G_n^g$  = minimum acceptable gap acceptable to driver  $n$ ;

$G_n$  = average acceptable gap; and,

$\varepsilon_n$  = unobserved component of critical gap.

For mandatory lane change, the minimum acceptable gap(in time headway) for driver  $n$  is given by:

$$G_n^g = \varepsilon_n + \begin{cases} G_{\max}^g & L_{rem} \geq L_{\max} \\ G_{\min}^g + (G_{\max}^g - G_{\min}^g) \frac{(L_{rem} - L_{\min})}{(L_{\max} - L_{\min})} & L_{\min} < L_{rem} \leq L_{\max} \\ G_{\min}^g & L_{rem} \leq L_{\min} \end{cases} \quad (4 - 12)$$

where,

$g \in \{\text{lead, lag}\}$ ;

$G_n^g$  = minimum acceptable gap for mandatory lane change for driver  $n$ ;

$G_{\max}^g, G_{\min}^g$  = upper and lower bounds that represent the range of acceptable gap;

$L_{min}, L_{max}$  = distances that define the range within which the critical gap varies from  $G_{max}^g$  and  $G_{min}^g$ ;  
 $L_{rem}$  = remaining distance to the point at which lane change must be complete; and,  
 $\epsilon_n$  = random term uniformly distributed (U{0.1,0.5}).

Same set of parameters were assumed for the lead and lag gap. They are shown in Table 4-4.

Table 4-4 The gap acceptance model parameters used in the original MITSIM

| Parameter        | Value |
|------------------|-------|
| $L_{min}$ , ft   | 500   |
| $L_{max}$ , ft   | 2000  |
| $G_{min}$ , sec. | 0.2   |
| $G_{max}$ , sec. | 0.5   |

The gap acceptance model used in MITSIM captures the fact that drivers become aggressive as they approach the point at which the lane change must be complete. However, the model has a major limitation from a behavioral point of view and does not capture the correlation between observations from the same driver.

The probability of acceptance of the gaps that were actually accepted (using the same FHWA data that was used for the gap acceptance model parameters estimation and for assessing the estimates in section 4.2.2) was estimated for each driver. Figure 4-7 shows a plot of the cumulative estimated probability. The mean estimated probability was 0.76. On 177 and 28 cases out of 286, the estimated probability was 1 and 0 respectively. The estimated probability was greater than 0.5 on 218 occasions. These are reasonable estimates. However, the median lag gap length is 15ft when the lag vehicle in the target lane travels at 50mph and the remaining distance to the point at which lane change must be complete is less than 500ft, and linearly increases to 18ft as the remaining distance

increases to 700ft. These values though, are not sensitive to the speed of the vehicle under consideration. For example, for a subject vehicle with 20mph speed and attempting to merge on the freeway, the estimated critical gap of 15ft may be very small considering that the lag vehicle in the target lane travels at 50mph.

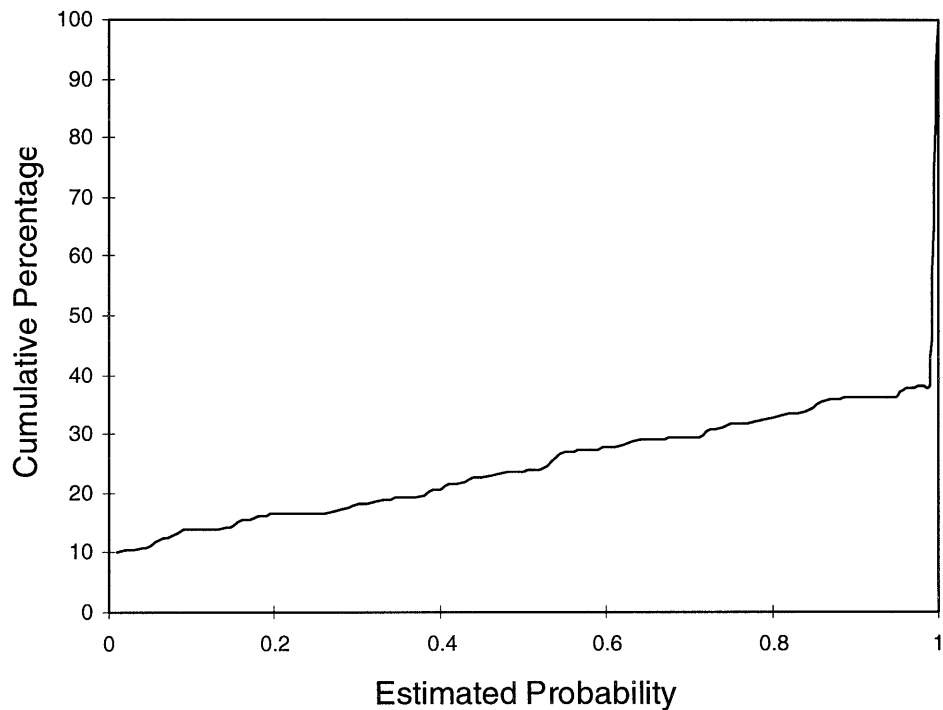


Figure 4-7 Cumulative estimated probability of acceptance of gaps that were actually accepted

#### 4.3.2 Number of Replications Necessary to Get an Estimate of Simulation Outputs and Measures of Goodness-of-fit

MITSIM uses stochastic driver behavior models. That is, some of the parameters that govern the nature of the movement of each vehicle are drawn from probability density functions in order to capture the non-homogeneity across the driving population. As a result, each simulation run generates different set of outputs (for example, speed, flow etc. at a certain section of the highway). Each set of output represents a sample.



Therefore, multiple samples or replications have to be collected to get estimates of simulated flows and speeds. These estimates represent mean measurement across all the replications for each time-space point.

Before describing the number of replications necessary or different measures of goodness-of-fit, it is necessary to identify an estimator of the simulated characteristic measure. Let,

$y_i$  = field observation of a characteristic measure at time-space point  $i$ ; and,

$y_{ir}^s$  = observation of that measure for time-space point  $i$  from the  $r$ -th run.

An unbiased estimator of the simulator generated characteristic measure is given by:

$$y_i^s = \frac{1}{R} \sum_{r=1}^R y_{ir}^s \quad (4 - 13)$$

where,

$y_i^s$  = average of characteristic measure across  $R$  replications for time-space point  $i$ ; and,

$R$  = number of replications.

Assuming that the simulation observations are drawn from a normal distribution with unknown variance, the required number of replications to produce a certain accuracy  $e$  at a certain level of significance  $\alpha$  is given by:

$$R = \left( \frac{s t_{\alpha/2}}{y_i^s e} \right)^2 \quad (4 - 14)$$

where,

$s$  = estimate of the standard deviation of the simulated characteristic measure of interest;

$t_{\alpha/2}$  = critical value of the of the  $t$  distribution at a significance level  $\alpha$ ; and,

$e$  = allowable error (in either positive or negative direction).

The normality assumption may not be realistic and therefore, the required number of replications estimated from the above equation should be used as a guideline. The values of  $s$  and  $y_i^s$  are estimates and therefore, the simulation has to be run several times to compute these estimates. Moreover, since there are many time-space points, the desired number of replications should be the most conservative value or the maximum over all the characteristics measures.

There are different measures of goodness-of-fit that can be used to compare the simulated data with field observations including:

- The root mean square error is given by:

$$rms\ error = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i^s - y_i)^2} \quad (4 - 15)$$

Where,  $N$  is the total number of time-space points. The rms error represents a measure of the deviation of the simulated measure from its actual counterpart. Another statistic is rms percent error, which is defined as

$$rms\ percent\ error = \sqrt{\frac{1}{N} \sum_{i=1}^N \left( \frac{(y_i^s - y_i)^2}{y_i^2} \right)} \quad (4 - 16)$$

- For each time-space point  $i$ , a percent error is given by:

$$d_i = 100.(y_i^s - y_i) / y_i \quad (4 - 17)$$

It represents the percent difference between the estimated simulated characteristic measure and the field observation for time-space point  $i$ . A positive percent error

indicates an over-prediction while a negative percent error indicates an under-prediction.

- When there are several time-space points it becomes difficult to judge whether there is any systematic under- or over-prediction. There are a number of univariate measures that serve this purpose, for example, mean percent error, mean positive percent error, mean negative percent error, maximum positive percent error, maximum negative percent error, number of positive errors and number of negative errors.

The mean percent error function over all time-space points is given by:

$$b = \frac{1}{N} \sum_{i=1}^N d_i \quad (4 - 18)$$

This measure represents an aggregate measure of any consistent under- or over-prediction across all time-space points.

The mean positive percent error is the mean across all observations exhibiting over-prediction and is given by:

$$p = \frac{1}{J} \sum_{j=1}^J d_j \quad (4 - 19)$$

where,

$j$  = index representing the time-space point at which the percent error  $d_j$  is positive; and,

$J$  = number of positive percent error.

Similarly, mean negative percent error is defined for all the observations showing under-prediction.

In addition to these statistical measures, a three-dimension plot of the percent error over time and space may be informative to identify if there are any systematic errors, for example, across a sensor station or during a certain time interval.

### 4.3.3 Validation

#### *Actual Freeway Data*

Aggregated data was obtained for a 6-mile stretch of I-880 in the vicinity of Hayward, California. The network, shown in Figure 4-8, has 4 on-ramps and 5 off-ramps (two of

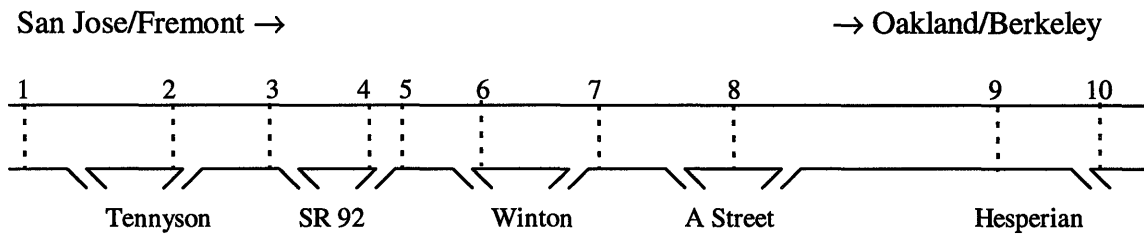


Figure 4-8 Schematic diagram of the network

(figure not drawn to scale and the numbers are sensor-station numbers)

them connecting I-880 with SR-92) and 10 sensor stations. Ten minute aggregated measures of mean speed and flow are available (see Table 4-5 and Table 4-6) for two hours and twenty minutes -- represented by 14 time intervals. Therefore, there are a total of 140 time-space observations.

Table 4-5 Observed mean speed in mph

| sensor station → | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  | 10 |
|------------------|----|----|----|----|----|----|----|----|----|----|
| no. of lanes →   | 5  | 4  | 5  | 4  | 6  | 5  | 5  | 5  | 5  | 5  |
| time interval ↓  |    |    |    |    |    |    |    |    |    |    |
| 1                | 58 | 58 | 56 | 60 | 58 | 59 | 61 | 60 | 25 | 40 |
| 2                | 57 | 58 | 54 | 58 | 58 | 60 | 62 | 60 | 23 | 35 |
| 3                | 53 | 54 | 52 | 56 | 55 | 58 | 60 | 58 | 40 | 34 |
| 4                | 54 | 55 | 52 | 57 | 55 | 58 | 59 | 59 | 44 | 37 |
| 5                | 54 | 38 | 47 | 55 | 53 | 55 | 56 | 57 | 41 | 35 |
| 6                | 55 | 22 | 47 | 57 | 55 | 59 | 60 | 58 | 41 | 38 |
| 7                | 57 | 27 | 48 | 57 | 55 | 59 | 61 | 61 | 54 | 41 |
| 8                | 57 | 44 | 48 | 57 | 56 | 59 | 60 | 60 | 55 | 41 |
| 9                | 58 | 28 | 49 | 59 | 56 | 60 | 62 | 62 | 57 | 40 |
| 10               | 60 | 43 | 49 | 58 | 55 | 59 | 60 | 60 | 59 | 41 |
| 11               | 61 | 60 | 57 | 61 | 57 | 62 | 62 | 62 | 58 | 40 |
| 12               | 60 | 59 | 55 | 62 | 59 | 62 | 63 | 63 | 61 | 43 |
| 13               | 60 | 60 | 58 | 62 | 59 | 62 | 62 | 63 | 62 | 44 |
| 14               | 61 | 61 | 58 | 62 | 60 | 62 | 62 | 62 | 63 | 38 |

Table 4-6 Observed flow in no. of vehicles per 10 minute interval

| sensor station → | 1    | 2   | 3    | 4   | 5    | 6    | 7    | 8    | 9    | 10   |
|------------------|------|-----|------|-----|------|------|------|------|------|------|
| no. of lanes →   | 5    | 4   | 5    | 4   | 6    | 5    | 5    | 5    | 5    | 5    |
| time interval ↓  |      |     |      |     |      |      |      |      |      |      |
| 1                | 925  | 857 | 973  | 777 | 1042 | 972  | 1055 | 1011 | 1059 | 986  |
| 2                | 938  | 856 | 988  | 792 | 1091 | 1019 | 1092 | 1018 | 1137 | 1063 |
| 3                | 1017 | 902 | 1011 | 838 | 1128 | 1055 | 1157 | 1072 | 1188 | 1147 |
| 4                | 1055 | 932 | 1077 | 864 | 1189 | 1108 | 1216 | 1160 | 1251 | 1153 |
| 5                | 1053 | 907 | 1023 | 811 | 1212 | 1149 | 1275 | 1210 | 1281 | 1214 |
| 6                | 1092 | 908 | 1091 | 827 | 1191 | 1120 | 1221 | 1166 | 1302 | 1202 |
| 7                | 1060 | 925 | 1086 | 868 | 1188 | 1069 | 1174 | 1071 | 1196 | 1139 |
| 8                | 1012 | 905 | 1064 | 833 | 1146 | 1089 | 1213 | 1128 | 1194 | 1108 |
| 9                | 1037 | 940 | 1077 | 830 | 1194 | 1063 | 1138 | 1033 | 1153 | 1109 |
| 10               | 940  | 851 | 1052 | 779 | 1126 | 1043 | 1174 | 1083 | 1111 | 1038 |
| 11               | 970  | 878 | 968  | 719 | 1056 | 970  | 1084 | 995  | 1101 | 1026 |
| 12               | 958  | 844 | 972  | 698 | 974  | 889  | 1005 | 942  | 1023 | 959  |
| 13               | 860  | 760 | 827  | 623 | 889  | 784  | 900  | 836  | 898  | 845  |
| 14               | 841  | 742 | 840  | 638 | 921  | 850  | 944  | 880  | 955  | 916  |

Most of the aggregated speeds are in the range of higher fifties to lower sixties mile per hour. At the first eight sensor stations, aggregated speed decreases around the 6<sup>th</sup> and 7<sup>th</sup> time intervals and then increases again in the later time periods. Sensor station 9 was initially congested but congestion disappeared gradually with time. Flow (Table 4-6) for all the sensor stations gradually increases as time elapses and again decreases later on.

As mentioned in Chapter 1, MITSIM requires, as input, time-dependent O-D trip tables. Using the method described in Ashok and Ben-Akiva (1993), time-dependent O-D matrices were estimated from the observed traffic flows and speeds (one for each 10 minute interval). Vehicles are then simulated in the network shown in Figure 4-8. To determine the number of replications necessary, the simulator was run 10 times to get estimates of mean and standard deviation of speeds and flows for all time-space points. The first time interval is treated as warm up period since the vehicles are loaded in an empty network and therefore, excluded from all further calculations. Therefore, the total number of time-space observations reduced to 130. The maximum of the number of replications required for all speed and flow estimates to attain a  $\pm 5\%$  accuracy with 95% confidence interval was ten for the original MITSIM and nine for the revised MITSIM (in which the proposed gap acceptance model is used). In subsequent analyses outputs from all 10 runs were used.

To assess the performance of the gap acceptance, two sets of simulated speed and flow were estimated -- one using the original MITSIM and one using the revised MITSIM. Vehicle counts and speeds obtained from the sensor stations were aggregated over ten minute intervals for each sensor station. Table 4-7 shows the summary of the comparison. The root mean square percent error of flow for the original MITSIM was 2.51 percent as opposed to 2.57 percent for the revised MITSIM and for speed the corresponding rms percent errors were 23.46 and 24.33 percent respectively. Therefore, both the simulators replicated flow very well. A plot of the percent error for flow is shown in Figure 4-9 for the revised MITSIM and in Figure 4-10 for the original MITSIM. There is no

Table 4-7 Summary statistics of the comparison of the original  
 MITSIM and the revised MITSIM

| STATISTICAL MEASURE                | FLOW               |                   | SPEED              |                   |
|------------------------------------|--------------------|-------------------|--------------------|-------------------|
|                                    | original<br>MITSIM | revised<br>MITSIM | original<br>MITSIM | revised<br>MITSIM |
| root mean square percent error (%) | 2.51               | 2.57              | 23.46              | 24.33             |
| root mean square error (veh/10min) | 26.43              | 27.26             | 10.78              | 11.47             |
| mean percent error (%)             | -0.57              | -0.52             | -7.07              | -8.59             |
| average positive error (%)         | 1.86               | 1.88              | 29.17              | 31.99             |
| number of positive error           | 47                 | 51                | 26                 | 23                |
| maximum positive error (%)         | 6.55               | 6.21              | 120.83             | 119.85            |
| average negative error (%)         | -1.95              | -2.07             | -16.14             | -17.31            |
| number of negative error           | 83                 | 79                | 104                | 107               |
| maximum negative error (%)         | -7.58              | -7.89             | -44.94             | -45.24            |

persistent trends across either space or time. The root mean square error for flow was 26.43 and 27.26 veh/10min for the original and the revised MITSIM respectively. The root mean square error for speed was 10.78 and 11.47 mph for the original and the revised MITSIM respectively. The mean percent error for flow were less than one for both simulators. For speed, the original MITSIM exhibited a negative 7.07 mean percent error and the revised MITSIM exhibited a negative 8.59 mean percent error -- both exhibiting under-prediction of speed. This is also obvious from the plot of the percent error for speed shown in Figure 4-11 for the revised MITSIM and in Figures 4-12 for the original MITSIM. However, there are no persistent trends across either space or time. On 80 and 64 percent of the cases the original simulator under-predicted speed and flow respectively, and on 82 and 61 percent of the cases the revised simulator under-predicted speed and flow respectively.

## **4.4 Conclusions**

The estimated model shows that the lag critical gap progressively decreases as the distance to the point at which lane change must be complete decreases and as the speed matches with those in the target lane. Near the downstream end of the acceleration lane the median value becomes too small – this reflects that drivers become desperate at those points to complete merging. The other important explanatory variables were indicator for the first gap and delay in completing the lane change maneuver.

Although, the proposed gap acceptance model performed slightly worse than a naive gap acceptance model when tested using MITSIM, the estimated gap acceptance model parameters not only have the desired statistical properties, but they seem to replicate the behavioral aspect of the gap acceptance process reasonably well. Hence, we expect it to have more consistent performance and be easier to transfer to different networks.



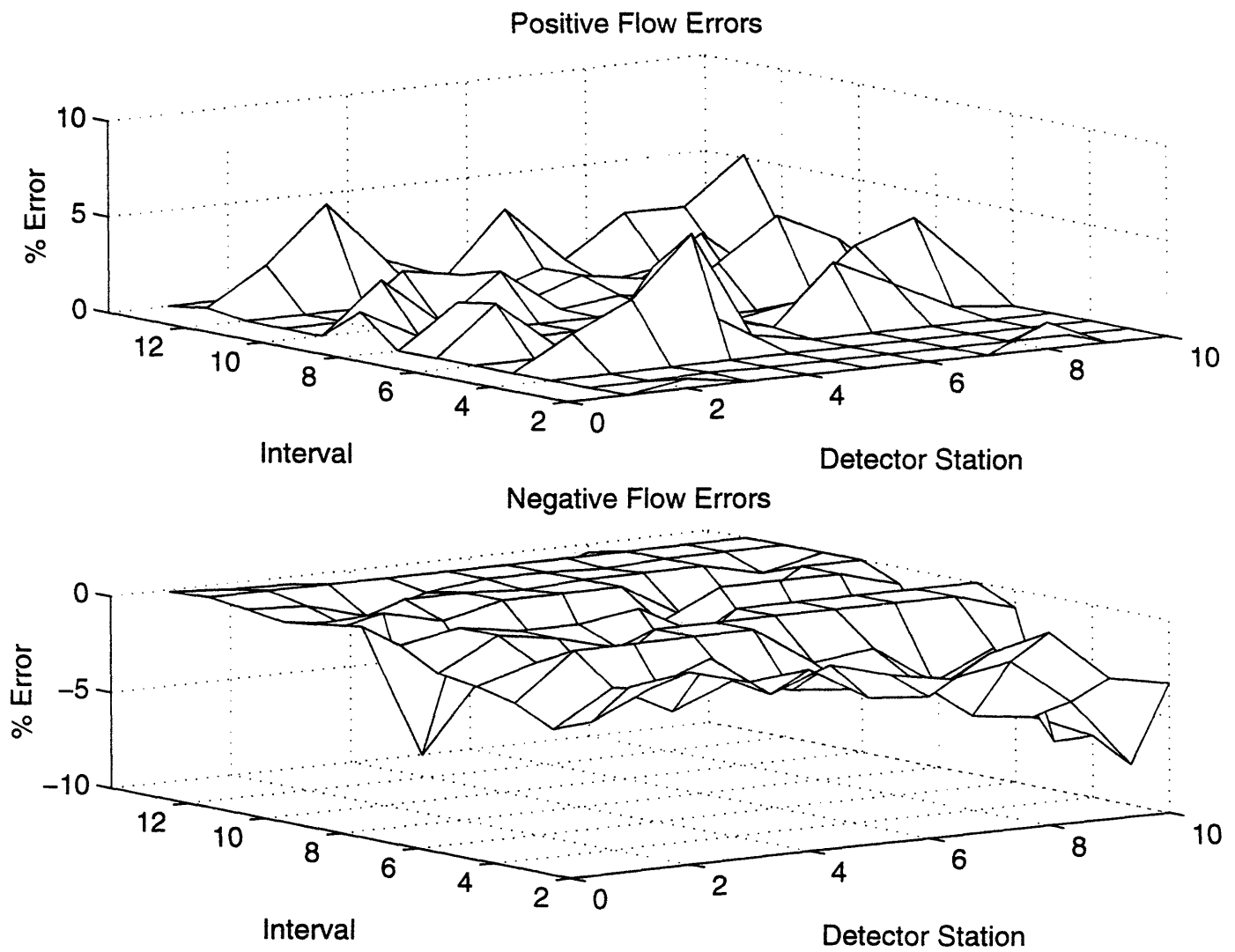


Figure 4-9 Flow Percent Error for the Revised MITSIM

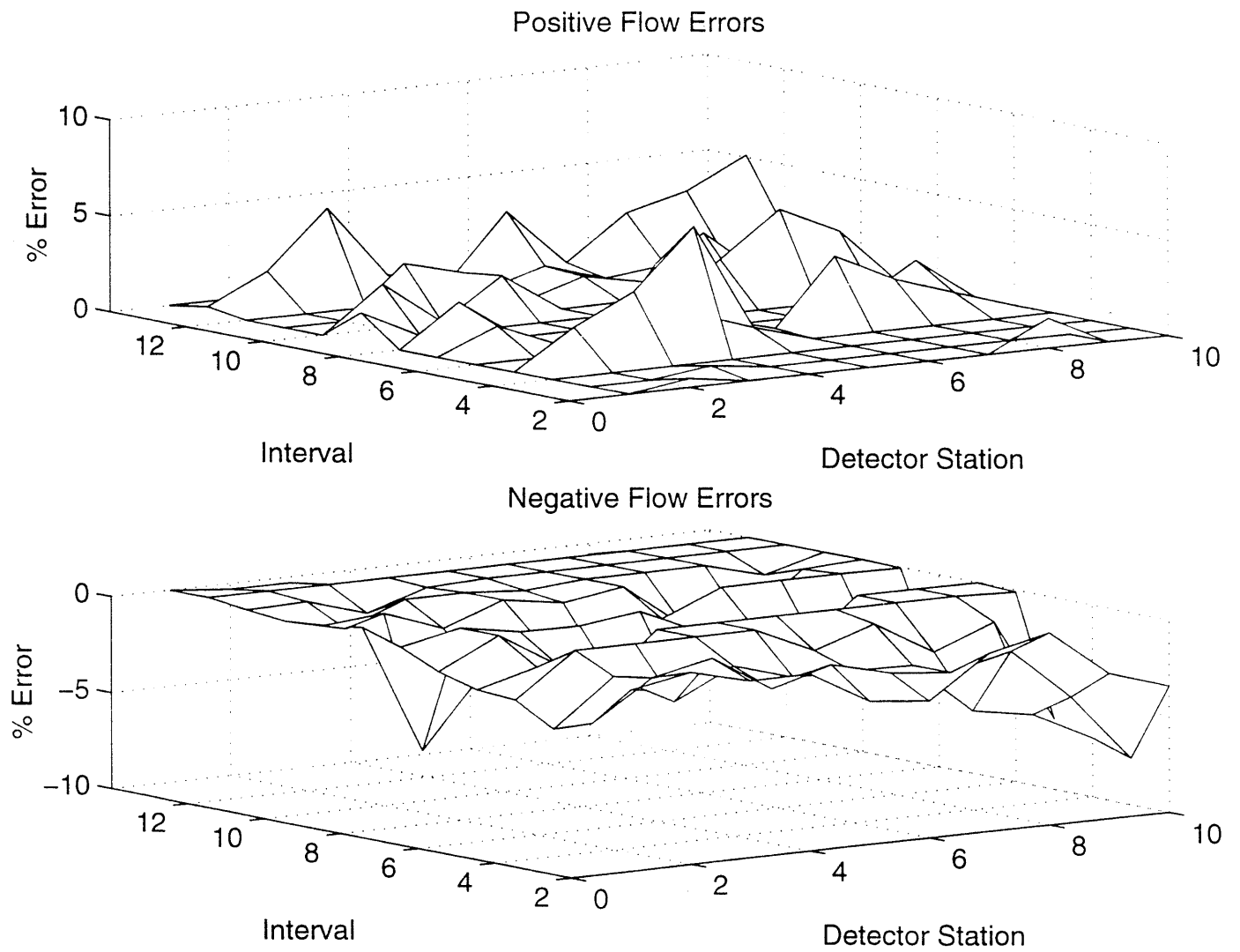


Figure 4-10 Flow Percent Error for the Original MITSIM

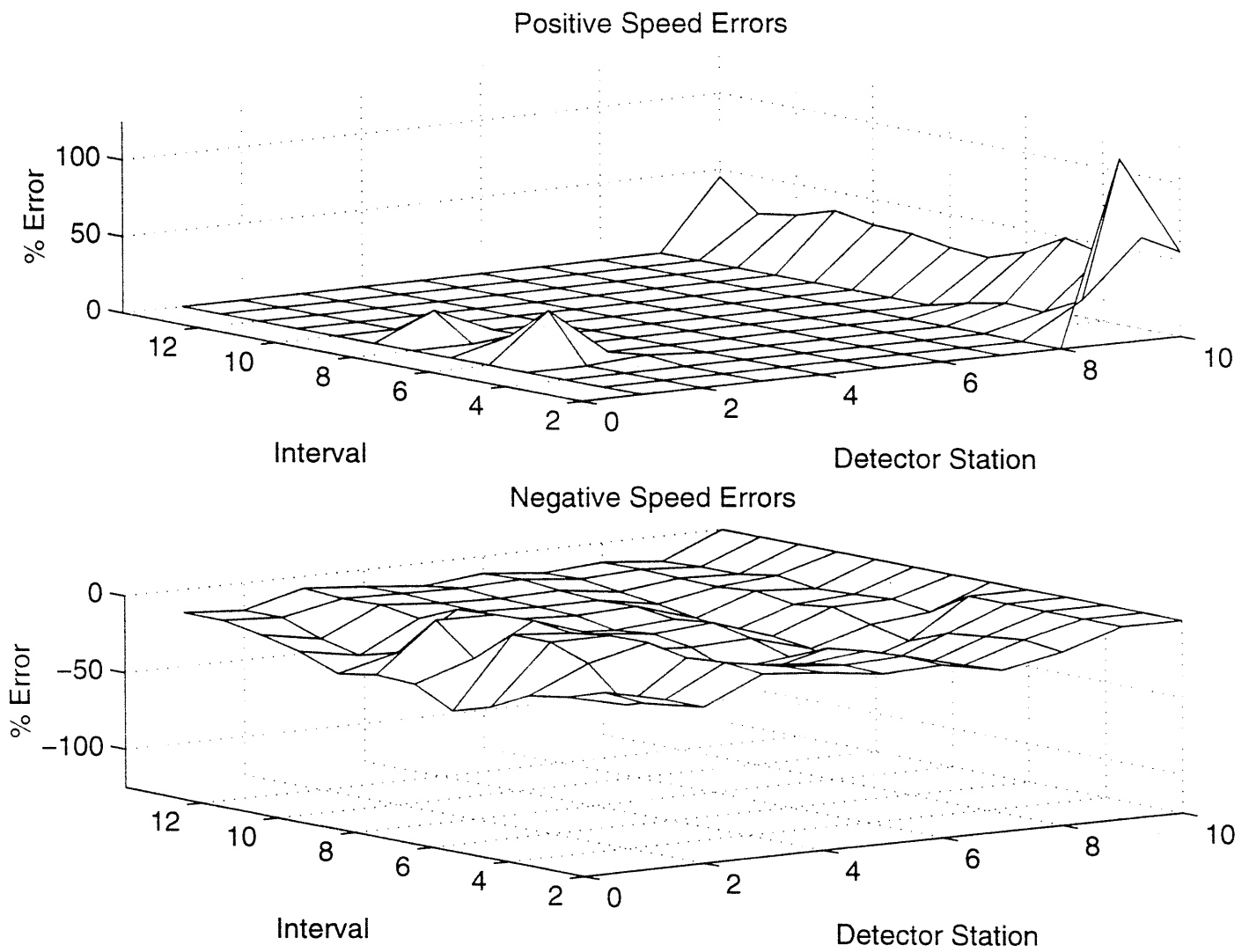


Figure 4-11 Speed Percent Error for the Revised MITSIM

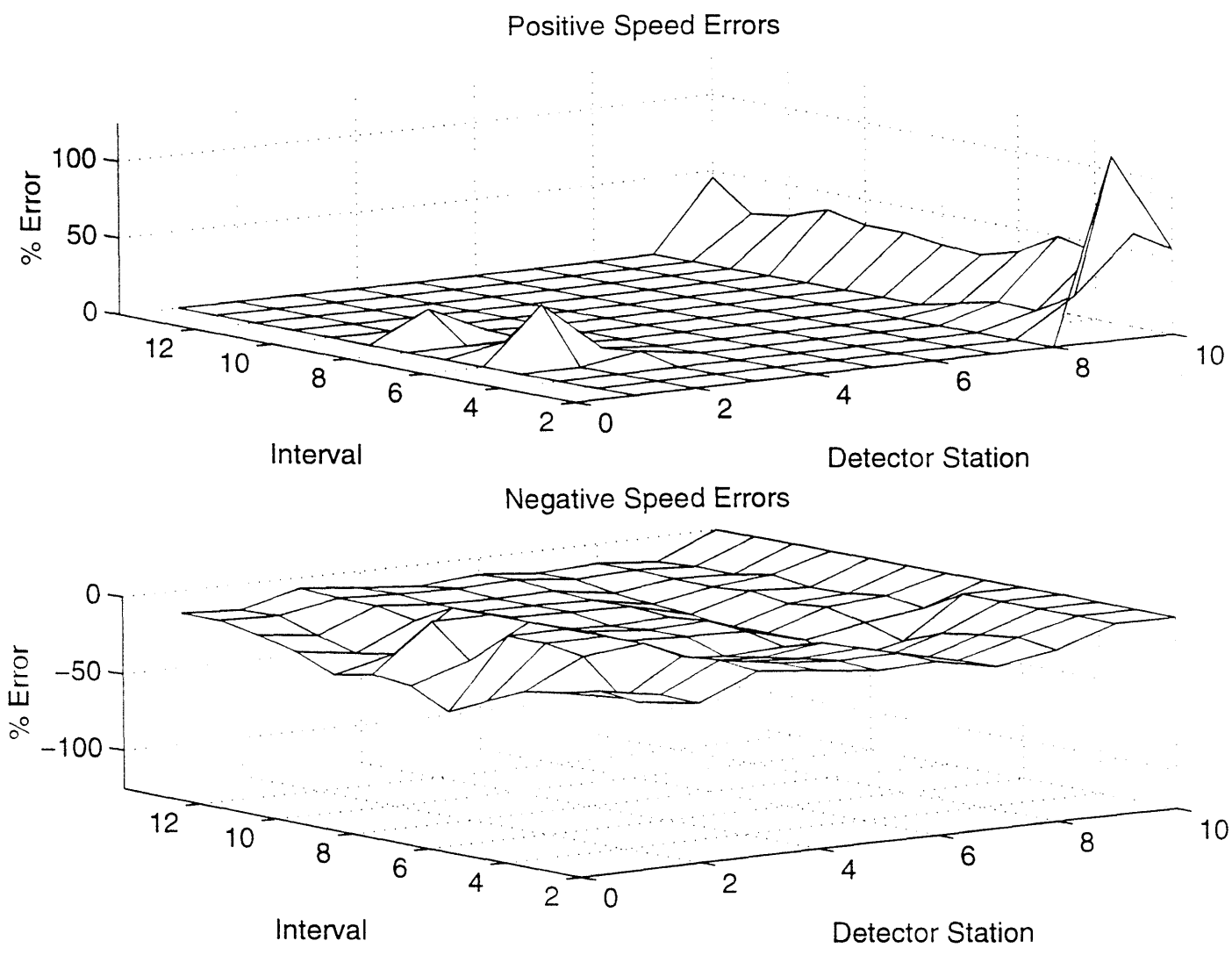


Figure 4-12 Speed Percent Error for the Original MITSIM

# **CHAPTER 5**

## **CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS**

This chapter summarizes the conceptual framework of the proposed lane changing model structure with the major contributions of this research and discusses directions for future research.

### **5.1 Summary of the Proposed Lane Changing Model**

Four activities take place during lane changing:

- decision to consider a lane change;
- choice of left or right lane;
- accepting a gap in the desired lane; and,
- performing the lane change maneuver.

Except for the action of changing lanes, the lane changing process is latent. The proposed model captures this fact and combines the decision part as well as the execution part of the lane change process in an integrated framework. The proposed model also allows for simultaneous estimation of the parameters of all the component models.

Different drivers respond to such a requirement differently (non-homogeneity in driver behavior) and furthermore, a driver may not respond identically at all times (inconsistency in driver behavior). The proposed model captures these characteristics of driver behavior by using appropriate discrete choice framework.

First, drivers check whether a lane change is necessary or desirable. If a lane change is necessary (mandatory lane change), the drivers respond to it immediately or delay the

response. If a decision is made to change lanes and both adjacent lanes are possible target lanes, the best lane is selected probabilistically. There are certain factors that make a lane attractive to a driver, for example, proximity of the lane speed to the driver's desired speed, and certain factors that make a lane unattractive to a driver, such as presence of heavy vehicles. The proposed model utilizes a discrete choice framework that allows for modeling these considerations simultaneously without prespecifying a priority to any factor.

The proposed gap acceptance model recognizes the importance of both the lead and the lag gaps for freeway merging. The model also captures the fact that, if an acceptable gap is found in the target lane, a lane change may not take place immediately due to, for example, reaction time and maneuver time.

## **5.2 Conclusions**

The proposed model was applied to a special case of merging from a freeway on-ramp. In this case, the lane changing model reduces to a simple gap acceptance model. Possible observable outcomes are change to the adjacent freeway lane and continue in the current (acceleration) lane. A *change to the freeway lane* can be observed only if an acceptable gap is found in it and lane change maneuver is completed.

The model was estimated using a data set provided by the FHWA (Smith, 1985). The site was a two-lane freeway with a weaving section on the right. Only drivers traveling from the upstream end of the weaving section and merging with the mainline were considered. State dependence was also captured since a well defined starting point for the process (that is the instant when the gap searching process started) was available.

The lead critical gap was found to be less sensitive to traffic conditions compared to the lag critical gap. The latter was found to be a function of the relative speed (with respect to the lag vehicle in the target lane), remaining distance to the point at which lane change

must be complete, and whether the gap was the first gap being considered or not. Across driver variance of the lead critical gap was found to be significantly lower than that of the lag critical gap. State dependence was captured by the variable delay. Delay is defined as the time elapsed since the gap searching process began. More delay makes a driver impatient and hence more aggressive, and the estimated parameter was found statistically significant.

To assess how the model replicates the actual process, the probability of acceptance of gaps that were actually accepted was estimated. The mean of the estimated probabilities was found to be 0.61 and the median or the 50 percentile probability was 0.60 -- which seems satisfactory. In addition, the median lead and lag critical gap length were estimated. The median lead critical gap was 15ft -- a reasonable value. The median lag critical gap changes with changing driving conditions. The value was extremely high when a driver just started traveling in the acceleration lane, essentially making it unlikely to accept the gap observed in the first time period. The median lag critical gap then progressively decreases as the driver travels in the acceleration lane depending on the driving conditions and position in the acceleration lane. When a driver approaches the downstream end of the acceleration lane the median lag critical gap becomes too small implying that drivers would be very aggressive in those regions.

The gap acceptance model was validated using simulation. MITSIM, the microscopic traffic simulator developed at MIT, was used to simulate a 6 mile stretch of I-880 in the vicinity of Hayward, California. Real data (speed and flow aggregated over 10 minutes time interval for all 10 sensor stations for a period of 2hrs and 20minutes) for this network was available and was used to validate the gap acceptance model. The output from two versions of MITSIM -- the original MITSIM and a revised MITSIM in which the gap acceptance model was applied only for merging from freeway on-ramps -- were compared with the real data. The root mean square percent error of flow for the original MITSIM was 2.51 percent as opposed to 2.57 percent for the revised MITSIM and for speed the corresponding rms percent errors were 23.46 and 24.33 percent respectively. Both the

simulators replicated flow very well. For speed, the original MITSIM exhibited a -7.07 mean percent error and the revised MITSIM exhibited a -8.59 mean percent error -- both exhibiting high under-prediction of speed. Although MITSIM with the proposed gap acceptance model performed marginally worse, the proposed model parameters have desirable statistical properties and its specification is reasonable from a driver behavior point of view. Hence, its performance should be more consistent compared to the gap acceptance model used in the original MITSIM.

### **5.3 Contributions**

In this thesis, a lane changing model is presented that uses a discrete choice framework. The framework has the following unique features:

- It is an integrated model that combines the lane changing decision process and the execution of the decision (that is the gap acceptance process);
- It models explicitly the elements of the roadway and traffic environment that have an effect on driver behavior;
- It allows for simultaneous estimation of the parameters of the two submodels -- the decision to change lanes and choice of left or right lane, and the gap acceptance model;
- It captures inconsistency and non-homogeneity in the driver population by formulating appropriate random terms;
- It models heterogeneity in the driver population; and,
- It has the flexibility to incorporate the impact of future technologies on driver behavior, for example, impact of red lane use sign on drivers' lane changing decision.

The gap acceptance model can be used for evaluating capacity and delays at intersections and ramps. The lane changing model can be used for developing geometric standards, such



as the length of a weaving section, and the length of an acceleration lane, and assessing capacity at weaving sections.

## **5.4 Future Research Directions**

The research presented in this thesis can be extended in several directions:

- Further testing is required to assess the performance of the estimated gap acceptance model and the integrated lane changing model still needs to be estimated for the general case;
- The entire lane change decision process is latent in nature. The exact time at which the decision to change lanes takes place cannot be observed (except for a mandatory lane change involving merging from a freeway on-ramp). Using a probabilistic framework to model all possibilities that may lead to changing lanes is computationally infeasible. For example, if a driver is observed once each second and at the 20th second a lane change is observed, the decision to change lanes may have been taken anywhere between the first to the nineteenth second. In addition, it might happen that the driver made the decision to change lanes and gave up -- which cannot be observed. Various modeling approaches and approximations should be considered in order to address these issues.
- Interaction between drivers' lane change behavior and acceleration behavior is lacking in the current model. For example, to fit into a gap a driver may need to decelerate or accelerate, or, to avoid applying a very high deceleration a driver may take a quick decision to change lanes. A comprehensive driver behavior model has to be formulated that captures the interactions between drivers' lane change and acceleration decisions.

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